THE VALUE OF IMPROVED ENSO PREDICTION TO U.S. AGRICULTURE

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Abstract. The economic value of long-range weather prediction is measured by the increase in social welfare arising from the use of the prediction in economic decisionmaking. This paper describes a study of the economic value of ENSO prediction to U.S. agriculture. The interdisciplinary study involved the analysis of data and models from meteorology, plant science, and economics under a framework based on Bayesian decision analysis. The estimated annual value of perfect ENSO prediction to U.S. agriculture is $323 million.

1. Introduction

Skill in interannual climate prediction has improved over the past decade. This improvement is due in large part to the ability to predict, up to a year in advance, oceanographic conditions in the equatorial Pacific Ocean relating to the phenomenon known as El Niño-Southern Oscillation (ENSO). A recent comprehensive review of ENSO prediction is given in Latif et al. (1994). Public investment in data acquisition, modelling studies, and other scientific activities should lead to further improvements in ENSO prediction and, as a result, to further improvements in climate prediction. For this reason, there is an interest in assessing the return to investment in this area.

In a previous study, Adams et al. (1995) estimated the value of improved ENSO prediction to agriculture in the southeast U.S. This paper describes an extension of the earlier study to all U.S. agriculture. Beyond its enlarged scope, the present study differs from the previous one in two respects. First, the report of the previous study was aimed primarily at economists. In contrast, the present paper stresses the interdisciplinary aspects of the study. Second, the present study improves on the previous one in certain technical areas, including a more comprehensive treatment

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of climate statistics and crops and improved modelling of decisionmaking under uncertainty.

The basic scenario considered here is the following. The ENSO year runs from October to September. Each ENSO year can be classified according to ENSO phase. There are three ENSO phases: warm event (or El Niño), cold event (or El Viejo), and non-event. Climate in the U.S. is affected by ENSO phase, although not all regions are affected and, those that are affected, are not necessarily affected in the same way. The regional climatic differences between different ENSO phases affect the yields of different crops. Thus, advanced knowledge of ENSO phase provides advanced knowledge of climatic conditions, which in turn provides advanced knowledge of agricultural yields. Since different crops respond differently to climatic conditions, advanced knowledge of yields provides information about the profitability of different cropping patterns. Individual farmers use this information about profitability in selecting their cropping patterns. The consequences of these individual decisions for the agricultural sector and ultimately for consumers are captured through the market for agricultural products.

In broad terms, the economic effect of improved ENSO prediction is the same as that of a technological improvement that increases the supply of agricultural products. The value to society of this shift in supply is the increase in the sum of consumer and producer welfare. The sum of these is referred to as economic surplus. Briefly, changes in consumer welfare reflect gains (or losses) due to lower (or higher) prices, while changes in producer welfare reflect changes in so-called quasi-rents, which in most cases are comparable to profits. The economic value of ENSO prediction is defined as the expected change in economic surplus arising from changes in cropping pattern due to the prediction.

To use this scenario as a basis for estimating the value of improved ENSO prediction, it is necessary to model (i) the climatic differences between different ENSO phases; (ii) the effects of these climatic differences on yields; (iii) the way in which information about yields affects planting decisions; and (iv) the way in which the behavior of individual farmers affects the market of agricultural products. These steps are described in the following sections.

2. Climatic Differences Between ENSO Phases

The first step in estimating the differences in monthly climate between the three ENSO phases was to classify each ENSO year in the 40-year study period 1947–1986 by ENSO phase. The classification rule was based on a 5-month moving average of the average sea surface temperature anomaly within the tropical Pacific region 4° S–4° N, 150° W–90° W constructed by the Japan Meteorological Agency. If the index exceeded 0.5 °C for 6 consecutive months including October–December, then the ENSO year was classified as El Niño phase. If the index fell below –0.5 °C for 6 consecutive months including October–December, then the

Table I
ENSO phase categorization, 1947–1986

Normal	El Niño	El Viejo
1950	1951	1947
1952	1957	1948
1953	1963	1949
1958	1965	1954
1959	1969	1955
1960	1972	1956
1961	1976	1964
1962	1982	1967
1966	1986	1970
1968		1971
1974		1973
1977		1975
1978		
1979		
1980		
1981		
1983		
1984		
1985		

year was classified as El Viejo phase. All other years were classified as non-event phase. The classification, which is similar to others (e.g., Kiladis and Diaz, 1989), is given in Table I.

Using this classification, monthly climate statistics were calculated for each ENSO phase at each of 54 stations. These stations, which are listed in Table II, were selected to provide balanced coverage of agriculturally significant regions. An agricultural region was associated with each of these stations. Both the climate differences between ENSO phases and the corresponding yield effects were assumed to be constant within these regions. Daily climate data for the representative stations were used to calculate monthly mean values of the following climate statistics:

– mean and standard deviation of daily minimum and maximum temperature;
– mean, standard deviation, and coefficient of skewness of daily precipitation;
– the number of wet days; and
– the one-step transition probabilities between wet and dry days.

Table II
Stations used to define agricultural regions

Place	State	Place	State	Place	State
Muscle Shoals	AL	Lafayette	LA	Corp. Chr.	TX
Union Springs	AL	Big Rap. Wat.	MI	El Paso	TX
Mesa Exp. Farm	AZ	Greenville	MS	Liberty	TX
Pocahontas	AR	Moorhead	MS	Marshall	TX
Davis	CA	Chinook	MT	Mexia	TX
Napa St. Hosp.	CA	Santa Rosa	NM	Muleshoe	TX
Redlands	CA	Kinston	NC	Snake Creek	UT
Fort Morgan	CO	Mt. Airy	NC	Columbia	VA
Bridgeville	DE	Mott	ND	Pullman	WA
Apalachicola	FL	Towner	ND	Buckhannon	WV
Ocala	FL	McConnelsville	OH	Spooner	WI
Covington	GA	Wooster	OH	Viroqua	WI
Aberdeen	ID	Geary	OK		
Duquoin	IL	Mangum	OK		
Monmouth	IL	Dufur	OR		
Berne	IN	Wellsboro	PA		
Clarinda	IA	West Chester	PA		
New Hampton	IA	Newberry	SC		
Independence	KS	Clark	SD		
Bowling Green	KY	Alice	TX		
Owensboro	KY	Ballinger	TX		

The selection of these statistics, which are more comprehensive than those used in the previous study, was based on a sensitivity analysis of the yield model described in the following section.

Details of this analysis, including an assessment of the statistical significance of observed climatic differences between ENSO phases, are presented in Sittel (1994a, b). Some selected results are shown in Figure 1. In broad terms, climatic differences between the phases are greatest during winter. In the southeastern U.S., where the ENSO signal appears to be most pronounced, El Niño years tend to be colder than normal in the fall and winter and warmer than normal in the spring and summer. El Viejo years generally exhibit patterns with the opposite sign, although typically not the same magnitude. For precipitation, El Niño years tend to be wetter than normal in the winter and spring and dryer than normal during the summer. Again, El Viejo years generally exhibit patterns of opposite sign, but different magnitude. These results are generally consistent with those found in other studies (e.g., Ropelewski and Halpert, 1986).

3. Yield Effects

The crops included in this study were barley, corn, cotton, hay, potatoes, rice, sorghum, soybeans, tomatoes, and wheat. This selection was based primarily on economic importance and on planting schedules, which determine the potential for incorporating long-range weather prediction into planting decisions. These crops account for over 90% of acreage and 80% of farm gate value in the U.S. For each crop, the effect of yield of climatic differences between ENSO phases were estimated for each region using a plant biophysical simulation model called the Erosion Productivity Impact Calculator (EPIC). This model, which is described in Williams et al. (1989) and Bryant et al. (1992), was originally developed to determine the relationship between soil erosion and productivity. However, because it uses climatic information in calculating yield, it is well-suited for this study.

The EPIC model estimates crop yield based on total biomass produced and a harvest index. Biomass and the harvest index increase through the growing season as a function of heat units. The harvest index may be reduced by high temperature, low solar radiation, or water stress during critical crop stages. Biomass may be reduced by water, temperature, and aeration stress and also by nitrogen and phosphorus stress.

The plant growth model in EPIC has been tested throughout the U.S. and in several other countries (Steiner et al., 1987; Williams et al., 1989; Bryant et al., 1992; Kiniry et al., 1995). The most comprehensive validation study was conducted by Williams et al. (1989). In that study, the model was tested for 6 crop species at 20 U.S. and 15 foreign locations with considerable variation in weather and soil characteristics. In all cases, mean simulated yield was within 7% of measured yield. Other studies found similar results.

The yield results for the stations shown in Figure 1 are given in Table III. Yield differences among summer crops were due mainly to differences in water stress. For example, corn in Mount Airy, NC and Bridgeville, DE suffered fewer days of summer water stress in El Viejo years than in El Niño and non-event years. In contrast, the enhancement of growing conditions at Corpus Christi, TX during El Niño years was due to higher crop-available water in the spring months. Winter wheat yields are more affected by temperature stress than by water stress. For example, higher winter wheat yields during El Viejo years were due mainly to reduced winter temperature stress.

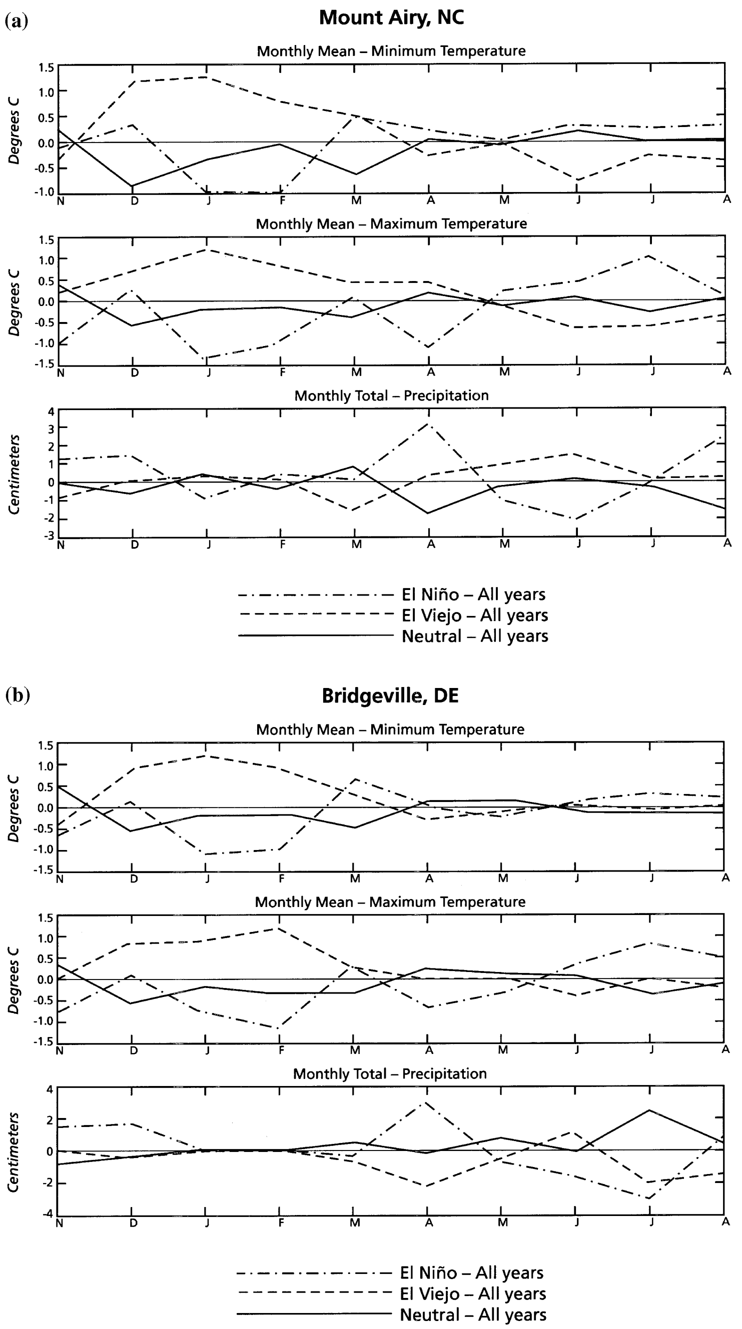
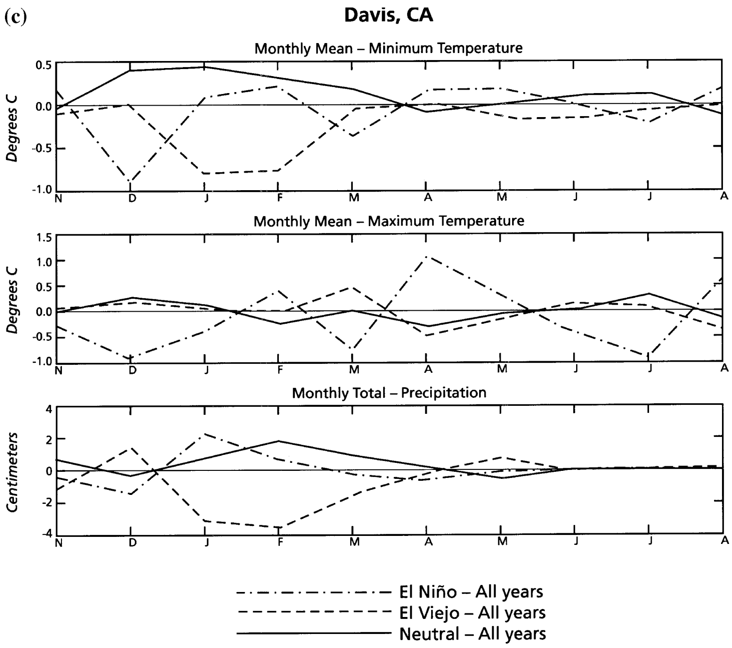

(a)
Mount Airy, NC
Monthly Mean – Minimum Temperature
Monthly Mean – Maximum Temperature
Monthly Total – Precipitation
Degrees C
Centimeters
N D J F M A M J J A
El Niño – All years
El Viejo – All years
Neutral – All years
(b)
Bridgeville, DE
Monthly Mean – Minimum Temperature
Monthly Mean – Maximum Temperature
Monthly Total – Precipitation
Degrees C
Centimeters
N D J F M A M J J A
El Niño – All years
El Viejo – All years
Neutral – All years

Figure 1a–b.

(c)



(d)

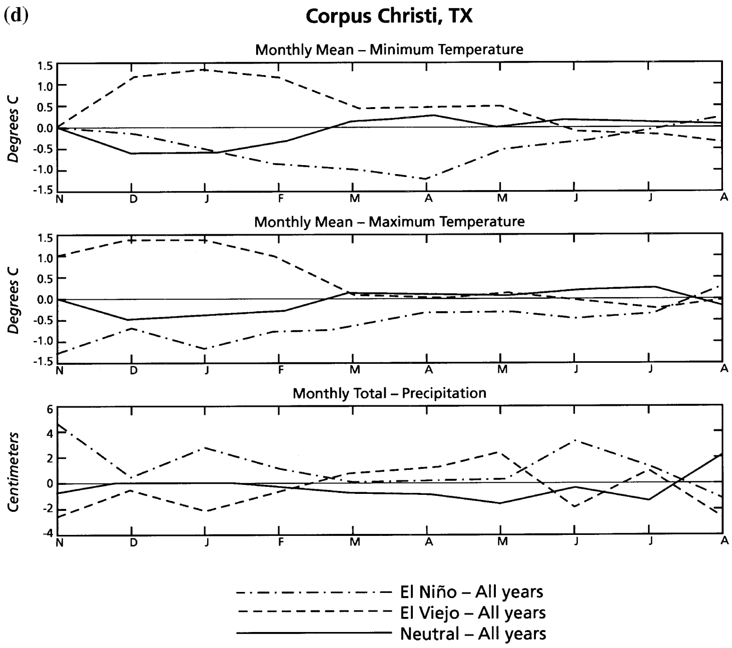


Figure 1c–d.

Figure 1. Effect of ENSO phase on monthly means of minimum (top panel) and maximum (middle panel) temperature and monthly precipitation totals (bottom panel) for (a) Mount Airy, (b) Bridgeville, (c) Davis, and (d) Corpus Christi. In each panel, monthly values are shown by dash-dotted line for El Niño, dashed line for El Viejo, and solid line for non-event.

Table III

Simulated crop yields under different ENSO phases for selected stations. Values are bushels per acre for corn, soybean, wheat; pounds of lint per acre for cotton; and hundred pounds per acre for sorghum

	Normal	El Niño	El Viejo
Mount Airy, NC			
Corn	141	141	154
Cotton	776	773	835
Soybeans	47	45	50
Wheat	42	41	48
Bridgeville, DE			
Corn	122	110	118
Soybeans	36	29	36
Wheat	51	48	54
Davis, CA			
Cotton	1014	1129	1073
Wheat	85	86	84
Corpus Christi, TX			
Corn	137	175	144
Cotton	544	708	576
Sorghum	67	87	72
Soybeans	26	32	26

4. Decisionmaking and the Value of Prediction

Under the scenario considered in this paper, the climatological implications of an ENSO prediction are used to formulate a prediction of crop yields. The prediction of yields is then used by farmers to optimize cropping patterns. The way in which farmers use this information can be formalized in terms of Bayesian decision theory (Kite-Powell and Solow, 1994). This formalization is outlined in this section.

Let a denote a particular cropping pattern and let the random variable S denote the ENSO phase. The possible values of S are E (El Niño), V (El Viejo), and N (non-event). Let s denote a realization of S and let $B(a \mid s)$ be the profit for cropping pattern a if the realized ENSO phase is s. In the absence of an ENSO phase prediction, the expected profit for a is:

$$E(B(a)) = \sum_s B(a \mid s)\pi(s) , \tag{1}$$

where $\pi(s)$ is the probability that $S = s$.

The optimal cropping pattern $a*$ maximizes $E(b(a))$. Note that, in the absence of an ENSO phase prediction, the farmer optimizes cropping pattern over long-run average climatic conditions. In particular, $a*$ does not change from year to year. On the other hand, crop production in a particular year resulting from cropping pattern $a*$ depends on the realized ENSO phase in that year.

For a given ENSO phase s, the economy-wide supply for each crop resulting from optimal cropping patterns of each farmer in all regions can be found using a model capturing both farmers' decisions across all production regions and the demand for each crop. Let $T_1(s)$ be the economic surplus arising from the aggregate supply curves – that is, from supplies summed across all farmers in all regions. In the absence of an ENSO phase prediction, the expected economic surplus is given by:

$$T_1 = \sum_s T_1(s)\pi(s)\,. \tag{2}$$

Suppose now that an annual ENSO phase prediction is issued prior to the planting season. Let the random variable X denote the predicted phase and let x denote a realization of X. As with S, the possible values of X are E, V, and N. Although only categorical predictions were considered in this study, the same general approach could be applied to probabilistic predictions. Suppose that the ENSO phase prediction X in a particular year is x. The farmer uses this prediction to update the probability distribution of S according to Bayes's Theorem:

$$p(s \mid x) = p(x \mid s)\pi(s)/p(x)\,, \tag{3}$$

where $p(s \mid x)$ is the probability that $S = s$ given $X = x$, $p(x \mid s)$ is the probability that $X = x$ given $S = s$, and:

$$\begin{aligned} p(x) &= \mathrm{prob}(X = x) \\ &= \sum_s p(x \mid s)\pi(s)\,. \end{aligned} \tag{4}$$

The likelihood $p(x \mid s)$ is a non-standard measure of prediction skill. For a perfect prediction:

$$p(x \mid s) = \begin{array}{ll} 1 & \text{if } s = x \\ 0 & \text{otherwise} \end{array} \tag{5}$$

in which case:

$$p(s \mid x) = \begin{array}{ll} 1 & \text{if } s = x \\ 0 & \text{otherwise}\,. \end{array} \tag{6}$$

In contrast, for a completely uninformative prediction, $p(x \mid s) = 1/3$ for each s, so that $p(s \mid x) = \pi(s)$.

The individual farmer behaves as before, choosing the optimal cropping pattern $a*(x)$ to maximize expected profit:

$$E(B(a) \mid x) = \sum_s B(a \mid s) p(s \mid x)\,. \tag{7}$$

Note that, by averaging over $p(s \mid x)$ in Equation (7), the farmer is taking account of the possibility of incorrect phase prediction. Otherwise, the farmer would simply choose a to maximize $B(a \mid x)$.

The optimal cropping pattern $a*(x)$ now depends on the realized ENSO phase prediction x. Let $T_2(x \mid s)$ be the economic surplus at the national level if $X = x$ and $S = s$. The conditional expected surplus given $X = x$ is found by averaging over the conditional distribution of S given $X = x$:

$$T_2(x) = \sum_x T_2(x \mid s) p(s \mid x) \tag{8}$$

and the unconditional expected surplus is:

$$T_2 = \sum_x T_2(x) p(x)\,. \tag{9}$$

Finally, the value of the ENSO phase prediction is given by $T_2 - T_1$. The same approach can be used to assess the value of an improvement in – as opposed to the establishment of – an ENSO phase prediction.

It is important to stress that the value of ENSO prediction is an average or long-term concept. In a particular year, an incorrect prediction may lead to a loss. However, on average – or equivalently, over time – the use of the prediction will lead to an increase in profits.

5. Implementation and Results

To implement the Bayesian approach outlined in the previous section, it is necessary to specify prior probabilities of the ENSO phases and the likelihood function of the prediction scheme. In the study described here, the prior probability $\pi(s)$ was taken to be the relative frequency of s in Table I, so that:

$$\pi(e) = 0.23 \qquad \pi(V) = 0.30 \qquad \pi(N) = 0.47\,.$$

As noted above, the likelihood function is a non-standard measure of prediction skill. In the present study, three hypothetical levels of prediction skill – modest, high, and perfect – were considered. In related work, we are attempting to estimate the likelihood function of a simple, model-based ENSO prediction scheme (A. R. Solow and M. Cane, in preparation). The likelihood function for perfect prediction is given in the previous section. Those corresponding to modest and high skill

Table IV
Hypothetical likelihoods $p(X \mid S)$ for modest and high skill predictions

	Modest		
	$S = E$	$S = V$	$S = N$
$X = E$	0.60	0.15	0.20
$X = V$	0.15	0.60	0.20
$X = N$	0.25	0.25	0.60
	High		
	$S = E$	$S = V$	$S = N$
$X = E$	0.80	0.05	0.10
$X = V$	0.05	0.80	0.10
$X = N$	0.15	0.15	0.80

Table V
Posterior probabilities $p(S \mid X)$ for modest and high skill predictions

	Modest		
	$S = E$	$S = V$	$S = N$
$X = E$	0.46	0.15	0.39
$X = V$	0.11	0.54	0.35
$X = N$	0.12	0.15	0.73
	High		
	$S = E$	$S = V$	$S = N$
$X = E$	0.68	0.06	0.26
$X = V$	0.04	0.74	0.22
$X = N$	0.05	0.07	0.88

prediction are given in Table IV. Using the prior probabilities given above, these likelihoods are converted into the posterior probabilities given in Table V.

For given posterior probabilities, an economic model called SPRASM was used to calculate expected surplus. This model is a stochastic programming version of the Agricultural Sector Model (ASM) that was used in the earlier study (Chang and McCarl, 1992). The ASM provides estimates of the changes in prices and quantities

Table VI
Expected economic value of ENSO prediction ($ million per year)

Skill	Expected value
Modest	240
High	266
Perfect	323

of agricultural products, and corresponding changes in economic surplus, due to changes in yields. This model was validated by solving for prices and quantities using 1992 yield data. The solutions were all within 2% of actual 1992 quantities and 5% of actual 1992 prices. Further details of this general approach to model validation are given in Fajardo et al. (1981). The incorporation of a stochastic component based on discrete stochastic programming (Lambert et al., 1995) provides a convenient and powerful way to capture decisionmaking under uncertainty. Under the combined model, farmers maximize expected profit subject to a market clearing condition and a set of resource constraints, while consumers utilize agricultural products with knowledge of prices. Again, it is important to stress that, under the decisionmaking component of this model, farmers take into account the possibility of incorrect phase predication as outlined in the previous section.

The results of the study are summarized in Table VI. These values, measured in 1995 dollars, are larger than those from the previous study. This increase is due, in part, to the larger geographic scope and the greater coverage of agricultural activities. However, due to the refinements of data and procedures in the present study, a direct comparison is not strictly possible. The annual values given in Table VI represent recurring gains to society. Assuming that future benefits are discounted at an annual rate of 6%, the net present value to the agricultural sector of a high skill ENSO prediction operating over 10 years is around $2 billion.

In interpreting the results in Table VI, it is important to distinguish between the economic value of improved ENSO prediction and the economic impacts of a particular ENSO phase. For example, in this study, the economic surplus associated with a single El Niño year is approximately $2.5 billion less than that associated with a non-event year. However, even with a perfect prediction, all of the negative effects (such as yield reductions) cannot be avoided, so that the value of predicting this event perfectly is considerably less.

6. Discussion

The study described here and in the earlier report represents the first systematic attempt to assess the economic value of ENSO prediction for a major sector of the U.S. economy. Although earlier attempts have been made (e.g., O'Brien, 1993), they have been based on *ad hoc* methods, rather than on a model of economic decisionmaking. The study described here documents the existence of ENSO signals in regional climate in the U.S. and identifies their consequences for crop yields. Advanced knowledge of these yield differences have potential value for farmers. The results of this study confirm the preliminary findings of the earlier study that ENSO prediction has substantial economic value to U.S. agriculture. While the specific results presented here seem reasonable, we believe that the main contribution of this paper is the description of a rigorous approach to assessing the value of long-range weather prediction. In implementing this approach, it is not necessary to use the EPIC model or the SPRASM model. Different or more elaborate models can be used. Incidentally, the same general approach can be used to assess the value of prediction to other sectors of the economy.

Turning to the specific results of this study, while the values in Table VI are substantial – particularly compared to the cost of ENSO prediction itself, they represent only around 1–2% of the net income of U.S. farmers. This may seem low, in light of the publicized effects of ENSO. There are features of the study that tend to underestimate the value of ENSO prediction to agriculture. For example, only cropping decisions were allowed to respond to ENSO prediction. No provision was made for other kinds of adjustments, such as alterations in inputs (e.g., fertilizers) or harvesting decisions. Also, some valuable vegetable and perennial crops were omitted from the analysis due to lack of information about potential yield effects. On the other hand, the study assumed that all farmers respond optimally to ENSO prediction. Failure of this assumption would lead to an overestimation of the value of ENSO prediction.

In addition to the technical problems associated with this kind of empirical analysis, the value of ENSO prediction to any sector is limited in two important ways. First, substantial climate variability remains within ENSO phases, particularly on the regional scale. To put it another way, even perfect ENSO prediction is far from perfect climate prediction. Second, as noted, the value of ENSO prediction is limited by the capacity of decisionmakers to respond to the prediction. In almost all cases, this capacity will fall far short of avoiding all losses due to inclement climate.

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References

Adams, R. M., Bryant, K. J., McCarl, B. A., Legler, D. M., O'Brien, J. J., Solow, A. R., and Weiher, R.: 1995, 'Value of Improved Long-Range Weather Information', *Contemp. Econ. Policy* **13**, 10–19.

Bryant, K. J., Benson, V. W., Kiniry, J. R., Williams, J. R., and Lacewell, R. D.: 1992, 'Simulating Corn Yield Response to Irrigation Timings: Validation of the EPIC Model', *J. Prod. Agric.* **5**, 237–242.

Chang, C. C. and McCarl, B. A.: 1992, *The Agricultural Sector Model*, Texas A & M University, Department of Agricultural Economics Paper, p. 62.

Fajardo, D., McCarl, B., and Thompson, R.: 1981, 'A Multicommodity Analysis of Trade Policy: The Case of Nicaraguan Agriculture', *Amer. J. Agric. Econ.* **34**, 23–31.

Kiladis, G. N. and Diaz, H. F.: 1989, 'Global Climate Anomalies Associated with the Extremes of the Southern Oscillation', *J. Clim.* **2**, 1069–1090.

Kite-Powell, H. L. and Solow, A. R.: 1994, 'A Bayesian Approach to Estimating Benefits of Improved Forecasts', *Meteorol. Appl.* **1**, 351–354.

Kiniry, J. R., Major, D. J., Izaurralde, R. C., Williams, J. R., Gassmann, P. W., Morrison, M., Bergentine, R., and Zentner, R. P.: 1995, 'EPIC Model Parameters for Cereal, Oilseed, and Forage Crops in the Northern Great Plains Region', *Can. J. Plant Sci.* **75**, 679–688.

Lambert, D., McCarl, B., He, Q., Kaylen, M., Rosenthal, W., Chang, C., and Nayda, W.: 1995, 'Uncertain Yields in Sectoral Welfare Analysis: An Application to Global Warming', *J. Agric. Appl. Econ.* **27**, 423–436.

Latif, M., Barnett, T. P., Cane, M. A., Flugel, M., Graham, N. E., von Storch, H., Xu, J.-S., and Zebiak, S. E.: 1994, 'A Review of ENSO Prediction Studies', *Clim. Dyn.* **9**, 167–180.

O'Brien, J. J.: 1993, *Report of the Workshop on the Economic Impact of ENSO Forecasts on the American, Australian, and Asian Continents*, Florida State University, Tallahassee, FL, p. 86.

Ropelewski, C. F. and Halpert, M. S.: 1986, 'North American Precipitation and Temperature Patterns Associated with the El Niño/Southern Oscillation (ENSO)', *Mon. Wea. Rev.* **114**, 2352–2362.

Sittel, M.: 1994a, 'Marginal Probabilities of the Extremes of ENSO Events for Temperature and Precipitation in the Southeastern U.S.', Florida State University, FL, COAPS Report 94-1, p. 155.

Sittel, M.: 1994b, 'Differences in Means of ENSO Extremes for Maximum Temperature and Precipitation in the U.S.', Florida State University, FL, COAPS Report 94-2, p. 76.

Steiner, J. L., Williams, J. R., and Jones, O. R.: 1987, 'Evaluation of EPIC Using a Dryland Wheat-Sorghum-Fallow Crop Rotation', *Agron. J.* **79**, 732–738.

Williams, J. R., Jones, C. A., Kiniry, J. R., and Spanel, D. A.: 1989, 'The EPIC Crop Growth Model', *Trans. Amer. Soc. Agric. Eng.* **March**, 497–511.

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