INFORMATION AS A RISK MANAGEMENT TOOL: AN ILLUSTRATION FOR CLIMATE FORECASTS

By

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The 1970's and 80's have been a time of dramatic and sudden shifts for U.S. agriculture. Within relatively short time periods, producers have moved from environments of great optimism to situations of severe economic stress. This series of events is, of course, well known to agricultural economists. In the process of assisting producers in responding to these rapidly changing conditions, numerous practical risk management procedures have been sought out and implemented.

One of these tools, which is commonly used but may not always be considered as a risk management tool, is information (Batte). Indeed in the early 1980's, there was a considerable body of popular literature which foretold of a coming information age in the developed societies (Naisbitt). Part of the rationale for this prediction was that greater amounts of information would be needed to respond to more rapidly changing circumstances. A term which encompasses this latter concept is that of environmental turbulence (Ansoff). Here environment is defined quite broadly to include economic, social, and political as well as the physical - forces affecting business operations. A way of summarizing our experiences of the last two decades is to assert that the level of environmental turbulence has been increasing. The decision maker is facing an environment where change is occurring more rapidly and those changes are more surprising than they were in previous eras.

This movement to a more turbulent environment is perceived by some as an evolutionary process (Ansoff). They assert that forces such as technological change, internationalization and deregulation imply that we need to develop management skills and tools which can evolve at the same pace as the changing environment. Information and its use is a key part of these reactions. Both in terms of monitoring the changing environment and in designing actions to react and/or exploit those changes, information becomes a more important element of the decision process. In agriculture, this is likely to mean a movement towards more flexible management styles and away from rigid, routine-based management approaches (Sonka).

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Climate Predictions as One Type of Information Input

Agricultural decision makers need access to a vast array of types of information. Examples include material needed to develop expectations relative to such diverse topics as output prices, growing season weather conditions, pest infestations, interest rates, input price movements, and government policies. Operationalizing the expected movement towards a more flexible management approach entails integrating diverse information types (such as those noted above) over very short, intermediate and long term time frames. If we are to aid decision makers to develop and implement these information tools, analyses are needed which carefully evaluate information alternatives.

Why climate predictions?

The information type considered here is climate prediction. In general, "a climate prediction is a statement of the expected general character of the weather for a period in the future whose length may be a part of a season (one or two months), a season, a year, a decade, or even longer" (Lamb, et. al.). In this study seasonal climate predictions are the topic of analysis. The specific seasons considered range from as short as a month to as long as four months in length.

Seasonal climate forecasts were selected as an area for analysis for several reasons. First there is considerable current use of climate information by agricultural managers and climate forecasts are thought to hold significant potential value (Lamb, et. al.; Easterling). Potential users consistently indicate that climate forecasts would have value, but only if those forecasts were sufficiently accurate. Yet in-depth discussions with those potential users reveal their considerable difficulty in articulating what "sufficiently accurate" is. Further those same users may be currently paying fees to receive climate forecasts, even though the current accuracy level is not thought to be particularly good (Lamb, et.al.). In addition to the accuracy dimension, there appears to be need for evaluation of alternative forecast design schemes if users are to maximize the potential benefit of that information.

An additional reason for analysis of climate forecasts is the current optimism with respect to potential increases in the accuracy of this technology. Currently the most promising results relate to the widely publicized El Nino/Southern Oscillation and its effects on tropical areas (Rasmusson). Recent advances in understanding the linkages between atmospheric, oceanic and land mass forces and the growing computational power to model these linkages suggest that additional strides may be possible.

Need for modeling

Although there is a general consensus that climate forecasts are potentially useful, several factors make it difficult for decision makers to specify the potential value of such a technology. In addition, it is also difficult for potential users to rigorously define the characteristics necessary if the technology is to be useful. To help identify these impediments, it is helpful to briefly consider the decision framework in which climate predictions might be used. Figure 1 summarizes a general overview of such a framework for a specific setting -- that of production decisions for an annual crop producer.

In Figure 1 the items above the dotted line represent factors that affect the production decision. (The production decision box is, of course, a simplistic representation of a vector of interrelated production choices that must be made by the decision maker.) Those factors listed below the dotted line and the production decision itself combine to determine the resulting crop yield. Figure 1 stresses that there are several diverse factors affecting production decisions. Included are expectations relative to economic and physical events, current physical conditions, and goals of society and the producer. An important implication of this general decision framework is to reinforce the concept that climate information, as with other kinds of information, does not directly affect production. Instead information acts to alter expectations, which in turn affect production through their influence on the production decision.

Evaluation of Figure 1 suggests two important reasons why modeling is essential for evaluation of information as an input in general and specifically for climate information. Climate forecasts, although potentially important, are only one of a large number of information types that the producer must utilize in making decisions. Therefore it is difficult for individuals to develop valuations of one information source in isolation of that larger set of factors. Second, Figure 1 specifically identifies the need to be able to distinguish the value of improved information (which leads to better decisions) from the occurrence of good outcomes. Observing the actual use of information by decision makers, even if possible, would likely not be sufficient to identify the influence of information from the occurrence of favorable or adverse events. When dealing with information sources which provide stochastic predictions, there is a need to be able to identify the value of improved information over the entire range of possible outcomes, not just those that may actually occur in a specific year.

Modelling Results

The remainder of this paper will provide an overview of the modelling efforts that our group has accomplished to date. Significant support for this effort has been provided to a multidisciplinary research team by the National Science Foundation. Because of the complexities involved, this team includes agricultural economists, agronomists, and meteorologists. In addition, the input of actual decision makers has been actively pursued and applied to the modelling process where appropriate. The effort which will be described here is exploratory in nature and the specific situation analyzed is quite limited in its general applicability. Future work by the research team will broaden the analysis both in terms of the realism of the situation postulated and of geographic applicability.

The remainder of this discussion will be organized as follows: First the decision situation to be analyzed will be described. The decision analysis tool used in the study will then be presented. Finally a sampling of the types of results obtained will be displayed. The paper's concluding remarks will consider implications of the current analysis and potentials for further analysis.

The decision process considered

Flexible management strategies require that producers reevaluate planning processes as additional information becomes available (Sonka). An interesting characteristic of decision making for the crop producer is that the process of producing one season's crop is not the result of a single decision. Instead, the decision process is composed of a series of interrelated choices made over a several month period. As the producer proceeds through those several months, the opportunity for information to alter some or all of those production choices occurs. At key points choices must be made and actions taken. As these actions are taken, the producer's flexibility is likely to diminish because some of these actions are irreversible. For example mid-summer rainfall may be critically important to the corn crop's development. Forecasts of rainfall conditions, however, must be received before all the production practices have been undertaken if those forecasts are to have value relative to production.

The specific situation considered in the study is corn production in east-central Illinois. To further limit the complexity of the modeling, the analysis is limited to production planning for an extremely small production area such as an acre. These limitations in part result from the desire to attempt to model a relatively large number of sequential and interrelated decision choices. Although prior analyses have considered the value of climate forecasts in a small number of agricultural situations (Baquet, et. al.; Katz, et.al.; Lave; and Winkler, et al.), none have attempted to replicate the sequential decision process in the detail considered here.

In formulating the set of decision choices to be included, extensive reviews of the agronomic and agricultural economic literature were completed. In addition, numerous formal and informal interviews were conducted with agronomic experts and actual decision makers. The resulting combinations of production periods and management decision alternatives are listed in Table 1. A more complete description of the conceptual process used to formulate those combinations is given in Sonka, et. al.

The eight stage production process defined encompasses approximately a year, starting in the fall immediately following harvest of a preceding crop and continuing until the harvest of the crop under consideration. The management practices considered can be grouped into three categories: fertilization, planting, and when to harvest. The fertilization decision includes the timing of applications and the amount of nitrogen to apply. The planting decision incorporates the time of planting, variety selection, and planting density. Practices not included in the model are tillage options, pest management alternatives, and application of phosphorous and potassium. These practices are not included primarily because expert opinion indicated they would be less sensitive to climate forecast information.

As noted by Antle, development of technical coefficients to describe the sequential decision process for crop production is a difficult task. Although we do not include all possible decision alternatives, the development of those coefficients formed a major part of the study team's efforts. The presence of physical scientists in the group allowed this process to be undertaken in considerable detail, however. Because of the detail required, simulated data were used to estimate production function coefficients. These data are the result of several modelling efforts. The major component of the physical data was derived from an existing model of the growth of the corn plant (Reetz). This model was supplemented to include the effects of alternative levels of fertilization based on an analysis by Hollinger and Hoeft. Additional physical models were developed to reflect the process of nitrogen loss during the winter months as well as the loss of moisture by the corn plant during the early fall period. A complete description of the development of these coefficients is given in Mjelde.

The decision model

The decision analytic approach has been shown to be a useful framework for valuing information relative to stochastic events (Byerlee and Anderson). In general the value of improved information can be assessed as:

$$V = \int \max \int W(0, X)\ p(0/p_K)d0\ p(K)dK - \max \int (0, X)\ p(0)d0$$

where $W(0, X)$ represents the decision maker's utility function, 0 a stochastic event which can take on various values, X the management decision set outlined in Table 1, $p(0/p_K)$ the probability of 0 occurring give forecast K, $p(K)$ the probability of receiving forecast K and $p(0)$ the historical probability density function of 0. The gain from information is the difference between the expected utility when the information is used optimally and the expected utility of the best decision that would be made without the additional information. Here profit maximization is used as an operational representation of the utility function. The decision maker's information base without additional climate forecasts is assumed to be equal to the actual weather events that have occurred in the area. As noted by Bessler, this assumption may overestimate the capability of individuals to produce subjective probability distributions.

Agricultural economists have an extensive background in modelling the firm's decision process. Key features of the climate information analysis include the intertemporal nature of the problem and the requirement that the problem be explicitly cast in a stochastic framework. Three optimizing techniques satisfy these requirements; optimal control, calculus of variations, and dynamic programming. The production coefficients depicting the corn decision process were formulated as discontinuous functions. Of the three techniques noted, only dynamic programming has the capability to accommodate such functions. Therefore the decision model was solved with the stochastic dynamic programming technique.

A distinguishing feature that arises from the desire to model decision choices for an entire production cycle is that differing biological and physical phenomena govern the state transitions between certain stages of the model. For the transition from fall to early spring, loss of nitrogen due to leaching and denitrification is the process of concern. For the growing season (from early spring to early harvest), processes associated with establishment and growth of the corn plant are of major importance. During the harvest period, the process by which the corn plant loses moisture is the process of concern. As noted previously, simulated data from a number of physical modelling efforts were used to generate the coefficients necessary for the decision model. Each of these required detailed meteorological data. Once the appropriate models were identified and/or developed, simulated production data for the years 1970-83 were estimated based on actual weather conditions recorded at Urbana, Illinois.

Although each of these physical models is based on field experimental data, it is somewhat disturbing to be utilizing simulated rather than actual field experimental data for the production relationships of the decision model. The sheer magnitude of the data needed to describe production practice/weather interactions makes that approach infeasible, however. For example, the models utilized to estimate the growing season production relationships considered the yield effects of five planting dates, three plant populations, three varietal types, and eight nitrogen application levels over a time horizon of 14 years of weather events. Clearly such a rich set of experimental data is not directly available. However, the simulation approach allows the agricultural economist access to a large body of experimental data and expertise in a form which is amenable for decision modelling (Boggess; Musser and Tew).

In total seven state variables are required for the decision model. Briefly defined, these are:

- the level of nitrogen applied
- the planting decision selected (includes planting date, variety and density)
- early growing season climate
- late growing season climate/nitrogen application interaction
- October climate
- grain moisture drydown

- a field time restriction which limits the activities that can be taken in spring or early summer if weather conditions prove unfavorable

Seven state variables are a relatively large number when solving a problem by dynamic programming. The special sequential nature of the corn production process meant that only four state variables were relevant at any one stage. This feature greatly reduced the computational burden of the effort. Table 2 presents the state variables and the number of possible values each state variable could take at each specific stage. A more formal and complete depiction of the decision model is available in Mjelde.

Results of Climate Valuation Experiments

Within the larger project from which this paper is drawn, several issues relating to the most appropriate design for climate forecasts were considered. For purposes of brevity, estimation results for only two of those issues will be discussed here. First the relationship of climate forecast decisions and economic parameters will be presented. Then the influence of accuracy of the climate forecast upon the usefulness of that forecast will be considered. For these purposes, categorical forecasts are assumed with three possible outcomes (good, fair or poor climate events) being forecast. The results presented here assess the annual value of forecasts where the probability distribution of climate events is based on the actual climate events occurring in the 14 years of the period 1970-83.

Relation to the economic environment: The value of information should be interrelated with the economic environment that exists. To test for the presence of such interrelations, the value of perfect climate forecasts for differing economic environments was estimated. The three economic factors considered were output prices, interest rates, and input costs. In each case two diverse levels were specified to bracket a range of possibilities. The results of this analysis are summarized in Table 3. For each scenario, the left-hand column expresses results in terms of dollars per acre. The corresponding values in each right-hand column are presented in percentage terms to allow comparison of values when output price is allowed to vary significantly. Comparison of the percentage data is probably the more appropriate means to consider the relation between economic environment and information value.

With respect to output price, these data indicate that climate forecast information has more value during periods of lower prices. This result occurs because with higher prices the producer is more motivated to select strategies which maximize yield regardless of expected climate conditions. The interest rate levels compared in the model appeared to have little relative effect on the value of the forecast information. Although the relative value is consistently higher for the lower interest rate, the difference tends to be small. Input cost levels also affect the value of forecasts. In general higher input prices reduce the value of the forecast information. However, at the lower interest rate and the higher output price, the forecast information had a slightly higher relative value when input prices were at the higher level.

Hilton suggests that, in general, monotonic relationships between information characteristics and the value of information should not be expected. With a nonlinear return function, interaction between prices, costs and interest rates, and a number of stochastic climate stages, it is not too surprising that a nonmonotonic relationship is reported.
On a yearly basis, the decision alternatives in the model most affected by climate information relate to fertilization. The fertilizer decision is composed of both a timing and a quantity dimension. Amounts of fertilizer applied range from a low of 66 pounds to a high of 300 pounds of effective nitrogen. Three application periods, fall, spring, and early summer, are available in the model. Timing choices selected in the model range from applying all of the fertilizer in one of the periods (with applications in each of the periods in differing years) to dividing the application between two periods.

Time of harvest also varied between the early and late harvest periods among years and economic scenarios. The planting decisions were quite stable, however. This stability probably arises because of the limited scope of the problem setting (a small land area with only one crop choice). The estimates of the value of climate information also are probably underestimated because of this limitation. Further work which expands the decision situation to include land quality factors, more than one crop and a more realistic depiction of resource constraints will indicate if this suspected undervaluation occurred.

<u>Accuracy:</u> Climate forecasts currently are not perfect and are unlikely to be so in the near future. Therefore it is of interest to investigate the relationship between various levels of inaccuracy and value of forecasts. In the schematic below, Pij is the probability of climate i given a forecast for climate j. The categorical prediction scheme reported here used three categories as follows:

	Climatic condition		
Prediction	Good	Fair	Poor
Good	Pgg	Pfg	Ppg
Fair	Pgf	Pff	Ppf
Poor	Pgp	Pfp	Ppp

A perfect forecast scheme would have the diagonal elements equal to 1.0 and the other elements all equal to 0.0. An imperfect forecast scheme is one that varies from that structure in any way. Clearly there are a large number of alternative formulations of imperfection that are possible. To reduce this number to a manageable set, the following framework was used.

First, the diagonal elements were forced to be equal (for example, Pgg=Pff=Ppp=.90). Then the off-diagonal elements were set equal to the value which would force each row of probabilities to equal 1.0. (For example, Pfg=Ppg=0.05 in this case.)

Forecasts of early summer climate conditions were found to have the most significant value. Therefore the illustration of the relation between accuracy and forecast value will focus on imperfect forecasts for the early summer stage. The results of this analysis are presented in Table 4. As expected, the value of climate information declines rapidly as accuracy diminishes. Although the absolute decline varies by output price, the rate of relative decline in value is nearly constant. Each 10 percent decline in the value of the diagonal element is associated with approximately a 20 percent decline in the value of the climate forecast.

Further work is needed relative to alternative schemes for describing forecast inaccuracy. In particular, attention could be focused on categorical breakdowns with more than three groupings and attention paid to schemes which were relatively better at predicting extreme events but did a poorer job of predicting average events. For example, a technology might be considered which did a relatively good job of predicting drought but was not particularly effective in predicting when above average conditions would occur.

Concluding Comments

Modeling the sequential and stochastic nature of the agricultural decision process is a complex process because the reality faced by the decision maker is itself complex. If the level of environmental turbulence experienced by producers continues at its more dynamic pace, or accelerates, the use of information in more flexible management approaches is likely to be desired. In such settings, the need to model and evaluate information alternatives will also increase. The research effort described in this paper illustrates that multidisciplinary research approaches can be effectively utilized to model alternative management strategies and the use of information in decision making.

The research reported here should be viewed as a progress report relating to an ongoing research process. The specific situation analyzed and computational limitations undoubtedly led to conservative estimates of the value of the climate forecast information which was the subject of this research. However the effort so far has led to the development of a powerful set of linked models which will serve as a base for further analysis. Immediate plans are to expand the realism of the farming situation considered by evaluating situations where more than one crop is grown and a more realistic set of constraints is imposed. Analysis for alternative geographical locations also will be performed.

A major constraint relating to the use of the stochastic dynamic programming approach revolves around its computational requirements and the problems associated with interpreting truly vast amounts of output when a large problem is evaluated. Rapidly proceeding advances in computational power may be relaxing these constraints, however. With greater capacity it may be feasible to use the computer's power to aid in the interpretation of complex results. For example, it may be possible to apply elements of the expert systems philosophy to develop optimization systems which include extensive explanation systems and user interfaces -- possibly including graphic output presentations. Although the results presented here are restricted because of the limited situation analyzed, the underlying approaches appear to hold considerable promise in future applications.

Table 1. Stages and Decisions Alternatives Modeled in the Corn Production Decision Model

Stage (Production Period)	Management Decision
Fall previous harvest (October 23-March 31)	Nitrogen Application 0,50,150,200,225, 267 lbs. N
	Do Nothing
Early Spring April 1 - May 15	Nitrogen Application 0,50,150,200,225 267 lbs. N.
	Hybrid Selection Full Season Medium Season Short Season
	Planting Density 20,000 plants/acre 24,000 plants/acre 32,000 plants/acre
	Do Nothing
Late Spring May 16 - June 10	Same as Early Spring
Early Summer June 10 - July 15	Nitrogen Application 0,50,150,200,225 267 lbs. N.
	Do Nothing
Mid-Summer July 15 - July 31	Do Nothing
Late Summer Aug. 1 - Sept. 30	Do Nothing
Early Harvest September 30	Harvest Corn Crop
	Delay Harvest
Late Harvest October 22	Harvest Corn Crop Do Not Harvest

TABLE 3. Expected Value of the Perfect Yearly Predictors in Dollars per Acre per Year Under Different Economic Scenarios and as a Percentage of Net Returns Over Variable Costs Under Prior (Historical) Knowledge of Climatic Conditions.

Interest Rate	.1646				.05			
Corn Price	2.83		2.02		2.83		2.02	
Input Costs[a]	$	%	$	%	$	%	$	%
Base	6.91	2.7	6.86	4.8	7.01	2.7	7.72	5.2
Alternative	6.27	2.5	5.49	4.1	7.88	3.1	6.07	4.3

[a] Base level input costs are consistent with price levels of 1983-85 in east-central Illinois. For the alternative costs level, prices for nitrogen fertilizer, seed, and fuel for drying are increased by 50 percent.

Table 4. Expected value of imperfect early summer forecasts for two corn prices with input costs at the base level and an interest rate of 16 %.

	Corn price			
	$2.83		$2.02	
Value of the diagonal	Expected Value	Percent of Perfect	Expected Value	Percent of Perfect
1.00	6.14	100	5.15	100
.95	5.49	88	4.57	89
.90	4.86	79	4.00	78
.80	3.63	58	2.97	58
.70	2.40	39	2.00	39
.60	1.19	19	1.07	21

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