

Making Good Decisions Without Predictions

Robust Decision Making for Planning Under Deep Uncertainty

Quantitative analysis is often indispensable for making sound policy choices. But when decisionmakers confront today's conditions of fast-paced, transformative, and even surprising change, they sometimes find that commonly used quantitative methods and tools prove counterproductive or lead them astray.

Typically, quantitative analysis provides decisionmakers with information about the future by making predictions. For example, computer models might predict whether a water agency's investments can ensure a reliable, cost-effective supply for its customers. Or a model might predict whether a piece of legislation before Congress will cost or save taxpayers money. But predictions are often wrong, and relying on them can be dangerous. Moreover, decisionmakers know that predictions are often wrong; this can cause them to discount or ignore the crucial information that quantitative analysis can provide.

Fortunately, the combination of new information technology and new insights from the decision sciences now enables innovative ways to support decisions with quantitative analysis. This research highlight describes how one such approach—Robust Decision Making (RDM)—informs good decisions without requiring confidence in and agreement on predictions and offers examples of its increasing impact in a wide range of policy areas.

Running the Analysis Backward

RDM rests on a simple concept. Rather than using computer models and data to describe a best-estimate future, RDM runs models on hundreds to thousands of different sets of assumptions to describe how plans perform in a range of plausible futures. Analysts then use visualization and statistical analysis of the resulting large database of model runs to help decisionmakers distinguish future conditions in which their plans will perform well from those in which they will perform poorly. This information can help decisionmakers identify, evaluate, and choose robust strategies—ones that perform well over a wide range of futures and that better manage surprise.

Traditionally, decisionmakers receive quantitative information about the future in a *predict-then-act* framework: Assemble the available evidence into best-estimate

Abstract

When policymakers and decisionmakers face a hard-to-predict, deeply uncertain future, they need more than traditional prediction-based decision analysis to help them choose among alternatives. Fortunately, there are new approaches, such as Robust Decision Making (RDM), that exploit increasingly capable computer tools and are well suited for such situations. RDM rests on a simple concept: Rather than using models and data to describe a best-estimate future, RDM runs models many hundreds to thousands of times to determine how plans perform in a range of plausible futures. Visualization and statistical analysis of the resulting database of runs then help decisionmakers distinguish those future conditions in which their plans perform well from those in which their plans perform poorly, assisting them in making their plans more robust. This research highlight discusses how RDM works and illustrates its benefits through two example applications: helping a water management agency adaptively plan for climate change and determining whether federal terrorism insurance would cost or save taxpayers money.

predictions of the future and then suggest the best course of action given these predictions. Such methods work well when predictions are accurate and uncontroversial. Otherwise, the approach can encourage either gridlock or overconfidence: the former when participants to a decision argue over projections rather than solutions, and the latter when they choose solutions that fail when the future turns out differently than expected.

RDM avoids these problems by running the analysis “backward.” Rather than start with predictions, the approach begins with one or more plans under consideration (often a current or best-estimate plan) and uses multiple runs of the model to identify the futures most relevant to the plan's success. Just as people routinely use search engines, such as Google, to scan millions of websites to find information that interests them, RDM analyzes data across many model runs to help decisionmakers address such questions

as “What are the key characteristics that differentiate those futures in which a plan succeeds from those in which it fails?” and “What steps can be taken so a plan may succeed over a wider range of futures?”

Analytics to Facilitate a New Conversation Among Decisionmakers

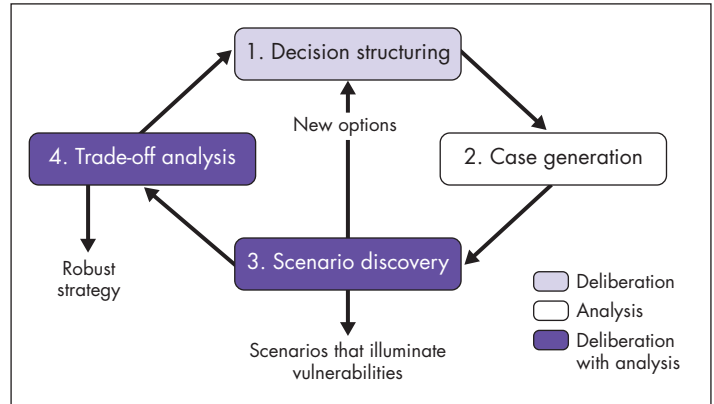
Decades of experience and research make clear that analytics—the discovery and communication of meaningful patterns in quantitative information—is most effective when closely linked to users’ needs. RDM’s analytics are specifically designed to improve conversations among decisionmakers under conditions of deep uncertainty. Deep uncertainty occurs when the parties to a decision do not know—or agree on—the best model for relating actions to consequences or the likelihood of future events.

RDM follows a “deliberation with analysis” process of decision support, as recommended by the U.S. National Research Council. The process begins with many participants to a decision working together to define their objectives and other parameters. Participants next engage with experts to generate and interpret decision-relevant information and then revisit choices and objectives based on this information. RDM adds to this general approach the concepts of running the analysis backward—that is, beginning with a proposed decision—and testing plans against many different plausible futures.

The RDM process, shown in Figure 1, begins with a decision structuring exercise in which decisionmakers define the goals, uncertainties, and choices under consideration (step 1). Analysts then use computer models to generate a large database of runs (step 2) in which each case represents the performance of a proposed policy in one plausible future. Computer visualization and statistical analysis of this database help decisionmakers identify clusters of scenarios that illuminate the policies’ vulnerabilities (step 3). These scenarios can then help decisionmakers identify potential new ways to address those vulnerabilities (back to step 1) or evaluate through trade-off analysis whether these choices are worth adopting (step 4). The process continues until decisionmakers settle on a robust strategy.

RDM fosters a new conversation among decisionmakers by combining the best features of two traditional approaches to uncertainty management: scenarios and probabilistic risk analysis. Scenarios describe potential future conditions. By presenting a set of plausible and contrasting futures worthy of consideration, scenarios can help break down the cognitive and organizational barriers that often limit decisionmakers’ ability to consider a sufficiently wide range of potential futures and alternative decision options. But with traditional approaches, the choice of a small number of scenarios to summarize many futures can appear arbitrary or biased.

Figure 1. Iterative, Participatory Steps of an RDM Analysis



In contrast, probabilistic risk analysis—a predict-then-act approach—uses quantitative predictions of risk (often defined as the predicted probability multiplied by the predicted consequence of an event) to systematically inform decisions about the allocation of effort to reduce risk. While often useful when uncertainties are well understood, the approach faces the perils of prediction when uncertainties are deep.

RDM draws from both scenarios and probabilistic risk analysis by running the latter backward to ask which policies reduce risk over which range of assumptions, inquiring, for example, “What assumptions would we need to believe were true for us to reject option A and instead choose option B?” Doing so identifies high- and low-risk scenarios that, as in the example cases below, can prove useful in contentious policy debates. These scenarios can also inform creative thinking on robust plans and help decisionmakers assess trade-offs among these plans, as shown in Figure 1.

RDM uses computer models in a way that is fundamentally different from the approach used in predict-then-act analyses. The latter regard models as representations of reality that are sufficiently accurate to recommend the best response to an uncertain future. In contrast, RDM regards models as mapping assumptions to consequences. Often, RDM can significantly enhance the value of decisionmakers’ existing models (designed for predict-then-act analysis) by running them numerous times to identify vulnerabilities and to find plans that are robust over many combinations of assumptions.

By embracing many plausible futures within a quantitative analysis, RDM can help reduce overconfidence and the deleterious impacts of surprise, can systematically include imprecise information in the analysis, and can help decisionmakers and stakeholders with differing expectations about the future reach a well-grounded consensus on action, even when uncertainties are deep.

Improving Real-World Decisions

RDM has helped decisionmakers successfully confront difficult challenges in many policy areas. Here, we present two examples from the domains of water management and terrorism insurance. The first highlights how RDM helped an agency use imprecise projections to develop flexible and robust plans while preserving analytic rigor and public accountability. The second explains how RDM—by including assumptions about a wider range of crucial but hard-to-forecast factors—can produce different and more-effective answers than traditional predict-then-act analysis.

Making Water Plans Flexible, Robust, and Accountable

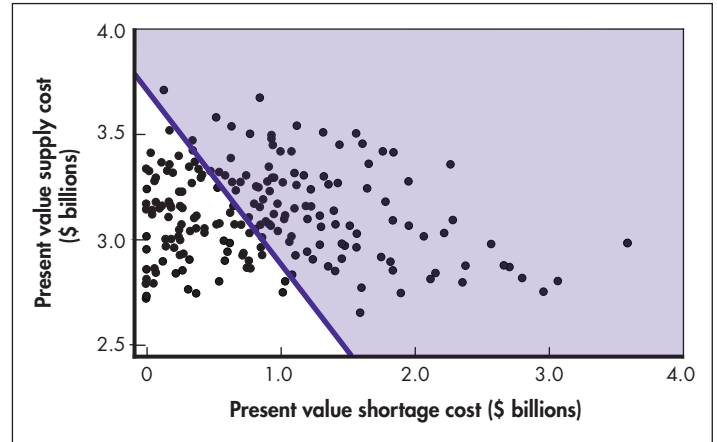
Challenge. Many water management agencies develop long-range plans that look out several decades to help set investment priorities and facilitate discussion with constituents about priorities and goals. Although such plans are generally updated every few years, the current state of the art in water management involves testing plans against, at most, a handful of scenarios, and it regards plans as fixed over their lifetime. Water managers recognize that robustness and flexibility often provide the best response to deeply uncertain future conditions. But they have lacked a means to make plans robust and flexible while preserving analytic rigor and being accountable to their constituents.

How RDM Addressed the Challenge. In 2005, Southern California’s Inland Empire Utilities Agency (IEUA), a wholesale water provider and wastewater processor for a region in the midst of a transformation from agriculture to rapid urban growth, used traditional methods to develop its long-range urban water management plan (UWMP). The plan aimed to meet growing regional demand by increasing groundwater use by 75 percent and recycled water use by 600 percent. But in doing so, IEUA did not consider the potential impacts of climate change. Thus, in 2007, RAND helped the agency revisit its 2005 UWMP—an effort that also helped IEUA improve its overall planning capabilities.

Following the steps shown in Figure 1, RAND developed a computer model, based on the WEAP (Water Evaluation And Planning) platform, to explore the performance of IEUA’s water plan over hundreds of cases that reflected a wide range of alternative assumptions about the future climate, IEUA’s ability to meet its water recycling and groundwater goals, the future cost of imported water, and the future use of water-saving technology.

In workshops with IEUA managers and constituents, RAND used visualizations of the results of many computer model runs (like the one shown in Figure 2) to facilitate discussions about IEUA’s goals, key uncertainties, and actions that could be taken in response. The figure shows the 2005 water plan’s performance out to the year 2030 over a statisti-

Figure 2. Performance of IEUA 2005 UWMP in 200 Cases

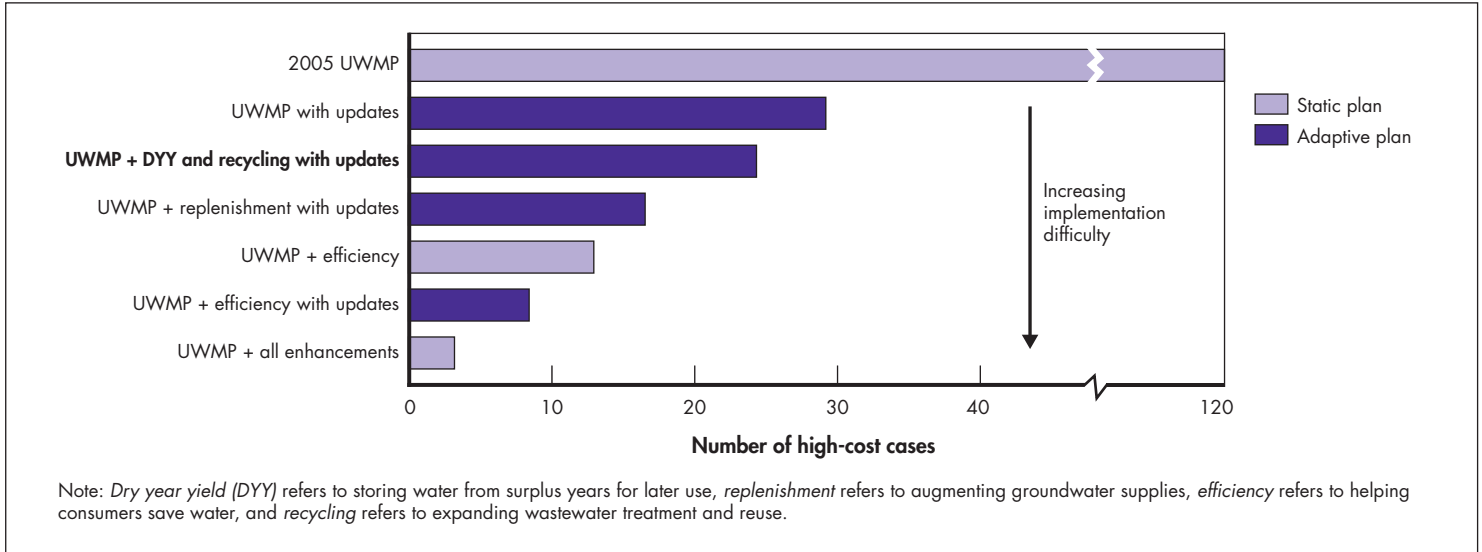


cally representative sample of 200 cases—each one based on a given set of assumptions about the future climate, the agency’s ability to implement its plan, and future socioeconomic conditions. Each point, or case (many of which overlap), shows the plan’s cost: the present value cost of implementing the plan and the additional present value cost of any shortages. The shaded region in the figure shows the 120 cases in which the plan generally failed to meet its goals—determined by IEUA to be any case in which the total cost of implementing the 2005 UWMP (implementation plus shortages) was at least 20 percent higher than the best-estimate cost in the case used to develop the plan.

Statistical analysis of the database of model runs then determined the most important factors leading to such high-cost cases. Of the six uncertain parameters considered, only a specific combination of three led to high costs: a 10-percent or greater decrease in precipitation, a 3-percent or greater drop in the average amount of precipitation that percolates into the region’s aquifers, and larger-than-expected climate effects on imports. This set of three conditions illuminates the main vulnerability of IEUA’s 2005 water plan. Importantly, these factors affect IEUA’s plan only when they occur in combination. If all three occur over the next few decades, the plan will result in high costs. Otherwise, the plan should fare reasonably well.

This information helped IEUA consider potential responses to this vulnerability. In particular, IEUA managers asked which actions they might take immediately and which they could defer. To answer this question, RAND used the computer model to compare static and adaptive plans. Static plans, like the 2005 UWMP, consider fixed 25-year schedules of investments and policy actions. Adaptive plans include a 25-year schedule of investments and policies, key trends to monitor, and updates to be made if particular trends are observed. Specifically, RAND considered adap-

Figure 3. Comparative Performance of 2005 UWMP with Static and Adaptive Plans



tive plans in which IEUA would monitor every five years the difference between projected supply and demand and would respond with corrective action if the gap grew larger than a preset threshold.

Figure 3 compares the 2005 UWMP (at the top) with six alternative static (light purple) and adaptive (dark purple) plans by counting the number of cases in which each plan exceeds the cost goal. As noted, the 2005 UWMP exceeds the cost goal in nearly 120 of the 200 cases considered. Just making the current plan adaptive—taking the same near-term actions as in the 2005 UWMP while monitoring and updating as necessary—drops the number of high-cost cases to about 30 (the dark purple “UWMP with updates” bar). If IEUA adopted all the near-term enhancements shown in the figure (the light purple “UWMP + all enhancements” bar), it would eliminate almost all the future vulnerability identified by the analysis.

Figure 3 lists the plans in order of increasing implementation difficulty (because no better cost data were readily available). Thus, IEUA faced a trade-off between near-term implementation difficulty and reducing future vulnerability. These results helped IEUA choose, as an appropriate balance, to augment its 2005 UWMP as an adaptive plan with additional near-term enhancements to its recycling and DYY program, reducing the number of high-cost cases from 120 to 25 (the option in bold type in the figure).

Impact. RDM helped IEUA incorporate uncertain climate projections into its long-range plans and develop with confidence a robust and flexible response to climate and other uncertain future conditions. RDM helped the agency build consensus for this plan among its constituents and ratepayers, even those who were dubious about climate

change. Since this initial application, a large number of other water agencies have begun to integrate RDM into their planning.

Evaluating Whether Federal Terrorism Insurance Would Save Taxpayers Money

Challenge. In the aftermath of the September 11, 2001, terrorist attacks, insurance companies dropped terrorism coverage for commercial real estate, a move that threatened the economies of areas that were deemed at risk of future attacks (such as Manhattan). In response, Congress passed the Terrorism Risk Insurance Act (TRIA) in 2002 to provide a federal guarantee to compensate insurers for losses from very large terrorist attacks in return for insurers offering insurance against attacks of all sizes. In 2007, when Congress began to debate whether to reauthorize TRIA, one central concern was whether the legislation would save or cost taxpayers money. But uncertainties about the likelihood of large terrorist attacks and other key factors made it difficult to reliably answer this question.

How RDM Addressed the Challenge. To inform these deliberations, RAND developed a computer model that projected the costs to taxpayers, the insurance industry, and commercial property owners given various assumptions about the size and type of any future terrorist attacks, the behavior of the insurance industry and its customers, and the willingness of future Congresses to compensate property owners without insurance.

To estimate the likelihood of future terrorist attacks, analysts used estimates from Risk Management Solutions (RMS), a leading provider of risk information to the insurance industry. They built an economic model to estimate the

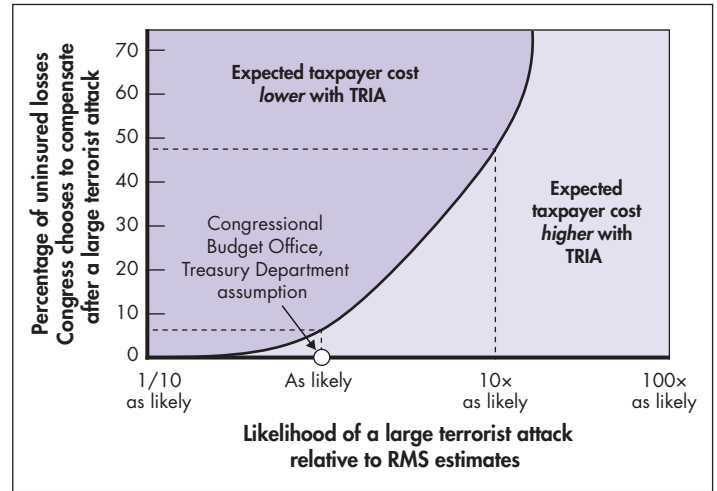
behavior of insurance companies and their customers. With little ability to predict the behavior of future Congresses, the analysts assumed that future Congresses would compensate anywhere between 0 and 100 percent of uninsured losses. They then ran the computer model over thousands of different combinations of 17 parameters to explore the consequences of these various assumptions.

Figure 4 summarizes the results. Statistical analysis of the database of thousands of model runs indicated that of the 17 uncertain parameters considered, two most strongly differentiated the cases in which TRIA saved taxpayers money from those in which it did not. These parameters, shown on the axes of Figure 4, were the likelihood of a large terrorist attack and the amount that Congress compensates the uninsured. The analysis also identified the relevant threshold for a large attack as one with more than \$40 billion in losses, about twice that suffered on 9/11. The horizontal axis in Figure 4 shows the likelihood of a terrorist attack that generates losses larger than the \$40 billion threshold relative to what RMS predicted. The vertical axis shows the percentage of uninsured losses that Congress chooses to compensate after an attack.

The dark-shaded region in Figure 4 represents a scenario in which the taxpayer cost is lower when TRIA is reauthorized than when it is allowed to lapse. Taxpayer costs are higher in the lightly shaded region. Decisionmakers can clearly see that TRIA provides a net benefit to taxpayers over a very wide range of plausible assumptions—in particular, over a wide range of estimates of the hard-to-predict behavior of a future Congress.

Impact. The RDM analysis made significant contributions to the congressional debate. Importantly, the analysis arrived at the opposite conclusion from that of the Congressional Budget Office and the U.S. Department of the Treasury. Using predict-then-act analysis, these two agencies had no way to represent uncertainty about the behavior of future Congresses. Thus, they assumed that Congress would do nothing—that is, offer no compensation to the uninsured after a large terrorist attack—and estimated that TRIA would prove costly to taxpayers (as shown by the white dot in Figure 4). Many regarded this assumption as unrealistic. As Figure 4 makes clear, had these agencies assumed compensation at almost any other level, they would have come to a different answer. Congress decided to reauthorize TRIA.

Figure 4. Expected Annual Taxpayer Cost With and Without TRIA



This RDM analysis and its framing proved very effective as a way of presenting uncertain information in this contentious political debate.

RDM: A New Approach to the Challenge of Planning for a Deeply Uncertain Future

Decisionmakers often require quantitative analysis to inform good choices, but with today’s conditions of fast-paced, transformative, and often surprising change, traditional predict-then-act approaches to policy analysis can lead them astray. RDM provides a systematic approach to informing good decisions under conditions of deep uncertainty when predictions are unreliable. The approach runs traditional analysis backward, using computer models and data to explore outcomes over many plausible futures and to help decisionmakers identify conditions under which their plans will perform well or poorly. This information helps decisionmakers identify and choose more-robust plans. In many applications—including water management, energy resources, flood risk management, and national defense—RDM facilitates a new relationship between decisionmakers and their analytics, helping them shift from the often unanswerable question of “What will the future bring?” to the more effective and impactful query of “What steps can we take today to most assuredly shape the future to our liking?”

This research highlight draws from RAND research on RDM methods and specific applications in the following publications:

Methods

Hall, Jim W., Robert J. Lempert, Klaus Keller, Andrew Hackbarth, Christophe Mijere, and David J. McInerney, "Robust Climate Policies Under Uncertainty: A Comparison of Robust Decision Making and Info-Gap Methods," *Risk Analysis*, Vol. 32, No. 10, October 2012, pp. 1657–1672.

Lempert, Robert J., and Nidhi Kalra, *Managing Climate Risks in Developing Countries with Robust Decision Making*, Washington, D.C.: World Resources Institute, 2011.

Bryant, Benjamin P., and Robert J. Lempert, "Thinking Inside the Box: A Participatory, Computer-Assisted Approach to Scenario Discovery," *Technological Forecasting and Social Change* Vol. 77, No. 1, January 2010, pp. 34–49.

Fischbach, Jordan R., *Managing New Orleans Flood Risk in an Uncertain Future Using Non-Structural Risk Mitigation*, Santa Monica, Calif.: RAND Corporation, RGSD-262, 2010, http://www.rand.org/pubs/rgs_dissertations/RGSD262.html.

Groves, David G., and Robert J. Lempert, "A New Analytic Method for Finding Policy-Relevant Scenarios," *Global Environmental Change*, Vol. 17, No. 1, 2007, pp. 73–85.

Lempert, Robert J., and Myles T. Collins, "Managing the Risk of Uncertain Threshold Responses: Comparison of Robust, Optimum, and Precautionary Approaches," *Risk Analysis*, Vol. 27, No. 4, August 2007, pp. 1009–1026.

Lempert, Robert J., David G. Groves, Steven W. Popper, and Steven C. Bankes, "A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios," *Management Science*, Vol. 52, No. 4, April 2006, pp. 514–528.

Popper, Stephen W., Robert J. Lempert, and Steven C. Bankes, "Shaping the Future," *Scientific American*, April 2005, pp. 66–71.

Lempert, Robert J., Steven W. Popper, and Steven C. Bankes, *Shaping the Next One Hundred Years: New Methods for Quantitative Long-Term Policy Analysis*, Santa Monica, Calif.: RAND Corporation, MR-1626-RPC, 2003, http://www.rand.org/pubs/monograph_reports/MR1626.html.

Lempert, Robert J., "A New Decision Sciences for Complex Systems," *Proceedings of the National Academy of Sciences*, Vol. 99, Suppl. 3, May 14, 2002, pp. 7309–7313.

Applications

Lempert, Robert J., and David G. Groves, "Identifying and Evaluating Robust Adaptive Policy Responses to Climate Change for Water Management Agencies in the American West," *Technological Forecasting and Social Change*, Vol. 77, No. 6, July 2010, pp. 960–974.

Dixon, Lloyd, Robert J. Lempert, Tom LaTourrette, and Robert T. Reville, *The Federal Role in Terrorism Insurance: Evaluating Alternatives in an Uncertain World*, Santa Monica, Calif.: RAND Corporation, MG-679-CTRMP, 2007, <http://www.rand.org/pubs/monographs/MG679.html>.

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