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Changing Midstream

Providing Decision Support for Adaptive Strategies using Robust Decision Making: Applications in the Colorado River Basin

Evan W. Bloom
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This document was submitted as a dissertation in December 2014 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Rob Lempert (Chair), David Groves, and Craig Bond.
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Abstract

Climate change in the American West, including the Colorado River Basin, presents a new policy problem for natural resource planners (Groves, Davis et al. 2008). A wide range of conditions may unfold over an extended time horizon (Brekke, Dettinger et al. 2008) but scientists, stakeholders, and planners have not formed consensus regarding what the future may hold (Deser, Knutti et al. 2012). Increasingly, water agencies recognize that adaptive strategies, designed to evolve in response to new information, may yield better solutions for climate change than strategies not designed to take advantage of learning (National Academy of Sciences 2011). Such strategies can also allow stakeholders to reach consensus by deferring some contentious decisions until later when more is known (Lempert, Popper et al. 2003). However, adaptive strategies are complex. Planners still must make choices among near-term actions, contingencies, and responses to new information (Walker, Rahman et al. 2001). As many choices are deferred until later, these strategies require a framework in which planners can integrate new information into an analytic process that supports on-going deliberations (National Research Council 2009, Swanson, Barg et al. 2010).

Effective decision support is thus necessary to support the development of adaptive strategies, as planners consider near-term actions and prepare for future deliberations.

In this dissertation, I examine how Robust Decision Making (RDM) (Lempert, Popper et al. 2003) can provide decision support to planners as they create, evaluate, and deliberate about adaptive strategies. I provide a discussion of the structure of adaptive strategies, the choices that planners face when crafting an adaptive strategy, and the role that RDM can play in supporting planners’ decisionmaking. I present a model describing RDM’s application to policy contexts with multiple time-periods for decisionmaking and a mathematical definition of adaptive strategies. I then provide a policy application, extending a recent analysis for the Colorado River Basin Study (U.S. Bureau of Reclamation 2012f, Groves, Fischbach et al. 2013). This analysis first explores choices that planners may make when considering how to respond to new information and tradeoffs between alternative responses. I also generate planning scenarios, identifying the conditions under which specific near-term actions or contingencies are necessary and long-term implementation schedules perform well. Finally, I propose a naïve-Bayes’ model to assist planners in integrating new information with their current beliefs, providing guidance on what information in the next decade may cause them to adjust the strategy.
Executive Summary

Introduction
The Colorado River is the single most important source of water in the southwestern United States, providing water and power for nearly 40 million people and water to irrigate more than five million acres of farmland across seven states and for 22 Native American tribes (Smerdon, Betancourt et al. 2007, U.S. Bureau of Reclamation 2012f). Water from the Colorado River is apportioned to users in the seven Colorado River Basin States according to a series of federal laws and agreements, beginning with the Colorado River Compact of 1922. This agreement allocates 15 million acre-feet (maf) of water equally between the Upper Basin States (Colorado, New Mexico, Utah, and Wyoming) and the Lower Basin States (Arizona, California, and Nevada).

Water delivery in the Basin is increasingly threatened by increasing demand and deeply uncertain future supply. It has become clear in recent decades that the River was significantly over allocated when the Compact was signed. Flow measurements over the hundred-year period of record from 1906 to 2005 show an average flow of about 15 maf per year, not 16.4 as was assumed in the Compact. The paleoclimatological record (time periods prior to direct measurement of flow) show even dryer conditions than the recent historical record; natural flow over a time span of more than a thousand years ranged from 13.5 to 14.7 maf per year (Stockton and Jacoby 1976, Woodhouse 2003, Woodhouse, Gray et al. 2006, Meko, Woodhouse et al. 2007). Additionally, recent climate research suggests that the Colorado River Basin will face a new hydrologic regime (Milly, Betancourt et al. 2008), climate change will lead to persistent drying in the Southwest (Nash and Gleick 1993, Christensen and Lettenmaier 2007, Seager, Ting et al. 2007). Although these studies vary in their estimates, most suggest an average streamflow reduction of 10 to 20 percent over the next 50 to 100 years (Groves, Fischbach et al. 2013).

To begin the process of planning for an uncertain future, the seven Basin States and the U.S. Bureau of Reclamation collaborated to evaluate the ability of the river to meet water delivery and other objectives across a range of future conditions, publishing the Colorado River Basin Supply and Demand Study (U.S. Bureau of Reclamation 2012f) in 2012. This extensive report examines how demand, supply, and operations of the reservoirs may change over the next half century. It identifies the vulnerabilities of the current management of the system and evaluates the potential for water management actions to address those vulnerabilities.

Among the many important issues explored in the Basin Study is a tradeoff between water delivery reliability and the cost of water management actions. The study analyzed various water management actions—each with potential to increase water delivery reliability (and help meet other objectives) to some degree but at some level of effort or associated cost. The Basin Study identified that different plausible hydrologic futures have different needs (U.S. Bureau of Reclamation 2012e). Thus, strategies that evolve in response to new information—adaptive strategies—can offer a mechanism to address water delivery as necessary in each future while avoiding over-investment in others. The Basin Study employed a decision analytic approach
referred to as Robust Decision Making (RDM) to identify the vulnerabilities of the system and evaluate some adaptive strategies across a broad range of plausible future conditions.

During the Basin Study process, planners invested in tools to model and evaluate strategies that change over time. However, as the planning continues, there remains an opportunity for new tools and techniques to inform decisions about the water management actions explored in the Basin Study over a long-term planning horizon and how observations of relevant information will be integrated into those decisions.

This dissertation extends the analysis of adaptive strategies in the Basin Study to address the following policy questions:

- How do various adaptive strategies perform in the Colorado River Basin and how can planners choose among them?
- When must planners make decisions about water management actions and under which conditions should the actions be implemented?
- What information might planners observe in the next decades that would make them believe actions beyond those considered in the Basin Study are necessary?

To address these questions, this dissertation presents an approach for iteratively repeating an RDM analysis to provide decision support when generating and evaluating adaptive strategies. To do so, it draws on lessons from other disciplines such as economics and engineering to describe the structure of adaptive strategies. It presents a number of decision aids that can help planners choose among actions and the decision-rules that would define when actions are to be implemented.

The analysis reveals a number of key policy insights. First, the findings suggest that if planners wish to prepare for the driest futures, consistent with recent climate change projections, planners should implement water management actions in seemingly normal years. If planners believe drying conditions are likely in the long run, individual years with streamflow near the historical average do not constitute sufficient evidence that the driest futures are not occurring. Additionally, this dissertation identifies that over the next decade, planners cannot rule out that the driest scenarios are occurring solely from observations of streamflow. If some planners believe the driest futures are likely, observations high streamflow conditions would need to be paired with strong evidence in the supporting climate literature to overcome this prior belief.

**Methodology**

Strategies that evolve in response to new information, can be considered adaptive strategies (Lempert, Popper et al. 2003), and there is an emerging consensus that they can help address climate change (National Academy of Sciences 2011). These strategies are "sequential combinations of policy options. Some options are to be implemented right away; others are designed to be implemented at an unspecified time in the future or not at all if conditions are inappropriate. The policy includes contingency plans as well as a specification of conditions under which the entire policy should be reconsidered. The policies themselves are, therefore, designed to be incremental, adaptive, and conditional" (Walker, Rahman et al. 2001).
This definition of adaptive strategies is similar to a structure of a closed-loop system as described by control theory, a branch of engineering that considers systems with feedback. Control theory describes that planners may choose to implement actions—the control variables—while they monitor the system—using state variables. Control theory uses computational methods such as dynamic programming help planners identify the optimal decision-rules. Dynamic programming reveals an insight important to any application of adaptive strategies: the decisions about actions in early time periods will interact with decisions in future periods. One cannot make decisions about actions in the near term without considering the decisions in future periods.

However, dynamic programming and other tools used in control theory require strong assumptions about the probabilities of future events. In problems such as climate change, planners and stakeholders may not agree on the likelihood of future events, a condition referred to as deep uncertainty. RDM is a methodology designed to facilitate the exploration of strategies across a range of different beliefs about the future.

The RDM process begins with a decision structuring step in which planners define the goals, uncertainties, and policy choices under consideration. Analysts then use computer models to generate a large database of simulation runs in which each case represents the performance of a proposed policy in one plausible future. Computer visualization and statistical analysis of this database help planners identify clusters of scenarios that illuminate the policies’ vulnerabilities. These scenarios can then help planners identify potential new ways to address those vulnerabilities or evaluate through trade-off analysis whether these choices are worth adopting. The process continues until planners settle on a robust strategy (Lempert, Popper et al. 2013). This dissertation describes how multiple iterations through the RDM process can be used to support the creation and evaluation of adaptive strategies, shown in Figure S-1.

*Figure S-1: Expanded RDM process to generate adaptive strategies with multiple iterations*
In the first iteration through the RDM process, analysts and planners consider some baseline strategy—either the current management of a system or some other predefined default strategy. They work through the RDM process to generate scenarios that define when alternative actions are necessary. In the process proposed in this dissertation, the vulnerability analysis is expanded to identify early indicators that a scenario is likely—the signpost variables.

Using this information, planners and analysts return to the scoping phase and begin a second iteration. In this second scoping phase, they develop new strategies that include decision-rules that determine when planners enact new policy actions over the course of a planning horizon based on observations of signpost variables. Next, they work through the RDM process to evaluate these adaptive strategies. They may repeat this step multiple times, identifying vulnerabilities and iteratively testing new decision-rules as necessary.

Planners will then consider the tradeoffs among various strategies, and this dissertation proposes two analyses to assist planners as they choose a strategy. The first analysis helps planners consider tradeoffs among alternative decision-rules. Planners face a choice about how they respond to new information, and these choices are represented in a simulation model with alternative decision-rules. Their choices depend on assessments of the costs and benefits of responding to new information and their own subjective beliefs about the future. The first analysis helps quantify these costs and benefits across a range of plausible beliefs, allowing to planners consider which strategies adequately balance the tradeoffs they face.

The second analysis assists planners as they consider which actions to implement and when to implement those actions over the course of the planning horizon. Rather than relying on decision-rules in a model, which may be dependent on specific assumptions about timing and information available, an additional analysis characterizes implementation in a more generalizable form. Planners can receive aids to help them consider the choices among actions, the exogenous conditions that require implementing those actions, and the points in time at which key decisions will need to be made.

**Developing Adaptive Strategies in the Basin**

**Factors of Analysis**

The scope of an RDM analysis can be defined by the uncertainties considered (X), the levers available to planners to address challenges (L), the measurements which define the whether a policy meets or fails to meet objectives (M), and the relationships between them (R). The factors of analysis considered in the dissertation are described below.
<table>
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<th>Management Strategies and Portfolios (L)</th>
</tr>
</thead>
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<td>Current Management</td>
</tr>
<tr>
<td>• Recent historical record (103 futures)</td>
<td>Portfolio of Conservation, Desalination, Reuse, and other water management actions</td>
</tr>
<tr>
<td>• Statistical blend of the recent historical record and the paleoclimatic record (500 futures)</td>
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</tr>
<tr>
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<td>• <em>Baseline</em> adaptive strategy (using some triggers identified in the Basin Study)</td>
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<tr>
<td></td>
<td>• Adaptive Strategies defined by other triggers along a continuum of conservative to aggressive</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Relationships or Systems Model (R)</th>
<th>Performance Metrics (M)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colorado River Simulation System (CRSS)</td>
<td>Upper Basin Water Delivery reliability</td>
</tr>
<tr>
<td>• Simulated Planning Agent</td>
<td>Lower Basin Water Delivery Reliability</td>
</tr>
<tr>
<td></td>
<td>Annual Yield</td>
</tr>
<tr>
<td></td>
<td>Annual Total Cost</td>
</tr>
</tbody>
</table>

This analysis examines uncertainty (X) in future climate and hydrologic conditions. The performance of the system is analyzed for 715 plausible streamflow futures, drawn from the analysis in the Basin Study (U.S. Bureau of Reclamation 2012b). The ensemble contains futures drawn from three different sources. The first source is the recent historical record (103 futures). The second source is a statistical blend of the recent historical record and the paleoclimatic record (500 futures). The third source is derived from the projections of future climate conditions from 16 global climate models and three global carbon emissions scenarios. Each future is derived from downscaled results from a single GCM projection (112 futures).

This dissertation uses the Bureau of Reclamation’s long-term planning model (R), the Colorado River Simulation System (CRSS), to evaluate the performance of the system. CRSS simulates operations at a monthly time-step from 2012-2060, modeling the network of rivers, demand nodes, and 12 reservoirs with their unique operational rules. This model also contains representations of the various water management actions that planners may consider implementing (L): municipal and industrial conservation, agricultural conservation, reuse, desalination, and others. CRSS was also modified for the Basin Study to simulate the process of planners acting adaptively. It includes a simple simulated planning agent that observes information and implements water management.
actions over the course of a simulation. This planning agent monitors past observations of streamflow and reservoir levels on an annual basis, which serve as signpost variables. If the signpost variables drop below predefined trigger values, the planning agent implements the next available water management action from a prioritized list.

This analysis focuses on just two of the many policy objectives (M) considered in the Basin Study: Upper and Lower Basin water delivery reliability. Upper Basin water delivery is measured by the ability to deliver an average of 7.5 maf per year to Lee Ferry, AZ, a condition outlined in the Colorado River Compact (1922). Deliveries to the Lower Basin states are closely tied to the pool elevation of Lake Mead. As such, Lower Basin water delivery is measured by Lake Mead elevation. Any future where Lake Mead’s elevation drops below 1000 feet in one or more years is considered vulnerable (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013). To measure the cost and level of effort associated with meeting the water delivery objectives, this analysis also tracks the total annual yield of actions implemented and the annual total cost of those actions.

**System Vulnerabilities**

The Basin Study identified a set of streamflow conditions where the current management of the system fails to meet water delivery objectives—referred to as a decision-relevant scenario. This dissertation identified an additional set of decision-relevant scenarios that describes when even the most expansive set of actions (referred to as Static Implement-All-Actions strategy) would fail to meet the water delivery objectives. These are described in Table S-2.
Table S-2: Definitions of decision-relevant scenarios to describe vulnerabilities of various strategies in Upper and Lower Basin

<table>
<thead>
<tr>
<th>Business-as-Usual Scenario (Current management meets objective)</th>
<th>Upper Basin decision-relevant scenarios</th>
<th>Lower Basin decision-relevant scenarios</th>
</tr>
</thead>
</table>
| **Low Historical, Stationary, or Increasing Supply** | • Long-term average streamflow > 13.8 maf or  
• Minimum eight-year rolling average streamflow > 11.2 maf | **Stationary or Increasing Supply**  
• Long-term average streamflow > 15.0 maf or  
• Minimum eight-year rolling average streamflow > 13.0 maf |

<table>
<thead>
<tr>
<th>Adaptive scenario (Actions in portfolio can meet objective)</th>
<th>Declining Supply</th>
<th>Low Historical Supply</th>
</tr>
</thead>
</table>
| • Long-term average streamflow < 13.8 maf and  
• Minimum eight-year rolling average streamflow < 11.2 maf and  
• Long-term average streamflow > 12.9 maf or  
• Minimum eight-year rolling average streamflow > 10.2 maf | • Long-term average streamflow < 15.0 maf and  
• Minimum eight-year rolling average streamflow < 13.0 maf and  
• Long-term average streamflow > 12.9 maf or  
• Minimum eight-year rolling average streamflow > 10.2 maf |

<table>
<thead>
<tr>
<th>Transformative scenario (Actions in portfolio fail to meet objective)</th>
<th>Severely Declining Supply</th>
<th>Severely Declining Supply</th>
</tr>
</thead>
</table>
| • Long-term average streamflow < 12.9 maf and  
• Minimum eight-year rolling average streamflow < 10.2 maf | • Long-term average streamflow < 12.9 maf and  
• Minimum eight-year rolling average streamflow < 10.2 maf |

The conditions where the current management strategy is likely to meet objectives represent business-as-usual scenarios. Should planners believe these scenarios are likely, they can expect to meet the two objectives considered in this dissertation with the current management of the system and would not need to implement new actions or otherwise adapt to maintain these particular measures of water delivery reliability.

The scenarios where the system meets water delivery objectives with the Static Implement-All-Actions strategy but the not with the Current Management strategy (Declining Supply in the Upper Basin and Low Historical in the Lower Basin) represent adaptive scenarios. If these scenarios occur and planners maintain current management of the system in these futures, then the Basin will likely fail to meet water delivery objectives. However, the set of available actions provides the potential to
meet objectives. If managed properly, planners can address the challenges with the set of actions considered in the Basin Study. Should these conditions occur, planners could likely engage in a process of adaptation. Though such management is possible, it may be difficult. This dissertation examines the process of adapting to address this scenario.

The scenarios where the system does not meet water delivery objectives even after implementing the Static Implement-All-Actions strategy (Severely Declining Supply conditions in both regions) may be considered the transformative scenarios. Should these conditions occur, planners are still unlikely to meet the water delivery objectives after implementing a large yield of additional water conservation and many expensive infrastructure projects. They would need to look beyond the current set of solutions. This may require new strategies such as different allocations of water or reconsidering the objectives of the policy as whole, for example, relaxing the constraints imposed by the Colorado River Compact.

**Adaptive Strategies**

In the Basin Study and this dissertation, adaptive strategies are modeled in CRSS through a simple simulated planning agent. This agent monitors signpost variables on an annual basis. If the reservoirs' pool elevation and the previous five years of observed streamflow drop below predefined trigger values, the planning agent implements the next available water management action from a prioritized list (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

As an example, Figure S-2 illustrates how the simulated planning agent observes signpost variables, triggers new actions, and alleviates an impending failure to meet Lower Basin water delivery objectives. The dark line shows Lake Mead’s elevation with the Current Management strategy where Lake Mead first drops below 1,000 feet in 2041. The orange line represents the same future streamflow conditions, but with the Baseline adaptive strategy—using the triggers evaluated in the Basin Study—in place. When the planning agent observes a trigger value, in a year demarked by a triangle, it implements a water management action. Over time, the simulated planner observes multiple trigger values. As conservation and additional supply come on-line, Lake Mead’s elevation diverges from the elevation with the Current Management strategy. However, in this particular future, the strategy does not observe sufficient signposts or implement the necessary actions to avoid Lake Mead dropping below 1000 feet. A more aggressive strategy (green line), with higher trigger values, implements more actions sooner, and allows the Lower Basin to meet its water delivery objectives.
Table S-3 lists the candidate adaptive strategies developed in this dissertation. These strategies were developed primarily through iteration. These strategies produce results that range from nearly no increased resilience from the Current Management to a strategy that more closely resembles the Static Implement-All-Actions Strategy.
Table S-3: Trigger values for candidate adaptive strategies. Additional actions taken when both triggers are observed.

<table>
<thead>
<tr>
<th></th>
<th>Upper Basin</th>
<th>Lower Basin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lake Powell Elevation</td>
<td>Lake Mead Elevation</td>
</tr>
<tr>
<td></td>
<td>5-year average streamflow at Lees Ferry</td>
<td>5-year average streamflow at Lees Ferry</td>
</tr>
<tr>
<td><strong>Current Management</strong></td>
<td>No additional water management actions implemented</td>
<td></td>
</tr>
<tr>
<td><strong>Baseline (from Basin Study)</strong></td>
<td>Less than 3490 feet</td>
<td>Less than 12.39 maf</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less than 1040 feet</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Moderate</strong></td>
<td>Less than 3525 feet</td>
<td>Less than 13.15 maf</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less than 1050</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Moderately Aggressive</strong></td>
<td>Less than 3550 feet</td>
<td>Less than 13.25 maf</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less than 1075 feet</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Aggressive</strong></td>
<td>Less Than 3600 feet</td>
<td>Less than 13.5 maf</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less than 1100 feet</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Very Aggressive</strong></td>
<td>Less Than 3600 feet</td>
<td>Less than 14.0 maf</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Less than 1125 feet</td>
</tr>
<tr>
<td><strong>Static Implement-All-Actions</strong></td>
<td>Every water management action implemented in first year available.</td>
<td></td>
</tr>
</tbody>
</table>

The Baseline strategy only implements actions after what would generally be considered dry short-term conditions. In the Upper Basin, it defines a trigger value as a five-year period with an annual average natural streamflow of 12.39 maf. This threshold is significantly below the 15 maf average that has been observed in the recent historical record. The trigger value for Lake Powell occurs when pool elevation drops below 3490 feet, the “Lower Elevation Balancing Tier” of its operations. Because the Lower Basin can fail to meet objectives under less severe conditions, the strategy observes a trigger value when a five-year period with an average of 13.35 maf of natural flow occurs. This value is still well below the annual average streamflow in the recent historical record. Lake Mead’s trigger values are defined by pool elevation dropping below 1040 feet, consistent with the second tier of shortage and which is below the minimum elevation for efficient power generation. The trigger value represents a relatively low volume for Lake Mead (U.S. Department of the Interior 2014).
At the other end of the spectrum, the Very Aggressive strategy implements actions under what are typically considered normal conditions. For example, it sets trigger values in the Lower Basin when the five-year average streamflow is at the historical average of 15 maf and Lake Mead’s elevation is 1125 feet, within the range of normal operations (U.S. Department of the Interior 2014). Thus, the triggers in the more aggressive strategies are generally observed in early years of the simulation, and often begin implementing actions as soon as they become available.

How do various adaptive strategies perform in the Colorado River Basin and how can planners choose among them?

Performance of Adaptive Strategies

Figure S-3 presents performance of each adaptive strategy across the ensemble of streamflow futures in the Lower Basin. Each of the horizontal panels presents a candidate strategy. Within each panel, each point represents a single future, ordered by the annual average natural streamflow at Lees Ferry (horizontal axis) with the driest futures on the left and wettest futures on the right. The vertical axis represents the over-investment or under-preparedness. A point sitting above the zero-line measures the total annual cost of water management actions beyond what would have been necessary to keep Lake Mead above 1000 feet—a measure called implementation regret. A point sitting below the zero line represent the total annual yield of additional actions that either would have been necessary to maintain Lake Mead levels. If no strategy could maintain Lake Mead levels, then it is the difference between the total yield implemented and that strategy and the maximum possible volume of implementation. This measure is called vulnerability regret. Note that in some futures vulnerability regret can be as high as 5 maf (particularly for the Current Management strategy), but axis is stopped at 3 maf to capture the range of the most important results. In this graphic a perfectly performing strategy would sit on the zero-line across all futures, but this is not possible without perfect information about the future.
Figure S-3: Lower Basin vulnerability and implementation regret by long-term average streamflow conditions.
This representation of the adaptive strategies reveals some key policy insights about their performance. First, the strategies that do not change in response to new information (Current Management and Static Implement-All-Actions strategies) can have higher levels of regret more frequently than adaptive strategies. This suggests that strategies that respond to new information can help reduce regret in many futures; reservoir levels and streamflow can inform long-term infrastructure and conservation investments. Second, in contrast to the static strategies, the adaptive strategies have their highest levels of regret in the more moderate futures—between 12 and 16 maf of average annual long-term streamflow. In the more extreme futures, the adaptive strategies receive a clear signal about whether the future will be wet or dry and implement actions in according. In the more moderate futures, these signals are often not sufficiently clear. Other signals, particularly those that can make better forward looking decadal forecasts of streamflow, could help planners adapt with lower regret in all futures.

This figure also illustrates the tradeoffs that planners face in their response to new information regarding their willingness to risk over-investment and avoiding the threat of vulnerability. The more conservative strategies tend to under-invest with greater magnitudes and higher frequently than the more aggressive strategies. Planners who are most concerned about ensuring water delivery reliability may see these as large risks, and prefer a more aggressive approach. On the other hand, the more aggressive strategies tend to cause over-investment, and planners concerned with keeping costs low may find these strategies unacceptable.

Similarly, these tradeoffs vary across planners’ beliefs about the futures. The more conservative strategies tend to experience their highest levels of regret in the moderately dry futures—between 12 and 14 maf. On the other hand, the more aggressive strategies tend experience their highest levels of regret in wetter futures. Thus, planners who believe the dry futures are likely may prefer an aggressive strategy. With such a strategy, they will implement many water management actions when necessary, and believe they face a lower threat of the futures where over-investment occurs. Planners who believe hydrology will remain stationary may prefer the more conservative strategies, as to not risk over-investing when they do not believe much action is necessary. This dissertation presents many visual aids drawn from the modeling to help quantify these tradeoffs.

This modeling exercise reveals that to adequately prepare for many of the drying futures—particularly those consistent with climate change projections—planners need to implement new water management actions in even seemingly ordinary years. The aggressive strategies perform well in the drying futures. If planners believe these drying futures are likely, they will wish to use triggers similar to those contained in such strategies. Normal streamflow years are not sufficient evidence to delay further action.

**Evaluating tradeoff among adaptive strategies across different subjective beliefs**

This dissertation also provides many visual decision-aids to help planners consider their choices in how they respond to new pieces of information. These aids are designed to facilitate an examination of the tradeoffs among strategies, regarding planners’ preferences for over-investment and under-preparedness and their subjective beliefs about the future. Analysts statistically
summarize the cost and effectiveness of each strategy using the previously described decision-relevant scenarios. These statistical summaries serve as the basis for tradeoff curves, which are generated for a range of different assumptions about the likelihoods of the decision-relevant scenarios. Such aids allow planners to consider the probability of meeting water-delivery objectives and the expected costs of meeting those objectives for varied beliefs about the future.

Figure S-4 is one such aid, illustrating the performance of strategies across a range of subjective probabilities of the decision-relevant scenarios in the Lower Basin. Each point in each triangle represents a different set of plausible future beliefs. The horizontal axis represents the subjective likelihood of Severely Declining Supply conditions; the vertical axis represents the subjective likelihood of Stationary or Increasing Supply. When the sum of these values does not equal 100 percent (not on the diagonal boundary), the difference is the subjective likelihood of Low Historical conditions. Points closer to the lower-left corner have higher likelihoods of this scenario. The colors represent the lowest cost strategy that has an 80 percent likelihood of meeting water delivery objectives in the Lower Basin across a range of plausible beliefs (note this is based on absolute cost and percent of futures that meet water delivery objectives, not the regret-based metrics presented previously). Each point is colored by the strategy with the lowest expected implementation regret that has an 80 percent chance of meeting objectives. The size represents the expected implementation regret of the strategy. The black circles represent sets of beliefs where no strategy can meet objectives, but presents the expected implementation regret for the Static Implement-All-Actions strategy.
This figure suggests that if planners believe the *Severely Declining Supply* scenario is more than 30 percent likely, they cannot achieve an 80 percent likelihood of meeting their objective, regardless of strategy. When conditions are less severe, they can choose among the strategies. If planners are confident the *Low Historical, Stationary, or Increasing Supply* scenario is 80 percent likely, the *Current Management* performs satisfactorily. The *Aggressive* strategy performs well for the widest range of beliefs. It does well when planners either believe the *Low Historical* scenario is between 50 and 100 percent likely or the *Severely Declining Supply* scenario is not likely. It also performs well.
when the *Severely Declining Supply* scenario is between 10 and 30 percent likely and the *Stationary or Increasing Supply* scenario is between 50 and 80 percent likely.

**When must planners make decisions about water management actions and under which conditions should be implemented?**

Though the adaptive strategies presented previously are useful guides for considering the response to new information, they are dependent on various assumptions about planners’ ability to commit to decision-rules, the information available to planners, and the timing of actions. This section uses the simulations to extract some more generalizable results about the timing of implementing actions, the conditions under which planners should implement various actions, and the multiple pathways that they may consider. To do so, it characterizes the implementation of the modeled adaptive strategies across the range of plausible future beliefs.

This analysis first identifies the low-cost set of actions that meet water delivery objectives in each future, if such a set of actions exists—*a low-regret strategy*. For example, if the low-regret strategy in a particular future implements no actions, it suggests that no actions are necessary to meet the objectives. In another future, the low-regret strategy may consist of 200 kaf of municipal and industrial conservation implemented in 2020, an additional 200 kaf of municipal and industrial conservation and 200 kaf of agricultural conservation implemented in 2025, and a new desalination plant providing 300 kaf of yield brought online in 2030. This schedule of implementation would represent the cheapest set of actions among the strategies explored that meet the water delivery objectives. This should also serve as a near approximation of the best way to avoid vulnerability in a particular future. However, planners face a large number of plausible futures, each requiring their own levels of implementation. Statistical characterization of the levels of implementation and the external conditions that require those levels can help planners understand the commonalities among futures.

Scenarios can help planners consider the streamflow conditions that are associated with each level of implementation. These scenarios can serve as the basis for deliberations among the total yields planners consider implementing by describing the external streamflow conditions associated with each implementation strategy. These *implementation scenarios* are described in terms of long-term average streamflow and average streamflow in driest eight-year period.

**Considering the Total Yield of Water Management Actions**

Figure S-5 presents the implementation scenarios for the Lower Basin overlaid on a scatter plot of the streamflow conditions associated for each sampled future. Each point in the figure represents one future, characterized by long-term mean annual flow (vertical axis) and mean annual flow during the driest eight-year period (horizontal axis). The symbols demark the low-regret level of implementation necessary to maintain Lake Mead levels in a particular future. No action is necessary, demarked by open circles, in wet futures found in the upper right corner. The current set
of actions is available is insufficient, demarked with an X, in the driest futures in the lower left corner. The colors present the definitions of implementation scenarios. The *Stationary Average Streamflow* scenario is shaded green, containing primarily futures where no action is necessary, and is defined by average annual streamflow above 15 maf. The *Severely Declining Average Streamflow* scenario is shaded gray, defined by average annual streamflow less than 12.4 maf and contains primarily futures where the current set of available actions is insufficient to address Lower Basin water delivery objectives. The *Below Historical Streamflow with Severe Drought* scenario is shaded red containing primarily futures where the yield between 4 and 5 maf is necessary, where average annual streamflow is between 12.4 and 15 maf and there is an 8-year drought with average annual streamflow less than 11.4 maf. Finally, the *Below Historical Streamflow* contains futures where streamflow is between 12.4 and 15 maf, but the driest 8-year drought has average annual streamflow greater than 11.4 ma, a yield between 3 and 4 maf is generally the low-regret strategy.

*Figure S-5: Implementation scenario definitions in the Lower Basin*

These scenarios can become the basis for considering how planners should increase the total yield of actions over time. Figure S-6 presents a visual guide for considering implementation over time across these scenarios. The horizontal axis shows each decade and the vertical axis shows the implementation scenarios. Each box presents the 90\textsuperscript{th} percentile of yield implemented for low-regret strategies across all futures in the scenarios. This figure can be read as a decision matrix. The volumes represented in each box serve as a recommendation of the yield to implement in each
decade to prepare for each scenario. The dotted lines present some feasible pathways through different sets of implementation.

*Figure S-6: Decision matrix with some pathways for implementation over time in the Lower Basin*

<table>
<thead>
<tr>
<th></th>
<th>2012-2020</th>
<th>2021-2030</th>
<th>2031-2040</th>
<th>2041-2050</th>
<th>2051-2060</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stationary Average Streamflow</strong></td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td><strong>Below Historical Streamflow</strong></td>
<td>0.0</td>
<td>1.9</td>
<td>3.1</td>
<td>3.5</td>
<td>3.9</td>
</tr>
<tr>
<td><strong>Below Historical Streamflow With Severe Drought</strong></td>
<td>0.4</td>
<td>2.1</td>
<td>3.6</td>
<td>4.8</td>
<td>5.0</td>
</tr>
<tr>
<td><strong>Severely Declining Average Streamflow</strong></td>
<td>0.4+</td>
<td>2.1+</td>
<td>3.6+</td>
<td>4.8+</td>
<td>5.0+</td>
</tr>
</tbody>
</table>

90th Percentile Implementation [maf]

- Pathway A: Prepare for *Below Historical Streamflow* maf scenario
- Pathway B: Prepare for *Below Historical Streamflow* scenario through 2040, Adjust to Yield *Below Historical Streamflow With Severe Drought* scenario after 2040
- Pathway C: Prepare for *Below Historical Streamflow With Severe Drought* scenario through 2030. Reconsider implementation after 2030

*Inspired by Kwakkel and Haasnoot (2012)*

Pathway A represents the simplest decision planners can make to prepare for a single set of conditions over the entire time horizon. In this case, if planners determine that they need to be resilient to the conditions described by the *Below Historical Streamflow* scenario, they do not need to implement any actions in by 2020, implement 1.9 maf by 2030, 3.1 maf by 2040, 3.5 maf by 2050 and 3.9 maf by 2060. Implementing such a yield would ensure that water delivery objectives are met in 90 percent of futures.

Pathway B shows how planners may begin planning for one scenario, but then switch to another as new information becomes available. Through 2040, Pathway B follows the same path as Pathway A, as planners prepare for the *Below Historical Streamflow* scenario. Planners may learn and update their beliefs about scenarios as they observe streamflow conditions, reservoir levels, and monitor climate change predictions. After 2040, they may determine that they need to be resilient to the...
conditions described by the *Below Historical Streamflow With Severe Drought* scenario and adjust course. Planners would need to expedite implementation of an additional 1.3 maf (increasing yield from 3.1 maf in 2040 to 4.8 maf, rather than 3.5 maf) in 2050, rather than the 3.5 maf they originally planned for). So long as such a rapid change in implementation is feasible, planners can change course.

Pathway C recognizes that planners may not wish to commit to a single course of actions for the entire time horizon. Instead, they design a basic plan that is explicit that some decisions will be made at a later point. In Pathway C, planners commit to prepare for the *Below Historical Streamflow With Severe Drought* scenario between now and 2030, implementing 0.4 maf of yield by 2020 and 2.1 maf of yield by 2030. Such a path may be attractive, as both the *Below Historical Streamflow* scenario and the *Below Historical Streamflow With Severe Drought* scenario require similar levels of implementation by 2030. The implementation requirements diverge after 2030 and planners may specify that they will make a next set of decisions after 2030. At this point, they may choose to only increase yield from 2.1 maf to 3.1 maf, to prepare for the *Below Historical Streamflow* scenario. They may instead choose to increase yield to 3.6 maf, maintaining preparedness for the *Below Historical Streamflow With Severe Drought* scenario. Alternatively, they may determine that the *Severely Declining Average Streamflow* scenario is sufficiently likely, and begin deliberating a wider set of actions in addition to implementing all available actions.

Pathways B and C both recognize that planner's beliefs about the implementation scenarios presented in this chapter may change over time. Planners can observe streamflow or the other exogenous climate indicators, and do a further analysis identify which pieces of information they need to observe by 2030 to generate consensus about which pathway to follow in subsequent decades. Such an approach is discussed in a subsequent section.

**Considering a single water management action—Desal Yuma**

Total yield is not the only way to characterize the various low-regret strategies; each strategy is comprised of multiple individual water management actions that planners may choose among. This dissertation presents some further analysis of these individual actions. It explores an example of how planners may consider one particular action— a desalination facility in Yuma, Arizona (referred to as Desal-Yuma). The Basin Study describes that this plant would be designed to decrease the salt content of brackish (water that has higher salinity than freshwater, but not as much a seawater) groundwater near Yuma, Arizona (U.S. Bureau of Reclamation 2012d). This action is available to address Lower Basin water delivery objectives and would first be available in 2021. This action is implemented in approximately 70 percent of the futures in the *Below Historical Streamflow* scenario. In the *Below Historical Streamflow With Severe Drought* scenario, it is implemented in approximately 90 percent of futures with only 2 years of delay.

A subsequent analysis identifies the streamflow conditions that are specific to the decision about implementing Desal-Yuma. Table S-4 presents these scenarios. If planners wish to prepare for conditions with long-term average streamflow less than 14.4 maf and a drought with less than 12.3 maf of average annual flow, they should implement this action in the near term. However, if they
observe a period where streamflow is only slightly below the recent historical average over the
next 20 years, they can reasonably defer implementation of this action by slowing the process or
delaying certain decisions. Alternatively, planners may choose to defer this action with the
expectation that the next two decades will have more than 14.5 maf in annual average natural flow.
However, if they observe increasing evidence that the long-term average flow will fall below 15.0
maf, they should begin the process of implementing the Desal-Yuma water management action.

Table S-4: Implementation scenarios for Desal-Yuma

<table>
<thead>
<tr>
<th>Action</th>
<th>Begin implementing Desal-Yuma in next 10-years</th>
<th>Implement Desal-Yuma at later point</th>
<th>Desal-Yuma unnecessary</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scenario Definition</strong></td>
<td>Long term average flow less than 14.4 maf</td>
<td>Long term average flow between 13.4 and 15.0 maf</td>
<td>All other streamflow conditions</td>
</tr>
<tr>
<td></td>
<td>–and– Minimum 8-year average flow less than 12.3 maf</td>
<td>–and– Average annual flow between 2012 and 2030 greater than 14.5 maf</td>
<td></td>
</tr>
</tbody>
</table>

Scenarios such as these can help planners deliberate whether or not to implement individual
actions. This analysis could be replicated for other individual water management actions in the
Basin. Furthermore, these scenarios can become the basis of a subsequent round of an RDM
analysis; planners can develop signposts and decision-rules specific to these individual actions and
scenarios.

**What information might planners observe in the next decades that would make them believe actions beyond those considered in the Basin Study are necessary?**

The previous two sections consider various ways that planners may implement water management
actions over time in order to meet the Basin’s water delivery objectives. However, there are many
plausible futures where these objectives cannot be met and planners may need to consider a
broader set of actions or reconsider the basic objectives of the system—the *Severely Declining
Supply* transformative scenario. This section provides analysis about information that planners
might observe in the near-term, which would make them believe this scenario is increasingly likely.
The *Severely Declining Supply* scenario is defined by long-term average annual streamflow less than 12.9 and an 8-year drought with less than 10.2 maf of annual streamflow. By definition, planners cannot know whether this scenario has occurred until the end of planning horizon. However, short-term observations of streamflow and observing other climate indicators may help planners consider the scenario’s likelihood over time as new information is learned.

There is a relationship between observations of streamflow in next decade, and the long-term average streamflow. Figure S-7 demonstrates the relationship between short-term observations of average streamflow and the decision-relevant scenarios. It presents a histogram of average annual streamflow from 2012-202 for all futures that eventually fall into each decision relevant scenario. Each bar presents the percent of futures (y-axis) that fall into the range of 1 maf of annual average streamflow from 2012 to 2020 (x-axis) for futures classified in each decision-relevant scenario (horizontal panels).

*Figure S-7: Distribution average annual streamflow across futures in decision-relevant scenarios (2012-2020)*

The mean and skewness of the distribution of average annual streamflow from 2012-2020 is lower in *Severely Declining Supply* conditions than in other scenarios. A higher proportion of futures in the dry decision-relevant scenario have low average annual streamflow in the first decade than wet scenarios, and a higher proportion of futures in wet scenarios have high average annual streamflow in the first decade than dry scenarios.

**An example of how planners may update beliefs over time**

The information in this histogram can serve as an estimate of the conditional probability of an observation, allowing planners to update their belief through Bayes’ Law. Figure S-8 presents one example of how planners may update their beliefs over time, showing the time series of streamflow in a single future. The top panel shows the average annual streamflow in this particular future. The lower panels represent how planners may update their beliefs about the likelihoods of the various decision-relevant scenarios, using Bayes’ Law for two different sets of current beliefs about the scenarios.
In the top panel, the black line represents the average annual streamflow within the decade demarked on the x-axis. The blue bars represent the cumulative average annual streamflow from 2012 until the year presented on the horizontal axis; the average of all prior years streamflow. The bars are also labeled with the bin containing each particular level of streamflow, in the histograms above. This future begins with an average annual streamflow of 15 maf during the first decade. If such a streamflow were maintained over the entire planning horizon, it would be consistent with Low Historical, Stationary, or Increasing Supply conditions. By 2060, this future's long-term average streamflow is less than 13 maf and is consistent with the definition of the Severely Declining Supply scenario. As planners observe dryer decades, they collect evidence that the drier scenarios are increasingly likely.
The middle panel shows how planners may update their beliefs over time, for those who have believe that the Declining Supply scenario is 50 percent likely and the remaining scenarios are each 25 percent likely, shown by the colored circles on the left. As these planners observe dryer and dryer conditions, they will believe the probability of the Low Historical, Stationary, or Increasing Supply scenario drops to zero. However, the Declining Supply scenario remains the most likely over the entire time horizon.

However, planners may have differing beliefs about the likelihood of these scenarios. The bottom panel demonstrates how planners may update their beliefs if they initially believe the Severely Declining Supply scenario is 50 percent likely, and the remaining two scenarios are each 25 percent likely. In 2020, the Severely Declining Supply scenario remains the most likely, but all scenarios are relatively close in likelihood, ranging from 22 percent to 43 percent. Over time, the likelihood of the scenarios separate from one another. As evidence mounts that the prior was correct, the likelihood of the Severely Declining Supply increases to nearly 75 percent.

This analysis demonstrates that observations of streamflow prior to the end of the planning horizon can influence planners’ beliefs about future periods. Furthermore, it demonstrates an approach using ensemble of futures and Baye’s law to demonstrate how these observations will influence beliefs. However, planners may have varied prior beliefs about the likelihoods of scenarios, and the future observations of streamflow are unknown; further analyses are necessary to summarize the observations that will generate consensus about future conditions.

**Exploring over multiple indicators and a range of beliefs**

Planners may also update their beliefs using other pieces of information. This dissertation describes some other pieces of information that planners may wish to use as they learn and update their beliefs about the various scenarios—referred to as *exogenous indicators*. The decision-relevant scenarios can serve as way to link the research by climate scientist examining these exogenous indicators to a decision framework. While climate researchers would likely not be able to provide an assessment of whether a specific contingency is necessary, they may be able to provide updated assessments on the relative likelihood of a decision-relevant scenario. The four pieces of information described in this dissertation are summarized below:

1) There is a cyclical nature of the streamflow in the basin. An understanding of these cycles can help planners identify whether a dry period is an indicator of future dry years or a temporary drought period.

2) Observations of Sea Surface Temperature (SST) in the Pacific Ocean have strong effects on precipitation, runoff, and streamflow in the Basin. They may be useful indicators to monitor in addition to local streamflow.

3) Forward looking decadal predictions of precipitation and streamflow may help planners anticipate future drought periods. Such predictions will likely be drawn in large part from SST phenomena, rather than relying solely on local observations.

4) Forward looking long-term climate predictions may continue to improve over time, which may help planners predict long-term hydrologic conditions in the Basin.

XXXV
While Bayes’ law provides the mathematical relationship to describe how planners can update beliefs, planners may have a range of prior beliefs about the scenarios and observations of streamflow and other exogenous indicators are uncertain. This dissertation presents the results of a computational experiment, exploring across each of these factors, to identify the prior beliefs and observations that would make planners believe the *Severely Declining Supply* scenario is the most likely scenario, in 2020.

Figure S-9 presents a map of prior beliefs, exogenous indicators, and observations of streamflow that would make planners believe the *Severely Declining Supply* is most likely in 2020. Each horizontal panel shows a different value of average annual streamflow from 2012 to 2020. The horizontal axis illustrates the likelihood that other exogenous indicators would be observed conditional on the *Severely Declining Supply* scenario occurring (indicators consistent with the *Severely Declining Supply* scenario are presented on the left, while indicators unlikely to be observed should the *Severely Declining Supply* scenario occur are presented on the right). The vertical axis shows plausible planners’ beliefs about the likelihood of the *Severely Declining Supply* scenario. For example, the top row represents planners who believe the *Severely Declining Supply* is 90 percent likely, prior to observing any information. The color indicates the percent of instances where the *Severely Declining Supply* scenario is most likely after observing information about average annual streamflow in 2020. As there are multiple instances layered on top of one another, those that are darker red represent more instances where the *Severely Declining Supply* is more likely.

*Figure S-9: Observations and beliefs leading to Severely Declining Supply most likely scenario (2012-2020)*

This graphic shows that if planners observe average annual streamflow near 10 maf, the *Severely Declining Supply* scenario is almost certain to be the most likely scenario. In this case, it will be the most likely scenario regardless of prior beliefs or the information contained in other indicators. On
the other hand, if planners observe annual streamflow near 18 maf, the **Severely Declining Supply** scenario cannot necessarily be ruled out. If other exogenous indicators have a 50 percent chance of being observed in the **Severely Declining Supply** scenario, then planners who believe the **Severely Declining Supply** scenario is 50 percent or more likely in 2012 can agree that that this scenario is most likely.

The results of this computational experiment can be described in some more generalizable rules-of-thumb, that describe what planners need to observe in the next decade to generate consensus for planners with certain prior beliefs to believe the **Severely Declining Supply** scenario is the most likely scenario. These are presented in Figure S-10

*Figure S-10: Rules-of-thumb for observations and beliefs leading to Severely Declining Supply most likely scenario (2012-2020)*

If planners observe streamflow less than or equal to 13 maf and other exogenous indicators are 20 percent or more likely to be observed in **Severely Declining Supply** scenario, then all planners who believe that the scenario has a likelihood of 20 percent or more in 2012 will agree that it is the most likely scenario in 2020. That is, if streamflow is less than or equal to 13 maf, unless there is weak exogenous evidence for the **Severely Declining Supply** or planners believe it is less than 20 percent likely, there will be consensus that this is the most likely scenario.

Even if streamflow is greater than 13 maf, planners may still believe **Severely Declining Supply** scenario is the most likely. If exogenous indicators observed have a 50 percent or greater conditional probability of being observed in the **Severely Declining Supply** scenario, then the planners who believe the scenario is 50 percent or more likely will still believe it is the most likely scenario. That is, streamflow above 13 maf does not preclude the possibility that **Severely Declining**
Supply is the most likely, but it does require observing somewhat strong external evidence and predisposition to believing the scenario is likely.

However, the designation “most likely scenario” can cover a large range of updated beliefs (anywhere between 34 and 100 percent). This analysis was repeated for a stricter threshold, to find the observations that would make planners believe the Severely Declining Supply scenario is 90 percent likely. If streamflow is 10.5 maf or less and other exogenous indicators are somewhat consistent with the Severely Declining Supply, then planners who currently believe that the Severely Declining Supply is at least equally likely to the other two scenarios will have confidence the scenario is occurring. If streamflow is between 10 maf and 13.5 maf, only planners with strong prior beliefs will think the Severely Declining Supply is likely and they must be presented with strong exogenous indicators. With streamflow higher than 13.5 maf, planners will not have confidence that the Severely Declining Supply will occur.

These rules-of-thumb can be used to inform on-going deliberations about the strategy to address Basin objectives. At the very least, they provide some benchmarks of the streamflow conditions that planners can observe, that may make them believe the Severely Declining Supply scenario is becoming increasingly likely. They may also be more explicitly incorporated into adaptive strategies, and planners can use the thresholds as triggers, to re-open deliberations about the set of actions available to Basin planners.

Integrating the analyses
RDM is an iterative process, and the information revealed in each step of the analysis can help planners generate new adaptive strategies. This section combines the previous analyses to consider how planners may choose to implement actions and the pieces of information that should influence their choices. It combines the various pathways planners can use to adapt with the signpost variables that they can observe—generating new strategies and decision-rules.

This section presents two views of the decision among water management actions. The first is a system wide approach, where planners consider the total annual yield of actions they would need implement. In this approach, planners can identify some pathways through the various total volumes of water management actions, the key decision-points, signpost variables that will influence their decisions, and threshold values of those variables that would require their implementation. In the second view, planners consider the choice to implement an individual water management action in the near-term or defer it for the opportunity to observe new information and periodically reconsider. It focuses on the example presented above—Desal-Yuma.

Figure S-11 shows one possible basic plan for implementing water management actions over the planning horizon. This plan is Pathway C from Figure S-6; planners commit to a level of implementation between now and 2030 and then face a decision of the yield to implement in subsequent decades. Planners may have settled on this basic plan after examining the decision-matrix and various pathways presented in Figure S-6, determining which level of yield was necessary based on their current expectations. After settling on this particular basic plan, with a decision-point in 2030, the Bayesian rules-of-thumb analysis in Figure S-10 is replicated for the
various implementation scenarios. This graphic presents the threshold values of streamflow, other indicators, and streamflow conditions that would make planners believe the *Severely Below Average Streamflow* scenario is the most likely in 2030. If they observe these conditions by 2030, planners will need to strongly consider additional actions beyond those described in the Basin Study, and follow the bottom row of the graphic.
Figure S-11: A plan for implementation, with a decision point and key indicators to monitor

<table>
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<tr>
<th>Year</th>
<th>2012-2020</th>
<th>2021-2030</th>
<th>2031-2040</th>
<th>2041-2050</th>
<th>2051-2060</th>
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<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Below Historical Streamflow</td>
<td>0.0</td>
<td>1.9</td>
<td>3.1</td>
<td>3.5</td>
<td>3.9</td>
</tr>
<tr>
<td>Below Historical Streamflow with Severe Drought</td>
<td>0.4</td>
<td>2.1</td>
<td>3.6</td>
<td>4.8</td>
<td>5.0</td>
</tr>
<tr>
<td>Severely Declining Average Streamflow</td>
<td>0.4+</td>
<td>2.1+</td>
<td>3.6+</td>
<td>4.8+</td>
<td>5.0+</td>
</tr>
</tbody>
</table>

90th Percentile Implementation [maf]

---

Prepare for Yield 4-5 maf scenario through 2030. Reconsider implementation after 2030

---

**Severely Declining Supply Scenario most likely (2012-2030)**

- **Average Annual Streamflow**
  - 12 maf
  - Exogenous indicators consistent with Severely Declining Average Streamflow scenario
  - Prior beliefs for Severely Declining Average Streamflow scenario

- **Average Annual Streamflow**
  - 12-16.5 maf
  - Exogenous indicators consistent with Severely Declining Average Streamflow scenario
  - Prior beliefs for Severely Declining Average Streamflow scenario

---

**Note:** The thresholds in this figure were generated from analysis of the Severely Declining Supply scenario, not the Severely Declining Average Streamflow scenario. The definitions of these scenarios are similar, and replicating the analysis for the Severely Declining Average Streamflow should generate similar thresholds. Before being used for any decision-making, this analysis should be replicated using the Severely Declining Average Streamflow scenario.
Analysts could next simulate such a strategy using CRSS, to estimate the costs and benefits of using these threshold values as triggers. They may try other trigger values, such as those that imply the *Severely Declining Average Streamflow* scenarios is 90 percent likely. Such an analysis could help planners better understand the tradeoffs of requiring higher or weaker or levels of evidence before committing to a volume of implementation.

Figure S-12 presents an example of the various pathways of implementation from analysis of the Desal-Yuma plant. First, planners must consider whether Desal-Yuma should be implemented in the near term and operated over the entire planning horizon, shown with the green line. If they believe that long-term average streamflow is less than 14.4 maf and average annual streamflow in the worst 8-year drought is less than 12.3 maf is sufficiently likely, they should follow this path. Alternatively, planners may determine that they can safely not implement the action is the first time-period and reconsider the decision periodically, shown with the blue pathway. At whatever point in time planners determine that long-term average streamflow between 13.3 and 15.0 maf is sufficiently likely, they would begin preparing and operating the Desal-Yuma plant. Planners must choose between the green path and the blue path with their current information, their priors. At each blue circle, planners would periodically reconsider whether they need to implement the Desal-Yuma plant. Planners would inform this decision by monitoring observed streamflow and other exogenous indicators.

*Figure S-12: Considering implementation of Desal-Yuma plant in response to new information*
Knowing that the scenario for implementing Desal-Yuma is based primarily on long-term average streamflow, the same indicators described as those for the other decision-relevant scenarios should facilitate learning about the middle scenario’s likelihood. Observations of streamflow, as well as learning from other indicators, should influence planners’ beliefs about the decision-relevant scenarios.

An analysis similar to the one presented in Figure S-11 could be replicated for each decision point in this figure. However, instead of partitioning futures based on the scenarios that describe system vulnerability futures would be partitioned based on the implementation scenarios specific to Desal-Yuma. Low streamflow observations in each decade would suggest that the middle scenario is increasingly likely, and planners should be preparing Desal-Yuma. This analysis can be utilized to generate rules-of-thumb and some candidate threshold values for decision-rules.

Conclusions
This dissertation presents expansion of the usual RDM process to provide decision support when generating and evaluating adaptive strategies. In doing so, it offers a definition of adaptive strategies, signposts, triggers, and decision-rules. It then expands on the analysis in Colorado River Basin.

The analysis presents decision aids that can help planners consider various pathways through implementing actions, the interpretations of new information they may observe over time, and the cost and benefits of different decision-rules, across a range of subjective beliefs about the futures. These visualizations could be used in a process of stakeholder engagement, as planners deliberate how to respond to new information and which actions to implement.

In addition to the specific decision support aids this dissertation presents, it also finds some generalizable policy conclusions. First, if planners wish to prepare for the driest futures, consistent with recent climate change projections, they should respond aggressively to new information. If planners believe that the drying conditions are likely in the long run, years with streamflow near the historical average do not constitute sufficient evidence that the driest futures are not occurring. Additionally, this dissertation finds that over the next decade, planners cannot rule out that the driest scenarios are occurring solely from observations of streamflow. If planners observe the wettest streamflow conditions but there is strong evidence in the supporting climate literature that the driest futures are likely, some planners will continue to believe that the drying scenarios are likely.
Acknowledgements

I would like to thank the members of my dissertation committee, Rob Lempert, David Groves and Craig Bond for their insight and support. Rob, your research on robust decision methods forms the foundation of this research; I am grateful for you mentorship and enthusiasm. Dave, collaborations with you have trained me to be the researcher that I am today; thank you for the opportunities to work on interesting projects and guidance throughout this process. Craig, you have provided a much-needed outside perspective through the process. Chris Weaver’s insight as outside reader has been invaluable.

I have also benefited greatly from my interactions with other RAND researchers. Steven Popper, your work on Robust Decision Making was also foundational for my research and your mentorship first led to my excitement about using these methods. Jordan Fischbach, you began advising me as a student and conversations with you throughout the Basin Study process inspired much of this work. Gery Ryan, you taught me many valuable lessons for integrating the complex modeling tools with client organizations that actually need to make decisions. I have also been influenced by many other RAND (or former RAND) researchers, including Debra Knopman, David Lowsky, Nidhi Kalra, Jeff Drezner, Constantine Samaras and Tom Light. Thank you all.

The Pardee RAND Graduate School provided me the opportunity to learn from many other intelligent and kind students, making this program a truly great experience. Friends, consider yourselves thanked. A few require special acknowledgement. Ryan Keefe, you taught me much of what I know as an RDM researcher, thank you for helping me get my start. David Johnson, conversations with you over the years have been enormously helpful in figuring out exactly what I am doing. Edmund Molina-Perez, collaborating with you has been a pleasure and you have always been willing to act as a sounding board. I am also indebted to the faculty and staff at PRGS, particularly Dean Marquis and Associate Dean Rachel Swanger. This work has been supported by the Energy and Environment dissertation award and I thank the generous donors to PRGS who support this fund.

This would not have been possible without the help and support of countless friends and family. In particular, Andrew Person and Miki Heller suffered through reading parts of the dissertation. Many more suffered through hearing me talk about it constantly: Ariel Seroussi, Subechya Person, Jake Heller, Aaron Wolk, and Leah and Micah Newman-Glass-Seigel-Balls. I am also grateful for the support of my family: Jan, Marta, Sarah and David Herrman and Ken and Michelle Bloom. My parents, Jerry and Roberta Bloom, have helped me through this process. Dad, you were the first one who suggested I “check out the school at RAND,” and your constant encouragement has helped me down this path.

Saving the best for last, to my wife, Becca: you have been a source of inspiration and support through this whole process. Thank you very much for tolerating my constant ramblings about RDM, making our lives work around my ridiculous schedule, inspiring me to continue when the work seemed overwhelming, reading the entire dissertation, and most importantly helping me enjoy the times I was not working.
A note about the Colorado River Basin Study

In large part, this dissertation extends the analysis of adaptive strategies from Colorado River Basin Study published by the U.S. Bureau of Reclamation, to which I along with many others contributed. I have great admiration for the way a complex policy topic was addressed using deliberations with analysis through the process of writing the Basin Study and much respect for the final product. On a personal note, I am honored to have been involved in such an important study, which can lay a framework for addressing climate change in one of the most complex policy environments dealing with natural resource management in the United States.

Throughout my dissertation, I make changes to the design of the analysis, provide new analyses and results, and provide policy conclusions or commentary beyond what was included in the Basin Study. Such content represents my own conclusions based on research I conducted for this dissertation and does not necessarily represent the views of anyone else involved in the Study. Additionally, no changes additional analyses included in this dissertation should be interpreted as criticism of either the conclusions in the Basin Study or the process leading up to its publication. This dissertation addresses a more limited set of research question, which sometimes require different interpretations of the data. I also do not have the benefit of receiving frequent stakeholder feedback, and some analytical decisions may have been different if this analysis occurred in a deliberative context.

I would like to thank the RAND team of researchers involved with this project, for giving me the opportunity to participate and contribute: David Groves, Jordan Fischbach, and Debra Knopman. I am also grateful to RAND Justice, Infrastructure, and Environment for supporting RAND’s initial involvement with the Basin Study. I am also grateful Bureau of Reclamation’s Terry Fulp, Director, Lower Colorado Region, for his support of RAND’s involvement in the Basin Study, and to Carly Jerla, Colorado River Basin Study Director, for her leadership of the Colorado River Basin Study. My involvement with Basin Study, which directly influenced this dissertation, entailed significant collaboration with the other members of the study team, Jim Prairie (Bureau of Reclamation), Ken Nowak (Bureau of Reclamation), Armin Munevar (CH2M Hill), Klint Reedy (Black and Veatch), and the Center for Advanced Decision Support for Water and Environmental Systems (CADSWES). In particular, I am grateful to Alan Butler (Bureau of Reclamation), who has continued to collaborate with me through my dissertation, providing training, support, and tools that have made this possible. Thank you.
## Acronyms

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>af</td>
<td>Acre-feet</td>
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<tr>
<td>BIC</td>
<td>Bayesian Information Criterion</td>
</tr>
<tr>
<td>CDF</td>
<td>Cumulative Distribution Function</td>
</tr>
<tr>
<td>CRBS</td>
<td>Colorado River Basin Study</td>
</tr>
<tr>
<td>CRSS</td>
<td>Colorado River Simulation System</td>
</tr>
<tr>
<td>ENSO</td>
<td>El Niño Southern Oscillation</td>
</tr>
<tr>
<td>IPCC</td>
<td>Inter-governmental Panel on Climate Change</td>
</tr>
<tr>
<td>kaf</td>
<td>Thousand acre-feet</td>
</tr>
<tr>
<td>maf</td>
<td>Million acre-feet</td>
</tr>
<tr>
<td>MOC</td>
<td>Meridional Overturning Circulation</td>
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<tr>
<td>PDF</td>
<td>Cumulative Distribution Function</td>
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<td>PDO</td>
<td>Pacific Decadal Oscillation</td>
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<td>RDM</td>
<td>Robust Decision Making</td>
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<td>SST</td>
<td>Sea Surface temperature</td>
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<tr>
<td>XLRM</td>
<td>Uncertainties, levers, relationships, and measures of merit</td>
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Glossary of Selected Terms

**Action**
The laws, regulations, infrastructure, taxes, or subsidies, or other policy tools available to decisionmakers.

**Adaptive strategy**
A strategy that evolves in response to new information over time.

**Annual yield**
Expected annual volume of new water supply or decreased water demand associated with a water management action or portfolio of actions.

**Case**
A unique combination of uncertain factors and levers, representing a single run of a simulation model.

**Closed-loop system**
A system that responds to feedback.

**Colorado River Basin Study**
A report published by the U.S. Bureau of Reclamation in 2012 evaluating the management of the Colorado River Basin in the face of uncertain supply and demand until 2060. Also referred to as “the Basin Study”

**Colorado River Simulation System**
A hydrologic model of the Colorado River Basin, maintained by the U.S. Bureau of Reclamation, programmed in Riverware.

**Decision-relevant scenario**
Concise descriptions of combinations of future conditions under which many futures fail to meet objectives (note, in Chapters 4,5,6, scenario, may be used as shorthand for decision-relevant scenario. In the Basin study, decision-relevant scenarios are referred to as “vulnerable conditions”).

**Decision-Rule**
The mathematical functions that planners can use to determine whether actions are implemented or adjusted.

**Formal review and continuous learning**
An adaptive process where deliberations are paired with analysis to consider how new information has changed the understanding of the system and how policy should be adjusted.

**Fully-automatic policy adjustment**
A type of adaptation where predefined actions are taken in response to predefined sets of new information.
<p>| <strong>Future</strong> | When used as a noun, a single time series of exogenous variables that is used to simulate the time evolution uncertainty. In Chapters 4, 5, 6 and 7 refers specifically to a time series of streamflow. |
| <strong>Implementation Regret</strong> | The difference between yield implemented for a strategy that fails to meet water delivery objectives and the lowest yield strategy to meet objectives in a given future. |
| <strong>Implementation scenario</strong> | A form of decision-relevant scenario that describes the exogenous conditions under which a specific action or set of actions should be implemented. |
| <strong>Lees Ferry</strong> | A location along the Colorado River in the Northern Arizona, that is commonly used to measure streamflow of the river. |
| <strong>Lever</strong> | A variable that decisionmakers can adjust or alter. In control theory, this is referred to as a control variable. |
| <strong>Lower Basin</strong> | Nevada, Arizona, California |
| <strong>Lower Basin cost</strong> | A metric, measuring the total annual cost of operating water management actions that address water-delivery reliability of the Lower Basin. |
| <strong>Lower Basin water delivery objectives</strong> | Maintaining Lake Mead’s pool elevation above 1000 feet |
| <strong>Lower Basin yield</strong> | A metric, measuring the total annual yield of operating water management actions that address water-delivery reliability of the Lower Basin. |
| <strong>Natural Streamflow</strong> | The streamflow in absence of human intervention. |
| <strong>Optimize and characterize</strong> | An approach defined by this dissertation, where analysts use exploratory modeling to identify optimal sets of actions to implement across a sample of plausible and provide statistical summaries and visual aids to describe the optimal sets of actions |
| <strong>Option</strong> | The right but not the obligation to the implement, defer, or somehow alter an action (note, this is a different use of the term “option” from the Basin Study; what the Basin Study refers to as “options” are referred to as “water management actions” in this dissertation). |
| <strong>Portfolio</strong> | A specific set of water-management actions to be implemented over time by the water-management model in response to emerging vulnerabilities. |
| <strong>Portfolio development tool</strong> | A tool designed over the course of the Basin Study to facilitate generating prioritized lists of water management actions consistent with stakeholders’ underlying strategy. |
| <strong>Regret</strong> | For a specific strategy, the difference between a metric in a given future and the metric for the best performing strategy in that same future. |
| <strong>Semi-automatic policy adjustment</strong> | A form of adaption allowing for some constrained deliberations before making decisions. |
| <strong>Signpost</strong> | Variables that are monitored over time |
| <strong>Simulated planning agent</strong> | The module in CRSS that observes signpost variables and implements actions. |
| <strong>Strategy</strong> | A specific approach for addressing some policy problem. In chapters 4, 5 and 6, it refers to a specific approach, in terms of the types of actions used and the decision-rule, that address water delivery objectives |
| <strong>Total annual cost</strong> | The expected annual cost of a water management action, or portfolios of actions, encapsulating the amortized cost of capital and the operations and maintenance. |
| <strong>Trigger</strong> | A specific type of decision-rule, where a binary decision to implement or adjust and actions is made after observing a threshold value of a signpost variable. |
| <strong>Trigger Value</strong> | The threshold value of a signpost variable that defines whether an action is implemented or adjusted. |
| <strong>Upper Basin</strong> | Colorado, Utah, Wyoming, New Mexico |</p>
<table>
<thead>
<tr>
<th>Term</th>
<th>Description</th>
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<tr>
<td>Upper Basin cost</td>
<td>A metric, measuring the total annual cost of operating water management actions that address water-delivery reliability of the Upper Basin.</td>
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<tr>
<td>Upper Basin water delivery objectives</td>
<td>Maintaining deliveries of 75 maf to the Lower Basin over every 10-year period</td>
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<tr>
<td>Upper Basin yield</td>
<td>A metric, measuring the total annual yield of operating water management actions that address water-delivery reliability of the Upper Basin</td>
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<td>Vulnerability Regret</td>
<td>The difference between the cost of a strategy that meets water delivery objectives and the lowest cost strategy to do so in a given future</td>
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<tr>
<td>Water management action</td>
<td>The set of investments in infrastructure and conservation available to address water delivery reliability in the Colorado River Basin.</td>
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Chapter 1: Planning for an uncertain future in the Colorado River Basin

The planning challenge in the Colorado River Basin

Water planners in the Colorado River Basin will face new policy challenges over the next half-century.¹ The Basin faces increasing water demand and deeply uncertain future water supply. This dissertation is about decision-analytic tools that can help Basin planners build policies that incorporate new information over time. Such policies may offer a solution to the challenges that lie ahead, allowing planners to learn and incrementally respond to changing conditions.

This chapter describes the policy context in the Basin and how this dissertation expands current methodologies and research in the Basin. It begins by charactering importance of the Colorado River to the western U.S. and the planning challenge in the Basin due to increasing demand and uncertain future supply. It next outlines a recent multi-stakeholder planning process in the Basin to begin addressing this challenge—The Colorado River Basin Supply and Demand Study (U.S. Bureau of Reclamation 2012f) (referred to as the Basin Study). In particular, it describes how the Basin Study considered strategies that respond to new information. Finally, it describes how this dissertation expands on the methodology used in the Basin Study and offers new analyses of strategies in the Basin.

The Colorado River is the single most important source of water in the southwestern United States, providing water and power for nearly 40 million people and water to irrigate more than five million acres of farmland across seven states and for 22 Native American tribes (Smerdon, Betancourt et al. 2007, U.S. Bureau of Reclamation 2012f). The river supports billions of dollars of economic activity—irrigating 15 percent of U.S. crops, for example—and is also the lifeline for two dozen National Parks, Wildlife Refuges, and Recreation Areas (U.S. Bureau of Reclamation 2012f).

The Colorado River system is made up of the River itself, tributary streams and rivers, and water storage and delivery infrastructure (dams and reservoirs, hydropower facilities, canals, aqueducts, and pumps). Significant infrastructure on the River includes Lake Powell in Utah (Glen Canyon Dam), Lake Mead in Nevada (Hoover Dam), the Central Arizona Project (which delivers water from the River to Arizona farms and municipalities), and the Colorado River Aqueduct and the All-American Canal (which collectively divert water to Southern California users). Much of this infrastructure is operated and maintained by the U.S. Bureau of Reclamation, the agency that helps manage the Colorado Basin system and ensure that major water users reliably receive their water deliveries each year.

¹ A recent RAND Report describes the planning challenge in the Colorado River Basin (Groves, Fischbach et al. 2013). I was a co-author of this report. Some language in this section is drawn from this report.
Water from the Colorado is apportioned to users in the seven Colorado River Basin States and adjacent areas that receive river water according to a series of federal laws and agreements, beginning with the Colorado River Compact of 1922 (the Compact), a statute which still stands today. Based on two decades of unusually high river flow, Compact negotiators believed the natural flow of the Colorado River to be about 16.4 million acre-feet (maf) per year on average in 1922 (MacDonnell, Getches et al. 1995). Using this estimate, the Compact initially allocated 15 maf of water between the Upper Basin States (Colorado, New Mexico, Utah, and Wyoming) and the Lower Basin States (Arizona, California, and Nevada). Figure 1-1 provides a map of the Colorado River Basin.
**Figure 1-1: Map of Colorado River Basin**

![Map of Colorado River Basin](image)

*Source: U.S. Bureau of Reclamation (2012)*

**Increasing demand and uncertain future supply**

In coming decades, the Basin may be operating with less average annual water supply than the Compact and subsequent agreements to manage the system, referred to as the “Law of the River,” were designed to accommodate. It has become clear in recent decades that the River was significantly over allocated when the Compact was signed. Flow measurements over the hundred-year period of record from 1906 to 2005 show an average flow of about 15 maf per year, not 16.4 as
was assumed in the Compact. The paleoclimatological record (time periods prior to direct measurement of flow) show even dryer conditions than the recent historical record; natural flow over a time span of more than a thousand years ranged from 13.5 to 14.7 maf per year (Stockton and Jacoby 1976, Woodhouse 2003, Woodhouse, Gray et al. 2006, Meko, Woodhouse et al. 2007).

Additionally, recent climate research suggests that the Colorado River Basin will face a new hydrologic regime (Milly, Betancourt et al. 2008), climate change will lead to persistent drying in the Southwest (Nash and Gleick 1993, Christensen and Lettenmaier 2007, Seager, Ting et al. 2007). Although these studies vary in their estimates, most suggest an average streamflow reduction of 10 to 20 percent over the next 50 to 100 years in response to a temperature increase between 1 and 4 degrees Celsius (Groves, Fischbach et al. 2013).

Figure 1-2 shows past and projected water supply and demand in the Basin. The left side shows the moving 10-year average of historical water supply and water consumptive use per year in the Basin. Water demand in the Basin has also steadily increased over the last 90 years. Due to a growing population and increased economic development, demand is projected to continue to increase over the next half-century. Annual water use first increased above annual supply in 1993 and has exceeded supply consistently since 2003, but the Basin has relied on storage to fill the deficit. On the right, it summarizes various projections of future supply and demand. As demand increases over the next half-century and supply remains constant or decreases, it appears likely the gap will remain. In some of the most severe projections, there will be a gap of 2-3 maf immediately and it will continue to grow over time. Even the most optimistic projections anticipate a gap by 2060 (U.S. Bureau of Reclamation 2012f).
Figure 1-2: Historical and projected future supply demand gap

Source: U.S. Bureau of Reclamation (2012f)

Multi-stakeholder planning environment

Since the Compact was first signed in 1922, the Basin States, Federal Government, and other stakeholders have adjusted management of the Basin to meet the changing needs of the system. In December 2012, Pat Mulroy, then General Manager of Southern Nevada Water Authority described that the seven Basin States have “organically evolved” a system of water management with the Colorado River Compact as the foundation (Mulroy 2012).

The U.S. Bureau of Reclamation constructed the Hoover Dam forming Lake Mead (completed in 1936) and the Glen Canyon Dam forming Lake Powell (completed in 1966). In 2007, the Basin States negotiated the Colorado River Interim Guidelines of Lower Basin Shortages and the Coordinated Operation for Lake Powell and Lake Mead (U.S. Bureau of Reclamation 2007) which adjusts the operations of the system to prioritize storage in wet years, as to better prepare for dry years. Various other agreements among states and partnerships with stakeholders have altered the management of the Basin over the last century.

Then Secretary of the Interior Kenneth Salazar described in 2012 that over the past two decades stakeholders have adapted by “work[ing] together and develop[ing] long-term cooperative river management on the Colorado River.” He describes that together, “the seven states, the Federal
government, the tribal interests, the environmental groups and others [have found] creative solutions to solve some very tough problems” (Salazar 2012).

However, with many stakeholders with differing preferences and sometimes-competing objectives, adaptation has been contentious at times. For example, Arizona did not ratify the Compact until 1944 and parts of the agreement were not settled until the U.S. Supreme Court upheld the Compact in 1963 in California v. Arizona (1964).

As the Basin faces a changing climate and growing demand in the next half-century, differences among stakeholders may be accentuated. Water planners in Basin States wish to ensure a reliable water supply for their own citizens. Similarly, 29 Native American tribal entities with rights to water from the river wish to ensure continued delivery to support their needs. Several species of fish have been listed as endangered, and the Upper Colorado River Endangered Fish Recovery Program is designed to help these species recover and prevent other threatened species from becoming endangered (U.S. Bureau of Reclamation 2012c). Many non-governmental conservation organizations wish to safeguard healthy flows in the Colorado River and its tributaries to protect natural habitats. Similarly, marinas and other organizations rely on sufficient streamflow and reservoir levels to support the recreational industry in the Basin (U.S. Bureau of Reclamation 2012c). These various stakeholders all hope to ensure a healthy river that can meet everyone’s requirements. However, if water resources become scarce then Basin planners may face some difficult decisions.

**Basin Study considers future plans through deliberations with analysis**

To begin the process of planning for climate change, the seven Basin States and the U.S. Bureau of Reclamation collaborated to evaluate the ability of the river to meet objectives across a range of future conditions, publishing the Basin Study(U.S. Bureau of Reclamation 2012a). This extensive report examines how demand, supply, and operations of the reservoirs may change over the next half century. It identifies the vulnerabilities of the current management of the system and evaluates the potential for water management actions to address those vulnerabilities.

**Scope of the Basin Study**

The Basin Study evaluates the ability of the river meet a broad set of water delivery, electrical power, flood control, water quality, recreational, and ecological objectives across a range of plausible future supply and demand conditions between 2012 and 2060. It then considers how different water management actions can address the vulnerabilities of the system.

To evaluate plausible changes in future water supply, the Basin Study evaluates performance of the system for 1,959 unique plausible traces of natural streamflow (streamflow in the absence of human intervention). These traces are based on four different sources: the recent historical record, the paleoclimatological record, a statistical blend of the first and second sources, and projections of climate change. The climate change projections are drawn from 16 global climate models and three global carbon emissions scenarios. The climate change projections encapsulate a larger range of
plausible average supply than the historical and paleoclimatological records and contains many futures that are significantly drier (U.S. Bureau of Reclamation 2012b). Figure 1-3 presents the distribution of average annual natural streamflow at Lees Ferry AZ (a point along the Colorado River frequently used to monitor streamflow), across the traces drawn from each source. Streamflow in the historical record is clustered around the historical mean and significantly higher than streamflow from 1991 to 2010. The median average annual streamflow from downscaled climate change projections is below average annual streamflow in the last 20 years, but a small number of traces are wetter than the historical average.

*Figure 1-3: Summary of plausible long-term average streamflow futures by source*

*Source: Groves, Fischbach et al. (2013)*

To consider the range of future demand, six scenarios were developed for the study. These demand scenarios encapsulate differing assumptions regarding population and demographic changes, economic growth, and water use patterns across the Basin. The six scenarios include a continuation of long-term trends, slowing growth, rapid growth, and increased environmental awareness. In these scenarios, increases in demand for water range from 5 percent to 14 percent between now and 2060 (U.S. Bureau of Reclamation 2012b).
To calculate the effect that the sequences of supply and demand may have on objectives described above, the study uses the Bureau of Reclamation's long-term planning model, the Colorado River Simulation System (CRSS) developed in the RiverWare® hydrologic modeling software (Zagona, Fulp et al. 2001, U.S. Bureau of Reclamation 2012e). This model contains a representation of the hydrologic network in the Basin and calculates hundreds of outcomes, including allocations of water, reservoir levels, managed streamflow, and power production for each sequence of supply and demand.

The simulations are used in the Basin Study to quantify the impacts that the various demand scenarios and traces of plausible streamflow may have on various indicator metrics to represent the objectives described above. The study considers six resource categories of indicator metrics: water delivery, electric power, recreation, ecological, water quality, and flood control.

The analysis in the Basin Study quantifies various characteristics that traces of future streamflow that are closely associated with the Basin failing to meet some key water delivery objectives. It finds that low long-term average natural streamflow coupled with an eight-year period of nature low streamflow are associated with the system failing to meet objectives. It also identifies different threshold values of these two measurements of streamflow for each objective (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

The Basin Study then evaluates a wide array of supply augmentation and demand-reduction water management actions that could improve system performance and reduce vulnerabilities. Unique water management actions are grouped into various portfolios (U.S. Bureau of Reclamation 2012d). By simulating future hydrology in the Basin with these portfolios in place, the Basin Study quantifies the ability of these actions to address vulnerabilities and meet objectives in challenging future conditions. This analysis also identifies some promising initial actions for Basin planners to consider implementing (U.S. Bureau of Reclamation 2012e).

**Basin Study process using deliberations with analysis**

The Basin Study was written over a three-year period from 2010 to 2012, referred to in this dissertation as the Basin Study Process (U.S. Bureau of Reclamation 2012h). This process included analysis paired with stakeholder deliberations, allowing the analysis to be guided by the valuable insight of Basin planners and stakeholders to ensure it was consistent with the planning problem they faced.

The Basin Study Process incorporated many elements of the “deliberations with analysis” framework for addressing climate change described by the National Research Council (2009). In this mode of learning, planners “interact with technical experts and analysts to develop a shared understanding of the issues at stake, of what needs to be understood and how scientific research and assessment and the interpretation of available knowledge are likely to feed into decisionmaking.” Next, “analysts can develop knowledge and information that are likely to be used in further decision-focused deliberations” (National Research Council 2009).
During the Basin Study Process, analysts from the U.S. Bureau of Reclamation and other contracting organizations, referred to as the Study Team, engaged in a large-scale research project. The process to complete this research entailed modifying simulation models, generating scenarios, analyzing the impact of exogenous future conditions, characterizing water management actions, estimating their impact, and producing visualizations to summarize results.

This research was completed with interaction and input from various stakeholders. A team of representatives from the Basin States, the Project Team, worked with the Study Team to “provide expertise, experience, and knowledge” (U.S. Bureau of Reclamation 2012a). Over the course of the Basin Study Process, the Project Team held monthly in-person meetings. At these meetings, Study Team members would frequently present the latest results from continuing analyses to elicit feedback from the planners on the Project Team. This feedback would often require the team of analysts to modify, adjust, or adapt analyses to be consistent with the planners’ expertise and conception of the planning problem at hand. Members of the Study Team and Project Team frequently collaborated in smaller sub-teams (which would also engage additional experts as necessary) to address specific issues in the analysis in greater detail (U.S. Bureau of Reclamation 2012i).

Additionally, the Project Team engaged in extensive outreach activities to obtain feedback. These activities included meetings, webinars, and conference calls with tribal groups, conservation organizations, and other relevant stakeholders (U.S. Bureau of Reclamation 2012g).

For example, one area where the Study Team elicited information from the Project Team and other stakeholders was in the development of portfolios of water management actions. These portfolios were designed to be consistent with underlying strategies reflecting the preferences and objectives of various stakeholder groups. The process began by eliciting proposals for actions that planners could implement from various team members, other stakeholders, and the public at large, resulting in 160 concepts. The Study Team organized an Options and Strategies Sub-Team to characterize each concept, carrying forward approximately 80 unique water management actions. This team characterized actions by 17 different criteria including timing, cost, yield and other qualitative criteria such as technical feasibility (U.S. Bureau of Reclamation 2012d).

Researchers from the Study Team organized this data into a portfolio development tool, designed to help planners and stakeholders combine specific water-management actions they would consider implementing into portfolios to evaluate. Using the criteria described, users of the tool could screen out actions that were inconsistent with their underlying strategy. They could also adjust the timing or priority of the remaining actions based on other criteria or their own expert knowledge (U.S. Bureau of Reclamation 2012d, Groves, Fischbach et al. 2013).

This portfolio development tool was used to generate two\(^2\) portfolios of actions consistent with stakeholder objectives and preferences. Portfolio B (Reliability Focus) emphasizes actions with high technical feasibility and long-term reliability. Water planners in the seven Basin States contributed to the development of this portfolio and it emphasized their objective to reliably deliver water to

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\(^2\) The Basin Study evaluates four portfolios in total, but only two were designed to reflect specific stakeholder preferences.
users. *Portfolio C (Environmental Performance Focus)* emphasizes actions that would increase streamflow while excluding actions with high-energy intensity. Non-governmental organizations primarily concerned with the health of the river and protecting the natural habitat contributed to the development of this portfolio (U.S. Bureau of Reclamation 2012d, Groves, Fischbach et al. 2013). By including portfolios that reflect various stakeholder preferences, the Basin Study team was able to elicit expertise from a range of stakeholders and describe various ways Basin planners could address challenges over the next half-century.

Because the study successfully integrated Basin planners’ and stakeholders’ expertise and knowledge into an analytical process, its reach was felt at the highest levels of government. Days after the Study's release, Secretary Salazar praised the “rigorous and unequivocal detail that is provided by the Basin Study.” He stated that the “the study is a call to action, that must be answered” but would require “diligent planning and collaboration from all stakeholders to identify and move forward with practical solutions” (Salazar 2012).

Ms. Mulroy echoed this sentiment describing, “The Basin Study paints the possibilities. It paints the possible futures that we may have to face together” and the detailed analysis in the study “will give [the Colorado River water users] the time and the diligence to work through the myriad of issues it will bring in its wake” (Mulroy 2012).

Though the study did not recommend any solutions, its publication has led to some significant next steps, also using a deliberations and analysis framework. Three new working groups have been established to consider strategies to address the challenges ahead.3 These working groups consist “of members with subject-matter expertise from various entities in an effort to bring important and varying perspectives to build on collaborative findings to pursue the next steps identified in the Study” (U.S. Bureau of Reclamation 2013).

**Basin Study begins an evaluation and development of adaptive strategies**

**Cost-reliability tradeoff**

Among the many important issues explored in the Basin Study is a tradeoff between water delivery reliability and the cost of water management actions. Each water management action analyzed in the Study has the potential to increase water delivery reliability (and help meet other objectives) to some degree but also has some level of effort associated with it. For example, the most expansive portfolio of actions analyzed includes 6.3 maf of total yield of new resources, with an estimated annual cost of $7.7 billion by 2060 (U.S. Bureau of Reclamation 2012d). The analysis in the Basin study reflects an assumption that planners would prefer to not implement actions in futures where

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3 The three workgroups consider three categories of solutions:

1) Municipal and Industrial Conservation and Water Reuse
2) Agricultural Conservation, Productivity and Water Transfers
3) Environmental and Recreational Flows.
they are not necessary to maintain reliability, but may be willing to accept the costs in futures where they are.\(^4\)

Planners face therefore a choice between the total cost and yield of actions they choose to implement and the water delivery reliability they achieve. The Basin Study begins with a baseline evaluation of system reliability without any additional water management actions, characterizing the reliability and vulnerability of the system across a broad range of plausible futures. This analysis identifies that planners will fail to meet water delivery objectives in many future conditions and will underinvest if they do not act. It next assesses a “static” portfolio, which considers implementing the same set of actions in each plausible future. This analysis identifies that the static portfolio can meet water delivery objectives in many futures that the current management could not, but still cannot meet objectives in every future. However, the Basin Study notes that such a strategy is expensive, and implements more actions than would be necessary in many futures (U.S. Bureau of Reclamation 2012e).

The Basin Study identifies that different futures have different needs (U.S. Bureau of Reclamation 2012e). The analysis in the study implicitly assumes that planners seek to identify a package of actions that maintains water delivery reliability in each future while minimizing the cost of the actions they implement\(^5\). However, planners face uncertainty in future streamflow conditions. The subsequent sections of this chapter describe an adaptive approach to implement new water management actions based on new information over time. This approach allows planners to take advantage of new evidence and better estimate the needs of the system.

**Adaptive approach to planning**

As the Study Team designed the scope of analysis, they were confronted with a complex long-term planning problem. Like many water managers in the American West, planners in the Basin face a new policy problem (Groves, Davis et al. 2008)—a wide range of conditions may evolve over an extended time horizon, (Brekke, Dettinger et al. 2008) but scientists, stakeholders, and planners have not formed a consensus regarding what the future may hold (Deser, Knutti et al. 2012).

Standard planning paradigms generally used to support water agency planning are predict-then-act approaches; the most likely future is estimated and strategies are created to address that particular future (Lempert, Popper et al. 2003, Lempert and Groves 2010). Strategies developed using these techniques are generally static—a set of actions is defined and implemented regardless of how the future may unfold. If planners are confident in what the future holds, contingency planning is of little value. But when there are a wide range of plausible conditions, the identified plan may not perform well in other futures (Lempert, Popper et al. 2003). Planners know this and often update plans periodically as new information becomes available. Under this predict-then-act-then-revise process, even though the plans change as conditions require, the planning still considers strategies that remain static.

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\(^5\) This assumption is not explicitly stated in the Basin study, but the design of the adaptive strategies reflects that planners are willing to increase number of water management actions to address drying conditions.
There can be consequences from using predict-then-act-then-revise approaches. Various methodologies across disciplines describe ways in which planning process that do not anticipate changes in response to new information may be costly (Dixit 1994, Lee 1994, Trigeorgis 1996). Analysis may prescribe plans that ultimately become more expensive as they change to accommodate uncertainty. Planners may commit resources prematurely to plans that are eventually altered, or they may take actions that close off other potential opportunities. Conversely, a predict-then-act-then-revise approach may underestimate the resilience of a system and over-invest in actions that are not needed. Moreover, predict-then-act approaches do not provide guidance on how planners should respond to new information, as planners may be slow to react when changes are needed or over-react to short-term indicators.

Instead, there is an emerging consensus that strategies to address climate change should be adaptive. Adaptive strategies “evolve over time in response to new information” (Lempert, Popper et al. 2003). Walker et al.” (2001) expand on this definition, stating that adaptive strategies are “policies that comprise sequential combinations of policy options. Some options are to be implemented right away; others are designed to be implemented at an unspecified time in the future or not at all if conditions are inappropriate. The policy includes contingency plans as well as a specification of conditions under which the entire policy should be reconsidered. The policies themselves are, therefore, designed to be incremental, adaptive, and conditional.

**New techniques to consider adapting in the Basin Study**

During the Basin Study process, planners and analysts recognized that policy would continue to change as conditions require and analysis should be consistent with an adaptive framework. They sought a set of methods that moved beyond the predict-then-act-then-revise approach.

To help address this need, researchers from the RAND Corporation joined the Study Team to provide new modeling and analytic techniques using Robust Decision Making (RDM) (Groves, Fischbach et al. 2013). This approach establishes a framework for considering multiple plausible futures and builds strategies to address challenges in those futures. RDM provides a set of modeling statistical, and data visualization tools embedded in a process of stakeholder engagement. RDM helps planners develop adaptive strategies by iteratively evaluating the performance of proposed strategies against a wide array of plausible futures, systematically identifying the key vulnerabilities of those strategies and using this information to suggest responses (Lempert, Popper et al. 2003, Lempert and Collins 2007). RDM is explained in detail in subsequent chapters of this dissertation.

Consistent with the adaptive approach, the Basin Study “evaluate[s] how the system reliability could be improved using a portfolio that triggers options in response to evolving conditions suggestive of increasing vulnerability—the dynamic framework” (U.S. Bureau of Reclamation 2012e). The Basin Study also “analyze[s] the frequency and timing of [action] implementation in the dynamic portfolios gaining insight toward effectiveness of options at improving system reliability” (U.S. Bureau of Reclamation 2012e).
The analytical approach in the Basin Study includes three innovative elements to consider strategies that adapt as conditions require. First, insights from exploring a large ensemble of plausible futures were used to design decision-rules that planners can use to respond directly to the vulnerabilities of the system. Second, analysts updated CRSS to include a simple simulated planning agent that could mimic an adaptive process for implementing water management actions. Finally, the set of simulation results was used to characterize the timing and frequency of actions that may be required (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013). These will each be described in detail in this dissertation.

As made apparent in the Basin Study, Basin planners are on the forefront of recognizing that they will need plans that can evolve as new information becomes known. The Basin Study and subsequent next step activities represent the start of an adaptive planning process. The modeling techniques used in the Basin study demonstrate planners and analysts have invested in tools to model strategies that change over time. As the planning continues, there remains an opportunity for new tools and modeling techniques decisions about the water management actions explored in the Basin Study over a long-term planning horizon and how observations of relevant information will be integrated into those decisions.

Dissertation extends discussion and analysis of adaptive strategies
This dissertation examines how RDM can provide decision-support to planners as they create, evaluate, and deliberate about adaptive strategies. To provide an application, it extends the analysis of adaptive strategies provided in the Basin Study.

This dissertation makes two primary contributions to the literature. First, it offers an extensive treatment of the use of RDM to provide decision support when generating and evaluating adaptive strategies. Second, it demonstrates tools that can be used to support decision-making in the Basin drawing some policy conclusions for how planners should adapt.

While RDM literature frequently describes that adaptive strategies are important elements of long-term planning under deeply uncertain conditions, the methodology does not present a consistent approach to support deliberations about such policies. This dissertation proposes such an approach, by augmenting the traditional RDM process with three additional analyses: identify signposts, evaluating tradeoffs among decision-rules, and characterizing implementation.

Next, this dissertation uses this approach to support planning in the Colorado River Basin. It provides assessments of the implications of short-term observations of new information, the tradeoffs among strategies defined by different decision-rules, and visual aids to show the choices planners face as they implement water management actions. In doing so, these analyses are able to offer some policy recommendations for planners, as they design strategies to adapt over time. In addition to offering specific policy recommendations, the analyses in this dissertation serve as demonstrations of new tools that planners can incorporate into future deliberations.

The second chapter offers a discussion of decision-support for adaptive strategies. First, it defines components of adaptive strategies. Next, it describes methodologies that have been used to support
decision-making when designing such strategies. Finally, it proposes a series of analysis within the iterative RDM process to address particular decision support needs when considering adaptive strategies. Throughout the text, it provides examples in the Colorado River Basin.

The third chapter considers the design of an RDM analysis with multiple time-periods for decision-making. It begins with discussion of how uncertainties, levers, and measures of merit can defined for multiple time periods within the context of an RDM analysis. This leads to a definition of adaptive strategies using decision-rules based on observations of signpost variable as means implement new actions. This chapter then proposes a stylized model, consistent with the RDM process, which describes tradeoffs that planners may face among alternative decision-rules. Finally, the chapter provides discussion of how analysts may summarize the results of simulations to characterize the implementation of actions and provide planners with decision-aids as they choose among actions.

The fourth chapter describes the factors of analysis in this dissertation. It describes the future hydrologic uncertainties, the portfolios of water management actions that comprise strategies, simulation model of the Basin, and the metrics for considering whether Basin objectives are met.

The fifth chapter extends the analysis in the Basin to assist planners as they integrate new information. It offers a Bayesian interpretation of signpost variables as they are integrated with planners’ current beliefs to generate new assessments of the likelihood of planning scenarios. In doing so, it proposes a Naïve-Bayes estimator model, to consider how planners may update beliefs after monitoring short-term observations of streamflow and other exogenous climate indicators. An exploratory analysis of this model describes how planners with disparate beliefs may update their beliefs in response new information. This model is used identify observations that will generate consensus that a scenario is occurring among stakeholders who fall within a certain range of prior beliefs.

The sixth chapter explores the tradeoffs among decision-rules that Basin planners may use. Basin planners have dual objectives: maintaining water-delivery reliability and minimizing costs. As they balance both objectives in the face of uncertain information, they risk of either being under-prepared or over-investing. This analysis demonstrates that a relatively simple set of triggers to implement water management actions based on observation of streamflow and reservoir levels can help planners manage these competing risks. However, it finds planners will still make decisions with imperfect information and different triggers will balance the under-preparedness/over-investment tradeoff differently. This chapter provides analysis of these tradeoffs over the next-half century in the Basin, examining the relative performance of a range of alternative decision-rules. It evaluates the performance of the strategies across different streamflow conditions and compares the expected payoffs for various subjective beliefs about the future. The chapter concludes with some policy implications of this analysis to inform a process where planners continue to deliberate.

The seventh chapter offers an analysis of the implementation of water-management actions, as Basin planners adapt over time. It characterizes the water-management actions that the modeled adaptive strategies implement across the ensemble of futures. It also demonstrates how planners
may wish to increase the total-yield of water-management actions over time and address different sets of streamflow conditions. The analysis then turns to individual water-management actions, deriving scenarios that describe the streamflow conditions that require the implementation of specific actions. This information is summarized in visual-aids that explore the different pathways planners may take to address different conditions.

The eighth chapter provides some conclusions to the analyses in this dissertation and discusses possible next steps.
Chapter 2: Adaptive strategies, decision support, and Robust Decision Making

Introduction

“Climate change is a long-run problem that will provide us with many opportunities to learn and to revise our strategy over many decades. Thus, it is best conceived of as a problem requiring sequential decision-making under uncertainty rather than requiring a large, one shot, ‘bet-the planet’ decision” (Weyant 2008). Like climate change, many policy problems that require long-term planning can be considered as a series of sequential decisions that present opportunities to adjust, update, and revise strategies as information is learned over time.

When strategies are designed explicitly to take advantage of the opportunities described above and evolve in response to new information, they are called “adaptive strategies” (Lempert, Popper et al. 2003). Such strategies are “sequential combinations of policy options. Some options are to be implemented right away; others are designed to be implemented at an unspecified time in the future or not at all if conditions are inappropriate. The policy includes contingency plans as well as a specification of conditions under which the entire policy should be reconsidered. The policies themselves are, therefore, designed to be incremental, adaptive, and conditional” (Walker, Rahman et al. 2001).

When planners design adaptive strategies, they may face a multitude of potentially complex and interacting decisions. First, they have choices about which policy actions to implement—the laws, regulations, infrastructure, taxes, or subsidies, or other policy tools available. Planners’ choices among multiple candidate actions will depend on attributes of the actions, the needs of the system, implementation constraints, the information available to planners, and planners’ preferences. Planners also obtain new information over time, but face choices regarding what pieces of information they invest resources in tracking and observing—a process referred to as monitoring. Finally, planners face decisions on how to react to new information. As Lee describes, planners must transform new information into learning to “correct error, improve their imperfect understanding and change action and plans” (Lee 1994).

Complex decisions such as these often require an environment where information and analysis is paired with interactions between planners and stakeholders. Lee elegantly describes this process as having two elements: “the compass”—the physical and social sciences that inform decisions and “the gyroscope”—the interactions and debate among various stakeholders and planners in the context of democratic institutions (Lee 1994). The National Research Council (2009) describes a
similar process of *deliberations with analysis* as a “collaborative, broadly based, integrated, and iterative analytic-deliberative processes” that provides a “method of choice for organizing scientific analysis to serve public decision making.” They describe four elements of the process: 1) diagnosis of the planning challenge, 2) collaboration to identify techniques to address the challenges, 3) monitoring new information to assess the success or failures of those techniques, and 3) iteration to change decisions.

Central to both these approaches is a multi-stakeholder environment where planners and stakeholders make policy decisions through interactions, collaboration, debate, and deliberations. Such environments can introduce situations where the various parties involved may have differing preferences and objectives. Additionally, these parties (or the scientific community informing these parties) may have differing assessments of the likelihood of various future conditions—a situation referred to as *deep uncertainty* (Lempert, Popper et al. 2003).

In a deliberation and analysis process, scientific and analytic approaches inform the multiple parties generating policy. The interactions among those providing scientific and analytic information and those involved in the decision-making process is referred to as *decision-support*. This can be described as “decision tools, messages, and other products that convey user-relevant information in ways that enhance user understanding and decision quality. These products may include models and simulations, mapping and visualization products, websites, and applications of techniques for structuring decisions, such as cost-benefit analysis, multi-attribute decision analysis, and scenario analysis, among others” (National Research Council 2009). Decision-support includes many analytic activities ranging from decision structuring frameworks to mathematical modeling techniques to visualizations.

Analysts can use a variety of tools to provide decision-support for adaptive strategies. Emerging from literature on scenario planning and robustness, Assumption Based Planning (Dewar, Builder et al. 1993) and Adaptive Policymaking (Walker, Rahman et al. 2001) help planners identify the vulnerabilities of a strategy and develop plans that monitor information which suggests these vulnerabilities may occur. Adaptive Robust Design (Hamarat, Kwakkel et al. 2012) draws insights from exploratory modeling to structure policies consistent with Adaptive Policymaking. Adaptive Pathways (Kwakkel and Haasnoot 2012, Haasnoot, Kwakkel et al. 2013) also emerges from this literature, focusing on innovative graphics that planners can use to consider the choice among different sets of actions.

Other disciplines also consider the mathematical relationships describing the interactions among policy outcomes, policy actions and new information. This includes control theory, a branch of engineering concerned with feedback within a system (Kirk 2012). Control theory has previously been applied to policy problems such as monetary policy (Hansen and Sargent 2000), ecosystem management (Bond and Iverson 2011) and climate change (Funke and Paetz 2011). Closely related, real options is the branch of economics concerned with valuing different types of flexibility in investment decisions (Dixit 1994, Trigeorgis 1996, Linqüiti and Vonortas 2011). These both draw heavily on dynamic programming, a mathematical technique for identifying optimal strategies over time (Bellman 1956).
One decision-support approach designed to address deep uncertainty is Robust Decision Making (RDM). RDM is a systematic and objective approach for developing and evaluating adaptive strategies that are robust to uncertainty about the future (Lempert, Popper et al. 2003, Lempert and Groves 2010, Means, Laugier et al. 2010). RDM helps planners develop adaptive strategies by iteratively evaluating the performance of proposed options against a wide array of plausible futures, systematically identifying the key vulnerabilities of those strategies and using this information to suggest responses to the vulnerabilities identified (U.S. Bureau of Reclamation, Lempert, Popper et al. 2003, Lempert and Collins 2007, Means, Laugier et al. 2010). Successive iterations develop and refine adaptive strategies that are increasingly robust. Final decisions among strategies are made by considering a few robust choices and weighing their remaining vulnerabilities.

The support provided with an RDM analysis can be useful to planners when generating adaptive strategies. First, an RDM analysis evaluates strategies across a wide range of plausible belief. Such an analysis evaluates strategies with a robustness criterion—the ability to perform sufficiently well across a range of plausible futures. Adaptive strategies generally perform well by this criterion as they can evolve to address a wide array of conditions (Rosenhead 1989, Walker, Rahman et al. 2001, Lempert, Popper et al. 2003). Additionally, analysis helps planners identify the key uncertainties which drive outcomes and can illuminate information that planners should monitor (Lempert, Popper et al. 2003, Lempert and Collins 2007). Finally, an RDM analysis includes a consideration of tradeoffs, allowing stakeholders and planners to consider the performance of various methods of adaption across different objectives and different plausible beliefs about the future.

This chapter offers a discussion of adaptive strategies, a brief summary of some methods of decision-support and an in-depth consideration of the use of RDM to support adaptivity. It also adds to the literature by consolidating and expanding on multiple definitions of adaptive strategies, compiling an overview of various decision-support methods used for adaptive strategies and providing a discussion of how the RDM process can be augmented to more explicitly assist the creation of adaptive strategies. Although the chapter’s discussion is broad, as adaptive strategies are appropriate for many policy problems and planning contexts, it presents examples from the Colorado River Basin as tangible applications of complex concepts. Additionally, this section provides a framework for the analyses in the subsequent chapters of this dissertation.

This chapter begins by offering a definition of adaptive strategies. This definition begins with describing a continuum of ways in which planners may respond to new information and an example of each in the Basin. It then describes three distinct elements of adaptive strategies: 1) the basic plan and initial actions, 2) contingencies and policy adjustment and 3) monitoring and learning. It draws from various pieces of decision-support literature to expand on each element, focusing on the various choices that planners and stakeholders face.

Next, is an overview of a set of decision-support methods related to adaptive strategies. The chapter is able to extract some lessons learned for considering strategies under deep uncertainty by summarizing multiple methods of varied decision-support analyses.
Finally, this chapter provides a discussion of how RDM can support the generation and evaluation of adaptive strategies. RDM and adaptivity are closely linked and this chapter carefully considers various pieces of decision-support that RDM provides to inform an adaptive process.

**Defining adaptive strategies**

Adaptive strategies evolve over time in response to new information (Lempert, Popper et al. 2003). This definition is intentionally broad. A simple version of an adaptive strategy may be a plan that resembles a decision tree—planners take one action if a certain piece of information is observed and another if not. A more complex adaptive strategy may be a system containing mechanisms designed to dynamically take advantage of new information—such as a market economy (Lempert, Popper et al. 2003).

This dissertation primarily focuses on adaptive strategies where planners and possibly stakeholders are working together to generate consensus regarding a set of policy actions to address specific policy objectives by adjusting plans as new information becomes available. The adaptive strategies are deliberately designed with some pre-specified scope that contains a set of objectives, mechanisms for how the strategies will evolve, and a defined set of actors that deliberates plans and make decisions. The contours of the adaptive strategy may still be broad, allowing it to evolve in unexpected directions as necessary. This definition stands in contrast to a broad mechanism for adaptivity such as a market economy with less specific objectives or a lack of centralized decision-making.

While adaptive strategies can take advantage of information as it becomes available and offer a way to prepare for a wide range of conditions, they also carry some risks. For an adaptive strategy to remain effective, it requires institutions and processes that can support continuous updating of a strategy (Lee 1994). However, this may stand in contrast to strategies that are enacted during a “policy window”, (Kingdon and Thurber 1984), which represents a period of time where the political will for action exists and policies are likely to be enacted. If a policy is not committed to during this window, circumstances may change to hamper or discontinue an adaptive strategy (Lee 1994). Therefore, designing adaptive strategies often requires consideration of the political institutions that can convene the relevant stakeholders, support deliberations, monitor conditions, and implement plans (Fischbach, Lempert et al. 2014). Designing such intuitions, however, is beyond the scope of this dissertation.

**Continuum of planning responses to new information**

Strategies can be adaptive in various ways; they fall along a continuum describing the relative amounts of deliberation or automation in the response to new information. At one end this continuum is *fully-automatic policy adjustment* where predefined actions are taken in response to predefined sets of new information (Swanson, Barg et al. 2010). This requires consensus among stakeholders and planners regarding the behavior of a system and how best to respond to new information, but accommodates uncertainty in what the future may hold. On the other end of the continuum is *formal review and continuous learning* where a multi-stakeholder deliberative process
is paired with analysis to consider how new information has changed the understanding of the system and how policy should be adjusted (Swanson, Barg et al. 2010). Such review occurs periodically over time, either according to a preset schedule or as new information warrants deliberations. Between these two extremes falls semi-automatic policy adjustment—some deliberation is necessary but in a more constrained form than formal review and continuous learning. Predefined sets of information may trigger deliberations and the scope of deliberations may be in some ways constrained to a predefined set of policy-responses (Swanson, Barg et al. 2010). Figure 2-1 depicts this continuum and expands on the definition provided by Swanson et al. by describing some of the conditions in which each form of adaptation may be useful.

Figure 2-1: Continuum of responses to new information in adaptive strategies

Adapted from: Swanson, Barg et al. (2010)

The different types of adaptivity may be useful in different circumstances. Fully-automatic policy adjustment is well suited for systems that are well understood but future conditions remain uncertain (Swanson, Barg et al. 2010). Such a method avoids costly deliberations each time new information becomes available, instead allowing for a rapid response to new information. As such, this method may be effective when actions can be implemented and altered relatively quickly. In some ways, this method can be flexible by allowing for quick responses to changing conditions. In other ways, the strategy may be rigid, as planners commit to a response to new information at the start of a planning horizon.

Formal review and continued learning is well suited for systems that are not well understood and planners cannot form consensus about how to respond (Swanson, Barg et al. 2010), thus, requiring a continued deliberation and analysis process. This type of adaptivity may also be best when actions must be committed to far in advance of their implementation, as there will be the less clarity and consensus. However this process can be slow and costly, which presents it own risks such as policy window closing before decisions are made.
Semi-automatic policy adjustment falls somewhere between these two extremes. Deliberations may be constrained by the policy adjustments or the new information considered. Planners may have a strong understanding of the system but no consensus about the policy response. In these cases, planners may design a system with deliberations after observing predetermined pieces of information. Alternatively, planners may agree on a prioritization of policy responses but may not agree on which pieces of evidence would necessitate their implementation. In these cases, planners may wish to review new information periodically and deliberate whether a policy response is warranted (Swanson, Barg et al. 2010). As deliberations are more constrained, the method adaptivity more resembles fully-automatic policy adjustment and facilitates a faster response to new information. Less constrained deliberations may allow for a broader consideration of the ways a system may change, but can be costly or slow.

This continuum is a simplification of nearly infinite possible policy responses to new information. For example, a strategy may include some fully-automatic components, serving as a default strategy. However some entity may be empowered to review or some how alter the automatic default, thus inserting some semi-automatic elements judgment into the strategy. Alternatively, as planners deliberate actions in the context of a semi-automatic policy adjustment, they may realize that new information is needed or additional actions should be considered; the scope of deliberations may expand to more closely resemble formal review and continuous learning. Additionally, a formal review and continuous learning process may result in a broad policy framework, which is then implemented through multiple narrower fully and semi-automatic policy adjustments.

Many adaptive strategies contain multiple responses to new information that span across the continuum. A policy may include fully-automatic elements to manage operational decisions, semi-automatic elements to make smaller-scale changes in policy regularly, and formal review and continuous learning to periodically reassess larger changes. Frequently, different parts of government are responsible for different types adaptation. For example, formal-review and continuous learning may be mapped to larger policy debates that are addressed at the legislative level, where fully-automatic policy adjustment may be the rules and regulations that are enforced by individuals in a government agency (Fischbach, Lempert et al. 2014). Additionally, an adaptive strategy may include mechanisms for elements of the strategy to move between the types of responses, such as a review board with the ability to change the decision-rules used in automatic policy adjustment.

The current management of the Colorado River Basin represents an adaptive strategy utilizing all three approaches. The Law of River, including the Compact and the Interim Guidelines, represent a set of fully-automatic policy adjustments. It defines how water is allocated among states on an annual basis and facilitates the operation of reservoirs in the system. These rules allow the basin to manage annual and decadal uncertainty in water supply with systemized rules. However, the Interim Guidelines also include a semi-automatic response to new information, with a clear trigger for renewed deliberations. Should Lake Mead’s pool elevation drop below 1025 feet, the Department of the Interior will initiate new deliberations to discuss allocation of water in these dry circumstances (U.S. Bureau of Reclamation 2007). The broader planning activities such as the Basin
Study (U.S. Bureau of Reclamation 2012f) and subsequent Next Steps (U.S. Bureau of Reclamation 2013), represent formal review and continuous learning. They are an opportunity for planners to consider new water management actions to address future challenges and collect the information to make prudent decisions. Together, these three elements lay a solid foundation for adaptation in the Basin.

**Examples in the Colorado River Basin**

As the Basin confronts new threats of increasing supply and changing demand, planners may need to expand the adaptive processes to include the implementation of new water management actions—the subject of this dissertation. This section describes some hypothetical examples of each type of response to new information that can facilitate such adaptation in the Basin. Figure 2-2 provides a summary of the examples.

Figure 2-2: Examples of adaptive Strategies in Colorado River Basin along continuum of responses to new information

An example of formal review and continued learning in the Basin would be an agreement to update the Basin Study every 10 years. In this example, the Basin States and the U.S. Bureau of Reclamation would reconvene a Project Team and Study Team to evaluate a wide range of water-management actions across a broad set of futures. The team would solicit new information from stakeholders regarding plausible future scenarios and policy responses. The Project Team could be empowered to provide policy recommendations to the Federal and Basin State governments. While each subsequent study could build on the analysis and framework of the previous study, the Study Team would develop new tools and collect new information in each iteration. This would ensure the study incorporates the most up-to-date assessments and considers emerging threats to the system.

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6 At this point, this chapter does not provide any recommendations on which type is best suited to address the challenges in the Basin. Similarly, the details of each policy are simply illustrative, not meant to recommend specific details for how the Basin should establish a policy.
Such a process could be slow relative to the evolution of the system and costly due to the level of effort required each time the study process commences. Adjustments to strategies would be infrequent due to the periodic nature of the assessment. On the other hand, these updates would provide a forum to fully explore the changing environment. Such a process could be particularly important if the range of future uncertainty changes, new threats emerge or planners’ objectives change.

An example of semi-automatic policy adjustment in the Basin could be the commission of a panel of Basin State representatives to make recommendations each year regarding conservation and infrastructure projects to implement. The structure of such an agreement may place constraints on the scope of deliberations. For example, representatives may only consider conservation until 2025. Only if the panel exhausted all feasible conservation actions after 2025 could their recommendations include desalination plants and wastewater reuse. This panel would be charged with monitoring streamflow, reservoir levels, and external assessments of future climate change to inform their recommendations. The group would attempt to balance both water-delivery reliability and cost of actions.

In this example, deliberations occur each year. Unlike the previous example, the deliberations are constrained in scope, limited by the information monitored and the set of actions considered. These constraints facilitate faster and cheaper deliberations. The exact outcomes of deliberations are unknown, but the constraints impose a limited set of feasible results. In this example, individuals charged with implementing the policy actions would be assured that desalination and reuse are not to be implemented until after 2025 and could instead focus efforts on conservation projects. The panel could respond rapidly to new information; if they believed a drying future w(Walker, Rahman et al. 2001) as increasingly likely, their annual recommendations would reflect this updated assessment. However, using a set of standard tools and assessments, they would not broadly consider other emerging risks. Similarly, they would have limited jurisdiction to identify and deliberate new and creative solutions to challenges in the Basin.

A second example of semi-automatic policy adjustment recognizes that certain information requires a policy response, but that planners cannot commit a-priori to the response. In this case, when specific streamflow conditions are observed representatives from Basin States may convene to design a set of water management actions in response. Such a panel may consider a broader set of actions than the previous example, but only after observing specific triggers.

Finally, an example of fully-automatic policy adjustment might entail an agreement by Basin States to implement certain levels of conservation and infrastructure after observing certain streamflow conditions. For example, the agreement may read:
"If between 2012 and 2020, the Colorado River experiences less than 15 maf of average annual natural streamflow, each Basin State will identify 25 kaf of permanent conservation to implement by 2025. If they observe less than 14 maf of average annual streamflow, each will identify 50 kaf of permanent conservation. If they observe less than 13 maf, each will identify 50 kaf of permanent conservation and 25 kaf of additional supplies through desalination and water-reuse.”

This type of fully-automatic policy adjustment for long-term plans does not completely eliminate the need for further deliberations. Each Basin State would need to construct their own strategy to meet the targets, which may require deliberations between planners in state level and local water agencies. However, this version of fully-automatic policy adjustment provides those planners with explicit targets and defined thresholds for when various actions are required. It ensures that necessary action is implemented while taking advantage of new information that may become available over the next decade. However, such an agreement is rigid to new risks or new solutions, only addressing decreasing streamflow through conservation and specific pieces of infrastructure.

Elements of adaptive strategies

Rosenhead describes planning as a series of sequential decisions (Rosenhead 1989). Under this definition, planners make near-term decisions with current information while new information learned over time can influence decisions regarding additional policy actions or adjusting plans. Both Rosenhead’s (Rosenhead 1989) and Walker’s (Walker, Rahman et al. 2001) definitions of planning and adaptivity encapsulate three important elements described below.

1) The Basic Plan and Initial Actions: Those actions implemented or committed to in the initial time period of an adaptive strategy based on planners’ initial set of information.

2) Contingencies and Policy Adjustments: Those actions deferred beyond the initial period, new actions that become available, or modifications to already implemented actions. Planners can make decisions about these actions after the initial period as new information becomes available.

3) Monitoring and Learning: The process of observing new data, updating expectations of the future and incorporating this information into planning to implement contingencies and policy adjustments.

Figure 2-3 summarizes how these various elements of adaptive strategies can be used across the continuum of adaptive strategies shown before. The following sections describe each element in greater detail.

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7 This is purely an illustrative example, not a proposal. This dissertation recognizes in a complex multi-stakeholder environment there would be significant hurdles to generating a fully-automatic agreement in the form presented above. This dissertation does not mean to imply that this agreement is a likely form of adaptation. However, if Basin stakeholders put a high level of effort into establishing such an agreement, it may be feasible. Additionally, this example is extremely crude in structure. A more realistic agreement may have different requirements for the different Basin States and more specific definitions for actions that can account for these conservation or additional yield targets. The thresholds and yield requirements only serve as examples as further deliberations and analysis would be necessary to justify these decisions.
The basic plan and initial actions

Rosenhead describes that strategies begin with an “initial decision package”—the firm commitments that need to be made at the start of a planning process (Rosenhead 1989). Unlike strategies that are not adaptive, this package is determined with an expectation that it will be revisited as new information becomes available (Lempert, Popper et al. 2003). This chapter refers to these as initial actions.

Walker et al. (2001) describe a similar concept—the basic policy. The basic policy encapsulates a broader plan than merely a set of actions to implement at the start of the planning horizon; the basic policy is a combination of actions coupled with plans for their implementation (Walker, Rahman et al. 2001). A basic plan can serve as a default policy.

Like initial actions, planners determine a basic plan with information available at the start of a planning process. However, it extends a longer time horizon than initial actions and may foreshadow interim commitments to actions that are ultimately implemented in later time steps. For many actions in a strategy, implementation requires years of planning and interim outlays of resources (building political will, research, design, and construction of infrastructure) even if the benefits will not be realized until far into the future. Planners may still have the ability to defer, abandon, or expedite policy actions over a longer time horizon, but at some cost. Anticipating the ability to alter the basic policy, planners should design the basic policy with the expectation that it can be altered.

When a strategy updates decisions in a process resembling fully-automatic policy adjustment, a set of initial actions may be preferable to defining basic policy. New information will allow planners to update and adjust policy frequently and quickly. An extended plan for implementing actions may quickly become obsolete as new information becomes available.
Returning to the example of fully-automatic policy adjustment in the Colorado River Basin, planners may wish to establish some baseline level of conservation in addition to what is described in the agreement. Alternatively, they may agree that no initial conservation is necessary and that all actions can be defined by the decision-rules. A baseline level of action would be necessary if planners agree the Basin is likely to require some level of conservation before new information is available.

Planners may prefer to generate a more complete basic policy for a process more closely resembling formal review and continuous learning. The longer deliberative process may cause less frequent policy adjustments. However, the policy should still be designed anticipating that it will be revisited. The basic policy may specify key milestones stating when future decisions will be made. For example, planners may begin some preliminary implementation steps on many actions, anticipating that some will be abandoned prior to their final implementation.

In the example of formal review and continuous learning in the Colorado River Basin, planners may wish to generate a default set of actions to implement, in addition to the agreement to update the Basin Study every 10 years. For example, it could specify that planners in Basin States will identify 200 kaf of conservation every 10 years. Alternatively, the basic plan could designate that feasibility studies and permitting commence immediately for some desalination plants and that planners will make final decisions regarding their implementation in 2025. If planners reach consensus that some action is likely to be necessary, this basic plan would prevent a default strategy of no action. It still provides opportunities for planners to revise the strategy each 10-year cycle.

The basic plan and initial decisions may support the infrastructure and institutions necessary to maintain an adaptive strategy. Lee argues “the adaptive approach is not free: the costs of information and the political risks of having clearly identified failures are two of the barriers to use” (Lee 1994). Such investments may include technology and individuals to support monitoring or the creation of a commission to reassess policy over time.

**Contingencies**

Adaptive strategies contain some decisions that can be deferred beyond the initial period, referred to as contingencies. A contingency may be a change or adjustment to an action that can occur after the initial period. A contingent action is an action not implemented in the initial period; planners can *wait-and-see*.

The ability to defer decisions about actions can be described by options attached to them. An option is the right but not the obligation to change or alter an action. The economics literature on real options has characterized various types of options; some are described below: (Trigeorgis 1996)

1. Option to defer: the right to wait a period of time before implementing an action
2. Option to alter operating scale: the right to expand or decrease the scale of an action
3. Option to abandon: the right to abandon current action permanently
4. Time to build option: staging a single action into a series of separate actions, creating a series of options to abandon prior to paying the full cost
5. Option to switch: the ability to change the outputs of an action or create the same outputs using different inputs
6. Growth Option: taking a single action as a prerequisite to creating options to undertake additional opportunities

The decisions to adjust policies or implement contingencies can occur at various scopes and scales. In the simplest cases there may be an option to alter the scale within a relatively small range. These relatively small, well-understood or easy-to-alter contingencies are strong candidates for use in fully-automatic policy adjustment.

As the scope, scale, or complexity of the options attached to contingencies grow, deliberations may become necessary. In some cases, planners may consider a portfolio of adjustments that substantially alter a basic plan. Planners may identify and deliberate fundamentally new actions to address unforeseen events. When considering these complex adjustments, stakeholders may not have a clear sense of how the contingency will interact with the system. Such adjustments may require more learning and deliberation, requiring an adaptive process closer on the continuum to formal review and continuous learning.⁸

This dissertation primarily considers the case where there is an option to defer a discrete action. These deferred actions are contingency actions. When planners cease to defer the action, they exercise an option to implement the contingent action. Most language in this dissertation refers specifically to this case, unless otherwise noted.

**Monitoring and learning**

The value of deferring decisions is that planners may observe more data to avoid unneeded costs or damages. The process of monitoring information and integrating it into plans is a type of learning (Field, Barros et al. 2012).

Literature describes different classifications of organizational learning (Lee 1994, Field, Barros et al. 2012). When new information allows planners to simply update current information in models and beliefs, it is referred to as single-loop learning. This allows planners to react to new information. In such cases, fully-automatic policy adjustment or semi-automatic policy adjustment are reasonable methods of adaptivity. For example, Basin planners may observe a single year of below average streamflow. After observing such a year, planners have new information about the state of the system and can update plans accordingly. A single below average year is a possibility that planners were prepared for and existing plans, such as the Interim Guidelines, are designed to respond to such an observation.

Alternatively, new information may fall beyond planners' framing of a policy problem and cause them to question the basic assumptions of a system. This process is referred to as double-loop

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⁸In some cases, it may be possible for planners to reconceive of these larger and more complex contingencies as a set of smaller, simpler, inter-related real options (Trigeorgis 1996) Doing so may allow for less complex deliberations prior to implementation creating circumstances for greater flexibility and adaptivity.
learning (Lee 1994) and represents a reframing of the policy problem (Field, Barros et al. 2012). When confronted with new information of this sort, planners may require further deliberations supported with analysis. This type of learning may require an adaptive process consistent with a less constrained form of semi-automatic policy adjustment or formal review and continuous learning. The Basin Study can be considered an example of double-loop learning. After experiencing a longer-term drought and recognizing an evolving literature regarding climate change, Basin planners undertook a large scale planning exercise. This required gather new information, generating new tools, and considering new water management actions.

Triple-loop learning occurs when new information causes planners to reconsider “possible interventions, allowable costs, and appropriate strategies” and requires a reevaluation of the policy objectives or constraints on the policy, transforming the strategy as a whole (Field, Barros et al. 2012). This type of learning may require generating an entirely new strategy. Walker et al. suggest that adaptive strategies include a mechanism for reassessment when new information causes planners to reconsider the strategy as a whole (Walker, Rahman et al. 2001). If planners observe some of the worst projections of climate change, they may need to reconsider some fundamental objectives of the system, such as the basic allocation of water and revisiting the Law of the River.

One objective of adaptive strategies is to build this process of learning into the strategy by anticipating information that would ordinarily be unexpected and building processes to respond to new information (Lee 1994). The development of a strategy should allow planners to consider information that would have previously inspired double-loop or triple-loop learning so that it more closely resembles single-loop learning.

When designing an adaptive strategy, planners seek to operationalize the learning described above into adjusting strategies. Thus, planners monitor information and implement contingencies or exercise options on actions after sufficient evidence is acquired. Literature suggest that planners should monitor the uncertain conditions most associated with a system’s vulnerabilities (Dewar, Builder et al. 1993, Walker, Rahman et al. 2001). When a system contains many interacting and complex uncertainties, planners and analysts should seek to identify those that are most critical to the success or failure of the default policy. The variables that are monitored over time to suggest vulnerability are referred to as signposts (Dewar, Builder et al. 1993, Walker, Rahman et al. 2001).

The process of learning from signposts can be considered a Bayesian updating process. This process suggests that there is some underlying probability of outcomes. As information is observed planners can update their beliefs about this probability using an information-processing rule such as Bayes’ Rule.9 There is a vast literature on Bayesian learning. Bond and Iverson (2011) provide a review of how planners may update strategies as new information is monitored in a Bayesian updating process. In the example of semi-automatic policy adjustment, planners may update their beliefs about the necessary volume of conservation after observing streamflow in the Basin.

When the signpost variables present sufficient evidence that vulnerability is likely, planners should implement contingencies. When a strategy uses fully-automatic policy adjustment, the definition of

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9 Other information processing rules also exist.
sufficient evidence should be pre-specified in the form of decision-rules. The threshold values of the
signpost variables that require planners to implement contingencies or adjustments are called
triggers (Walker, Rahman et al. 2001). In the Colorado River Basin example described above, the
policy explicitly defines triggers for additional action— the pre-specified thresholds of annual
streamflow that imply conservation.

A process nearer to semi-automatic policy adjustment or formal review and continuous learning
may be more appropriate when there is no single interpretation of the signpost variables. In this
case, new information on its own may not generate consensus among stakeholders about what
information is necessary. For example, planners may know that low streamflow conditions in the
Basin require a response, but are unsure what threshold value would require additional water
management actions. During the deliberations, planners can collect other pieces of information,
receive decision support, and build consensus or compromise on strategies that are acceptable to
the multiple parties involved.

When the process requires triggers, planners must identify and choose among multiple candidate
triggers. These triggers should be observable and accurate indicators of a vulnerability, prior to its
occurrence (Dewar, Builder et al. 1993). In the example of the fully-automatic policy adjustment in
the Basin, planners should choose the threshold values of streamflow not because they imply the
Basin is already suffering from adverse effects, but because the low streamflow values imply
shortages are likely in the future.

However, because uncertainty is often not fully resolved when decisions are made (Dixit 1994,
Trigeorgis 1996), triggers may not be entirely accurate. Planners may observe a trigger that
suggests enacting a contingency when it turns out to not be required—a false positive. In the Basin
example, planners could observe low streamflow from 2012-2020 and implement additional
conservation. However, annual stream-flow in the years after 2020 could surpass historical levels,
and the additional conservation would not have been necessary. Water users in the Basin would
bear the expense of conservation, but there would be little benefit.

On the other hand, planners may fail to observe a trigger when an action would have been
necessary—a false negative. In the Basin illustration, planners could observe streamflow above 15
maf from 2012-2020 and, therefore, not need to implement any additional conservation. However,
annual stream-flow in the years after 2020 could drop precipitously and the Basin could face water
shortages and planners would wish to have invested in additional conservation. Water users in the
Basin face shortages, having failed to make the necessary investments.

Amongst a set of well-defined triggers, these two measures can be in tension with one another,
choosing a trigger with a lower likelihood of a false-positive would mean increasing the likelihood
of a false-negative (Fawcett 2006). The choice among decision-rules with different relative
measures of accuracy can have significant policy impacts. In the example in the Basin, if a false-
positive occurs planners will have over invested. On the other hand, if a false-negative occurs,
planners will not have invested in necessary action resulting in vulnerability.
Planners will need to make decisions about their willingness to accept false-positives and false-negatives based on their own preferences and beliefs about the future. While science generally has a bias toward avoiding false-positives, in policy applications these decisions will be based on stakeholders own values, beliefs about the future, and interpretations of the information at hand (Lee 1994).

**Elements of decision-support**

As described in the introduction, designing adaptive strategies is accomplished through science and analysis informing a deliberative decision-making process—decision-support. Regardless of the manner in which new information is integrated into planning, planners and stakeholders face potentially difficult decisions about what actions to implement in the near term, which adjustments to implement if conditions require, and how to incorporate new information into plans. For strategies using fully-automatic policy adjustment, planners face decisions at the start of the planning period regarding which pieces of information will call contingencies. For strategies on the other end of the continuum, planners require ongoing decision-support to facilitate the integration of new information into continued deliberations.

Figure 2-4 shows a series of iterative analysis and decision-making steps when acting adaptively. It is adapted from an emerging framework for addressing climate change in long-term natural resource plans (National Academy of Sciences 2011), with modifications to be consistent with this dissertation. It is similar to other descriptions of the adaptive process (Williams, Szaro et al. 2007). This framework highlights three key analytical tasks to support planners as they make and implement decisions: assessing vulnerabilities, identifying and appraising actions, and monitoring and learning. In assessing vulnerabilities, analysts characterize the threats to the system that an adaptive policy must confront. In identifying and appraising actions, analysts assist planners to identify and choose among actions. In monitoring and learning, analysts help planners collect and assimilate new information into plans.

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10 This diagram makes some significant changes from the National Academies of Science version to reflect the discussion in this dissertation. First, it changes the language from “assess risk” to “assess vulnerabilities” to be consistent with Robust Decision Making and broader climate change literature. Second, it collapses the “identify and appraise actions” from two separate steps into a single step, as they are closely related. It changes step seven from “Monitor and Reassess Decision” to “Monitor and Learn” for two reasons. First, other pieces of literature cited in this dissertation offer a different definition of the term “reassess”; it is reserved for reconsidering the strategy as a whole, as may occur with double or triple loop learning. Second, the process of changing a decision does not actually occur in this step. It occurs when the process loops back to either Step 1, Steps 3 and 4, or Step 6. Finally, an arrow is added to connect Step 7 to Steps 3 and 4, recognizing a form of adaptivity that requires new analyses, but not restarting the entire planning process.
Adapted from: National Academy of Sciences (2011)

This framework recognizes that the three analytic tasks may be iteratively repeated, depending on which types of adaptivity are elements of the strategy. Fully-automatic policy adjustment is shown on the figure where “monitoring and learning” loops back to “implementing decision” and little deliberation occurs between monitoring and implementation. Semi-automatic policy adjustment is shown where “monitoring and learning” loops back into Steps 3 and 4 and deliberation with analysis resumes. Formal review and continuous learning is demonstrated when monitoring and learning is followed by beginning the process again and reconsidering the basic objectives of a strategy.

This section describes some decision-support techniques for addressing the three major analytical tasks mentioned in this framework.\(^\text{11}\)

**Exploratory Modeling Approaches**

In complex policy environments, such as water planning and climate change, decision-support approaches often rely on a computer simulation model. Lee describes that such models offer value

\(^{11}\) They are not necessarily complete; there are many other approaches that can also be used. Additionally, this overview can only reasonably be accomplished at a very high level, as it is not meant to be specific to any particular planning problem. As problems are more carefully defined, the ability for any of these decision-support tools to more specifically address the needs of that particular problem can be explored in detail.
in a number of ways. First, the process of generating a model requires “enough careful thought that the relationships that are logically linked tend to emerge.” A second use of models stems from their ability to hold large amounts of data. Lee states “models are indispensable simply to do routine bookkeeping on large quantities of data.” Finally, he explains a use of models to support identifying vulnerabilities and evaluating strategies by “explor[ing] the structure of assumptions built into the model’s mathematic dynamics” (Lee 1994). Thus some decision-support products are software, facilitating computer simulations of important hydrologic relationships, such as the Stockholm Environment Institute's Water Evaluation and Planning System (WEAP) or CADSWES's RiverWare (Zagona, Fulp et al. 2001).

The third use of models described by Lee is consistent with an approach referred to as exploratory modeling. Exploratory modeling recognizes that systems are often sufficiently complex that planners may not intuitively be able to estimate the impacts of uncertain factors or policy actions on a system. Planners and analysts thus use models quantify costs, benefits, and other effects of various strategies or under different assumptions about the future (Bankes 1993).

Bankes (1993) describes exploratory modeling as the use of “computational experiments to explore the implications of varying assumptions and hypotheses.” He describes a process of question-driven exploratory modeling which “searches among an ensemble of plausible models to answer a question of interest or illuminate policy choices.” This analysis can help identify patterns and “determin[e] the regions of parameter space where certain properties are true.” In this process, analysts exercise human judgment “to focus attention on the aspects of the modeling that appear most critical for the question at-hand” (Bankes 1993). Thus, exploratory modeling recognizes that an important use of computer simulations models is to build intuition about the system in question.

**Robust Decision Making**

RDM formalizes exploratory modeling into a form of decision support that can assist in the analytical tasks described in the adaptive decision-making framework above. To do so, RDM contains a set of modeling, statistical and data visualization tools designed to be embedded in a process of stakeholder engagement. It first considers experiments focus on some baseline strategy across a range of plausible assumptions. This allows planners to understand to the impact of uncertain parameters on outcomes. Using intuition built in this step, planners then craft alternative strategies and iteratively improve them. The four-step process of an RDM analysis is shown below.
RDM begins with decision-structuring step. It uses the XLRM framework to define the scope of the analysis and provide planners a clear outline of the decision they face. In this step, planners and analysts define the uncertainties the analysis will explore (X), identify the policy levers (L), and enumerate the performance metrics of interest. The relationships between these three factors of analysis are compiled in a computer analytic model (R) (Lempert, Popper et al. 2003).

In the second step, RDM uses the analytical model to evaluate a baseline strategy and some candidate alternatives across an expansive set of plausible assumptions about future conditions. Analysts generate an experimental design of plausible futures without an initial focus on their likelihood, drawing from the uncertainties defined in the previous step. The strategies are then simulated across the ensemble of plausible futures, to generate a large database containing the key performance metrics (Groves, Fischbach et al. 2013).

Assessing Vulnerabilities
RDM uses a form of scenario analysis to assess the vulnerabilities of a system. In a scenario analysis “groups of analysts, decision makers, and informed observers work together to create several plausible stories of how the future may evolve” (Groves 2006). The resulting scenarios are “coherent, internally consistent, and plausible descriptions of a possible future state of the world” (Schwartz 1991, Nakicenovic and Swart 2000).
To use scenarios to assess vulnerabilities, RDM draws from Assumption Based Planning—an approach for using qualitative scenarios to consider the uncertainties most associated with the vulnerabilities of a particular strategy (Dewar, Builder et al. 1993). This approach helps identify important assumptions, “if [their] negation would lead to significant changes in the current operations or plans” (Dewar, Builder et al. 1993). By identifying important assumptions, planners gain awareness of the uncertain factors that matter most to the success or failure of some default strategy. Planners can build scenarios from changes in these important assumptions. The key insight of this approach is that an identification of vulnerabilities should be considered in the context of the current plans and scenarios can describe the ability of a plan to meet objectives or not.

RDM builds on this approach by using computational experiments and statistical clustering techniques to identify the important assumptions and build scenarios. Analysts and planners explore the results of the computational experiments and seek to identify the key combinations of future conditions where one or more candidate strategies might not meet planning objectives. This is accomplished using statistical-clustering algorithms and interactive visualizations.

The analysis in this step generates concise descriptions of combinations of future conditions to which a strategy is vulnerable, called decision-relevant scenarios. These scenarios focus planners’ attention on the uncertain conditions most important to their decisions, facilitating discussions about the best ways to respond to challenges (Lempert, Groves et al. 2006, Bryant and Lempert 2010). With this new information, planners and analysts may return to the decision-structuring step and modify strategies to address vulnerabilities.

**Appraising Actions**

In Step 4, information on potential vulnerabilities is paired with additional information about costs and other impacts of strategies in interactive visualizations prepared to support meaningful deliberations over different strategies. This analysis allows planners to explore the tradeoffs among strategies across different metrics and beliefs about decision-relevant scenarios (Lempert, Groves et al. 2006). Based on this trade-off analysis, planners may identify a robust strategy or elements of robust strategies (the outward arrow in Figure 2-5). They may also decide that none of the strategies under consideration are sufficiently robust, and return to the decision structuring step (the arrow back to Step 1 in Figure 2-5) with deeper insight into the strengths and weaknesses of the strategies (Groves, Fischbach et al. 2013).

**Other Exploratory modeling approaches**

Walker et al. (2001) expand on exploratory modeling to establish an approach to design adaptive strategies, referred to as Adaptive Policy-making. This approach suggests that planners first identify a basic plan and then iteratively augment it. It describes that they may augment the basic policy with mitigating actions—actions taken in the initial period to reduce certain vulnerabilities, and hedging actions—actions taken in the initial period to spread the risk of vulnerabilities. After this augmented basic policy is developed, the approach emphasizes identifying contingencies to address remaining vulnerabilities, in the form of either corrective actions—adjustments to the
policy or defensive actions—actions taken to clarify a policy or preserve its benefits (Walker, Rahman et al. 2001).

One way the Adaptive Policy-making approach has been operationalized is through the Adaptive Pathways methodology, which evaluates policy actions across a range of plausible future conditions. Across a set of plausible conditions, analysts identify the earliest date at which an individual action no longer meets the policy objectives. Analysts then iteratively identify which actions can augment that initial action in order to meet the objectives. The analysis results in a graphic plotting actions over time that resembles a map. This visualization planners to consider different plausible pathways through the actions to avoid vulnerabilities (Kwakkel and Haasnoot 2012, Haasnoot, Kwakkel et al. 2013).

This approach explicitly considers the timing of various policy actions, and key decision points regarding those actions. This approach presents the various policy actions the fundamental elements of a strategy, helping planners consider choices among actions, the timing of their implementation, and the conditions that require their implementation.

The Adaptive Robust Design is another exploratory approach to operationalize the Adaptive Policy-making framework. The approach uses models to explore various assumptions regarding uncertainty and identifies assumptions that prove to be problematic for a basic plan. It uses many of the approaches described in RDM to identify the key assumptions. It then applies robust optimization techniques to generate decision-rules that implement actions to address those problematic regions (Hamarat, Kwakkel et al. 2013). In contrast to the Adaptive Pathways approach, this approach focuses on the decision-rules that describe when actions are to be implemented. It uses algorithms to search for decision-rules that will automatically implement action to avoid vulnerability.

**Classical decision analysis**

The exploratory approaches described represent an alternative to more classical decision analyses. These classical approaches are generally more appropriate in less complex planning environments, where preferences can be represented with a single objective function or uncertainty is relatively well-defined. Such approaches address a more specific set of questions, such as identifying an optimal set of actions or decision-rules. They have been frequently used consider policy contexts where decisions are made across multiple time periods and can provide insight into designing adaptive strategies.

Classical decision analyses are generally designed to identify a rank ordering of strategies, based on expected utility theory as first described by Von Neumann and Morgenstern (Von Neumann and Morgenstern 1944). In such an approach, planners and analysts define an objective function in terms of probabilistically weighted utilities. They then generate a mathematic model to describe the relationships among utility, choice variables, and other parameters through a set of constraints. The
analysis then attempts to find the set of plausible actions that maximizes the expectation of the utility function across a set of probabilistic futures.\textsuperscript{12}

Dynamic programming is a technique to facilitate a classical decision analysis across multiple time periods. Dynamic programming is based on the Bellman Principle of Optimality which states "An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision" (Bellman 1956). This describes a recursive relationship, where planners optimize actions in a prior period contingent on knowing they will optimize in the future. Dynamic programming problems can often be solved through backwards induction: solving for the optimal action in the last time period first, conditional on the prior state, then optimizing penultimate time period incorporating the optimal solution in the last period.\textsuperscript{13} When this approach accommodates well-characterized uncertainty, it is referred to as stochastic dynamic optimization.

Because dynamic programming problems require well defined objective functions and well-characterized uncertainty, they may not be appropriate for the types of complex, deeply uncertain, multi-stakeholder planning contexts described in this dissertation. However, the fundamental relationship encapsulated in the Bellman equation, shows that decisions in prior periods depend on decisions in future periods. This insight has important implications for the RDM and adaptive strategies: near-term decisions cannot be made without considering the decisions that will follow.

Control theory is a branch of engineering that identifies optimal decision-rules in systems with feedback. It can be used to characterize a process of monitoring outcomes of interest in a system—the state variables—and adjusting variables that can alter the state—the control variable (Kirk 2012). Systems in which the control is altered due to changes in the state variable are referred to as closed loop systems. Dynamic programming is one of many tools that control theory uses to identify the relationship between controls and state variables. Such methods have been used in applications for climate change (Kelly and Kolstad 1999).

The design of adaptive strategies can be described using the language of control theory. The policy actions in an adaptive strategy are control variables, the outcomes are state variables, and the functions that define when the values of control variables change are the decision-rules. Control theory suggests that decision-rules should be functions of the state variable, so that they respond to feedback in a system. Critically, this suggests that when designing decision-rules for adaptive strategies in an RDM analysis, it is not sufficient to monitor exogenous uncertainties. Adaptive strategies should also monitor state variables, which measure the impact of both uncertainty and previously implemented actions.

Another discipline that draws heavily on dynamic programming is real options analysis, which seeks to identify an economic value of a strategy recognizing that planners will continue to actively

\textsuperscript{12} A similar approach can be used to minimize expected costs. In some cases, Planners and analysts may use alternative objective functions aside from maximizing expected utility. For example, they may choose to solve similar problems with reference to robustness criteria, also known as robust optimization.

\textsuperscript{13} There are other alternative methods, which can sometimes solve these problems without beginning in the last time period
manage and adjust elements of the strategy. It assumes that planners will exercise options as necessary, altering the risk profile as new information becomes available. As a valuation tool it can help planners identify the economic value of a strategy as a whole, knowing there will be opportunities to adjust. The techniques to support such an analysis stem from the financial options literature and are applications of the Merton-Black-Scholes model or binomial lattices (a form of decision trees) (Dixit 1994, Trigeorgis 1996). Other analyses, particularly those that consider multiple dimensions of uncertainty use Monte-Carlo simulations (Dixit 1994, Linquiti and Vonortas 2011). This approach has also been applied to adaptation to climate change (Linquiti and Vonortas 2011). Previous applications of RDM have considered models where agents in the model respond to information over time using a real options approach (Mahnovski 2006).

In RDM, real options can serve as a conceptual framework to treat strategies as a set of options. Planners must identify whether the additional benefit from exercising an option in the near term outweighs benefits of learning more information (Dixit 1994, Trigeorgis 1996). Strategies should implement actions when this condition holds. With disparate preferences and beliefs, stakeholders can reasonably disagree about whether the value of new information outweighs the benefit of action, emphasizing the need to measure the performance of strategies across a range of plausible beliefs and conditions.

**Robust Decision Making for adaptive strategies**

In the standard description of RDM provided above, there is no mention of how the methodology addresses the "Monitor and Learn" step of the framework for adaptive decision-making in Figure 2-4, or how strategies can be designed to loop back to previous steps.

However, there is a clear connection between RDM and adaptive strategies. Frequently, the vulnerability and tradeoff analysis will reveal that one particular strategy is preferred if certain conditions occur and another is preferred under different conditions. When possible, elements of each strategy can combined to increase robustness. This can be accomplished by making the strategy adaptive—one set of actions should be implemented if conditions require, otherwise an alternative is. Lempert et al. describe this approach, stating, “Algorithms incorporate new information by monitoring one or more key trends in the internal or external environment. They may then specify new actions contingent on these observations” (Lempert, Popper et al. 2003).

This dissertation proposes one plausible path through the RDM process to help generate robust adaptive strategies, demonstrated in Figure 2-6. This requires two iterations through the RDM process described in Figure 2-5.
In the first iteration through the RDM process, analysts and planners consider some baseline strategy—either the current management of a system or some other predefined default strategy. They work through the RDM process to generate decision-relevant scenarios that define when alternative actions are necessary. In this process, the vulnerability analysis is expanded to identify early indicators that such a scenario is likely—the signpost variables.

Using this information, planners and analysts return to the scoping phase and begin a second iteration. In this second scoping phase, they develop new strategies that include decision-rules, based on signpost variables, to enact new policy actions over the course of a planning horizon. Next, they work through the RDM process to evaluate these adaptive strategies. They may repeat this step multiple times, identifying vulnerabilities and iteratively testing new decision-rules as necessary.

They ultimately arrive at a tradeoff analysis, which can be split into two sub-analyses. The first analysis considers the tradeoffs among alternative decision-rules. This can provide planners with information about the costs and benefits of responding to new information in different ways, helping them interpret decision-rules, and consider the tradeoffs among alternatives. The second analysis characterizes how actions are implemented over the course of the simulations. This analysis recognizes that in some deliberations, planners will continue to frame a strategy as a choice among actions (rather than among decision-rules), and summarizes the simulations in such terms. The results of this analysis can provide decision aids to planners considering the choices among actions.

The subsequent sections consider this process in detail.
Identifying signpost variables

In Step 3 of the traditional RDM process, analysts and stakeholders use the simulation results to identify the external conditions associated with vulnerability. The results of this analysis are decision-relevant scenarios, which describe the exogenous conditions under which a strategy may succeed or fail to meet objectives. For example, the Basin Study identifies that low long-term average streamflow on the Colorado river coupled with an 8-year drought would decrease water delivery reliability (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

In an RDM analysis, these scenarios serve as a basis for designing an adaptive strategy. By understanding the conditions in which a strategy fails to meet objectives, planners and analysts can understand what conditions a strategy needs to adapt to address. However, the usual RDM process does not distinguish between scenarios, which are often summaries of long-term conditions and the early indicators of those scenarios. For example in the Basin, planners would not be able to observe whether the long-term average streamflow is low until the end of the planning horizon; by this point, shortages would have already occurred.

This augmented process recognizes that planners will rely on signposts variables to inform their judgment as to whether alternative actions are necessary. The vulnerability analysis is therefore expanded, to help planners identify and interpret useful signposts. These signposts should have two attributes: they should be observable at the point at which decisions are made and they should be an accurate predictor that a decision-relevant scenario is occurring.

The definition of decision-relevant scenarios is often a useful starting point as analysts identify signposts. The long-term characterizations that lead to vulnerability can often indicate observable shorter-term factors that planners should monitor. For example, the Colorado River Basin Study identifies that short term observations of low streamflow are indicator of longer-term dry periods (Groves, Fischbach et al. 2013).

There are also other pieces of information planners may wish to monitor. As planners implement new actions, the behavior of system changes and the external conditions associated with vulnerability diverge from the decision-relevant scenario defined for the baseline strategy. RDM analysis should also seek to identify signpost variables that monitor the system state.

For example, planners may wish to expand the illustration of fully-automatic policy adjustment in the Basin described previously. They may wish to extend the decision-rules beyond 2020 and define some decision-rules based on monitoring signposts between 2020 and 2030. However, they should not generate decision-rules based on observations between 2020 and 2030, without considering what occurred between 2012 and 2020. If they observed low streamflow between 2012 and 2020, additional conservation would have been enacted. Planners could monitor reservoir elevation, as it is influenced by both the effect of the low-streamflow conditions and the compensating effect of previously implemented conservation.

The analysis of signpost variables should support planners’ interpretation of new information they may learn by monitoring. Analysts can model a Bayesian updating process, to demonstrate how
new information can influence beliefs. They can use this model explore how planners with disparate beliefs will respond to new information, and identify observations that will generate consensus among stakeholders who fall within a certain range of prior beliefs. Such an analysis can identify indicators that would have many stakeholders agree that a decision-relevant scenario is likely to occur and some alternative action is necessary. Chapter 3 of this dissertation provides a simple numerical example this exploratory analysis. Chapter 5 extends the analysis of the Basin Study, demonstrating how a Bayesian updating process and exploratory analysis can help identify pieces of new information that can generate consensus.

**Strategies as portfolios of options**

As planners return to the scoping phase at the start of the second phase, they design strategies that allow planners to respond to new information. In a typical RDM analysis, strategies are generally portfolios of various policy actions that planners may implement. However, adaptive strategies are fundamentally different, as there is no single set of actions implemented in every future. Instead, planners may change, alter, or defer the actions as new information becomes available. Therefore, this dissertation proposes that strategies should be conceived of as portfolios of real options on various actions.

In this approach, when planners and analysts identify and characterize plausible actions, they should also characterize the options associated with each action. Generally, analysts and planners describe the various candidate actions by a set of policy relevant criteria, such as cost, timing, or expected effect. They should also characterize the options attached to actions. In some cases this task may be trivial; there may be a single continuous lever and planners have the option to alter the operating scale at any time for low or minimal cost. In other cases, actions may have multiple actions with many options interacting with one another. Analysts and planners may make analytic decisions regarding options that are integral to an analysis, and other that may be safely ignored for tractability. Thus, a strategy is not simply a set of actions planners will implement. Instead, a strategy is a set of actions, or adjustments to some actions, that they will implement if circumstances require. The strategy therefore contains descriptions of the costs and constraints related to those decisions.

Next, the options attached to actions should be incorporated in the computer simulation model. Just as an RDM analysis requires the various policy levers to be represented in a model, so should the various options. By definition, adaptive strategies will exercise different options on actions in each alternative future. A model requires some algorithms, simulated planning agent, or other mechanism to determine when these actions are to be implemented over the course of a planning horizon. This mechanism should make decisions regarding the cost and benefits of exercising the various options attached to actions. The sixth chapter of this dissertation describes the simulated planning agent designed for the Basin Study, with the ability to implement various actions subject to certain constraints.

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14Analysts and planners may use various methods to create candidate portfolios, such as an optimization in some baseline scenario, a random sample, or hand-crafted portfolios.
In different analyses, the computer model may use alternative methods to identify when options are to be exercised. The analysis can be designed to mimic fully-automatic policy adjustment and the model would include simple decision-rules that planners can actually follow as they exercise options throughout the strategy. Alternatively, the analysis could be prescriptive, attempting to provide insight into what planners should implement in each plausible future. In this case, analysts may wish to design the model to identify the optimal set of options exercised for each future. The following sections provide a description of both approaches.

**Designing and evaluating decision-rules**

One form of modeling adaptive strategies is by generating decision-rules, which simulate how planners may make decisions over the course of planning horizon. Decision-rules should be designed to make decisions on whether or not to exercise options on various policy actions while balancing the costs and benefits of doing so. Previous applications of RDM have used such “rule-based” approaches to building adaptive strategies (Popper, Berrebi et al. 2009, Lempert and Groves 2010, U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013). In these applications, analysts program a planning agent into the computer simulation model of the system capable of observing information and implementing actions or calling options. This planning agent uses simple decision-rules that planners could feasibly use when making decisions.

When adaptive strategies use fully-automatic policy adjustment, the decision-rules that planners use to implement contingencies are elements of a strategy. Planners will need to commit to a set of decision-rules at the start of planning horizon. In these applications, analysts should model representations of the candidate decision-rules just as they would model any other policy lever.

In other cases, a strategy may not be fully-automatic but decision-rules can still serve as approximations to how planners may ultimately act. For example in the Basin, planners may know they will observe streamflow and reservoir levels prior to making decisions about actions. However, they may not know a-priori which threshold values of streamflow would result in them taking actions. A set of candidate decision-rules in a model may reasonably represent the various ways in which they would respond to new information. Such representations will be more realistic for strategies that fall near to fully-automatic policy adjustment on the continuum and have more constrained deliberations. Similarly, planners may more reasonably be able to interpret the decision-rules as choices that they face when strategies resemble fully-automatic policy adjustment.

In both cases, the decision-rules can be treated as the levers in the context of RDM analysis. Alternative strategies can be defined by differing decision-rules. Analysts can work through the RDM process, running strategies defined for alternative decision-rules across an ensemble of plausible futures, identifying the vulnerabilities of strategies with various decision-rules, and evaluate the tradeoffs among the alternative decision-rules for different beliefs of the future. This can help planners iteratively identify decision-rules that increasingly robust to a range of plausible
conditions and weigh the costs and benefits of the various decision-rules. In applications using fully-automatic policy adjustment, this can directly help plans identify rules as elements of their strategy. In applications using semi-automatic policy adjustment, the analysts can help planners interpret the decision-rules to represent different plausible pathways for responding to new information over a planning horizon.

A simple example, describing the tradeoffs among alternative adaptive strategies is provided in Chapter 3. Chapter 6 provides a detailed tradeoff analysis for the Colorado River Basin.

**Characterizing the implementation of actions**

In other applications, planners may continue to frame a strategy as a choice among actions. The algorithms or decision-rules used to exercise options over the course of a simulation may be very specific to the simulation model. Planners may not have the ability to commit to decision-rules a priori, have access to different sets of information than are available in the model, or be subject to different timing constraints. Though the decision-rules may represent some form of adaptation, they may have limited policy interpretation. Planners may not consider the decision-rules described in the previous section as the levers that define a strategy. In these cases, planners will require a decision-support that considers more generalizable choices among actions.

Thus, the augmented RDM process includes a second form of tradeoff analysis that characterizes which actions are implemented over the course of simulation. By exploring across ensemble of plausible futures, it generates decision aids that allow planners to consider which actions are necessary in which conditions. They can then weigh the tradeoff among certain investments relative to the external conditions they wish to prepare for. Similar to the adaptive pathways approach (Haasnoot, Kwakkel et al. 2013), this analysis generates visual aids, allowing planner to consider the choices among various planning actions.

This approach has two steps. The first step requires using simulations to identify which actions should be implemented in each future in the ensemble. This a different interpretation of the algorithms and decision-rules modeled in a simulation than described in the previous section. Rather than approximating how planners will act, these model runs provide recommendation on how planner should act. The simulations represent quasi-optimized portfolio of actions for each sampled future, as they are a description of how planners would adapt if they had perfect foresight into the future. In the second step, analysts use visualizations, summary statistics, and analyses to

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15 Many of these previous applications of rule-based approaches do not consider various ways to incorporate new information into decision-rules as elements of a strategy that planners can control ((Popper, Berrebi et al. 2009, Groves, Fischbach et al. 2013) For example, in the analysis of Israel’s energy future, the analysis discusses the tradeoffs of procuring energy from different sources when a decision-rule suggests more energy is needed. However, the analysis does not focus heavily on what information planners should observe to suggest that more energy is needed. Responding to new information through alternative actions is the subject of analysis, but not the process of incorporating new information into plans.
describe when various actions are implemented across the ensemble of futures. Thus, this dissertation refers to this approach as **optimize and characterize**.

In some sense, using multiple runs of the model to identify the perfect foresight strategy is a departure from a robustness analysis as it searches for optimal sets of actions rather than robust sets of actions in individual futures. In contrast to a standard RDM approach, stakeholders do not define the strategy in advance during the scoping phase. Instead, an automated algorithm attempts to identify the best-performing strategy for a particular future.\(^{16}\) This approach recognizes a single set of actions cannot perform well in every future, and instead characterizes the choices planner will have to make as they implement different sets of actions.

In other ways, this approach is largely consistent with RDM. First, the analysis still seeks to identify strategies that perform well across a range of futures. However, it recognizes that a strategy cannot be defined solely in terms of the actions implemented. Instead, it seeks to identify actions that are frequently elements of well performing portfolios across many futures. Second, the analysis still relies on satisficing. In the optimizing approach described above, these satisficing criteria are described in the constraints of the optimization. Third, the analysis emphasizes understanding the external conditions that make certain actions promising candidates. This is similar to the focus of an RDM analysis on understanding the external conditions where a strategy performs well. The implementation scenarios are a form of the decision-relevant scenarios generated in an RDM analysis and similar data-mining techniques are used to create them.

By running a model with these algorithms imbedded across a large ensemble of futures, the simulations generate a database containing the actions implemented in each future. Each future will have different actions implemented at different times. Because there are a large number of plausible futures, each with a potentially different set of implemented actions, to provide useful summaries of implementation, it is necessary provide numerical and statistical characterizations the actions implemented across the ensemble of futures.

Analysts can generate characterizations of the implementation as appropriate problem at hand. They may work with planners to identify the most useful characterizations. For example they may calculate the aggregate volume or cost of actions implemented. Alternatively (or additionally) they may report the percentage of future that individual actions are executed and some statistics summarizing the timing of actions. This may be useful to help identify candidate initial actions: Actions that are frequently implemented across futures at the start of a planning horizon are strong candidates. Others, implemented less frequently or further into the future, are contingencies. Some actions may never be implemented and can be eliminated from further consideration.

To support an understanding of how the uncertain factors drive which actions should be implemented, analysts can identify regions of the uncertainty space that implies their implementation. They can use statistical clustering techniques from the RDM vulnerability analysis, such as PRIM (Friedman and Fisher 1999) or CART (Breiman, Friedman et al. 1984) to identify simple restrictions on the uncertainty space that imply planners should implement specific actions.

\(^{16}\) This, perhaps, can be considered a simple form of adaptive sampling, as has been frequently discussed (but not-yet implemented) on the uncertainty side. In this case, the adaptive sampling is used on the lever space.
These implementation scenarios are a form of decision-relevant scenario (Lempert, Groves et al. 2006) as they describe a set of external conditions most relevant to the decision about a specific action.

The implementation scenarios offer a means to consider futures where planners would make different decisions—it can be useful to present summary statistics for various strategies conditional on these implementation scenarios. For example, Chapter 7 demonstrates how implemented actions can be summarized over time conditional on implementation scenarios to demonstrate the multiple pathways that planners may as they implement actions.

Chapter 3 provides further discussion of the functions that define when actions are to be implemented, and a more formal definition of implementation scenarios. Chapter 7 provides examples of such an analysis, building from the Basin Study.
Chapter 3: Multi-time-period RDM analysis to generate and assess adaptive strategies

This chapter uses many variables to describe various elements of the RDM process. The following table lists and defines all the variables for reference. A fuller explanation of each is provided in the text.

Table 3-1: Summary of notation used in Chapter 3

<table>
<thead>
<tr>
<th>Uncertainties</th>
<th>Levers</th>
<th>Relationships</th>
<th>Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X^i$</td>
<td>$L^j$ Matrix representing a strategy: a portfolio of values for individual actions implemented over time</td>
<td>$r()$ The functional form of relationships that define how a future and strategy interact to produce measures of merit</td>
<td>$M^{i,j}$ A vector representing measures of merit, in each time period for particular future and a particular strategy</td>
</tr>
<tr>
<td>$T$ Number of time periods in planning horizon</td>
<td>$Y$ Number of individual levers considered in each portfolio</td>
<td></td>
<td>$h()$ A function summarizing a particular measure of merit across time periods, such that there is a single value combination of a particular future and a particular strategy</td>
</tr>
<tr>
<td>$N$ Number of uncertain factors explored in experimental design</td>
<td>$J$ Number of strategies considered in RDM analysis</td>
<td></td>
<td>$\bar{M}^{i,j}$ A measure of merit for a particular future and a particular strategy, summarized</td>
</tr>
<tr>
<td>$I$ Number of futures sampled in experimental design</td>
<td>$l_{t,y}^j$ The value of lever $y$ in time period $t$ for strategy $j$</td>
<td></td>
<td>$\bar{M}^{i,j}$ A measure of merit for a particular future and a particular strategy, summarized</td>
</tr>
<tr>
<td>$x_{n,t}^i$ The value of uncertain factor $n$ in time period $t$ for sampled future $i$</td>
<td>$l^*$ A particular discrete value of $l_{t,y}^j$</td>
<td></td>
<td>$h()$ A function summarizing a particular measure of merit across time periods, such that there is a single value combination of a particular future and a particular strategy</td>
</tr>
<tr>
<td>$f()$ Data generation function future uncertainties</td>
<td>$\varepsilon_t$ Random variable generating stochastic uncertainty in data generation function</td>
<td></td>
<td>$\bar{M}^{i,j}$ A measure of merit for a particular future and a particular strategy, summarized</td>
</tr>
<tr>
<td>$d^i$ Vector of input variations for $f()$</td>
<td>$\bar{x}_n^{i}$ A summary statistic of a particular uncertain factor in a particular future</td>
<td></td>
<td>$h()$ A function summarizing a particular measure of merit across time periods, such that there is a single value combination of a particular future and a particular strategy</td>
</tr>
<tr>
<td>$\bar{x}_{n,T'}$ A summary statistic of a particular uncertain factor, which has been censored to only use data until $T'$</td>
<td>$x_{n,T'}^{*}$ A threshold value of a particular uncertain factor, which has been censored to only use data until $T'$</td>
<td></td>
<td>$h()$ A function summarizing a particular measure of merit across time periods, such that there is a single value combination of a particular future and a particular strategy</td>
</tr>
<tr>
<td>Symbol</td>
<td>Description</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------------</td>
<td>-----------------------------------------------------------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\bar{M}^*$</td>
<td>A threshold value for a particular measure of merit, indicating whether objectives are satisfactorily met</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>A decision-relevant scenario</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$V$</td>
<td>An uncertain event, where a future fails to meet policy objectives</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P()$</td>
<td>The probability of an event occurring</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{P}()$</td>
<td>An estimator of the probability of an event occurring</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S()$</td>
<td>A planner’s subjective probability of a scenario occurring</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$g()$</td>
<td>A function that defines the realizations of $l_{i,y}^j$ over the course of a simulated future. This function may be interpretable to planners as a decision-rule. Alternatively, it may be a more complex algorithm, to identify realizations of $l_{i,y}^j$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$L^0$</td>
<td>A predetermined baseline strategy</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^0$</td>
<td>A decision-relevant scenario describing when the baseline strategy fails to meet objectives</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha$</td>
<td>An observed value of a signpost variable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$H_n^*$</td>
<td>A threshold value of a signpost variable that implies actions should be implemented: a trigger value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$V$</td>
<td>An uncertain event, where a future fails to meet policy objectives</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D$</td>
<td>The cost that planners bear should the future fail to meet policy objectives: damages</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$x_1$</td>
<td>Observations of an uncertain factor in the first time period: the signpost variable</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$x_2$</td>
<td>Observations of an uncertain factor in the second time period</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R$</td>
<td>A decision relevant scenario</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$q$</td>
<td>A scaling factor, decreasing the probability of failing to meet objectives, should an action be implemented</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C$</td>
<td>The cost associated with implementing a particular action</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$z_1$</td>
<td>A particular threshold value of a signpost variable, used in Strategy 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$z_2$</td>
<td>A particular threshold value of a signpost variable, used in Strategy 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Z_1$</td>
<td>A random event, of observing a signpost variable less than $z_1^*$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Z_2$</td>
<td>A random event, of observing a signpost variable less than $z_2^*$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P(Z</td>
<td>R)$</td>
<td>An estimate of the probability of observing a trigger value conditional on the decision-relevant scenario occurring</td>
<td></td>
</tr>
<tr>
<td>$P(Z</td>
<td>\neg R)$</td>
<td>An estimate of the probability of observing a trigger value conditional on the decision-relevant scenario not occurring</td>
<td></td>
</tr>
</tbody>
</table>

**Scenario Discovery and Tradeoff Analysis**

<table>
<thead>
<tr>
<th>Term</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R$</td>
<td>A decision-relevant scenario</td>
</tr>
<tr>
<td>$V$</td>
<td>An uncertain event, where a future fails to meet policy objectives</td>
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<td>A function that defines the realizations of $l_{i,y}^j$ over the course of a simulated future. This function may be interpretable to planners as a decision-rule. Alternatively, it may be a more complex algorithm, to identify realizations of $l_{i,y}^j$</td>
</tr>
<tr>
<td>$L^0$</td>
<td>A predetermined baseline strategy</td>
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<tr>
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<td>A decision-relevant scenario describing when the baseline strategy fails to meet objectives</td>
</tr>
<tr>
<td>$\alpha$</td>
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</tr>
<tr>
<td>$H_n^*$</td>
<td>A threshold value of a signpost variable that implies actions should be implemented: a trigger value</td>
</tr>
</tbody>
</table>

**Adaptive Strategies**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{M}^*$</td>
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</tr>
<tr>
<td>$R^0$</td>
<td>A decision-relevant scenario describing when the baseline strategy fails to meet objectives</td>
</tr>
<tr>
<td>$\alpha$</td>
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<tr>
<td>$H_n^*$</td>
<td>A threshold value of a signpost variable that implies actions should be implemented: a trigger value</td>
</tr>
</tbody>
</table>

**Decision Model**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V$</td>
<td>An uncertain event, where a future fails to meet policy objectives</td>
</tr>
<tr>
<td>$D$</td>
<td>The cost that planners bear should the future fail to meet policy objectives: damages</td>
</tr>
<tr>
<td>$x_1$</td>
<td>Observations of an uncertain factor in the first time period: the signpost variable</td>
</tr>
<tr>
<td>$x_2$</td>
<td>Observations of an uncertain factor in the second time period</td>
</tr>
<tr>
<td>$R$</td>
<td>A decision relevant scenario</td>
</tr>
<tr>
<td>$q$</td>
<td>A scaling factor, decreasing the probability of failing to meet objectives, should an action be implemented</td>
</tr>
<tr>
<td>$C$</td>
<td>The cost associated with implementing a particular action</td>
</tr>
<tr>
<td>$z_1$</td>
<td>A particular threshold value of a signpost variable, used in Strategy 1</td>
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<tr>
<td>$z_2$</td>
<td>A particular threshold value of a signpost variable, used in Strategy 2</td>
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<tr>
<td>$Z_1$</td>
<td>A random event, of observing a signpost variable less than $z_1^*$</td>
</tr>
<tr>
<td>$Z_2$</td>
<td>A random event, of observing a signpost variable less than $z_2^*$</td>
</tr>
<tr>
<td>$P(Z</td>
<td>R)$</td>
</tr>
<tr>
<td>$P(Z</td>
<td>\neg R)$</td>
</tr>
</tbody>
</table>
Introduction
This chapter examines the approaches described in Chapter 2 in greater technical detail. It begins by describing how RDM has been used in many previous applications to consider planning across multiple time periods. To do so, it describes each step of the RDM process, examining both the structure of the data used in computational experiments and the methods used to summarize this data to support decision-making.

The design of an RDM analysis with multiple time periods for decision-making leads to a definition of adaptive strategies where the actions that planners implement are a function of previously observed information. This chapter examines this definition; it considers how new information may affect planners’ beliefs within the context of a planning process using RDM, recommends pieces of information to monitor, and proposes a simple form of decision-rule that implements actions after specific pieces of information are observed.

Finally, this chapter describes two tradeoff analyses that an RDM analysis with adaptive strategies can provide to planners. The first analysis considers the tradeoff among alternative decision-rules, demonstrating that even when choosing amongst a fixed set of actions, planners face choices in how they respond to new information. The second analysis proposes characterizing the implementation actions, and describes the external conditions where those actions are necessary.

Using RDM with multiple time periods
This section describes the structure of RDM analyses that considers decision problems with multiple time periods. It begins by describing the factors of analysis: uncertainties (X), the strategies (L), the metrics of interest (M) and the relationships among these three factors (R). It then uses factors of analysis to explain the development of decision-relevant scenarios and their utility when considering the tradeoffs among multiple strategies.

The approaches described in this chapter are a formalization of methods used in many recent applications of RDM. However, the description provided in this chapter does not exclude alternative approaches to address multiple time periods; analysts frequently improve RDM methods to take advantage of new technological opportunities and tailor the tools to address new policy problems.

Scoping the analysis
In the first step of the RDM process, analysts and planners design computational experiments that become the basis for subsequent analysis. They define the uncertainties that the analysis will explore (X), the strategies planners will choose among (L), the performance metrics of interest (M) and the relationships between these three factors (R). This section describes the various dimensions of each element across multiple time periods.
**Uncertainties (X)**

An RDM analysis explores a large ensemble of plausible uncertain futures. Each future is defined by multiple uncertain factors that can have unique realizations across multiple periods. The following section describes both the structure of this data and some processes for generating the ensemble of plausible futures.

A single future, $X^i$, is generally comprised of multiple uncertain factors. In application not concerned with multiple timer periods, a future with $N$ uncertain factors can be represented as a vector of input variables, $X^i = (x^i_1, x^i_2, ..., x^i_N)$, where $x^i_1, x^i_2, ..., x^i_N$, are each realizations of uncertain factors 1 through $N$ (Groves 2006). When considering multiple time periods, each uncertain factor may have unique values at each time step, $t$. A future with $N$ uncertain factors evaluated over $T$ time periods can be represented as a $T \times N$ matrix:

$$
X^i = 
\begin{bmatrix}
\begin{array}{ccc}
    x^i_{1,1} & x^i_{1,2} & \cdots & x^i_{1,N} \\
    x^i_{2,1} & x^i_{2,2} & \cdots & x^i_{2,N} \\
    \vdots & \vdots & \ddots & \vdots \\
    x^i_{T,1} & x^i_{T,2} & \cdots & x^i_{T,N}
\end{array}
\end{bmatrix}
$$

Various applications of RDM use different methods to generate time series for each uncertain factor. One approach is to define a functional form for the time series, $x^i_{t,n} = f(t, a^i)$, where $a^i$ is a set of exogenous factors.\textsuperscript{17} Analysts then generate a random sample (typically using a Latin Hypercube Sample), drawing different values of $a$ to create an ensemble of $I$ time series for each uncertain factor. An analysis in the California Water Plan uses this technique to generate nine land-use scenarios (Groves and Bloom 2013).

The time series of inputs may also include stochastic uncertainty. When representing stochastic uncertainty, the functional form also includes random variables, $\varepsilon_t$, as an element of the data generating function, such that $x^i_{t,n} = f(t, a^i, \varepsilon_t)$. The values of the uncertain factors in future time periods may also depend on realizations in previous time periods, such as a random walk or an autoregressive relationship. In these applications, the data generating function will also include previous observations of the uncertain factor, such that $x^i_{t,n} = f(t, a^i, \varepsilon_t, x^i_{1,n} \ldots x^i_{t-1,n})$. In addition to exploring across different values of $a$, the experiment can specify alternative parameters of the distributions from which $\varepsilon_t$ is drawn, or even alternative distributions.

Alternatively, analysts may identify a non-random sample of time series for some exogenous uncertainties. They may find some convenient or generally accepted set of plausible future time series for uncertain factors. Though a complex data generation process may underlie the time series of uncertain factors, analysts and planners may be able to more easily interpret the results if they represent the uncertainty in subsequent analyses using the elements of time series, $x^i_{t,n}$, rather than the parameters of the data generation process.

\textsuperscript{17} When a function is use to define the time series of data, in some cases it is most appropriate to consider $a^i$, the uncertainty and the generating function part of the model (R).
Various applications of RDM in water resource planning use this approach (Groves and Bloom 2013, Groves, Bloom et al. 2013, Groves, Fischbach et al. 2013). In these applications, time series of temperature, precipitation, and streamflow are drawn from historical records and downscaled general circulation models. Multiple climate models, emissions paths, and transformations of the historical record create an ensemble of plausible climate or hydrologic futures. The values for each $x_{t,n}^i$ are defined by these data sources, not a random sampling process. However, analysts and planners analyze the uncertain futures using future temperature, precipitation, or streamflow rather than the models, emission pathways, or statistical transformations that generate the data (Groves and Bloom 2013, Groves, Bloom et al. 2013, Groves, Fischbach et al. 2013).

**Strategies (L)**

Analysts and planners design a set of strategies to evaluate across the ensemble of futures. Strategies are generally a portfolio of individual policy actions (generally referred to in RDM analyses as levers, and in control theory as control variables) that can be implemented at various time steps. Analysts and planners generally choose an initial set of strategies to explore by combining planners’ expert knowledge with other analytical tools. Throughout the RDM process, they may return to this step to iteratively improve strategies. This section discusses the structure of such strategies across multiple time periods.

Candidate strategies are combinations of individual actions implemented at each time step. A strategy $L^j$, with $Y$ actions over $T$ time periods can be represented as a $T \times Y$ matrix:

$$L^j = \begin{bmatrix}
  l_1^j & l_{1,2}^j & \ldots & l_{1,Y}^j \\
  l_2^j & l_{2,2}^j & \ldots & l_{2,Y}^j \\
  \vdots & \vdots & \ddots & \vdots \\
  l_T^j & l_{T,2}^j & \ldots & l_{T,Y}^j
\end{bmatrix}$$

An analysis will typically consider multiple strategies; denoted $J$. An RDM analysis is generally expansive in the set of futures explored but more limited in the set of strategies, i.e., $I \gg J$. To limit the number of strategies considered, while $l_{t,j}^j$ may be a continuous variable, frequently only a small number of discrete values are included for each action. When defining the set of actions as discrete values, the space defining a strategy can be re-indexed as binary variables, representing whether a particular action is implemented at a specific level. The table below shows an example strategy with one action, $l$, which can be set to one of two threshold levels, $l = l^*$ or $l = l^{**}$. The strategy can then be re-indexed, such that $l^1$ is a binary variable indicating that $l = l^*$, and $l^2$ is a binary variable indicating that $l = l^{**}$.
Table 3-2: Defining strategies as discrete levers

<table>
<thead>
<tr>
<th>Levers:</th>
<th>$l = l^*, l = l^{**}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Period</td>
<td>Binary Variables</td>
</tr>
<tr>
<td>$t = 1$</td>
<td>$l_{1,1}^1 \in [0,1], l_{1,1}^2 \in [0,1]$</td>
</tr>
<tr>
<td>$t = 2$</td>
<td>$l_{2,1}^1 \in [0,1], l_{2,2}^2 \in [0,1]$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>$t = T$</td>
<td>$l_{T,1}^1 \in [0,1], l_{T,2}^2 \in [0,1]$</td>
</tr>
</tbody>
</table>

The analysis completed for the California Water Plan provides an example of re-indexing continuous actions as discrete choices. As a lever, the set of candidate strategies includes a percent reduction in agricultural demand through increased efficiency. Though any value could theoretically have been tested in this analysis, to limit the number of strategies analysts and planners chose to only consider 0, 5, or 10 percent reductions (Groves and Bloom 2013).

Various applications of RDM use a range of methods to choose the policy actions that define an initial set of candidate strategies. Generally, an analysis will include some baseline strategy, either representing a continuation of current plans (Groves and Bloom 2013, Groves, Bloom et al. 2013, Groves, Fischbach et al. 2013, Ryan, Bloom et al. 2014) or some other baseline strategy that has already been proposed by planners and stakeholders (Lempert, Groves et al. 2014). To generate a set of alternative strategies, analysts and planners may work together to hand-craft some candidates (Groves and Bloom 2013), use optimization routines in some chosen baseline future (Kasprzyk, Nataraj et al. 2013) or a small set of representative futures (Lempert, Groves et al. 2014).

An RDM analysis tests some candidate strategies, and iteratively refines them through the process. As the analysis works through the steps of the RDM process presented in Chapter 2, planners and analysts generate new strategies that improve upon the first candidates. The process is designed to allow participants to improve strategies based on insights from the deliberations and analysis process about the relationships between actions, uncertainties and objectives. The final section of this chapter describes one method for how designing adaptive strategies may facilitate this.

**Relationships (R)**
A planning model, $r$, evaluates the combinations of actions and strategies and captures the mathematical relationships most important to the policy decision. In some applications, analysts will build the planning model specifically for the RDM analysis (for example (Ryan, Bloom et al. 2014)), while other applications will rely on a pre-established planning model (for example (Groves, Fischbach et al. 2013)).

**Metrics (M)**
In the scoping phase, planners and analysts also identify some measures of merit to track throughout the analysis. These measures of merit are representations of planning objectives and offer a way to compare the performance of strategies across the ensemble of futures.
The planning model calculates the measures of merit, $M^{i,j}$, for a single future, $X^i$, and strategy, $L^j$, such that $M^{i,j} = r(X^i, L^j)$. An RDM analysis evaluates each candidate strategy across the ensemble of futures, generating a set of performance metrics (Groves 2006) shown below. A unique combination of a strategy and a future is referred to as a case; cases serve as the basic unit of analysis. Subsequent steps of the RDM analysis rely on variation between cases to draw insight into the performance of strategies.

Table 3-3: Measures of merit as a function of futures and levers

<table>
<thead>
<tr>
<th>Futures:</th>
<th>$X^1$ ... $X^X$ ... $X^I$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strategies</td>
<td>Measures of Merit</td>
</tr>
<tr>
<td>$L^1$</td>
<td>$M^{1,1}$ ... $M^{2,1}$ ... $M^{I,1}$</td>
</tr>
<tr>
<td>...</td>
<td></td>
</tr>
<tr>
<td>$L^2$</td>
<td>$M^{1,2}$ ... $M^{2,2}$ ... $M^{I,2}$</td>
</tr>
<tr>
<td>...</td>
<td></td>
</tr>
<tr>
<td>$L^I$</td>
<td>$M^{1,I}$ ... $M^{2,I}$ ... $M^{I,I}$</td>
</tr>
</tbody>
</table>

Many applications of RDM are multi-criteria decision problems, and the analysis will track multiple policy-relevant measures of merit. In these applications, $M^{i,j}$ is a vector of multiple performance metrics.

Frequently, the planning model calculates a measure at each time period, $m^{i,j}_t$. Because the analysis relies on variation across cases, analysts summarize the measures of merit at the case level by collapsing the data across the time dimension. For example, planners may be most interested in the value of the metric at the end of the planning horizon, such that $M^{i,j} = m^{i,j}_T$. In the California Water Plan, groundwater levels were evaluated at the end of the planning horizon (Groves and Bloom 2013). Alternatively, the performance metric may be a statistical summary across the entire planning horizon, such that $M^{i,j} = h(m^{i,j}_1, m^{i,j}_2, ... , m^{i,j}_T)$. Examples of this approach include the percentage of years that all water demand is met (Groves and Bloom 2013), the minimum reservoir storage level (Groves, Fischbach et al. 2013) or a net present value of building infrastructure (Lempert, Groves et al. 2014).

The RDM methodology requires planners and analysts to identify a threshold value of a measure of merit that indicates whether or not policy objectives are met, $M^*$. The decision analysis focuses on whether $M^{i,j} > M^*$ (or alternatively, whether $M^{i,j} < M^*$). When the threshold value is not achieved, a case can be described as failing to meet objectives. This is necessary to evaluate strategies with reference to a first definition of robustness, which requires finding strategies that minimize the number of plausible futures where some negative outcome occurs (Rosenhead 1989). This definition draws from the concept of satisficing, where some threshold value of the decision metric defines whether or not policy objectives have been met (Simon 1959).
Identifying decision-relevant scenarios and assessing tradeoffs

After scoping the analysis, analysts then run a large number of simulations to calculate the measure of merit (m) for the candidate strategies (i) across the l sampled plausible futures (x), and store the results in a database. The RDM process then includes two analytical steps to facilitate an exploration of the results and to support planning. These analyses are described in detail below.

Defining decision-relevant scenarios

The third step of RDM helps planners understand the relationships between the uncertain factors and the planning objectives for a given strategy. Analysts use statistical techniques and interactive visualizations to collapse the dimensionality of the planning problem in a manner that planners can interpret.

This approach helps planners consider a second definition of robustness: identifying strategies that satisfy over a wide range of future conditions (Rosenhead 1989, Lempert, Groves et al. 2006). Analysts use statistical techniques to identify ranges of uncertain factors that describe a space with a high concentration of futures that fail to meet objectives for a particular strategy. This analysis results in decision-relevant scenarios, which identify sets of futures in the form of easily-interpretable planning scenarios that describe when a particular strategy fails to meet objectives. These scenarios can become the basis for deliberations (Lempert, Groves et al. 2006).

The chief characteristic of a decision-relevant scenario, R, is that it highly differentiates between the futures with a high probability of failing to meet objectives should the scenario occur, \( P(M^j < M^* | R) \), and should it not occur, \( P(M^j < M^* | \neg R) \), for a particular strategy. Generally analysts will choose some baseline strategy to begin the analysis. Analysts use the database of results and statistical techniques to identify some definition of R, such that the following condition is true:

\[
3. \quad (M^j < M^* | R) \gg P(M^j < M^* | \neg R)
\]

To identify the range of various uncertain factors that define decision-relevant scenarios, analysts use statistical-clustering techniques such a Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999) or Classification and Regression Trees (CART) (Breiman, Friedman et al. 1984). These techniques help analysts identify a combination of a small number of uncertain factors, among all that are considered, that are most important in distinguishing those futures in which a particular strategy meets its objectives from those where it does not. These techniques also identify the threshold values of the uncertain factors, above or below which objectives are frequently not met.

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19 Some other definitions will be defined throughout this chapter. An RDM analysis generally uses multiple definitions of robustness, allowing planners to consider various ways in which a strategy may be robust and evaluate tradeoffs among alternatives. Alternative definitions may be more or less useful in any particular application.

20 The analysis can also be used to identify sets of futures with a high concentration that meet objectives. This dissertation discusses everything in terms of failing to meet objectives; analysis can easily be reoriented to focus on futures that meet objectives.
These tools can help identify multiple candidate decision-relevant scenarios and analysts then choose among them.

When deciding among candidate decision-relevant scenarios, analysts evaluate the quality of the scenario on three metrics: density, coverage, and interpretability. Density describes the percentage of futures within the scenario that fails to meet objectives. Coverage describes the percentage of futures that fail to meet objectives that fall within the scenario. Interpretability is less precisely defined, as it depends on feedback from participants in the analysis. The number of uncertain factors and threshold values required to define the scenario is generally a useful proxy (Bryant and Lempert 2010).

In an application of RDM using data generating functions for uncertain factors with parameters not indexed by time, the definition of the decision relevant scenario will take the following form:

4. $x^i \in R$ if $a^i < a^{''}$ for all $a^i$ and $a^{''}$

Where $a'$ is a subset of $a$. Analysts use the data-mining techniques to identify values of $a^{''}$ that effectively differentiate futures that meet objectives and do not meet objectives for a particular strategy.

In other applications, the parameters of the data generating function are either unknown or do not have policy interpretations. In these cases, analysts generate decision-relevant scenarios using the elements of $x_n^i$. However, $M^i,j > M^*$ is not indexed by time, but $x_n^i$ is a vector indexed across time. For example, in the Colorado River Basin Study, the primary uncertainties of interest are observations of streamflow. Each future is defined by unique time series of monthly streamflow along the river, which are a determining factor in whether or not a particular strategy met objectives (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

To address this, analysts generate summary statistic of the time series, such that $ar{x}_n^i = h(x_n^i, x_{n,2}^i, ..., x_{n,T}^i)$ (Groves and Bloom 2013, Groves, Bloom et al. 2013, Groves, Fischbach et al. 2013). $ar{x}_n^i$ is a summary statistic of the time series data, and $h$ is a function that defines the summary statistic. Analyst may generate and test a large number of candidate summary statistics before settling on those that are most useful for generating a decision-relevant scenario. In the Basin Study analysis, a large number summary statistics were generated such as average annual streamflow, over the 50-year planning period and average annual streamflow of the driest eight-year period, the minimum annual streamflow, the variance of the annual streamflow, and many others (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

In these applications, the statistical clustering algorithms can help analysts identify which set of summary statistics, $ar{x}$, and define threshold values of the summary statistics, $ar{x}^{''}$, effectively differentiate between futures that meet objectives and fail to meet objectives (as measured by density, coverage and interpretability$^{21}$). Ultimately, in the Basin Study, decision relevant scenarios are defined by average annual streamflow over the 50-year planning period and average annual

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$^{21}$ When analysts generate summary statistics, one element of interpretability is ensuring that planners and stakeholders can easily interpret the summary statistics used to define decision-relevant scenarios
streamflow of the driest eight-year period (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

In such a case, future falls within a decision-relevant scenario if the following condition holds:

$$5. \quad x^i \in R \text{ if } \mathbb{X}_n^i < \mathbb{X}_n \text{ for various } \mathbb{X}$$

In previous applications of RDM to water resource planning, the summary statistics of uncertain factors most useful for defining decision-relevant scenarios are summaries of the entire planning horizon (Groves and Bloom 2013, Groves, Bloom et al. 2013, Groves, Fischbach et al. 2013). That is, $h'(x^1_t, x^2_t, x^3_t)$ is frequently a better predictor of $M^i > M^*$ than $h'(x^1_t, x^2_t, ..., x^3_T)$, where $T > T'$. In these cases, there is generally more signal encapsulated in $h'(x^1_t, x^2_t, ..., x^3_T)$ than $h'(x^1_t, x^2_t, ..., x^3_T)$. In these cases, the most useful decision-relevant scenarios require observing information across the entire planning horizon. However, planners will not be able to observe whether a scenario has occurred at the point in time at which they are making decisions.\(^{22}\)

**Assessing tradeoffs across subjective probabilities**

The final tradeoff analysis of an RDM analysis considers the subjective probability of failing to meet a satisficing threshold, or satisficing over a range of probability distributions. This definition suggests that planners should identify a threshold for the probability that a strategy fails to meet objectives. If a strategy is sufficiently likely to meet objectives, the plan is acceptable, but if the probability that the strategy fails to meet objectives is great, planners should consider alternatives (Lempert and Collins 2007, Nassopoulos, Dumas et al. 2012). RDM uses the decision-relevant scenarios to provide a framework for considering these probabilities when faced with deep uncertainty.

In an RDM analysis, the decision-relevant scenarios serve as a device for planners and stakeholders to consider the likelihoods. Each analysis only generates a small number of decision-relevant scenarios, focusing attention on the uncertain factors that matter most to a decision and allowing analysts to more easily assess the probability of the scenario compared to a complex joint probability distribution. However, in many applications, analysts will still not be able to generate credible estimates to which all stakeholders agree. By reducing the dimensionality of uncertainty space, the decision-relevant scenarios allow analysts to explore across multiple subjective assessments of their likelihood.

Rather than needing to estimate and explore what may be a vast array of subjective joint probability distributions for all plausible futures, decision-relevant scenarios only require a single subjective estimate of the scenario, $S(R)$ where $S()$, denotes a subjective probability function.\(^{23}\)

\(^{22}\) Note that this insight is not categorically true, as different systems, models, and strategies may be sensitive to different factors. For example, there may be models where initial conditions matter most and information in later time steps is primarily noise. In these cases, analysts may be able to identify good decision-relevant scenarios based on observations early in the planning horizon.

\(^{23}\) Or if there are multiple decision-relevant scenarios, a small number of estimates.
random event where a strategy fails to meet planning objectives can be demarked as \( V \). The subjective likelihood of this event, \( S(V) \) can be estimated as follows:

\[
6. \quad S(V) = S(R) \times P(V|R) + (1 - S(R)) \times P(V|R^{-})
\]

However, this assessment requires generating estimates of \( P(V|R) \) and \( P(V|R^{-}) \), demarked as \( P(V|R) \) and \( P(V|R^{-}) \). Various approaches can be used to estimate \( P(V|R) \) and \( P(V|R^{-}) \). It may be sufficient to estimate that \( P(V|R) = 1 \) and \( P(V|R^{-}) = 0 \), as the scenarios are designed to be highly differentiated; this would represent a perfectly differentiated scenario. Alternatively, practitioners often estimate \( P(V|R) \) as equal to the percentage of futures within the definition of the decision-

relevant scenario where the strategy fails to meet objectives. This is generally accomplished by weighting each future equally, conditional on the scenario that is occurring (Lempert and Groves 2010, Groves and Bloom 2013, Groves, Bloom et al. 2013), although sensitivity analysis can be used to test various weighting schemes (Dixon, Lempert et al. 2007, Lempert, Sriver et al. 2012). This approach avoids weighting certain futures across the entire ensemble, but does assume weights conditional on the scenario occurring or not occurring to facilitate this exploration.

The RDM analysis may then compare multiple strategies to one another, that is, compare \( S(V) \) for the various strategies across values of \( S(R) \). Based on this approach, analysts may identify a probability threshold of the decision-relevant scenario, \( S(R)^* \), where a particular strategy has a higher likelihood of failing to meet objectives than another. If planners believe that \( S(R) < S(R)^* \), then one strategy may be favored, and if planners believe that \( S(R) > S(R)^* \), then they will prefer an alternative.

**Using RDM to design adaptive strategies**

In the previous discussion of an RDM analysis, planners determined candidate strategies as a portfolio of actions at the start of the analysis. However, when strategies are adaptive, planners have opportunities to adjust and revise their decisions over time as new information becomes available. This section expands on the discussion of adaptive strategies provided in the second chapter, using the RDM framework described in the previous section of this chapter.

**Defining decision-rules using RDM**

Adaptive strategies exist when planners do not commit to a portfolio of actions for the entire planning horizon prior to the first time period. Instead, planners have options to implement or adjust actions over time, and their decisions are a function of previously-observed information. Because planners can adjust their actions as new information about uncertainties becomes available, they will implement different actions in different futures, similar to a closed-loop control.

Equation 7 provides an example of an adaptive strategy. \( L^{i} \) is a matrix of individual actions that planners may implement over time in a specific future \( i \). There are \( Y \) unique actions that may have unique values over \( T \) time periods. In this example, planners and analysts determine the value for each action in the initial period (first row) based on current information. In the second period
(second row), the value of each action is determined by a function, $g$, of the realizations of the uncertain factors in the prior period, $x^i_t$. The strategies implemented in the final period, $T$, are a function of all information observed in prior time periods ($x^i_1, x^i_2, ..., x^i_{T-1}$).

$$L^{ij} = \begin{bmatrix}
        l^{ij}_{1,1} & l^{ij}_{1,2} & \cdots & l^{ij}_{1,y} \\
        l^{ij}_{2,1} = g_{2,1}(x^i_1) & l^{ij}_{2,2} = g_{2,2}(x^i_1) & \cdots & l^{ij}_{2,y} = f(x^i_1) \\
        \vdots & \vdots & \ddots & \vdots \\
        l^{ij}_{T,1} = g_{T,1}(x^i_1, x^i_2, ..., x^i_{T-1}) & l^{ij}_{T,2} = g_{T,2}(x^i_1, x^i_2, ..., x^i_{T-1}) & \cdots & l^{ij}_{T,y} = g_{T,y}(x^i_1, x^i_2, ..., x^i_{T-1})
\end{bmatrix}$$

When these functions have a policy interpretation, they can serve as decision-rules. These decision-rules may function as a set of instructions, explicitly defining when planners should implement actions conditional on the information they observe. Alternatively, the decision-rules may function as an approximation in a model, to represent how planners may respond to new information over the course of a planning horizon. This design requires analysts and planners to define some functional form with a clear policy interpretation.

To begin, analysts and planners should characterize which pieces of information the functions can observe. All, some, or none of the uncertainties may be observable at various points across the planning horizon. For example, uncertainties may only be observable after some lag and $g_{t,y}$ may be a function of fewer than $t - 1$ observations of $x^i$. Similarly, planners may need to commit to some actions multiple periods prior to their implementation, and the functions defining these actions would therefore include an incomplete set of prior lags.

**Decision-making process**

This section describes how analysts and planners may work together to design decision-rules for adaptive strategies, drawing on the decision-support provided in an RDM analysis. To frame this process, Figure 3-1 describes how planners may consider information and make decisions within the context of planning processes that use RDM.
In the first step, planners use decision-relevant scenarios to consider the likelihood of the current strategy to meet planning objectives. An RDM analysis generally begins with the evaluation of some baseline strategy, $L^0$. Analysts then identify a decision-relevant scenario, $R^0$, that describes when the baseline strategy fails to meet objectives. Because the scenario cannot be observed until the end of the planning period, planners assess the likelihood of the scenario.

In the second step, using the decision-relevant scenario as a framing device, planners make the decision to implement actions. If they believe the scenario is sufficiently likely, they may choose to implement some alternative actions. If they believe the scenario is unlikely, they may determine that no additional action is necessary. If they are unsure, they may choose to defer any decisions until a later time period.

In the third step, planners observe the realizations of the uncertain factors that become available in this time step. With this information, they return to the first step in the process. As they return to this first step, they may incorporate the information they have observed into their probabilistic assessment of the decision-relevant scenario. This process is iteratively repeated over the entire planning horizon.

In the final step, planners assess whether they have met planning objectives over the course of the time horizon.

**Signpost Variables**

In the process described above, planners observe new information and update their beliefs about decision-relevant scenarios. The following section describes how they may update beliefs as new information becomes available. The new pieces of information that planners monitor over time are referred to as *signpost variables*.

While planners cannot observe the full time series of information that defines a decision-relevant scenario, they may be able to monitor past observations of the same uncertain factors. The same uncertain factors observed over a shorter period of time can influence planners’ beliefs about the likelihood of the scenario, as $h'(x^1_{1,n}, x^1_{2,n}, \ldots x^1_{T',n})$ and $h'(x^1_{1,n}, x^1_{2,n}, \ldots x^1_{T,n})$, where $T' < T$, are likely to be correlated.
There are at least two plausible reasons why signposts variables of this form would be correlated with the uncertain factors defining the decision-relevant scenario. First, the realization of the uncertainty in earlier periods of the planning horizon may contribute to the over-all summary statistic. For example, if a decision-relevant scenario is defined by average annual streamflow over a 50-year period, the first 10 years of streamflow will contribute to the 50-year average. Second, there also may be some structure in the realizations of uncertain factors between time periods. That is, \( h(x_{1,n}^i, x_{2,n}^i, \ldots, x_{T,n}^i) \) may be correlated with \( x_{T'+1,n}^i, x_{T'+2,n}^i \ldots x_{T,n}^i \). In cases where analysts generate the set of plausible futures, these correlations may either be well-understood or purposefully explored. However, when using a non-random sample of futures, analyst may seek to understand whether such correlations exist in the set of considered futures.

Analysts may also identify other signpost variables, which include information beyond simple short-term summary statistics of the same uncertain factors. Analysts may identify different summary statistics of the short-term observations that are better correlated with the statistical summaries used in the decision-relevant scenario. That is, they may find that, \( h'(x_{1,n}^i, x_{2,n}^i, \ldots, x_{T,n}^i) \) and \( h(x_{1,n}^i, x_{2,n}^i, \ldots, x_{T,n}^i) \) are correlated, where \( h' \) has a different functional form than \( h \). For example, analysts may identify a decision-relevant scenario based on the most severe drought in a 50-year period. However, the most severe-drought in a 10-year period may not be the best predictor of a drought in a 50-year period. The average streamflow in this 10-year period may be a better.

Alternatively, analysts and scientists may identify other exogenous indicators to monitor. For example, planners may understand that sea-surface temperatures in the Pacific Ocean drive the low streamflow conditions in the Colorado River Basin. Observing sea-surface temperature may therefore inform beliefs about the decision-relevant scenario.

Analysts can explore the correlations between various candidate signpost variables and the characterizations of decision-relevant scenarios. They may identify multiple plausible signpost variables, drawn from the uncertain factors explored in the analysis. Those that are strong indicators of decision-relevant scenarios are signpost variables that planners should consider monitoring.

Note that when an RDM analysis uses a simple data generation process, \( h(x_{1,n}^i, x_{2,n}^i, \ldots, x_{T,n}^i) \) and \( h(x_{1,n'}^i, x_{2,n'}, \ldots, x_{T,n'}^i) \) may be perfectly correlated in the sampled set of futures. For example, an analysis may assume that population increases linearly from some starting point. The experimental design would explore different rates of population growth. In this case, analysts will be able to identify the population at the end of the time period by simply observing growth in the first period. Analysts must assess whether these early observations are truly policy insights (i.e., they believe population will only grow linearly) or simply an approximation that is not useful as a signpost (i.e., they believe population growth will include noise and not be perfectly linear, but the randomness is not explored).

In other applications, early observations may contain some signal and some noise. In these cases, the exploratory analysis described above is more appropriate, and analysts will explore the
structure of data contained in a non-random sample of futures. Analysts should consider whether the structure identified is the result of random variation in the data, or a policy insight that is likely to hold in the future. In other applications, the noise will be generated by a stochastic term defined in the modeled data generating process. Analysts will need to consider whether identified signposts are an artifact of the chosen data-generating function and would differ if they chose represent the noise differently. Alternatively, signposts may be a policy insight discovered using the design of the analysis.

**Updating subjective beliefs of decision-relevant scenarios through Bayes’ Law**

The decision process shows that as planners observe signpost variables, their subjective beliefs about decision-relevant scenarios may change. This section describes how these changing beliefs can be modeled as a Bayesian updating process.

Observations of signpost variables can affect planners’ subjective assessments of the likelihood of the scenario. If signpost variables are correlated with factors defining decision-relevant scenarios, then \( S(R|\text{Signpost Variables} = \alpha) \neq S(R) \), where \( \alpha \) is some observed value of a signpost variable. If \( S(R|\text{Signpost Variables} = \alpha) > S(R) \), planners should be more willing to implement actions after observing new information. If \( S(R|\text{Signpost Variables} = \alpha) < S(R) \), then planners should be less willing to implement actions.

This suggests a Bayesian updating process, where planners update their assessment of the scenario, \( S(R|\text{Signpost Variables} = \alpha) \), as new information becomes available. Equation 8 rewrites Bayes’ law using the decision-relevant scenario, subjective probability, and signpost variable notation established throughout this chapter.

\[
8. \quad S(R|\text{Signpost Variables} = \alpha) = \frac{P(\text{Signpost Variables} = \alpha|R) \cdot S(R)}{P(\text{Signpost Variables} = \alpha|R) \cdot S(R) + P(\text{Signpost Variables} = \alpha|\neg R) \cdot (1 - S(R))}
\]

This formula describes how planners can process new information as it becomes available, in reference to the decision-relevant scenarios. To understand how new information influences beliefs, planners may require some estimator of probabilities of observing signpost variables of the observed values, conditional on the decision relevant scenarios, \( P(\text{Signpost Variables} = \alpha|R) \) and \( P(\text{Signpost Variables} = \alpha|\neg R) \).

When signposts variables are short-term summaries of uncertainties considered in the RDM process, \( h(x_{1,n}, x_{2,n}, \ldots, x_{T',n}) \), analysts can generate estimators of the conditional probabilities using the sample of futures. Analysts can do so by calculating the summary statistic for each future in the sample. They can estimate the probability of observing a particular summary statistic for futures that fall within a decision relevant scenario as well as those that do not. There are various methods used to estimate conditional probabilities, such as the histogram approach and fitting the probability density function to a defined probability distribution.

In this approach, analysts summarize the ensemble of futures while only making assumptions about the likelihood of each future, conditional on a decision-relevant scenario. This is consistent with the approach, described above, used to generate estimates of the probability of failing to meet
objectives, $P(V|R)$. The statistical properties of these estimators may be unknown, as the underlying probability distributions of the future are unknowable. Nonetheless, this approach facilitates an exploration of the implications of the sampled set of futures.

Stakeholders’ subjective assessments of the posterior probability of a scenario also depend on their prior assessments of the probability of the decision-relevant scenario occurring, $S(R)$. When facing deep uncertainty, stakeholders frequently have differing beliefs about the scenario’s likelihood. Analysts can use Bayes’ law and the estimators of conditional probability to explore the implications of new information across a range of plausible subjective beliefs.

A simple numerical example shown in Figure 3-2 illustrates this point. Consider a situation where planners observe a signpost variable that analysts estimate has a 90 percent chance of being observed should the decision-relevant scenario occur, $(\text{Signpost Variables} = a|R) = 0.9$. Analysts also estimate that it has 10 percent chance of being observed should the scenario not occur, $P(\text{Signpost Variables} = a|\neg R) = 0.1$. The horizontal axis of Figure 3-2 shows a range of prior subjective beliefs regarding the decision-relevant scenario, and the vertical axis shows the updated posterior beliefs. If stakeholders believe the prior probability of the scenario occurring is 40 percent, after observing signpost variable, they should update their beliefs to estimate that the scenario is 86 percent likely.

*Figure 3-2: An example of updated beliefs across a range of subjective prior beliefs*

Other stakeholders, observing the same signpost variable, may interpret the information differently. For example, stakeholders who believe that the scenario is 20 percent likely will update their beliefs to consider it 69 percent likely. Observing the new information increases their assessment of the likelihood of the scenario, but they still believe the scenario is less likely than a stakeholder who initially believes the scenario is 40 percent likely.

---

$^{24}$ Note that $P(\text{Signpost Variables} = a|R)$ and $P(\text{Signpost Variables} = a|\neg R)$ do not need to sum to 1.
This exploration can help identify regions of consensus among stakeholders. For example, planners may agree that if the decision-relevant scenario is at least 70 percent likely, some action is necessary. Among stakeholders who initially believe the probability of the scenario ranges between 25 percent and 100 percent, there would be no consensus on whether or not they should implement this action. After observing the signpost variable, however, all these stakeholders would update their beliefs to consider the scenario greater than or equal to 70 percent likely. In this case, the stakeholders can generate consensus that action is necessary by deferring the decision until the signpost variable is observed.  

This analysis provides planners a way to update their assessments of scenarios as new information becomes available. Scenarios are tools to facilitate deliberation and in the case of semi-automatic policy adjustment or formal review and continuous learning such an analysis on its own may be useful to planners. However, when there are limited or no deliberations, such information should be an input into decision-rules.

**Signpost variables as planners implement new actions**

The decision-making process in Figure 3-1 shows that planners have an opportunity to implement actions prior to observing new information. By definition, decision-relevant scenarios are a function of the actions taken. Once planners implement or adjust actions, the external conditions to which the system is vulnerable may change. Ideally, as planners implement new actions, the system becomes vulnerable to a decreasing range of exogenous conditions.

The scenarios, and thus the relevant signposts, may change based on both uncertain factors and implemented policy actions. However, repeating the analytical steps of an RDM analysis may be too costly or time-intensive throughout the planning process (particularly when adaptation falls near fully-automatic policy adjustment). Similarly, as analysts generate decision-rules to program into simulation models, it will likely be too computationally expensive to mimic the process of redefining decision-relevant scenarios each time an action is implemented.

Instead, analysts may wish to design adaptive strategies that endogenize the measurement of the effect of new actions over the course of the planning horizon. The functions that define such a strategy would look to other pieces of information beyond the exogenous uncertain factors. The actions implemented may be functions of actions in prior time steps, or they may monitor the impact previously enacted actions.

\[
9. \quad I_{ij} = \begin{cases} 
I_{ij}^{l_1} = \frac{g(x_{ij}^{l_1}, l_1^{ij}, m_1^{ij})}{l_1^{ij}} \\
I_{ij}^{l_2} = g(x_{ij}^{l_1}, l_1^{ij}, m_1^{ij}, l_2^{ij}, m_2^{ij}, ..., m_{T-1}^{ij}) 
\end{cases}
\]

---

25 This analysis assumes that planners are willing to agree that they have a reasonable estimate of \( P(V|R) \), even if they disagree on \( S(R) \). At the other extreme, if planners fundamentally disagree on \( P(V|R) \), then new information may not help generate at consensus all, because the new information has different meaning to different planners. As a follow up study, one could design an analysis that treats the estimate \( P(V|R) \), as uncertainty itself, to explore the combinations of estimates and subjective beliefs that generate consensus.
This approach draws from control theory, which describes systems that can be monitored using state variables. Systems in which the actions are altered due to changes in the state variable are referred to as closed-loop systems. This approach identifies that signpost variables may include a wider set of information than simply the exogenous uncertain factors. Analysts and planners may wish to identify state variables, which are correlated directly with whether or not a strategy meets objectives, and use them to bypass the decision-relevant scenarios.

For example, in the Colorado River Basin, observing natural streamflow may be a strong indicator of whether the current management of the system is unlikely to meet objectives. However, as new actions are implemented, planners may wish to observe reservoir levels, which will increase as new actions are implemented. If the reservoirs are relatively full, low water delivery reliability will be unlikely.

Using this approach, the decision-rules based on a state variable do not explicitly define a decision-relevant scenario at each step. Instead, they represent some implicit decision-relevant scenario that evolves as actions alter the system. Such an approach has the advantage that it is computationally simpler than generating decision-relevant scenarios at each step and identifying policy-relevant triggers. It has the disadvantage that the triggers cannot be interpreted by their relationships to the decision-relevant scenario.

**Triggers**

The interpretation of adaptive strategies provided above suggests that when planners obtain sufficient evidence that a decision-relevant scenario is likely, they should implement alternative actions. This suggests a particular form of decision-rule when planners face a discrete\(^{26}\) choice to implement an action. That is, if a signpost variable is below (or above)\(^{27}\) some threshold value, planners will implement an action. This form of decision-rule is referred to as a *trigger*, and can be represented as the following:

\[
10. \text{ if } h(x_{1,n}^i, x_{2,n}^i, ..., x_{t-1,n}^i) < H_n^* \text{ then } i_{t,y}^{i,j} = 1 \text{ else } i_{t,y}^{i,j} = 0
\]

The threshold value, \(H_n^*\), that implies an action should be implemented is referred to as a *trigger value*. An uncertain event \(Z\) occurs when planners observe a signpost variable below a trigger value, \(h(x_{1,n}^i, x_{2,n}^i, ..., x_{t-1,n}^i) < H_n^*\).

For planners to assess whether new pieces of information constitute sufficient evidence that implementing an action is necessary, they require estimates of the probability of observing a trigger value, conditional on a decision relevant scenario occurring \(P(Z|R)\) and the scenario not occurring \(P(Z|\neg R)\). Analysts can estimate these probabilities from the sample of futures, using the process described in previous sections of this chapter. These estimators, \(P(Z|R)\) and \(P(Z|\neg R)\), are measures of the accuracy of a trigger.

\(^{26}\) Though decisions do not necessarily need to be discrete, note that as described previously, RDM analyses generally describe the choices among actions as discrete choices.

\(^{27}\) For ease of reading, the text will only refer to below the threshold value
The first measure, $P(Z|R)$, is the true-positive rate (Fawcett 2006): the probability of observing a trigger value conditional on the future being in the decision-relevant scenario. A high true-positive rate ensures that if the future is in the decision-relevant scenario, then planners observe a trigger. In a case where planners are considering implementing new actions to avoid vulnerability, a trigger with a high true-positive helps avoid the consequences of being under-prepared.

The second measure of accuracy, $P(\overline{Z}|\overline{R})$, is the false-positive rate (Fawcett 2006): the probability of observing a trigger value conditional on the future not being in the decision-relevant scenario. The false-positive rate is equal to one minus the true-negative rate, $P(\overline{Z}|\overline{R}) = 1 - P(Z|\overline{R})$. A high true-negative rate ensures that a trigger is not observed if the future is not the decision-relevant scenario, and serves as a signal that implementing an additional action is not necessary.

However, when choosing among alternative trigger values, there is often a frontier where these two measures of accuracy trade off with each other (Fawcett 2006). Along this frontier, an increase in the true-positive rate corresponds to a decrease in the true-negative rate, forcing a choice between alternative trigger values and decision-rules.\(^{28}\)

**Assessing tradeoffs between decision-rules**

The decision-rules that are elements of an adaptive strategy are policy choices, and planners may face tradeoffs among alternatives. Critically when decision-rules are triggers, planner may choose among trigger values with different true-positive and true-negative rates. If no trigger value dominates the others, planner’s choices may depend on their subjective assessments of decision-relevant scenarios. This section explores such tradeoffs in greater detail.

This section proposes a simple decision model that demonstrates the choice between adaptive strategies with two different trigger values. This model is presented as a decision-tree to demonstrate the decision steps as planners update their beliefs about decision-relevant scenarios. The analysis also identifies some characteristics of effective triggers, and finally provides a simple numerical exploratory analysis of this model, demonstrating the regions of the uncertainty space where planners may agree on a trigger.

**A simple decision model**

In this decision model, planners attempt to minimize total expected costs across a range of plausible beliefs about future conditions. In accordance with a robustness analysis, they rely on a satisficing threshold to define meeting policy objectives. A random event where a strategy fails to meet objectives is demarked $V$. Should a strategy fail to meet objectives, planners bear a cost of $D$, while if a strategy meets objectives, planners face a cost of zero.

This model assumes one uncertain factor, $x$, which is realized in two time periods, $x_1$ and $x_2$. The observation of $x$ in the first time period is a signpost variable. An RDM analysis has identified some

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\(^{28}\) Signal detection theory is a discipline that focuses on this. The receiver operator curve is a graphic that plots true-positive and true-negative rates against one another, and shows the rate at which different triggers can trade off with one another. (Fawcett 2006)
decision-relevant scenario, defined as a function of \( x_1 \) and \( x_2 \). If the future is in the decision-relevant scenario, \( R \), planners are more likely to fail to meet objectives than if the future is not in the decision-relevant scenario: \( P(V|R) > P(V|\neg R) \). An RDM analysis generates estimators of the conditional probability of failing to meet objectives, \( P(\bar{V}|\bar{R}) \) and \( P(\bar{V}|\neg \bar{R}) \).

Planners are considering whether to implement a single action, \( l \), and can determine whether to implement that action after observing \( x_1 \). By committing to this action, planners can decrease the probability of failing to meet actions, \( P(V) \). The probability of failure will be reduced by a scaling factor, \( q \), such that \( 0 \leq q < 1 \). RDM analysis generates an estimate of this scaling factor, \( q \). If implemented, the action has a cost of \( C \).

This model assumes that planners are willing to adapt, as it is preferable to defer the action until after a trigger is observed rather than implement the action in the first period. Planners will always implement that action if and only if they observe a trigger value.\(^{29}\) Planners consider the choice between two trigger values \( z_1^* \) and \( z_2^* \). A random event of observing a trigger value, such that \( x_1 < z^* \), is demarked \( Z \). RDM analysis generates estimates of the conditional probabilities of observing the trigger values, \( P(Z|R) \) and \( P(Z|\neg R) \).

Figure 3-3 presents the simple model of a decision that planners may face when determining how to act adaptively.

\(^{29}\) Appendix 3-A shows a simple model that defines when such conditions hold.
The decision process is described below:

1) Prior to observing any information, planners choose between two adaptive strategies. Each strategy uses decision-rules in the form of triggers. Strategy 1 is defined by a trigger value of $Z^*_1$ and Strategy 2 is defined by a trigger value $Z^*_2$.

2) There is some underlying probability of the future being in some decision-relevant scenario, $R$. Planners may form a subjective assessment of the probability that this scenario occurs, $S(R)$. Planners cannot observe whether the future falls into this scenario until after vulnerability occurs and damages are assessed.

3) Planners monitor the signpost variable, $x$, to assess whether the trigger value is observed. If the future is in the decision-relevant scenario, the trigger value is more likely to be observed: $P(Z|R) > P(Z)$. If the future is not in the decision-relevant scenario, the trigger value is less likely to be observed: $P(Z|R) < P(Z)$.

4) If the chosen trigger is observed, then planners implement the action. If the chosen trigger is not observed, they do not implement the action.

5) Dependent on the decision-relevant scenario, there is some probability of a vulnerability occurring. If the future is in the decision-relevant scenario, vulnerability is much more likely than if not.
6) The payoffs are assessed. If vulnerability occurs, damages of $D$ are incurred. If the action is implemented, a cost of $C$ is incurred.$^{30}$

In this model, analysts have a number of pieces of information available to them. $q$, $C$, and $D$ are all known, as are the estimates of the conditional probabilities of observing triggers and experiencing vulnerability, $P(\overline{Z}_j|R)$, $P(\overline{Z}_j|\overline{R})$, $P(\overline{V}|R)$, and $P(\overline{V}|\overline{R})$. Finally, analysts also know the planners’ subjective assessments of the decision-relevant scenarios. Using all of this information, analysts can calculate the expected total cost of a strategy:

$$11. \text{Expected Total Cost} = C \left[ P(\overline{Z}_j|R) \cdot S(R) + P(\overline{Z}_j|\overline{R}) \cdot (1 - S(R)) \right] + D \left[ q \cdot P(\overline{Z}_j|R) \cdot S(R) + P(\overline{V}|R) + P(\overline{Z}_j|\overline{R}) \cdot (1 - S(R)) \cdot P(\overline{V}|\overline{R}) \right] + (1 - P(\overline{Z}_j|\overline{R})) \cdot (1 - S(R)) \cdot P(\overline{V}|\overline{R})$$

As analysts and planners identify signposts variables and trigger values that can facilitate an effective adaptive strategy, they seek to characterize effective triggers and describe the tradeoffs among them. Using comparative statics, the expected change in total future payoff with respect to a change in the true-positive rate is shown below:

$$12. \frac{\partial V}{\partial P(\overline{Z}_j|R)} = S(R) \cdot \left[ C - D \cdot (1 - q) \cdot P(\overline{V}|\overline{R}) \right]$$

The expected total cost of a strategy will decrease as the true-positive rate increases if the following condition holds:

$$13. C < (1 - q) \cdot D \cdot P(\overline{V}|\overline{R})$$

An increase in the true-positive rate is preferable when the cost of action is less than the expected decrease in damages from the action, conditional on the decision-relevant scenario occurring. If a planner is willing to take the action policy action, this condition will hold.$^{31}$ Thus, any time planners are will to act adaptively, a decision-rule relying on a trigger value with a higher true-positive rate is preferable.

The change in expected total future payoff with respect to a change in the false-positive rate is shown below:

$$14. \frac{\partial V}{\partial P(\overline{Z}_j|\overline{R})} = (1 - S(R)) \cdot \left[ C + D \cdot (1 - q) \cdot P(\overline{V}|\overline{R}) \right]$$

---

$^{30}$ Note that this example only considers expected costs. It could be easily expanded to consider risk references by including a utility function. Such a generalization is not necessary to demonstrate the results in this chapter.

$^{31}$ Appendix A shows that for planners to be willing to take a policy action, the following condition must hold: $\frac{C}{D} \cdot P(V|R) \cdot P(R|T) \cdot P(\overline{V}|\overline{R}) \leq (1 - q)$. To include the decision relevant scenario, this condition can be rewritten as:

$$\frac{C}{D} \cdot (P(V|R) \cdot P(R|T) + P(\overline{V}|\overline{R}) \cdot (1 - P(R|T))) \leq (1 - q)$$. By definition: $P(V|R) > P(\overline{V}|\overline{R})$, $P(V|R) \geq P(V|R) \cdot P(R|T) + P(\overline{V}|\overline{R}) \cdot (1 - P(R|T))$, $P(V|R) \geq P(V|T)$. Thus, $P(V|R) \geq P(V|T)$. That is, by construction $R$ i is a more clear signal of vulnerability than $T$ i. Thus, for planners to be willing to act at all, it must be true that $\frac{C}{D} \cdot P(V|R) \cdot P(R|T) \leq (1 - q)$.
The expected total cost will increase as the false-positive rate decreases (that is, the true-negative rate increases) if the following condition is true:

\[ C < (1 - q) * D * P(\overline{V} \mid R) \]

An increase in the true-negative rate is preferable when the cost of action is greater than the expected decrease in damages conditional on the decision-relevant scenario not occurring. For the planner to be willing defer a policy action until triggers are observed as opposed to implementing the action in the first period, this condition must necessarily hold.\(^{32}\)

These two conditions imply that any time planners are willing to act adaptively, they will (weakly) prefer a decision-rule based on a trigger value of \(Z^1\) to \(Z^2\) if either true-positive or true-negative rate increases for \(Z^1\) or the other does not decrease. That is, Strategy 1 is preferable to Strategy 2 if the following condition holds:

\[ P(Z^1 \mid R) \geq P(Z^2 \mid R) \text{ and } P(\overline{Z}^1 \mid \neg R) \geq P(\overline{Z}^2 \mid \neg R) \]

However, when these two measures tradeoff with one another, there may not be a dominant strategy. The following statement defines the conditions in which planners will prefer Strategy 1 to Strategy 2:

\[ 17. \quad C * (1 - S(R)) * \left[ P(\overline{Z}^1 \mid \neg R) - P(\overline{Z}^2 \mid \neg R) \right] \]
\[ + C * S(R) * \left[ P(Z^1 \mid R) - P(Z^2 \mid R) \right] \]
\[ + D * q * S(R) * P(\overline{V} \mid R) * \left[ P(Z^1 \mid R) - P(Z^2 \mid R) \right] \]
\[ + D * q * (1 - S(R)) * P(\overline{V} \mid \neg R) * \left[ P(Z^1 \mid \neg R) - P(Z^2 \mid \neg R) \right] \]
\[ + D * S(R) * P(\overline{V} \mid R) * \left[ P(Z^2 \mid R) - P(Z^1 \mid R) \right] \]
\[ + D * (1 - S(R)) * P(\overline{V} \mid \neg R) * \left[ P(Z^2 \mid \neg R) - P(Z^1 \mid \neg R) \right] < 0 \]

The estimated true-positive and false-positive rates impact which set of triggers is preferable. However, cost, damages, effectiveness, and the subjective probability of the decision-relevant scenario also affect planners’ preferences between triggers. For example, if costs are high, and the decision-relevant scenario is unlikely, then the difference in the false-positive rate between the two triggers will much less important. That is, when the scenario is unlikely, planners’ will believe that observing a trigger is relatively likely to be a false-positive, and implementing the action will accrue unnecessary costs.

**Numerical Example**

This section presents a numerical example, to facilitate further examination of the tradeoffs between the two strategies. This exploratory analysis identifies threshold values of cost, damages,

\(^{32}\) A method similar to that in footnote 31 would demonstrate this.
and subjective beliefs that may change which strategies planners prefer, and determines regions of the parameter space where planners agree on the preferred strategy. This analysis assumes the following values for parameters:

Table 3-4: Values used in numerical example

<table>
<thead>
<tr>
<th>Assumption</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{q} )</td>
<td>0.4</td>
</tr>
<tr>
<td>( P(\overline{V}</td>
<td>R) )</td>
</tr>
<tr>
<td>( P(\overline{V}</td>
<td>\overline{R}) )</td>
</tr>
<tr>
<td>( P(Z_1</td>
<td>R) )</td>
</tr>
<tr>
<td>( P(Z_1</td>
<td>\overline{R}) )</td>
</tr>
<tr>
<td>( P(Z_2</td>
<td>R) )</td>
</tr>
<tr>
<td>( P(Z_2</td>
<td>\overline{R}) )</td>
</tr>
</tbody>
</table>

The trigger value for Strategy 1, 0.95, has a higher true-positive rate than Strategy 2, 0.55. Strategy 1 also has a higher false-positive rate (and therefore a lower true negative rate), 0.45, compared to the trigger value for Strategy 2, 0.05.

This analysis first identifies the preferred strategy across a range of subjective probabilistic assessments of the decision-relevant scenarios for fixed assessments of costs and damages. As stakeholders may reasonably disagree in the subjective likelihood of the decision-relevant scenario, the analysis explores across the range of plausible values. Figure 3-4 shows expected total cost on the vertical axis and likelihood of the decision-relevant scenario occurring on the horizontal axis. The red line shows the payoff for Strategy 1 and the gray line shows the payoff for Strategy 2.

Figure 3-4: Expected total costs across subjective beliefs about decision-relevant scenario
As seen in Figure 3-4, expected costs increase as the subjective likelihood of the decision-relevant scenario increases. If planners believe that the scenario is likely, then they anticipate the system is more likely to experience vulnerability and suffer damages. Planners also have higher expectations of observing a trigger and bearing the cost of implementing the action.

Importantly, when planners assess a low likelihood of the decision-relevant scenario, they will believe that Strategy 2 is preferable to Strategy 1. If they believe the scenario is less likely, planners will interpret the observation of a trigger value as relatively more likely to be a false-positive. Planners would thus prefer a strategy with a low false-positive rate, to ensure they are not investing in unnecessary action.

Considering the overall probability of observing a false-positive can further illuminate this result. The probability of a false-positive can be calculated by multiplying the false positive rate by the underlying subjective probability of the scenario not occurring. For example, when $S(R) = 0.2$, the probability that of observing a false-positive when using Strategy 1 is:

$$18. \quad S(\neg R) * P(Z_1 | \neg R) = 0.8 * 0.45 = 0.36$$

That is, there is a 36 percent likelihood of observing a false-positive and investing in action when not needed. Strategy 2, on the other hand, only has a 4 percent likelihood of over-investing:

$$19. \quad S(\neg R) * P(Z_2 | \neg R) = 0.8 * 0.05 = 0.04$$

When the scenario is unlikely, Strategy 2 avoids over-investment at a rate that is sufficiently beneficial for planners to sacrifice the true-positive rate of Strategy 1 for the improved true-negative rate of Strategy 2. As $S(R)$ increases, false-positives and over-investment become a smaller share of the total expected costs; if $S(R) = 0.8$, the probability of observing a false-positive drops to 9 percent for Strategy 1 and 1 percent for Strategy 2.

The expected costs of the two strategies are approximately equal when the decision-relevant scenario is 29 percent likely. Thus, 29 percent serves as the probability threshold of the decision-relevant scenario that requires changing strategies, when using the third definition of robustness described above.

As the likelihood of the decision-relevant scenario increases, the expected cost of Strategy 1 decreases relative to Strategy 2. Strategy 1 is preferred when the likelihood of the scenario is relatively high. Under these conditions, planners will believe a trigger indicates that the scenario is occurring. Planners are less concerned with false-positives and over-investing under these conditions, and are instead more concerned with avoiding false-negatives and being under-prepared.

Stakeholders may also disagree on their assessments of other key assumptions. For example, stakeholders may disagree on the damages associated with vulnerability, $D$. The following example continues to explore across multiple subjective beliefs about the decision-relevant scenario, but
also adds an exploration of different assessments of $D$. Keeping all of the other assumptions from the example above, this example relaxes the assumption that $D = $300 and examines a range from $200$ to $1000$.

Figure 3-5 identifies the preferred strategy for the range of plausible beliefs about the decision-relevant scenario and assessments of damages. Each point on this figure represents a unique combination of beliefs about the future (horizontal axis) and assessment of damages associated with failing to meet objectives (vertical axis). The red circles represent beliefs for which planners would prefer Strategy 1 and the gray circles represent those for which planners would prefer Strategy 2.

*Figure 3-5: Preferred strategies across a range of beliefs and assessments of damages*

This figure demonstrates that as the assessment of damages increases, planners will prefer the strategy with a higher true-positive rate, all else equal. For example, when $S(R) = 0.15$, planners will prefer Strategy 1 if damages are at least $500$, otherwise Strategy 2 is preferred. In these cases, planners can avoid the high costs associated with failing to meet policy objectives by implementing actions when triggers accurately indicate that such an event is likely. As the assessment of damages increases, the cost of failing to meet objectives becomes a larger share of planners’ expected costs relative to the cost of implementing actions. Planners will have more tolerance to over-invest, so long as the strategy avoids failure to meet objectives.

This figure also demonstrates that there are different critical thresholds of subjective probability that require switching strategies for different beliefs about damages. If the assessment of damages is low, at $200$, Strategy 1 is not preferred unless $(R) \geq 0.5$. If the assessment of damages is higher, at $1000$, then Strategy 1 is preferable across the entire range of subjective beliefs. When the cost of...
damages is relatively low, planners will be more concerned with spending to implement actions that prove to be unnecessary and will favor strategies with low false-positive rates, as they can tolerate some level of damages.

Importantly, this tradeoff analysis can identify ranges of plausible beliefs where planners may agree on a strategy. Figure 3-5 shows that there are certain regions where there is a dominant strategy and planners with divergent beliefs may still be able to agree on a strategy. For example, if planners can agree that the decision relevant scenario is more than 50 percent likely, Strategy 1 will always be preferred to Strategy 2, regardless of the planners’ assessments of damages (within this range). Alternatively, amongst those who agree that damages are $300 or greater, all planners who believe the scenario is at least 30 percent likely will agree that Strategy 1 is preferable to Strategy 2.

Stakeholders may also disagree in their assessments of the cost of action, C. Figure 3-6 demonstrates how preferences between triggers may vary across different beliefs, assessments of damages, and assessments of costs. Each horizontal panel represents a different likelihood of the decision-relevant scenario occurring. Within each panel, the horizontal axis shows different assessments of the cost of action ranging from $60 to $100. The vertical axis shows different assessments of damages, D, ranging from $200 to $1000. The red circles represent beliefs for which planners would prefer Strategy 1 and the gray circles represent those for which planners would prefer Strategy 2.

*Figure 3-6: Preferred strategies across a range of beliefs and assessments of damages and costs*

This figure demonstrates that all else equal, the strategy with a higher true-negative rate is preferred when the cost of action is high. For example, if planners assess the decision-relevant
scenario as 25 percent likely and the cost of damages as $400, then they will prefer Strategy 1 if the policy action costs $70 or less. If the policy action costs $70 or more, however, they will prefer Strategy 2. If the cost of action were high relative to damages then planners would prefer not to take an action unless it is necessary; they prefer a strategy with a low false-positive rate.

In this example, a high true-positive rate ensures that when the decision-relevant scenario occurs, a trigger will be observed; this avoids not having implemented actions when they are necessary and being under-prepared to address vulnerability. Similarly, the true-negative rate ensures that when the future is not in the decision-relevant scenario, the trigger will not be observed. This helps planners to avoid investing in actions when they would not be necessary and over-investing.

When vulnerability is likely, the relative cost of not being prepared can be high. Planners would prefer to slightly over-invest but be prepared should a vulnerability occur. Similarly, when the cost of action is low, the cost of over-investing is relatively low, and planners can be less concerned with over-investing. Conversely, when the cost of damages is low, the decision-relevant scenario is unlikely, or the cost action is high, there is substantial risk of over-investing. In these cases, a strategy with a high true-negative rate would be preferred to ensure that an action is not taken when it is not necessary.

This example demonstrates that the tools in RDM analysis can be used to help planners characterize tradeoffs between alternative strategies with different triggers. The ability of the trigger signpost variable and trigger to predict a decision-relevant scenario can serve as the basis for comparing strategies. Visual aids similar to the region plots presented above can help planners identify whether there are regions of consensus, or whether alternatives need to be considered.

**Characterizing actions to implement**

Equations 7 and 9 show that the actions implemented over time in adaptive strategies are functions of previously observed information. The previous sections of this chapter discuss the structure of these functions. Planners choose between alternative decision-rules. This definition of a strategy stands in contrast to a more traditional RDM analysis— the decision-rules that planners choose among as levers define a strategy, rather than the actions themselves.

However, in many policy contexts, planners will not simply implement actions according to predefined decision-rules. Instead, planners will continue to deliberate and choose among various policy actions as new information becomes available. In such applications, planners may prefer to define a strategy by the actions implemented, rather than the decision-rules that implement actions. Planners are more likely to maintain this framing in policy applications further from fully-automatic policy adjustment they are on the continuum. In such applications, planners may not have policy interpretations of decision-rules used in the model. The modeled decision-rules may be too specific to model and not generalizable for the larger decisions that planners continue to deliberate.

This section describes how the simulations of adaptive strategies that rely on decision-rules can be interpreted to provide planners with information about which actions to implement. In such
applications, the functions defining when actions are to be implemented, \( g \), have a different interpretation. They serve as a search mechanism within the simulation model, identifying which actions planners would implement over the course of a specific future. If analysts can effectively simulate the process planners will use to make decisions, these functions can serve as a projection of an adaptive process that will occur. Alternatively, the functions can serve as optimization routine, to inform planners which actions they should implement in a specific future. The functions identify a well-performing set of actions in each future.\(^{33}\) As the model is simulated, a database tracks each action that is implemented in each time step in each future.

A different set of actions will be implemented in each future, as \( L_i^j \) is indexed across futures. As the RDM analysis considers a large ensemble of plausible futures, inspection of each \( L_i^j \) may not be feasible. Additionally, inspection of a single \( L_i^j \) will draw limited insight about which actions planners should implement across a range of uncertain conditions. Instead, this dissertation proposes an additional analysis, characterizing the realizations \( L_i^j \) across the ensemble of futures.

The first step of such an analysis is to report summary statistics characterizing the implementation of actions; planners and analysts work together to identify policy-relevant summary statistics. For example, to provide planners with an assessment of which actions will be necessary regardless of future conditions, analysts may report the percent of futures in which each action is implemented.

To provide planners with an assessment of the timing of actions, analysts may report the time period in which an action is first implemented in 50 percent of futures (i.e. the median time period of implementation). Analysts can generate interactive graphics, which allow planners to consider these statistics across different ranges of future conditions, by filtering or sub-setting the cases to only include specific futures.

In the initial period, planners wish to identify robust initial actions, which are necessary in the near-term regardless of what the future may hold. Thus, the analysis can identify specific actions that are implemented in early time periods in a large percentage of futures.

However, if the statistics only summarize implementation across the entire ensemble of futures, then they implicitly weight each future as equally likely. This dissertation proposes another approach consistent with exploratory modeling, where the analysis seeks to identify regions of the uncertainty space where specific actions are implemented at specific times. Using the same process and tools as described for scenario discovery, the analysis can identify scenarios, \( R \), where the simulated adaptive strategies implement an action in a particular time period, \( l_{t,y} \):

\[
20. P(l_{t,y} = 1 | R) \gg P(l_{t,y} = 1 | \neg R)
\]

Analysts would then search for summary statistics, \( \bar{x} \), and threshold values of the summary statistics, \( \bar{x}' \), that define the scenario. A future falls within a decision-relevant scenario if the following condition holds:

\[^{33}\text{In this case, analysts may wish to relax the assumption that actions implemented are only a function of previously observed information, and instead assume that they provide a perfect foresight for optimization. Chapter 2 discusses the implications of this approach in detail.}\]
21. $x^i \in R$ if $\bar{x}^i_n < \bar{x}^*_n$ for various $\bar{x}$

This dissertation refers to this form of decision-relevant scenario as an implementation scenario.

The interpretation of these scenarios differs from the decision-relevant scenarios described in previous sections. Traditional decision-relevant scenarios imply that a particular strategy will likely fail to meet objectives should the scenario occur. Instead, these scenarios imply that a particular action is likely to be an element of a well-performing portfolio of actions, should the scenario occur. These scenarios can become the basis for planners’ decisions about individual actions, as they weigh whether or not the scenario is sufficiently likely to warrant implementing the action.

After analysis generates some useful implementation scenarios, analysts may present other summary statistics that are conditional on the scenario occurring. For example, an analysis may identify a scenario that describes the conditions under which planners implement a specific action in any time period. Analysts may then present the percent of futures in which the scenario action is implemented in the first time period. This approach only requires weighting futures conditional on the decision-relevant scenario.

Once these scenarios are defined, information may be used in various ways. First, the definitions of scenarios can be combined to provide decision aids to planners that are considering whether to implement various actions. Chapter 7 of this dissertation provides some example of pathways through implementation that use decision-relevant scenarios. Alternatively, analysts and planners can iterate through the RDM process again, identifying indicators that scenarios are likely.34

**Conclusions**

This chapter describes the design of an RDM analysis with multiple time periods for decision-making. It then provides an in depth discussion of three subsequent analyses that can support the design of adaptive strategies: identifying signposts, comparing decision-rules, and characterizing implementation.

Different application of RDM may require different emphasis. For example, planners may be particularly interested in identifying signpost variables that suggest whether a strategy will fail to meet objectives. Such signposts may inform planners that deliberations should be renewed to consider other strategies. For some applications, this may be sufficient. In other applications, planners may be most interested in identifying which conditions require specific actions. However, they may not find an analysis of the decision-rules that defines when actions are necessary to have a policy interpretation. Thus, in differing applications, analysts may emphasize some or all of the techniques described in this chapter.

The subsequent chapters of this dissertation provide examples of each technique, building from the analysis in the Colorado River Basin.

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34 This information can be used to generate new decision-rules. This may be useful if the initial functions defining when actions are implemented are too abstract for planners to easily interpret. Alternatively, the decision-aides may be the conclusion of the analysis, as planners may not wish to design new decision-rules.
Appendix 3-A: The Decision to be Adaptive

This appendix provides a simple example of the decision to be adaptive. This model helps define the boundary conditions that demonstrate when planners would prefer to defer decisions and be adaptive rather than commit to actions in advance.

This model ignores deep uncertainty and assumes that planners can estimate the likelihood of each future, and thus have estimates of \( P(V) \), \( P(V|Z) \), and \( P(Z) \). Deep uncertainty is re-introduced using decision-relevant scenarios in the main body of the text. In this model, planners do not know the underlying probabilities, but rely on estimates, demarked as \( \overline{P(V)} \), \( P(V|Z) \), and \( \overline{P(Z)} \). The decision model is presented in Figure 3A-1.

Figure 3A-1: The decision to be adaptive

This model has the following characteristics:

1) In the first period, planners can either implement the policy action or do nothing.
2) Planners then monitor the signpost variables to see if a trigger is observed. The trigger is observed with some probability, \( P(Z) \).
3) If the planners did not take action in the first period, they have the choice on whether to take action in the second period.
4) There is some underlying probability that vulnerability occurs. This probability is conditional on observing the trigger. Vulnerability is more likely if the trigger is observed, \( P(V|Z) > P(V|\neg Z) \). If the action is implemented, the probability that the vulnerability occurs decreases.

5) The payoffs are assessed. If vulnerability occurs, then damages, \( D \), are incurred. If the action is implemented, a cost of \( C \) is incurred.

To minimize expected costs, planners would be willing to invest in action in the second period after observing the trigger if the following condition holds:

1. \( C \leq D \cdot (1 - q_2) \cdot P(V|Z) \)

If this condition does not hold, because \( P(V|T) > P(V|\neg Z) \), it follows that:

2. \( C > D \cdot (1 - q_2) \cdot P(V|Z) > D \cdot (1 - q_2) \cdot P(V|\neg Z) \)

Thus, if a planner would not enact an action after not observing the trigger, they will not act at all when faced with the decision in the second period.

Planners will be willing to invest in action if they do not observer trigger if:

3. \( C \leq D \cdot (1 - q_2) \cdot P(V|\neg Z) \)

If this condition holds, planners will always be willing to take action in the second period regardless of what they observe. The expected payoff is:

4. \( C + D \cdot q_2 \cdot [P(V|Z) \cdot P(T) + P(V|\neg Z) \cdot (1 - P(Z))] \)

Because \( q_2 > q_1 \), if a planner is always willing to take the action in the second period, they will prefer to take action in the first period. The total expected cost of acting in the first period would be lower than in the second:

\[
D \cdot q_2 \cdot P(V|Z) \cdot P(Z) + P(V|\neg Z) \cdot (1 - P(Z)) \leq D \cdot q_2 \cdot [P(V|Z) \cdot P(Z) + P(V|\neg Z) \cdot (1 - P(TZ))] 
\]

Therefore, for a planner to be willing to defer the action but still consider implementing it, the following conditions must hold:

5. \( C \geq D \cdot (1 - q_2) \cdot P(V|\neg Z) \) And \( C \leq D \cdot (1 - q_2) \cdot P(V|Z) \)

This can be rewritten as follows:

6. \( \frac{C}{P(V|\neg Z) \cdot D} \leq (1 - q_2) \leq \frac{C}{P(V|Z) \cdot D} \)

That is, the decrease in likelihood of vulnerability is greater than the ratio of cost to expected damage if the trigger is observed, but less than the ratio of cost to expected damage if the trigger is not observed. For a set, \( C, D, q_2 \), one can search for an effective trigger that fulfills the criteria.
above. If a trigger does not have a $P(V|Z)$ and $P(V|\neg Z)$ that allow this criteria to hold, the trigger
will differentiate between when planners should and should not take action.

The expected payoff for acting adaptively is:

7.  

$$[D \cdot q_2 \cdot P(V|Z) + C] \cdot P(Z) + D \cdot P(V|\neg Z) \cdot (1 - P(Z))$$

A second necessary condition for being willing to defer is that the expected cost of acting adaptively
is less than the cost of acting in the first period:

8.  

$$[D \cdot q_2 \cdot P(V|Z) + C] \cdot P(Z) + D \cdot P(V|\neg Z) \cdot (1 - P(Z)) < C + D \cdot q_1 \cdot P(V|Z) \cdot P(Z) + P(V|\neg Z) \cdot (1 - P(Z))$$

This can be simplified as follows:

9.  

$$D \cdot [P(V|Z) \cdot P(Z) \cdot (q_1 - q_2) + P(V|\neg Z) \cdot (1 - P(Z)) \cdot (1 - q_1)] < (1 - P(Z)) \cdot C$$

For example, this suggests when $(q_1 - q_2)$ is small, planners are more likely to prefer to act
adaptively, as there is little cost (in terms of decreased efficacy) to deferring.
Chapter 4: Factors of analysis in the Basin and system vulnerabilities

Introduction
This chapter describes the scope of RDM analysis presented in this dissertation. This chapter first describes the various uncertainties (X), metrics (M), levers and strategies (L) and the analytic model used to analyze them (R) in this dissertation. It then summarizes the primary vulnerabilities of the system, addressing the following policy questions:

1. Under what future streamflow conditions will the current management practices fail to meet its water delivery objectives?
2. Under what future streamflow conditions will an aggressive set of infrastructure and conservation water-management actions fail to meet its water delivery objectives?

To answer the first question presents an analysis first described in the Basin Study (U.S. Bureau of Reclamation 2012e) and subsequent RAND report, identifying decision-relevant scenarios that illuminate the streamflow conditions that drive whether the Basin is likely to meet its water delivery objectives with current management of the system. It next presents a new analysis of decision-relevant scenarios, that describe the conditions when even an aggressive portfolio of water management actions fail to meet planning objectives. These factors of analysis and decision-relevant scenarios form the basis for the subsequent analysis of adaptive strategies presented in Chapters 5, 6, and 7.

The design of the RDM analysis presented in this chapter, and referred to in Chapters 5, 6 and 7, draw heavily from the models and data, analytical approach, and results of analysis described in the Colorado River Basin Study (U.S. Bureau of Reclamation 2012f). As a rule, the phrase “this analysis” is used to denote analytical decisions or results specific to this dissertation. When describing decisions or analysis completed in the Colorado River Basin Study or other prior analyses, it refers directly to the Basin Study or subsequent RAND report. Additionally, it provides footnotes that highlight and describe significant changes from the Basin Study.

In general, changes between the Basin Study and this analysis should not be interpreted to imply that the Basin Study analysis was somehow incorrect or incomplete in its approach. This dissertation focuses on a more targeted set of research questions than the Basin Study, relating specifically to the process of adapting. In most cases, changes in the research design are most appropriate to explore the specific research questions considered in this dissertation.
Scope of analysis in the Colorado River Basin

This analysis considers water delivery reliability to the Upper and Lower Basins across a range of plausible future hydrologic conditions. Table 4-1 summarizes the uncertainties, strategies, metrics, and relationships between those factors that comprise this analysis. Each element is then described in detail in subsequent sections.

Table 4-1: Uncertainties, strategies, metrics, and relationships (XLRM)

<table>
<thead>
<tr>
<th>Uncertainties or Scenario Factors (X)</th>
<th>Management Strategies and Portfolios (L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplies via river flows (3 supply scenarios, 715 futures)</td>
<td>Current Management Static Implement-All-Actions Portfolio A (Inclusive)</td>
</tr>
<tr>
<td>• Recent historical record (103 futures)</td>
<td></td>
</tr>
<tr>
<td>• Statistical blend of the recent historical record and the paleoclimatic record (500 futures)</td>
<td></td>
</tr>
<tr>
<td>• Downscaled Global GCM (112 futures)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Relationships or Systems Model (R)</th>
<th>Performance Metrics (M)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colorado River Simulation System (CRSS)</td>
<td>Upper Basin water delivery reliability Lower Basin water delivery reliability</td>
</tr>
</tbody>
</table>

Uncertainty in future streamflow (X)

This analysis examines uncertainty in future climate and hydrologic conditions. The performance of the system is analyzed for 715 plausible streamflow futures, drawn from the analysis in the Basin Study (U.S. Bureau of Reclamation 2012b). The ensemble contains futures drawn from three different sources. The first source is the recent historical record (103 futures). The second source is a statistical blend of the recent historical record and the paleoclimatic record (500 futures). The third source is derived from the projections of future climate conditions from 16 global climate

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35 The Basin Study also considers uncertainty in water demand and future reservoir operations. The Basin Study analysis revealed that in range considered, demand did not have a significant effect on the broad basin-scale outcomes. The reservoir operations did have small, measurable effects on the outcomes, but did not significantly change the policy story. For simplicity and to best utilize computing resources, only one demand scenario and one future reservoir operations scenario are considered in this analysis.
models and three global carbon emissions scenarios. Each future is derived from downscaled results from a single GCM projection (112 futures).³⁶

Each future is defined by a unique time series of natural streamflow (flows absent human use or management) at various locations along the Colorado River and its tributaries. In both the Basin Study and this analysis, natural streamflow is summarized at one point along the Colorado River—Lees Ferry, Arizona.

Figure 4-1 presents the distribution of annual mean streamflow (left), the annual mean streamflow of the driest eight-year period (middle), and the standard deviation of the rolling eight-year average streamflow (right) across the ensemble of futures considered. The long-term average natural flow ranges from 10.1 maf to 18.4 maf while 75 percent of futures fall between 13 and 16 maf. As a point of reference, the average streamflow from 1906 to 2007 is 15 maf. Many climate change models predict that this will decrease over the next half century; more than half of the futures drawing from the set of climate projections have a long-term mean average flow of less than 14 maf.

Figure 4-1: Histogram of statistics summarizing ensemble of streamflow futures (2012-2060)

Across all the considered futures, the driest eight-year period ranges from 7.5 maf to 15.5 maf. The recent historical record contains two eight-year dry periods of note, one with 11.2 maf of average annual flow and another with 12.4 maf. These droughts frequently appear in the futures drawn from the historical record, generating the two spikes in the distribution.

The standard deviation of the eight-year average flow ranges between 320 kaf and 4200 kaf. This measure of decadal variation is only loosely correlated with the long-term flow (0.21 correlation

³⁶ To generate the full ensemble of futures, futures from each source are resampled to ensure than an equal mix of the three sources are represented. Each of the 500 futures Paleo\Historical Blend is included. The two other sources are resampled up to 500 futures. The Basin Study analysis also includes a set of futures drawn solely from the Paleo record (1,244 futures). These are omitted from this analysis to decrease the amount of time necessary to run the ensemble. The futures omitted have similar characteristics to those included in this analysis. Sensitivity analysis during the Basin Study determined that these additional futures do not significantly alter the aggregate ensemble results.
coefficient). In this set of data, the decadal variation in the GCM sequences is largely consistent with those generated in the paleo-conditioned natural flows.

**Metrics to evaluate water delivery reliability (M)**

This analysis focuses on just two of the many policy objectives considered in the Basin Study: Upper and Lower Basin water delivery reliability. Upper Basin water delivery is measured by the ability to deliver an average of 7.5 maf per year to Lee Ferry, AZ, a condition outlined in the Colorado River Compact (1922). Failure to supply 75 maf of flow over any ten-year period is referred to as a Lee Ferry Deficit. Should there be a Lee Ferry Deficit, there is the potential for curtailment of water supply in the Upper Basin to meet this condition (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

Deliveries to the Lower Basin states are closely tied to the pool elevation of Lake Mead. As such, Lower Basin water delivery is measured by Lake Mead elevation. Should Lake Mead’s pool elevation level drop below 1000 feet, Southern Nevada Water Authority can no longer withdraw water and Las Vegas would lose a majority of its water supply. Thus, when Lake Mead’s pool elevation drops below 1000 feet it serves as a useful, though severe, threshold and any future where this occurs in one or more years is considered vulnerable (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

This analysis focuses primarily on the ability of the system to meet these water delivery objectives between 2031 and 2060.38

**Simulating the Colorado River system (R)**

The Basin Study and this dissertation use the Bureau of Reclamation’s long-term planning model, the Colorado River Simulation System (CRSS), to evaluate the performance of the system. CRSS simulates operations at a monthly time-step from 2012-2060. CRSS models 12 reservoirs (Fontenelle, Flaming Gorge, Starvation, Taylor Park, Blue Mesa, Morrow Point, Crystal, Navajo, Powell, Mead, Mohave, and Havasu) and their unique operational rules. The key inputs to a single simulation include natural monthly streamflow at 29 locations throughout the Basin, schedules for water demand by the Basin’s water-using entities (of which there are more than 400), minimum-flow requirements at various parts of the River, and rules for the operation of its reservoirs. CRSS calculates results of hundreds of variables, representing the response of the system, including

37 Focusing on these two metrics is consistent with the RAND report describing their involvement with the Colorado River Basin Study.  
38 The Basin Study considers the ability to meet objectives across the entire time horizon, but measures it in three distinct time periods (2012-2026, 2027-2040,2041-2060). Additionally, the Basin Study considers two metrics, the percent of futures failing to meet the objectives and the percent of years failing to meet objectives. This analysis only considers the percent futures failing to meet objectives. As described in subsequent chapters, sufficient actions are not available prior to 2031 to allow the actions to meet objectives in many otherwise vulnerable futures. Including these years in this analysis would mask the effectiveness of implementing actions.
depletions from the system, reservoir levels, and modeled streamflow (U.S. Bureau of Reclamation 2012e). CRSS is developed in the RiverWare® modeling software (Zagona, Fulp et al. 2001).

Figure 4-2 shows a simplified schematic of the CRSS network. The black line represents the model schematic of the Colorado River and its tributaries. The red and purple symbols indicate major demands represented by the model. The colored regions denote individual basins that contribute supply to the Basin. The light blue line represents the actual route of the Colorado River and its tributaries across the seven-state region.

Figure 4-2: Simplified Schematic of CRSS Network

Source: Groves, Fischbach et al. (2013)
Water management strategies (L)

The Basin Study and this analysis first evaluate water delivery reliability assuming the Current Management of the system continues over the next half century—the baseline analysis. This represents the current water allocations to users in the Basin States in accordance with the Law of the River and the operational rules currently in place to balance reservoir storage between Lakes Powell and Mead. It reflects the Interim Guidelines (U.S. Bureau of Reclamation 2007) and assumes that they will continue after they expire, in 2026.

Next, this analysis evaluates water delivery reliability assuming a portfolio of water management actions. Most of the actions either increase water supply through infrastructure (such as desalination) or decrease water demand (through efficiency and conservation).\textsuperscript{39} This analysis carries forward just one of the four portfolios designed for the Basin Study: Portfolio A (Inclusive).\textsuperscript{40} This strategy represents the most expensive list of plausible actions considered in the Basin Study. The Basin Study and subsequent reports describe in detail how these portfolios were designed and the individual actions contained in them (U.S. Bureau of Reclamation 2012d, Groves, Fischbach et al. 2013).

Figure 4-3 lists the water management actions included in this Portfolio A (Inclusive). Actions are ordered vertically in the figure by their relative priority. The horizontal axis defines the first year an action is available. The colors provide information about the type of action, while the size provides the yield of each action. For the analysis in this chapter, each action is implemented the first year it is available, as a static strategy—referred to as the Static Implement-All-Actions strategy.

\textsuperscript{39} Details about specific water management actions are available in TR-F of the Basin Study.
\textsuperscript{40} This analysis uses Portfolio A (Inclusive) for two reasons. First, it represents the maximum potential of the considered water management strategies to address vulnerability. Second, it allows the greatest variation among outcomes through adaptivity; the ability to measure the effect of different responses to new information is less constrained by a limited set of actions.

The version of Portfolio A (Inclusive) evaluated in this dissertation differs slightly from the version evaluated in the Basin Study. The Basin Study version of Portfolio A (Inclusive) includes an Upper Basin water bank which allows them to store conserved water to reduce the probability and magnitude of the Lee Ferry Deficit (described in TR-G Appendix 2 of the Basin Study). This was not included in this paper for two primary reasons. First, including this action nearly doubles the amount of computing time necessary to run simulations. Excluding it allows for further exploration of additional strategies. Second, this action generates a tradeoff between Upper Basin and Lower Basin water delivery reliability. Upper and Lower Basin water delivery reliability is correlated in the variation of most other factors of analysis. Not including this action simplifies interpretations of tradeoffs due to signposts and triggers, the primary aim of this particular study.
Figure 4-3: Water management actions included in Portfolio A (Inclusive)

<table>
<thead>
<tr>
<th>Watershed-Weather Mod (Step 1)</th>
<th>Watershed-Weather Mod (Step 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ag Conservation (Step 1)</td>
<td>Ag Conservation (Step 2)</td>
</tr>
<tr>
<td>Watershed-Dust (Step 1)</td>
<td>Ag Conservation-Transfer (Step 1)</td>
</tr>
<tr>
<td>Ag Conservation (Step 3)</td>
<td>Ag Conservation (Step 4)</td>
</tr>
<tr>
<td>Watershed-Tamarisk</td>
<td>Desal-Yuma Area Groundwater</td>
</tr>
<tr>
<td>Ag Conservation (Step 3)</td>
<td>M &amp; I Conservation (Step 1)</td>
</tr>
<tr>
<td>Ag Conservation (Step 4)</td>
<td>Desal-Socal Groundwater</td>
</tr>
<tr>
<td>Desal-Salt Sea Drainwater (Step 1)</td>
<td>M &amp; I Conservation (Step 2)</td>
</tr>
<tr>
<td>Desal-Salt Sea Drainwater (Step 2)</td>
<td>Ag Conservation (Step 5)</td>
</tr>
<tr>
<td>Desal-Salt Sea Drainwater (Step 3)</td>
<td>Ag Conservation-Transfer (Step 5)</td>
</tr>
<tr>
<td>Desal-Pacific Ocean-Mexico</td>
<td>M &amp; I Conservation (Step 3)</td>
</tr>
<tr>
<td>Reuse-Municipal (Step 1)</td>
<td>M &amp; I Conservation (Step 4)</td>
</tr>
<tr>
<td>Reuse-Municipal (Step 2)</td>
<td>M &amp; I Conservation (Step 5)</td>
</tr>
<tr>
<td>Import-Rural-SE</td>
<td>Desal-Pacific Ocean-CA (Step 1)</td>
</tr>
<tr>
<td>Reuse-Municipal (Step 3)</td>
<td>Desal-Pacific Ocean-CA (Step 2)</td>
</tr>
<tr>
<td>Reuse-Municipal (Step 4)</td>
<td>Energy Water Use Efficiency-Air Cooling</td>
</tr>
<tr>
<td>Reuse-Municipal (Step 5)</td>
<td>Local-Coalbed Methane</td>
</tr>
<tr>
<td>Desal-Gulf (Step 1)</td>
<td>Reuse-Industrial</td>
</tr>
<tr>
<td>Desal-Gulf (Step 2)</td>
<td>Desal-Gulf (Step 2)</td>
</tr>
<tr>
<td>Local-Rainwater Harvesting</td>
<td>Reuse-Grey Water</td>
</tr>
</tbody>
</table>

Source: Groves, Fischbach et al. (2013)

Together, these two strategies represent some boundaries on any future adaptive process in the Colorado River Basin. The Current Management of the system reflects a business-as-usual strategy where planners do not alter the management of the Basin and forgo opportunities to increase supply and decrease demand to improve water delivery reliability in the Basin. The Static Implement-All-Actions strategy represents the other extreme. Planners implement every action available at the soonest date it may be available to maintain reliability at considerable expense.

**Scenarios that describe water delivery vulnerability**

This section describes the vulnerability analysis step of the RDM process. It identifies decision-relevant scenarios that describe the exogenous condition where the Basin is likely to fail to meet water delivery objectives between 2031 and 2060. The vulnerability analysis for the *Current*
Management of the system was presented in the Basin Study and described in detail in the subsequent RAND report. It is summarized in this dissertation to provide necessary context. The decision-relevant scenarios that describe when the Static Implement-All-Actions strategy fails to meet objectives are new to this dissertation.

Vulnerability of the current management

Analysis of Current Management reveals that both the Upper Basin and Lower Basin may fail to meet water delivery reliability objectives within the range of plausible future conditions considered. The Upper and Lower Basin both face vulnerability when the future has relatively low long-term average streamflow coupled with more severe drought periods. The Lower Basin may fail to meet objectives under less severe conditions than the Upper Basin.

The Upper Basin is susceptible to a Lee Ferry Deficit when long-term average streamflow declines beyond what has been observed in the recent historical record and is similar to some of the driest periods in the paleoclimatic record. The Upper Basin is unlikely to meet its water delivery objectives when the long-term average annual natural flows at Lees Ferry are below 13.8 maf per year and the driest eight-year period of natural flows averages 11.2 maf per year. A decision-relevant scenario called Declining Supply describes these conditions (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

Lake Mead is likely to have its pool elevation drop below 1000 feet in the next half century if hydrological conditions are similar or dryer than what has been observed in some of the dryer periods of the recent historical record. If the long-term average streamflow at Lees Ferry falls below 15 maf and an eight-year drought with average flows below 13 maf occurs, the Lower Basin is susceptible to water delivery vulnerability. A decision-relevant scenario called Low Historical Supply refers to such conditions. Though Lake Mead’s elevation has not dropped below 1000 feet.

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41 For the Current Management strategy, the definitions of the decision-relevant scenarios were first generated for the Basin Study. These definitions include the statistical summaries of streamflow conditions and their threshold values. The design of the graphics that visualize the scenarios was also first presented in the Basin Study. The graphics included in this dissertation are altered to include only the futures considered in this analysis and the objectives in the time period analyzed in this dissertation—2031-2060. Similarly, the summary statistics of the scenarios (density and coverage) reflect the futures and time horizon described in this dissertation.

42 These scenarios are an extension of the vulnerability analysis described in the Basin Study. They use similar summary statistics and visualizations. The Basin study presents decision-relevant scenarios to describe the vulnerability of other strategies, but this particular strategy; these definitions are new to this dissertation.

43 Futures that meet both of these conditions—that is, they have low long-term mean flows and an eight-year drought of this magnitude—lead to a Lee Ferry Deficit 86.8 percent of the time (density). In addition, Declining Supply captures 77.7 percent of all futures with at least one Lee Ferry Deficit (coverage). This is the same definition used in the Basin Study and RAND report, though the set of futures and time period considered are slightly different in this dissertation.

44 Lower Basin objectives are not met in 82.3 percent of futures with these conditions (density). The conditions also describe 90.4 percent of all futures that lead to a failure to meet objectives (coverage).
In the past, conditions similar to the historical record may not provide sufficient supply due to projected increases in demand (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013).

Figure 4-4 visually summarizes these conditions. Each point in the figure represents one future, characterized by long-term mean annual flow (vertical axis) and mean annual flow during the driest eight-year period (horizontal axis). Red Xs indicate futures where the Basin does not meet objectives and gray Os mark futures in which it does. The yellow region in each panel (lower left) presents the boundaries of the decision-relevant scenario. Panel A (left) shows the conditions for an Upper Basin water delivery vulnerability and Panel B (right) shows the conditions for a Lower Basin water delivery vulnerability.

**Figure 4-4: Decision-relevant scenarios for describing vulnerability of current management of the Basin**

![Graph showing decision-relevant scenarios for describing vulnerability of current management of the Basin]

*Adapted from: U.S. Bureau of Reclamation (2012e)*

**Vulnerability of implementing all actions**

Even with the *Static Implement-All-Actions* strategy, the Upper Basin is still vulnerable to futures with long-term average streamflow below 12.9 maf and a dry eight-year period of streamflow below an average of 10.2 maf.45 These actions decrease the conditions associated with vulnerability

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45 Upper Basin objectives are not met in 74.0 percent of futures with these conditions (density). The conditions also describe 84.6 percent of all futures that lead to a failure to meet objectives (coverage).
by 900 kaf in the long-term average streamflow and 1.0 maf in the average flow during a drought period. A decision-relevant scenario referred to as *Severely Declining Supply* describes these conditions.

The Lower Basin is also vulnerable to the *Severely Declining Supply* conditions.\(^6\) The *Static Implement-All-Actions* adds resilience of 2.1 maf in the long-term flow and 2.8 maf in the average flow during a drought period. Figure 4-5 presents the definition of *Severely Declining Supply* conditions.

*Figure 4-5: Decision-relevant scenarios describing vulnerability of Static Implement-All-Actions strategy*

This scenario is quite severe. It is dryer than any streamflow conditions observed in either the recent historical record, or the paleohistorical record. Approximately 30 percent of downscaled GCM futures fall into the definition of this scenario.

**Business-as-usual, adaptive, and transformative scenarios**

The scenarios described above can help planners consider how best to respond to the risk of low water delivery reliability. Table 4-2 presents the definitions of the decision-relevant scenarios in the Upper Basin and Lower Basin.

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\(^6\) Lower Basin objectives are not met in 71.6 percent of futures with these conditions (density). The conditions also describe 73.3 percent of all futures that lead to a failure to meet objectives (coverage).
Table 4-2: Definitions of decision-relevant scenarios to describe vulnerabilities of various strategies in Upper and Lower Basin

<table>
<thead>
<tr>
<th>Business-as-Usual Scenario (Current management meets objective)</th>
<th>Upper Basin decision-relevant scenarios</th>
<th>Lower Basin decision-relevant scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Low Historical, Stationary, or Increasing Supply</strong></td>
<td>Long-term average streamflow &gt; 13.8 maf or Minimum eight-year rolling average streamflow &gt; 11.2 maf</td>
<td>Stationary or Increasing Supply Long-term average streamflow &gt; 15.0 maf or Minimum eight-year rolling average streamflow &gt; 13.0 maf</td>
</tr>
<tr>
<td><strong>Declining Supply</strong></td>
<td>Long-term average streamflow &lt; 13.8 maf Minimum eight-year rolling average streamflow &lt; 11.2 maf Long-term average streamflow &gt; 12.9 maf or Minimum eight-year rolling average streamflow &gt; 10.2 maf</td>
<td>Low Historical Supply Long-term average streamflow &lt; 15.0 maf and Minimum eight-year rolling average streamflow &lt; 13.0 maf Long-term average streamflow &gt; 12.9 maf or Minimum eight-year rolling average streamflow &gt; 10.2 maf</td>
</tr>
<tr>
<td><strong>Severely Declining Supply</strong></td>
<td>Long-term average streamflow &lt; 12.9 maf and Minimum eight-year rolling average streamflow &lt; 10.2 maf</td>
<td>Severely Declining Supply Long-term average streamflow &lt; 12.9 maf and Minimum eight-year rolling average streamflow &lt; 10.2 maf</td>
</tr>
</tbody>
</table>

In the Upper Basin, the Static Implement-All-Actions strategy is unlikely to meet objectives should the Severely Declining Supply scenario occur. Declining Supply describes conditions where the Current Management is unlikely to meet objectives but the Static Implement-All-Actions strategy is likely to meet objectives. In this dissertation, the Declining Supply does not include futures in Severely Declining Supply conditions. The futures where the Current Management is likely to meet objectives are referred to as Low Historical, Stationary, or Increasing Supply conditions.
In the Lower Basin, the Static Implement-All-Actions strategy is unlikely to meet objectives in the Severely Declining Supply scenario. Low Historical Supply describes conditions where the Current Management is unlikely to meet objectives but the Static Implement-All-Actions strategy is likely to meet objectives. The Low Historical Supply scenario does not include futures in Severely Declining Supply conditions. A final set of conditions describe futures where the Current Management is likely to meet the Basin’s objectives, referred to as Low Stationary or Increasing Supply conditions.

The conditions where the current management strategy is likely to meet objectives represent business-as-usual scenarios. Should planners believe these scenarios are likely, they can expect to meet the two objectives considered in this dissertation with the current management of the system and would not need to implement new actions or otherwise adapt to maintain these measures of water delivery reliability.

The scenarios where the system meets water delivery objectives with the Static Implement-All-Actions strategy but the not with Current Management (Declining Supply in the Upper Basin and Low Historical in the Lower Basin) represent adaptive scenarios. If these scenarios occur and planners maintain current management of the system in these futures, then the Basin will likely fail to meet water delivery objectives. However, the set of available actions provides the potential to meet objectives. If managed properly, planners can address the challenges with the set of actions considered in the Basin Study. Should these conditions occur, planners could likely engage in a process of semi-automatic policy adjustments to identify actions to implement. These scenarios represent ranges of conditions that planners are, at some level, prepared to address and they can update plans using single-loop learning. Though such management is possible it may be difficult and subsequent chapters of this dissertation examine the process of adapting to address this scenario.

The scenarios where the system does not meet water delivery objectives even after implementing the Static Implement-All-Actions strategy (Severely Declining Supply conditions in both regions) may be considered the transformative scenarios. Should these conditions occur, planners are still unlikely to meet the water delivery objectives after implementing a large yield of additional water conservation and many expensive (and potentially controversial) infrastructure projects. They would need to look beyond the current set of solutions and engage in double-loop or triple-loop learning. This may require new strategies such as different allocations of water or reconsidering the objectives of the policy as whole, for example, relaxing the constraints imposed by the Colorado River Compact.
Chapter 5: Identifying early-warning indicators of vulnerability in the Colorado River Basin (signposts)

Introduction
A distinctive feature of adaptive strategies is that decisions do not need to be made today; rather, they can be deferred until more is known. In the Colorado River Basin, planners still have time to monitor new information before determining whether they need to respond to the adaptive scenario, the transformative scenario, or can use a business-as-usual approach. This is particularly true in the Upper Basin, as a Lee Ferry Deficit does not occur prior to 2020 in any of the sampled futures.

Planners may find that a reasonable strategy is a wait-and-see approach. They may begin planning and implementing some low-regret water management actions in near term, while continuing to monitor indicators. If the Severely Declining Supply scenario becomes likely, planners and stakeholders can open deliberations on a broader set of issues. The analysis in this chapter seeks to inform this wait-and-see approach by providing insight into the information that planners should monitor in the coming decades. It provides a Bayesian analysis to assess how new pieces of information may influence planners’ estimates of the likelihood of the various scenarios.

This chapter identifies and interprets signpost variables that can serve as early warning indicators of the decision-relevant scenarios describing water delivery vulnerabilities in the Basin. It applies the methods described in Chapters 2 and 3 of this dissertation to the factors of analysis considered in Chapter 4. This chapter addresses the following policy questions:

1. What are some leading indicators that suggest the Colorado River Basin is increasingly likely to fail to meet its water delivery objectives?
2. What specific observations of these leading indicators would cause planners with varied beliefs to believe that the Colorado River Basin is unlikely to meet its water delivery objectives?

The first policy question recognizes that planners may not need to determine which course of action is most appropriate in the immediate future. Instead, they will have multiple opportunities in the coming decades to observe information, revise their assessments of the future, and consider which path is most suitable. The results of this analysis provide insight into which pieces of information planners should monitor as they consider their decisions over time.

The second policy question recognizes that the future is deeply uncertain; various planners and stakeholders may have differing beliefs about the future and they may observe a wide range of information. This analysis seeks to identify observations that may cause planners with varied beliefs to agree that a particular scenario is becoming increasingly likely over time.

To address these policy questions, this chapter presents a three-step analysis. This process includes visualizations of a single future, computational experiments, and summarizing the experiments to
generate some rules-of-thumb observations that may generate consensus. This process is summarized in Figure 5-1 below.

Figure 5-1: Three-step process for interpreting how planners may update beliefs with signpost variables

In the first step, it uses Bayes’ Law to show that planners’ current beliefs about the decision-relevant scenarios can be combined with observations of streamflow and other indicators to generate updated beliefs over time. This analysis presents a single example streamflow future, and considers how planners may update their beliefs as the new information becomes available. It shows a small number of handcrafted scenarios to represent planners’ prior beliefs and pieces of information they may observe. In the process of this analysis, a simple interactive visualization dashboard was built which could allow planners to explore different futures.47 This chapter presents some of the graphics from the dashboard.

However, in multi-stakeholder environments, planners can have varied prior beliefs and they may observe different levels of streamflow or other indicators. This chapter next describes a second step of the analysis: a computational experiment that reveals how planners may update their assessments of scenarios across a large number of combinations of beliefs and observations. This chapter presents the design of this experiment.

Finally, the third step of the analysis consolidates the results of the computational experiments into some generalizable rules-of-thumb. RDM’s scenario discovery techniques are used to identify threshold values of beliefs and observations that would generate consensus that a decision-relevant scenario is likely and that corresponding policy response should be taken. These thresholds can serve as rules-of-thumb for interpreting new information over time.

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47 This tool can help planners gain understanding of how observing streamflow should influence their beliefs. They can learn which observations of streamflow would represent significantly strong evidence that their assumptions about the future may need to change.
In particular, this chapter considers the relative likelihood of *Severely Declining Supply* conditions to the other scenarios in the Upper Basin. Such an analysis allows planners to consider whether current set of actions under consideration is sufficient.

This analysis could be replicated for other decision-relevant scenarios. For example, planners may prefer to see this analysis framed in terms of the likelihood of the *Declining Supply* conditions occurring. The analysis could be adapted to address the needs of planners as necessary. Regardless of the scenario considered, the conclusion that near-term observations of streamflow would update planners’ assessments of the scenarios holds true for each of the decision-relevant scenarios.

**Updating beliefs about decision-relevant scenarios**

**Bayesian updating**

As the second and third chapters of this dissertation explain, Bayes’ law is a mathematical relationship that can be used to describe how planners may update beliefs. The subjective beliefs about decision-relevant scenarios at the start of the planning horizon are referred to as *prior beliefs*, or *priors*. The updated beliefs, after observing new information, are referred as *posterior beliefs*, or *posteriors*. Planners’ subjective prior beliefs of the likelihood of decision-relevant scenarios can be combined with new information to generate updated assessments of the scenario’s likelihood. The following equation demonstrates how Bayes’ law can be rewritten to describe this process.

\[
P(\text{Severely Declining Supply} | \text{Observations}) = \frac{P(\text{Observations} | \text{Severely Declining Supply}) \times S(\text{Severely Declining Supply})}{\text{Evidence}}
\]

Where

\[
\text{Evidence} = P(\text{Observations} | \text{Severely Declining Supply}) \times S(\text{Severely Declining Supply}) + P(\text{Observations} | \text{Declining Supply}) \times S(\text{Declining Supply}) + P(\text{Observations} | \text{Low Historical, Stationary or Increasing Supply}) \times S(\text{Low Historical, Stationary or Increasing Supply}).
\]

*S* is a subjective assessment of the underlying probability of the scenario and *Observations* represent any information that planners may monitor.

The first piece of information required to use this equation is the subjective assessments of the decision-relevant scenarios. By design, an RDM analysis generates only a small number of them. With attention focused on these scenarios, planners and analysts may generate reasonable assessments of the probabilities. However, if planners and scientists still have insufficient information to create credible assessments of the scenarios, the small number of scenarios allows an analysis to explore across many plausible beliefs.

Second, to create substantial differences between the prior and posterior distributions, this formulation requires analysts to identify some observations that differ between scenarios. The
defining characteristics of these observations are that
\( P(\text{Observations} \mid \text{Severely Declining Supply}) \), \( P(\text{Observations} \mid \text{Declining Supply}) \), and
\( P(\text{Observations} \mid \text{Low Historical, Stationary or Increasing Supply}) \) are differentiated from one another.

Third, the analysis requires numerical estimates of the conditional probabilities for these observations. To use Bayes’ law to calculate posterior estimates of the likelihood of decision-relevant scenarios, the analysis requires estimators for the conditional probabilities:

\( P(\text{Observations} \mid \text{Severely Declining Supply}) \), \( P(\text{Observations} \mid \text{Declining Supply}) \), and
\( P(\text{Observations} \mid \text{Low Historical, Stationary or Increasing Supply}) \).

The following sections describe how various observations can be used with Bayes’ Law to generate updated assessments.

**Monitoring Colorado River streamflow**

Because long-term streamflow conditions define the decision-relevant scenarios, short-term observations of streamflow may be useful indicators of the scenario’s likelihood. This section describes the mechanisms by which short-term observations of streamflow may differentiate between decision-relevant scenarios. It then presents a histogram approach to estimating conditional probabilities. Finally, it presents a simple example of how planners with various priors may update beliefs based on short-term observations of streamflow.

**The relationship between early observations of streamflow and decision-relevant scenarios**

The first reason short-term observations of streamflow may have a relationship to the long-term trends is definitional—any subset of observations of streamflow within the planning horizon is a component of the long-term average. For example, if the average annual streamflow is relatively low in the first ten years of the planning horizon, then approximately one fifth of the years in the long-term average will have experienced low streamflow. If the annual streamflow at Lee’s Ferry is independent between years, one can expect the long-term average to be lower if the early years of the time horizon are dry than if they are wet.

Because the system of reservoirs in the Basin is designed to store nearly a decade of supply, dry years early in the planning horizon can have a lasting effect. Lake Powell will be depleted in these dry years, and the Upper Basin will have less in water in storage that they can deliver to the Lower Basin. The Upper Basin may then need to curtail their own use to meet the conditions described in the compact. Thus, a dry period at the beginning of the planning horizon can increase the likelihood of failing to meet Upper Basin water delivery objectives in all years of the planning horizon.

Second, individual years and decades of hydrology may not be independent from each other. Dry years at the start of the planning horizon may be an indicator that future years are relatively more likely to be dry.
The set of futures evaluated in this analysis reflects such a signal to some degree. Among the hydrology sequences derived from downscaled general circulation models, the annual average streamflow from 2012-2020 is weakly correlated with streamflow from 2021-2060 (0.435 correlation coefficient across futures). On the other hand, it may be reasonable to believe that such correlations are largely noise, and that future years will revert to the mean. The streamflow sequences derived from the recent historical record are offset in a manner that ensures little correlation between the first decade of the simulation and future years (-0.147 correlation coefficient) across the ensemble. The ensemble as a whole reflects relatively small correlation (0.243 correlation coefficient) between the first decade and the subsequent years. When comparing average annual streamflow from 2012-2030 to average annual streamflow from 2031-2060, the correlation coefficient somewhat increases (to a 0.320 correlation coefficient).

The ensemble of considered futures reflects both a contribution of the early years to a long-term average and some correlation between the beginning period and the end period. There is an observable correlation between the first decade (2012-2060) and the entire planning horizon (2012-2060) — 0.512 and even greater correlation between the first two decades (2012-2030) and the entire planning horizon (2012-2060)—0.723.

**Estimating streamflow likelihood conditional on decision-relevant scenarios**

Figure 5-2 demonstrates the relationship between short-term observations of average streamflow and the decision-relevant scenarios. It presents a histogram of average annual streamflow from 2012-2020, for each decision relevant scenario. Each bar presents the percent of futures (y-axis) that fall into the range of 1 maf of annual average streamflow from 2012 to 2020 (x-axis) for futures classified in each decision-relevant scenario (horizontal panels).

*Figure 5-2: Distribution average annual streamflow across futures in decision-relevant scenarios (2012-2020)*

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48 For the hydrologic simulation analysis used in this dissertation, only 3 sources of streamflow data are used. A fourth source of streamflow data has been included in this Bayesian analysis, the paleo-historical record. This source was used in the Basin Study.
The mean and skewness of the distribution of average annual streamflow from 2012-2020 are lower in SeVERely DeclIning Supply conditions than in other scenarios. In SeVERely DeclIning Supply conditions, 39 percent of futures have average annual flow less than 12 maf. Only 16 percent of futures in DeclIning Supply conditions have such a streamflow and 3 percent in Low Historical, Stationary, or Increasing Supply conditions. On the other hand, 45 percent of futures in Low Historical, Stationary, or Increasing Supply conditions have greater than 15 maf of average annual flow, as compared to 24 percent in DeclIning Supply conditions and 14 percent in SeVERely DeclIning Supply conditions. A higher proportion of futures in dry decision-relevant scenarios have low average annual streamflow in the first decade than wet scenarios, and a higher proportion of futures in wet scenarios have high average annual streamflow in the first decade than dry scenarios.

Figure 5-3 repeats this information for streamflow in subsequent decades. Each vertical panel shows the distribution of average annual streamflow from 2012 until the noted year. The pattern described above (dry scenarios have low average annual streamflow) is accentuated over time. Because a larger share of the data used to define decision-relevant scenarios is observed, the contributing observations to the long-term average become especially pronounced. This mechanism also causes the observations of streamflow converge over time to a smaller range of conditions. In DeclIning Supply conditions, average annual streamflow from 2012 to 2020 ranges from 10 maf to 18 maf. In 2040, the range decreases to between 11 maf and 15 maf, and by 2060 it decreases to between 12 maf and 14 maf. A similar pattern holds for each of the decision relevant scenarios.
Figure 5-3: Distribution average annual streamflow across futures in decision-relevant scenarios by decade

The analysis uses the histograms as estimators of conditional probability distributions. For example, the probability that annual average streamflow from 2012 to 2020 ranges from 12 to 13 maf conditional on the Declining Supply scenario is estimated to be 0.14.

\[ P(12 \text{ maf} < \text{Average Streamflow } 2012 - 2020 < 13 \text{ maf} | \text{Declining Supply}) = 0.14 \]

Using histograms as an estimate of probability avoids identifying a functional form of an underlying distribution, and is a commonly accepted practice for estimating probabilities (John and Langley 1995).

Such an approach assumes an equal weighting of futures within the decision-relevant scenarios, but does not require any assumptions regarding the probability of the decision-relevant scenario occurring. This is a rather strong assumption about the interpretation of the ensembles of futures.
The probabilities are dependent on the set of futures used to generate the analysis, which are often the result of subjective decisions made by analysts and participants. Though imperfect, this assumption is consistent with a common RDM practice of weighting futures within a scenario. On the other hand, the set of futures considered in this analysis represents a rich set of plausible futures. To ignore the correlations present in the data at hand requires refusing to draw insights from existing data. The approach described in this dissertation mitigates against the risk of making such a strong assumption by grouping futures most relevant to the decision at hand and exploring multiple plausible beliefs about the decision-relevant scenarios.

These histograms suggest that observations of average annual streamflow are effective signpost variables. After even the first decade of the planning horizon, the distribution of streamflow is differentiated among the scenarios. If planners observe low streamflow, they are more likely experiencing a future in a dry scenario than if they observe higher streamflow. Over time, the conditional distributions are more differentiated, which suggests even stronger evidence. While it is not surprising that observations of the streamflow in the early decades of the planning horizon are an indicator of the decision-relevant scenario, using the ensemble of futures to estimate conditional probabilities provides an approach for understanding how strong the indicators are.

**An example of updating beliefs over time after observing streamflow**

This section provides an example of how Bayes’ law can help planners consider the relationship between streamflow in early decades of the planning horizon and the likelihood of a decision-relevant scenario.

Figure 5-4 presents the time series of streamflow in a single future. This sequence is drawn from the ensemble of plausible futures, specifically from the climate change projections. The y-axis indicates the average annual streamflow. The black line represents the average annual streamflow within the decade demarked on the x-axis. The blue bars represent the cumulative average annual streamflow from 2012 until the year presented on the horizontal axis— the average of all prior years streamflow. The bars are also labeled with the bin containing each particular level of streamflow in the histograms above. In this future, average annual streamflow from 2012-2040 is between 12 and 13 maf. By 2060, this future’s long-term average streamflow is less than 13 maf and is consistent with the definition of the *Severely Declining Supply* scenario.

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49 Chapter 3 includes references to discussion of some weighting schemes
This future begins with an average annual streamflow of 15 maf during the first decade. This volume of streamflow is near the historical average. If such a streamflow were maintained over the entire planning horizon, it would be consistent with Low Historical, Stationary, or Increasing Supply conditions. However, average annual streamflow decreases over time. By end of the planning horizon, average annual streamflow is 12.2 maf. Accordingly, as planners observe subsequent years of decreasing streamflow, they may consider it mounting evidence of a drying scenario.

Figure 5-5 presents the probability of observing the average annual streamflow conditional on each decision-relevant scenario occurring, for the future represented in Figure 5-4. Results are presented from 2010-2050 (results are not presented for 2060 as planners will know with certainty whether the Severely Declining Supply scenario has occurred and water delivery objectives have not been met). Each colored line represents results for each of the decision-relevant scenarios. These conditional probabilities can be identified in the histograms above, by extracting the probability associated with the range of long-term average streamflow.

The probability of streamflow from 14 to 15 between 2012 and 2020 is approximately 25 percent in the Low Historical, Stationary, or Increasing Supply scenario. Though this represents the greatest conditional likelihood of the three scenarios, all likelihoods are within a relatively small range.
conditional likelihood of observing this streamflow in the other scenarios is 14 percent. By 2040, the likelihoods are more differentiated. The likelihood of observing average annual streamflow between 12 and 13 maf in the Low Historical, Stationary, or Increasing Supply scenario drops to zero.

Using Bayes’ Law, one can calculate how planners may update their beliefs regarding the likelihood of decision-relevant scenarios. Figure 5-6 presents the posterior probability each scenario, as colored lined after observing every decade of streamflow, for the same future presented in Figures 5-4 and 5-5. This figure assumes prior beliefs that the Declining Supply scenario is 50 percent likely and the remaining scenarios are each 25 percent likely, shown by the colored circles on the left.

Figure 5-6: Updating probabilities of decision-relevant scenarios over time after observing streamflow

In 2020, a planner with these prior beliefs would assess the Declining Supply scenarios as 43 percent likely, the Low Historical, Stationary, or Increasing Supply scenario as 35 percent likely, and the Severely Declining Supply scenario as 21 percent likely. The evidence observed in this first decade increases the planner’s assessments of the likelihood of the Low Historical, Stationary, or Increasing Supply, while decreasing the likelihood of the other two. However, the evidence in this first decade is not very strong; the planners’ prior belief is nearly unchanged, as they would still believe the Declining Supply scenario is the most likely scenario. This suggests that in this first decade (for this particular level of streamflow and set of priors) the new information should influence but not dominate the planners’ prior beliefs.

Over time, the posterior beliefs become more differentiated as streamflow continues to decrease and evidence accumulates. The probability of the Low Historical, Stationary, or Increasing Supply decreases to less than 1 percent by 2040. Additionally, the probability of the Severely Declining Supply increases above 25 percent defined by beliefs in 2030. However, in this example, the evidence is not sufficient to overcome the prior beliefs. In 2050, planners will believe the Declining Supply scenario is still the most likely, though it is the wrong classification.
However, the probabilities of these scenarios are deeply uncertain; planners may have differing beliefs about the likelihood of these scenarios. Figure 5-7 presents the same analysis, but for a different set of priors. It demonstrates how planners may update their beliefs if they initially believe the **Severely Declining Supply** scenario is 50 percent likely, and the remaining two scenarios are each 25 percent likely. In 2020, the **Severely Declining Supply** scenario remains the most likely, but all scenarios are relatively close in likelihood, ranging from 22 percent to 43 percent. Over time, the likelihood of the scenarios separate from one another. As evidence mounts that the prior was correct, the likelihood of the **Severely Declining Supply** increases to nearly 75 percent.

*Figure 5-7: Updating probabilities of decision-relevant scenarios over time after observing streamflow with a different set of prior beliefs*

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**Monitoring other indicators**

Planners may more reliably update their expectations when also considering other pieces of relevant information. This section surveys some other information they may monitor such as historical cycles in streamflow, sea surface temperature (SST) and the El Niño–Southern Oscillation (ENSO). It describes current research using these other indicators to generate better predictions of decadal and long-term climate conditions over the course of the planning horizon.

This section proposes that such information can be summarized with decision-relevant *exogenous indicators*. These indicators would inform planners whether the exogenous information is consistent with decision-relevant scenarios. Finally, it provides a simple example of how such an indicator would allow planners to more reliably anticipate whether a decision-relevant scenario is occurring.
Relationship between sea surface temperature and hydrologic cycles in the Basin

A brief review of the literature suggests that predictions of future hydrologic conditions may be improved by considering pieces of information beyond simple observation of streamflow. In particular, it focuses on four interrelated pieces of information, summarized below and then described in greater detail.\(^{50}\)

1) There is a cyclical nature of the streamflow in the basin. An understanding of these cycles can help planners identify whether a dry period is an indicator of future dry years or a temporary drought period.

2) Observations of SST in the Pacific Ocean have strong effects on precipitation, runoff, and streamflow in the Basin. They may be useful indicators to monitor in addition to local streamflow.

3) Forward looking decadal predictions of precipitation and streamflow may help planners anticipate future drought periods. Such predictions will likely be drawn in large part from SST phenomena, rather than relying solely on local observations.

4) Forward looking long-term climate predictions may continue to improve over time, which may help planners predict long-term hydrologic conditions in the Basin.

The previous analysis relies on a simple relationship in the set of futures considered: those dry in early decades of the planning horizon tend to be dryer over the entire planning horizon. However, Nowak et al. describe a cyclical time pattern in annual streamflow at Lees Ferry on the Colorado River. They identify two cycles in the recent historical record: a “low-frequency” mode, which occurs at 64-year intervals related to temperature oscillations and a “decadal” component more closely tied to precipitation. An analysis of the pale-historical record indicates the strength of the decadal cycle is further modulated in 75-year increments (Nowak, Hoerling et al. 2012). Further evidence suggests that decadal variations account for between 20 and 50 percent of the variance in annual precipitation on the Western U.S. (Cayan, Dettinger et al. 1998). These patterns indicate that there is a more complex relationship between long-term hydrological conditions and observing a dry period at the start of the planning horizon, as a dry period may be due to the cyclical nature of streamflow rather than a long-term signal.

Furthermore, there is a well-established relationship between hydrologic and climatic conditions in the Basin and other broader climate phenomena. In particular, sea surface temperatures in the Pacific Ocean, which varies cyclically through the El Niño— Southern Oscillation and the Pacific Decadal Oscillation (PDO) can affect the Basin’s hydrologic conditions. Evidence suggests the decadal variations in precipitation in the Basin are linked to SST in the Pacific (Cayan, Dettinger et al. 1998). In the Southwestern U.S., cold season precipitation is wetter than normal during El Niño events and dryer than normal during La Niña events, while the opposite effect holds in the Northwest (McCabe and Dettinger 1999, Hidalgo and Dracup 2003). There is also evidence of changes in Colorado River streamflow due to another cyclical change in the SST in the Pacific ocean, - the Pacific Decadal Oscillation (PDO) (Hidalgo and Dracup 2003). Recent research suggests that variability in SST related to these phenomena plays a significant role in drought events in the

\(^{50}\) There may be other policy-relevant indicators not included here
Western U.S. (Barlow, Nigam et al. 2001). Recent studies show the variability of SST related to ENSO has increased by 50 percent to 60 percent in the past two decades, which may be related to climate change (Zhang, Guan et al. 2008). However, while there is likely a complex interplay between these SST events and climate change (Diaz, Hoerling et al. 2001), much uncertainty remains about the impact of climate on the ENSO variability. Collins et al. state “it is not yet possible to say whether ENSO activity will be enhanced or dampened, or if the frequencies of events will change” (Collins, An et al. 2010). These relationships suggest that predicting future hydrologic conditions in the Basin may be best achieved by monitoring and incorporating the cyclical patterns in the Pacific Ocean.

If researchers skillfully and accurately predict SST as climate conditions change, they may able to generate useful decadal predictions of hydrologic conditions in the Basin. The most current IPCC assessment describes an emerging field of decadal climate prediction (Kirtman, Power et al. 2013). Currently, skillful and accurate predictions face an “initial value problem” where detailed knowledge of the current conditions are necessary to properly calibrate models (Meehl, Goddard et al. 2009). As decadal predictions are relatively new, there still remain challenges to achieving accurate predictions as scientist require data to initialize models, techniques to initialize decadal predictions, and the ability to validate models (Kirtman, Power et al. 2013). Nonetheless, some early studies have had some success predicting El Niño and La Niña events (Smith, Scaife et al. 2013). Multi-model ensembles have made more skillful predictions than any single model, although the skill depends heavily on the season (Jin, Kinter III et al. 2008). However, it may be reasonable to believe over the next half century that these predictions can be improved. If so, indicators from these predictions should be incorporated into planner’s projections of decision-relevant scenarios.

Predicting longer-term climate related phenomena is also an active area of research. Keller et al. provide an example of an observation system for North Atlantic Meridian Overturning Circulation (MOC) that may detect a threshold response before it occurs. Such a prediction requires more frequent and lower error observations than are currently available (Keller, Deutsch et al. 2007), as centuries of observation may be necessary for reliable prediction—considerably more data than is necessary to detect such an event as it occurs (Keller and McNerney 2008). Other analyses demonstrate that a similar Bayesian framework can be used to design policies anticipating the value of learning important climate parameters such as radiative forcing (Kelly and Kolstad 1999, Webster, Jakobovits et al. 2008). However, when planners base decisions on information that ultimately prove inaccurate, others identify that some predictions may prove unreliable and negative learning may occur (Oppenheimer, O’Neill et al. 2008). Climate scientists may have already developed techniques to predict climate and hydrologic conditions that are more sophisticated than those suggested in this analysis. If applied to the Basin, such research may provide planners with longer-term climate assessments, which can then be related back to decision-relevant scenarios. Additionally, this is an active area of research and these predictions may continue to improve over time.

**A notional indicator of other exogenous information**

To incorporate this science into adaptive strategies, planners will likely require these four pieces of information pieces (and another information omitted here) to be consolidated into an easily
interpretable *exogenous indicator* relevant to the decision at hand. This indicator would be a simple assessment of whether current climatic research findings are consistent with the decision-relevant scenario.

Predictions of future climate can be simplified by providing assessments that reference these scenarios directly. Planners may be best served by understanding whether specific predictions increase or decrease the likelihood of a decision-relevant scenario. Rather than providing planners with an assessment that El Niño years will become some percentage more or less frequent with climate change, or that precipitation has some percent likelihood of decreasing by some percentage, an index could inform planners whether such observations and predications are consistent with decision-relevant scenarios.

Because decision-relevant scenarios are described in terms of external conditions, they also provide a useful linkage between policy and climate science. While climate researchers would likely not be able to provide an assessment of whether a specific contingency is necessary, they may be able to provide assessments on the relative likelihood of a decision-relevant scenario. For example, while climate scientists may be able to assess whether a specific desalination plant is necessary, they may be able to provide assessments on whether long-term average streamflow conditions will be below 14.4 maf and there will be an eight-year drought with an average streamflow below 11.2 maf (the implementation scenario for this action, described in Chapter 7).

The analysis presented in this chapter considers a single notional decision-relevant exogenous indicator to encapsulate other climate research. This indicator is characterized by the probability of observing the exogenous signals conditional on each decision-relevant scenario:

\[
P(\text{Exogenous Indicator} | \text{Decision – Relevant Scenario})
\]

Such assessments would allow planners to see the probability that the signal is consistent with the scenario in question or the alternative scenarios. It also allows planners to integrate this information with prior subjective beliefs. This indicator provides a useful proxy for the state of exogenous climate information to support the exploratory analysis presented in this chapter.

This analysis presents a model where the information from the exogenous climate signal is considered independent of streamflow conditions.\(^{51}\) With this assumption, the posterior probability can be calculated as

\[
P(\text{Severely Declining Supply} | \text{Observations & Exogenous Indicators}) = \\
P(\text{Observations} | \text{Severely Declining Supply}) * \\
P(\text{Exogenous Signal} | \text{Severely Declining Supply}) * \\
\frac{S(\text{Severely Declining Supply})}{\text{Evidence}}
\]

Where

\[
\text{Evidence} = P(\text{Observations} | \text{Severely Declining Supply}) * S(\text{Severely Declining Supply}) +
\]

\(^{51}\) Models that assume independence between the conditional probabilities are referred to as naïve-Bayes’ models.

103
\[
P(\text{Observations | Declining Supply}) \ast S(\text{Declining Supply}) + \\
P(\text{Observations | Low Historical, Stationary or Increasing Supply}) \ast \\
S(\text{Low Historical, Stationary or Increasing Supply})
\]

An example of updating beliefs after observing other exogenous information

Figure 5-8 shows a simple hand-crafted example of how such an indicator may evolve over time. In this case, the indicator can simply reports the probability that the current set of exogenous information would be observed if the Severely Declining Supply scenario is occurring (orange line), and the probability that it is observed in the other scenarios (blue line). In this example, the signal is not well differentiated in 2020, as the probability given Severely Declining Supply scenario is only slightly above 50 percent (53 percent) and the probability given the other two scenarios is slightly below 50 percent (47 percent). The conditional probabilities of the indicator differentiate over time as more information is collected and prediction techniques improved. In 2050, the probability given Severely Declining Supply scenario is 66 percent and the probability given the other two scenarios is 37 percent.\(^{53}\)

Figure 5-8: Evolutions example of exogenous climate indicator’s probability conditional on decision-relevant scenarios.

This example of the indicator assumes that signal changes linearly over time. In actuality, there will be no requirement that learning about the likelihood of decision-relevant scenarios evolves linearly. The interactive version of this tool allows users to vary both the starting point and the rate at which the signal converges. Though this does not cover all the plausible ways in which the accuracy of these indicators may evolve, it does allow the user to explore a broad range of possible exogenous indicators.

Figure 5-9 demonstrates how planners may update their beliefs about the decision-relevant scenario with the exogenous indicator. It shows the same future presented in Figure 5-4 with the same prior beliefs presented in Figure 5-6 (Severely Declining Supply scenario is 50 percent likely, and the remaining two are 25 percent likely). However, this calculation includes the effect of the

\(^{52}\text{This example assumes }P(\text{Exogenous Signal|Declining Supply})=P(\text{Exogenous Signal|Low Historical, Declining Supply, or Increasing Supply}). This assumption is relaxed for the exploratory analysis.\)

\(^{53}\text{Note that these probabilities do not sum to 1. They do not need to, as they are not additive.}\)
exogenous indicator, demonstrating how other climate information can influence planners’ beliefs. By 2030, the *Severely Declining Supply* scenario is the most likely scenario. The likelihood of *Declining Supply* drops to 25 percent by 2050.

*Figure 5-9: Updating probabilities of decision-relevant scenarios over time after observing streamflow with a exogenous indicator*

![Graph showing posterior probabilities over time](image)

- **Posterior Probabilities**
- **Prior Probabilities**

*Figure 5-10* presents one further example, using the same future and priors as presented previously, but the signals among scenarios differentiate more rapidly. The top panel shows the conditional probabilities of the exogenous indicator, and the bottom panel shows planners’ posterior beliefs. In 2020, the probability of observing the indicator given the *Severely Declining Supply* is 58 percent and probability given the other two scenarios is 42 percent. The conditional probabilities of the indicator differentiate more rapidly over time as more information is collected and prediction techniques improved. In 2050, the probability given *Severely Declining Supply* scenario is more than 95 percent.
Figure 5-10: Updating probabilities of decision-relevant scenarios over time after observing streamflow with different time series of exogenous indicators

The example above only presents a single time sequence of future streamflow. It considers this scenario for two handcrafted examples of planners’ plausible subjective beliefs, and two arbitrary illustrations of how information from exogenous indicators may evolve over time. The small set of examples limits the insight that can be drawn. The next section presents an experiment designed to help planners understand what information they may observe over the next two decades that would suggest the Severe Declining Supply scenario is likely.

Designing an experiment to explore across indicators and beliefs

This section uses the Bayesian approach presented above to examine how planners with various beliefs about decision-relevant scenarios may update their assessments after observing streamflow and other exogenous information. The analysis identifies which pieces of information may make planners within various ranges of prior beliefs agree that the Severe Declining Supply conditions are the most likely scenario. The observations that may cause planners to agree can serve as simple rules-of-thumb, which suggest that the transformative scenario lies ahead.
These rules-of-thumb can suggest to planners specific thresholds of the observations to look for in the near term. At the very least, they provide benchmarks that planners can use to interpret new information. If planners observe any of the rules in the next few decades, they may be more willing to consider reassessing plans. Thus, these rules-of-thumb can serve as triggers for a process of reassessment within an adaptive strategy.

**Design of exploratory analysis**

This analysis takes the relationships defined by the naïve-Bayes model proposed above and explores across a wide range of plausible observations in the first two decades of the planning horizon. PRIM is used to identify key threshold values of new information that would suggest the *Severely Declining Supply* scenario is likely. The results of the data-mining analysis create simple scenarios suggesting what planners should look to observe in the early years of the planning horizon; they are referred to as rules-of-thumb for future observations.

The exploratory analysis can be described in parts: the Bayesian updating model (R), threshold values interest of posterior probabilities (M), and the uncertain observations that may occur in the future (X).

**Bayesian updating model**

The key Bayesian updating relationship at the center of this analysis is described in detail in the previous section. This model contains the estimates of the conditional probability of observing a level of average annual streamflow between 2012 and 2020.

The model used for the exploratory analysis contains one significant change from the examples provided above. Estimates of probability distribution functions are fit to the conditional likelihood estimates for average annual streamflow rather than using the histogram approach. This approach was taken to remove some discontinuities in the data, instead assuming the conditional likelihoods increase or decrease in a relatively smooth manner for each scenario. The disjointedness observable in the histograms is likely an artifact of ensemble of streamflow futures chosen, as opposed to true relationship of streamflow. For example, in the histograms for streamflow in 2012-2020 (Figure 5-3), the conditional probability of observing 11 maf in the *Severely Declining Supply* is less than both 10 maf and 12 maf. Fitting a probability distribution to the data ensures that the data likelihoods increase or decrease in a manner consistent with the definition of the distribution.

The observations of streamflow are from a deeply uncertain process, and there is no theoretical reason to fit the data to any particular distribution function. This analysis tests various functional forms, identifying one for each histogram that fits well. After some examination, it was determined that normal, log-normal, and gamma distribution were reasonable candidates. The streamflow data is fit to each of these three distributions using the method moments. The distribution with the

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54 Computational experiments where this step was not taken generate to a decision-space with many local maxima and minima. After implementing data-smoothing step, results were more intuitive and interpretable.
lowest Bayesian Information Criterion (BIC) is then selected. Table 5-1 presents the distribution chosen for each scenario and time period. It also presents parameter estimates for the distribution.

Table 5-1: Distribution functions fitted to conditional observations of average annual streamflow

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Severely Declining Supply</th>
<th>Declining Supply</th>
<th>Low Historical, Stationary, Increasing Supply</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012-2020</td>
<td>Log-normal distribution</td>
<td>Log-normal distribution</td>
<td>Log-normal distribution</td>
</tr>
<tr>
<td></td>
<td>Log-standard deviation: 0.1677</td>
<td>Log-standard deviation: 0.125</td>
<td>Log-standard deviation: 0.119</td>
</tr>
</tbody>
</table>

Figure 5-11 present the fits of the estimated distributions of average annual streamflow conditional on decision-relevant scenarios for 2012-2020. Each figure contains three vertical panels representing each decision relevant scenario. The top figure in each panel shows a histogram of average annual streamflow (bars). The curve overlaid on the histogram represents the probability density function (pdf) for the chosen distribution. The bottom figure shows the cumulative distribution function (cdf). The points represent the cdf observed in the sample of data, while the curve represents the estimated cdf. The closer the cdf observed in the sample of data, the better fit it represents. For the 2012-2020 streamflow data, the pdf and cdf for the Low Historical, Stationary, or Increasing Supply provide a very close fit. For the Severely Declining Supply scenario, the data fits the distribution less well with levels of streamflow where conditional likelihood increases or decreases non-monotonically. In this case, the less precise fit is a feature of this exercise, smoothing the discontinuities in the distribution.
Figure 5-11: Fit of conditional probability distribution for average streamflow 2012-2020 by decision-relevant scenario

Uncertainties and experimental design

This analysis explores three uncertainties: the realizations streamflow observation over the next two decades, observations of other exogenous indicators and planners’ prior beliefs regarding decision relevant scenarios. This section discusses these uncertainties and the experimental design of the analysis in detail.

While the model describes the relationship between data that could be observed and the decision-relevant scenario, the realization of information observed remains uncertain. For example, at this point it is unknown whether the annual streamflow on the river will average 12 maf or 14 maf between now and 2020. This is an uncertainty that will only be identified after the decade of data is observed. For each decade, this analysis considers the implications of realizations of streamflow ranging from 10 maf to 18 maf (by increments of 0.5 maf).

Similarly, the exogenous indicators of information are unknown. One cannot state with certainty what projections and other indicators will suggest about the decision-relevant scenarios in 2020. This analysis considers the range of attributes of exogenous indicators, exploring the conditional probabilities of observing the notional indicator in 2020. This analysis explores 300 random combinations of indicators generated by a Latin hypercube sample.
The third uncertainty this analysis explores is planners’ prior beliefs. As described previously in this dissertation, there is a diversity of planners and they may have a range of beliefs regarding the likelihood of decision-relevant scenarios. This analysis explores how those prior beliefs may interact with new information as planners update their beliefs. In absence of elicitations from planners about their beliefs, the analysis explores the entire range of plausible beliefs from 0 percent likely to 100 percent likely. This analysis considers 66 possible combinations of prior beliefs, spanning the range from 0 to 100 percent (by increments of 10 percent) for each scenario.

Table 5-2 summarizes the experimental design, with 341,700 plausible combinations of prior beliefs, observed streamflow conditions, and observed exogenous indicators.

Table 5-2: Experimental design to explore impact of signposts on beliefs

<table>
<thead>
<tr>
<th>Uncertain Factor</th>
<th>Prior Beliefs</th>
<th>Future Short Term Observations of Streamflow</th>
<th>Probability of Observing Exogenous Information Conditional On Decision-Relevant Scenario</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Description of Sample</strong></td>
<td>All plausible combinations of beliefs</td>
<td>10 maf-18 maf; increments of 500 kaf</td>
<td>0-100 percent for each scenario</td>
<td></td>
</tr>
<tr>
<td><strong>Number of Draws in Sample</strong></td>
<td>All plausible combinations, 66 sets of priors</td>
<td>(17 observations)</td>
<td>Latin hypercube of 300</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Full-factorial of 3 factors</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>341,700 instances</td>
<td></td>
</tr>
</tbody>
</table>

*Posterior Probabilities*

The posterior probabilities of the decision-relevant scenarios are calculated for each of the sampled 341,700 instances. This generates a large database of posterior probabilities associated with uncertain prior beliefs and observations.
This analysis identifies the conditions under which planners may believe the *Severely Declining Supply* scenario is likely. It considers two measures of merit. The first measure is whether planners believe the *Severely Declining Supply* is the most likely scenario. This condition holds when the posterior probability of the *Severely Declining Supply* scenario is greater than the posterior probability of both the *Declining Supply* and *Low Historical, Stationary, Increasing Supply* scenarios. This discrete measure can include cases where planners still have significant disagreements about the posterior probability of the scenario; the most likely scenario can have a probability ranging anywhere between 34 percent and 100 percent likely. Thus, a second measure considers whether planners can agree that the *Severely Declining Supply* is overwhelmingly likely, defined as a posterior probability greater than or equal to 90 percent.

**Rules-of-thumb to interpret information about changing scenarios**

The results of computation experiments provide some insight into the conditions that will cause planners to believe the *Severely Declining Supply* scenario is likely. If average annual streamflow through 2020 years is less than 13 maf, stakeholders who currently believe the *Severely Declining Supply* scenario is at least twenty percent likely will have reason to believe the scenario will be the most likely. If observations of streamflow are even lower, planners with a wider range of beliefs will agree the scenario is most likely. Additionally, high streamflow cannot rule out this scenario. Even if average annual streamflow is 18 maf over the next decade, other indicators can convince planners with strong prior beliefs that the scenario is likely. The following section provides visualizations and results of a PRIM analysis to generate more detailed rules-of-thumb for interpreting new information.

Figure 5-12 presents a map of prior beliefs, exogenous indicators, and observations of streamflow that would make planners believe the *Severely Declining Supply* is most likely. Each horizontal panel shows a different value of average annual streamflow from 2012 to 2020. The horizontal axis illustrates the likelihood that other exogenous indicators would be observed conditional on the *Severely Declining Supply* scenario occurring (indicators consistent with the *Severely Declining Supply* scenario is presented on the left, while indicators unlikely to be observed should the *Severely Declining Supply* scenario occur are presented on the right). The vertical axis shows plausible planners’ beliefs about the likelihood of the *Severely Declining Supply* scenario. For example, the top row represents planners who believe the *Severely Declining Supply* is 90 percent likely, prior to observing any information. The color indicates the percent of instances where the *Severely Declining Supply* scenario is most likely after observing information about average annual streamflow in 2020 (horizontal axis). As there are multiple initiations layered on top of one another, those that are darker red represent more futures where the *Severely Declining Supply* is more likely.
Figure 5-12: Observations and beliefs leading to Severely Declining Supply most likely scenario (2012-2020)

If planners believe the Severely Declining Supply is likely, they observe low average streamflow, or other exogenous information is consistent with this scenario, then they will believe the Severely Declining Supply conditions are the most likely scenario in 2020. This relationship is not surprising, but this map can help draw specific conditions that would cause this belief. For example, if planners observe average annual streamflow near 10 maf, the Severely Declining Supply scenario is almost certain to be the most likely scenario. In this case, it will be the most likely regardless of prior beliefs or the information contained in other indicators.

On the other hand, if planners observe annual streamflow near 18 maf, the Severely Declining Supply scenario cannot necessarily be ruled out. If other exogenous indicators have a 50 percent chance of being observed in the Severely Declining Supply scenario, then planners who believe the Severely Declining Supply scenario is 50 percent or more likely in 2012 can agree that that this scenario is most likely. However, if planners agree the scenario is 20 percent or less likely in 2012, there is almost no information that would make them believe that it is the most likely in 2020 (after observing streamflow of 18 maf or greater).

Figure 5-13 presents the results of a scenario-discovery analysis, presenting rules-of-thumb generated by scenario discovery algorithms that summarize the information on the previous figures. The red shaded region represents the conditions that must hold for planners to believe the Severely Declining Supply scenario is the most likely.
Figure 5-13: Rules-of-thumb for observations and beliefs leading to Severely Declining Supply most likely scenario (2012-2020)

If planners observe streamflow less than or equal to 13 maf and other exogenous indicators are 20 percent or more likely to be observed in Severely Declining Supply scenario, then all planners who believe that the scenario has a likelihood of 20 percent or more in 2012 will agree that it is the most likely scenario in 2020. That is, if streamflow is less than or equal to 13 maf, unless there is weak exogenous evidence for the Severely Declining Supply or planners believe it is less than 20 percent likely, there will be consensus that this is the most likely scenario.

Even if streamflow is greater than 13 maf, planners may still believe Severely Declining Supply scenario is the most likely. If exogenous indicators observed have a 50 percent or greater conditional probability of being observed in the Severely Declining Supply scenario, then the planners who believe the scenario is 50 percent or more likely will still believe it is the most likely scenario. That is, streamflow above 13 maf does not preclude the possibility that Severely Declining Supply is the most likely, but it does require observing somewhat strong external evidence and predisposition to believing the scenario is likely.

Because the range of probabilities that falls into the "most likely" categorization is quite large, this analysis is repeated for a higher threshold on the likelihood of the Severely Declining Supply scenario. Figure 5-14 considers the observations and beliefs that would cause planners to believe that the Severely Declining Supply has a 90 percent or greater likelihood of occurring. Instead of planners simply believing it is the most likely scenario, this considers a threshold that represents a belief that the scenario will occur. If average annual streamflow in the first 10 years is 10 maf, there is strong evidence the Severely Declining Supply scenario is occurring. However, the evidence is less strong than the belief that the scenario is most likely, signified by less dark red space on this
graphic. If annual average streamflow is 14 maf, only planners with the strongest prior beliefs can have 90 percent confidence in the scenario occurring. To do so, they would also have to observe strong evidence in exogenous indicators. When streamflow is above 14 maf, there is little evidence that could make any planners believe the scenario is at least 90 percent likely, and they are not presented.

*Figure 5-14: Observations and beliefs for observations and beliefs leading to Severely Declining Supply 90 percent likely (2012-2020)*

Figure 5-15 presents some rules-of-thumb that will lead to a consensus that the scenario is 90 percent likely. If annual average streamflow is 10.5 maf or less and exogenous indicators with a 30 percent conditional likelihood were observed, then planners who assess the *Severely Declining Supply* scenario as 30 percent or more likely would expect the *Severely Declining Supply* scenario to occur. If streamflow is greater than 10.5 maf but less than or equal to 13.5 maf, planners may still assess the scenario as 90 percent likely. However, they require significantly more evidence in the exogenous indicators. The exogenous indicators must be consistent with the *Severely Declining Supply* at 60 percent or greater likelihood and have less than a 50 percent likelihood of being observed in the *Declining Supply* scenario. If all these conditions are met, then planners who believe the *Severely Declining Supply* scenario is 60 percent likely in 2010 will agree there is high likelihood of the scenario occurring.
Figure 5-15: Rules-of-thumb leading to Severely Declining Supply 90 percent likely (2012-2020)

These conditions suggest that if streamflow is 10.5 maf or less and other exogenous indicators are somewhat consistent with the Severely Declining Supply, then planners across a range of prior beliefs will have confidence the scenario is occurring. However, even this requires planners to have prior beliefs that the Severely Declining Supply is nearly equally likely to the other two scenarios. If streamflow is between 10 maf and 13.5 maf, only planners with strong prior beliefs will think the Severely Declining Supply is likely, and they must be presented with strong exogenous indicators. With streamflow higher than 13.5 maf, planners will not have confidence that the Severely Declining Supply will occur.

This analysis is also replicated for observation of streamflow after 2030. As more information becomes available, less extreme observations of streamflow send a stronger signal about the likelihood of the Severely Declining Supply scenario. For example, planners will believe the Severely Declining Supply scenario is 90 percent likely, if they observe less than 11.5 maf in average annual streamflow (so long as they have a prior beliefs that the scenario is all 20 percent likely). As more evidence mounts, over a longer time period, planners can have greater levels of certainty about the scenario.
Policy Conclusions

If planners believe the *Severely Declining Supply* scenario is likely, they will need to consider a wider range of water management actions and reassess the current process of adaptation. This may require changing objectives or constraints of the system, such as allocating water differently or modifying parts of the Law of the River. This scenario, while plausible, is beyond any hydrologic conditions observed in either the recent historical or the paleohistorical record; planners may not believe it is very likely. It is however consistent with some climate change futures. Regardless of likelihood, planners likely have some time until the most severe outcomes occur, allowing them to take a wait-and-see approach.

This chapter informs such a wait-and-see process, providing an interpretation of indicators that planners may observe. Natural streamflow over the next two decades can be an indicator of whether planners must transform their objectives. Additionally, planners can work with climate scientists to improve their predictions, monitoring cyclical trends in the Pacific Ocean and using ever-improving climate change prediction tools.

The analysis in this chapter can help planners interpret new information they may observe in the coming decades. As new observations of streamflow and other climate change literature become available over time, planners would generally require decision-support and analysis to understand how the information should influence strategies—a process of double-loop learning. Visual-aids and the generalizable rules-of-thumb provided in this analysis provide a method to make this double-loop learning more closely resemble single-loop learning. These aids can tell planners a-priori what pieces of evidence would suggest certain scenarios are likely.

Because the decision-relevant scenarios are by definition tied to different preferred strategies, understanding which scenarios are likely provides planners with guides about which actions to implement. For instance, this suggests that if planners observe less than 10 maf of average annual streamflow by 2020, they should begin considering a wider range of water management actions than was evaluated in the Basin Study. If by 2030, they observe planners observe less than 11.5 maf of average annual streamflow they should consider they should do the same.

However, subjective beliefs can influence the perception of the evidence, and planners may reasonably disagree on these conclusions. Planners who believe the *Severely Declining Supply* scenario is less than 20 percent likely—which may be reasonable as the scenario primarily contains some of the most severe climate change projections—may not believe any observations are sufficient to convince them by 2020. However, as more information is accumulated over time, the signal become stronger and certain pieces of evidence may convince them. Completing this analysis further into the future could describe what those pieces of evidence would be.

This analysis considers questions regarding which information constitutes sufficient evidence to change strategies can be informed by this analysis—the signposts. However, designing an adaptive strategy also requires other inputs. The costs and consequences of choosing the wrong strategy are critical in this decision. Additionally, key decisions on certain action may need to be made at certain points—this analysis doesn’t necessarily tie observations to those actions. The following chapters more explicitly tie these observations to actions that planners may take. Analysis in the subsequent
chapters consider water management actions to implement, and is designed to help planners balance the risks of over-investing and being under-prepared.
Chapter 6: Assessing alternative decision-rules for adapting in the Colorado River Basin (decision-rules)

Introduction: Acting adaptively to ensure water delivery reliability at low-cost
The Colorado River Basin Study implemented new modeling techniques to design, simulate, and evaluate adaptive strategies, described in the first chapter of this dissertation. The adaptive strategies address one challenge when planning for climate change: the water management actions are costly and though planners may be willing to implement them to ensure water delivery reliability, planners would prefer to not implement them if they are not necessary. However, planners face an uncertain future and may not be able to anticipate the precise needs of the system.

Planners need to make decisions about which actions to implement in the absence of perfect information. They risk over-investing—expending resources and effort to invest in additional water management actions in the future where they are not necessary. They also risk being under-prepared—failing to meet water delivery objectives because the necessary actions were not implemented.

The analysis in the Basin Study recognizes that an adaptive approach could mitigate these risks. Planners can observe new information over time and update their assessments of the needs of the system. The previous chapter showed how observations of streamflow and other external climate change indicators such as sea surface temperature could indicate long-term drying conditions before they occur. To approximate a process of learning, the project team for the Basin Study designed a series of decision-rules for implementing actions. These decision-rules rely on observations of streamflow and reservoir levels, implementing water management actions after observing different threshold values of these signpost variables.

Even when acting adaptively, planners will need to make decisions with imperfect information. They face choices in how they respond to new information. Planners may determine that they require over-whelming evidence that the system is unlikely to meet objectives before they act, reducing the risk for over-investment but increasing the risk of being under-prepared. Alternatively, they may implement actions after observing a lower threshold of evidence to ensure they are not under-prepared, but then they risk over-investing.

To explore alternative ways of responding to new information, this dissertation expands the analysis of adaptive strategies in the Basin Study to examine a broader set of alternative adaptive strategies. It modifies the simulation module, CRSS, to include strategies defined by decision-rules that implement actions after observing various threshold values of streamflow and reservoir levels. These alternative adaptive strategies can be described along a continuum: aggressive strategies favor implementing actions at the risk of over-investing while conservative strategies require a higher burden of proof that conditions are degrading before planners act.
In any adaptive process that ultimately unfolds in the Basin, planners will likely need to make informed assessments of which actions are necessary while relying on imperfect indicators. The modeling assumptions that define adaptive strategies reflect a simplified version of an adaptive process, yet, represent a real choice that planners face. For example, they will need to decide how aggressively or conservatively they respond to new information. Thus, this chapter seeks to inform planners about the costs, benefits, and tradeoffs of responding to information in different ways, across a wide range of plausible future conditions and expectations for the future.

This chapter asks the following policy questions:

1) Does a baseline strategy, using the decision-rules proposed in the Colorado River Basin Study, help the Basin effectively meet water delivery objectives in the Upper Basin and Lower Basin across a range of conditions, and at what costs?

2) What tradeoffs do planners face between ensuring water delivery objectives are met and risking over-investment in unnecessary actions across different decision-rules?

3) Can remaining vulnerabilities of these strategies be further reduced with alternative or improved decision-rules?

To provide insight into these policy questions, this chapter uses an RDM approach to evaluate and iteratively improve the design of adaptive strategies in the Basin. The first section of this chapter describes the scope of analysis. In particular, it discusses a simulated planning agent programmed into the hydrologic simulation model of the Basin, designed to observe new information and implement actions when necessary. This first section also describes the alternative adaptive strategies analyzed in this chapter and the criteria by which they are compared.

Next, this chapter provides an assessment of a baseline strategy that relies on the triggers used in the Basin Study. It compares a strategy based on these triggers to two reference strategies—a strategy that implements no subsequent water management actions and a strategy that implements a wide set of actions as soon as they are available. This section identifies that the Basin Study’s adaptive strategy distinguishes wet future conditions from dry future conditions. However, it finds that the strategy is relatively conservative, preventing it from ensuring water delivery reliability in many futures where a more aggressive set of decision-rules might.

This chapter next evaluates a wider range of adaptive strategies with decision-rules that implement water management actions more aggressively. It compares these strategies to one another. This analysis identifies that the adaptive strategies tend to perform similarly to one another in very wet or very dry futures when there is a clear signal. However, in less extreme futures planners face some significant cost-reliability tradeoffs among strategies. This section provides some decision-aids to help planners weigh the tradeoffs among alternative strategies.

Finally, the chapter concludes with some policy interpretations of the simulations and results.

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55 This *Current Management* strategy is the baseline assessment presented in the Basin Study
56 This is the *Static Implement-All-Actions* strategy, evaluated in the Basin Study and described in Chapter 4.
Scope of analysis of adaptive strategies for the Colorado River Basin

Chapter 4 describes many of the factors of analysis, which are carried forward in this chapter. Chapter 4 presents an ensemble of uncertain streamflow futures, a portfolio of water management actions, the Colorado River Simulation System (CRSS), and the measurements of water delivery reliability in the Upper and Lower Basin. This section describes some additional factors to facilitating the analysis of various strategies that adapt over time. Table 6-1 summarizes each factor. The new factors are bolded.

Table 6-1: Uncertainties, strategies, metrics, and relationships for adaptive strategies (XLRM)

<table>
<thead>
<tr>
<th>Uncertainties or Scenario Factors (X)</th>
<th>Management Strategies and Portfolios (L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supplies via river flows (3 supply scenario, 715 futures)</td>
<td>Current Management Portfolio A (Inclusive)</td>
</tr>
<tr>
<td>• Recent historical record (103 futures)</td>
<td>• Static Implement-All-Actions</td>
</tr>
<tr>
<td>• Statistical blend of the recent historical record and the paleoclimatic record (500 futures)</td>
<td>• Baseline adaptive strategy (using some triggers identified in the Basin Study)</td>
</tr>
<tr>
<td>• Downscaled Global GCM (112 futures)</td>
<td>• Adaptive Strategies defined by other triggers along a continuum of conservative to aggressive</td>
</tr>
<tr>
<td>Relationships or Systems Model (R)</td>
<td>Performance Metrics (M)</td>
</tr>
<tr>
<td>Colorado River Simulation System (CRSS)</td>
<td>Upper Basin Water Delivery reliability</td>
</tr>
<tr>
<td>• Simulated Planning Agent</td>
<td>Upper Basin Annual Yield</td>
</tr>
<tr>
<td></td>
<td>Upper Basin Annual Total Cost</td>
</tr>
<tr>
<td></td>
<td>Lower Basin Water Delivery Reliability</td>
</tr>
<tr>
<td></td>
<td>Lower Basin Annual Yield</td>
</tr>
<tr>
<td></td>
<td>Lower Basin Annual Total Cost</td>
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</tbody>
</table>

The following sections present the factors of analysis that were not previously described in Chapter 4.

Metrics to evaluate effort and reliability (M)

This dissertation previously described two measures of water delivery reliability—Upper Basin water delivery (measured by a Lees Ferry deficit) and Lower Basin water delivery (measured by Lake Mead’s elevation). However, a strategy’s effect on water delivery reliability is only part of the decision that planners face; they must weigh this benefit against the cost of the strategy—the level of effort associated with implementation. This analysis uses two additional metrics to measure the
level of effort associated with implementing the various strategies: annual yield and total annual cost.

The Basin Study estimates the annual yield associated with each water management action. It first estimates the expected annual volume of new water supply or decreased water demand associated with each water management action. By summing the yield of each individual actions implemented, the Basin Study estimates the annual yield of a strategy in a given year of a particular future (2012d, U.S. Bureau of Reclamation 2012e).

The Basin Study also estimates the total annual cost of a portfolio of implemented actions. It begins with a levelized cost approach for each water management action, estimating an annualized cost per acre-foot for each of the considered actions, amortizing the cost of capital and the annual cost of operations and maintenance. This levelized cost is expressed in dollars per acre-foot per year. The total annual cost of an action in a given year can be calculated by multiplying the cost per acre-foot with the expected yield. The total annual cost of a strategy sums the cost across all the water management actions operating in a particular year (U.S. Bureau of Reclamation 2012e, U.S. Bureau of Reclamation 2012d).

In the Basin Study, each water management action is defined to address Upper Basin water delivery, Lower Basin water delivery, or both objectives. If all the actions available address Upper Basin water delivery objectives were implemented, they would represent 2.7 maf of total annual yield by 2060 and would cost $3.4 billion annually. The actions available to address Lower Basin water delivery objectives represent 5.0 maf in annual yield and would cost $7.0 billion annually (U.S. Bureau of Reclamation 2012d).

In contrast to the Basin Study, this analysis defines Upper Basin yield as the total annual yield of actions operating in a given year to address water delivery reliability in the Upper Basin. It defines Upper Basin cost as the total annual cost of those actions. It also defines Lower Basin yield and Lower Basin cost similarly. Because some actions can address both Upper Basin and Lower Basin water delivery objectives, these measures are not cumulative. For example, the Upper Basin yield summed with the Lower Basin yield in a particular future may be greater than the total yield implemented in the Basin.57

This chapter considers Upper Basin and Lower Basin the water delivery reliability objectives separately, evaluating the impact that various strategies have on each of the two objectives. This is not to suggest that the Basin should not take an integrated approach to planning—many actions address water delivery both in the Upper and Lower Basin. However, this approach provides granular information about the strategies necessary to meet the various objectives. Planners may use information about each to generate an integrated plan.

57 The Basin Study evaluated each strategy against a large number of outcome metrics spanning the entire Basin, recognizing that the Basin is integrated. As this dissertation weighs the cost and benefits of specific decision-rules, tied to the two objectives, it measures the costs of each decision-rule separately.
Consistent with the Basin Study, this analysis presents annual costs and yields for the end of the time period in question. For example, if a strategy is evaluated from 2031-2060, the cost of that strategy is the annual cost in 2060 (U.S. Bureau of Reclamation 2012e).

While the analysis in this chapter was completed for the both the Upper and Lower Basin, this chapter focuses on results Lower Basin. It presents a detailed evaluation of the reliability, cost, and yield of the candidate strategies in the Lower Basin. To consolidate the discussion, it provides less detail and presents only a small number of key figures for the Upper Basin.

**Simulating adaptive strategies in the Basin (R)**

This analysis uses CRSS, described in Chapter 4, to model the hydrology of the Basin. In addition to representing the hydrologic network, streamflow, and requested depletions, CRSS was modified for the Basin Study to simulate the impacts of the various water management actions. Each water management action is modeled as either additional streamflow or a decrease in demand at a specific geographic location along the network (U.S. Bureau of Reclamation 2012e).

CRSS was also modified for the Basin Study to simulate the process of planners acting adaptively. It includes a simple simulated planning agent that observes information and implements water management actions over the course of a simulation. This planning agent monitors signpost variables on an annual basis. If the signpost variables drop below predefined trigger values (henceforth referred to as observing a trigger value), the planning agent implements the next available water management action from a prioritized list (U.S. Bureau of Reclamation 2012e, Groves, Fischbach et al. 2013). This is akin to a closed-loop control rule; the simulated agent observes the state of the system and implements a pre-committed action accordingly.

The prioritized list of actions that the simulated planning agent has the option to implement are generated using the Portfolio Development Tool (Groves, Fischbach et al. 2013). The various water management actions are ranked by their cost-effectiveness and constrained by an assessment of the earliest date they could feasibly be implemented. When the simulated planning agent observes a trigger value, it implements the most cost-effective available action that has yet to be implemented. Strategies of this form contain an assumption that each of the actions in the portfolio provides a marginal benefit greater than the marginal cost of failing to meet objectives and is therefore a worthwhile investment. Actions where this criterion is not true should not be included in the portfolio.58

Figure 6-1 illustrates how the simulated planning agent observes signpost variables, triggers new actions, and alleviates an impending failure to meet Lower Basin water delivery objectives. The dark line shows Lake Mead’s elevation with the Current Management strategy where Lake Mead first drops below 1,000 feet in 2041. The lighter line represents the same future streamflow conditions, but with an adaptive strategy in place. When the planning agent observes a trigger

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58 Different stakeholders may value the costs and benefits of each action differently. Therefore the Basin Study evaluated multiple portfolios, as described in Chapter 1. This dissertation assumes this condition is met for all actions in Portfolio A, but could be replicated for other portfolios of actions.
value, in a year demarked by a triangle, it implements a water management action. Over time, the simulated planner observes multiple trigger values. As conservation and additional supply come on-line, Lake Mead’s elevation diverges from the elevation with the Current Management strategy. In this case, the adaptive strategy successfully prevents the elevation from dropping below 1,000 feet.

Figure 6-1: Illustration of simulated planning-agent’s implementation of adaptive strategy in Lake Mead

The Basin Study evaluates an adaptive strategy in which the planning agent monitors recent past observations of streamflow and reservoir elevation. Each year, the simulated planning agent calculates the average natural flow at Lees Ferry from the previous five years. It also monitors the elevation of two key reservoirs in the system, Lake Mead and Lake Powell. If both the average annual streamflow over the previous five years and the reservoir levels drop below pre-defined trigger values, the simulated planning agent implements a water management action.

Chapter 5 described the relationship between streamflow in early decades and the decision-relevant scenarios; observations of low streamflow in early time periods of the planning horizon indicate low long-term average streamflow. However, the signpost variables in this chapter take a slightly different form than those in Chapter 5. The planning agent makes decisions each year, based on observations of streamflow in the previous five years. Many short-term periods of low streamflow are also closely associated with low long-term average streamflow. Additionally, the reservoir levels measure the system state, incorporating feedback by measuring the effects of
previous action. Rules of this form are used because they allow the strategy to inclemently implement actions and incorporate feedback in the system from previously implemented actions.

The decision-rules in the Basin Study and this chapter approximate decisions that planners may actually make. First, they monitor only information that would be observable to planners at the time of the decision. They are also designed to be relatively simple, as they are based on information already frequently observed and reported in the Basin. However, these rules are limited by the practical constraint of using only information available in the hydrologic model and exclude other relevant pieces of information such as SST.

Defining alternative adaptive strategies (L)

CRSS can be modified to represent different adaptive strategies by altering the decision-rules the simulated planning agent uses. This dissertation explores the impact of setting different trigger values. Figure 6-2 presents an example of alternative adaptive strategy, using the same portfolio of actions and relying on the same signpost variables. This alternative adaptive strategy implements actions when streamflow and reservoir levels are higher than the threshold levels used in the Basin Study, implementing actions more frequently. In this particular future, the Lower Basin fails to meet its water delivery objectives with the Current Management of the system (red line). A strategy using the trigger values from the Basin Study (orange line) increases Lake Mead’s elevation above the baseline. However, it implements too few actions too late and the Lower Basin still fails to meet objectives. A more aggressive strategy (green line), with higher trigger values, implements more actions sooner. This more aggressive strategy allows the Lower Basin to meet its water delivery objectives.
This dissertation explores a set of alternative strategies. It begins by considering two strategies that do not respond to new information— the Current Management strategy and the Static Implement-All-Action strategy (both described in Chapter 4 of this dissertation). The Current Management strategy and the Static Implement-All-Action strategies serve as bounding cases. They, respectively, implement no actions or each action at the earliest date available. It also evaluates the Baseline strategy using the trigger values defined in the Basin Study.

The adaptive strategies in this dissertation only use triggers designed to implement actions to address the Upper Basin water delivery objectives and Lower Basin water delivery objectives described in Chapter 4. The Basin Study considered additional water delivery objectives, and designed additional triggers to address those objectives. In particular, the Basin Study considered two other measures of Lower Basin shortage and shortages on demand above what is apportioned by the Law of the River. These triggers call actions under less severe conditions and implement more actions sooner (U.S. Bureau of Reclamation 2012e). Because this dissertation does not evaluate strategies with reference to those objectives, including to triggers to address those objectives would obfuscate this analysis. In practice, this means the Baseline strategy is more conservative than the strategy evaluated in the Basin Study. For this reason, the Baseline adaptive strategy is not directly comparable to the adaptive strategy used in the Basin Study.
This analysis then examines a wider set of adaptive strategies, defined by a range of different trigger values. Some of the strategies implement actions after observing relatively high values of natural streamflow and reservoir levels. The trigger values in these strategies have a high-true positive rate, ensuring that many actions are implemented prior to when is necessary, but risk implementing actions when they are not necessary. These strategies are referred to as aggressive.

Other strategies only implement actions after observing relatively low values of streamflow and reservoir levels. The trigger values defining strategies have a high-true negative rate, only implementing actions when it is highly likely that they are necessary. These are referred to as conservative strategies.

Table 6-2 lists the candidate adaptive strategies. These strategies were developed primarily through iteration. These strategies produce results that range from nearly no increased resilience from the Current Management to a strategy that more closely resembles the Static Implement-All-Actions Strategy.
<table>
<thead>
<tr>
<th></th>
<th>Upper Basin</th>
<th>Lower Basin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lake Powell Elevation</td>
<td>Lake Mead Elevation</td>
</tr>
<tr>
<td></td>
<td>5-year average streamflow at Lees Ferry</td>
<td>5-year average streamflow at Lees Ferry</td>
</tr>
<tr>
<td><strong>Current Management</strong></td>
<td>No additional water management actions implemented</td>
<td></td>
</tr>
<tr>
<td><strong>Baseline from Basin Study)</strong></td>
<td>Less than 3490 feet</td>
<td>Less than 1040 feet</td>
</tr>
<tr>
<td><strong>Moderate</strong></td>
<td>Less than 3525 feet</td>
<td>Less than 13.15 maf</td>
</tr>
<tr>
<td><strong>Moderately Aggressive</strong></td>
<td>Less than 3550 feet</td>
<td>Less than 13.25 maf</td>
</tr>
<tr>
<td><strong>Aggressive</strong></td>
<td>Less Than 3600 feet</td>
<td>Less than 13.5 maf</td>
</tr>
<tr>
<td><strong>Very Aggressive</strong></td>
<td>Less Than 3600 feet</td>
<td>Less than 14.0 maf</td>
</tr>
<tr>
<td><strong>Static Implement-All-Actions</strong></td>
<td>Every water management action in <em>Portfolio A: Inclusive</em> implemented in first year available.</td>
<td></td>
</tr>
</tbody>
</table>
At the other end of the spectrum, the *Very Aggressive* strategy implements actions under what are typically considered normal conditions. For example, it has trigger values in the Lower Basin when the five-year average streamflow is at the historical average of 15 maf and Lake Mead’s elevation is 1125 feet, within the range of normal operations (U.S. Department of the Interior 2014). Thus, the triggers in the more aggressive strategies are generally observed in early years of the simulation, and often begin implementing actions as soon as they become available.

These specific threshold values in these strategies do not necessarily carry policy significance—planners may be interested in testing the performance of alternative strategies. Instead, the thresholds presented in this dissertation are simply representative strategies, they span a range of reasonable strategies that planners may consider. Other strategies with similar thresholds would likely produce similar results, and the strategies presented in this dissertation can serve as benchmarks. The previous chapter suggested there are conditions so severe that planners will need to consider new actions or change objectives.

The strategies considered in this chapter (and Chapter 7) are designed with the assumption that planners will wish to implement as many actions from the portfolio as possible when needed to eliminate vulnerabilities. This assumption is consistent with an interpretation that under the driest conditions, additional supply or decreased consumption would have its highest value. Assuming marginal water supply strictly declines, the futures with the least natural flow will be the futures where water has the highest marginal value (Brown 2007, Duffield, Neher et al. 2007, Harou, Pulido-Velazquez et al. 2009). This would justify the greatest investment in water management actions. As such, the decision-rules do not decrease the rate at which actions are implemented when evidence mounts that the *Severely Declining Supply* scenario is likely.

**Evaluating the Current Management, Static Implement-All-Actions, and Baseline strategies**

This section examines the *Baseline* strategy by comparing it to the *Current Management* and *Static Implement-All-Actions* strategies. First, it presents the impact that the *Baseline* strategy has on water delivery reliability across the ensemble of futures. It then characterizes cost and level of effort of this strategy. The *Current Management* and *Static Implement-All-Actions* strategies serve as benchmarks, demonstrating the risk of failing to meet objectives without any incremental water management actions and the maximum potential to address vulnerability with the set of available actions. They also represent the benchmarks for the cost of the strategy. The *Current Management* strategy represents zero incremental cost and the *Static Implement-All-Actions* represent the highest potential cost in all futures.

Figure 6-3 presents the percent of futures that fail to meet objectives for the *Current Management*, *Baseline*, and *Static Implement-All-Actions* strategies (rows) in each of the decision-relevant scenarios defined in Chapter 4 (columns). The top panel shows results in the Upper Basin, while the bottom panel shows results in the Lower Basin. The *Baseline* strategy decreases the frequency with which the Upper Basin fails to meet water delivery objectives from 78 percent to 48 percent in *Declining Supply* conditions, while the *Static Implement-All-Actions* strategy would decrease the
frequency to 10 percent. In *Low Historical Supply* conditions, the *Baseline* strategy decreases the percent of futures in which the Lower Basin fails to meet objectives from 79 percent to 69 percent, while the *Static Implement-All-Actions* strategy shows the potential to decrease the frequency to 6 percent.59

**Figure 6-3: Percent Futures Failing to Meet Objectives for Current Management, Baseline, and Static Implement-All-Actions Strategies**

<table>
<thead>
<tr>
<th></th>
<th>Upper Basin</th>
<th>Lower Basin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Severe Declining Supply</td>
<td>Declining Supply</td>
</tr>
<tr>
<td>Current Management</td>
<td>100%</td>
<td>78%</td>
</tr>
<tr>
<td>Baseline</td>
<td>87%</td>
<td>48%</td>
</tr>
<tr>
<td>Static Implement-All-Actions</td>
<td>74%</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>0% 50% 100% Percent Futures Failing to Meet Objectives</td>
<td>0% 50% 100% Percent Futures Failing to Meet Objectives</td>
</tr>
</tbody>
</table>

Figure 6-4 illustrates the percent of futures when each strategy fails to meet objectives across the range of plausible long-term average streamflow conditions. The horizontal axis shows the long-term average natural flows at Lees Ferry. Similar to a histogram, this graphic bins all futures with average streamflow within an increment of 500 kaf—the point at 12.5 maf represents all futures.

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59 These results are different from the adaptive strategies assessed in the Basin Study. There are two primary reasons for this. First, the Basin Study strategies included additional decision-rules to address other objectives. These decision-rules generally implemented more actions sooner, as the Current Management failed to meet objectives in less extreme circumstances. Additionally, the Basin Study strategies include some actions that are implemented in every future, not responding to signpost variables. To focus on the effect of various decision-rules, the adaptive strategies modeled in this study do not have any actions that are implemented in all futures.
between 12 and 12.5 maf of long-term average streamflow. The vertical axis shows the percent of futures that fail to meet water delivery objectives for futures with long-term average streamflow within the range defined on the horizontal axis.

Figure 6-4: Percent Futures Failing to Meet Objectives for Current Management, Baseline, and Static Implement-All-Actions Strategies by Long-Term Average Streamflow

This figure demonstrates that as conditions become dryer, both the Upper Basin and Lower Basin fail to meet water delivery objectives at a higher rate, across all three strategies. When long-term average annual streamflow is less than 11.5 maf, all strategies fail to meet both objectives in all futures. When long-term average annual streamflow is greater than 16.5 maf, all strategies meet both objectives in all futures. The Static Implement-All-Action strategy increases the percent of futures that meet objectives within a range of streamflow conditions. In the Upper Basin, it is most effective between 12 and 14 maf. In the Lower Basin, the Static Implement-All-Action strategy increases the percent of futures to meet objectives to greater than 90 percent when streamflow long-term average annual streamflow is greater than 13 maf.

This figure also presents the Baseline strategy’s performance relative to the other two strategies. In the Upper Basin, when streamflow is between 11.5 and 13 maf, the Baseline strategy decreases the percent of futures that fail to meet objectives below the level with Current Management, but it is
still significantly higher than the level with the Static Implement-All-Action strategy. This is even more pronounced in the Lower Basin where the Static Implement-All-Action strategy more drastically decreases the percent of futures that fail to meet objectives than for the Baseline when streamflow is between 11.5 and 16maf.

This figure demonstrates that the Baseline strategy is fairly conservative when it comes to addressing water delivery objectives. Though the Baseline strategy prevents the Upper Basin and Lower Basin from failing to meet objectives in some futures (and it is more effective in the Upper Basin than in the Lower Basin), when compared to the Static Implement-All-Actions strategy, it fails to meet objectives in many futures where objectives could have been met. This suggests that the Baseline is leaving something on the table, more actions could be implemented and the objectives could be met in wider range of conditions.

The ability to meet objectives across a range of futures is not the only criteria by which to judge the strategy. Each water management action has a cost and level of effort associated with it. Figure 6-5 presents the Lower Basin yield and cost of the Current Management, Baseline, and Static Implement-All-Actions strategies by long-term average streamflow conditions. The figures on the left show Lower Basin yield, while those on the right present Lower Basin cost. In the graphics in the top panel, each point represents yield or cost of the Baseline strategy in a particular future (vertical axis). The horizontal axis shows the long-term average annual streamflow of that particular future. The reference lines show the yield and cost of the Current Management and Static Implement-All-Actions strategy. The bottom graphics present similar results, using boxplots to summarize the distribution of cost and yield for futures with similar average annual streamflow (segmented by units of one million af).
This figure demonstrates that the *Baseline* strategy successfully increases the yield of actions in the driest futures. When long-term average streamflow is less than 13 maf, nearly the maximum potential yield is implemented in each future. When streamflow is greater than 16 maf, very little or no actions are implemented. In between, the yield increases incrementally as streamflow decreases.

Importantly, it demonstrates that the *Baseline* strategy is significantly cheaper than the *Static Implement-All Action* strategy in many futures. In the wettest futures, the *Baseline* strategy does not accrue any costs. When streamflow is between 13 maf and 15 maf, the strategy does have some costs, but it is frequently less than what the Static Implement-All Action strategy would cost. Only in
the driest futures, when all actions are necessary, does the strategy have similar costs to Static Implement-All Action strategy.

Results are similar in the Upper Basin.

This analysis confirms that the Baseline adaptive strategy meets many of the basic requirements of an adaptive strategy. Planners can use reservoir levels and short-term observations of streamflow as signpost variables to distinguish wet futures from dry futures; strategies based on these indicators implement actions in the futures where they are most necessary. Such a strategy uses new information that becomes available over time to successfully distinguish between wet and dry futures and incrementally increases the volume of actions it implements to address the challenges in the dry futures. In some percentage of futures, the strategy meets water delivery objectives when the current management would not. By acting adaptively, the strategy does not accrue unnecessary costs in many of the wettest futures.

However, this analysis suggests that the particular trigger values in the Baseline adaptive strategy are conservative. The strategy does not meet objectives in many of the futures that the Static Implement-All actions strategy does. This suggests that the adaptive strategy either implements insufficient water management actions or implements them too late to have the desired impact.

The following sections consider a larger set of adaptive strategies designed to address this.

**Evaluating a continuum of aggressive to conservative adaptive strategies**

This section evaluates a larger ensemble of adaptive strategies. It begins by characterizing the performance of each strategy. Next, it proposes two regret-based metrics to consider the opportunity cost of implementing a strategy that fails to meet water deliver objectives or over-invests in a single future. Using these metrics, it evaluates the tradeoffs among alternative strategies across the range of plausible future streamflow conditions and stakeholder beliefs about those future conditions.

**Performance of adaptive strategies**

Figure 6-6 presents the distribution of Lower Basin yield and Lower Basin cost of the alternative strategies across the range of plausible streamflow futures. This figure has the same design as the bottom two panels in Figure 6-5, repeated for each strategy. For each partition of streamflow, the distribution of yield and cost is higher for more aggressive strategies than for the more conservative strategies. This confirms that the more aggressive strategies generally implement more water-management actions over the course of a simulation.60

60 While it is not necessarily surprising that the most aggressive strategies implement the most actions, this result is not built into the definitions of the strategies. It is theoretically possible that the more aggressive strategies would implement more actions earlier, sufficiently addressing vulnerability and increasing the
Having confirmed that adaptive strategies with higher trigger values implement more actions, the analysis next evaluates the performance of the additional adaptive strategies. Figure 6-7

reservoir levels above the threshold values. It is conceivable that calling more actions sooner and experiencing more years of benefit would have implemented a lower volume. However, the results presented in Figure 6-6 suggest this is not frequently occurring.
summarizes the primary performance metrics—water delivery reliability, yield and cost in the Lower Basin. Each row is one candidate strategy. The left-most panel shows the percent of futures that fail to meet objectives, the middle panel shows the distribution of Lower Basin yield, and right-most panel shows the distribution of Lower Basin cost across an entire ensemble of sampled plausible futures.

Figure 6-7: Percent futures that fail to meet objectives and distribution of yield, and cost for candidate strategies in the Lower Basin across ensemble of futures

The more aggressive strategies meet water delivery objectives in more futures than strategies that are more conservative. This set of adaptive strategies spans the range of water delivery reliability between Current Management and the Static Implement-All-Actions strategy. The Very Aggressive strategy approaches the performance of the Static Implement-All-Actions strategy failing to meet water delivery objectives in 16 percent of futures (compared to 11 percent with the Static Implement-All-Actions strategy). However, the more aggressive strategies implement more actions at higher costs. The Basin Study Triggers strategy has a Lower Basin cost of less than $700 million in approximately half the sampled futures, while the Very Aggressive strategy has a Lower Basin cost of more than $4.9 billion in approximately half the sampled futures.

Figure 6-8 shows similar results in the Upper Basin. The most conservative strategies perform similarly to the Current Management of the system, and the Very Aggressive strategy meets water delivery objectives in two percentage points more futures than the Static Implement-All-Actions strategy. The more aggressive strategies have higher costs in many futures than the Baseline strategies, but are frequently significantly cheaper than the Static Implement-All-Actions strategy.
These two figures demonstrate that even when acting adaptively, planners face a tradeoff between the annual expenditures and their risk of failing to meet water delivery objectives. The more aggressive strategies meet objectives in a greater percentage of futures, but have a higher total cost in both the Upper Basin and the Lower Basin. The conservative strategies generate lower costs, but have the expense of failing to meet objectives in a greater percentage of futures.

However, it is unclear whether the additional costs associated with strategies that are more aggressive are necessary to meet water objectives. The strategies may implement yield, thus increasing costs only scaling up to meet water delivery objectives. If this were the case, planners may strictly prefer the Very Aggressive strategy, viewing the increased cost as necessary to meet objectives. On the other hand, the Very Aggressive strategy may increase costs in every future, even when unnecessary to meet water delivery objectives. To this point, the costs associated with the strategies are not tied to the performance of the strategy in any particular future. The analysis in the next section addresses this issue more explicitly.

**Measuring the opportunity cost of imperfect adaption: implementation and vulnerability regret**
In any particular future, a strategy may invest in an insufficient amount of actions to meet water delivery objectives, invest more than was necessary, or invest in the least amount of actions among alternatives while meeting objectives. Lempert et al. (2003) suggest that under deeply uncertain conditions, planners may prefer to measure performance with a regret based metric, which considers the difference between the actual outcome of an adaptive strategy and the “best” choice strategy. Such a measure considers the opportunity cost of choosing the wrong strategy.

In most futures, this dissertation considers best choice strategy the one that meets objectives for the least expense. This definition assumes that planners are willing to take all the water management actions in Portfolio A (Inclusive) to meet objectives, but seek to identify the cheapest possible combination of actions to do so.

A strategy can fail to be the best strategy in two primary ways, represented in this analysis with two corresponding measures of regret. The strategy can fail to invest in sufficient action to meet objectives. This analysis uses a measure referred to as vulnerability regret to characterize when a strategy implements insufficient actions to meet the water delivery objectives. Vulnerability regret measures the additional yield that would be necessary to meet objectives. With this measure, planners can gain an understanding of how close a particular strategy comes to meeting objectives.

Alternatively, a strategy can invest in more action than the best strategy, meeting objectives but bearing unnecessary expense. This is measured with implementation regret. Implementation regret measures the financial cost of the actions implemented, beyond what was necessary to meet objectives, considering the level of effort in terms of the annual costs as it focuses on the financial over-investment of a particular strategy. In a given future, a strategy may only have non-zero implementation regret or vulnerability regret.

Though vulnerability regret and implementation regret could be measured in the same units (both with either yield or cost), this dissertation presents them in terms of different units for two reasons. First, vulnerability regret is a measure of what would have been necessary to meet water delivery objectives. Many water planners will primarily consider which actions would need to be taken to meet objectives in terms of the total yield necessary. On the other hand, implementation regret is primarily a measure of financial over-investment. Second, some water planners may have strong preferences to meet water-delivery objective and avoid vulnerability regret, even at the expense of excess implementation regret. Keeping the two measures in different units helps ensure planners do necessarily weight vulnerability regret the same as implementation regret without careful consideration.

Figure 6-9 demonstrates these two types of regret in three different plausible example futures. Each point marks the total yield implemented for a single strategy; red points fail to meet Upper Basin water delivery objectives while those in gray meet objectives. The top row shows yield on the vertical axis and the bottom row shows cost on the vertical axis. The vertical panels present three different types of futures: one where all strategies meet objectives (left), one where some, but not all strategies meet objectives (middle), and one where no strategies meet objectives (right). The two measures of regret are labeled with brackets.
When all strategies meet objectives, no strategy has vulnerability regret. Any strategy that implements any actions will have implementation regret. In these cases, implementation regret is simply the cost of the actions implemented; the best strategy would have been to implement no actions.

In a future where some but not all strategies meet objectives, some strategies will have implementation regret and others will have vulnerability regret. One particular strategy will meet objectives with the least yield and lowest cost (the Strategy B in the example above). This is the no-regret, best strategy. Strategies that invest in more actions than the no-regret strategy and meet objectives have positive implementation regret and zero vulnerability regret. Strategies that implement less than the no-regret strategy and fail to meet water delivery objectives) have positive implementation regret and non-zero implementation regret.61

When all strategies fail to meet objectives, no strategy will have implementation regret. The Static Implement-All-Actions strategy becomes the default best choice strategy. Vulnerability regret is

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61 In a small number of cases, a strategy will implement greater yield than the no-regret strategy and still fail to meet objectives. This is generally because a more conservative strategy implements actions later in a simulation, but ultimately implements more actions as the reservoir levels do not recover. In these cases, there is negative implementation regret. They are a minor part of the policy story.
measured as the difference between the yield implemented in a strategy and the yield implemented by the Static Implement-All-Actions strategy. This measure recognizes that in futures where failing to meet objectives is unavoidable within the constraints of this simulation model, strategies should implement as many water-management actions as possible.

Implementation and vulnerability regret are calculated separately for both the Upper Basin and Lower Basin, using the different water delivery objectives and measurements of cost and yield.

Planners may have divergent preferences regarding their willingness to accept under-investment or over-investment. In the context of the Basin, planners likely place a high value on meeting the water delivery objectives. Many planners may be insensitive to small levels of over-investment, but have high disutility from slightly under-investing. However, different planners and stakeholders can reasonably have different preferences regarding these two risks.

Figure 6-10 presents the 90th percentile regret for each strategy across the entire ensemble of futures in the Lower Basin. The graphs on the left show vulnerability regret and those on the right present implementation regret. This figure presents the same cost-reliability tradeoff demonstrated in the previous sections. The more aggressive strategies experience lower average vulnerability regret, but greater implementation regret.

**Figure 6-10: 90th percentile regret across ensemble of futures in Lower Basin**

<table>
<thead>
<tr>
<th>Current Management</th>
<th>Baseline</th>
<th>Moderate</th>
<th>Moderately Aggressive</th>
<th>Aggressive</th>
<th>Very Aggressive</th>
<th>Static Implement-All-Actions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower Basin Vulnerability Regret [af]</td>
<td>$0.0B</td>
<td>$2.0B</td>
<td>$4.0B</td>
<td>$6.0B</td>
<td>Lower Basin Implementation Regret</td>
<td></td>
</tr>
<tr>
<td>1.0M</td>
<td>2.0M</td>
<td>3.0M</td>
<td>4.0M</td>
<td>5.0M</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This figure also demonstrates the high costs of the two static strategies. The Current Management strategy experiences more than triple the vulnerability regret of Vulnerability Only strategy in the Lower Basin. In the Upper Basin, the vulnerability regret is higher by more than a factor of ten between these two strategies. Implementation regret of the Static Implement-All-Action strategy is nearly a $2 billion greater than the Very Aggressive strategy in the Upper Basin.

This figure presents just one summary statistic of the tradeoff between vulnerability regret and implementation regret. As planners will need to make choices about how they respond to new information, this measurement can assist in quantifying that tradeoff. However, planners’ choices between strategies depend on a number of factors, including performance in particular futures and
their assessments of the likelihoods of those futures. Subsequent sections of this chapter provide more detail on those tradeoffs.

**Comparing regret across streamflow futures for adaptive strategies**

While the figures above show that regret can vary among the strategies, it does not present the wide variation in regret among futures within a strategy. As planners may wish to prepare for futures with particular characteristics, visualizations that show performance in each future can assist in their decisions. Figure 6-11 presents the implementation and vulnerability regret across the ensemble of streamflow futures in the Lower Basin for each candidate strategy. Each of the horizontal panels presents a candidate strategy. Within each panel, each bar (vertical axis) represents regret for a single future, ordered by the annual average natural streamflow at Lees Ferry (horizontal axis). The line in the middle of each panel represents zero regret. Bars emerging upwards from the axis show implementation regret and lines emerging downward represent vulnerability regret. Note that in some futures, vulnerability regret can be as high as 5 maf (particularly for the *Current Management* strategy), but the axis is censored at 3 maf to capture the range of the most important results.
Figure 6-11: Lower Basin vulnerability and implementation regret by long-term average streamflow conditions
On this figure, a perfectly performing strategy would sit on the zero regret line across the entire range of futures. This would be a perfect foresight strategy, where planners could perfectly predict which actions to implement in each future. However, this figure identifies that with the set of candidate strategies with imperfect information, such a result is not feasible.

The two static strategies (Current Management and Static Implement-All-Actions strategies) both have highly skewed distributions of regret. The Current Management strategy has no regret if long-term average streamflow is above 16.1 maf. In these conditions, the strategy meets objectives and the Current Management strategy incurs no incremental cost. As streamflow decreases, the Current Management strategy quickly accrues high vulnerability regret as no actions are implemented though objectives are not met. In futures where long-term average streamflow is below 15 maf, the Current Management strategy has an average of 3.2 maf vulnerability regret, and in futures below 12.5 maf, it has an average of 4.9 maf. On the other extreme, the Static Implement-All-Actions strategy has almost no regret of either type in futures with long-term average streamflow below 12.0 maf. However, it experiences average implementation regret nearly $5 billion in futures where long-term average streamflow is above 13 maf. Though the static strategies are the best performing strategies in some futures, they experience high regret in many others.

The adaptive strategies have less extreme outcomes than the static strategies. When an adaptive strategy experiences regret, it is often a much lower magnitude than the static strategies. For example, in futures where the Baseline adaptive strategy experiences positive vulnerability regret, the median regret is 847 kaf. In strategies where the Current Management strategy experiences vulnerability regret, the median regret is 4.3 maf. Similarly, the Static Implement-All-Actions strategy has a $5.1 billion median implementation regret, conditional on experiencing implementation regret, while the Very Aggressive strategy only has $2.7 billion median implementation regret.

Unlike the static strategies, the adaptive strategies experience their highest levels of regret in the more moderate futures. In the driest futures, all adaptive strategies implement close the maximum yield, generating small, but largely negligible, implementation regret. When long-term average streamflow is less than 12 maf, no adaptive strategy has more than 600 kaf of implementation regret. In the driest futures, all adaptive strategies observe enough triggers to implement nearly all of the water management actions regardless of trigger value. Similarly, in the wettest futures, the adaptive strategies do not observe many triggers and implement very few or no actions. In these futures, the adaptive strategies are not highly differentiated from one another. It is only in the more moderate futures that the strategies cannot observe a clear signal and risk high levels of regret.

However, the adaptive strategies do not all perform the same, and there are tradeoffs among the various strategies. The more aggressive strategies experience higher magnitudes of implementation regret, experience it in more futures, and are vulnerable to experiencing it in wetter conditions. For example, the Very Aggressive strategy has a median of $2.6 billion of implementation regret in futures where long-term average streamflow is greater than 15 maf. In the same futures, the

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62 Implementation regret is frequently non-zero because of some assumptions regarding how actions can interact with one another
moderate strategy only has a median implementation regret of $0. On the other hand, strategies that are more conservative experience larger magnitudes of implementation regret in more futures.

As planners weigh the tradeoffs demonstrated in these graphics, they should consider their preferences between under-preparedness and over-investment and beliefs about the likelihoods of futures. Though this graphic does not make any assumptions about probability or preferences, presents them in a manner that gives every sampled future and both measures equal weight. For example, the Aggressive strategy has more blue shading than the Baseline strategy. In this case, the bars represent more frequency and higher volumes of implementation regret with Aggressive strategy. However, if a planner would rather over-invest than be under-prepared, they are less sensitive to implementation regret than vulnerability regret. They may still prefer the Aggressive strategy. Additionally, the Aggressive Strategy experiences much of its implementation regret in wetter futures, where the Baseline strategy experiences less regret of either type. If a planner does not believe these futures are likely, they may wish to weigh this increase in implementation regret less heavily. Analysis presented in subsequent sections is considers these tradeoffs more explicitly.

**Low-regret strategies**

To summarize effectiveness of the various strategies across the ensemble of plausible future conditions, this analysis uses a definition of low-regret. In the Upper Basin, a strategy is low-regret in a particular future if vulnerability regret is less than 120 kaf and implementation regret is less than $500 million. In the Lower Basin, a strategy is low-regret in a particular future if vulnerability regret is less than 250 kaf and implementation regret is less than $500 million. While somewhat arbitrary, 250 kaf reflects that the thresholds which define water delivery objectives are already quite severe, and planners are likely very averse to meeting these thresholds. Furthermore, under such dry conditions, planners are unlikely to have to many additional temporary actions they can take to maintain objectives. The $500 million threshold for implementation regret reflects that planners are likely willing to over-invest by a larger margin to meet these objectives. These thresholds were effective at separating futures that largely had zero (or extremely close to zero) regret from those that had larger amounts. Other thresholds were explored, and the ordinal rankings of strategies and trends discussed below were largely similar.

Figure 6-12 shows the percent of futures with low regret by long-term average streamflow conditions for some candidate strategies. Each line represents an alternative strategy. It only presents the Current Management, Baseline, Aggressive and Static Implement-All-Actions strategies as representative examples. Each point on the line represents the percentage of futures with low regret, for futures within an interval of one maf of long-term average streamflow. The top panel shows results for the Upper Basin and the bottom panel shows results for the Lower Basin.
Figure 6-12: Percent futures with low regret by streamflow conditions

The two static strategies each represent an extreme tradeoff. In the Lower Basin, the Current Management has the highest percentage of futures with low regret when long-term average streamflow is greater than 15 maf, but consistently does not have low regret when long-term average streamflow is less than 14 maf. On the other hand, the Static Implement-All-Actions strategy is consistently a low-regret strategy when long-term average streamflow is less than 13 maf, but rarely a low regret strategy when long-term average streamflow is greater than 15 maf. A similar pattern holds in the Upper Basin, as the two static strategies are most frequently low-regret near the extremes.

The two adaptive strategies shown on this figure are more balanced. In the Lower Basin, the Aggressive adaptive strategy has a slightly smaller percentage of low-regret futures than the Static Implement-All-Actions strategy in the driest conditions. Similar to the Static Implement-All-Actions, the percentage of futures with low regret decreases as conditions become wetter until streamflow is less than 16 maf. Above 14 maf, the percentage of futures that are low-regret begins increasing again, as fewer trigger values are observed and fewer actions are implemented. The Baseline adaptive strategy is similar, but has more low-regret futures in wet conditions relative to the
*Aggressive* strategy than dry conditions. It more closely resembles the *Current Management*. A similar pattern also holds in the Lower Basin.

The strategies shown in this figure suggest there is not one optimal approach. If planners are confident they will face the driest conditions, the *Static Implement-All-Actions* strategy offers a low-regret approach. If planners are confident they face the wettest conditions, the *Current Management* appears adequate. The two adaptive strategies form a hedge, serving as form of robustness, with a more balanced number of low-regret futures across the range of streamflow conditions. However, there are still tradeoffs between the two adaptive strategies.

**The relationship between regret and decadal variation of streamflow**

Other characteristics of a hydrologic sequence, in addition to long-term average natural streamflow, can also influence whether or not a strategy will turn out to be low-regret in a particular future. This analysis reveals that the standard deviation of eight-year rolling average streamflow, a measure of the decadal variability, is also an important determinant.

The vulnerability analysis for water delivery objectives, presented in Chapter 4, suggests that decadal observations of streamflow are important drivers of outcomes in the Basin. The system is designed to store excess supply to last nearly a decade of shortage and a Lees Ferry deficit is calculated using a rolling ten-year average; therefore are decadal streamflow is an important driver of outcomes in the Basin.

The relationship between decadal variation and the comparative performance among strategies is complex. The boundary between low-regret and high regret strategies is an upward sloping relationship between decadal variation and average annual streamflow. When conditions are relatively dry, a strategy is more likely to under-invest in low variance futures than high variance futures. On the hand, when conditions are relatively wet, a strategy is more likely to over-invest in high variance futures than in low variance futures.

Figure 6-13 presents the effect of the standard deviation of the eight-year rolling average on Lower Basin regret, respectively. Each point on the graphic is a different future, plotted by its long-term average natural flow (x-axis) and the standard deviation of the eight-year rolling average (y-axis). Gray circles represent futures where a particular strategy has low regret and red X’s represent futures where the strategy does not. The red shaded region represents a set of conditions that have high density and coverage of high-regret futures. This figure shows the *Current Management, Baseline, Aggressive* strategies, and *Static Implement-All-Actions* strategies. The graphic demonstrates a clear relationship between standard deviation and long-term average streamflow among the futures with vulnerability, with the upward slope of red points, for each strategy (though the threshold values and exact slopes are different). A similar relationship also holds in the Upper Basin.

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63 Identified using a modified version of PCA PRIM.
Figure 6-13: Lower Basin low-regret futures by streamflow conditions

<table>
<thead>
<tr>
<th></th>
<th>Current Management</th>
<th>Baseline</th>
<th>Aggressive</th>
<th>Implement-All-Actions</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD &gt; (AVG-14.2 maf)*3</td>
<td>SD &lt; (AVG-10.5 maf)*4 &amp; SD &gt; (AVG-14.1 maf)*2</td>
<td>SD &lt; (AVG-13.5 maf)*8 &amp; SD &gt; (AVG-15.2 maf)*1</td>
<td>SD &lt; (AVG-12.1 maf)*2</td>
<td></td>
</tr>
<tr>
<td>Density: 87%</td>
<td>Density: 60%</td>
<td>Density: 93%</td>
<td>Density: 94%</td>
<td></td>
</tr>
<tr>
<td>Coverage: 91%</td>
<td>Coverage: 94%</td>
<td>Coverage: 90%</td>
<td>Coverage: 97%</td>
<td></td>
</tr>
</tbody>
</table>

64 The following table presents the boundaries of the shaded region. (SD = standard deviation of eight-year rolling average; AVG = annual long-term average)
Figure 6-14 presents two example traces, which illustrate why this relationship between decadal variation and average annual streamflow exist. It presents the *Aggressive* strategy in two plausible time series of future streamflow. Neither of these futures experience Lake Mead dropping below 1000 feet with the *Current Management* of the system. The top panel shows Lake Mead pool elevation and indicates whether a trigger value is observed or not. The bottom panel shows the eight-year running average streamflow. Both futures have similar long-term average streamflow, but the future on the left has streamflow with low decadal variation and the future on the right has high decadal variation. The low-decadal-variation future does not observe any trigger values and implements no actions. The high-decadal-variation future experiences some years with low streamflow and reservoir levels and implements actions. However, streamflow is sufficiently high that Lake Mead never drops below 1,000 feet and objectives are always met.

*Figure 6-14: Low decadal variation and high decadal variation streamflow futures*

In these futures, streamflow is relatively high and Lake Mead’s pool elevation never drops below 1,000 feet. In the low variation future, the eight-year rolling average streamflow is consistently between 15 and 20 maf. Planners would never be concerned that Lake Mead’s elevation is likely to drop below the threshold. In the high variation future, the eight-year rolling average streamflow is
between 12 and 15 maf between 2020 and 2030. Without knowing what is coming in the future, planners may reasonably be concerned that streamflow will stay within this range and the Lower Basin is at risk. With the Aggressive strategy, streamflow and reservoir levels are sufficiently low such that planners implement action. These actions are ultimately unnecessary as streamflow recovers and remains above 15 maf over the rest of the planning horizon. If planners could reliably forecast the next decade of streamflow, rather than simply rely on past observations, they could more accurately anticipate this recovery and avoid the investments between 2020 and 2030.

This relationship suggests a more robust adaptive strategy would account for decadal variation in streamflow. This vulnerability illuminates that many futures considered in this analysis contain a more complex hydrology than simply increasing or decreasing streamflow trends. Many individual futures include a period where streamflow increases and other periods where it decreases; observing a dry decade is not necessarily a guarantee that the next decade will also be dry. The strategies analyzed in the Basin Study and dissertation rely the fact that relatively low streamflow in puts the Basin at larger risk as the reservoirs have emptied. They also reflect some degree of indication streamflow will continue to be low the future. However, the strategies perform relatively poorly in the futures where there are decades that differ from this.

Other indicators could help planners identify whether these observations are signs of further declines or a simply a temporary condition. If planners could integrate forward-looking projections of streamflow—for example from decadal climate projections (described in Chapter 5), they may be able to better anticipate whether subsequent decades require a different course of action. If strategies can successfully integrate better forward looking projections, the tradeoffs between over-investment and under-preparedness would decrease.

**Weighing the cost-reliability tradeoffs**

As the previous sections have suggested, Basin planners face a tradeoff when determining how best to respond to new information during the adaptive process. If they act aggressively, they will meet water delivery objectives in many futures, but also over-invest in many others. On the other hand, if they act conservatively to keep costs low, they will not implement sufficient actions to meet objectives in many futures. How planners choose to balance these two risks will depend on their own preferences between the outcomes and their expectations of the future. This section presents trade-off curves, allowing planners to understand the relative tradeoffs between these two risks, and explore across multiple subjective beliefs about the future.

**Tradeoffs across the ensemble of futures**

Figure 6-15 shows the tradeoff between over-investment and under-preparedness across the candidate strategies, for the entire ensemble of futures. The vertical axis represents the percent of futures in which a strategy fails to meet water delivery objectives—non-zero vulnerability regret. The horizontal axis shows average implementation regret across each future. Each point represents one candidate strategy. The top panel shows results for the Upper Basin and the bottom panel shows results for the Lower Basin.
Figure 6-15: Curves presenting the tradeoff between over investment and under preparedness across all futures

This figure clearly illustrates the tradeoff described in previous sections. The more aggressive strategies have a meeting objective in more future, but come with increased average implementation regret. On the other hand, the less aggressive strategies invest in lower magnitudes of unnecessary action, but present planners with an increased likelihood of failing to meet objectives. The downward slope between the strategies represents this tradeoff.

If planners are willing to make an assumption that each future is equally likely (an assumption that will explored further in subsequent sections), the vertical axis can be considered the likelihood of meeting objective and the horizontal axis measures the expected implementation regret. Planners can identify the strategy with outcomes that are most consistent with their preferences. If they wish to maximize the likelihood of meeting objectives and are insensitive to cost, they would choose the Static Implement-All-Actions strategy. However, they may identify that they can achieve most of the benefit of this strategy with significantly lower expected costs with the Very Aggressive strategy. However, if they are sensitive to over-spending, planners may prefer a more conservative strategy.

In the Upper Basin, some strategies nearly dominate others, represented by relatively flat points on the tradeoff curve. For example, the Moderately Aggressive strategy creates only a small increase in
the likelihood of meeting objectives when compared to the *Baseline* strategy (18 to 16 percentage points). To achieve this reduced risk, the strategy carries a high increase in expected implementation regret ($0.3 billion to $0.9 billion). In this relatively flat range of the tradeoff curve, unless planners are willing to risk a lot of over-investment for a small decrease in failing to meet objectives, they would likely prefer the *Baseline* to either *Moderate* or *Moderately Aggressive* strategy.

In the Lower Basin, the strategies tradeoff more smoothly and they trace a convex curve. This convex curve represents diminishing marginal returns to expected implementation regret. As the strategies become more aggressive, planners risk marginally more implementation regret for the same increase in the likelihood of meeting water delivery objectives. At the conservative end of the continuum, planners can decrease the likelihood of failing to meet objectives from 54 percent with the *Current Management* strategy to 48 percent with the *Baseline* strategy, while increasing their expected implementation regret by only $100 million. For a similar decrease between the *Very Aggressive* and *Static Implement-All-Actions* strategy (16 percent to 11 percent likelihood of failing to meet objectives), expected implementation regret increases from $1.9 to $4.2 billion.

**Tradeoffs dependent on decision-relevant scenarios**

When addressing climate change, planners are faced with deep uncertainty about the future and stakeholders may reasonably disagree about the likelihood of different future conditions occurring. Though the previous analysis presented an interpretation assuming each future is equally likely, the ensemble of futures is not designed to represent any credible probability distribution. It does not represent a scientific assessment of the likelihood of the various futures, nor does it necessarily represent any stakeholder beliefs. Thus, the analysis presented in the assumption that all futures are equally likely is an over-simplification of a deeply uncertain future.

To examine how the tradeoffs vary in different sets of future conditions, this section uses the decision-relevant scenarios described in Chapter 4. These scenarios reveal the tradeoffs among the strategies vary between different future scenarios. Figure 6-16 shows the same tradeoff curves as above focusing on the Lower Basin, but partitions the futures by the various decision-relevant scenarios.\(^{65}\)

\(^{65}\)Futures are weighted equally within the scenario. Other weighting could be explored at this point.
Figure 6-16: Tradeoff between over-investment and under preparedness for the decision-relevant scenarios in the Lower Basin

To consider the tradeoffs among strategies, one can weight each future as equally likely within the scenario, without making any assumptions about the likelihood of the scenario occurring. Using this approach, the percent of futures that fails to meet objectives can be interpreted as a conditional likelihood and then the average implementation can be interpreted as an expected value.

There is a relatively small range of performance among the strategies in the driest scenarios. Even the most aggressive strategies have a low likelihood of meeting water delivery objectives. Within this range, the more aggressive strategies nearly dominate the conservative strategies. They have a higher likelihood of meeting objectives, but all strategies have similar risks of over-investment. If planners believe this scenario is highly likely, the Static Implement-All-Actions or Very Aggressive strategies bear little risk.

In the wettest scenarios, the more aggressive strategies only add cost with little increase in the likelihood of meeting objectives. Even the most conservative strategies have little risk of failing to meet water delivery objectives; the marginal benefit of implementing an aggressive strategy is close to zero. However, these aggressive strategies increase the risk of over-investment significantly. If planners believe this scenario is highly likely, they will prefer to implement the most conservative strategies.

The strategies only truly tradeoff with one another in the middle scenarios, Low Historical Supply conditions in the Lower Basin. Moving from the Baseline strategy to the Very Aggressive strategy decreases the likelihood of failing to meet water delivery objectives from 69 percent to 12 percent. However, the Very Aggressive strategy generates $1.7 billion in expected implementation regret as

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66 Other weighting schemes can also be considered
compared to $100 million implementation regret with the Baseline strategy. Planners are faced with a convex curve in this scenario. If planners are preparing for these scenarios, they must deliberate based on preferences between expenditures and water delivery reliability.

This result also suggests that planners may wish to change decision-rules over time if their beliefs about the scenarios change. For example, planners may wish to respond to new information using moderate decision-rules, to act as a hedge between over-investment and under-preparedness. However, if an evolving climate literature suggests Severely Declining Supply conditions are becoming more likely, planners may wish to switch to trigger values that are more aggressive.

**Tradeoffs across different expectations of the decision-relevant scenarios**

When planners make choices among the various strategies, they do not know with certainty which scenario will occur. Additionally, they face deep uncertainty about the likelihoods of these scenarios and cannot credibly estimate each scenario’s likelihoods. Thus, planners face tradeoffs among the strategies. If they believe the wetter scenarios are likely, they will wish to act conservatively and if they believe the drier scenarios are likely, they will wish to act aggressively. Planners must determine the rate at which they wish to prepare for the dry scenarios and the cost they are willing to accept in the wet scenarios to do so. Additionally, within the middle scenarios, they must determine which strategy is most consistent with their own preferences between over-investment and under-preparedness. This analysis examines the tradeoffs among strategies across multiple plausible expectations of the decision-relevant scenarios.

Figure 6-17 presents the tradeoffs between over-investment and meeting reliability objectives for multiple subjective beliefs about the decision-relevant scenarios in the Lower Basin. Each curve, demarked by its color, shows one set of plausible subjective likelihoods of decision relevant scenarios.\(^67,68\) Each point on the curve represents a different strategy, demarked by a symbol.

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\(^67\) Within each scenario, all futures are weighted equally.

\(^68\) This graphic becomes complicated when too many subjective beliefs are shown. Therefore, it only shows a small number of plausible subjective beliefs. Interactive visualizations can allow planners to explore alternative sets of beliefs.
Figure 6-17: Tradeoffs between over-investment and under preparedness based on different subjective beliefs

This figure suggests that when planners believe the wet scenarios are more likely, they can expect lower risk of failing to meet objectives, but higher risk of over-investment. Stationary or Increasing Supply conditions are associated with a high likelihood of meeting water delivery objectives (greater than 90 percent). However, if Low Historical Supply conditions are 50 percent likely, the probability of failing to meet objectives ranges from between 44 percent and 3 percent, depending on the strategy planners implement. Additionally, as the probability of Declining Supply conditions increases, expected implementation regret decreases for each strategy.

Figure 6-18 presents another view of these results. It explores the range of subjective probabilities of decision-relevant scenarios in the Lower Basin in greater detail. Each point in each triangle represents a different set of plausible future beliefs. The horizontal axis represents the subjective likelihood of Severely Declining Supply conditions; the vertical axis represents the subjective likelihood of Stationary or Increasing Supply. When the sum of these values does not equal 100 percent (not on the diagonal boundary), the difference is the subjective likelihood of Low Historical conditions. Points closer to the origin have higher likelihoods of this scenario. The color of each point represents an expected result for the set of beliefs shown on the axis. The upper panel shows the likelihood of failing to meet water delivery objectives. As a guide, the shape of the point indicates whether there is a greater than 80 percent chance of meeting water delivery objectives. The lower panel presents expected implementation regret. Each vertical panel presents a different strategy: Current Management, Baseline, Aggressive, and Static Implement-All-Action.
These results show a clear tradeoff between the likelihood of failing to meet objectives and expected implementation regret across different beliefs about the future. The Baseline strategy has low expected implementation regret across the entire range. On the other hand, this strategy experiences a relatively high rate of failing to meet water delivery objectives across a wide range of beliefs. As Severely Declining Supply conditions increase in likelihood, the expectation of failing to meet water delivery objectives increases up to 10 percent. There is only a greater than 80 percent chance of meeting water delivery objectives with this strategy when the Stationary or Increasing Supply scenario is greater than 80 percent likely.
The *Aggressive* strategy has different implications. It has a much lower likelihood of failing to meet objectives across a range of beliefs. The likelihood of meeting water delivery objectives is greater than 80 percent even when the *Stationary or Increasing Supply* scenario has no chance of occurring, so long as the *Severely Declining Supply* scenario is also unlikely. However, expected implementation regret is greater than $1 billion unless the *Severely Declining Supply* scenario is at least 30 percent likely.

Figures similar to 6-16, 6-17, and 6-18 could be generated in the Upper Basin. In general, they present similar results.

Planners must balance this tradeoff as they make decisions in response to new information. One way planners can choose among the strategies is to set a threshold on the expected likelihood of achieving water delivery objectives. For example, they may decide they will bear the expense to ensure there is an 80 percent chance of meeting objectives. They can then identify the lowest cost strategy that meets those objectives.

Figure 6-19 presents the lowest cost strategy that has an 80 percent likelihood of meeting water delivery objectives in the Lower Basin across a range of plausible beliefs. The axes are the same as Figure 6-18, representing the likelihood of the decision-relevant scenarios. Each point is colored by the strategy with the lowest expected implementation regret that has an 80 percent chance of meeting objectives. The size represents the expected implementation regret of the strategy. The black circles represent sets of beliefs where no strategy can meet objectives, but presents the expected implementation regret for the *Static Implement-All-Actions* strategy.
This figure suggests that if planners believe the SevereDecliningSupply scenario is more than 30 percent likely, they cannot achieve an 80 percent likelihood of meeting their objective, regardless of strategy. When conditions are less severe, they can choose among the strategies. If planners are confident the LowHistorical, Stationary, or IncreasingSupply scenario is 80 percent likely, the CurrentManagement performs satisfactorily. The Aggressive strategy performs well for the widest range of beliefs. It does well when planners either believe the LowHistorical scenario is between 50 and 100 percent likely or the SevereDecliningSupply scenario is not likely. It also performs well
when the *Severely Declining Supply* scenario is between 10 and 30 percent likely and the *Stationary or Increasing Supply* scenario is between 50 and 80 percent likely.

Figure 6-20 presents similar results in the Upper Basin.

*Figure 6-20: Lowest implementation-regret strategy with at least 80 percent likelihood of meeting water delivery objectives (Upper Basin)*
Policy implications of simulations and analysis

This analysis has important implications for how the Colorado River Basin enacts policies and adapts to address the threat of climate change over the next half century. The following section summarizes these implications and provides policy recommendations.

Different futures require different water management actions. No static strategy will provide sufficient levels of resilience across the range of plausible future conditions without over-investing in many other futures. Planners’ ability to distinguish whether the future will be wet or dry is critical to ensuring that water delivery objectives are met at low cost. The Basin can achieve most of the benefit of water-management actions by incrementally investing as evidence of dry conditions begins to mount, while avoiding costs if they are unnecessary.

Even simple signposts and triggers can have success in addressing long-term challenges. The Basin has long been using observations of reservoirs and streamflow to manage the operations of the Basin and allocate water during shortage. Basin planners can use reservoir levels and streamflow to consider the timing and implementation of long-term infrastructure and conservation actions in the Basin. These signpost variables perform adequately to help distinguish the wettest futures from the driest futures. Planners may track these indicators to inform future deliberations.

However, these simple signposts and triggers are imperfect. Planners face risks when acting adaptively and must consider tradeoffs amongst those risks. If they are overly cautious, they may not be able to sufficiently address climate change. Thus, adaptively responding to climate change cannot mean indefinitely deferring water management actions or requiring overwhelmingly strong evidence. To increase resilience to the driest futures, actions may need to be implemented under seemingly ordinary conditions. On the other hand, planners should be aware that acting aggressively risks increasing costs and investing in futures where it is not necessary. Should planners act on too little evidence, they risk over-investing during the wettest futures to the order of billions of dollars per year.

The preferred responses to new information depend on planners’ beliefs about the long-term future conditions. If planners are confident that supply is severely decreasing, they should implement actions after observing reservoir levels and streamflow that are within the normal bounds of operations as large investments in water management actions are necessary to increase resilience. In these futures, there is little risk of over-investing. On the other hand, if planners are confident that supply is stationary or increasing, there is little need for action. Planners can safely not invest in action or only invest in actions after observing the driest years. If planners in the Upper Basin believe streamflow conditions are declining, they can address water-delivery shortages by acting adaptively, but must confront tradeoffs in the face of imperfect information. The same is true for conditions slightly below the recent historical record in the Lower Basin. Because planners can have divergent subjective beliefs about the future, they may disagree on how best to respond to new information. However, the analysis provided in this dissertation can help inform planners the scale of these tradeoffs as they seek to identify an adequate solution.
If planners commit to a set of decision-rules a-priori, consistent with fully-automatic policy adjustment, these decisions must be based on their current beliefs— the priors discussed in Chapter 5. Planners will thus seek a set of triggers that performs adequately well across the range of stakeholder beliefs, which the analysis in this chapter is designed to help inform. After committing to the set of decisions-rules, the subsequent monitoring and implementation defines how planners would incrementally update their beliefs and act accordingly.

Planners should also look to other information, beyond reservoir levels and streamflow, to inform their expectations of the future. They can look to an evolving literature on climate change. If planners have opportunities to revise their adaptive strategies, they may change their decision-rules over time. While the indicators based on streamflow and reservoir levels considered in this chapter encapsulate the Bayesian updating that would occur from observing streamflow, the other exogenous indicators described in Chapter 5 are not incorporated. An additional analysis revealed that in the near-term, it might be more effective for planners to respond aggressively to new information. Because planners are constrained in the actions they can take in the near-term, there is not a risk of over-investing by too much during the first decades of the planning horizon. Then, if evidence suggests that the future is not drying, the can become more conservative at this point.

Additionally, more research should continue to develop sophisticated indicators to reliably classify the future and identify water management actions, including the decadal variation in streamflow. It may require sustained investments in improving decadal forecasts of climate and streamflow. Planners can install processes to monitor and interpret complex hydrological relationships to inform better decisions, and reduce the tradeoffs among strategies.
Chapter 7: Implementing water management actions while adapting in the Colorado River Basin (implementation)

Introduction: Considering the choices among water management actions
The previous chapter of this dissertation examines a set of adaptive strategies that are defined primarily by a choice among the decision-rules that planners can use to implement actions. These strategies are modeled in CRSS; they rely on assumptions about the information available, planners’ ability to commit to decision-rules, and the speed at which actions can be implemented. If the Basin adapts through a process of fully-automatic policy adjustment, these definition of adaptive strategies may be sufficient representations of the adaptive process.

However, the adaptive process is likely to be more complex. In the Colorado River Basin, adaptation is likely to occur through a process of continued deliberation and analysis. Planners’ decisions may be influenced by other pieces of information beyond observations of streamflow and reservoir levels. For example, they may incorporate an evolving climate literature. Additionally, some actions require years of planning and cannot simply be implemented when a decision-rule of the form modeled in the previous chapter requires. The decision-rules presented in the previous chapter may be too specific to fully define the adaptive strategy in the Basin going forward.

Information from the specific modeling results presented in Chapter 6 can be summarized into more generalizable decision-aids. Such aids can help planners consider the choices among implementing various water management actions. This chapter presents summaries of which actions are implemented and when they are implemented across the ensemble of futures. Recognizing that different streamflow conditions require different policy responses, it presents decision-relevant scenarios specific to the choices planners face about implementing actions.

These decision-aids can help basin planners frame an adaptive strategy not as a choice among decision-rules but as a choice among actions. Instead of asking, “what decision-rules should planners use to respond to observing low-streamflow and reservoir levels?”—a planning question framed around the response to new information, this analysis answers “what actions should be implemented under which conditions?”—a planning question framing the decision about specific actions.

These two policy questions are closely related. Within the simulation model, the decision-rules are the representation of how planners make decisions about those actions. However, in a continued
deliberations process, planners may not make decisions in the exact way that they are modeled. Solely answering the first question, as was addressed in Chapter 6, may have limited interpretability. Answering the second question will allow planners to consider their plans and the tradeoffs among alternatives at a higher level.

The objective of this analysis is to understand which water management actions are necessary across a wide range of plausible future, the specific conditions which require certain actions, and the timing of those actions. This chapter therefore considers the following policy questions:

- What is the total yield of actions that the low-regret adaptive strategies implement across futures? What are the exogenous streamflow conditions that require different yields?
- What opportunities will planner have to adjust, alter, or change implementation as information about conditions unfolds over time?
- Contingent on these conditions, which individual water management actions should planners implement in the near term, and which actions can be deferred until later?

The chapter iterates through a three-step process to answer these policy questions. The process is described summarized in Figure 7-1 below.

*Figure 7-1: A three-step process for characterize the choice among water management actions in an uncertain future*

In the first step, this chapter presents an alternative interpretation the simulated strategies. The simulated adaptive strategies help identify the set of actions required to meet water delivery objectives at the approximate lowest cost in each future—the low-regret strategies. This chapter first characterizes which water management actions comprise the low-regret strategies at a high level, the total yield implemented in each future.
Next, this chapter identifies the streamflow conditions that require similar low-regret strategies. It presents decision-relevant scenarios, which summarize the streamflow futures that implement similar yields of water management actions. These implementation scenarios can serve as the basis for considering which level of yield is necessary.

In the next step, water management actions are summarized across time, contingent on the implementation scenarios. The distribution of yield implemented over time is summarized in a visualization that resembles a roadmap. This map describes the multiple pathways planners may take to scale up the implementation across decades. It shows how planners may prepare for specific scenarios and when they will have opportunities to alter their. Next, it considers individual actions. It identifies those that need to be implemented in the near-term and those that can be deferred, in each scenario.

Imbedded in this process is a proposed hierarchy for how planners can consider the many implementation decisions they face. The first level is a system-wide approach, where planners consider the total yield of actions necessary to meet their water management objectives by the end of the planning horizon. This decision can be informed by their subjective beliefs about the long-term streamflow conditions that require certain levels of yield. Planners also consider the rate at which to implement this yield over time. At a second level, planners consider the individual water management actions that comprise a strategy. In particular, they may consider which of these actions should be implemented in the near-term—the candidate initial actions—and which can by reasonably deferred—the contingencies.

**Characterizing low-regret implementation strategies**

**Interpreting simulations results as quasi-optimized implementation schedules**

The analysis in the chapter first identifies the lowest cost set of water management actions that meet water delivery objectives in each individual future. Identifying these sets actions will facilitate an analysis of the commonalities and differences among implementation and timing of actions across many futures.

In complex hydrologic systems, identifying the lowest cost set of water management actions to meet a planning objective can be a difficult analytical task. Such systems have memory between time steps, are non-linear (both in the hydrological relationships and in operating rules that manage a system), and supply and demand have annual variation. Thus, the gap between supply and demand in given year may deviate from the average annual difference between average supply and average demand. Thus, it can difficult to estimate the total yield of actions necessary to meet objectives—the gap.

Even once the total volume of actions necessary is calculated, there may be multiple ways to add supply or reduce demand to fill the gap. For example, there may be a particular future where Lake Mead drops below 1000 feet in 2050 and would require an additional 500 kaf of supply in that year.
to ensure it stays above that threshold level. Even knowing this, it unclear whether the Basin should implement 500 kaf of water management actions in 2050, just in time, or a single water management action in 2045 that provides 100 kaf per year. This would depend on the costs associated each action as well as operations of the system—whether the additional water could be stored.

Over the course of a simulation, planners may have options to implement many actions, each of various size, scale, cost and availability. The simulation may also reveal multiple years with shortages of various magnitudes to address. In such a case, the decision becomes even more complicated. Is it best to implement a small number of available actions early, even if they are high cost, or should planners scale up just in time to meet the deficit? Even assuming perfect foresight, identifying the cheapest set of water management actions to ensure delivery objectives would require testing many possible solutions in a simulation model that captures the relevant complexities of the system.

Dynamic-programming optimization routines could search the space of plausible actions until converging on a set of actions that meets constraints for minimum cost in each future. However, such routines often require long run-times, iterating many times until converging. However, the compute times associated with a single run of CRSS (approximately three minutes per sampled future) imply such rigorous optimization routine could decrease the ability to explore a wide range of plausible futures.

Instead, the simulated adaptive strategies presented in the previous chapter offer the means to identify a low cost set of actions that meet objectives—the zero-regret strategies. The analysis uses two mechanisms to find this “optimal” set of actions—one that meets water delivery objectives for the lowest possible cost—in each future. First, decision-rules serve as simple search heuristics within each simulation, increasing the yield of actions implemented as conditions require. A second post-processing analysis compares the actions implemented in each of the candidate decisions-rules to identify lowest cost set of actions that meet water delivery objectives in each future. As these strategies are only approximately optimal, they can be considered quasi-optimized strategies.

First, within a given simulation, the decision-rules are designed to distinguish wet futures from dry futures and incrementally implementing actions as necessary. They rely on short-term observations of average streamflow to implement actions after a dry period that may be precursor to failing to meet objectives while refraining from implementing actions after a wet period. The decision-rules monitor reservoir levels, identifying when the actions have sufficiently altered the system and led to a recovery from any threat of failing to meet the objectives.

These decision-rules serve as simple search heuristics, using information in the simulation model to assess the needs of the system in a particular future and implementing the appropriate actions to address those needs. However, individually, each decision-rule relies on somewhat inaccurate indicators and they can over-invest with a Type-I error and under-invest with a Type-II error. Because each is somewhat prone to error, this analysis tests multiple candidate decision-rules.
A secondary, post-processing analysis identifies the set of implemented actions from the candidates with the lowest cost that achieves various objectives for each individual future. The quasi-optimal strategies are not defined by a single consistent set of decision-rules in all futures. Instead, this is the perfect foresight strategy among the candidates tested in the previous step, and an approximation set actions that planners would choose if they had perfect information.\textsuperscript{69}

This analysis produces a low-cost set of actions that meet water delivery objectives in each future (if such a set of actions exists), the low-regret strategy. For example, if the low-regret strategy in a particular future implements no actions, then no actions are necessary to meet the objectives. In another future, the low-regret strategy may consist of 200 kaf of municipal and industrial conservation implemented in 2020, an additional 200 kaf of municipal and industrial conservation and 200 kaf of agricultural conservation implemented in 2025, and a new desalination plant providing 300 kaf of yield brought online in 2030. This schedule of implementation would represent the cheapest set of actions among the strategies explored in the previous chapter that meet the water delivery objectives. This should also serve as a near approximation of the best way to avoid water vulnerability in that particular future.

However, a database containing low-regret set of actions for each sampled future is of limited utility to planners—there are a large number of plausible futures, each with a potentially different set of water management actions. To provide useful summaries of implementation, it is necessary provide numerical and statistical characterizations the actions implemented across the ensemble of futures.

\textsuperscript{69}This quasi-optimization approach used in this analysis is admittedly simple. The approach attempts to balance the tradeoffs among the complexity of a model, the range of future conditions considered, and the rigor of the optimization routine. This optimization approach uses the modeling infrastructure that was in place during the Basin Study. Despite the simplicity of this quasi-optimization routine, the policy questions explored in the paper may be of sufficiently low resolution that the optimization routine is appropriate. The policy questions in this paper are focused on identifying level implementation yield within 1 maf, or the decade in which a specific action is implemented.

When compared to the implementation characterizations presented in the Basin Study, the quasi-optimization routine described in this analysis provides a second level of consideration before implying an action is an important element to a strategy. The Basin Study did not consider multiple decision-rules, and an action was considered necessary only if it was implemented by the single adaptive strategy. However, this meant that no consideration was given to whether that set of actions met objectives in a particular future, or if there was any cheaper alternative. The quasi-optimization routine in this analysis considers multiple decision-rules. It ensures that portfolio implemented actions meets objectives in a particular future, and does so at the lowest cost of the considered alternatives. While the quasi-optimization routine may not rigorously search the entire set of feasible actions to avoid vulnerability, it represents a marginal improvement to the approach used in the Basin Study.
Multiple characterizations of low-regret strategies are presented throughout this chapter. It begins by charactering the total yield of actions implemented across futures to meet objectives. Using scenarios derived from these high-level strategies, it next describes the multiple pathways planners may follow to increase yield over time. Finally, the chapter breaks these high level considerations of total yield into a number of smaller decisions about the individual water-management actions that comprise a strategy. It provides some decision-aids to support deliberations about these actions.

**Characterizing total yield of actions across ensemble of futures**

A first analysis characterizes the portfolio of implemented actions by their total yield. It uses the two measures of yield implemented as described in Chapter 4: one for the Upper Basin water delivery and one for the Lower Basin. It demonstrates that different yields are necessary in different futures to meet objectives, and characterizes the yield implemented by different future conditions. Figure 7-2 presents box plots, which summarize distribution of Upper Basin and Lower Basin yields for low-regret strategies across the ensemble of futures (by the decision-relevant scenarios defined in Chapter 4). The top panel shows the implemented yield for the Upper Basin and the bottom panel shows results for the Lower Basin.

*Figure 7-2: Box-plots representing distribution of yield implemented by low-regret strategies across decision-relevant scenarios*

In the **Severely Declining Supply** conditions, the low-regret strategies implement near the maximum potential yield from the available options. This is demonstrated with a box-plot that is condensed
near the top of the axis. Note that for most futures, even implementing the maximum yield by 2060 would not eliminate vulnerabilities. So this analysis assumes that the options available in the Basin Study are all that would be possible. In futures in the wettest conditions (Low Historical, Stationary, or Increasing Supply for the Upper Basin and Stationary or Increasing Supply for the Lower Basin), the current management of the system frequently meets water delivery objectives, and low-regret strategies frequently implement no additional yield.70

In Declining Supply conditions in the Upper Basin and Low Historical Supply conditions the Lower Basin, different futures require different yields of actions to meet objectives. In the Upper Basin, the distribution is weighted towards the maximum potential yield; low-regret strategies implement greater than 2.5 maf in 50 percent of futures and greater than 1.5 maf in 75 percent of futures. In the Lower Basin, low-regret strategies implement yield spanning a wider range, with a median implementation of 3.4 maf.

To provide closer examination of the yield required in different future conditions, Figure 7-3 provides a summary of Upper Basin yield implemented by low-regret strategies across futures with different streamflow conditions. The vertical axis shows the long-term average streamflow (2012-2060) and the horizontal axis shows the mean annual flow during the driest eight-year period. Each circle is a summary of futures with similar streamflow conditions, aggregating futures within 500 kaf in each dimension. For example, the circle in the bottom left, at 10 maf on the vertical axis and 7.5 maf on the horizontal axis, summarizes all futures where average annual streamflow is between 10 maf and 10.5 maf over the entire planning horizon and between 7.5 and 8 maf during drought periods. The circles are labeled with 75th percentile of Upper Basin yield for low-regret strategies (also represented with color).71 This figure also demarks the definitions of the decision-relevant scenarios.

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70 Recall that these scenarios are decision-relevant scenario designed by PRIM. The scenarios have a density of less than 100 percent. Thus, the definition of the Severely Declining Supply scenario describes some futures where water delivery objectives can be met with less than the full set of actions. Similarly, the Stationary or Increasing Supply scenario contains some futures that fail to meet objectives unless actions are taken. Both these results are relatively rare, but account for the outlier points in Figure 7-2.

71 The 75th percentile is presented to provide a summary statistic at the higher end of the distribution of implemented yield, recognizing that planners likely have a preference to avoid failing to meet water-delivery objectives and risk over-investment than to risk being under-prepared. Interactive versions of these graphics can allow users to explore other summary statistics.
Figure 7-3: Summary of yield implemented by low-regret strategies across streamflow futures (Upper Basin)

This figure demonstrates that different yields of actions are necessary to meet objectives in different future streamflow conditions. Low-regret strategies frequently implement the maximum potential yield in Severely Declining Supply conditions and zero yield in Low Historical, Stationary, or Increasing. Futures with greater streamflow conditions and less severe droughts require less total yield. In much of Declining Supply conditions, low-regret strategies frequently implement near the maximum potential yield.

Figure 7-4 presents a similar representation of yield implemented for the Lower Basin. No actions are necessary in the wettest future and the maximum potential yield is necessary in the driest futures. This figure shows that futures in the Low Historical Supply conditions do not necessarily require full implementation to avoid vulnerability. However, the required implementation increases quickly as conditions degrade. For example, in futures with an 8-year drought period with average flow of 11.0 maf, no yield is necessary when long-term average streamflow is above 15.0 maf. However, if streamflow drops by 500 kaf to 14.5 maf, 3.8 maf of new additional yield is necessary if necessary to meet objectives.

This result serves to highlight why the quasi-optimization routine described previously is necessary. Without testing multiple strategies of various yields, planners may naively assume they
need an additional 500 kaf to meet objectives, when this analysis suggests a larger quantity of yield would be necessary.\textsuperscript{72}

\textit{Figure 7-4: Summary of yield implemented by low-regret strategies across streamflow futures (Lower Basin)}

These figures provide planners with a clear demonstration that different yields of water-management actions are required in different futures to meet water delivery objectives. The required yields are closely related to the long-term average streamflow and the streamflow in the driest 8-year period from 2012 to 2060. However, planners cannot determine with certainty which future will occur, and which level of streamflow they should prepare to address.

\textsuperscript{72} There are multiple reasons for this effect. First, these figures present the total yield implemented by 2060, not the average annual yield over the course of a simulation. A future may be 2 maf below the long-term average over the course of simulation. Even if a strategy implements 4 maf of yield by 2060, it may not implement an average 2 maf per year over the course of a simulation, and the system may be operating at a deficit.

Additionally, if storage has been generally depleted by a low long-term average streamflow, one extremely dry year may cause the strategy to fail to meet objectives. The yield provided by water management actions may need to compensate for the driest years rather than the long-term average. Planners may need to address the gap in the driest years, similar to a safe-yield analysis, rather than plan to address the averages. Increasing demand may exacerbate this issue. After these Upper Basin and Lower Basin water delivery objectives were met, if excess yield was stored in reservoirs, the system would have more resilience to the driest year. Instead, some of this excess yield is allocated to meet demands above what is allocated by the Law of River and storage does not increase at the same rate as the yield.
Each future has a precise yield of water management actions necessary to implement by 2060 in order to meet water delivery objectives. However, when faced with uncertainty in future hydrologic conditions, planners may not be able to predict the precise yield that would meet objectives in that future. Instead, they will look for an overall strategy that performs adequately well across a range of conditions. Planners can consider implementation strategies, characterized by an approximate total yield of water management actions—within a range of 1 maf—that planners should implement by 2060. After considering this high-level scenario, they can consider the timing of increasing this implementation and the specific water management actions that comprise the strategy.

The seven possible implementation strategies are listed below:

- **No Action Necessary**
- **Yield 0-1 maf**
- **Yield 1-2 maf**
- **Yield 2-3 maf**
- **Yield 3-4 maf**
- **Yield 4-5 maf**
- **Available Actions Insufficient**

In each future, only one implementation strategy is the low-regret strategy. Figure 7-5 provides a summary of the percent of futures requiring each implementation strategy. In both the Upper and Lower Basin, the *No Action Necessary* strategy is low-regret in the highest proportion of futures. The available actions are insufficient in approximately 10 percent of futures. In the Upper Basin, 10 percent of futures require 2-3 maf and 4 percent of futures require 1-2 maf. In the Lower Basin, 13 percent of futures require 3-4 maf and 19 percent of futures require 4-5 maf.
Conditions that describe which investments are necessary—implementation scenarios

In both the Upper and Lower Basin, the No Action Necessary strategy is most frequently the low-regret strategy across the ensemble of futures. However, simply because the No Action Necessary strategy is most frequently the low-regret strategy in this particular ensemble of futures does not mean that it is most likely to be the low-regret strategy—planners face deeply uncertain future supply as each future in the ensemble is not necessarily equally likely.

Scenarios can help planners consider the streamflow conditions that are associated with each implementation strategy. These scenarios can serve as the basis for deliberations among the total yields planners consider implementing. This section presents implementation scenarios, which
describe the external streamflow conditions associated with each implementation strategy. The implementation scenarios are described in terms of long-term average streamflow and average streamflow in driest eight-year period.

Figure 7-6 presents the implementation scenarios for the Lower Basin overlaid on a scatter plot of the streamflow conditions associated for each sampled future. Each point in the figure represents one future, characterized by long-term mean annual flow (vertical axis) and mean annual flow during the driest eight-year period (horizontal axis). The symbols demark the low-regret implementation strategy in a particular future. The No Action Necessary strategy, demarked by open circles, is low-regret in wet futures found in the upper right corner. The Available Actions Insufficient strategy, demarked with an X, is low-regret in the driest futures in the lower left corner. The colors describe the definitions of implementation scenarios. The Stationary Average Streamflow scenario is shaded green, containing primarily futures where the No Action Necessary strategy is low-regret, and is defined by average annual streamflow above 15 maf. The Severely Declining Average Streamflow scenario is shaded gray, defined by average annual streamflow less than 12.4 maf and contains primarily futures where the current set of available actions is insufficient to address Lower Basin water delivery objectives. The Below Historical Streamflow with Severe

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The analysis uses Classification and Regression Trees (CART) (Breiman, Friedman et al. 1984) to identify implementation scenarios CART is used because it can identify scenarios for each strategy simultaneously. CART produces a tree (much like a decision tree) that partitions the space of explanatory variables (streamflow conditions). These partitions are range restrictions, describing the streamflow conditions in which an implementation strategy is preferable. By definition, these scenarios are mutually exclusive and span the entire uncertainty space. PRIM would only classify regions where a strategy is low-regret one at a time and may create overlapping scenarios. When using CART, analysts face some subjective decisions, which affect the accuracy with which the scenario describe the low-regret strategy and the interpretability of the scenarios.

First, users must determine which external factors to include in the analysis. This analysis tests long-term average streamflow, minimum streamflow during 8-year periods, and standard deviation of rolling eight-year average flow—three characterizations which were found to be useful in previous PRIM analyses (which were previously chosen from a wider set). Ultimately, to facilitate the generation of two-dimensional scenario maps, only long-term average streamflow, and minimum streamflow are included. While the measure of decadal variation is a useful indicator, it is of less importance than the other two.

Second, when using classification trees, CART attempts to minimize a loss function. This loss function defines a penalty for misclassifying an observation. Users can determine the parameters of this loss function. In this case, the loss function reflects the assumption that planners are likely to prefer to slightly over-invest and avoid failing to meet water delivery objectives than to under-invest. The loss function is defined to penalize an under-estimate twice as heavily as an over-estimate. Defining these parameters is similar to choices that analysts face when choosing between density and coverage, as they attempt to balance true-positive and true-negative classification in a policy-relevant manner.

Third, CART begins by generating an expansive set of restrictions to minimize the loss function. This often leads to many restrictions and terminal nodes, which may describe only a small number of futures. A large number of restrictions will likely be difficult for planners to interpret. CART includes algorithms to “prune” the tree, balancing the number of restrictions and terminal branches with the accuracy of the predictions. Analysts face choices in how this algorithm weighs the accuracy of predictions and the number of terminal nodes. This is similar to decisions that users of PRIM make when balancing the number of restrictions (the interpretability) with the density and coverage.
Drought scenario is shaded red containing primarily futures where the Yield 4-5 maf strategy is necessary, where average annual streamflow is between 12.4 and 15 maf and there is an 8-year drought with average annual streamflow less than 11.4 maf. Finally, the Below Historical Streamflow contains futures where streamflow is between 12.4 and 15 maf, but the driest 8-year drought has average annual streamflow greater than 11.4 ma, and Yield 3-4 maf is generally the low-regret strategy.74

Figure 7-6: Implementation scenario definitions in the Lower Basin

In the Upper Basin, planners face a more distinct choice. As the distribution of implementation is so highly skewed towards implementing 2-3 maf of yield, planners only need to consider whether they

74 76.6 percent of futures where the No Action Necessary strategy is the low-regret strategy are contained in the Stationary Average Streamflow scenario (coverage). In 93 percent of futures in this scenario, the No Action Necessary strategy is low-regret (density). 62.7 percent of futures where the available actions are insufficient are contained in the Severely Declining Average Streamflow scenario (coverage). In 83.4 percent of futures in this scenario, available actions are insufficient (density). 78.4 percent of futures where the Yield 4-5 maf is the low regret strategy are contained in the Below Historical Streamflow With Severe Drought scenario (coverage). 48.7 percent of futures in the scenario have Yield 4-5 maf as the low regret strategy (density). 77.1 percent of futures where the Yield 3-4 maf is the low regret strategy are contained in the Below Historical Streamflow (coverage). 45.3 percent of futures in the scenario have Yield 3-4 maf as the low regret strategy (density).
will implement no actions, the maximum total yield, or need to consider a wider set of actions beyond the maximum total yield. Planners could describe the choice among these implementation strategies using the Severe Declining Supply, the Declining Supply, and Low Historical, Stationary, or Increasing Supply scenarios.\textsuperscript{75} Figure 7-7 presents the implementation scenarios for the Upper Basin overlaid on a scatter plot of the streamflow conditions associated for each sampled future.

*Figure 7-7: Implementation scenario definitions in the Upper Basin.*

**Characterizing Implementation Over Time**

The previous analysis describes the exogenous conditions most relevant to the decisions regarding which actions to implement over the entire time horizon. However, the strategies considered in this dissertation to address water delivery vulnerability are adaptive; they entail many sequential decisions made over a long time horizon. The low-regret strategies can be characterized by the yield implemented over different periods of time. To understand the different actions that are necessary in different futures, the summaries are conditional on the implementation scenarios generated in the previous section. Such visual aids can help planners examine how to scale up implementation to address different sets of future conditions.

\textsuperscript{75} Note that some scenarios were generated using CART as test, but it was determined that scenarios presented in earlier section generated by PRIM did a comparable job characterizing the scenarios where different sets of actions are necessary.
Considering Yield Across Decades Across Scenarios

Figure 7-8 examines implementation in the Lower Basin. It presents the distribution of implementation in low-regret strategies in each implementation scenario over time. On the vertical axis, it presents the yield implemented by a low-regret strategy, with the final year of the decade on the horizontal axis. Each point represents a single future, and the quartiles of the distribution are summarized by the boxplots.

Figure 7-8: Boxplots of the distribution of implementation over time in low-regret strategies, by implementation scenario in the Lower Basin

This figure shows that in the wettest conditions, almost no action is implemented in any decade. The box-plots are all condensed near zero implementation.

In Severely Declining Average Streamflow scenario when the current set of actions is insufficient, planners would prefer to implement as many actions as possible in each decade with little variation. In this scenario, the 75th percentile of implementation is 0.4 maf by 2020, 2.1 maf by 2030, 3.6 maf by 2030, 4.8 maf by 2050 and 5.0 by 2060.

Low-regret strategies have greater variation in the two other scenarios. In the Below Historical Streamflow scenario, median implementation is less than 1 maf until 2050, after which median implementation rapidly increases to 2.3 maf. The 75th percentile of implementation is significantly higher, consistently above 2 maf after 2030.\footnote{To some extent, the variation is a function of the loss function used in CART to design these scenarios. This function penalized predicted classifying a future that requires high levels in implementation in a scenario that that describes when low-levels of implementation are necessary twice as strong as the reverse, to ensure that} Though the Below Historical Streamflow With Severe

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Drought scenario also has variation in the volume implemented each decade, low-regret strategies implement greater volumes of yield in each decade than the Below Historical Streamflow scenario.

Figure 7-9 distills the information in Figure 7-8 into a higher-level summary. The horizontal axis shows each decade and the vertical axis shows the implementation scenarios. Each box presents the 90th percentile of yield implemented for low-regret strategies77 across all futures within the scenario. This figure can be read as a decision matrix. The volumes represented in each box serve as a recommendation of the yield to implement in each decade to prepare for each scenario. Based on their own subjective beliefs about the scenarios, planners can use this figure to identify the quasi-optimal yield to implement. The dotted lines present some feasible pathways through different sets of implementation.78

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77 The 90th percentile is presented to be consistent with the assumption that planners would likely prefer to over-invest than fail to meet water deliver objectives. Interactive versions of this graphic allow planners to explore other thresholds.

78 The design of this figure is inspired the by the Robust Adaptive Pathways methodology, as described in Chapter 2 of this dissertation. While the visualization that described the pathways is in some ways similar, this approach highlights the choices between preparing for different scenarios, while the Robust Adaptive Pathways images focus on individual actions.
Figure 7-9: Decision matrix with some pathways for implementation over time in the Lower Basin

<table>
<thead>
<tr>
<th></th>
<th>2012-2020</th>
<th>2021-2030</th>
<th>2031-2040</th>
<th>2041-2050</th>
<th>2051-2060</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stationary Average Streamflow</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Below Historical Streamflow</td>
<td>0.0</td>
<td>1.9</td>
<td>3.1</td>
<td>3.5</td>
<td>3.9</td>
</tr>
<tr>
<td>Below Historical Streamflow With Severe Drought</td>
<td>0.4</td>
<td>2.1</td>
<td>3.6</td>
<td>4.8</td>
<td>5.0</td>
</tr>
<tr>
<td>Severely Declining Average Streamflow</td>
<td>0.4</td>
<td>2.1</td>
<td>3.6</td>
<td>4.8</td>
<td>5.0</td>
</tr>
</tbody>
</table>

90th Percentile Implementation [maf]

- **Pathway A:** Prepare for Below Historical Streamflow maf scenario
- **Pathway B:** Prepare for Below Historical Streamflow scenario through 2040, Adjust to Yield Below Historical Streamflow With Severe Drought scenario after 2040
- **Pathway C:** Prepare for Below Historical Streamflow With Severe Drought scenario through 2030. Reconsider implementation after 2030

**Inspired by:** Kwakkel and Haasnoot (2012)

Pathway A represents the simplest decision planners can make to prepare for a single set of conditions over the entire time horizon. In this case, if planners determine that they need to be resilient to the conditions described by the Below Historical Streamflow scenario, they do not need to implement any actions in by 2020, implement 1.9 maf by 2030, 3.1 maf by 2040, 3.5 maf by 2050 and 3.9 maf by 2060. Implementing such a yield would ensure that water delivery objectives are met in 90 percent of futures. This pathway represents a basic plan (defined in Chapter 2 of this dissertation). There could be similar horizontal pathways on this figure for each of the implementation scenarios.

Pathway B shows how planners may begin planning for one scenario, but then switch to another as new information becomes available. Through 2040, Pathway B follows the same path as Pathway A, as planners prepare for the Below Historical Streamflow scenario. In this pathway, planners update their beliefs about scenarios as they observe streamflow conditions, reservoir levels, and monitor climate change predictions. After 2040, they determine that they need to be resilient to the
conditions described by the Below Historical Streamflow With Severe Drought scenario and adjust course. Planners would need to expedite implementation of an additional 1.3 maf (increasing yield from 3.1 maf in 2040 to 4.8 maf, rather than 3.5 maf) in 2050, rather than the 3.5 maf they originally planned for). So long as such a rapid change in implementation is feasible, planners can change course. This represents a basic plan adjusted to respond to new information.

Pathway C recognizes that planners may not wish to commit to a single course of actions for the entire time horizon, instead designing a basic plan that is explicit that some decisions will be made at a later point. In Pathway C, planners commit to prepare for the Below Historical Streamflow With Severe Drought scenario between now and 2030, implementing 0.4 maf of yield by 2020 and 2.1 maf of yield by 2030. Such a path may be attractive, as both the Below Historical Streamflow scenario and the Below Historical Streamflow With Severe Drought scenario require similar levels of implementation by 2030. The implementation requirements diverge after 2030 and planners specify that they will make a next set of decisions after 2030. At this point, they may choose to only increase yield from 2.1 maf to 3.1 maf, to prepare for the Below Historical Streamflow scenario. They may instead choose to increase yield to 3.6 maf, maintaining preparedness for the Below Historical Streamflow With Severe Drought scenario. Alternatively, they may determine that the Severely Declining Average Streamflow scenario is sufficiently likely, and begin deliberating a wider set of actions in addition to implementing all available actions.79

Pathways B and C both recognize that planner’s beliefs about the implementation scenarios presented in this chapter may change over time. Planners can observe streamflow or the other exogenous climate indicators presented in Chapter 5. They may use a Bayesian process to update their beliefs that a scenario is sufficiently likely that they must plan for it. For example, one could replicate the analysis presented in Chapter 5 for the Below Historical Streamflow, Below Historical Streamflow With Severe Drought, Severely Declining Average Streamflow scenarios. Using such a method, planners could identify which pieces of information they need to observe by 2030 to generate consensus about which pathway to follow in subsequent decades.

Pathways A, B, and C are only a few examples of how planners may choose to navigate implementation over the planning horizon. Planners can examine this decision matrix, or use an interactive version to explore some different percentiles of the distribution, to identify other pathways.

In the Upper Basin, the decision space is less complex; even when planners can meet water delivery objectives, they frequently do so by implementing the full set of available actions. Planners can choose among implementing all actions as soon as possible while consideration additional actions, implementing all actions as soon as possible with confidence that the set of actions will be sufficient, or implementing no actions.

For completeness, results are presented for Upper Basin. Figure 7-10 presents the distribution of yield implemented in each decade across low-regret strategies for futures in each implementation

79 Though recommended yields in the Yield 4-5 maf and Actions Insufficient scenario are identical, the implications are very different; in the Actions Insufficient scenario, planners would consider additional or different actions to implement beyond those represented in the simulations.
scenario. Low-regret strategies in the *Low Historical, Stationary, or Increasing Supply* scenario do not implement any actions in any time period. Low-regret strategies in the *Actions Insufficient* scenario steadily increase actions over a relatively small range (particularly after 2040). Low-regret strategies implement a range diversity of yield in the early periods *Declining Supply* scenario. However, the highest percentiles, which would be required to be resilient to all futures in the scenarios, are near the maximum potential yield.

*Figure 7-10: Boxplots of the distribution of implementation over time in low-regret strategies, by implementation scenario in the Upper Basin*

*Figure 7-11* presents some implementation pathways for the Upper Basin.
Figure 7-11: Decision matrix with some pathways for implementation over time in the Upper Basin

<table>
<thead>
<tr>
<th></th>
<th>2012-2020</th>
<th>2021-2030</th>
<th>2031-2040</th>
<th>2041-2050</th>
<th>2051-2060</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Historical,</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Stationary, or</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Increasing Supply</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Declining Supply</td>
<td>0.28</td>
<td>1.56</td>
<td>2.00</td>
<td>2.58</td>
<td>2.62</td>
</tr>
<tr>
<td>Severely Declining</td>
<td>0.28+</td>
<td>1.58+</td>
<td>2.03+</td>
<td>2.62+</td>
<td>2.68+</td>
</tr>
<tr>
<td>Supply</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

90th Percentile Implementation [maf]

Pathway A: Prepare for Declining Supply scenario
Pathway B: Prepare for Severely Declining Supply scenario through 2040, adjust to Severely Declining Supply maf scenario after 2040

Pathway A represents a basic plan where planners prepare for the Declining Supply scenario. In this case, they would plan to implement 180 kaf by 2020, 1.56 maf by 2030, 2.00 maf by 204, 2.58 maf by 2050 and 2.62 maf by 2060. Pathway B represents a situation where planners begin preparing for the Severely Declining Supply scenario. After 2030, they determine that conditions are less severe than originally anticipated and decrease implementation to the levels required in the Declining Supply scenario. Though planners can consider alternative pathways, this matrix demonstrates that the decision-space in the Upper Basin is more limited than the Lower Basin.

**Considering individual water-management actions over time**

The low-regret strategies are comprised of many individual water management actions. Though the strategies were characterized solely by the total yield implemented in the previous sections, the strategies can also be described by their component water-management actions. Table 7-1 provides a brief summary of the water management actions that comprise the strategy.
Table 7-1: Brief description of each type of action included in the portfolio analysis

<table>
<thead>
<tr>
<th>Action Type</th>
<th>Description</th>
<th>Action Included in Portfolio A (Inclusive)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural</td>
<td>Actions that increase water conservation in the agriculture sector and reduce demand for Colorado River water in either the Upper or Lower Basin. Actions are disaggregated into 200 kaf/year “steps” to represent likely project phasing.</td>
<td>• Ag Conservation with Transfers (Upper and Lower Basin)</td>
</tr>
<tr>
<td>Desalination</td>
<td>Actions to desalinate (1) ocean water off the California and Gulf of Mexico coasts, (2) agricultural drainwater, and (3) brackish groundwater.</td>
<td>• Desal-Salton Sea Drainwater • Desal-Pacific Ocean-California • Desal-Gulf</td>
</tr>
<tr>
<td>Import</td>
<td>Options to increase the overall water supply of the Basin from other river basins. Imports from the Missouri River and the Mississippi River were considered to augment supply in the Colorado Front Range and reduce the amount of Colorado River exported to these regions.</td>
<td>• Import-Front Range-Missouri</td>
</tr>
<tr>
<td>Local Supply</td>
<td>Local supply actions capture local water sources that would otherwise go unused.</td>
<td>• Local-Coalbed Methane</td>
</tr>
<tr>
<td>M &amp; I Conservation</td>
<td>Actions that increase water conservation in the municipal and industrial sectors and reduce demand for Colorado River water in either the Upper or Lower Basins.</td>
<td>• M &amp; I Conservation (Upper and Lower Basin)</td>
</tr>
<tr>
<td>Reuse</td>
<td>Reuse of existing municipal and grey water supplies increase the overall water supply in the Basin.</td>
<td>• Reuse-Municipal • Reuse-Grey Water</td>
</tr>
<tr>
<td>Watershed Management</td>
<td>Actions that could increase the supply of the Basin by increasing river runoff. Key approaches include Tamarisk control, Forest Management, Brush Control, Dust Control, and Weather Modification</td>
<td>• Watershed-Weather Mod • Watershed-Dust</td>
</tr>
</tbody>
</table>

Note: Large actions are disaggregated into 200 kaf/year “steps” to represent likely project phasing.

Source: Groves, Fischbach et al. (2013)

Though some high-level planning will focus on the total yield of the supply-requirement described in previous sections, planners will also make multiple smaller decisions about individual actions that comprise a low-regret strategy. This section examines the choices among individual water management actions in detail, to provide planners insight into need to implement an action and the timing of those actions. It begins by providing some information about the distribution of years that low-regret strategies implement the water management actions. It classifies actions either as initial actions or contingencies, contingent on the implementation scenarios. Finally, it considers a single action in greater detail. It presents scenarios specific to the implementation of that action.
Identifying initial actions and contingencies

For the low-regret strategy in each future, individual water management actions are each implemented at a unique point time. For example, in one future the low-regret strategy may require that a desalination plant is implemented in 2035, in another it may be implemented in 2050, and in another it may not be implemented at all. Figure 7-12 summarizes the timing of each water management action for the Lower Basin. Each row presents an individual water management action, summarized for the low-regret strategies in futures contained in each implementation scenario (vertical panels). The horizontal axis presents the start year for an action and the coloring presents the deciles of the distribution of timing of the actions. When the panel is white (furthest to the left), the action is implemented in fewer than 10 percent of futures. Darker colors show that action is implemented in a greater percentage of futures by the given year. The darkest red (furthest to the right) represent years in which the low-regret strategies implement the action in greater than 90 percent of futures. The thick black lines on the left indicate that in the first year an action is available to be implemented. For example, in the Below Historical Streamflow With Severe Drought scenario, low-regret strategies implement the first step of Agricultural Conservation in 40 percent of futures by 2018, 70 percent of futures by 2025, and 80 percent of futures by 2033.
Figure 7-12: Distribution of year water management actions are implemented in low-regret strategies in the Lower Basin

In the Stationary Average Streamflow scenario, low-regret strategies implement no actions. In the Severely Declining Average Streamflow scenario, low-regret strategies implement actions nearly as soon as they are available. In the Below Historical Streamflow scenario, low-regret strategies begin
implementing actions after they become available, frequently with some delay. Actions near the top of the list are implemented in a majority of futures by the end of the time horizon, but do not need to be implemented immediately to achieve water delivery objectives. Actions near the bottom of the list are generally implemented in a small percentage of futures, even by the end of the planning horizon. In the Below Historical Streamflow With Severe Drought scenario, actions are frequently implemented sooner than in the Below Historical Streamflow scenario.

Figure 7-13 presents similar results in the Upper Basin. Low-regret strategies implement no actions in the Low Historical, Stationary, or Increasing Supply scenario, and nearly all the actions with little delay in the Severely Declining Supply scenario. In the Declining Supply scenario, most actions are implemented by the end of the planning horizon, but some actions are delayed beyond their start year in many futures.

Figure 7-13: Distribution of year water management actions are implemented in low-regret strategies in the Upper Basin

<table>
<thead>
<tr>
<th>Implementation Start Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 Dec</td>
</tr>
</tbody>
</table>

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The information provided in these figures summarizes how the low-regret strategies implement the individual actions across the ensemble of futures. However, it does not provide planners with any decision-making criteria. The following paragraphs distill the information from simulation results into figures that can help planners choose among actions.

Planners may wish to characterize the frequency and timing of the individual actions that are contained in low-regret strategies within each implementation scenario. This analysis first provides planners the percent of futures in which low-regret strategies implement each action. This characterization provides a measurement of relative likelihood that an action will be necessary at any point within the planning horizon. Planners wishing to prepare for a particular implementation scenario will need to implement the action at some point if low-regret strategies implement it in 100 percent of futures in the scenario. Planners will never need to implement a particular action to prepare for the scenario if low-regret strategies never implement it. Generally, actions implemented in a higher percentage of futures, within the implementation scenarios, are more likely to be necessary than those implemented in a smaller percentage of futures. 80

To summarize when planners may need to begin planning for a particular action, if implemented, this analysis uses a measure referred to as delay. 81 A water management action’s delay is the year implemented in a particular future less the year it first becomes available. The Basin Study defined the year an action becomes available by earliest date it could feasibly be implemented if effort began immediately (in 2012). Hence, delay represents the number of years beyond 2012 that planners defer prior to putting effort into implementing an action. This analysis characterizes delay for every action in every future, if implemented.

Delay is a measure of the amount of time planners can reasonably wait before making a decision about a particular action. Planners may wish to implement actions with little delay soon, to ensure the elements of low-regret strategies address vulnerabilities.

Figure 7-14 distills the information about timing and implementation of water management actions in Lower Basin from Figure 7-13 into a higher-level summary using the measures described above. 82 It shows the percentage of futures low-regret strategies implement an action on the horizontal axis. On the vertical axis, it shows the 25th-percentile of delay across futures for each

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80 Generally (though not always), actions are implemented in the order listed in Figure 7-12. This means if a particular action is implemented in fewer futures than another action, the action is implemented in a subset of the futures the other action is. As each future has (weakly) positive probability, even if they are not equally likely, actions implemented in more futures than another are generally more likely to be implemented than another.

81 This measure of delay was first defined in the Basin Study (U.S. Bureau of Reclamation 2012e).

82 Delay and Implementation were first presented in the Basin Study to identify promising initial actions. The scatterplots, which show the Delay and Implementation for each action contingent on decision-relevant scenario, were presented in the subsequent RAND report (Groves, Fischbach et al. 2013). While summaries presented here are new, as they are specific to the analysis completed in my dissertation, the presentation is not. However, this dissertation does add two unique components to these summaries. First, it uses low-regret strategies to identify quasi-optimized sets of actions, rather than simply reporting actions implemented from a single set of simulations. Second, while the previous reports presented results conditional on decision-relevant scenarios, this dissertation uses implementation scenarios specific to the choices about how much action to implement.
action,\textsuperscript{83} conditional on implementation. Each point on the graph represents a unique water management action. Symbols represent the type of action and some actions of note are labeled by name. The figure summarizes results separately for futures in each implementation scenario. In the lower right corner, the figure presents actions frequently implemented with little delay. A gray box highlights actions implemented in 50 percent or more futures, with a 25\textsuperscript{th} percentile delay of five or less years.\textsuperscript{84} Based on these criteria, these actions are strong candidates for initial actions contingent on the scenario planners wish to prepare for.

\textsuperscript{83} The 25\textsuperscript{th} percentile is chosen to represent planners’ preference to ensure water management actions are met. Interactive versions of this figure can allow planners to explore and consider alternative percentiles.

\textsuperscript{84} Planners may consider other thresholds. These are wider thresholds than are used in the RAND report, reflecting a desire by planners to ensure water delivery objectives are met.
Figure 7-14: Frequency and timing of actions implemented by low-regret strategies in the Lower Basin

In the Stationary Average Streamflow scenario, low-regret strategies implement actions in a negligible percentage of futures. If planners only wish to be resilient to the conditions described by this scenario, they can implement no actions. Similarly, in the Severely Declining Average Streamflow scenario, low-regret strategies implement in all futures with little delay. If planners wish to prepare for these conditions, they should begin planning to implement all actions in the near term. In the

Adapted from: Groves, Fischbach et al. (2013)

Figure with this design were first presented in the RAND report (Groves, Fischbach et al. 2013)
Below Historical Streamflow scenario, some actions are candidate initial actions. Few actions are implemented in 100 percent of futures, but many actions are implemented in a majority of futures. Amongst those that are implemented, different actions are required with different levels of delay. Planners may wish to consider implementing actions in the lower right corner in the near term.

In the Below Historical Streamflow With Severe Drought scenario, low-regret strategies implement the water management actions with greater variation than the Severely Declining Average Streamflow scenario. Actions are generally implemented frequently and sooner than the Below Historical Streamflow scenario. Most actions meet the defined criteria for candidate initial actions. Table 7-2 presents a simple summary of those actions that are implemented frequently and with little delay.
Table 7-2: Candidate initial actions in the Lower Basin

<table>
<thead>
<tr>
<th>Contingency</th>
<th>Candidate Initial Action</th>
<th>Stationary Average Streamflow</th>
<th>Below Historical Streamflow</th>
<th>Below Historical Streamflow With Severe Drought</th>
<th>Severely Declining Average Streamflow</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ag Cons-Transfer1-LB</td>
<td>2016</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Local-Rain</td>
<td>2016</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>M &amp; I Conservation 1-LB</td>
<td>2016</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Ag Cons-Transfer2-LB</td>
<td>2021</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-SoCal groundwater</td>
<td>2021</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Yuma</td>
<td>2021</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>M &amp; I Conservation 2-LB</td>
<td>2021</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Reuse-Grey Water</td>
<td>2021</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Reuse-Industrial</td>
<td>2021</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Reuse-Municipal1</td>
<td>2021</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Watershed-Tamarisk</td>
<td>2023</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Ag Cons-Transfer3-LB</td>
<td>2026</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Ag Cons-Transfer4-LB</td>
<td>2026</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Ag Cons-Transfer5-LB</td>
<td>2026</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Pacific Ocean-MX</td>
<td>2026</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Salton Sea1</td>
<td>2026</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Gulf1</td>
<td>2028</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Pacific Ocean1</td>
<td>2031</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Salton Sea2</td>
<td>2031</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>M &amp; I Conservation 3-LB</td>
<td>2031</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Reuse-Municipal2</td>
<td>2031</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Gulf2</td>
<td>2033</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Pacific Ocean2</td>
<td>2036</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Desal-Salton Sea3</td>
<td>2036</td>
<td>•</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Reuse-Municipal3</td>
<td>2036</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Watershed-Dust2</td>
<td>2036</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Import-Front Range-Missouri</td>
<td>2041</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>M &amp; I Conservation 4-LB</td>
<td>2041</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Reuse-Municipal4</td>
<td>2041</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Reuse-Municipal5</td>
<td>2046</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>M &amp; I Conservation 5-LB</td>
<td>2051</td>
<td>•</td>
<td>•</td>
<td>✓</td>
</tr>
</tbody>
</table>

Planners can use this table to consider actions to begin working implement with the next five years, based on the streamflow conditions to which they wish to be resilient. To prepare for the Below Historical Streamflow scenario, planners should begin to implement significant levels of agricultural conservation, begin the planning the Salton Sea Desalination facility, and work to implement certain levels municipal-reuse and municipal and industrial conservation.
Note that the second step of the municipal-reuse and third step of the municipal and industrial conservation are candidate initial actions. This means they cannot be delayed much beyond their start year. However, by definition the lower levels of these two actions are to be implemented first. Thus, while planners may have a slightly longer period of time to consider these previous steps, they will still be necessary in many futures.

If planners wish to be resilient to the conditions described by the Below Historical Streamflow With Severe Drought scenario, they must begin planning a much wider set of actions; they can only safely defer the highest-level step of municipal reuse and the desalination plant in the Pacific Ocean.

Figure 7-15 and Table 7-3 present similar results for the Upper Basin.

*Figure 7-15: Frequency and timing of actions implemented by low-regret strategies in the Upper Basin*
Table 7-3: Candidate initial actions (Upper Basin)

<table>
<thead>
<tr>
<th>Contingency</th>
<th>Low Historical, Stationary, or Increasing Supply</th>
<th>Declining Supply</th>
<th>Severely Declining Supply</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ag Cons-Transfer1-UB</td>
<td>2016</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Local-Rain</td>
<td>2016</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>M &amp; I Conservation 1-UB</td>
<td>2016</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Watershed-Weather Mod1</td>
<td>2016</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Ag Cons-Transfer2-UB</td>
<td>2021</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Energy Conservation</td>
<td>2021</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Local-Coalbed Methane</td>
<td>2021</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>M &amp; I Conservation 2-UB</td>
<td>2021</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Reuse-Grey Water</td>
<td>2021</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Reuse-Industrial</td>
<td>2021</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Reuse-Municipal1</td>
<td>2021</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Watershed-Weather Mod2</td>
<td>2021</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Ag Cons-Transfer3-UB</td>
<td>2026</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Ag Cons-Transfer4-UB</td>
<td>2026</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Ag Cons-Transfer5-UB</td>
<td>2026</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Watershed-Dust1</td>
<td>2026</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>M &amp; I Conservation 3-UB</td>
<td>2031</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Reuse-Municipal2</td>
<td>2031</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Watershed-Dust2</td>
<td>2036</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Import-Front Range-Missouri</td>
<td>2041</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>M &amp; I Conservation 4-UB</td>
<td>2041</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>M &amp; I Conservation 5-UB</td>
<td>2051</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Planners face fewer implementation choices in the Upper Basin. As implied in the previous analyses, nearly all water management actions should be implemented with little delay, unless planners are confident the Low Historical, Stationary, or Increasing Supply scenario will occur.

The water management actions to address Upper Basin and Lower Basin water delivery objectives are not necessarily mutually exclusive and many actions address both. As the Basin is an integrated system, planners may wish to consider items from both lists to meet both objectives. However, different streamflow conditions cause the system to fail to meet objectives, and actions may be needed on different timetables for the various objectives. Characterizing the low-regret strategies in separately for each objective allows planners to consider which is necessary in each region of the Basin. An integrated plan can then pull from each list, to ensure all both Basin objectives are met.

**Scenarios that describe conditions when specific actions are necessary**
The tables above suggest some strong candidates for initial actions. However, they are simply proxy measures, designed to help planners identify actions that are frequently implemented with little delay. After identifying some reasonable candidates, planners may wish to examine the candidates in greater detail.

This analysis more deeply considers one particular action— a desalination facility in Yuma, Arizona (referred to as Desal-Yuma). The Basin Study describes that this plant would be designed to decrease the salt content of brackish (water that has higher salinity than freshwater, but not as much a seawater) groundwater near Yuma, Arizona (U.S. Bureau of Reclamation 2012d). This action is available to address Lower Basin water delivery objectives, and would first be available in 2021. This action is a candidate initial action if planners wish to prepare for the Below Historical Streamflow With Severe Drought scenario but not in the Below Historical Streamflow scenario.

Figure 7-16 plots the futures where low-regret strategies implement the Desal-Yuma with a delay of ten or fewer years. Each point represents one future, characterized by long-term mean annual flow 2012-2060 (vertical axis) and mean annual flow during the driest eight-year period (horizontal axis). Orange asterisks represent futures where low-regret strategies implement this action within ten years. Blue circles represent futures where they do not.

*Figure 7-16: Initial-action implementation scenario for Desal-Yuma water management action*

The shaded region in the lower left represents an implementation scenario, describing the streamflow conditions where Desal-Yuma is necessary with ten or fewer years of delay. In futures where the long-term mean annual flow is less than 14.4 maf and mean annual flow during the driest
eight-year period is less than 12.3 maf, low-regret strategies implement this action with minimal delay. Across all futures, low-regret strategies implement this action within ten years 39 percent of the time. Within this this implementation scenario, low-regret strategies implement this action in 79 percent of futures (density). This scenario also contains 82 percent of futures where Desal-Yuma is implemented within ten years (coverage).

This implementation scenario contains a wider range of streamflow conditions than Severely Declining Supply conditions but less severe conditions that Low Historical Supply conditions. Some futures drawn from the recent historical record are consistent with definition of this scenario. This suggests that if planners believe the future will be similar to some of the dryer periods of recent observed past, they should implement this action.

Planners may also consider the conditions that would make them desire to implement the Desal-Yuma water management actions further into the future. Figure 7-17 shows futures where low-regret strategies implement this action after 10 or more years of delay (in 2031 or later). Futures where low-regret strategies implement the action in such a time frame are demarked with orange asterisks, while futures where is it not (either implemented prior to this time frame or not at all) are demarked with blue circles. The long-term average streamflow from 2012 to 2060 is shown on the vertical axis. The annual average streamflow from 2012 to 2030 is shown on the horizontal axis.

Figure 7-17: Contingent-action implementation scenario for Desal-Yuma water management action

The shaded area represents an implementation scenario where this action would be implemented with some delay. This action is frequently implemented when the future is dry but not severely dry
and the first two decades of planning horizon are relatively wet. Specifically, when long-term average streamflow ranges between 13.3 maf and 15.0 maf and average streamflow in the first two decades of the planning horizon is greater than 14.5 maf, low-regret strategies implement this action. Low-regret strategies implement this action with 10 or more years of delay in 16.6 percent of total futures. In the implementation scenario, low-regret strategies implement this in 53.6 percent of futures (density) and the scenario represent 53.9 percent of futures where this action is implemented with such a delay (coverage). Planners should find these conditions intuitive, as this action is necessary if there is less than 15.0 maf in long-term average flow (consistent with Low Historical Supply conditions) but the early decades are relatively wet and it is not necessary immediately.

Table 7-4 summarizes the two figures above. If planners wish to prepare for conditions with long-term average streamflow less than 14.4 maf and a drought with less than 12.3 maf of average annual flow, they should implement this action in the near term. However, if they observe a period where streamflow is only slightly below the recent historical average over the next 20 years, they can reasonably defer implementation of this action by slowing the process or delaying certain decisions. Alternatively, planners may choose to defer this action with the expectation that the next two decades will have more than 14.5 maf in annual average natural flow. However, if they observe increasing evidence that the long-term average flow will fall below 15.0 maf, they should begin the process of permitting and implementing the Desal-Yuma water management action.

Table 7-4: Implementation scenarios for Desal-Yuma

<table>
<thead>
<tr>
<th>Action</th>
<th>Begin implementing Desal-Yuma in next 10-years</th>
<th>Implement Desal-Yuma at later point</th>
<th>Desal-Yuma unnecessary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario Definition</td>
<td>Long term average flow less than 14.4 maf and Minimum 8-year average flow less than 12.3 maf</td>
<td>Long term average flow between 13.4 and 15.0 maf and Average annual flow between 2012 and 2030 greater than 14.5 maf</td>
<td>All other streamflow conditions</td>
</tr>
</tbody>
</table>

The analysis presented above for the Desal-Yuma can be replicated for other water management actions of interest to planners. The information generated from these scenarios allows planners to consider whether certain actions are necessary in the near term or if they can be reasonably deferred. Planners can then consider whether those conditions are sufficiently likely that implementation is warranted. Understanding the conditions where an action is necessary if
deferred can allow planners to identify signposts that they should monitor specific to the individual actions.
Conclusions

Planners face choices about how they implement actions over time and what sets of actions they commit to in advance. Different conditions require different actions. This chapter summarizes the modeling to results to provide some decision aids to help planners consider the timing and implementation of the actions. The decision space in Upper Basin is less complex; nearly the maximum potential yield of water management actions is necessary to meet water delivery objectives in most futures that are at risk. Thus, planners face a relatively simple decision and must consider whether the scenarios that require actions are likely. If they are, planners should implement actions. As a caveat, it is possible the low resolution of the quasi-optimization routine drives this result. An improved optimization routine may find more nuanced levels of implementation, driving a richer decision-space. This could be tested by including additional triggers in the analysis in Chapter 6, allowing for a more granular exploration of sets of implemented actions.

In the Lower Basin, where planners face a more complex decision context, different actions are necessary in different futures. To simplify the decision space, this chapter identified four scenarios that describe when different levels of implementation are necessary, and summarized the modeling to results to suggest how planners may consider implementing actions over time to address those scenarios. A second analysis focused on the decisions planners face among individual actions in the near term as they prepare for these scenarios.

This information can help Basin planners generate basic plans, identify initial actions, and detect some key decision points. It allows them to frame the choice of actions against the exogenous streamflow conditions to which they need be resilient. The analyses are provided in the chapter can serve as a starting point, to scope some strategies for another iteration of the RDM process. This would allow planners to carefully evaluate the performance of the strategy, identify any remaining vulnerabilities, and weigh the cost-reliability tradeoff among the strategies.
Chapter 8: Conclusions

Introduction

This dissertation demonstrates that planners in the Colorado River Basin have an opportunity to act adaptively to prepare for climate change. Over the next 50 years they can observe streamflow, reservoir levels, and other climate indicators while implementing a portfolio of water management actions to meet water delivery objectives at low cost. However, this dissertation also shows that planners face tradeoffs as they consider how best to respond to new information and choose among different actions.

To do so, it presents three analyses demonstrating how RDM and exploratory modeling tools can support planners as they face decisions while adapting. First, it shows how decision-relevant scenarios can serve as the basis for considering new information using a model of Bayesian updating. This model facilitates an exploration across a wide range of plausible prior beliefs about the future. The second analysis helps planners evaluate the performance and tradeoffs of different strategies defined by decision-rules. The third analysis generalizes always from the specific decision-rules and provides planners with insight regard schedules of implement actions as they consider different scenarios to address.

The analyses in this dissertation serve three purposes. First, they provide a demonstration of new planning tools that can be used to support an adaptive process in the Basin. Many of these tools were first used in some form in the Basin Study and then expanded upon in this dissertation. As the Basin adapts using deliberations with analysis process, these tools can continue to provide decision support. Second, they provide some policy recommendations for how to manage the Basin and adapt over the half-century. The analyses lead to some policy conclusions on the subjects of signposts, decision-rules, and implementation. Chapters 4, 5, 6, and 7 present these conclusions alongside the analyses. Third, the analyses in this dissertation serve as an example of a process that can be applied in other applications of RDM to support adaptive strategies. Chapters 2 and 3 provide context and technical definitions for this decision-analytical process.

In particular, this dissertation highlights the role of learning over time. As planners learn, they can commit to actions that are more specific to the futures they face. In some sense, to be robust over the long-term, planners trade some level of robustness for increased optimality. They can only do this as they collect information to support that learning. This chapter first provides some further discussion of the role of learning, subjective beliefs and adaptive strategies. Building from this discussion, this chapter provides an example of how the various analyses presented in this dissertation can integrated. RDM is an iterative process, and multiple iterations through the separate analyses presented in Chapter 5, 6 and 7 can be combined to further refine the adaptive strategies.
Finally, the analyses presented in previous chapters of this dissertation also suggest opportunities for further research. This chapter next discusses how the tools may be improved to provide more refined decision support in an adaptive process. In doing so, it first describes how the tools could be integrated into a more well-defined deliberations and analysis process in the Colorado River Basin. This suggests ways in which analyses could be altered to reflect specific planning needs. Next, it discusses some additional research activities to ensure that the analytic process and presentation of analysis is useful to planners.

**Integrating the multiple analyses to generate new adaptive strategies**

This dissertation shows that adaptive strategies function when planners collect new information and implement new actions over time. It demonstrates how planners can use a Bayesian updating process to learn about which futures are becoming increasingly likely and then implement actions specific to those futures. In a deeply uncertain future, learning over time and tailoring strategies to increasingly likely futures is a way increase robustness—the analysis in Chapter 6 demonstrates that the adaptive strategies in general have much lower regret than strategies that do not respond to new information. In some sense, this suggests if planners wish to be robust over the long term, they should find ways to narrow the set of plausible futures in the near term. Acting robustly converges on optimizing for a smaller set of futures as more information is learned.

Even when planners wish to prepare for a wide range of plausible futures, probabilities cannot be ignored. Planners will collect new information, and consider a range the range of plausible updated probabilities, and prepare for those particular futures. For an adaptive strategy to be successful, planners need to learn over time and decrease the uncertainty by the point at which decisions are made.

RDM’s scenario approach provides the tools to consider updated probabilities while exploring across a range of subjective prior beliefs. At the start of the planning horizon, these scenarios may be deeply uncertain and planners can reasonably disagree about their likelihood. Despite this, planners may need to make decisions in the face of that uncertainty, based on current information. The general RDM approach is to find strategies that are consistent with a broad set of beliefs. Next, to act adaptively planners can try to define a smaller set of likely futures over time. This dissertation proposes an approach for using Bayesian updating tools to describe which scenarios are becoming increasingly likely, limiting the set of futures for which planners prepare. These tools present the signpost variables that planners monitor and provide some analytic aids to assist planners as they learn.

Planners will make decisions after observing signpost variables over time. In cases of fully-automatic policy adjustment, these choices are operationalized through decision-rules. In other cases, planners will continue to deliberate but signpost variables will influence their decisions. By modeling various decision-rules, analysts can provide insight into the costs and benefits of different response to information.
RDM is an iterative process, and the information revealed in each step of the analysis can help planners generate new adaptive strategies. This section combines the previous analyses to consider how planners may choose to implement actions and the pieces of information that should influence their choices. It combines the various pathways planners can use to adapt with the signpost variables that they can observe—generating new strategies and decision-rules.

This section presents two views of the decision among water management actions. The first is a system-wide approach, where planners consider the total annual yield of actions they would need implement. In this approach, planners can identify some pathways through the various total volumes of water management actions, the key decision-points, signpost variables that will influence their decisions, and threshold values of those variables that would require their implementation. In the second view, planners consider the choice to implement an individual water management action in the near-term or defer it for the opportunity to observe new information and periodically reconsider. It focuses on the example presented above—Desal-Yuma.

Figure 8-1 shows one possible basic plan for implementing water management actions over the planning horizon. This plan is Pathway C from Figure 7-9; planners commit to a level of implementation between now and 2030 and then face a decision of the yield to implement in subsequent decades. Planners may have settled on this basic plan after examining the decision-matrix and various pathways presented in Figure 7-9, determining which level of yield was necessary based on their current expectations. After settling on this particular basic plan, with a decision-point in 2030, the Bayesian rules-of-thumb analysis in Figure 5-13 is replicated for the various implementation scenarios. This graphic presents the threshold values of streamflow, other indicators, and streamflow conditions that would make planners believe the Severely Below Average Streamflow scenario is the most likely in 2030. If they observe these conditions by 2030, planners will need to strongly consider additional actions beyond those described in the Basin Study, and follow the bottom row of the graphic.
Figure 8-1: A plan for implementation, with a decision point and key indicators to monitor

<table>
<thead>
<tr>
<th></th>
<th>2012-2020</th>
<th>2021-2030</th>
<th>2031-2040</th>
<th>2041-2050</th>
<th>2051-2060</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stationary Average Streamflow</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
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<td>0.0</td>
</tr>
<tr>
<td>Below Historical Streamflow</td>
<td>0.0</td>
<td>1.9</td>
<td>3.1</td>
<td>3.5</td>
<td>3.9</td>
</tr>
<tr>
<td>Below Historical Streamflow with Severe Drought</td>
<td>0.4</td>
<td>2.1</td>
<td>3.6</td>
<td>4.8</td>
<td>5.0</td>
</tr>
<tr>
<td>Severely Declining Average Streamflow</td>
<td>0.4+</td>
<td>2.1+</td>
<td>3.6+</td>
<td>4.8+</td>
<td>5.0+</td>
</tr>
</tbody>
</table>

90th Percentile Implementation [maf]

Prepare for Yield 4-5 maf scenario through 2030. Reconsider implementation after 2030

**Severely Declining Supply Scenario** most likely (2012-2030)

- Exogenous indicators consistent with Severely Declining Average Streamflow scenario
- Prior beliefs for Severely Declining Average Streamflow scenario

Note: The thresholds in this figure were generated from analysis of the Severely Declining Supply scenario, not the Severely Declining Average Streamflow scenario. The definitions of these scenarios are similar, and replicating the analysis for the Severely Declining Average Streamflow should generate similar thresholds. Before being used for any decision-making, this analysis should be replicated using the Severely Declining Average Streamflow scenario.
Analysts could next simulate such a strategy using CRSS, to estimate the costs and benefits of using these threshold values as triggers. They may try other trigger values, such as those that imply the Severely Declining Average Streamflow scenarios is 90 percent likely. Such an analysis could help planners better understand the tradeoffs of requiring higher or weaker or levels of evidence before committing to a volume of implementation.

Figure 8-2 presents an example of the various pathways of implementation from analysis of the Desal-Yuma plant. First, planners must consider whether Desal-Yuma should be implemented in the near term and operated over the entire planning horizon, shown with the green line. If they believe that long-term average streamflow is less than 14.4 maf and average annual streamflow in the worst 8-year drought is less than 12.3 maf is sufficiently likely, they should follow this path. Alternatively, planners may determine that they can safely not implement the action is the first time-period and reconsider the decision periodically, shown with the blue line. At whatever point in time planners determine that long-term average streamflow between 13.3 and 15.0 maf is sufficiently likely, they would begin preparing and operating the Desal-Yuma plant. Planners must choose between the green path and the blue path with their current information, their priors. At each blue circle, planners would periodically reconsider whether they need to implement the Desal-Yuma plant. Planners would inform this decision by monitoring observed streamflow and other exogenous indicators.

Figure 8-2: Considering implementation of Desal-Yuma plant in response to new information
Knowing that the scenario for implementing Desal-Yuma is based primarily on long-term average streamflow, the same indicators described as those for the other decision-relevant scenarios should facilitate learning about the middle scenario’s likelihood. Observations of streamflow, as well as learning from other indicators, should influence planners’ beliefs about the decision-relevant scenarios.

An analysis similar to the one presented in Figure 8-1 could be replicated for each decision point in this figure. However, instead of partitioning futures based on the scenarios that describe system vulnerability futures would be partitioned based on the implementation scenarios specific to Desal-Yuma. Low streamflow observations in each decade would suggest that the middle scenario is increasingly likely, and planners should be preparing Desal-Yuma. This analysis can be utilized to generate rules-of-thumb and some candidate threshold values for decision-rules.

Such a process could be iterated through many times, based on different individual actions, implementation scenarios, and exploration of new pieces of information, until planners converge on an acceptable adaptive strategy. Additionally, over time, the analyses could be updated as new information and tools become available. At such a point in the future, planners may have updated beliefs, based on what is observed between now and then, and the analysis could focus solely on the range updated beliefs.

**Additional research in analysis of the Basin**

The analysis in this dissertation presents some visual-aids and tools to support a deliberations process in the Colorado River Basin, however further refinement could tailor them for actual use by planners. The following section describes two primary areas for improvement. First, the research presented in this dissertation could be better integrated into a deliberations with analysis process, and incorporate feedback from planners. Second, there could be further refinements to specific analyses to ensure the results are as robust as possible.

**Integrating analysis with deliberations**

As described in the first chapter of this dissertation, planners in the Basin have not yet articulated an adaptive strategy. As the Colorado River Basin spans across seven states and utilizes water to meet planning objectives, there will likely not be one decision-making body with authority to implement actions for the Basin as a whole. Instead, there are various planners, with various jurisdictions, making some decisions in coordination with one another while others are made independently. Thus, it is unclear what decisions can be made by fully-automatic policy adjustment, by limited deliberations in semi-automatic policy adjustment, and which will require a process of formal review and continued learning.

Without a better-defined adaptive strategy, the analysis in this dissertation does not perfectly represent planning decisions, resulting in somewhat limited policy implications of this research. For example, if planners wish to address different objectives, they may prefer different strategies. Similarly, planners may not be willing to implement some of the actions included in *Portfolio A:*
Inclusive. If planners consider a more limited set of actions, the Basin will face an altered set of vulnerabilities and the decisions-rules may perform differently.

For the analysis to more accurately reflect the decision-process in the Basin, it could be better integrated into the Basin’s planning process. The Colorado River Basin Study was completed in a process of deliberations and analysis—the analytical process included frequent interactions among analysts, planners, and other stakeholders. It benefited greatly from the expertise of planners and stakeholders because analysts were able to tailor the modeling and presentation of results to planners’ specific needs. Many analytical decisions were made in this dissertation with the intention of representing how planners may confront certain choices. However, the analysis in this dissertation could have been more tailored to planners’ needs had there been opportunities to interact with stakeholders. This section summarizes some decisions that may have been made differently with feedback from stakeholders.

Scoping the analysis

The analysis may have been scoped differently if planners participated in the first step of the RDM process. This dissertation includes specific decisions regarding the planning objectives (M) and strategies (L). These decisions have specific implications for the subsequent analysis. Some of these decisions and their implications are described in this section.

This dissertation evaluates the health of the Basin using two water delivery objectives, preventing a Lee Ferry Deficit and maintaining Lake Mead’s pool elevation above 1,000 feet. Both these measures focus on just one Basin objective: water supply reliability. However, Basin planners may consider many other objectives including maintaining streamflow for wildlife habitats and recreational use or managing the reservoirs to maintain power production. Additionally, failure to meet either of the two water delivery objectives would represent historically unprecedented levels of shortage. Planners concerned only with water delivery would likely wish to maintain a higher-level reliability and would consider other water delivery objectives (such as the definitions of Lower Basin shortage included in the Basin Study).

The analysis in this dissertation is limited because it only reports the performance of the various strategies with reference to these two objectives. To support Basin planners in an adaptive process, this analysis would likely need to expand the set of objectives considered. Additional analysis could report the performance of various strategies on the wider set of objectives, presented in the Basin Study.

By only considering these two objectives, the analysis assumes planners are only adapting to maintain Upper Basin and Lower Basin water delivery. If planners are willing to adapt to address different objectives, the system as a whole will change. For example, if planners are trying to achieve a higher level of water delivery reliability in the Lower Basin, they will likely implement more water management actions sooner. Because planners will be more aggressive to meet this alternative objective, it is possible they could afford to be more conservative when considering decision-rules specific to Lake Mead. Alternatively, planners in the Basin may design new instream flow requirements to maintain endangered species’ natural habitats. Such requirements may decrease the flows available for consumptive use and planners would need to be more aggressive
with other actions to maintain supply reliability. The choice of objectives used in this analysis not only determines the information provided to planners, but also influences the structure of the decision-relevant scenarios, decision-rules and implementation schedules. All these results may have been different, with feedback and interactions with stakeholders.

Similarly, this dissertation only investigates a single portfolio of water management actions. This portfolio includes actions inconsistent with some planners underlying preferences for how the Basin should be managed. For example, Portfolio A: Inclusive includes an option to import additional water resources from the Missouri River. Such an action would likely be expensive, require high levels of energy use, and have important environmental impacts in other regions in the U.S.; many also consider it politically infeasible. The Basin Study assesses three additional portfolios to reflect different planning preferences and the tools generated during the Basin Study could facilitate an evaluation of even more portfolios. Interactions with stakeholders could have helped identify a set of alternatives, which better reflect their planning preferences.

Again, there are two limitations of not considering additional portfolios. First, this dissertation does not address an important decision that planners face: which actions they will implement. More importantly, the simple decision model in Chapter 3 shows that planners preferred strategies that depend on both cost and expected effect of the actions considered; the decision-rules cannot be considered in isolation of the actions. For example, planners may determine that imports from the Missouri River are infeasible and choose not to include them in a portfolio. In this alternative portfolio, it could be beneficial to act more aggressively allowing the system to begin storing excess water sooner. Thus, this dissertation only presents decision-rules and implementation schedules consistent with the actions included in Portfolio A: Inclusive.

The sixth chapter of this dissertation considers strategies defined by different trigger values of streamflow and reservoir levels. The strategies were identified by iteratively testing different trigger values that produce a range of outcomes. Planners may have been able to identify some policy-relevant trigger values—thresholds with some meaningful interpretations. For example, there may be certain threshold values of pool elevations of Lake Mead and Lake Powell that planners already monitor and use to make decisions. Feedback from planners could have ensured that the various candidate adaptive strategies are easily interpretable to planners.

Chapter 6 of this dissertation also presents two new metrics designed to help planners measure the relative costs of under-investment and over-preparedness—implementation regret and vulnerability regret. Various analytical choices defined these measures. For example, implementation regret could have just as easily been measured in terms of cost rather than yield. The analysis imposes a definition of “low-regret”, threshold values that define when the strategies perform acceptably in terms of these two metrics. Planners and stakeholders could have provided feedback on the design and interpretability of these metrics and thresholds.

If different strategies were considered or different metrics were used to measure the effectiveness of the strategies, the exact tradeoffs that planners would face would be presented differently. It is likely that the primary policy story would remain the same—planners face a tradeoff between over-preparedness and under-investment. However, the last section of Chapter 6 presents tradeoff
curves to help planners identify a strategy that best matches their preferences across a range of plausible beliefs. With different sets of strategies or different metrics to measure their performance, these tradeoffs would look different, and planners may choose different strategies to implement.

**Participating in the analytical process**

In a deliberations with analysis process, stakeholders and analysts would interact frequently. The RDM process is not simply designed to receive feedback from planners solely at the beginning; there are various other points throughout the analytical process where planners could participate. Such participation could have altered several pieces of analysis, some of which are described below.

Chapter 5 of this dissertation considers how planners may reasonably update their beliefs about three decision-relevant scenarios as new information becomes available. This analysis explores across a range of plausible current beliefs about the scenarios, and it reflects that planners may believe each scenario is anywhere between 0 and 100 percent likely. However, this may be unrealistic. The *Severely Declining Supply* scenario represents unprecedented decreases in average annual streamflow, below even the driest periods of paleohistorical record. Additionally, a majority of the global climate change projections present suggest wetter future conditions. It is quite likely that no planners consider this scenario 100 percent likely and possibly no planners currently consider this the most likely scenario. One could elicit the reasonable range of beliefs about the scenarios. If the analysis explored a more limited range of prior beliefs, the analysis would provide a detailed rules-of-thumb within the most-relevant ranges of beliefs.

The sixth chapter describes some strategies that range across a continuum of aggressive to conservative responses to new information. These candidate strategies were designed by iteration, with the objective to span a range between the *Current Management* and the *Static Implement-All-Actions* strategies. It then uses information learned in the initial analysis to propose and evaluate two additional strategies: an *Increasingly Aggressive* and *Decreasingly Aggressive* strategy. Planners could have been party to this iterative process, ensuring that strategies provided enough detail in the ranges they had the most interest. For example, planners may have reasonably expressed a preference that any strategy would need to meet Lower Basin water delivery objectives in at least 30 percent of futures. In such a case, the analysis could have focused more finely on strategies between *Moderately Aggressive* and the *Static Implement-All-Actions* strategy, rather than exploring the entire range.

Chapter 7 makes a large number of analytical decisions designed to reflect planners’ preferences. Certain parameters in the CART analysis generating implementation scenarios reflect a preference to meet water delivery objectives at the expense of over-investing. The scenarios also reflect a high value on their interpretability and limit the number of restrictions defining the scenarios; scenarios that are more complex may have classified futures more accurately. Had planners and stakeholders participated in the process of identifying scenarios, the analysis could have ensured that the scenarios provided the greatest utility in a planning process. Additionally, the various implementation pathways present specific summaries of the simulation data (the 90th percentile), which reflect a preference to maintain a certain level of reliability. The figures in this dissertation could have reported different levels if planners had provided feedback.
Completing analysis without interactions with planners also deprives planners of an opportunity to learn and build intuition. The process of planners and analysts working together would have allowed planners to more fully consider many subjects covered in this dissertation. For example, had the analysis in Chapter 5 elicited a reasonable range of probabilities from planners, they would have had the responsibility to consider the definitions of these scenarios. They may have asked additional questions or turned to other research to support their estimates. Creating such informed assessments may have allowed planners to consider whether the set of actions evaluated in this dissertation is sufficient to meet objectives.

Similarly, the analyses in Chapter 7 present various implementation schedules to address different sets of streamflow conditions. These schedules can help planners consider how to implement actions to address different future conditions. However, the utility of the analyses may not actually be decision-pathways presented. Planners may face an entirely different set of decisions by the time 2030 or 2040 occur. Instead, interactive versions of the visualizations could provide planners with the ability to explore the implications of different implementation schedules. The interactive process of investigating different scenarios and summary statistics across different time periods with these tools could help planners gain intuition regarding the performance and robustness of various implementation schedules. Planners may not be presented with precisely the same decisions discussed in this dissertation, but the insight drawn from exploring the results using these tools may make future decisions more closely resemble single-loop learning than double-loop learning.

**Improvements to analysis**

There are also some further analytical tasks that could refine the analysis presented in this dissertation, regardless of the interactions with stakeholders. This section describes some potential additional analyses, which could improve the results presented in this analysis.

Chapter 5 describes a process where climate scientists generate exogenous indicators of decision-relevant scenarios. At this point, these indicators are simply notional. They represent an extremely broad set of information, drawing from an evolving climate science literature. Further collaboration with climate researchers could help generate more specific and realistic indicators. First, climate scientists may be able to evaluate the feasibility of generating the proposed indicators. Additional research could estimate plausible ranges for those indicators. It may also identify other policy relevant signpost variables.

The Bayesian model proposed in Chapter 5 includes an assumption that the exogenous indicator is independent from the observed streamflow conditions. This assumption is acceptable when the indicator is simply notional, as it can represent only information not captured by the streamflow signal. However, as further research more clearly defines information included in this indicator and it becomes more specific, this assumption may need to be revisited. It is possible that the various indicators will be somehow correlated with another. If so, treating them as independent may overstate the strength of the signal. As more clearly defined indicators are generated, one could more carefully evaluate the independence assumption used in the naïve-Bayes classifier model.
At various points, the analyses in Chapters 5, 6 and 7 utilize an assumption that all futures are weighted equally, conditional on a decision-relevant scenario. In Chapter 5, the naïve-Bayes model uses conditional probabilities distributions, which were fit with this assumption. In Chapter 6, the expected likelihood of meeting water delivery objectives, and the expected implementation and vulnerability regret are calculated using this assumption. In Chapter 7, the summary statistics describing percentiles of implementation in each time period also implicitly rely on this assumption. A sensitivity analysis could identify other reasonable weighting schemes and characterize the extent to which the result relies on this assumption.

The analyses in this dissertation could be improved with estimates of the economic cost of failing to meet water delivery objectives and discounted cash flows for the costs of implementing the various water management actions. Chapter 6 provides a cost-effectiveness analysis, measuring the relative annual cost required to meet water delivery objectives. Similarly, in Chapter 7, the objectives in meeting water delivery are treated as a constraint. With improved estimates, the analysis could provide recommendations on minimum cost strategies, rather than characterize results as a tradeoff between the risk of under-investment and over-preparedness. If there were remaining uncertainties regarding harms or costs, they could be further explored as parameters in an RDM analysis.

In Chapter 6, the tradeoffs among strategies defined by different decision-rules are specific to the signpost variables being considered. The adaptive strategies assume planners monitor the five-year running average of natural streamflow at Lees Ferry and reservoir levels at the end of a year. First, planners could rely on different measurements of hydrologic conditions. It is conservable that alternative measurements could produce different results. For example, the seven-year running average streamflow may be a better predictor (having a higher true-positive and true-negative rate) than the five-year average. Some simple analyses during the Basin Study considered alternative characterizations, which did not suggest dominant alternatives. However, it remains possible that better hydrologic signpost variables exist, which could change the tradeoffs planners face.

More importantly, planners will likely monitor other pieces of information that could reduce both Type I and Type II errors. For example, researchers are actively exploring improved decadal projections of climate and hydrologic conditions. If information from this research can be reasonably incorporated into decisions-rules, there may be strictly dominant strategies to those considered in this dissertation. To represent such decision-rules in the hydrologic model, a more sophisticated simulated-planning agent could be developed; the model could explicitly consider different information sets that the planning agent would have. Such an improved model could estimate the value of these additional pieces of information, identifying the reductions in expenditures, the futures that fail to meet objectives, or the regret generated by more accurate signposts variables. In turn, this could provide policy recommendations regarding investments in improved forecasts or the ability to monitor climate literature.

86 This assumption is discussed in both in Chapter 3 and Chapter 5

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Chapter 7 describes a low-resolution quasi-optimization routine used to identify low-regret strategies. This dissertation did not investigate alternative, more robust optimization routines. The resulting low-regret implementation strategies may have been different with alternative strategies. The analysis in the Upper Basin reveals that many futures require nearly the maximum potential yield to meet objectives. It is possible this result is a feature of the optimization routine, and alternative methods of optimization could have found more varied portfolios of implemented actions across the set of futures. Further research could integrate improved optimization routines with CRSS. Using a set of optimized strategies with a more robust optimization routine, one could reassess the implementation scenarios and schedules.

**Implications for using RDM with adaptive strategies**
This dissertation also contributes to the RDM literature, proposing an approach to support adaptive strategies. Chapters 2 and 3 of the dissertation describe an augmented RDM process that iterates through the RDM cycle multiple times. This dissertation aims to have implications for the practice of RDM beyond the Colorado River Basin. It suggests a toolkit that analysts can use when providing decision support to planners creating adaptive strategies. While the analysis draws from previous applications of RDM, including but not limited to the Colorado River Basin study, many of the analyses presented in this dissertation are new.

The analyses represent methodological advancements in the use of RDM to support the development of adaptive strategies. Chapter 5 demonstrates that decision-relevant scenarios can serve as the basis for a Bayesian updating process. Chapter 6 uses standard RDM tools to consider tradeoffs among alternative responses to new information. It is not the first time an RDM analysis has considered decision-rules as part of the strategy, but is among the first to explicitly consider the tradeoffs that arise from different responses to the same information. Chapter 7 presents a new approach, referred to as optimize and characterize, to generate insight regarding how adaptive strategies should implement actions in different futures.

Additional research is necessary to validate these methods and improve them. This chapter discusses two directions for further research. Further research can ensure the tools, analysis and visual-aids proposed in this dissertation provide effective decision-support to planners. Analysis alone is not decision-support. It becomes decision-support when it provides utility to planners as they confront choices when designing policy. One could evaluate the impact that the analyses in this dissertation have on decision-making.

The second area for research recognizes that by definition, there are multiple sequential decisions within an adaptive strategy. The analyses in this dissertation are in some sense static as the analysis only uses information available at the time of its own publication. However, planners will require decision-support throughout the entire planning horizon. Additional research could build tools, which update the analyses with new information quickly and easily. Such tools would provide decisionmakers with access to up-to-date decision-support as they confront new decisions over the planning horizon.
Analysis as decision-support

The National Research Council (2009) describes a "science of decision support", which uses social sciences to ensure that tools, aids, and analysis help planners make better-informed decisions. Such research can include experiments, focus groups, surveys or other methods to evaluate planners' ability to cognitively understand information presented in analyses. It can also evaluate planners' confidence in their decisions after using decision-support tools and analysis. Many previous RDM methodological developments have undergone such examination (Groves, Knopman et al. 2008, Parker, Srinivasan et al. 2014)

The research presented in this dissertation aims to provide effective decision-support to planners. However, many of the sub-analysis provided in this dissertation (the Rules-of-Thumb, Implementation Scenarios, and Implementation-Pathways) are new to this dissertation. At this point, one cannot claim that they provide better decision-support; this has yet to be tested. Though the methods and presentation described in this dissertation are extensions of previous RDM and decision-support literature, it is likely that they can continue to be improved. This dissertation solely takes a first step in improving decision-support by proposing some analyses. Further research and iteration could continue to improve either the analysis or its presentation and ensure it has the greatest utility for planners.

This need is perhaps most apparent in Chapter 5 of this dissertation. The analysis in this chapter identifies pieces of information that will cause planners to change their beliefs about decision-relevant scenarios if observed. The usefulness of this analysis relies on two underlying hypotheses. First, it assumes that individuals often rely on heuristics to update their beliefs rather than using an efficient information process rule such as Bayes’ Law. 87 Thus, providing them with tools and analyses can help them interpret new information appropriately. Secondly, it assumes planners will more easily and rapidly respond to new information if they have some guide to how it may affect their beliefs before the information becomes available. Further research could confirm whether these two hypotheses are correct. If so, new tools can assist planners to be ready to appropriately respond to the new information once it becomes available.

Chapter 5 presents two aids to help planners anticipate which signposts will change their beliefs. The first is a series of visualizations that contain a set of prior beliefs, time-series of future streamflow, and the resulting posterior beliefs. These visualizations have been built into an interactive dashboard that allows users to manually adjust prior beliefs and cycle through multiple futures. Planners can use this tool to interactively explore how different observations would update posterior beliefs. The second aid is the "rules-of-thumb" analysis. This approach uses exploratory modeling to generate a database of plausible beliefs and signposts. Statistical techniques reduce the dimensionality of this space, describing ranges of beliefs and observations where planners may have specific posterior beliefs. Further research could confirm whether either of these approaches effectively address the gaps in knowledge hypothesized above. It may also suggest one approach is better than the other or propose refinements to either to ensure that they have the greatest effect.

87 This hypothesis has been supported in various pieces of research about human behavior, such as Tversky and Kahneman (1974)
on planners. If these aids are in fact helpful, they have the ability to useful in the context of negotiations—as planners will not need to agree on what the current state of the world is, they would only need to agree on what they would need observe in order to agree. Essentially, this creates a conditional forward looking agreement.

Chapter 5 is not the only place in this dissertation where such research could be beneficial; other analysis and visualizations could also benefit from evaluation and iterative improvement. For example, one could confirm that the second iteration through the RDM process described in Chapter 2 is a process that planners can understand and is useful to analysts as they frame their research steps. One could ensure that many of the visual aids presented in Chapter 7 are useful to planners or that interactive versions help provide planners with new insight.

**Updating analyses over time**

A distinctive feature of adaptive strategies is that planners make multiple decisions over time. Planners do not simply require decision-support at the start of the planning horizon. Though the analysis presented in this dissertation looks into the future and assumes plans will change, it is in some sense fixed. The analysis in this dissertation is based on information currently available—it reflects physical systems, relies on scientific assessments, and attempts to address planners’ beliefs, preferences, and objectives from 2012, the year the Basin Study was published.

Once a single decision is made or new information becomes known, the system may change from what was analyzed. An RDM analysis attempts to be broad enough to reflect many possible ways in which the system may change. However, new information becomes available, new actions become feasible, objectives change, and systems are altered over the course of a 50-year planning horizon. For example, just in the time since the Basin Study was published, a severe drought has occurred in the Western U.S. and a new set of climate change projections from the 5th IPPC assessment have become available.

Because decision-making is not static, the tools that support it also cannot be static. Many of the analyses described in this dissertation require a fair amount of work by analysts to prepare decision-support. There is frequently a substantial period of time between when analysis begins and deliberations occur. However, new automated tools could help support a dynamic decision-making process.

Using computing resources available during the Basin Study and the writing of this dissertation, it took multiple weeks to run simulations evaluating the candidate strategies across the ensemble of plausible futures. New super-computing resources or scalable-cloud computing can allow more instances of the simulation model to be run in parallel, decreasing the time between designing portfolios and their analyses.

Following the simulation process, analysts generally use data with statistical tools to design decision relevant scenarios, based on the objectives defined in the scoping process. There may be ways to integrate these statistical tools into a user-friendly platform. One could imagine a process where planners could easily scope a computational experiment and upload the results into a
graphical-user interface that allows them to explore results and build scenarios. If the tools and analyses presented in this dissertation improve the decisions that planners make, benefits could be drawn by more frequent updates. As tools improve, analysts can expend effort on considering new analyses, rather than simply updating old analyses with the newest information.
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