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Forecast value: descriptive decision studies

THOMAS R. STEWART

1. Introduction

Studies of the value of forecasts necessarily consider — either explicitly or implicitly — the decisions made by users of the forecasts. Most such studies involve both description (how users actually decide) and prescription (how they should decide). The purpose of this chapter is to present the descriptive approach to studying the value of weather forecasts and to compare it with the prescriptive approach that is treated in several other chapters of this volume (especially Chapter 4).

Both descriptive and prescriptive approaches are based on the belief that the value of weather forecasts is derived primarily from their effects on the decisions of individuals engaged in weather-sensitive activities (McQuigg, 1971), and both approaches require decision-making models to assess those effects. The critical differences between the two approaches are the methods used to develop the decision-making models and the criteria employed for evaluating them. Descriptive models are evaluated according to their ability to reproduce the behavior of decision makers. Prescriptive models are evaluated according to their ability to produce decisions that are optimal according to some normative theory of decision making.

The descriptive and prescriptive approaches are compared in Section 2. In Section 3, a representative sample of descriptive studies is classified and reviewed. Selected results from descriptive research on judgment and decision making that apply to weather-information-sensitive decisions are presented in Section 4. Section 5 includes a brief overview of two broad classes of methods for descriptive decision modeling.

2. Comparison of descriptive and prescriptive studies

In this chapter, the value of forecasts is treated from the perspective of an individual decision maker or a group of decision makers with common interests. Important issues arise when estimating the value of forecasts to an industry composed of individuals who all have the same information (e.g., Lave, 1963) or in determining the value of forecasts at the national level (Johnson, 1990), but these issues are not treated here (also see Chapter 3 of this volume).

2.1. Requirements for a complete descriptive study

Davis and Nnaji (1982) list six types of evaluative information needed to estimate the value of a forecast (p. 463): (i) a payoff function and decision rule based on the information (e.g., a rule for issuing a flood warning based on stream gage readings and a payoff function specifying the costs of all possible combinations of forecasts and events); (ii) a conditional probability distribution of the state of nature given the information; (iii) a probability distribution over the information that might be generated; (iv) the average number of information events per unit time; (v) all the users of the information, their decision rules, and their payoff functions; and (vi) the cost of the information.

These requirements apply to both descriptive and prescriptive studies. The key difference is how the user's decision rules (which constitute a decision model) are obtained. In a prescriptive study, the decision model is based on a normative theory (e.g., Bayesian decision theory) that specifies an "optimal" decision rule (e.g., maximize subjective expected utility). In a descriptive study, the decision model is determined by the user's behavior, and the goal is to obtain an accurate model of the user's actual decision process. As a result, a prescriptive study will yield an estimate of the expected value of the forecast to an idealized user who behaves optimally according to a decision criterion derived from the normative theory; a descriptive study will yield an estimate of the actual value of the forecast to a real user who may or may not use information in an optimal fashion.

Figure 5.1 outlines the steps required for a complete descriptive study that results in an estimate of forecast value. Although a literature search described below found no single study that completed all steps, every descriptive study provided information relevant to at least one step.

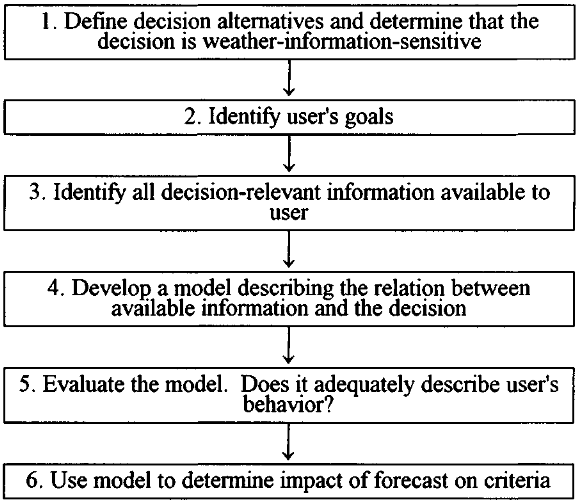

Figure 5.1. The steps in a descriptive study.

The steps in Figure 5.1 are similar to those required for a prescriptive study. In fact, the results of steps 1 through 3 may be similar for both descriptive and prescriptive studies (although in practice this may not be likely). The fundamental differences between descriptive and prescriptive studies are in steps 4 and 5 — model building and evaluation. The standard for evaluating a descriptive model is the user's actual behavior; that is, the model is valid if it adequately describes the user's behavior. Models developed for prescriptive studies need not be evaluated against actual behavior. Discrepancies between prescriptive models and actual behavior are expected because people do not necessarily follow prescriptive models when they make decisions (see Section 4).

Different criteria for evaluating the two types of models dictate different methods for building them. The prescriptive modeler begins with a normative theory, develops the appropriate structure, and collects the data necessary to apply the theory to the decision. The descriptive modeler begins with data obtained from the user's verbal reports and from observations of the user's behavior and, if possible, develops a model that explains the data. Ideally, selection of the type of descriptive model and modeling method is determined by observations and data. In contrast, the prescriptive modeler chooses a model to solve the normative version of the decision problem, not necessarily to match the user's decision process.

To complete step 6, a payoff function must be developed for evaluating decision outcomes, and conditional probability distributions of forecasts and other information must be estimated (or a representative set of scenarios based on historical data could be used). Using the decision model developed in steps 4 and 5, the net payoff of the distribution of possible outcomes is evaluated for different assumptions about the availability and quality of forecasts. Forecast value is computed (assuming the user's utility function is linear in monetary gains and losses) by subtracting the estimate of payoff without the forecast from the estimate of payoff with the forecast. Although this final step is logically required to estimate the value of a forecast, it has rarely been carried out in descriptive studies because, as will be shown below, such studies have rarely resulted in decision models that are sufficiently complete to simulate actual decisions. In contrast, prescriptive studies generally include this step.

2.2. Prescriptive versus descriptive estimates of value

In order to simplify the following discussion, the term "decision" is used to refer to a single action or to a sequential series of actions that may be made in response to a forecast. To clarify the distinction between the expected value of a decision (or series of decisions) and the expected value of information, we will use the term "expected payoff" to refer to the former. The expected value of information is determined by comparing the expected payoff of the decision that would be made with the information and the expected payoff of the decision that would be made without the information. For simplicity here, we assume that utility functions are linear. Methods for estimating value of information when utility functions are nonlinear are described elsewhere in this volume (see Chapters 3 and 4).

If prescriptive and descriptive models are based on the same information and assumptions, the descriptive model will never select a decision that yields a higher expected payoff than the decision selected by the prescriptive model (because, by definition, the prescriptive model chooses the decision with the optimal expected payoff). That does not mean, however, that descriptive

Table 5.1. Economic consequences of decisions in a hypothetical concrete pouring example

	Decision	
Weather state	Do not pour	Pour
Rain	–$250	–$1,000
No rain	–$250	$1,700

studies will necessarily result in lower estimates of forecast value than their prescriptive counterparts. Forecast value estimates in descriptive studies must be based on a comparison of the expected payoffs of decisions selected with and without the information being evaluated. Because the decisions without the weather information might result in lower expected payoff in a descriptive study than in a prescriptive study, the difference in expected payoff might be greater in a descriptive study even though both decisions have higher payoff in the prescriptive study.

Prescriptive models that are based on an *ex ante* approach to information valuation cannot result in a negative value of information (before the cost of information is subtracted). In an optimal model, useless information is simply ignored (i.e., does not change any decisions) and has zero value. If a descriptive model is used to estimate forecast value, however, negative values are possible (Davis and Nnaji, 1982). If, for example, the user misinterprets a probability forecast, that forecast might turn out to have negative value. The following hypothetical example illustrates how a descriptive study differs from a prescriptive study and how it might result in either a negative value of information or a value of information greater than that obtained from a prescriptive study.

Suppose that Jill is a contractor who needs to pour concrete. She does not want to pour if it will rain before the concrete sets. The economic consequences of the possible decision outcomes (in dollars) are given in Table 5.1.

The prior (or climatological) probability of rain is 0.26, so without a forecast Jill's best choice (assuming she is risk neutral) is to pour (expected payoff = $998). Suppose that a perfectly reliable probability of precipitation forecast is available to Jill. Its perfor-

Table 5.2. Statistical properties of probability forecast

Forecast probability	Probability of forecast	Probability of rain given forecast
0.05	0.40	0.05
0.20	0.30	0.20
0.50	0.20	0.50
0.70	0.05	0.70
0.90	0.05	0.90

mance is described in Table 5.2. With the forecast, evaluation of her decision options shows that Jill's best strategy is to pour unless the forecast is for 90% probability of rain. Her expected payoff will then be $1,022, yielding a forecast value (based on prescriptive decision modeling) of $24 per day.

Suppose further that a descriptive model of Jill's decision-making process was developed by interviewing her. In the interview, it was learned that if Jill did not have the precipitation forecast, she would look at the sky in the morning and she would not pour if it were cloudy. This provides a simple descriptive decision rule for the "without forecast" condition:

(i) If cloudy, do not pour;
(ii) If not cloudy, pour.

The expected payoff obtained using this rule depends on the conditional probability of rain when it is cloudy (Table 5.3). Since morning cloudiness is a poor predictor of rain, Jill's decision model yields an expected payoff of $596, which is substantially lower than the expected payoff of $998 that she would obtain by not looking at the sky and always pouring.

In the interview, Jill also said that, with the forecast, she would not pour any time the forecast indicated a 50% probability of rain or greater. This rule yields an expected payoff of $899, which is $303 higher than her expected payoff based on morning cloudiness. Therefore, the expected value of the forecast based on the descriptive analysis is $303, which is much greater than the $24 estimate obtained using the prescriptive model.

Another contractor, Jack, said that he would not pour anytime the forecast indicated a 20% chance of rain or greater. Assuming

Table 5.3. Statistical properties of cloudiness as predictor of rain

Morning cloud condition	Probability of cloud condition	Conditional probability of rain given cloud condition
Cloudy	0.40	0.35
Clear	0.60	0.20

that he also adopts Jill's "without forecast" approach, his expected payoff would be only \$476, which is \$120 lower than the expected payoff based on morning cloudiness. Therefore, for Jack, the forecast has negative value.

Because the descriptive value of forecasts is based on the behavior of individuals, the results vary depending on how the forecasts are used. For example, the value of the forecast to Jill and Jack could be changed, and their profits improved, by convincing them to pour unless there is a forecast of 90% probability of rain. They would then have an expected payoff of \$1,022, and the estimated value of the forecast *plus* training in how to use it would be \$426 (i.e., \$1,022 – \$596). Of course, the results of prescriptive studies will also vary with characteristics of the individual such as risk preferences and the information available to the individual in the absence of the forecast (Roebber and Bosart, 1996). Chapter 6 of this volume includes a more detailed prescriptive treatment of decision-making models similar in structure to this example.

Because estimates of forecast value from descriptive studies are sensitive to the user's knowledge and sophistication in using the forecasts, the investigator must decide whether a descriptive study will focus on the value of forecasts given current decision-making practices or on the potential value given improved practices that might be implemented through information or training programs. This is also true, at least to some extent, for prescriptive studies because, for example, the results are sensitive to assumptions made about the information used by the decision maker in the absence of forecasts. The effect of such training programs on actual decision-making practices would have to be determined empirically.

2.3. Differences between descriptive and prescriptive studies

In practice, descriptive and prescriptive modelers may bring quite different perspectives, and usually different types of training and experience, to their work. Those perspectives might guide their research in different directions and produce even greater differences in results than the formal differences between their purposes and methods would suggest.

For example, descriptive and prescriptive studies will require different amounts and types of involvement of the user. It might even be possible to do a prescriptive study with no user involvement by relying on secondary data (Sonka, Changnon, and Hofing, 1988). In a typical prescriptive study, one or more users might be interviewed to determine what information is available and to ascertain decision alternatives, constraints, subjective probabilities and utilities, and other parameters required by the prescriptive model. A descriptive study requires more extensive involvement of a representative cross section of users, focusing on the subjective model by which they process information and make choices.

Differences in the results provided by the two approaches can be illustrated by comparing the descriptive study of the fruit-frost problem by Stewart, Katz, and Murphy (1984, hereafter referred to as SKM), based on interviews with fruit growers, the local National Weather Service (NWS) forecast office, and various experts in crop protection with the prescriptive study of Katz, Murphy, and Winkler (1982, hereafter referred to as KMW), based on a dynamic decision-analytic model. Differences are apparent at every step in Figure 5.1.

First, the fruit growers' alternatives were defined in different ways (step 1). KMW considered two alternatives for each night during the frost season: protect or do not protect. SKM found that the important nightly decision was *when* to initiate protection and, of less importance, when to stop protection. KMW's choice was limited somewhat by modeling restrictions. Since they were developing a model that was dynamic over the frost season, their model would have become unmanageably complex if dynamic processes during each night were also included.

Both models recognized that crop protection and minimization of heating costs were the primary goals (step 2), but SKM identified another goal often mentioned by the growers: psychological comfort. Since they faced substantial financial risk during the frost season, growers wanted to have confidence that they could anticipate frost hazard and would be ready to react. Thus, a frost forecast might provide psychological comfort to fruit growers even though their decision to protect their crops might be based on other information. It would be difficult or impossible to assign a monetary value to such a psychological effect, but that does not make it any less important to the user. In a prescriptive modeling approach, such psychological effects could be reflected in the utility function.

The KMW model omitted an item of information (step 3) that growers use to decide when to protect their crops. Almost all large growers have temperature sensors located in their orchards and frost alarms by their beds that are set to wake them when temperatures approach the critical range. SKM found that the frost alarms initiated a period of vigilance that would result in protective measures (usually wind machines) being turned on if temperatures dropped close to the critical level. Consequently, the evening frost forecast was not the trigger for protective action, as assumed in the KMW model.

KMW were able to develop a dynamic decision-analytic model that produced a quantitative estimate of frost-forecast value (steps 4 through 6). SKM had to be content with a qualitative description of the process and were unable to estimate a monetary value for the frost forecast. Although, in principle, a descriptive model could be used to estimate the monetary value of forecasts, this process has rarely been completed. If the objective of a study is to estimate the value of a forecast in monetary units, a combination of prescriptive and descriptive approaches should prove quite valuable, as SKM observe.

Finally, it is important to note that most prescriptive studies necessarily involve descriptive elements. For example, both KMW and Mjelde, Dixon, and Sonka (1989a) developed dynamic models because they recognized that these models better represent the decision processes under study. In their study of crop management, Mjelde et al. assumed that "the farmers are addressing a stochastic intertemporal optimization problem" (p. 1). They solved the crop management problem using stochastic dynamic programming to maximize expected profits with respect to historical climatological probabilities. They found that the static model produced differences in profits ranging from 4% to 10%, relative to the more realistic (i.e., descriptive) dynamic model.

3. Examples of descriptive studies

The DPA Group, Inc. (1985) searched 10 abstract series and data files for studies of forecast value. Their search was updated for this chapter using the sources they found most useful (*Meteorological and Geoastrophysical Abstracts* and the National Technical Information Service). In addition, a bulletin board message was posted on OMNET (a computer network used by atmospheric scientists) asking for information about descriptive studies, and several people active in the field were contacted directly. An annotated bibliography prepared by Mjelde and Frerich (1987) and a review by Mjelde, Sonka, and Peel (1989b) were also examined. This process uncovered only one descriptive study that completed step 6 and resulted in an estimated economic value of a forecast. The remaining studies addressed one or more steps, but few resulted in a complete model that could be used to explain or predict behavior.

Descriptive studies can be roughly classified into four groups: (i) anecdotal reports and case studies, (ii) user surveys, (iii) interviews and protocol analysis, and (iv) decision experiments. Studies representative of each group are briefly reviewed and their contribution to understanding the economic value of forecasts is discussed.

3.1. Anecdotal reports and case studies

Many anecdotes about the value of weather information have been published. For example:

> We interviewed a grain grower who told us how he was able to save thousands of dollars by checking the weather forecast before beginning his harvest. On one occasion, the farmer was about to swath his grain but decided not to do so based on the forecast of precipitation for the following day. The precipitation occurred as forecast and the poor drying conditions persisted for a full three weeks. This farmer figured his grain as No. 3 grain rather than feed. The economic value to him was almost $30,000. (Aber, 1990, p. 55)

Because they suggest an activity for which forecasts have value, such anecdotes might provide the stimulus for serious descriptive or prescriptive studies, but, by themselves, they are of little use for determining the value of forecasts. For example, the value of $30,000 assigned to a single forecast in the anecdote above must be seriously questioned. How accurate is the grower's estimate of his crop's value? How many times did a forecast result in such gains? How many times did it result in losses? What other factors influenced the grower's decision not to cut?

Case studies, usually conducted after decisions have been made, involve more systematic study of the use of weather or climate information than anecdotal reports. For example, Glantz (1982) studied the case of a seasonal water supply forecast for the Yakima Valley, Washington, that turned out to be inaccurate. Based on a forecast of water availability during the irrigation season of less than half of normal, the Bureau of Reclamation allocated 6% of the normal water allocation to holders of junior water rights and 98% of normal to holders of senior rights. In preparation for the predicted water shortage, some farmers had wells dug, leased water rights from other farmers at high prices, and even physically moved their crops to the Columbia River basin where water was more plentiful. Cloud seeding activities were carried out in the Cascade mountains in an attempt to increase snowpack. Actual water availability turned out to be much greater than forecast, and many farmers filed legal actions. Claims for forecast-related losses totaled approximately $20 million.

This case study showed that the forecast clearly did influence the actions of farmers; that is, they took actions that they would not have taken otherwise. It also showed that significant costs could be attributed to the erroneous forecast, and Glantz argued that studies of the value of forecasts should account not only for the value of a good forecast, but also for the potential costs of an erroneous one. In addition to monetary costs associated with the forecast, there are nonmonetary costs. For example, the Bureau of Reclamation lost much of its credibility with farmers, possibly limiting its ability to discharge its responsibilities effectively.

Glantz also pointed out that it is difficult to "separate the influence of the water supply projections from other competing economic influences that might also have been at play in Yakima in 1977" (p. 11). He cited the example of the cattle industry, which was already in trouble and may have been spurred by the forecast to take actions, such as reducing their herds, that they should have taken anyway. It is also possible that actions taken in response to the forecast had longer-term benefits that may have offset their costs. For example, spraying crops for frost protection is more cost-effective than using wind machines, and some of the wells that were dug in anticipation of the 1977 water shortage were later used to supply water for frost protection.

Some case studies include general descriptions of classes of decisions that use weather information. For example, Brand (1992) describes several U.S. Navy decisions that are assisted by weather and climate information. Ryder (1990) reports several uses of weather information in the United Kingdom, and Hawando (1990) presents Ethiopian case studies. Del Greco (1983) describes case studies involving offshore fishing vessels where substantial costs apparently could have been averted if weather forecasts had been used. Changnon and Vonnhame (1986) discuss the use of a seasonal precipitation forecast in a water management problem.

Although difficulty in determining causation is inherent in the case study approach, and the results cannot necessarily be generalized beyond the particular situation studied, case studies do serve an important function in describing forecast value. In depth case studies dramatically show that forecasts are used in complex social, economic, political, and cultural contexts, and that context is an important factor in determining forecast value. Case studies are an important complement to descriptive or prescriptive modeling studies that sometimes must use simplified representations of decision processes in order to develop tractable models.

3.2. User surveys

One approach to studying the economic value of forecasts is simply to ask (by interview, mail, or telephone survey) a representative sample of users how valuable they are. Some surveys (e.g., Easterling, 1986; McNew et al., 1991; Del Greco, 1983) have included questions about whether users are aware of weather services, whether they use them, whether they value them, and how to make the services more valuable. These are essentially marketing studies and may yield useful information for providers of forecasts, such as suggestions for improving services. Other than providing some information about user awareness of weather information, however, they are of little use for deriving realistic estimates of the value of forecasts because they do not reveal how forecasts are used. They should be considered studies of "perceived usefulness" of forecasts rather than their actual value.

Murphy and Brown (1982) review a number of studies of user requirements for short-range weather forecasts. They conclude that two approaches have been taken to the study of user requirements: passive and active. In passive studies, user requests for forecasts are analyzed. The active approach involves the use of a survey method. Murphy and Brown point out that surveys are inherently flawed, because they are based on users' *perception* of needs rather than on either a descriptive or prescriptive decision model.

Some surveys have asked users to estimate the value of forecasts in monetary terms. It is highly unlikely that a user can provide a valid estimate of the economic value of a forecast (see the literature on contingent valuation studies for a list of reasons why, e.g., Fischhoff and Furby, 1988; Mitchell and Carson, 1989). For example, only 8 of 95 people interviewed in one survey of households (Prototype Regional Observing and Forecasting Service, 1979) could provide estimates of the value of weather forecasts in commuting, recreation, and shopping. In their survey of four agribusiness firms, Hofing, Sonka, and Changnon (1987) found that most respondents could not quantify the economic value of better climate information.

Brown and Murphy (1987) sent questionnaires to natural gas companies. One questionnaire requested estimates of savings to the company and willingness to pay for several different types of climate forecasts. They found that many respondents were unable or unwilling to make these quantitative estimates. The estimates that were obtained were highly variable and differed greatly among companies. Of course, such differences might reflect different operating conditions among companies, but it is likely that they are also influenced by the subjectivity involved in making difficult quantitative judgments of forecast value.

Surveys can, however, be used to examine the determinants of *subjective* forecast value. Ewalt, Wiersma, and Miller (1973) incorporated information from 6 case studies of farming operations in 4 Indiana counties lying in different forecast zones and varying in soil type into an interview schedule that was administered to 145 farm operators. Each operator was asked to rate the value of precipitation and field condition forecasts (using a five-point scale) for different field operations, crops, and seasons. Thus, rather than asking users for a quantitative estimate of the monetary value of forecasts, the investigators asked users to rate the relative value of forecasts under different conditions — a much easier and more meaningful task for the user. The rated value of the forecasts was heavily dependent on soil region, crop, field activity (plowing, planting, seedbed preparation, cultivation), and season. Differences in forecast quality across regions were not related to differences in rated value.

The Ewalt et al. (1973) study, like many descriptive and prescriptive studies, underscores the importance of decision-making context in determining forecast value. Although their study was not designed to obtain monetary values, it would not be surprising if monetary values were sensitive to the same kinds of factors that were associated with the operators' rating of forecast value. Both descriptive and prescriptive modeling approaches admit the possibility that, across decision contexts, forecast quality may not be the most important determinant of forecast value.

Other surveys do not address value directly but seek information about how forecasts are used. For example, Curtis and Sites (1987) surveyed 100 recreational anglers along the Strait of Juan de Fuca during the peak of salmon season in the summer of 1986. They found that one-third of the anglers surveyed did not use the available NWS marine warnings and advisories, and 14% were unaware of them. They also found that nearly 90% had never cancelled a fishing trip as a result of a marine forecast. When asked if they ever modified or adjusted NWS forecasts to account for local conditions, 78% responded that they did so at least half the time. The authors speculate that marine warnings make small-boat anglers more alert.

Although it did not produce an estimate of economic value, this survey did provide important information about the value of marine forecasts. It suggested that the decision to cancel a fishing trip is, for many anglers, not weather-information-sensitive. One reason may be that many have limited days off, so that a cancelled trip is lost because the option of delaying the trip a day or two is not available. This result highlights the importance of making a thorough analysis of the user's alternatives before proceeding with a study of forecast value.

The investigators found that 14% of the anglers were unaware of the forecast. For them it had zero value. Apparently, 19% (33% minus 14%) were aware of the forecast but claimed not to have used it. This is a statement about their subjective model (Figure 5.1, step 4), which implies that the forecast has no weight. The finding that many anglers adjust the forecasts is also relevant to step 4. For these people, a descriptive model would have to include a component that represents this forecast adjustment process.

Several user surveys have addressed a critical question that distinguishes descriptive from prescriptive studies. These surveys (Adams, 1974; Murphy et al., 1980; Murphy and Brown, 1983; and Curtis and Murphy, 1985) focused on how forecasts are interpreted by the public. They found (i) that forecasts mean different things to different people, and (ii) that the interpretation of forecasts by the public does not always match what the issuing forecaster had in mind. Mroz and Raven (1993) reviewed literature on public understanding of weather information and reported that research in this area indicates that "weather information in all forms is poorly understood, often misinterpreted, and, at times, even manipulated by the public" (p. 426).

For example, based on a survey of 458 beach users, Adams (1974) concluded that forecasts were underutilized in planning recreational beach trips; he attributed this, in part, to a tendency of users to underestimate the reliability of weather forecasts, to their belief that the forecasts were influenced by an optimistic bias, and to users' misinterpretation of the forecasts. He argued that forecasters should share responsibility for users' misunderstanding of forecasts and should strive to improve communication with the public. Results like these indicate that descriptive models must account for users' interpretations of forecasts.

Although surveys are generally not appropriate for producing descriptive models of user decision making, they may provide useful information to help guide the modeling process. One inescapable conclusion from surveys is that there are important individual differences among users of weather and climate information. As a result, it will generally not be possible to develop a single descriptive (or prescriptive) model that represents all users even in the case of a specific application. For example, the model for those who are aware of the forecast but don't use it will differ from the model for those who do use the forecast, and that model will differ from the model for those who use the forecast but adjust it first. For this reason, descriptive modeling must be idiographic rather than nomothetic (Hammond, McClelland, and Mumpower, 1980, pp. 117–119); that is, models will have to be developed for individual users rather than for user groups. Any modeling process that involves averaging over groups of users without accounting for individual differences is likely to produce misleading results. This problem also arises in the case of prescriptive models.

3.3. Interviews and protocol analysis

In these studies, descriptions of users' decision-making strategies, or "protocols," are developed from verbal reports obtained from interviews or from analysis of other written materials. The SKM study of fruit growers described above is an example of this approach.

Another example is a study by Glantz (1980), who interviewed 60 experts regarding possible responses to a hypothetical El Niño forecast. This study addressed primarily step 1 in Figure 5.1 (alternatives and weather-information sensitivity). He found that political, economic, and other constraints might limit the flexibility of decision makers in Peru or elsewhere to respond to an El Niño forecast. Although he did not make a quantitative estimate of the value of the forecast, Glantz concluded that, even though an El Niño forecast may be useful in theory, "in practice it appears that its value may be quite limited" (p. 449).

Glantz (1977) analyzed the responses of more than 100 people representing "a wide range of fields" in the Sahel regarding what they would have done if an accurate forecast of rainfall and temperature had been available in 1973, a devastating drought year. He organized the responses into those describing "what should be" and those describing "what is." He tentatively concluded that "given the national structures in the Sahelian states in which a potential technological capability would be used, the value of a long-range forecast, even a perfect one, would be limited" (p. 156). He also argued that the distinction between "what should be" and "what is" is particularly useful for analyzing the implications of a long-range forecast because it helps to avoid the pitfalls of adopting either a utopian standpoint or a reality standpoint, and it can be used to "draw attention to the often implicit assumptions concerning the potential benefits for society of new technology" (p. 157).

Changnon (1992) conducted extensive interviews with 27 agribusiness executives regarding their use of climate predictions. He found that climate predictions are seldom used in making major decisions, which implies that they have little economic value. The study identified major impediments to the use of climate predictions and potential strategies for improving their usefulness. Similar results were obtained from a mail survey of 114 respondents reported by Sonka, Changnon, and Hofing (1992) and from interviews of 56 decision makers in 6 power utilities regarding their use of climate forecasts (Changnon, Changnon, and Changnon, 1995).

Occasionally an agency, business, or individual develops and documents an explicit model for the use of weather information. For example, the Federal Aviation Administration (FAA) regulations for the use of terminal forecasts (Mathews, 1992) require commercial air carriers to carry extra fuel if the terminal forecast indicates any possibility of ceiling height below 2,000 feet or visibility less than three miles within one hour of arrival. The FAA regulations can be translated directly into a simple model for the use of the terminal forecast (Figure 5.2). This is an example of one form that a descriptive decision model can take. If the necessary data about conditional distributions of weather events and costs were obtained, the model could be used to estimate the value of terminal forecasts. Of course, estimating costs (e.g., passenger inconvenience) would be no simple matter.

Studies by Suchman, Auvine, and Hinton (1979, 1981) involved an attempt to develop simple decision models and use them with historical data to estimate the economic benefits of forecasts. They contacted business and government clients of a private weather service using a questionnaire and, in some cases, a followup phone call and personal visits. The responses were used to develop simple decision models indicating what the users would do given various forecast scenarios. Using the data on forecasts and actual events for a year, Suchman et al. were able to estimate (retrospectively) yearly "direct economic losses" resulting from incorrect forecasts for various user groups. The monetary values computed were not measures of forecast value, but estimates of yearly loss resulting from imperfect forecasts. The authors pointed out that these values did not measure the value of the weather service relative to

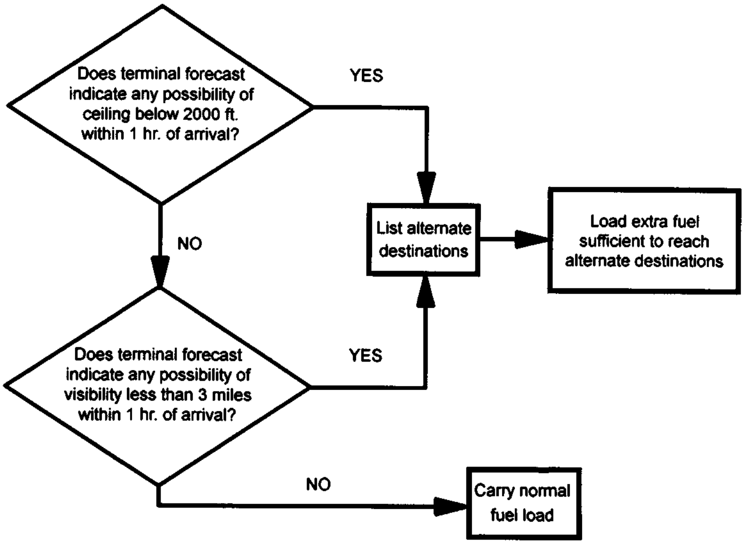

Figure 5.2. Descriptive model of use of terminal forecasts based on FAA regulations.

some realistic alternative; at best, they measured the maximum additional value that could be obtained by improving forecasts. Suchman et al. (1981) attempted to estimate the economic benefit of satellite data by comparing costs of imperfect forecasts during the two years before satellite data were available to the consulting firm with the year after the data became available. The method failed, however, because of large differences in weather during the two periods. The authors note that a much larger sample size would be needed to make a realistic comparison of this type.

As descriptive studies of the value of weather information, the Suchman et al. studies have two major limitations. First, monetary values were estimated for perfect information relative to the actual forecasts, rather than for the actual forecast relative to some alternative such as climatology or publicly available forecasts. Such a procedure is useful for estimating the maximum value of forecast improvements, but not for estimating the value of the forecast itself. Second, the users' decision models were not validated and were almost certainly oversimplified because they did not account for the context of decisions. As the authors point out, the use of their method assumes that users actually do what they report on the questionnaire. The validity of that assumption was not examined. Furthermore, the decision models were based only on the forecasts. That is, the investigators assumed that the forecast alone determined user action, regardless of other information or circumstances existing at the time. This assumption is unlikely to be true for all users.

3.4. Decision experiments

Sonka et al. (1988) have proposed the use of "decision experiments" to assess the value of climate information and provide a study illustrating this approach. They interviewed two key managers responsible for production planning in a major seed corn producing firm. The participants were given 8 climate prediction scenarios (representative of actual growing season climate conditions) and asked what actions they would have taken if they had received this information when planning decisions had been made for the current season. The resulting decision model (Table 5.4) provides another example of the form that a descriptive decision model can take.

This decision model is hypothetical because it represents the managers' responses to perfect climate forecasts that are not currently available (Sonka et al. modeled responses to imperfect forecasts as well). Hypothetical models pose difficulties because there are no objective criteria for validating them; that is, they cannot be compared with actual behavior. It is often necessary to use them in descriptive work, however, because real decisions may not be available. If observations of real decisions are not available as a basis for modeling, then it is important to obtain the data for modeling under conditions that are similar to those present when real decisions are made. In other words, the data for descriptive decision modeling must be obtained under representative conditions. The necessity for representative design has been stressed by Brunswik (1956) and Hammond et al. (1975). Extensive research on descriptive modeling underscores the need for representative design and indicates that properly designed experiments can result in models that predict actual decisions (see Brehmer and Brehmer, 1988; Stewart, 1988).

As in the case of all decision models, the Sonka et al. model operates only within a limited range of circumstances. In this case,

Table 5.4. Decision model for seed corn producing firm

Type of seasonal climate prediction	Implications for corn production	Decision
A	Very serious	Shift varieties toward irrigated areas
B	Normal to favorable	No action
C	Moderately serious	Move varieties from site in east central Corn Belt toward western and northern plants sites
D	Very serious	Move midseason varieties away from areas in central Corn Belt areas
E	Somewhat serious	Move late-season varieties toward irrigated and eastern sites
F	Somewhat serious	Move late-season varieties toward irrigated areas and other eastern sites
G	Moderately serious	Move early varieties from eastern Corn Belt to west central Corn Belt and to three irrigated areas
H	Normal to favorable	No action

Source: Adapted from Sonka et al. (1988), table 1.

the model applies only to 1987 because, except for the climate prediction, all conditions in the experiment were defined by the 1987 crop season. The model also applies only to the range of weather types included in the set of predictions.

In order to estimate forecast value, Sonka et al. developed an empirical model of the firm's seed corn production process. By combining the decision model with the production model, they were able to simulate with- and without-information scenarios for 100 random 10-year scenarios. Information value was then calculated, and sensitivity of the estimated value to model parameters was investigated. This study demonstrates the feasibility of using a descriptive decision model to obtain quantitative estimates of forecast value. It is the only such example found in the literature search.

In another decision experiment, Baker (1984) asked citizens to respond to hypothetical scenarios describing hurricane threats.

For one group of 100 citizens, the scenarios varied on 4 factors: (i) severity of storm, (ii) storm track and position, (iii) National Hurricane Center "alert" status, and (iv) evacuation notice from local officials. A second group received the same scenarios plus a forecast specifying the probability that the storm would cause hurricane conditions. Baker developed logistic regression models to predict the percentage who would evacuate under each scenario. He found that provision of hurricane probabilities (in addition to National Hurricane Center alert information and all the other information) had a negligible effect on the percentage evacuating (around 5%). The most important factor was local officials' advice or orders to evacuate. No payoff function was developed, and forecast value was not estimated.

The descriptive model developed in Baker's study was intended to predict group behavior (i.e., evacuation percentage). As noted above, decision models must account for individual differences among users. Because such differences were not analyzed, the validity of the aggregated model is suspect.

3.5. Summary

Most descriptive studies can be classified as case studies or surveys. Although such studies provide information relevant to forecast value, they do not produce quantitative estimates of value. Studies involving the detailed interviews, protocol analysis, and decision experiments that are required to develop descriptive models for estimating forecast value are rare.

Although descriptive studies have rarely produced estimates of forecast value, they do suggest that users often do not obtain the maximum possible value of forecasts and that the usefulness of forecasts may be limited by: (i) constraints that deny the flexibility to respond to the information, (ii) lack of awareness of the information or ability to obtain it, (iii) misunderstanding or misinterpretation of forecasts, (iv) availability and use of locally specific information more appropriate to a specific decision than the forecast, (v) nonuse or nonoptimal use of forecasts, or (vi) low importance given to weather information because other nonweather factors are judged more important.

In addition, the studies indicate that there are important individual differences in the use of forecasts. Those individual differences may well translate into differences in the value of forecasts to different users, even if they face the same decision with the same payoff structure.

4. Factors that affect differences between descriptive and prescriptive models

Decisions that are likely to benefit from weather and climate forecasts always involve uncertainty. Also, they are usually complex decisions because they involve many interdependent elements, or because several different types of information must be considered before a decision is made, or both. Often, multiple criteria must be satisfied, and trade-offs between competing or conflicting criteria may be necessary. The decisions are often part of a dynamic process; that is, a sequence of decisions is made in the context of a changing environment where each decision depends, in part, on the outcomes of earlier decisions. Thus, weather and climate forecasts are likely to be used in decisions that involve uncertainty, complexity, multiple criteria, trade-offs, and dynamic processes. These characteristics are present in most of the kinds of decisions that interest judgment and decision researchers. For reviews of this research, see Janis and Mann (1977), Kahneman, Slovic, and Tversky (1982), Arkes and Hammond (1986), Hogarth (1987), Baron (1988), Dawes (1988), Brehmer and Joyce (1988), and Payne, Bettman, and Johnson (1992). In this section, a few illustrative results of descriptive research on judgment and decision making that may apply to weather-information-sensitive decisions are described.

Decision making under uncertainty has been a major topic of study in judgment and decision research. The major conclusions of this research are: (i) that people do not make decisions according to the subjective expected utility model (see Chapter 3 of this volume); and (ii) that people often ignore relevant information, are unduly influenced by irrelevant information and, consequently, often perform poorly in such situations. A series of descriptive studies of judgment, inspired by the work of Tversky and Kahneman (1974), has identified a number of mental strategies (heuristics) that can lead to errors in judgments (biases). Research results repeatedly recount numerous biases in judgment, the inconsistent and poorly controlled nature of the judgment process, the pervasiveness of cognitive limitations that can reduce the validity of judgments, and the difficulty of overcoming those limitations.

Although this research clearly demonstrates that prescriptive models do not necessarily describe human behavior, its applicability to actual decisions made by users of weather forecasts is difficult to determine. The generality of the heuristics and biases research conducted by Tversky and Kahneman and many others has been seriously challenged by a number of authors (e.g., Ebbesen and Konecni, 1980; Nisbett et al., 1983; Kruglanski, Friedland, and Farkash, 1984; Gigerenzer and Murray, 1987; Lopes, 1991; Fraser, Smith, and Smith, 1992). In this author's opinion, extreme caution should be exercised in making generalizations from this research to the behavior of decision makers in field (i.e., "real-world") settings. However, the possibility that human cognitive processes for coping with uncertainty are, under some circumstances, flawed cannot be discounted.

Complexity of the decision problem has also been studied in judgment and decision research. Complexity varies with amount of information, interdependence among variables, number of criteria to be satisfied and trade-offs among them, and whether the process is dynamic or static. Not surprisingly, because people are limited in their capability to process information, performance decreases with complexity. One might expect, therefore, that differences between descriptive and prescriptive models will increase as complexity increases.

Another set of studies has focused on the intuitive versus analytic nature of the judgment process. Prescriptive models are highly analytic; that is, they imply explicit problem structuring, formal reasoning, and solution by calculation. Human judgment processes can vary along a continuum from intuitive to analytic (Hammond, 1990; Hammond et al., 1987). Decision makers who use highly analytic processes generally can describe those processes in more detail and more accurately than those whose decision making is more intuitive. Therefore, we would expect greater differences between prescriptive and descriptive models for intuitive decision makers than for more analytic ones.

Although prescriptive studies generally focus on a single criterion for decision success (economic losses or gains), multiple (including nonmonetary) criteria can be handled within a prescriptive model (Keeney and Raiffa, 1976). In descriptive modeling, it is not unusual to find that a decision maker has more than one goal and that decision success is not always easily measured in monetary units. Thus, both prescriptive and descriptive studies may involve multiple criteria that include nonmonetary considerations. When decisions involve multiple criteria that cannot all be satisfied at once, trade-offs are necessary. Research suggests that people avoid trade-offs and prefer to make decisions based on a single dimension (Baron, 1988). In order to do this, they may try to think of reasons to ignore or discount other dimensions (Montgomery, 1984). This treatment of multiple criteria differs from the usual treatment in prescriptive models, which involves some weighted combination of criteria. When multiple criteria are involved, descriptive models will have to account for the decision maker's method of combining or selecting criteria in different contexts.

Studies of decision making in dynamic situations are a relatively recent development in descriptive decision-making research. Hogarth (1981) argued that many of the results obtained in the study of decision making under static situations might not apply to dynamic tasks, and that the heuristics that lead to poor performance in static tasks might produce good performance in dynamic tasks. Several recent studies have focused on delay of feedback, and found that people have difficulty performing well in tasks that involve a time interval between the time an event occurs and the time that they receive the information that it has occurred (e.g., Sterman, 1989; Brehmer, 1990). Further research is needed in order to understand the conditions under which human performance in dynamic tasks can approximate those of an optimal model.

In summary, the descriptive research on judgment and decision making has found important differences between prescriptive and descriptive models in decisions that involve uncertainty, complexity, and multiple criteria. In addition, differences between prescriptive and descriptive models are likely to be greater when the decision process is performed intuitively. The study of dynamic decision making is relatively new, and little is known about the relation between prescriptive and descriptive models for this type of problem.

5. Overview of descriptive modeling methods

Approaches to descriptive modeling of decision processes (step 4 in Figure 5.1) can be classified into two broad groups: (i) protocol analysis (or process tracing), and (ii) judgment analysis. These approaches are briefly summarized here.

Protocol analysis relies on users' verbal descriptions of their reasoning. Protocols are best obtained by asking individuals to "think aloud" while they work through a series of decisions. The protocols are analyzed to develop a model that consists of a number of "if . . . then . . ." relations that can be diagramed in the form of a flowchart. Protocol analysis has been used extensively by "knowledge engineers" to develop computer-based expert systems, and it has a long history in psychology as well (Kleinmuntz, 1968; Ericsson and Simon, 1984). Recently, the use of verbal reports to derive an "influence diagram," which can be considered a form of protocol, has become popular in decision analysis (Oliver and Smith, 1990).

Traditionally, many psychologists have been suspicious of verbal reports, and they have used methods for analyzing judgment that do not depend on a person's ability to provide accurate verbal descriptions of decision processes. Judgment analysis refers to a class of methods for deriving models of decision making by analyzing a sample of actual judgments or decisions. The user is required to do only what he or she does naturally; that is, to make decisions using familiar materials. The analyst develops a model to describe the inference process that produced the decisions.

The data required for the development of such a model are a number of cases of a particular type of decision. Each case includes the information used to make the decision and the resulting decision itself. Cases may be obtained in a natural setting (e.g., a fruit grower's decision to protect crops each night during the frost season) or in controlled settings. In the latter situation, the forecast user would be asked to make judgments based on a sample of real situations or hypothetical scenarios designed to represent real situations.

The items of information available to the user, called "cues," are considered independent variables in an analysis, and the decision is the dependent variable. Multiple regression analysis is one statistical technique that has been used with considerable success to fit a model to the data (Stewart, 1988), but a number of other methods have been applied as well, including analysis of variance and conjoint measurement. The analysis yields a model of the user that expresses the decision as a mathematical function of the cues and an index of how well the model fits the judgments (e.g., the square of the multiple correlation coefficient).

Although the use of statistical models of judgment can be found as early as 1923 (Wallace, 1923), extensive use of the method began in the mid 1950s (Hammond, 1955; Hoffman, 1960). Decision processes of a variety of experts have been modeled, including physicians, stockbrokers, clinical psychologists, polygraph interpreters, and weather forecasters (Stewart et al., 1989; Lusk et al., 1990). Descriptions of a theoretical foundation for judgment analysis and descriptions of the method itself can be found in Hammond et al. (1975) and Brehmer and Joyce (1988).

Judgment analysis offers one major advantage as a tool for developing descriptive models of the use of weather forecasts: It provides a modeling method that does not rely on the user's ability to describe his or her thinking process. This is important because the ability to make decisions is not always accompanied by the ability to describe accurately the process that produced the decisions, particularly when the process contains intuitive elements. Verbal descriptions of reasoning can be incomplete, inaccurate, or misleading. Some important aspects of the decision process may not be readily accessible and may be difficult to translate into words. The description obtained may be unduly influenced by the method used to elicit it. Questions posed by the investigator impose a "frame" on the problem. Seemingly irrelevant and inconsequential aspects of problem framing can have a powerful effect on judgment (Tversky and Kahneman, 1981). For these reasons, it is desirable to have a modeling tool that does not depend on the expert's ability to describe the inference process.

Judgment analysis can be used in combination with verbal protocols (Einhorn, Kleinmuntz, and Kleinmuntz, 1979), so that the investigator can take advantage of the insights provided by both while avoiding their pitfalls. If the investigator relies solely on the user's verbal statements, then both the efficiency of model development and the ultimate accuracy of the model will be limited by the user's ability to describe verbally his or her decision process. If, on the other hand, the investigator relies solely on judgment analysis, certain important, but rare, situations that are not represented in the sample of cases may be misunderstood. Although the two techniques complement each other well, few studies have combined them.

6. Conclusion

In order to understand fully the value of weather forecasts, both prescriptive and descriptive studies are necessary. Prescriptive studies provide estimates of the potential value of forecasts under the assumption that the decision maker follows an optimal strategy. They are relevant to the study of forecast value, but do not necessarily provide reliable estimates of the actual value to society given current decision practices. Descriptive studies can estimate the value of information given current users' decision-making practices, but this approach may overlook the possibility of additional value resulting from improvement in those practices.

Because the approaches are complementary, comparison of the results of descriptive and prescriptive studies of the economic value of the same forecast can be especially enlightening. Assuming that the decision maker is risk neutral (see Chapters 3 and 4 of this volume for a description of methods for calculating the value of information when the decision maker is not risk neutral) and that the expected value of information is calculated by comparing the expected payoff of decisions made with and without the forecast, Table 5.5 describes five possible outcomes of a comparison of descriptive and prescriptive studies. The implications of each of these outcomes are described below.

(i) *Both prescriptive and descriptive studies produce the same expected payoff of the decision made with the forecast.* This would imply that the decision payoff is not sensitive to the decision modeling approach, and an increase in payoff through training users to make better use of information (making the descriptive model more prescriptive) is unlikely. This result would indicate that the prescriptive model was actually a good descriptive model as well, as was found in a study of Sri Lankan rice farmers by Herath, Hardaker, and Anderson (1982). In this case, any differences in the value of information could be caused only by differences in the expected payoff of the "without-forecast" decision. If this expected payoff is lower for the prescriptive study than for the descriptive

Table 5.5. Possible results of comparison of prescriptive and descriptive studies

		Expected value of forecast		
		DEV > PEV	DEV = PEV	DEV < PEV
Expected payoff of decision with forecast	DEP = PEP	(1a)	(1b)	Not possible
	DEP < PEP	(2a)	(2b)	(2c)

Expected value of forecast = (Expected payoff with forecast) − (Expected payoff without forecast)

DEP represents the expected payoff of the "with forecast" decision estimated using descriptive modeling approach.

PEP represents the expected payoff of the "with forecast" decision estimated using prescriptive modeling approach.

DEV represents the forecast value estimated using descriptive modeling approach.

PEV represents the forecast value estimated using prescriptive modeling approach.

study, then the value of information is greater in the descriptive study [(1a) in Table 5.5]. If the expected payoffs are the same, then the expected value of information is the same for prescriptive and descriptive studies (1b). An example in which the prescriptive and descriptive approaches agree for the without-forecast condition is a case study of the fallowing/planting problem (Brown, Katz, and Murphy, 1986; Katz, Brown, and Murphy, 1987; and Chapter 4 of this volume). For the case of climatological information alone, the normative model prescribes an optimal policy of fallowing in alternate years, in agreement with observed behavior. The final logical possibility depicted in the first row of Table 5.5 cannot occur because it requires an expected payoff from the descriptive study to exceed the corresponding expected payoff from the prescriptive studies. As indicated above, this cannot occur if the two models are based on the same information.

(ii) *The prescriptive study yields a lower expected payoff than the descriptive study for the with-forecast decision.* This result would suggest that nonoptimal use of information is limiting its value to the user. Training or implementation of aids designed to help the user optimize information processing could be helpful and might increase the value of the forecast. Depending on the expected payoff of the decision without the forecast, the expected value of information obtained from the descriptive study could be greater than (2a), equal to (2b), or less than (2c) the corresponding value from the prescriptive study (see Table 5.5). Practically speaking, however, the important implication would be the same in all three cases: The value of information would be greater if users made better use of it.

Davis and Nnaji (1982) discuss the possibility that the descriptive study yields a negative estimate (before the cost of the forecast is subtracted). They state that it is most likely to occur when the information is quite uncertain and it is being used nonoptimally. They also state that "presently the negative value of information is more likely to be detected by observation than by analysis and is more likely to be corrected by obtaining more information than by utilizing a better decision rule" (p. 469). They provide no support for this statement. If both prescriptive and descriptive models are available, then it is possible to determine analytically to what extent "utilizing a better decision rule" will correct the situation. At the least, a better decision rule — that is, ignoring the information — can increase the value to zero.

Of course, differences between descriptive and prescriptive models may indicate that either or both of the models are incorrect. For example, either model might include incorrect assumptions about the constraints and limitations that decision makers face or the information that is available to them. Differences between models could serve to highlight areas that need further development and study.

Despite the potential for improved value estimates and insight into the use and value of weather forecasts from combined prescriptive/descriptive studies, no such studies have been conducted. A major reason for this is the lack of descriptive studies that have produced decision models that are sufficiently well-developed to be used to produce a forecast value comparable to that produced by prescriptive techniques. Methods for developing such descriptive models exist, and their application to the study of the use and value of weather forecasts should be encouraged. Such application should prove useful to the meteorological community by providing a more complete understanding of the factors that determine the value of forecasts.

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