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Obtaining Lower and Upper Bounds on the Value of Seasonal Climate Forecasts as a Function of Risk Preferences

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A methodological approach to obtain bounds on the value of information based on an inexact representation of the decision maker's utility function is presented. Stochastic dominance procedures are used to derive the bounds. These bounds provide more information than the single point estimates associated with traditional decision analysis approach to valuing information, in that classes of utility functions can be considered instead of one specific utility function. Empirical results for valuing seasonal climate forecasts illustrate that the type of management strategy given by the decision maker's prior knowledge interacts with the decision maker's risk preferences to determine the bounds.

Key words: climate forecasting, stochastic dominance, value of information.

Interest in ascertaining decision makers' willingness to pay for climate/weather forecasts has increased in recent years. Empirical studies such as Sonka et al.; Winkler, Murphy, and Katz; Baquet, Halter, and Conklin; and Brown, Katz, and Murphy have demonstrated that current and improved climate forecasts have potential economic value in decision making. This value depends critically on the structure of the decision set, the structure of the payoff function, degree of uncertainty in the decision maker's prior knowledge of climatic conditions, and the nature of the information system (Mjelde, Sonka, and Peel; Hilton). Embedded in the structure of the payoff function is the decision maker's relative preference for outcomes or, equivalently, the decision maker's risk preferences. Because risk preferences are difficult to quantify, this characteristic has received little attention in previous empirical studies valuing climate forecasts (for an example of valuing information with different utility functions see Baquet, Halter, and Conklin).

Risk preferences can be analyzed using stochastic dominance techniques to provide evidence on a decision maker's willingness to pay for information (Cochran and Mjelde; Rister, Skees, and Black; Bosch and Eidman). Stochastic dominance accounts for the difficulty in quantifying the risk preference with an inexact representation of the decision maker's risk attitude. The objective of this study is to build on and extend previous studies by utilizing stochastic dominance procedures to obtain a lower and upper bound on the value of perfect seasonal climate forecasts, given varying representations of risk preferences and different assumptions on the decision maker's prior knowledge. The analysis is based upon data presented in Mjelde et al. (1988) and involves corn production in east-central Illinois.

Decision Analytic Approach to Valuing Information

The value of climate information is normally based on the well-developed analytic frame-

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Texas Agricultural Experiment Station Technical Article No. 23372. This research was supported by Project Number 6507 of the Texas Agricultural Experiment Station.

The authors wish to acknowledge the helpful comments of Bruce A. McCarl, Thomas O. Knight, Steven T. Sonka, and the anonymous journal reviewers.

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work of decision theory (Winkler, Murphy, and Katz; Mjelde, Sonka, and Peel 1988). In empirical studies the common procedure is to assume the decision maker is risk neutral because of problems with specifying utility functions or quantifying risk preferences (Lin, Dean, and Moore). With this assumption the decision maker is concerned only with maximizing expected net returns. The value of information under risk neutrality is developed in this section for comparison to the stochastic dominance procedures. In this framework, θ represents the stochastic climatic conditions and Z represents the variable under the control of the decision maker. An interaction between θ and Z is a necessary condition for information on θ to possess economic value (Byerlee and Anderson). In the absence of any information other than the decision maker's prior knowledge, $p(\theta)$, the decision maker's problem is to maximize

$$\max_Z \int Y(\theta, Z)p(\theta)\, d\theta, \tag{1}$$

where $Y(\theta, Z)$ represents net returns.[1] Let the value of Z which maximizes equation (1) be represented by Z^*. Now the decision maker is given a particular climate forecast P_k which modifies $p(\theta)$ to $p(\theta \mid P_k)$. The problem the decision maker faces now is

$$\max_Z \int Y(\theta, Z)p(\theta \mid P_k)\, d\theta. \tag{2}$$

Let Z_k^* maximize equation (2). In order to ascertain the value of forecast, P_k, the expected net returns from not using the information when the climatic conditions that were forecasted occur must be obtained. These expected net returns are obtained by simulating the decision maker's decisions derived from not utilizing the information (Z^*) over the climatic conditions forecasted $p(\theta \mid P_k)$. This is given by

$$\int Y(\theta, Z^*)\, p(\theta \mid P_k)\, d\theta. \tag{3}$$

The value of the climate forecast P_k is given by the difference between equations (2) and (3); that is,

$$V_k = \max_Z \int Y(\theta, Z)p(\theta \mid P_k)\, d\theta - \int Y(\theta, Z^*)p(\theta \mid P_k)\, d\theta. \tag{4}$$

The gain in expected net returns is the difference between the expected net returns of using the information optimally and the expected net returns derived from the decision maker's prior knowledge (Z^*) when the actual climatic conditions occurring are those forecasted by P_k.

Prediction P_k is only one possible prediction that could be received by the decision maker. The expected value of the forecasting system which generates predictions P_k with probability distribution $p(P_k)$ is

$$V = \int \max_Z \int Y(\theta, Z)p(\theta \mid P_k)\, d\theta\, p(P_k)\, dP_k - \int\int Y(\theta, Z^*)p(\theta \mid P_k)\, d\theta\, p(P_k)\, dP_k. \tag{5}$$

The gain from the climate forecasts is the difference between the expected net returns when the information is used optimally and the expected net returns when the action is selected without utilizing the additional information. If $Z^* = Z_k^*$ for all k, the information system has no value to the decision maker. Thus the value of information is manifested in the altering of management decisions in response to the information.

Stochastic Dominance

Stochastic dominance is an approach that allows for the ordering of risky prospects according to set criteria. Two stochastic dominance criteria are utilized in this study, but the general procedure to obtain bounds on the value of information applies to the other stochastic dominance criteria. The two criteria considered here are second-degree stochastic dominance (SSD) and generalized stochastic dominance (GSD). More complete discussions of the stochastic dominance techniques can be found in Anderson, Kroll and Levy, Whitmore and Findlay, or Bawa.

The stochastic dominance criteria reduce a choice set of distributions to a smaller subset in such a manner that ensures that some member of the subset maximizes expected utility.

[1] The function $Y(\theta, Z)$ could also be defined as a utility function without altering the value of information given the decision-theoretic approach.

This subset is referred to as the efficient set. The efficient set is identified for an admissible class of utility functions. Each of the different stochastic dominance criteria is associated with a different class of admissible utility functions.

The SSD criterion allows for the predicting of a decision maker's choice between pairs of distributions without having any knowledge of a decision maker's utility function except that it displays risk aversion. In order to display risk aversion, two constraints are placed on the admissible utility functions, $U'(x) > 0$ and $U''(x) < 0$. Under SSD, choice distribution function F will dominate distribution function G if and only if

$$(6) \quad \int_{-\infty}^{x} [F(x) - G(x)]\, dx \leq 0 \text{ for all } x$$
$$< 0 \text{ for at least one } x,$$

where $F(x)$ and $G(x)$ are the cumulative distributions functions associated with choice distributions F and G, respectively.

GSD (Meyer) is a more flexible criterion in that alternative constraints on the admissible utility functions are defined with bounds on the Pratt absolute risk aversion function (Pratt). Let $U(r_1(x), r_2(x))$ be the set of decision makers with risk preferences represented by $r(x)$ satisfying

$$(7) \qquad r_1(x) \leq r(x) \leq r_2(x) \qquad \text{for all } x.$$

The function $r(x)$ is defined as the absolute risk aversion function and is given by

$$(8) \qquad r(x) = -U''(x)/U'(x).$$

Under GSD, F dominates G when

$$(9) \quad \int_{-\infty}^{\infty} [G(x) - F(x)]\, U'(r_1(x), r_2(x))\, dx \geq 0,$$

for all U subject to equation (7).

This is calculated by identifying the utility function from the admissible set which is least likely to result in F dominating G. If the expected utility of F is greater than that of G for this utility function, it is known that F is preferred to G by all admissible utility functions and, hence, G is dominated.

Stochastic Dominance and the Value of Information

A decision maker's willingness to pay for information can be thought of as a premium, π. This premium equals the amount the decision maker can be charged in each state of nature before the decision maker is indifferent to buying the information. This occurs when the expected utility of optimally using the information (and paying π) equals the expected utility of selecting the action without utilizing the information or paying π. For a specific utility function this premium could be calculated using the decision theoretic approach discussed earlier. Utilizing stochastic dominance criteria rather than specifying an exact utility function requires slight modifications to the perspective of the value of information.

Lower and upper bounds on this premium can be obtained with stochastic dominance by appropriate interpretations of the efficient set. To obtain these bounds, two distributions on net returns are necessary. The first choice distribution, $F(x)$, is generated using decisions obtained when the decision maker utilizes the climate forecast. The second distribution $G(x)$, is generated using decisions based on the decision maker's prior knowledge on climatic conditions. Generation of these two distributions is dependent on how the decision maker processes information. When $F(x)$ dominates $G(x)$, it is known that for all admissible utility functions the expected utility associated with distribution $F(x)$ is greater than the expected utility associated with distribution $G(x)$ The lower bound on the value of information is the minimum value of the premium, π, such that $F(x - \pi)$ no longer dominates $G(x)$. The premium is subtracted from each element in distribution $F(x)$ This is equivalent to a parallel shift in distribution $F(x)$ At this point for at least one utility function in the admissible class of utility functions, the expected utility associated with distribution $G(x)$ is greater than or equal to the expected utility associated with distribution $F(x)$. Mathematically the lower bound is given by

$$(10) \quad \min \pi \text{ such that } EU(F(x - \pi)) - EU(G(x))$$
$$\leq 0 \text{ for at least one } U \in \mu,$$

where E is the expectation operator and μ is the admissible class of utility functions.

The upper bound on the value of information is the minimum premium such that $G(x)$ dominates $F(x - \pi)$. At this point for all preferences in the admissible class, no decision maker is willing to pay the premium and still prefer $F(x - \pi)$ to $G(x)$. This bound is given by

(11) min π such that $EU(F(x - \pi)) - EU(G(x)) < 0$ for all $U \in \mu$.

Given the information on risk preferences, the range on the value of information associated with distribution $F(x)$ is given by the upper and lower bounds.[2] Between the two bounds, stochastic dominance is unable to rank the two distributions for the given class of admissible utility functions. In order to rank the distributions between the bounds, additional information on the risk preferences is required, that is, a narrowing of the admissible class of utility functions for SSD and GSD. Note that the definition of the two bounds holds for the different stochastic dominance criteria and not just SSD and GSD.[3]

Corn Production and the Value of Climate Forecasts

Using results presented in Mjelde et al. (1988), bounds on the value of perfect seasonal climate forecasts for corn production are obtained using both SSD and GSD. Mjelde et al. (1988) utilize a dynamic corn production decision model to obtain net returns from a single corn acre for the years 1970–83. The generated net returns for each year under different assumptions on the decision maker's prior knowledge of climatic conditions are given in table 1.[4] The model contains only decisions on inputs that were deemed sensitive to climate forecast and for which data were available. As such the net returns presented in table 1 are higher than accounting measures of net returns. That is, costs relating to inputs such as land payments, interest charges on land and machinery, and pesticide usage are not included in the decision model.

The decision model presented in Mjelde et al. (1988) is an intrayear dynamic programming (DP) model of corn production. Eight stages are defined for the corn production process. Decisions must be made in six of these stages, and no decisions are made in the remaining two stages. The six decision stages are fall preceding planting, early spring, late spring, early summer, early harvest, and late harvest. These correspond to the times when major decisions are made by corn producers in this region. The two stages when no decisions occur are midsummer and late summer. These stages are included because of the substantial effect of climatic conditions on corn yield during these times.

Decisions within the model pertain to the amount and timing of nitrogen application, planting period, planting density, hybrid planted, and harvest time. At each decision stage the producer can also do nothing. The producer is able to choose among six nitrogen levels (0, 50, 150, 200, 225, and 267 pounds per acre) at any stage where nitrogen can be applied. At the planting stages, early spring, and late spring, the producer can choose between three hybrids (short, medium, and full season) and three planting densities (20,000, 24,000, and 32,000 plants per acre). Because of agronomical and physical considerations, sidedressing can only occur in the stage immediately after planting.

Seven state variables are included in the model. The model is formulated so that at any one stage no more than four of the state variables can take on more than one value (Mjelde et al. 1987). Six of the state variables are associated with determining final yield. These are: (*a*) a plant state variable which incorporates the effect of planting density, hybrid planted, and time of planting, (*b*) a nitrogen state variable which is the amount of nitrogen applied in pounds per acre, (*c*) a climate state variable giving the cumulative effect of climatic conditions on yield, (*d*) a combined nitrogen and climate state variable which incorporates the interaction between nitrogen and climatic conditions, (*e*) a corn kernel percent moisture state variable which affects both field losses of corn and drying costs, and (*f*) an October climatic condition variable which affects corn field losses at late harvest. The seventh state variable limits the number of field op-

[2] In cases where it is unclear if F dominates G, the premium may have a negative value for one or both bounds. A negative lower bound but a positive upper bound indicates the decision rule generated from using the new information is preferred by some of the decision makers represented by the class of admissible utility functions but not by all of the decision makers in that class. If both bounds are negative, the information is unreliable or misleading, implying an inferior decision rule. The stochastic dominance procedure to value information is robust enough to handle these cases.

[3] The use of stochastic dominance to value information is facilitated by the availability of computer programs which calculate these bounds. One such program by Cochran and Raskin is available from the Department of Agricultural Economics and Rural Sociology, University of Arkansas, Fayetteville, Arkansas.

[4] Note the values in table 1 are transformed into dollars per hectare, although Mjelde et al. (1988) present the values in dollars per acre.

Table 1. Distribution of Net Returns for Corn Production in East-Central Illinois in Dollars per Hectare for Different Assumptions on the Decision Maker's Prior Knowledge of Climate Conditions

	Expected Net Returns Given Different Prior Knowledges				
Year	Perfect	*P1983*	*P1979*	Preceding Year	*PHist*
1970	668.08	615.38	668.06		640.48
1971	736.31	701.84	667.86	667.86	726.94
1972	689.48	565.27	654.91	636.65	627.31
1973	744.61	682.44	688.40	688.40	744.61
1974	619.16	557.09	602.73	478.81	602.73
1975	622.69	509.25	588.10	550.79	559.01
1976	730.28	648.32	675.25	675.25	730.25
1977	668.08	615.38	668.06	641.64	640.48
1978	641.42	576.76	641.42	608.43	608.43
1979	755.04	675.69	755.04	748.47	726.94
1980	632.23	615.38	588.30	588.30	560.69
1981	687.58	632.77	628.47	619.06	675.25
1982	689.48	564.30	654.91	616.42	615.55
1983	342.95	342.95	124.81	124.81	124.81
Mean[a]	659.10	593.06	614.74	588.07[c]	613.11
Standard deviation	101.63	90.09	147.54	154.14	153.61
Coefficient variation	15.42	15.19	24.00	26.21	25.05
E(value)[b]		66.04	44.36	70.34	45.99

Note: Net returns from corn production in dollars per hectare taken from Mjelde et al. (1988). Net returns changed from dollars per acre to dollars per hectare by using a conversion factor of 2.471 acres per hectare.
[a] Arithmetic mean of the expected net returns from the fourteen years.
[b] Expected value of perfect information assuming a risk-neutral (profit-maximizing) utility function when using the corresponding prior knowledge scenario in dollars per hectare per year.
[c] Summary statistics based on 13 years.

erations the producer can perform during early spring, late spring, and early summer if climatic conditions are unfavorable.

In table 1 net returns for four different assumptions on prior knowledge of climate conditions along with the net returns generated with perfect seasonal climate forecasts are given. The four assumptions on prior knowledge are denoted as *P1983, P1979, PYear,* and *PHist.* As discussed in Mjelde et al. (1988), these assumptions denote a range of attitudes toward climatic conditions. Prior knowledge, *PHist,* assumes that the decision maker knows the historical probabilities associated with the seasonal climatic conditions. The historical probabilities are based on the fourteen years within the data set with each year being equally likely. Various studies have demonstrated that individuals may not be accurate in their assessment of the probabilities of historical events (Bessler, Tversky and Kahneman). Because of this, Mjelde et al. (1988) investigated other assumptions on the decision maker's prior knowledge.

Prior knowledge, *P1983,* represents a management strategy that protects against poor climatic conditions. In Mjelde et al. (1988) 1983 was the year with the worst growing conditions for corn. A management strategy which takes advantage of good climatic conditions is represented by prior knowledge, *P1979.* The year 1979 had the best growing conditions in terms of corn production for the years included in the study. In each of these prior knowledge scenarios, the decision maker selected a management strategy which performs well if conditions like those in either 1983 or 1979 occur. Preceding year prior knowledge (*PYear*) represents a myopic view of climatic conditions. Under this prior knowledge the decision maker is assumed to expect the present year's climatic conditions to be identical to the preceding year.

The distributions presented in table 1 were generated as follows. First a set of decisions for each combination of state variables at every stage must be determined given a particular prior knowledge scenario. To facilitate this determination of decisions, the DP model is used

Table 2. Lower and Upper Bounds on the Value of Perfect Seasonal Forecasts Using SSD in Dollars per Hectare per Year

Prior Knowlege	Lower Bound	Upper Bound
P1983	0.00	68.48
P1979	44.15	218.14
PYear[a]	70.36	218.14
PHist	44.95	218.14

[a] Based on thirteen observations; the year 1970 was dropped from the perfect information distribution.

to obtain the decisions.[5] Using the climate probabilities associated with a given prior knowledge, a set of production practices based on the maximization of expected net returns is determined. These practices for *PHist, P1983,* and *P1979* are fixed between years. The practices associated with *PYear* vary dependent on the previous year. Each prior knowledge scenario allows for intrayear adjustment of input levels based on the current state of the system. Past climatic conditions and management decisions determine the current state. These intrayear input adjustments are based on the expectation that the climatic conditions from the current stage to harvest are given by the assumed prior knowledge. The yearly net returns are then obtained by simulating the production practices associated with a particular prior knowledge over the actual climatic conditions that occurred during the years 1970–83. These simulated net returns are presented in table 1.[6] The simulation procedure utilizes the Markov structure of the DP model, that is, the simulation is of the DP model itself. The perfect information distribution of net returns is generated using the DP model and assuming perfect knowledge of each year's climatic conditions.

Lower and upper bounds on the value of seasonal climate forecasts generated for SSD and GSD are given in tables 2 and 3, respectively. The bounds presented on these tables illustrate that both assumptions on prior knowledge and risk preferences affect the value of seasonal climate forecasts. For comparison purposes, the value of seasonal climate forecasts under the assumption of risk neutrality is given in table 1 in the row denoted as E(value).

In making the pairwise comparisons, caution should be exercised when sample sizes differ, particularly when one of the distributions is expected to dominate in a first-degree sense like the perfect forecast. Inclusion of additional observations may result in the estimated cumulative distribution functions displaying a relationship which is theoretically

Table 3. Lower and Upper Bounds on the Value of Perfect Seasonal Forecasts Using GSD and Various Risk Aversion Levels in Dollars per Hectare per Year

Prior Knowledge	Bounds on $r(x)$			
	.00 to .001		.00 to .005	
	Lower	Upper	Lower	Upper
P1983	65.00	66.50	54.75	66.50
P1979	44.50	51.00	44.50	105.50
PYear[a]	70.50	77.25	70.50	125.50
PHist	46.00	53.50	46.00	108.75
	.00 to .01		.00 to .025	
	Lower	Upper	Lower	Upper
P1983	31.50	67.00	1.50	67.25
P1979	44.50	186.25	44.50	218.00
PYear[a]	70.50	191.50	70.50	218.00
PHist	46.00	187.00	46.00	218.00
	.001 to .005		.005 to .01	
	Lower	Upper	Lower	Upper
P1983	54.75	65.25	31.50	55.00
P1979	51.00	105.50	105.50	186.25
PYear[a]	77.50	125.50	125.50	191.50
PHist	53.50	109.00	108.75	187.25
	−.001 to .001		−.001 to .005	
	Lower	Upper	Lower	Upper
P1983	64.75	67.25	54.75	67.75
P1979	40.00	51.00	40.00	105.50
PYear[a]	65.50	77.25	65.50	125.50
PHist	40.75	53.25	40.75	108.75

[a] Based on thirteen observations; the year 1970 was dropped from the perfect information distribution.

[5] As noted by a reviewer the derivation of decision rules with a risk-neutral DP model may introduce some bias into the results. But incorporating risk into the DP model would require that an exact utility function be specified; thus, the use of stochastic dominance would be unnecessary. The DP model was used to specify the decision rule because of the large number of decisions necessary with simulating a four-state variable DP model. Also using the DP model allows for intrayear updating in the decision rules.

[6] The mean net return value for *P1979* is slightly higher than *PHist* because, when climatic conditions are good, *P1979* results in a higher net return than *PHist* but, when climatic conditions are poor, both prior knowledge scenarios result in approximately the same net returns. This is reflected in that *P1979* is slightly more negatively skewed than *PHist* (−2.82 to −2.41).

impossible. A common practice to avoid this problem is to standardize sample sizes. Hence, in the pairwise comparisons involving the perfect forecast and *PYear,* the cumulative distribution functions have been constructed with only thirteen observations. The year 1970 was dropped from the perfect forecast distribution.

SSD is considered a criterion with weak powers of discrimination in that it is based on a relatively few constraints. The only assumption placed on the utility functions when using SSD is that the function displays risk aversion. Results in table 2 indicate that for decision makers displaying risk aversion, the value of perfect seasonal climate forecast ranges from \$0.00 to \$218.14 per hectare per year, depending on the prior knowledge scenario. For risk neutrality the range on the value of perfect forecasts is \$44.36 to \$70.34 per hectare per year. The differences in the ranges indicate that when risk preferences are taken into account, the value of climate forecasts may differ drastically from the risk-neutral case. A decision maker may be willing to pay a high premium for information that reduces the probability of low net returns. The converse is also true, that is, with certain utility functions a decision maker may not be willing to pay for any additional information.

The bounds in table 2 also illustrate one of the problems associated with the ability of SSD to discriminate and rank alternative distributions. The SSD admissible class of risk preferences is large and quite heterogeneous. It includes all risk-averse preferences and hence imposes a necessary condition that the lowest net return of the dominant distribution not be less than that of the unpreferred distribution (Anderson). This is often referred to as the left-hand tail problem because it places emphasis on the lower tails of the cumulative distribution functions under consideration. In the case of valuing information, this may lead to inaccurate estimates of the value of information if the most risk-averse preferences contained in the admissible class are not representative of decision makers' risk attitudes.

In all cases presented in table 1, the lowest net return is associated with the year 1983. The criterion of SSD gives as either the lower or upper bound the difference between the net returns associated with the year 1983 for perfect knowledge and for prior knowledge. This is because of the inclusion of maxi-min preferences in the class of admissible utility functions. Using prior knowledge *P1983,* this difference is zero and represents the lower bound. For the remaining prior knowledges the difference between the smallest net returns is \$218.14, and this represents the upper bound. Because of the left-hand tail problem and the low likelihood that the extreme risk-averse preferences allowed in the SSD-admissible class are truly relevant, GSD is often used in applied work (King and Robison 1984).

Table 3 gives lower and upper bounds on the value of perfect seasonal climate forecasts using GSD and different bounds on the risk preference function, $r(x)$. The bounds on this function $r_1(x)$ and $r_2(x)$ can be set by assumption, using an interval elicitation procedure (King and Robison 1981) or inferred from empirical studies (Raskin and Cochran). Because the exact values for $r_1(x)$ and $r_2(x)$ are not usually known, sensitivity analysis on these values is necessary. In addition to providing this sensitivity analysis, changing the values for $r_1(x)$ and $r_2(x)$ allows for the investigation of possible relationships between the risk preference function and the value of climate forecast.

Recall that the interpretation of the risk preference function is as follows. An $r(x)$ value of zero implies risk-neutral preferences. Positive values of $r(x)$ imply risk-averse preferences, with larger positive values relating to stronger risk aversion. Negative values for $r(x)$ correspond to risk-preferring preferences. Stronger risk-preferring behavior corresponds to larger (in absolute value) negative risk preference functions. The preference function can be interpreted as the percent change in marginal utility per unit of net return (Raskin and Cochran).

The results presented in table 3 suggest that both the prior knowledge assumed and risk aversion level affect the value of climate forecasts. For example assuming prior knowledge (*P1983*) and the bounds on $r(x)$ of 0.00 to .001, the value of perfect climate forecast ranges between \$65.00 to \$66.50 per hectare per year, whereas assuming prior knowledge (*PHist*) the value ranges between \$46.00 to \$53.50 per hectare per year. Changing the bounds on $r(x)$ to .005 and .01, the value of the forecasts ranges between \$31.50 to \$55.00 per hectare per year and \$108.75 to \$187.25 per hectare per year for *P1983* and *PHist,* respectively. These examples illustrate that the risk preference of the decision maker affects the value of climate forecasts.

Information is often characterized as a risk reducing input. But as a decision maker becomes more risk averse, he/she will not always be willing to pay more for the information and reduce his/her exposure to risk. Information does not always behave in such a monotonic fashion (Hilton). Results in table 3 indicate that, at a minimum, the decision maker's prior knowledge and risk preferences must be considered in determining the value of information. As the decision maker's risk aversion increases, the value of the perfect climate forecasts does not always increase.

Using prior knowledge *P1983,* an increase in the decision maker's risk aversion leads to a decrease in the value of the climate forecasts. For the remaining prior knowledges, an increase in the decision maker's risk aversion leads to an increase in the value of the climate forecasts. This converse finding is explained by examining the nature of the prior knowledges. Recall that *P1983* is a strategy that protects the decision maker from extremely low net returns. Risk-averse decision makers can, in general, be characterized as guarding against low net returns. Therefore, a highly risk-averse decision maker following a decision strategy that mitigates the potential for low net returns will value climate forecasts less than a less risk-averse decision maker following the same strategy. The remaining prior knowledges do not guard against the low net returns (namely the climatic conditions occurring during the year 1983). As risk aversion increases, a decision maker following the decision strategies associated with the remaining prior knowledges places a higher value on the climate forecasts. These empirical results are consistent with Hilton's theorem that "there is no monotonic relationship between the degree of absolute or relative risk aversion and the value of information" (p. 60).

Several other observations based on the ranges presented in tables 2 and 3 can be made. Most of the previous studies on valuing climate forecast have assumed risk neutrality. These studies may have been over- or underestimating the value of information depending on the interaction between the producer's risk aversion level and prior knowledge decision rule. If the decision maker is risk averse but follows a decision rule similar to the two more optimistic rules, *PHist* or *P1979,* assuming risk neutrality may underestimate the value of the forecasts. This is because the value of the forecasts under risk neutrality ($45.99/ha/yr for *PHist* and $44.36/ha/yr for *P1979*) is either at or below the respective lower bound on the value of forecasts obtained from GSD. But if the risk-averse decision maker follows a more conservative decision strategy, for example *P1983,* the value of the forecasts from assuming risk neutrality ($66.04/ha/yr) is always closer to the upper bound than the lower bound obtained from GSD. In this case assuming risk neutrality may lead to an overestimate of the value of climate forecasts. Second, allowing for risk-preferring behavior [a negative $r(x)$] in general decreases the lower bound on the value of the climate forecasts (table 3).

Conclusions

A procedure to obtain lower and upper bounds on the value of information with an inexact representation of risk preference is presented. This procedure is contrasted with the more traditional decision-analytic approach to valuing information. With the problems associated with eliciting risk preferences, the stochastic dominance procedure gives reasonable bounds for the different classes of risk preferences. These bounds provide more information than the single point estimate associated with traditional decision analysis approach, in that classes of utility functions can be considered instead of one specific utility function. Empirical results illustrate that the type of management strategy given by a decision maker's prior knowledge interacts with his/her risk preferences in determining the bounds on the value of climatic information.

The results indicate that previous studies may have been either over- or underestimating the potential value of climate forecasts to a decision maker. This inconclusive result occurs because of our lack of knowledge on the producer's risk aversion level and prior knowledge decision rules. The results here suggest that more research is necessary to further our knowledge in valuing information in general and climate forecast in particular. Finally, the value of the forecasts presented in this study pertains only to an individual corn producer and does not account for possible market effects (Mjelde et al. 1988).

[*Received January 1988; final revision received September 1988.*]

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