4

Forecast value: prescriptive decision studies

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1. Introduction

Many human activities and enterprises are affected by uncontrollable future weather conditions. The outcomes of numerous decisions, ranging from fairly trivial (such as opening a window or carrying an umbrella) to vitally important (substantially affecting the livelihoods of one or more individuals or firms), are therefore dependent on these same uncontrollable conditions. It is natural that individuals will seek out information about the future to help make better decisions. That there is substantial interest in, and demand for, weather forecasts indicates that people, at least informally, realize that weather forecasts can be valuable in decision making.

The quality of weather forecasts has gradually improved through time as fundamental knowledge and operational experience has accumulated (e.g., Caplan and White, 1989; Carter, Dallavalle, and Glahn, 1989). Yet it is clear from either informal exposure to weather forecasts, by comparing the local forecast to the ensuing weather in that region or from formal study of the performance of weather forecasts (see Chapter 2 in this volume), that a completely accurate specification of future weather is not possible. There are fundamental physical reasons for this situation, which are described in some detail in Chapter 1. Their implication is that even short-range weather forecasts will never achieve perfection, and that monthly or seasonal forecasts will always be subject to considerable uncertainty. Thus while forecasts can and do reduce the uncertainty associated with future weather events, individuals facing decisions whose consequences will be influenced by these events are now and will always be in a position of uncertainty.

A quite powerful treatment of weather-sensitive decisions made under uncertainty can be accomplished through the construction of what are called decision-analytic models (e.g., Clemen, 1996; Keeney, 1982; Winkler and Murphy, 1985; Winkler, Murphy, and

Katz, 1983). In this approach, described more fully in Chapter 3 of this volume, a decision problem is divided into four basic parts: (i) the actions available to the decision maker, (ii) the possible future unknown events that may occur, (iii) the probabilities associated with those future events, and (iv) specific known consequences following from each possible action-event pair. For the class of problems of interest here, the future uncertain events are meteorological, and the available probabilistic information describing their occurrence is derived.

These four elements are combined in a formal mathematical model of the decision problem under study. The consequences of alternative actions are evaluated with respect to the probabilities of the future events, and actions maximizing the expected (i.e., probability-weighted average) value of some measure of desirability of the outcomes, often monetary, are selected as the optimal decisions. Note that for this analysis to be meaningful and for the forecasts to have value, actions must be available that are capable of producing changes in the consequences. Otherwise the forecasts will offer no more than "entertainment value."

The use of decision analysis to model weather-sensitive decision problems has several advantages. One important result from a decision-analytic model is the specification of the optimal actions associated with particular information about the future: those decisions calculated to provide, on average, maximum benefit to the decision maker. Therefore the approach is sometimes called "prescriptive" in that it specifies, or prescribes, best actions in the face of particular circumstances. The results of a well-formulated prescriptive study are concrete, and can be used as either explicit recommendations or general guidance to help improve decisions made by real managers facing uncertain future events.

Intimately associated with the specification of optimal decisions is the notion of the value of information used in the decision-making process. Existence of a "best" decision implies preferences among at least some of the possible consequences: if a decision maker doesn't care what eventually happens, the decision in question is not a meaningful one. As described in Chapter 3 of this volume, when preferences among consequences can be described entirely by monetary outcomes, computing the value of information (VOI) becomes particularly simple. The improved decisions attainable through use of the information are associated with better monetary outcomes on average than decisions made without the information, and VOI can be computed as the difference between the two average outcomes. Information value, so computed, should be evidence of the advantages to be gained by the potential information user by changing from conventional, suboptimal decision rules. Use and value of hypothetically improved forecasts can also be modeled within this framework. Thus providers of forecasts can assess potential benefits that might be derived from new forecast products under consideration. Also possible is rational evaluation of a fair price for a user or group of users to pay for forecasts tailored to their needs.

On the other hand, while prescriptive models specify what optimal actions should be, these prescribed actions may or may not correspond well to the behavior of real decision makers. The complexity of a particular problem may be so great that the simplifications necessary to achieve computational tractability seriously compromise the relevance of the analysis to its real-world counterpart. That is, aspects of the decision-analytic model may be specified incompletely or even incorrectly. Even assuming that a prescriptive model is well constructed, there is no guarantee that real decision makers will behave optimally in practice. For example, they may be unaware of the superiority, or even the existence, of some of the available actions.

Chapter 5 of this volume reviews "descriptive" studies of the value of meteorological forecasts, which are concerned with analysis and description of the ways in which real decision makers actually use information and make decisions. Even though there will not always be agreement between optimal actions derived from prescriptive analyses and actual human behavior as understood through descriptive studies, the two approaches are complementary. For a prescriptive analysis to be meaningful, it should resemble the real-world decision process reasonably closely. Some rudimentary understanding of a problem is essential before it can be represented in a formal decision analysis. Thus a descriptive analysis could play an important role in the process of constructing a prescriptive model. Once the prescriptive decision model has been constructed, its results have meaning only in the context of the real-world problem. Thus some descriptive understanding of a given decision setting is also an essential component of the evaluation of a prescriptive decision analysis. Conversely, comparison of results from prescriptive and descriptive studies can suggest better or fuller use of available information than is conventionally achieved.

This chapter reviews prescriptive studies of "real" decision situations. This is in distinction to Chapter 6 of this volume, which focuses on "idealized" or prototype situations. Here, in addition to the probability structure associated with a weather/climate forecast setting, sets of potential decisions and their outcomes must be incorporated in a realistic and consistent way.

Actions available to particular decision makers will in general depend on the specifics of the problem at hand. In addition, it can be shown that there are no general monotonic relationships between information value and either the flexibility of actions, the valuation structure of the possible consequences, or the decision maker's level of wealth (Hilton, 1981). Therefore the literature necessarily consists of individual case studies rather than more general results.

2. Case study attributes

In Section 3, existing prescriptive case studies involving the use and value of meteorological forecast information are characterized according to a number of attributes and reviewed. Excluded from the review are studies that treat weather- or climate-sensitive decision problems but use only climatological, as distinct from true forecast, information. Many such studies are reviewed by Halter and Dean (1971), Kennedy (1981, 1986), and Omar (1980). Also excluded from consideration are studies using weather forecasts, but imposing prespecified decision rules rather than internally prescribing the optimal actions (e.g., Gupta et al., 1990a, b; Hashemi and Decker, 1969).

Certain classes of decision problems have been favored in the case studies. Analyses treating agricultural decisions are by far the most common. This should not be surprising, given the importance of food supply to human existence, the exposure of crop plants to environmental (prominently atmospheric) conditions, and the need for most crop plants to be managed and protected to some degree in order to produce economically viable yields. Within the class of agricultural decision problems, surprisingly few areas have received most of the attention. These are raisin production, frost protection, forage preservation, irrigation, crop choice, and fertilizer management. Of the existing nonagricultural studies, most pertain to only two general areas: forestry and transportation. The tables presented in Section 3 summarize the published work to date for each of the above areas, with respect to (i) overall structure of the decision problem, (ii) characteristics of the forecast information, and (iii) information valuation. These three attributes are described in the remainder of this section.

2.1. Structure of the decision problem

Two aspects of the structure of each decision analysis are categorized in the tables. The first of these is the nature of the decision to be considered; that is, the actions available to the decision maker. As indicated above, this is one of the four fundamental elements of any prescriptive decision study.

The second aspect of problem structure tabulated pertains to the relationship in time among decisions in a given setting. The analyses are classified as either "static" or "dynamic." Static analyses are by far the simpler of the two, and the majority of studies to date have adopted a static framework. A static framework implies either that the decisions to be made are single, isolated situations; or, if made in a sequence, that choices and outcomes of a given decision do not affect either available options or possible consequences for subsequent decisions. In either case each decision can be analyzed in isolation. As outlined in Chapter 3 of this volume, probability-weighted average outcomes are computed for each available action, and the action leading to the most desirable expected outcome for that single decision is chosen as optimal. Note that while many problems are well represented as static situations, others that have been analyzed as static problems conform to this model only approximately. Examples also exist of problems clearly not appropriate for analysis in the static framework, but which have been treated as such because of the ease and simplicity of this approach.

Some decision problems are inherently sequential in nature. Actions taken and events occurring at a given point in a sequence of decisions affect options, as well as the physical, biological, and economic consequences of those options, at later stages. Such problems are often referred to as "dynamic," in recognition of the fact that the interrelatedness of changes in their characteristics through time is an essential feature of their structure. It should not be surprising that such problems can become quite complex, and the analysis framework necessary to treat them is more elaborate than that appropriate for static problems.

The basic approach to solution of dynamic decision problems can be understood with reference to a graphical representation of the sequential decision process known as a "decision tree." Figure 4.1 shows a decision tree for a two-stage sequential problem. That is, there are two times at which decisions are to be made. Here squares indicate decision nodes, at which one of two decisions is chosen on the basis of probabilities pertaining to the subsequent uncertain events. These probabilities could be provided by forecasts. The circles represent event (or chance) nodes and, in this simple example, are restricted to two possibilities. At the end of the two decision stages, one of the $2^4 = 16$ terminal points on the right-hand side of the figure will be reached, depending on which choices were made at the decision nodes, and which events subsequently occurred at the chance nodes. Of course, a real decision problem may have more than two actions available at decision nodes, and more than two uncertain events at each chance node. It is assumed that the decision maker knows what each of the 16 terminal consequences is, and assigns a value (often monetary) to each. Since it cannot be known in advance which terminal outcome will occur, the problem is to find the action at each decision node leading to the largest expected (probability-weighted average, using probabilities derived from a forecast) outcome.

A seemingly odd feature of sequential decision problems is that they are solved backward. This is sometimes called "backward induction," or "averaging out and folding back" (Winkler, 1972; Winkler and Murphy, 1985). Consider the two actions, A_1 and A_2, leading to the four terminal consequences $C_1, \ldots, C_4$. The expected return following decision A_1 is simply the probability-weighted average of C_1 and C_2; that is, $\mathrm{ER}(A_1) = p_1C_1 + p_2C_2$. Similarly, $\mathrm{ER}(A_2) = p_1C_3 + p_2C_4$. Clearly, if the decision process has reached the node from which A_1 and A_2 originate, the optimal action is A_1 if $\mathrm{ER}(A_1) > \mathrm{ER}(A_2)$ and A_2 if the reverse is true. When the same computation is performed for each of the other three possible decisions in period 2, an optimal expected return will be associated with all four of these decisions. At that point

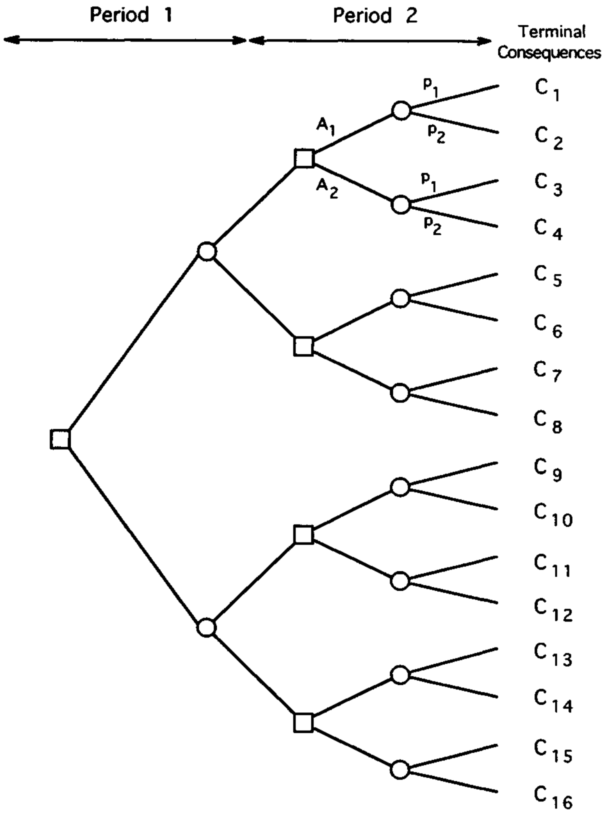


Figure 4.1. A simple decision tree representing a two-stage sequential problem. Squares indicate decision nodes, and circles indicate event nodes. Time runs from left to right; however, the problem is solved in reverse, from right to left.

it is possible to perform the analogous computation for the first decision (leftmost node), using the expected returns computed for each of the 4 second-period decisions where the terminal consequences had been used previously. The approach leads easily to the choice of optimal actions and, for sufficiently simple problems, can yield analytical expressions for the value of information (see Chapter 6 of this volume).

For more complex problems, backward induction is often implemented through a computational approach known as stochastic dynamic programming (e.g., Kennedy, 1986). As before, the goal is to maximize expected return over the full sequence of decisions. However, it is not necessary to draw, or even to imagine, the decision tree. This allows analysis of quite complex and realistic problems.

Regardless of the solution algorithm, the tractability of the approach requires that the status of the decision process at a given time can be specified, at least approximately, by the values of a few "state variables." As the solution procedure works backward in time, it is then not necessary to know the complete sequence of decision and event pairs in the preceding periods (which is good, since these will not have yet been computed), but only their cumulative effects as reflected in the values of the state variables. Thinking in terms of a decision tree, this means that there are as many decision nodes in a given decision period as there are possible combinations of values of the state variables. For example, if a problem is described by two state variables, each of which can take on 1 of 10 values at a given decision stage, then there are 100 decision situations needing to be evaluated at that stage for each possible forecast.

If a given state variable combination can be reached by more than one path through the decision tree, however, the calculations are consolidated as redundant decision tree branches are ignored. The disadvantage is that an analytical solution is not available for subsequent analysis, so that backward induction is often preferred for small, simple problems.

2.2. Forecast characteristics

The forecast information used in the studies reviewed here is characterized according to 5 criteria. The first three are nearly self-explanatory. First, the time scale refers to the length of the period to which the forecast pertains, and must correspond at least approximately to the natural time scale of the decision problem under analysis. Typically the time scale is also of the same order as the lead time, or projection into the future made by the forecast. Second, the predictand is simply the meteorological element or event being forecast. Third, forecast format refers here to whether the forecasts are probabilities (probabilistic forecasts) or statements that one event will occur to the exclusion of others (categorical forecasts).

Clearly the computation of expected returns requires probabilistic forecast information, so that use of categorical forecasts necessarily requires some type of transformation to yield probabilities. Probabilistic forecasts can be used at "face value" in the model computations if they are reliable (that is, well calibrated), in the sense that forecast probabilities correspond well to subsequent event relative frequencies. Otherwise probabilistic forecasts need to be transformed in some way as well. In all these cases, forecast verification (see Chapter 2 of this volume) plays a central role in derivation of the necessary event probabilities, conditional on the forecasts. The most general approach to computing the conditional event probabilities is use of Bayes' theorem, as described in Chapter 3. If it can be assumed that the decision maker's prior beliefs (i.e., information available before receiving the forecasts) are well represented by the climatological probabilities, then direct estimation of the relevant conditional event relative frequencies from a sufficiently large verification data set gives the same result as use of Bayes' theorem. In either case the basic information is contained in the joint distribution of the forecasts and the observations.

Forecast "type" indicates primarily the realism of the forecast information employed in each study. Idealized forecasts are those without a counterpart in current forecasting practice. They may pertain to meteorological events not presently forecast, lead times beyond those in operational use for a given predictand, or both. While studies constructed using idealized forecasts are clearly not useful for improving present-day decision making, they may provide information regarding sensitivity of particular decision problems to different kinds of forecast information, or potentially desirable directions for future forecast product development.

Forecasts denoted as "realistic" are based on actual, operationally available forecast products. Most often in the case studies appearing to date, these are forecasts produced by the U.S. National Weather Service (NWS), although forecasts from other sources are also suitable for use in this type of analysis. In addition to the model forecasts pertaining to the same variable(s) at the same lead time as some real-world forecast product, "realistic" forecasts exhibit statistical characteristics (e.g., accuracy and frequency of use) comparable to their real-world counterparts. For most studies this has meant that a parametric statistical model of the joint distribution of the forecasts and observations has been fitted to a set of forecast-observation pairs. The result is a compact representation of the conditional distribution of the observations given the forecasts, and the predictive distribution (i.e., marginal distribution, or the frequency-of-use) of the forecasts. These are the components of the "calibration-refinement factorization" of the joint distribution of the forecasts and observations (see Chapter 2 in this volume). For example, Katz, Murphy, and Winkler (1982) modeled the joint distribution of forecast and observed minimum temperatures as bivariate normal, with parameters fit using a sample of actual NWS forecasts and subsequent observations. This model yields univariate normal distributions both for the conditional distributions of observed temperatures given each forecast and for the predictive distribution. Note that, defined in this way, use of "realistic" forecasts implies that the climatological distribution of the meteorological event in question is realistically represented. This is because a good representation for the joint distribution of forecasts and observations also implies a good representation for the marginal distribution of the events, through the "likelihood-base rate factorization" (again, see Chapter 2).

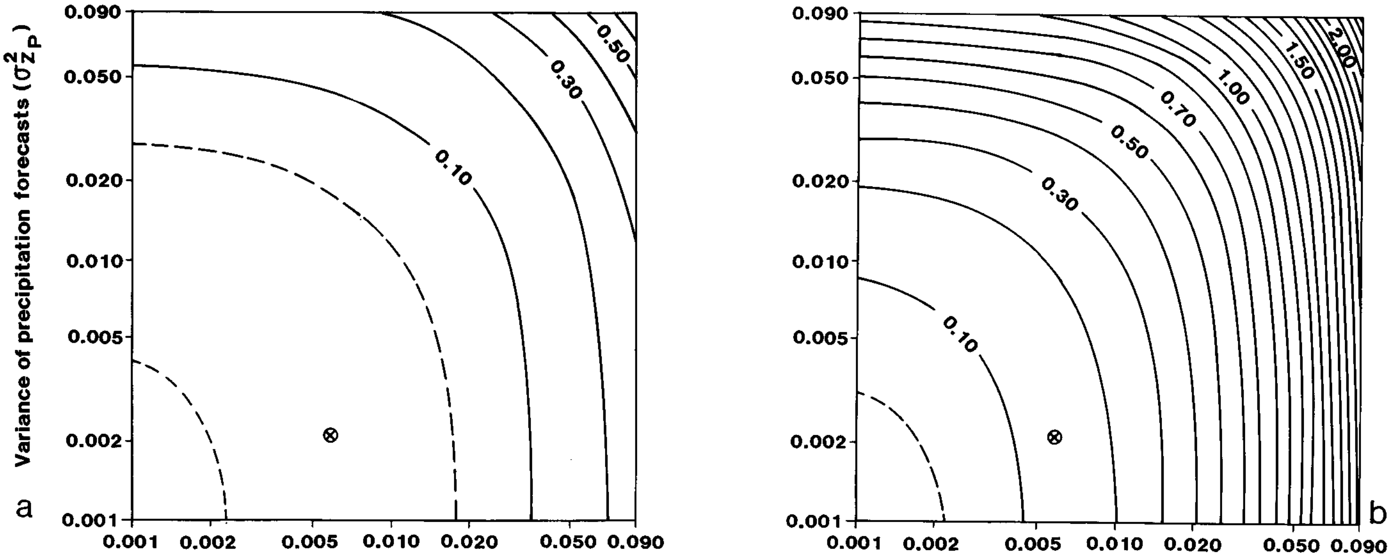
A potentially frustrating aspect of decision model construction is that realistic forecasts for a relevant predictand, or forecasts pertaining to a time scale imposed by the decision problem, do not always exist. One solution to this problem is to assume the existence of forecasts as needed, that is, to construct the analysis on the basis of idealized forecasts, as described previously. An alternative that is sometimes possible is to construct transformations of actual forecast products that yield forecasts of the desired form. These are denoted in the tables of Section 3 as "derived" forecasts. For example, many decision problems operate naturally on a daily time scale and may require forecasts of probability distributions for precipitation amounts. Generally available NWS short-term weather forecasts provide probabilities of precipitation occurrence (PoP forecasts) for 12-hour periods. This difficulty was accommodated by Wilks et al. (1993) by combining consecutive pairs of 12-hour PoP forecasts into single 24-hour PoP forecasts (Wilks, 1990a), and then inferring distributions for precipitation amounts on the basis of the PoPs and the climatological precipitation amount distributions (Wilks, 1990b). Once the derived forecasts are constructed, one can tabulate verification distributions for them using available records of forecast performance for the underlying operational forecasts.

It is often of interest to investigate the sensitivity of a given decision problem to changes in forecast quality. That is, in what ways would optimal actions differ if hypothetically improved forecasts were to become available, and what would be the implications of these improvements for forecast value? Studies investigating these quality/value questions are indicated in the "quality changes" rows of the tables in Section 3. This issue is most easily approached when a statistical model of forecast performance is used in the formulation of the decision problem. In that case forecast quality can be varied through adjustments of some of the parameters describing the joint distribution of the forecasts and observations. One approach, for example, is to increase the variance of the predictive distribution to simulate improved forecasts, and to decrease the variance of the predictive distribution to simulate degraded forecasts. In general, the variance of the predictive distribution of climatological forecasts will be zero, since the same forecast is issued on every occasion. At the opposite extreme, the variance of the predictive distribution of hypothetically perfect forecasts will be the same as the variance of the quantity being forecast, since the forecasts and observations match exactly.

It is then possible to present forecast value as a function of hypothetically changed forecast quality. For example, Figure 4.2 shows contours of quality/value surfaces as a function of the standard deviations of the predictive distributions of 90-day temperature and precipitation forecasts, for a choice-of-crop problem at four locations (Wilks and Murphy, 1986). In this case, limiting values of the standard deviation of the predictive distributions, corresponding respectively to climatological forecasts and perfect forecasts, bound the allowable range. Note also that if the predictive distribution is adjusted, corresponding changes in the joint distribution of forecasts and events are necessary for the implied climatological event distribution to remain unchanged.

2.3. Information valuation

One of the primary motivations for employing the decision-analytic framework is the desire to compute potential information value. This question can be thought of as calculating the maximum sum a decision maker should be willing to pay for the forecast information, assuming that the individual would act optimally. As


Variance of precipitation forecasts ($\sigma^2_{Z_P}$)
0.090
0.050
0.020
0.010
0.005
0.002
0.001
0.001 0.002 0.005 0.010 0.020 0.050 0.090
0.10
0.30
0.50
a
0.70
1.00
1.50
2.00
b

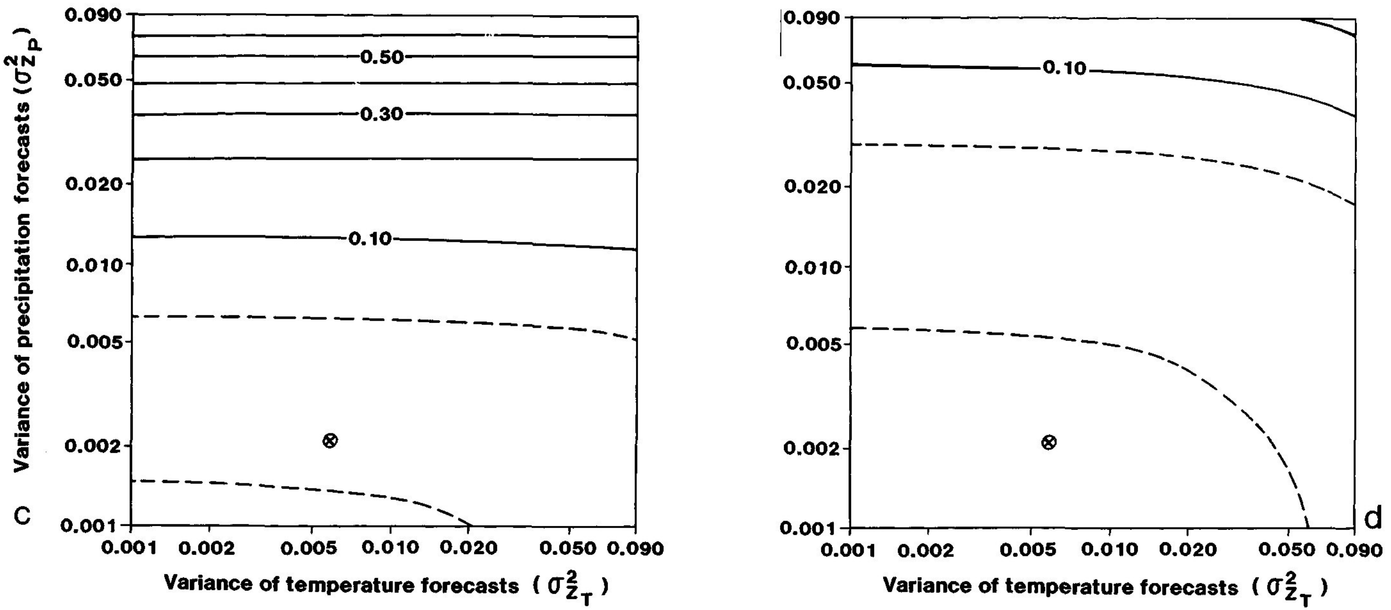


Figure 4.2. Contours of quality/value surfaces for a crop choice problem in four counties in North and South Dakota, using 90-day temperature and precipitation forecasts. The four panels represent a transect from north central North Dakota (a) to southeastern South Dakota (d). *Contour interval is \$0.10/ha-yr (solid contours), with the \$0.05 and \$0.01 contours dashed.* Circled "x" indicates current forecasts. (From Wilks and Murphy, 1986)

indicated above, this approach implies the existence of a baseline information source available to the decision maker in the absence of the forecast information under study.

Most commonly the information baseline adopted is climatological information. That is, the decision maker is assumed to know the historical relative frequencies for the meteorological events affecting the enterprise under analysis. This is probably a reasonable choice when the problem being considered is one with which decision makers have a reasonably long historical experience. A similar but somewhat more sophisticated alternative is "calibrated persistence," or a "conditional climatology." This information baseline recognizes the tendency for consecutive time periods to exhibit similar weather, and thus may be more appropriate for problems operating on a daily or shorter time scale. Rather than employing a single long-run climatological distribution, "persistence" information is represented as one of a set of conditional distributions for the relevant meteorological variable in the upcoming decision period, depending on the weather in the current decision period.

Often the response of the decision problem to hypothetical perfect forecasts is also investigated. Of course it is impossible for perfect forecasts ever to be realized, for reasons explained in Chapter 1 of this volume. Still, it is useful to study perfect forecasts, since these must provide an upper limit to information value for a given decision problem structure. Studies investigating hypothetically perfect forecasts are indicated in the tables as using a "perfect" baseline, even though the quantity usually computed is the value of perfect information with respect to the climatological information, rather than a negative value for imperfect forecasts relative to the perfect forecasts. One can, however, consider that imperfect forecasts have negative value with respect to perfect forecasts. Some studies transform forecast value to a normalized scale running from zero for climatological information to unity for perfect forecasts; that is, the relative increase in expected return $(\mathrm{ER}_{\mathrm{fcst}} - \mathrm{ER}_{\mathrm{clim}})/(\mathrm{ER}_{\mathrm{perf}} - \mathrm{ER}_{\mathrm{clim}})$.

Also presented in the valuation segments of the tables in Section 3 are specific monetary estimates for the value of information, where possible. These are presented separately for imperfect and perfect forecasts. As mentioned previously, the VOI estimates are very easy to compute if it is assumed that the decision maker acts to maximize monetary returns. In this case the information value is simply the arithmetic difference between the expected monetary return given optimal actions in response to the forecast information and the expected monetary return if only the baseline (e.g., climatological) information is available. Studies adopting this simple maximization of expected monetary value are indicated by "EV" (for expected value) in the "risk treatment" rows of the tables.

Computation of optimal actions through maximization of expected, usually monetary, value amounts to a tacit assumption that the decision maker is "risk neutral." Risk neutrality implies that the decision maker regards the intrinsic worth of money as directly proportional to its amount. For example, risk neutral individuals would be indifferent between the choice of receiving $1 with certainty, or $2 on the flip of a fair coin. Illustrated in this way, risk neutrality may appear to be a quite reasonable assumption and, indeed, many people are essentially risk neutral when small sums are involved. But consider what your reaction would be if offered the choice between $1 million with certainty, or $2 million on the flip of a coin. Unless you are already very rich, the sure million will probably look much more attractive. That is, $2 million is worth less than twice as much as $1 million from your personal perspective, indicating that you are risk averse.

It should be clear from this example that real-world decision makers might very well be sensitive to risk, at least when important decisions are concerned, and that ignoring this sensitivity could produce misleading results in some cases. It is possible to incorporate different risk attitudes into the decision-analytic framework by using the concept of a "utility function" (e.g., Winkler, 1972; Winkler and Murphy, 1985; and Chapter 3 of this volume). A utility function amounts to a mathematical transformation from the original, often monetary, scale to the utility scale, reflecting more fundamentally the perceived worth of each outcome to the decision maker. In terms of the example in the previous paragraph, the utility function, U, of a risk averse individual would satisfy the inequality $U(\$1{,}000{,}000) > U(\$2{,}000{,}000)/2$. Of course, many functions exist that satisfy this constraint, and this complicates the problem of including risk preferences in realistic decision models. Different individuals will have quite different utility functions (e.g., Baquet, Halter, and Conklin, 1976; Lin, Dean, and Moore, 1974; Hildreth and Knowles, 1986; Winkler, 1972), and the utility function of a single individual might change from time to time with their circumstance or even their mood. As a consequence, many studies that maximize expected utility do so using idealized, but (it is hoped) representative, utility functions rather than those elicited from real decision makers. The mechanics of accounting for risk preferences within the decision model is conceptually straightforward, once the utility function has been defined, although the estimation of information value is more complex (e.g., Hilton, 1981). The computations are performed as described previously, except that decisions are prescribed that maximize expected utility, rather than expected monetary value. Studies where utility representation of risk attitude has been employed are indicated in the tables by "EU" (for expected utility).

3. Case study tabulations

In this section, the existing case studies are tabulated according to the criteria explained in Section 2. Similar decision problems have been grouped together in each table. Most of the effort to date has been directed toward agricultural decision problems, and these are summarized in Tables 4.1 through 4.7. Forestry-related problems are tabulated in Table 4.8, and other, primarily transportation problems, are summarized in Table 4.9.

3.1. Raisins

Two early studies, summarized in Table 4.1, treat the problem of management of grapes for raisin production in the San Joaquin Valley of California. The decision pertains to avoiding rain damage during the sun-drying of grapes to preserve them as raisins in the fall. Kolb and Rapp (1962) consider protecting the raisins from rain damage during the drying process as a cost–loss ratio problem. This setting, treated more fully in Chapter 6 of this volume, involves the choice between protection against adverse weather (rain, in this application) at a cost, versus the loss sustained if adverse weather occurs without protection. In its simplest, static form, protection is optimal if the probability of adverse weather exceeds the ratio of the cost to the loss. Since the drying process extends over a period of weeks, the daily decision modeled by Kolb and Rapp should properly be a sequential problem. However, the

Table 4.1. Raisins: case study characteristics

	Kolb & Rapp (1962)	Lave (1963)
Structure:		
Decision	Protect from rain	Harvest timing, raisins or juice
Dynamics	No	Yes
Forecasts:		
Time scale	Daily	3-week
Predictand	Rain occurrence	Rain onset
Format	Categorical	Categorical
Type	Realistic, derived	Idealized
Qual. changes	No	No
Valuation:		
Baselines	Clim. & perf.	Clim.
VOI, imperf.	\$50 to \$140/ton raisins	Not reported
VOI, perf.	\$65 to \$155/ton raisins	\$225/ha-yr
Risk treatment	EV	EV
Comments:	Problem fit to the cost–loss framework. Categorical forecasts tailored to trigger the optimal decision.	Qualitatively consider market effects; conclude that negative aggregate value to producers is possible.

nature of the fall climate in this region is that precipitation is rare. Accordingly, the static framework is almost appropriate, since the likelihood of overprotection early in the decision sequence is slight.

Lave (1963) considers the somewhat longer-range problem of deciding whether and when to attempt making raisins, versus selling the grapes for juice. Significantly, effects of the use of forecast information on the availability of the local grape processing facilities and on the markets for grape products are considered, although in a qualitative way. This is in contrast to most of the studies reviewed in this chapter, which consider only single decision makers in isolation from the larger economy. Because raisin production is geographically localized, all producers experience essentially the same meteorological conditions in a given year, and have available the same forecast information. Lave speculated that, paradoxically, aggregate value of forecast information to producers could be negative. That is, producers might be better off if none of them had access to forecasts. Babcock (1990) has verified this speculation for conditions corresponding to Lave's analysis. Note, however, that even in this case the forecast information has positive value in the usual sense, since a producer choosing to ignore the information used by the competition would be even worse off. Potential effects on consumer benefits are as yet unanalyzed; as well as implications for commodities whose production is more widely distributed, so that different producers see different forecasts and experience different weather.

3.2. Frost protection

Both studies investigating use of weather forecasts in the frost protection decision are concerned with protecting blossoming fruit trees (Table 4.2). The basic problem, familiar to home gardeners, is whether to take some action to maintain plant canopy temperatures above freezing during nocturnal radiative cooling conditions. Both studies here model the decision to accomplish this by lighting heaters on nights when there is sufficiently high probability of frost, as indicated by the minimum temperature forecast. Since fueling and servicing the heaters is expensive, the orchard manager will want to avoid their unnecessary use.

Baquet et al. (1976) consider protection of pears as a collection of daily static cost–loss problems, rather than a sequence of related decisions, on 60 spring nights. One strength of this study is that it uses a variety of utility functions, elicited from real-world orchardists in the study area, and investigates the effects of their different risk preferences on the decision problem. These authors also approach the forecast verification aspect of the problem in a formal Bayesian way, combining empirical distributions for forecasts conditional on observed temperatures with assumed prior distributions. Most of the results pertain to use of the climatological distribution as the prior, which is equivalent to direct use of the conditional distribution of observed temperatures given the forecasts. However, some computations were also made using a diffuse prior (e.g., Winkler, 1972), yielding a substantial estimate for the value of climatological information to a hypothetical decision maker operating without the benefit of such baseline information.

Katz et al. (1982) consider essentially the same problem for apples and peaches, in addition to pears. In this study the problem is

Table 4.2. Frost protection: case study characteristics

	Baquet et al. (1976)	Katz et al. (1982)
Structure:		
Decision	Orchard heaters	Orchard heaters
Dynamics	No	Yes
Forecasts:		
Time scale	Daily	Daily
Predictand	Min. temp.	Min. temp.
Format	Categorical	Categorical
Type	Realistic	Realistic
Qual. changes	No	Yes
Valuation:		
Baselines	Clim. & perf.	Clim. & perf.
VOI, imperf.	\$798/ha-yr	\$667 to \$1,997/ha-yr
VOI, perf.	\$1,270/ha-yr	\$1,406 to \$3,047/ha-yr
Risk treatment	EU & EV	EV
Comments:	Formulated as a static cost–loss problem. Use a variety of real growers' utility functions.	Bivariate normal model for forecasts and observed temperatures. Dynamic programming solution.

properly treated in a dynamic framework. The solution is obtained through dynamic programming using cumulative bud loss as the single-state variable, and protective action is then prescribed as a function of the forecast, the level of damage so far sustained, and the date.

3.3. Forage preservation

The four studies summarized in Table 4.3 model decisions related to the preservation, usually as hay, of vegetative plant materials (forage) intended for livestock feed at a later date. The study of Byerlee and Anderson (1982) is different from the others, treating the problem of how much hay to store against unknown feed requirements in the following year. More stored feed will be required if the following year is dry, and less will be required if the following year is wet. The decision is thus based on very long-range precipitation forecasts.

Table 4.3. Forage preservation: case study characteristics

	Byerlee & Anderson (1982)	Dyer & Baier (1982)	McQuigg (1965)	Wilks et al. (1993)
Structure:				
Decision	Amount to store	Harvest timing	Harvest timing	Harvest timing
Dynamics	No	No	No	Yes
Forecasts:				
Time scale	Annual	Daily & 4-day	Daily	Daily
Predictand	Prec.	Prec.	"Haying weather"	Prec., temp. & evaporation
Format	Categorical	Categorical	Categorical	Categorical & probabilistic
Type	Realistic	Idealized	Idealized	Realistic, derived
Qual. changes	No	Yes	No	No
Valuation:				
Baselines	Clim. & perf.	Clim. & perf.	None	Clim., persist. & perf.
VOI, imperf.	\$59/farm-yr	Not reported	Not reported	\$94/ha-yr
VOI, perf.	\$520/farm-yr	Not reported	Not reported	\$140/ha-yr
Risk treatment	EU & EV	EU	EV	EV
Comments:	Risk treated using both utility maximization and mean-variance analysis.	Emphasize trade-off of forecast accuracy and lead time.	Idealized, focusing on different categorical forecast thresholds for different decision makers.	Treats serial correlation. Monte Carlo simulation to compute variances of returns and harvest and timing distributions.

The remaining three studies cited in Table 4.3 are concerned with the day-to-day harvest decision. Here the physical basis of the problem is the requirement that the forage be dried in the field for one to several days before it is suitable for storage. During this time it is subject to damage, if rain occurs. Rain will also extend the drying period, exposing the forage to the potential for further damage. The problem is complicated by the fact that the quality, and thus value, of the undamaged product decreases as harvests are delayed, so that the farmer cannot wait indefinitely for a very high probability of good drying weather.

The studies of Dyer and Baier (1982) and McQuigg (1965) are idealized formulations, with respect to both the assumed forecast characteristics and the imposition of a static framework on this intrinsically dynamic problem. However, these analyses do point out two important aspects of the use of weather forecasts in decision making. The early McQuigg study demonstrated that weather forecasts could be of value in real agricultural decision problems provided integration of biological, economic, and meteorological factors could be achieved. The Dyer and Baier study illustrates the potential trade-off between forecast accuracy and lead time, that is, that less accurate forecasts may be more valuable if received sufficiently far in advance. The Wilks et al. (1993) study formulates the sequence of daily cutting decisions over a growing season as a large (6 state variables) dynamic programming problem, allowing both the number and timing of cuttings to be prescribed by the model. Temperature forecasts are included to control plant yield and maturity, and as input to the derived evaporation forecasts.

3.4. Irrigation

Three studies, summarized in Table 4.4, have considered use of forecast information to optimize irrigation. Here the problem is to minimize economic crop damage produced by soil dryness, balanced against the costs, in labor and energy required for pumping, in addition to possible costs for the water itself. There is a fairly large literature on dynamic programming solutions to optimal irrigation scheduling (e.g., McGuckin et al., 1987; Rhenals and Bras, 1981) not considering weather forecasts. However, the decision maker would like to meet plant water requirements through rain-

Table 4.4. Irrigation: case study characteristics

	Allen & Lambert (1971a, b)	Rogers & Elliott (1988)	Swaney et al. (1983)
Structure:			
Decision	Irrigation timing	Irrigation timing & amount	Irrigation timing
Dynamics	No	No	No
Forecasts:			
Time scale	Daily	Daily	Daily
Predictand	Prec.	Prec.	Prec.
Format	Probabilistic	Probabilistic	Probabilistic
Type	Realistic, derived	Realistic	Realistic
Qual. changes	No	No	No
Valuation:			
Baselines	Conventional decision rule	Clim., persist., perf., & conventional decision rules	Clim.
VOI, imperf.	\$10.53/ha-yr	\$3.20 to \$19.46/ha	–\$7.70/ha-yr
VOI, perf.	Not reported	\$3.48 to \$18.56/ha	Not reported
Risk treatment	EV	EV	EV
Comments:	Cast as a cost–loss problem; no explicit consideration of rainfall amount.	Cast as a cost–loss problem, perf. VOI sometimes less than fcst. VOI because rainfall amounts not explicit.	Forecasts show negative value resulting from improper problem formulation.

fall, if possible, so that day-to-day precipitation forecasts should be of use in avoiding unnecessary irrigations. Another potentially interesting aspect of this problem, not considered by any of the studies summarized here, is that rainfall following an irrigation can lead to undesirable fertilizer and pesticide leaching.

There are serious shortcomings in all three of the cited studies of this difficult decision problem. In each case a static framework has been imposed on the inherently dynamic process. Also, all three include only forecasts for precipitation occurrence rather than probability distributions for precipitation amounts. These and other problems lead to some spurious results, such as the value of imperfect forecasts (or even conventional, nonforecast-based decision rules) being greater than perfect forecasts (Rogers and Elliott, 1988), or negative value for forecast information (Swaney et al., 1983).

It is worth noting that none of the three studies model irrigation decisions in arid regions, and for good reason. While irrigation is widely practiced in such places as California, the use of weather forecasts for irrigation management in these settings would be uninteresting. This is because the climatological probability of rain is so low that there is little scope for improving management practices using forecasts in such climates.

3.5. Crop choice

The issue of crop choice is another important weather-sensitive problem in agriculture. Here the problem is either to choose among crop alternatives or to allocate areas devoted to different crops, on the basis of their anticipated absolute and relative performance in the coming year. These problems thus operate naturally on relatively long time scales, and the near-independence of year-to-year weather generally allows use of the static analysis framework. There are many such problems, and the six analyzed to date and summarized in Table 4.5 by no means exhaust the possibilities.

The first two studies summarized in Table 4.5 focus on the response of the overall United States economy, in terms of producers' and consumers' surplus, to planting decisions. The idealized study of Agnew and Anderson (1977) considers wheat production in relation to hypothetical temperature and precipitation forecasts. Adams et al. (1995) consider choices among four crops in

Table 4.5. Crop choice: case study characteristics

	Agnew & Anderson (1977)	Adams et al. (1995)	Katz et al.* (1987)	Tice & Clouser (1982)	Wilks & Murphy (1985)	Wilks & Murphy (1986)
Structure:						
Decision	Wheat acreage	Allocations among cotton, corn, sorghum & soybeans	Wheat vs. fallow	Corn vs. soybeans	Pasture vs. hay	Corn vs. wheat vs. fallow
Dynamics	No	No	Yes	Yes	No	No
Forecasts:						
Time scale	Seasonal	Annual	Seasonal	Seasonal	Seasonal	Seasonal
Predictand	Temp. & prec.	El Niño	Prec.	"Good," "avg.," & "bad"	Prec.	Temp. & prec.
Format	Categorical	Categorical	Probabilistic	Categorical	Probabilistic	Probabilistic
Type	Idealized	Realistic	Realistic	Idealized	Realistic	Realistic
Qual. changes	Yes	Yes	Yes	No	Yes	Yes
Valuation:						
Baselines	Clim. & perf.	Clim. & perf.	Clim. & perf.	Clim.	Clim. & perf.	Clim. & perf.
VOI, imperf.	\$10.8 million/yr	\$96 to \$130 million/yr	\$0 to \$10/ha-yr	Not reported	\$0.00 to \$1.40/ha-day	\$0.00 to \$0.14/ha-yr
VOI, perf.	\$208 million/yr	\$144.5 to \$265 million/yr	\$116 to \$197/ha-yr	\$3.65/ha-yr	\$11.20 to \$17.30/ha-day	\$0.20 to \$2.40/ha-yr
Risk treatment	EV	EV	EV	EV	EV & EU	EV
Comments:	VOI for entire US, focusing on market effects & links to conventional economic analysis.	VOI for entire US, depending on farm programs. Decisions imposed centrally; not made by individual farmers.	Future-value discounting; VOI depends on location; actions are sensitive to price.	Consider only perfect fcsts., 2-stage dynamics. Also choose fertilization level.	VOI & actions depend on relative prices and DM's utility function.	VOI & actions depend on relative prices and location.

*Results of this study are also reported in Brown et al. (1986).

the southeastern United States in relation to forecasts for El Niño, although the optimal actions are taken to be those that maximize national economic welfare, rather than the expected return to the individual producer who would make the decisions.

Tice and Clouser (1982) consider acreage allocation between corn and soybeans. Fertilization management is also examined, which dictates a sequential model. This is an idealized study treating only perfect forecasts for a generalized predictand.

The three remaining studies use the 90-day outlooks issued monthly by the U.S. Climate Analysis Center (Epstein, 1988). Katz, Brown, and Murphy (1987) analyze the choice of whether to plant wheat, or to fallow (plant no crop) in order to conserve soil moisture for the following year, in the relatively arid climate of the northern high plains. The relevant forecast is for 90-day precipitation, and the year-to-year moisture carryover dictates that the decision be analyzed as a sequential problem. This study also includes use of a future-value discount factor, which reflects the cost of borrowed money or, equivalently, value associated with alternative uses of capital devoted to the farming enterprise. This is an important economic reality for sequences of decisions spanning years. Wilks and Murphy (1986) analyze a similar problem, allowing a second crop in addition to the fallowing choice, but ignoring the sequential nature of moisture storage resulting from fallowing. This study uses the 90-day temperature and precipitation outlooks simultaneously. Wilks and Murphy (1985) is the only study of the five to prescribe decisions maximizing expected utility, although real-world crop choice decisions should depend strongly on the risk attitude of the decision maker (e.g., Lin et al., 1974).

3.6. Fertilization

Amount and timing of fertilization are also important considerations in agricultural production. The three studies summarized in Table 4.6 all treat management of nitrogen, which is generally the most heavily applied plant nutrient, and which can be fairly expensive in times of high energy prices. It is often the case that optimum nitrogen levels depend on future levels of a limiting climatic element (e.g., precipitation in a water-limited climate), which will generally not be known at the time the fertilizer is applied. The two early studies of Byerlee and Anderson (1969) and Doll (1971)

Table 4.6. Fertilization: case study characteristics

	Byerlee & Anderson (1969)	Doll (1971)	Mjelde et al.* (1988)
Structure:			
Decision	Amount, on wheat	Amount, on corn; plant density	Amount & timing, on corn; planting & harvest timing
Dynamics	No	No	Yes
Forecasts:			
Time scale	Seasonal	Seasonal	Seasonal to annual
Predictand	Prec.	"Weather"	Prec. & crop-specific indices
Format	Categorical	Categorical	Probabilistic
Type	Realistic, derived	Idealized	Idealized
Qual. changes	No	Yes	Yes
Valuation:			
Baselines	Clim. & perf.	Clim. & perf.	Clim. & perf.
VOI, imperf.	\$0.01 to \$0.20/ha-yr	\$0.17 to \$0.54/ha-yr	\$0.10 to \$10.40/ha-yr
VOI, perf.	\$0.12 to \$0.89/ha-yr	\$9.93 to \$17.40/ha-yr	\$21.20 to \$46.00/ha-yr
Risk treatment	EV	EV	EV
Comments:	VOI varies as a function of initial soil moisture and fertility.	Focuses on future forecast accuracy necessary for forecast value.	VOI depends on forecast quality, lead time, and prices. Lower quality can lead to higher value if provided further in advance.

* Results of this study are also reported in Easterling and Mjelde (1987), Mjelde and Cochran (1988), and Sonka et al. (1987).

address themselves to the problem of supplying enough nitrogen to exploit the climatic opportunities in the upcoming growing season while trying to avoid unproductive overfertilization. These are cast as once-yearly problems, so that the static framework adopted is appropriate.

The Mjelde et al. (1988) study is much more detailed. In addition to the current-year fertilization problem treated in the other two papers, this study considers fall fertilization of the crop to be planted in the following spring. This decision is weather-sensitive because fall-applied nitrogen is subject to loss by leaching or volatilization if winter and/or spring weather is unfavorable. Also considered here are a variety of other tactical farm management decisions, requiring a sequential framework. An interesting lesson from this work is that forecasts for the most critical part of the growing season with respect to yield may have little or no value if, as is the case here with midsummer weather for corn, no decisions are available allowing use to be made of the information. This problem is an example of a weather-sensitive situation that lacks weather-information sensitivity.

3.7. Other agricultural problems

Two agricultural decision problems that do not fit neatly into one of the above six groups are summarized in Table 4.7. Both are representative of classes of problems that could be fruitfully extended to other crops and locations. Anderson (1973) studies the scheduling of harvest dates for peas, with the decision aided by anticipating their ripening rate using temperature forecasts. An interesting facet of this problem is the potential shortage of harvest equipment during warm years, when the scheduling of different fields must be balanced. Analogous problems occur in other agricultural settings as well, and interesting results will probably be forthcoming when examples of this general class of scheduling problem are analyzed in a dynamic framework.

The Carlson (1970) study is the sole example of another important class of weather-sensitive decision problem, that of scheduling pesticide use. In addition to considerations of expense, minimization of environmental pollution from unnecessary or misplaced pesticide applications is increasingly an important management goal. Carlson considers the level of fungicide necessary to respond to

Table 4.7. Other agricultural problems: case study characteristics

	Anderson (1973)	Carlson (1970)
Structure:		
Decision	Schedule pea harvest	Fungicide type and application schedule
Dynamics	No	No
Forecasts:		
Time scale	Daily & 6–10 day	3 weeks
Predictand	Temp.	Prec.
Format	Categorical	Categorical
Type	Idealized	Realistic, derived
Qual. changes	Yes	No
Valuation:		
Baselines	Clim.	Conventional practice
VOI, imperf.	\$0.64/ha-yr	Not reported
VOI, perf.	\$4.00/ha-yr	Not reported
Risk treatment	EV	EV & EU
Comments:	A cost–loss problem, considers trading off accuracy vs. lead time.	Focus on best decisions rather than VOI. Mean-variance framework for risk aversion.

future disease pressure brought on by weather conditions. Other meteorological factors can be important in pesticide scheduling and amenable to optimization using forecasts, including the effect of windspeed on unwanted pesticide dispersal, and rainfall leading to washoff of applied materials. Although weather forecasts have been incorporated into other pesticide decision-making problems (e.g., Vincelli and Lorbeer, 1988), the method has involved trial and error rather than comprehensive analysis.

3.8. Forestry

The three forestry-related studies cited in Table 4.8 model quite different decision problems. Anderson (1973) considers the possibility of avoiding the expense of graveling temporary logging roads if perfect precipitation forecasts for the upcoming week were to be available. Brown and Murphy (1988) model the allocation of

Table 4.8. Forestry: case study characteristics

	Anderson (1973)	Brown & Murphy (1988)	Furman (1982)
Structure:			
Decision	Gravel logging roads	Allocate fire-fighting resources	Initiate controlled burn
Dynamics	No	Yes	No
Forecasts:			
Time scale	Weekly	Daily	Daily
Predictand	Prec.	"Fire weather"	Temp., wind
Format	Categorical	Categorical	Categorical
Type	Idealized	Idealized	Realistic
Qual. changes	Yes	Yes	No
Valuation:			
Baselines	Conventional practice	Clim. & perf.	Clim., persist. & perf.
VOI, imperf.	Not reported	$6,084 per pair of fires	NA (utility scale)
VOI, perf.	7.6% of road costs	$16,594 per pair of fires	NA (utility scale)
Risk treatment	EV	EV	EU
Comments:	Value of near-perfect forecasts compared to conventional decision rules.	Idealized problem treating a sequence of two dissimilar decisions.	Utilities assessed by interviews with forest managers.

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fire-fighting resources between two fires, including the logistics of mobilization.

Furman (1982) addresses the very different problem of deliberately initiating forest fires as part of the management of the forest stand, where favorable weather consists of conditions unlikely to lead to the fires going out of control. This study is interesting in that there is no monetary underpinning to the preferences among outcomes, but rather utilities are elicited directly from forest managers. These utilities reflect preferences balancing several outcome attributes. In addition to incorporating the managers' risk aversion, they include meeting management objectives, containing costs, and minimizing detrimental environmental impacts.

3.9. Other decision problems

Finally, Table 4.9 presents characteristics of the remaining studies, all but one of which analyze different transportation decisions. The exception is the study by Alexandridis and Krzysztofowicz (1985), which analyzes the decision to generate electrical power, attempting to match demands for heating and cooling as anticipated through temperature forecasts. Results are derived both for the usual categorical temperature forecasts, as well as for probabilistic temperature forecasts (Murphy and Winkler, 1974). Forecast value for nonoptimal decision makers, acting as if the imperfect forecasts were perfect, is also computed.

The Nelson and Winter (1964) transportation study is a simple cost–loss example, where freight can be protected against rain damage if the probability of a nontrivial precipitation amount is sufficiently high. The two early studies of Glahn (1964) and Kernan (1975) are similar, in that the decision in each pertains to what forecast should be issued. In these early studies the problem is so framed because the forecast format was constrained to be categorical. In effect, then, the forecaster is also assuming the role of the decision maker. These two studies are also similar in that they use utility functions not mapped from monetary outcomes, as did the Furman (1982) forestry study.

The Howe and Cochrane (1976) study is unique in simultaneously considering related long-run and short-term decisions. The example pertains to municipalities optimizing investments in snow removal equipment, by using decision-analytic models of the daily

Table 4.9. Other decision problems: case study characteristics

	Alexandridis & Krzysztofowicz (1985)	Glahn (1964)	Howe & Cochrane (1976)	Kernan (1975)	Nelson & Winter (1964)
Structure:					
Decision	Electrical power generation	Ceiling height forecast	Snow removal	Declare air pollution alert	Protect truck freight
Dynamics	No	No	No	No	No
Forecasts:					
Time scale	Daily	5 hours	Daily & "long-run"	Daily	Daily
Predictand	Temp.	Ceiling height	Snow amount	Air pollution	"Heavy" rain
Format	Cat. & prob.	Categorical	Categorical	Categorical	Categorical
Type	Realistic (experimental)	Realistic	Realistic	Realistic	Idealized & derived realistic
Qual. changes	Yes	No	No	No	No
Valuation:					
Baselines	Clim. & perf.	Perf.	Perf.	Clim.	Clim. & perf.
VOI, imperf.	\$26,600–\$27,200/day	NA (utility scale)	Not reported	NA (utility scale)	\$6.40 to \$10.40/ truck-day
VOI, perf.	\$38,900/day	NA (utility scale)	\$118,000/yr for one city, relative to fcsts.	NA (utility scale)	\$18.40/truck-day
Risk treatment	EV	EU	EV	EU	EV
Comments:	Uses both categorical and probabilistic forecasts. Compares results for nonoptimal decision maker, who believes (imperfect) forecasts are perfect.	Decision is the forecast; choose among possible categorical forecasts to maximize airline utility.	Simultaneous treatment of long-term (equipment acquisition) & daily snow removal decision.	A cost–loss application. Optimize probability thresholds for categorical forecasts.	An early, simple cost–loss application.

snow removal problem given each of the possible levels of equipment purchase. This approach is potentially applicable to many other weather-related facility and investment decisions.

4. Concluding remarks

This chapter has reviewed prescriptive studies relating weather forecasts to real-world decisions, as distinct from the idealized studies described in Chapter 6 of this volume. In this context, decision-analytic models have been constructed and studied primarily for two purposes: (i) to examine quantitatively the potential benefits to be derived from existing expenditures on the meteorological infrastructure, or to examine whether possible future expansion of forecast activities would be justified economically; and (ii) to enable users of weather forecasts to make better decisions, by prescribing optimal actions together with a quantitative analysis of why forecasts lead to better outcomes on average.

More emphasis has been placed on the first of these two purposes to date, although in many ways the framework as applied to "practical" problems is better suited to the second. For reasons that follow from the results summarized by Hilton (1981) on the determinants of information value, it is necessary to analyze individual case studies rather than somehow to compute a value accruing to all users of a particular forecast product. Thus the best that can be expected in terms of breadth are models that reasonably represent a particular class of decision makers, faced with similar decisions under similar climatological conditions. A comprehensive analysis (or even listing) of all users of, for example, daily temperature forecasts does not seem feasible.

Even when a decision problem is well-formulated and realistic, two other problems emerge when representing overall forecast benefits by aggregating VOI over the individuals whose decision problem is described. First, it is not clear that any decision maker actually receives full value, as described in a model, from the forecasts. Real-world decision makers are not constrained to act optimally, which suggests that VOI calculations from prescriptive studies may overestimate forecast value. As discussed in Chapter 5 of this volume, however, these VOI calculations may be underestimates for other nonoptimal decision makers. Choice of the "zero-information" baseline will also influence the relationship between computed and received information value. Using the conventionally assumed climatological probabilities may underestimate VOI in cases where these are not accurately perceived by the decision maker (Mjelde et al., 1988), while in some problems a more sophisticated baseline such as persistence may result in more realistic forecast valuation (Wilks et al., 1993).

The market-level impact of meteorological forecast information on overall value has been investigated very little to date, although the potential exists for surprising effects (Babcock, 1990). Much more work is needed to investigate the relationships of aggregate and individual VOI estimates as a function of such influences as geographic distribution of forecast users and the correlation of their climates. Expansion of the basis of economic valuation from producers only to the larger society, including consumers, is needed as well.

Inevitably, decisions must be analyzed on a case-study basis. Often, designing the analytical structure is surprisingly difficult, especially for more realistic decision problems. One often finds that the available operational forecasts are not in the proper form, do not pertain to the most appropriate time scale, or do not predict the proper variable for the enterprise under consideration. The details of a decision setting are necessarily specific to the particular problem at hand, and an additional constraint is the rather large computational resources demanded by a realistic model structure (e.g., Burt, 1982). For some problems it is difficult to isolate decisions for which only one time scale is important. In addition, appropriately structured response models may not be immediately available, in which case original work that ranges into several disciplines is generally required before the formal modeling and analysis phase can be initiated.

There does seem to be great potential to improve real-world use of weather and climate forecast information through continued work on individual case studies. Many of the agricultural studies reviewed here could be fruitfully extended to analyze management of other commodities, or to prescribe actions at other locations (i.e., for different climates). Problems in such areas as livestock management, fisheries, and energy supply also seem ripe for progress. Realistic, and therefore complex, dynamic programming solutions to a variety of interesting real-world problems are increasingly within reach as the computational constraints lessen.

Results of sufficiently realistic decision analyses should be useful to real-world decision makers, but as an aid to, rather than a substitute for, their individual judgments.

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