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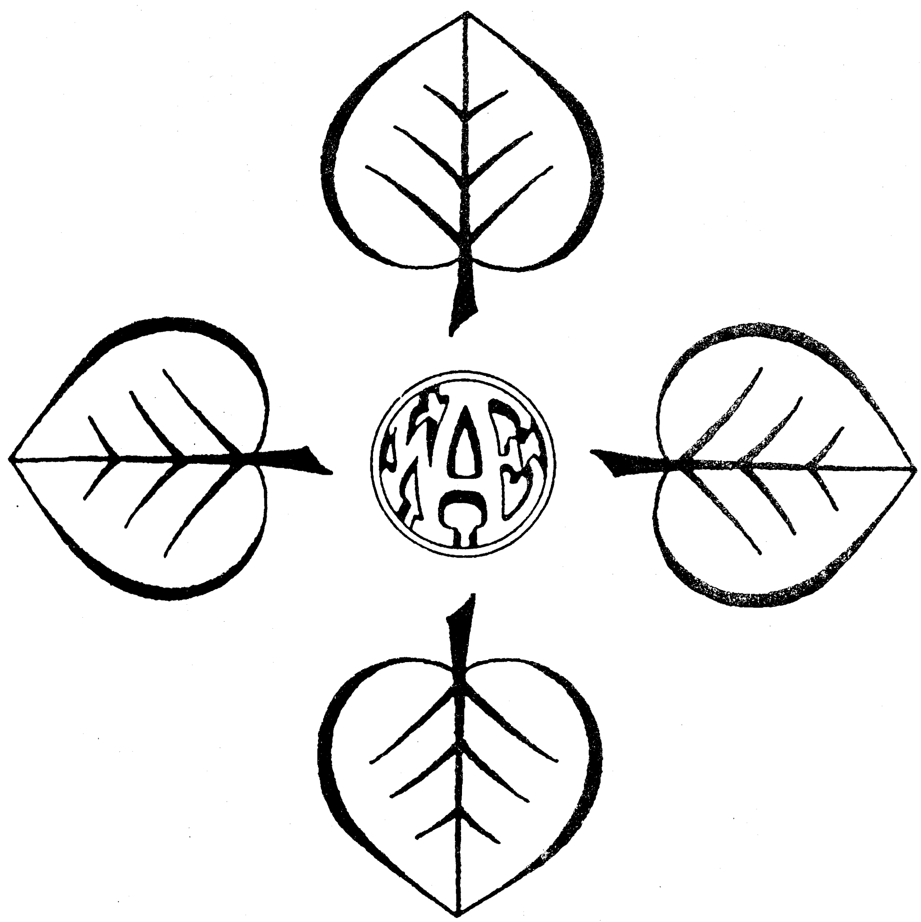

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The Role of Decision Maker Expectations in Valuing Climate Information

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Introduction

Information technology has been developing rapidly for more than a decade. The usefulness or value of information is sometimes questioned to help guide the development of information systems. This paper reports on a stream of research emanating from Lamb's (1981, p. 1001) call for expanded research on "how climate forecast schemes could/should be used." At issue has been the identification of factors affecting the value of climate information. Prior work, including that of others, has focused on the economic value of climate information in agricultural production (Mjelde et al., 1988; Katz, Murphy and Winkler, 1982; Byerlee and Anderson, 1982). Similar efforts continue to investigate which decisions are benefitted by climate forecasts and the characteristics of the forecasts that give rise to their value.

The methods used to value climate information are based on Hilton (1984). They describe the difference in the expected value of outcomes with and without information. That is, the value of information set p_k is:

$$V(p_k) = \max_{x_k} \int \pi(x_k,\theta)p(\theta|k)d\theta - \max_{x} \int \pi(x,\theta)p(\theta)d\theta \qquad (1)$$

where the outcome π is dependent upon a decision set (x_k or x), and a stochastic event (θ). The decision maker's perception of the probability distribution of θ is altered by the information set p_k, or, more specifically, by the prediction k. The outcome in this model, π, represents profit or return above variable costs (Mjelde et al.). Thus, the information only has value to the extent it alters the optimal decision set such that the solution to the first term is not equal to the solution to the second term, i.e. $x_k^* \neq x^*$. The value of the information system is the expected value of equation (1), where the expectation is taken over possible predictions coming from the information system. This model is easily adaptable to agricultural production, where climate is the stochastic event and decisions relate to the use of variable inputs.

Most research along this vein has endowed the decision maker with perfect knowledge of historic climate probabilities, which are used to establish the probability distribution of θ in the "no information" scenario. This assumption of perfect historical prior probabilities is challenged here. The theory behind the use of alternative prior probabilities is reviewed in the next section. This is followed by a comparison of information value when alternative prior probabilities are used. Then a report on an elicitation of climate expectations from a sample of agricultural producers is given, comparing their prior beliefs to historic probabilities. The last section describes an application of calibration theory, a method of assessing differences between the true and subjective probabilities.

Venture Theory: Decision Weights Instead of Probability

The process of decision making under uncertainty has a rich history in the literature of psychology, economics, and management science. Most models have used mathematical probabilities to prescribe behavior for risky choice. However, the use of probabilities breaks down in *describing* observed behavior of individuals making risky choices (Allais, 1953; Ellsberg, 1961). Where risk characterizes a situation if the decision maker knows the relative chance of each outcome, ignorance describes a situation if the decision maker has "no basis whatsoever on which to judge the relative likelihood of potential outcomes of [a] decision (Yates and Zukowski, 1976, p. 19)." Alternatively, ambiguous decisions lie between these two extremes; there is some basis for assessing relative probabilities, but not with precise confidence.

Einhorn and Hogarth (1985, 1987) describe a model of decision making under ambiguity which employs an "anchoring-and-adjustment strategy in which an initial probability is used as the anchor (or starting point) and adjustments are made for ambiguity (1987, p. 46)." The source of the initial probability may be any information, historical or otherwise, available to the decision maker. The subjective probability used in decision making, S(p), is given by:

$$S(p) = p_A + k \tag{2}$$
$$k = k_g + k_s \tag{3}$$

where p_A is the anchor probability and k is the adjustment. The adjustment is made from a mental evaluation of higher and lower values of p, where k_g is the effect of simulating higher values of p and k_s is the effect of simulating lower values of p.

Hogarth and Einhorn (1990) further expanded this theory to include other factors that affect the adjustment. Because these factors affect the assessment of subjective probabilities, they refer to the adjusted probabilities as decision weights, which are arrived at by "venturing" or mentally simulating outcomes. Adjustment factors include outcome uncertainty, the degree of ambiguity, the context of the decision, and the sign and size of payoffs.

Outcome uncertainty refers to the number of outcomes a decision maker anticipates experiencing. Consider a midwestern U.S. agricultural producer making a decision on the timing of fertilizer application. If he applies fertilizer in the fall there is some chance winter precipitation will be sufficiently heavy to leach nitrogen from the soil, rendering his expenditure ineffective. In this situation he experiences one outcome from the decision. Say the fertilizer application cost $10,000 and that there is a 50 percent chance that precipitation will be above some specified level that will cause the expenditure to be revisited in the spring. It is of little value to know that the expected outcome is -$5,000. Contrast this to a gambler at a slot machine with 1,000 coins, where the expected value of the payoff is more meaningful because of the number of plays; the net outcome is likely to be closer to the expected the value. Thus, there is less outcome uncertainty.

The maintained hypothesis is that for individuals exhibiting cautious behavior, the greater the outcome uncertainty, the more mental simulation takes place that results in the overweighting of losses and the underweighting of gains. The same is true for the degree of ambiguity; the less confident a decision maker is in his assessment of anchoring probabilities, the more mental simulation he performs. The degree of under- or overweighting is affected by the size of the payoff. The degree of caution exercised in the process of mental simulation is a function of the decision context. It is interesting that unlike probabilities, the decision weights need not sum to one, which is consistent with the Allais and Ellsberg decision paradoxes.

<u>A Comparison of Climate Information Value Under Alternative Priors</u>[1]

Recall from equation (2) that the value of information fundamentally depends on the prior probabilities (θ) and the adjusted probabilities given the forecast ($\theta|k$). To illustrate the differences in climate information value, consider an average farm in east central Illinois, growing 320 acres of corn. Assume the relevant climate parameters are 1) the amount of winter precipitation, 2) July rainfall, and 3) the general summer growing conditions (a composite of precipitation, solar radiation, temperature, and pan evaporation). Using historic climate probabilities, this decision maker would plan to apply 150 lbs. of nitrogen fertilizer per acre in the spring. In fact, this is the observed average application rate in this area, as well as a reasonable approximation of average corn acreage per farm (Illinois Department of Agriculture).

However, other practices are observed. These include applications of 150 pounds of nitrogen in the fall and only 100 pounds of nitrogen in the spring. Extremely minor modifications in the historic probabilities of the three climate parameters casts these observations as optimal decisions. Furthermore, it has been suggested that recent events affect decision weights more than distant events, suggesting an analysis of priors built on recent history. The value of climate information in these cases will depend upon how it affects the prior decision.

Table 1 contains the results of a model simulating corn production over actual climate from 1971 to 1985. A decision maker endowed with the full range of pertinent historical climate information (15-year prior) would expect to receive a maximum average annual benefit of $1,000 for adopting the information contained in a perfect forecast of the relevant events described above. Alternatively, a decision maker whose decision weights were based on the most recent three years' experience would expect to receive a maximum average annual benefit from the forecast of \$3,084, or \$9.64 per acre of corn. Again, this assumes that the forecast completely replaces any prior notion of the decision weights. For a farmer whose ambiguity leads to 150 lbs. per acre of fall applied nitrogen, the maximum average annual value of the forecast rises to \$5,237, or \$16.37 per acre.

The value of changing the ambiguous decision weights to coincide with historic climate probabilities is clear. For the farm modeled in this exercise, if rational behavior leads to fall nitrogen application there is a \$4,237 annual expected benefit simply from understanding the probabilities of winter precipitation. Thus, there appears to be a substantial benefit in changing farmers' perceptions of prior decision weights, bringing them more in tune with historical probability. To ascertain the frequency and magnitude of these discrepencies, research was conducted to elicit farmers' assessment of the probability of climate events that affect growing crops. The next section reports on the design and results of that survey.

Describing Farmer Expectations of Climate Variables

A survey was conducted to better understand the formation of farmers' climate expectations and observe their consistency with venture theory. Participating farmers were selected for their 1) cooperation with FBFM record keeping association, 2) their close proximity to a single weather reporting station (to mitigate the potential effects of widely differing experiences), 3) relatively large cash grain operation, and 4) understanding of probability concepts. Personal interviewers elicited 5 to 7 fractile breaks (i.e. the level of rainfall at which the 1, 10, 25, 50, 75, 90, and 99 cumulative percentiles occurred) through a series of questions posed in both the CDF framework and inverse CDF framework. After checking for internal consistencies, fifty-one useable surveys were collected. (Copies of the survey document are available from the authors upon request.) Specific variables of interest were April rainfall and July rainfall.[2] A large amount of April rainfall is considered a negative outcome as it delays planting. A large amount of July rainfall is considered a positive outcome as it supports crop growth. Thus, venture theory would suggest that probabilities of large April rainfall would be overweighted by respondents, while probabilities of large July rainfall would be underweighted.

Decision weights or subjective beliefs (PDF^S) are compared to the "objective" or "true" probability measure for each variable (PDF^O).[3] A variant of the Burr-3 distribution was used to model both PDF^O and each farmer's PDF^S. The Burr has zero support (negative levels are disallowed), may take on a wide range of skewness and kurtosis, and can be used to fit almost any set of unimodal data (Tadikamalla, 1980). The Burr PDF and CDF for rainfall, Y, with parameters λ, and τ are:

$$f_{BR}(Y|\lambda,\tau) = \lambda\tau Y^{-\tau-1}(1+Y^{-\tau})^{-\lambda-1} \text{ for } \lambda, \tau, Y > 0, \tag{4}$$
$$F_{BR}(Y|\lambda,\tau) = (1+Y^{-\tau})^{-\lambda} = (Y^{\tau}/(1+Y^{\tau}))^{\lambda} \tag{5}$$

This distribution has been used extensively in various forms to model precipitation amounts (Mielke; Mielke and Johnson), as a function for business losses (Lomax, Dubey) and by the insurance industry as a candidate for loss distributions.

Results

Historic weather data from 1903 to 1990 were used to estimate the parameters of the "true" distributions of April and July rainfall. Nonlinear least squares was used to estimate the parameters of each farmers' subjective distributions for both April and July rainfall.[4] The findings are both summarized across farmers and in terms of each farmers fit to the historic probability function. Figure 1 gives a sample of the farmers' subjective beliefs about April rainfall along with PDF^O.

Table 2 examines the cross section of farmer responses. For each fractile break elicited, the collective responses were summarized and compared to the actual. For example under April rainfall, at the 25% level (the level at which there is a 25% chance of observing less rainfall and 75% chance of observing more) the precipitation level corresponding to the true distribution is 2.34 inches. In other words, there is a 75% chance of observing at least 2.34 inches of rain in the month of April. Of the farmers surveyed, 63% replied with a higher number (i.e. expected more rainfall at the 25% level), the average of all responses was 2.785 inches and the standard deviation of the response to that question was 1.003. Notice that the average expected rainfall is greater than the true at all percentile levels greater than the 10 percentile level. Further, the percentage of farmers overstating expected precipitation is greatest at the 50th percentile of the true CDF. Clearly, this "negative outcome" is overweighted in subjective probability.

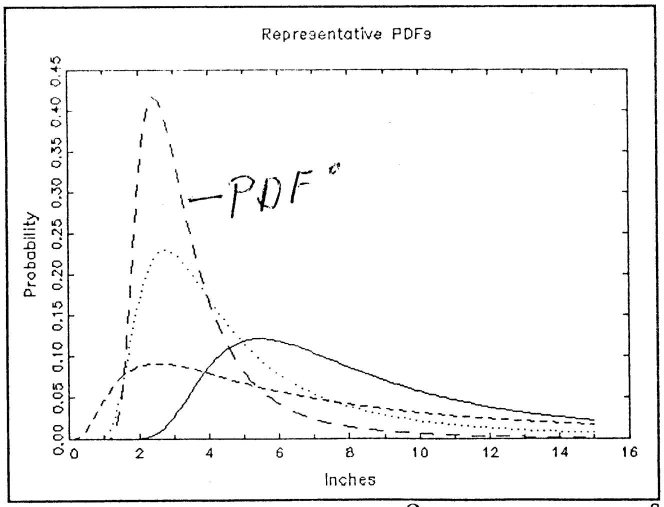

Figure 1. April Rainfall: PDF^{O} and Sample PDF^{S}

However, farmers, on average, understate the incidence of rainfall in July. For example, at the 90th percentile, the true level of July rainfall is 6.74 inches, but the average of the farmers' responses was 6.49 inches with a standard deviation of 2.23. Two-third of the farmers understated the 50th percentile level of rainfall, thus underweighting the probability of a positive outcome.

As was discussed earlier, for individuals, the value of climate information depends upon the entire prior distribution and the process of revising expectations through the adoption of information. Further, observed decisions indicate that much od the value of climate information (as it pertains to midwestern crop production) is contained in the historic distribution. Hence we need a method to conveniently represent the differences between expectations and objective measures at all levels of the CDF.

Calibration Tests

Calibration refers to the correspondence between a predicted and an actual event. In terms of distributions, calibration describes how close the predicted and resulting functions are. Heuristically, if there were a reason for the individual expectations to yield estimated parameters that required an adjustment to correspond to the "true" parameters, then this adjustment is termed the calibration function. Specifically, if the true parameters of a distribution are $\phi(x)$ and the estimates are $F(x)$, then $K(F(x)) = \phi(x)$ implicitly defines a transformation $K(\bullet)$ of F to generate estimates, $K(F(x))$, that are well calibrated or reliable (Sherrick, et al.). The function $K(\bullet)$ is called the calibration function.

A simple test for calibration may be performed by testing the uniformity of K, for if $F(\bullet)$ is already well calibrated, K is simply a uniform mapping. Regions of $K(\bullet)$ with slope greater than one correspond to regions of the CDF^{S} that need to have mass added and regions of $K(\bullet)$ with slope less than one correspond to regions of the forecasted distribution that have too much mass and need to be decreased. A parametric form can be chosen for the calibration function and estimated using standard methods. The parameters of the estimated function can shed light into the nature of the mis-calibration (Fackler and King). For the purposes of this study, the calibration function is based on the beta distribution with density

$$K(x) = x^{p-1}(1-x)^{q-1}/\beta(p,q), \qquad (6)$$

where $\beta(p,q)$ is the beta function with parameters p and q. As noted in Fackler and King, the Beta distribution is well known, flexible and contains the uniform distribution as a special case when $p=q=1$, implying perfect calibration. Thus a likelihood ratio statistic is easily constructed for the hypothesis that the calibration function is uniform. Other shapes of the fitted calibration curve indicate the "reweighting" of the estimated distributions needed to correspond to those subsequently observed. At least 5 general shapes for the calibration function emerge that serve well to summarize the nature of the miscalibration displayed by each individual. Figure 2 displays the sample calibration functions corresponding to the following cases: (1) well calibrated or uniform, $p=q=1$; (2) underconfidence or an overstatement of dispersion, $p>1$, $q>1$; (3) overconfidence or an understatement of dispersion, $p<1$, $q<1$; (4) overstatement of location, $p<1$, $q>1$; and (5) understatement of location, $p>1$, $q<1$. The slope of the calibration function reflects the reweighting of the subjective distribution that is needed to make it correspond to the true distribution.

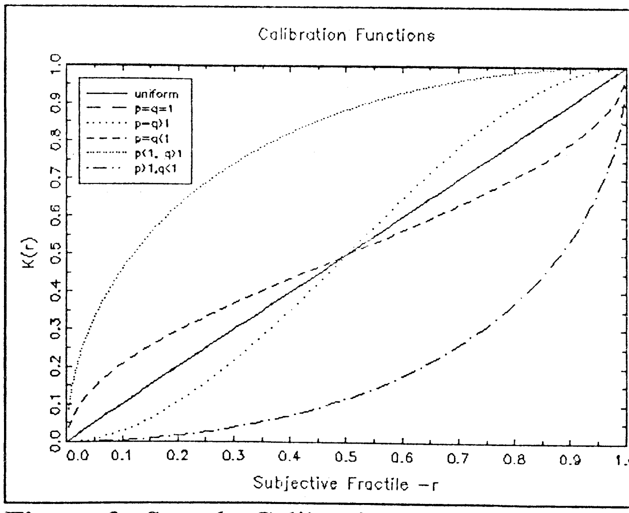

Figure 2 Sample Calibration Functions

Calibration functions were estimated for each sample farmers' CDF^S for both April and July rainfall. The results are given in table 3. With respect to April rainfall, the propensity is to understate variability and also understate location. The estimated July calibration functions suggest a different result -- that nearly half the farmers had subjective distributions that overstated variability. Further, the location tended to be understated reflecting pessimism about the likelihood for favorable July precipitation. Again, these observations are consistent with venture theory.

Conclusions

Interpreting the results of this study is quite clear; what to do in reponse is not so clear. The value of climate information in crop production has been shown to increase dramatically when decision makers' subjective assessment of probabilities is in need of calibration. A sample of farmers showed their subjective distributions of April and July rainfall were consistent with the adjustments predicted by venture theory, based both on the sign of the payoff and their ambiguity level. Calibration functions indicate the alterations necessary to equate their subjective beliefs with historic probability. This indicates that a mere educational program alone might not be sufficient make the distributions equal. Rather, it indicates that some exageration (both underweighting and overweighting) may be necessary.

Notes

1. This section reports on results of decision models whose development is beyond the scope of this paper. For more information on the construction of these models see Mjelde et al. and Mazzocco (1989) and related references therein.

2. Data were also collected on winter snowfall, expected prices, interest rates, and other variables affecting financial success.

3. We take the historic distributions to be an adequate characterization of the objective or true PDF of weather events. The possibility of climate change is thus not addressed.

4. The *Gauss* programming language was used on an IBM compatible microcomputer. Briefly, a nonlinear optimization routine with a quadratic loss function was used to recover parameters. Given the flexibility of the distribution function, the fit was typically very good in terms of squared distance between farmer responses and levels on the estimated CDFs. The procedure has unknown power though due to the prespecified interval breaks at which respondents were polled.

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Table 1. Value of Perfect 3-Category Forecast vs. Historical and Ambiguous Priors, E. Central Ill. Corn.

Prior Belief	Expected Value of Forecast ($) 320 acres	Per acre
15-year historical probability	1,000	3.12
Ambiguous, most recent 3 years	3,084	9.64
Ambiguous, resulting in 100 lbs. Spring N	3,133	9.79
Ambiguous, resulting in 150 lbs. Fall N	5,237	16.37

Source: Mazzocco (1989)

Table 2. Summary of Farmers' Subjective PDFs on Climate Events

			Percentile Level			
		10%	25%	50%	75%	90%
APRIL Rainfall (inches)	% of farmers >= actual	31.5	63	85.1	74.1	61.1
	True(inch)	1.57	2.34	3.47	4.93	6.54
	Average response	1.415	2.785	4.444	5.806	7.461
	Std. Dev.	0.551	1.003	1.219	1.426	2.035
JULY Rainfall (inches)	% of farmers <= actual	85.2	77.8	66.7	55.6	57.4
	True(inch)	1.27	2.05	3.27	4.89	6.74
	Average response	0.813	1.781	3.008	4.614	6.489
	Std. Dev.	0.528	0.704	0.821	1.164	2.23

Table 3. Calibration Functions Summary

Parameter Groups	April Rainfall (No. of farmers)	July Rainfall (No. of farmers)	Interpretation
P >1, Q >1	12	23	Over dispersed, under confident
P <1, Q <1	21	12	Over confident, under dispersed
P >1, Q <1	3	12	Overstated location
P <1, Q >1	15	4	Understated location
Uniform	*	**	Well calibrated

* 5 had pseudo P-values on the likelihood ratio test > .05 and could be considered well calibrated. However, the variance of the estimator is biased toward low values due to the procedures used to estimate subjective PDFs.

** 8 had pseudo P-values on the likelihood ratio test > .05 and could be considered well calibrated.