ENSO Forecast Value, Variable Climate and Stochastic Prices

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ABSTRACT: We evaluate ENSO forecasts when prices are variable and ENSO is a portion of overall climatic variability. Forecast responses include crop mix, cultivar,fertilization, and planting date. Price changes reduce forecast value by excluding responses. Predictable income variability (ENSO-related), as a share of the total, evaluates forecast skill.

1. Introduction

The tropical Pacific atmospheric-oceanic phenomenon known as ENSO (El Niño-Southern Oscillation) has important consequences for agriculture. ENSO is a variation between normal conditions and two extreme states associated with warm or cold sea surface temperatures in the tropical Pacific Ocean. Improved ENSO forecasting has important implications for agriculture as a technical improvement that increases the supply of agricultural products.

The predictability of climate and yield variability associated with ENSO suggests a potential to tailor agricultural production decisions to either mitigate the negative impacts of adverse conditions or to take advantage of favorable conditions. Research suggests a considerable potential value of ENSO forecasting to agriculture. Forecast value to agriculture in the southeastern U.S. may exceed $100 million annually (Adams et al. 1995), and for the entire U.S. the figure may be $200 million (Solow et al. 1998). Surveys of ENSO forecast value for agriculture include Johnson and Holt (1997), Mjelde et al. (1998), Weiher (1999) and Richard Katz' internet site (www.dir.ucar.edu/esig/HP_rick/agriculture.html). We develop and apply a stochastic, nonlinear optimization framework for evaluating regional ENSO forecasts. In comparison to previous climate forecast valuations, our framework is novel in that commodity prices are highly variable and ENSO may be a small proportion of overall climatic variability.

Relative price movements can limit the flexibility producers have in responding to a climate forecast by excluding some crops and management as feasible options. Also, forecast responses optimized for fixed prices will not always improve incomes when prices are variable.

If inter-event (within-phase) variability is large, as is typical of the ENSO signal in extra-tropical regions, ENSO-yield associations can be difficult to establish. Researchers have often relied on short historic climate records, limiting their ability to describe within-phase variability, since only a few events can be compared. Time records, for example, tell us little about how much Niña events can differ from one another. To expand on this capability, we use stochastic weather generators to produce longer distributions of weather variables for each ENSO phase. Our simulated crop yields based on these synthetic weather series reveal yield variability attributable to within ENSO phase weather variability.

Useful descriptions of associations between ENSO and crop yields can be derived from statistical analyses of historical data. This approach, however, has limitations. First, crop records frequently encompass only a limited number of ENSO events. If inter-event (within-phase) variability is large, as is typical of the ENSO signal in extra-tropical regions (Kumar and Hoerling, 1997), clear ENSO-yield associations may be difficult to establish. Second, it is difficult to determine the vulnerability of present agricultural production systems to climate variability using historical data, even if technology effects are somehow taken into account. Third, most historical analyses are performed at aggregation scales for which data are usually available (national, state, or crop district/county level). Spatial aggregation dampens crop yield variability, thus risk estimates from aggregated data may not be appropriate for decision-making at the farm or enterprise level (Garcia et al, 1987; Meinke and Hammer, 1995). Finally, the characterization of vulnerability requires not only a description of climate impacts, but also the consideration of other risk sources such as fluctuations in output prices. Modeling approaches can help overcome some of the limitations of historical analyses of agricultural data (Meinke and Hammer, 1995; Phillips et al, 1998; Rosenthal et al., 1998).

Our goal is to develop a risk management framework to evaluate seasonal agricultural applications of ENSO-related climate forecasts. This framework is based on the linkage of climatic, agronomic, and economic models. We combine long synthetic daily weather series with process-level crop simulation models and stochastically generated output prices to derive probability distributions of crop yields and economic returns by ENSO phase.

The risk management framework is illustrated for current cropping systems in central-eastern Argentina, the region known as the Pampas. The Pampas is among the major agricultural regions in the world; a large proportion of Argentina's crop production originates in this region. Hall et al. (1992) give a description of the climate, soils, and crop production systems in the Pampas. A clear association was shown between maize yields and ENSO-related climate variability in the Pampas: high (low) yields were more likely during warm (cold) events (Podestá et al., 1999 and references therein). The location under study is Pergamino, located in the Pampa Ondulada, the most productive subregion of the Pampas (Hall et al., 1992; Paruelo and Sala, 1993). The representative soil of this location is a typic Argiudoll with no physical constraints for agriculture (Paruelo and Sala, 1993). Typical crop rotations include maize, soybean, wheat, a wheat-soybean relay, and to a lesser extent, sunflower. Pergamino has a median annual precipitation of 937 mm. Seasonal patterns of rainfall per ENSO phase are shown in figure 1. One of the characteristics of the region's climate is a recurrent water deficit in December / January, which affects maize yields. This phenomenon occurs approximately once every 4 years (Hall et al., 1992).

2. Land Allocation Model

One important advantage of our approach is that the use of crop growth models allows us to explore a large portion of the potential multi-dimensional decision space, which would be impossible from statistical analyses of historical data. As possible responses to a given ENSO forecast, we include crop mix, cultivar, fertilizer amount and planting date. We assume that farmers allocate land to cropping enterprises so as to maximize the expected utility at the end of a one-year planning period. Expected utility is expressed as a power function of wealth, based on a constant relative risk aversion coefficient (Hardaker et al. 1997). We also assume that weather is unknown at decision time but that prices are known.

The farmer allocates land proportions, *x*, among 21 crop and management alternatives, *m*, subject to constraints on land and labor availability. The model is:

1) $\max E\{U(W_f)\} = W_f^{(1-R_r)}/(1-R_r)$, where

2) $W_f = W_o + \quad _{m=1} x_m y_m p_m - C_m - T_m$

subject to:

3) $_{m=1} x_m * labor_{m,mn} \quad labor^u{}_{mn}$

4) $_{m=1} x_m \quad land^u$

5) $C_m = \quad _{m=1} x_m * fixedcost_m$

where *C* is fixed costs, *x* is land allocation, *p* is price adjusted for variable costs, *labor* is the set of labor requirements, $labor^u$ is labor availability, $land^u$ is land availability, *T* is taxes, W_0 is initial wealth, W_f is wealth in the final period, *n* is the number of weather years, R_r is the coefficient of constant relative risk aversion (crra), and *y* is yields. Variable costs include those for harvest, trading and transportation, all of which are defined as a percentage of crop value. The labor constraint is expressed for each month, *mn*.

In the next section of the paper, we discuss the modeling framework we used to simulate crop yields and market prices, and we provide our data sources as well.

3. Nested Modeling Approach

Our risk management framework uses linked climatic, agronomic, and economic components to overcome some limitations of historic data. Our intent is to characterize the value of ENSO information in a context where ENSO is just one source of climatic variability and where prices are also variable. The climatic component simulates long synthetic daily weather series conditional on ENSO phase. The synthetic weather series then are input to the agronomic component, in which crop simulation models produce distributions of crop yields by ENSO phase. In the economic component, we stochastically generate crop prices. Each component is described in more detail below.

3.1 Synthetic Weather Series

Obtaining long-term daily weather data as input to agricultural risk management studies usually is difficult. An alternative solution is the use of stochastic weather generators, which can produce synthetic daily weather series with statistical characteristics similar to those of historical data. We used a stochastic weather generator generally based on the approach described by Richardson (1981; see also review in Semenov et al., 1998) to generate long synthetic daily weather series (maximum and minimum temperature, total precipitation, solar radiation) for each ENSO phase.

Unlike previous approaches, our precipitation generator was parameterized conditionally on ENSO phase. Typically, parameters of stochastic weather generators have been fit unconditionally (Wilks, 1989). That is, model parameters usually have been estimated using all historical data for a given period (e.g., a month). However, if a period shows an ENSO-related climate signal (e.g., enhanced or decreased rainfall), the parameters of precipitation models must differ among ENSO phases. Here, model parameters were estimated separately for warm and cold ENSO events and neutral years.

The modified stochastic weather generators showed advantages for a thorough assessment of agricultural risk associated with ENSO-related climate variability. ENSO-conditional models successfully captured differences among ENSO phases in precipitation processes in the Pampas (Grondona et al., 2000). In contrast, unconditional models underrepresented the frequency of both low and high monthly precipitation totals.

The ENSO-conditional stochastic weather generator produced 990 synthetic daily weather series for each ENSO phase. Each series encompassed the period from the beginning of crop model runs (see details below) in late March or early April to the crop's physiological maturity in February-March of the following year.

3.2 Crop Yield Simulation

Dynamic, process-level crop simulation models have proven useful for quantifying interactions between weather variability, management, and the physical environment (Boote et al., 1996). These models simulate the daily growth and development of a crop as a function of inputs such as daily weather, soil characteristics, genetic information, and management practices. We used crop models to estimate distributions of crop yields due to climate variability for a given set of soil parameters and initial conditions, cultivars and crop management scenarios.

Yields were simulated by the crop models included in version 3.5 of the Decision Support System for Agrotechnology Transfer (Jones et al., 1998): Generic-CERES (Ritchie et al, 1998) for maize and wheat, CROPGRO (Boote et al., 1998) for soybean and OILCROP-SUN (Villalobos et al., 1996) for sunflower. Minor modifications were performed on the CERES-Wheat model in order to better represent wheat behavior in the region described in the literature (Satorre & Slafer, 1999; Calderini et al., 1996). We also used a modified form of the sunflower model OILCROP-SUN. Local experts provided genetic coefficients for the wheat (E.H. Satorre, pers. Comm.), and soybean / maize (E. Guevara & S. Meira, Pers. comm.) models. Sunflower coefficients were calibrated using available field experiments (AACREA, unpublished data). Each crop model was run for 990 cropping cycles for each ENSO phase.

A central objective was to explore ENSO impacts on current cropping systems. The first step, therefore, was to define a set of typical or modal management practices for each crop. The modal management was defined through extensive interactions with local technical experts and farmers. Modal management defined for each location is shown in Table 1. We considered 21 different combinations of crops and management parameters, representing different alternative forms of management typical to the region. These management types include different crops, levels of fertilization within the same crop, and planting dates. Different varieties of each crop were sometimes assumed, responding to changes in planting dates, following current farmer practices. The range of planting dates allows optimization of the match between environmental supply and crop demand of resources. We used a fertilization scheme that follows a contemporary form of nitrogen management in the region (Satorre & Slafer, 1999; Soto, 1996). The nitrogen content in the first 60 cm of the soil profile is measured, and nitrogen is added in the form of urea up to a specified desired total nitrogen goal. We assume that this measurement is performed at the planting date.

3.3 Price simulation

While our focus is on ENSO-induced risk, output price variability is frequently the largest source of risk to agricultural producers. To explore the effects of output price variability on the economic performance of the cropping enterprises, we generated a simulated distribution of the four crop prices, consistent with historical variability. Crop prices were randomly drawn for each simulated cropping cycle (independent of ENSO phase, following Keppenne 1995 and Letson and McCullough, submitted) and used, together with simulated yields and information on production costs, to simulate economic net returns of the crop enterprises.

Realistic distributions of prices for the four crops considered in this study could not be derived directly from Argentine historical data because, prior to the early 1990s, commodity prices in this country were heavily distorted by governmental intervention. Lema and Brescia (1998) showed that crop prices in Argentina and the US were positively correlated after 1991, when the Argentine economy became less regulated (Estefanell, 1997). Unfortunately, the Argentine series of crop prices after deregulation was too short for an adequate characterization of historical price variability. For that reason, we used historical series (January 1979 to October 2000) of monthly average prices received by US farmers for maize, soybean, wheat and sunflower (National Agricultural Statistical Service, available from www.nass.usda.gov:81/ipedb). The historical US prices were subsequently linked to prices in Argentina.

For all crops, the US prices were converted to US dollars per dry ton, assuming average marketing moistures of 15.5, 13.0, 14.0, and 10.0% for maize, soybean, wheat and sunflower. The prices were deflated to 1998 dollars using the US Consumer Price Index (CPI). A non-parametric low-frequency trend component (Cleveland and Devlin, 1988) was fitted to the deflated prices for each crop to account for changes in market structure (e.g., improvements in technology and productivity, demographic shifts in supply and demand). Relative price residuals (expressed as proportion of their corresponding low-frequency trend component values) were computed. The relative price residuals were then deseasonalized using a procedure developed by Cleveland et al. (1990). For brevity, the deflated, detrended, and deseasonalized relative price residuals subsequently will be referred to simply as “residuals.”

In previous work focused on maize (Ferreyra et al., 2001), we stochastically generated prices by (a) fitting an empirical density function to the maize price residuals and (b) sampling from that empirical distribution. We could not repeat this approach for each of the four crops, as the univariate generation would not have respected the correlation among prices of different crops (for example, the correlation between wheat and maize price residuals was 0.734). Consequently, we followed an alternative procedure that involved the decomposition of the matrix of price residuals using principal components analysis (PCA). The PCA produced four time series of principal components that were uncorrelated. Prior to the PCA decomposition, the price residuals were transformed using a Box-Cox transformation,

6) $y^* = y$, for $\neq 0$

7) $y^* = \log(y)$, for $= 0$.

The exponents for transforming each crop's residuals were chosen to minimize the statistic of a Kolgomorov-Smirnov test comparing the transformed residuals with a Gaussian distribution. For sunflower, no transformation could be found that yielded a distribution not significantly different from normal, probably because the original residual distribution had a hint of bimodality. Quantile-quantile plots, however, suggested that deviations from normality were not too marked.

We fitted an empirical density function to each of the four time series of principal components (also referred to as amplitudes or scores) using a kernel filter (Bowman and Azzarini, 1997) with bandwidth selected following Sheather and Jones (1991). Each empirical density distribution was then sampled to generate 36,000 values. The synthetic values were then combined and back-transformed to reconstruct price residuals for each crop. The distributions of synthetic and historical price residuals were not significantly different according to Kolgomorov-Smirnov tests. Quantile-quantile plots confirmed that the historical distributions were well reproduced, except for very extreme high values. Finally, the correlation structure of the synthetic price residuals was similar to that of the historical data. The 1996-98 median deflated prices for maize, soybean, wheat, and sunflower (120.80, 301.06, 156.30, and 297.48 \$ ton^{-1}) were used to convert simulated relative residuals into absolute simulated US prices.

In the final step, an association was established between recent (January 1994 to October 2000) crop prices in the US and Rosario, Argentina, where most of the crops produced in the study location is traded. Daily crop prices in Rosario from Argentina's Bolsa de Cereales (Grain Exchange) were aggregated into monthly averages, adjusted for average marketing moistures, which are slightly different from those used for the US (14.5, 11.0, 14.0, and 13.5% for maize, soybean, wheat and, sunflower), and deflated to 1998 US dollars per dry ton. Rosario historical prices for each crop were regressed on US prices using a robust regression procedure that made the regression less sensitive to some extremely high crop prices in late 1995 and early 1996. The regressions were performed using data only for the periods in which the bulk of each crop is marketed in Argentina. These periods are April-June, May-July, December-February, and February-May for maize, soybean, wheat, and sunflower, respectively.

The regression equations and the average marketing moistures in Argentina were used to convert the 36,000 simulated US prices into simulated prices for Rosario, Argentina. We stress that the simulated distributions are not historical price distributions. Rather, they are simulated distributions approximately centered on average 1996-98 prices and with variability ranges and correlation structure consistent with the historical record.

3.4 ENSO phases

Table 2 lists our classification of years by ENSO phase. We define ENSO phase in terms of the Japanese Meteorological Agency's sea surface temperature anomaly index (JMA

SSTA), which selects well the known ENSO events. Several alternative ENSO phase definitions exist and are based on either atmospheric pressure patterns or on sea surface temperature anomalies in the tropical Pacific Ocean (Trenberth 1997). Our definition is a 5-month running mean of spatially averaged SST anomalies over the tropical Pacific: 4^oS-4^oN, 150^oW-90^oW. If the running mean exceeds 0.5^oC for 6 consecutive months (including OND), we categorize the ENSO year of July to the following June as warm (El Niño). If the running means are less than or equal to -0.5^oC over that time span, we classify the year as cold (La Niña). For all other possible index values, we define the year as neutral. JMA SSTA index values for each month of the 1868-1999 period are available via ftp. (www.coaps.fsu.edu/pub/JMA_SST_Index/).

3.5 Other Assumptions and Data Sources

Assumptions about our 450 hectare case study farm were based on information from the trade association AACREA (Asociacion Argentina de Consorcios Regionales de Experimentacion Agricola). Initial wealth is defined as liquid assets, estimated at 60% of the recent value of cropland. This definition is based on the assumption that a farmer will not sacrifice future income potential by selling cropland, but can borrow up to 60% of land value. We assumed the farmer owns his own land and does not carry debt on facilities or equipment beyond their salvage value. Productions costs for each crop management type were estimated using technical assumptions provided by AACREA (1998) and historic input prices given by SAGyP (Secretaria de Agricultura, Ganaderia, Pesca y Alimentacion), the national agricultural ministry. Variable production costs include: harvest costs equal to 8% of crop value; trading costs equal to 10% of value for maize, 8% for soybean, 7% for wheat and 6% for sunflower; and transportation costs. Fixed farm costs include administrative costs and property taxes. Sunflower prices include an 8% premium for oil content.

4. Results and Discussion

The land allocation model described in section 2 was solved using the MINOS5 algorithm in GAMS, to identify the set of areas allocated to each crop enterprise that would maximize expected utility. A randomized procedure that altered starting values helped ensure that the identified solutions each were global maxima. We repeated the optimization procedure for all the years of weather data and for the years in each ENSO phase. This provided the two sets of farm incomes optimized with and without using ENSO phase information required to estimate the potential value of ENSO information. Our key findings follow.

We begin by looking at the optimal crop management by forecasted ENSO phase and how those choices are influenced by the farmer's risk aversion level (figure 2). Five of the possible 21 management types were selected as optimal for at least one possible forecast/ risk aversion level possibility. Early planted maize is the favored crop management type for favorable conditions, e.g., warm events and risk neutrality. Early planted soybeans are the favored crop in neutral and cold phases. Sunflower is the favored hedge crop, since its returns exhibit low variability and low correlation with those of maize. At higher levels of risk aversion, the later planted varieties of soy and maize become attractive for the neutral and warm phases. Enterprise diversification does increase with risk aversion, but less than dramatically because of the binding labor constraint, which also induces diversification. While monocultures typically are expected under risk neutrality, the labor constraint usually induced a second crop even under those conditions.

The next result of interest is our estimated value of information (VOI) for the ENSO forecast. We follow others (e.g., Solow et al 1998) in expressing the value of forecast as the difference in expected economic returns to optimal decisions conditioned on ENSO phases and returns to optimal decisions based on the historic climatology. Formally,

8) VOI = ($_{i=1}$ $_{j=1}$ $^{*}{}_{ij}$ $_{k=1}$ $^{*}{}_{k}$)/n

where $_{ij}^{*}$ is farm income in year j of ENSO phase i, given optimal crop mix for phase j, and $_{k}^{*}$ is farm income in weather year k, given crop enterprise mix optimized for all n weather years. For ease of comparison, we express VOI on a ha^{-1} basis.

Figure 3 shows that our estimated forecast value ranges from about \$2 to \$18 per hectare (between 1 and 9% of annual income), depending on the level of risk aversion. Forecast value tends to increase with risk aversion, as might be expected in a fairly affluent setting such as Pergamino where forecasts are used mainly to take advantage of favorable opportunities. The relationship is not monotonic (Hilton 1981), however, since the precaution encouraged by higher levels of risk aversion does eventually limit forecast responses and thus value.

Another way to consider forecast value is to break it down by ENSO phase (figure 4) and to evaluate the probability that income with forecast use exceeds that without forecast use in a given year (figure 5). The value of forecast varies according to which phase is forecast, for a number of reasons including forecast skill and the availability of management responses. In our findings, the average warm event forecast is worth the most, about \$6/ha, while neutral phase and cold event forecasts each are worth less than \$3/ha. This finding is consistent with the perceptions of Pergamino farmers revealed in a recent survey (Letson et al., in press). Under the almost ideal agronomic conditions of Pergamino, a large share of forecast value stems from the opportunity to take advantage of the higher precipitation typical in warm events by planting early maize. Some value also results from avoiding the dry conditions typical in cold events, but the avoided losses are smaller in magnitude. The relative magnitudes of forecast value across ENSO phase are not sensitive to the level of risk aversion, and figure 4 displays only the normal risk aversion case (i.e., crra=1).

On the other hand, the probability that a farmer can improve his or her income in any given year by using forecasts does vary both by ENSO phase and risk aversion level (figure 5). Particularly in the risk neutral case, when no hedging occurs, a cold or warm event forecast is no sure bet to raise income, in any given year. Note that the possibility of zero or even negative forecast value exists here not because of incorrect ENSO phase forecasts, which we do not consider here, but because ENSO represents a small proportion of the overall climatic variability. If ENSO phase forecasts offer little skill in the proportion of climatic variability they can predict, that could discourage some potential users from adopting this emerging technology.

Histograms in figures 6 and 7 display our simulated distributions for the value of ENSO information. For brevity we focus on the case of warm events and normal risk aversion (i.e., crra=1). Figure 6 assumes fixed prices and reflects only yield variability, while for figure 7 a sub-routine sampled a different price year to go with each weather year, for the optimized responses. In figure 6, the mean (\$6.0/ha) and median (\$6.16/ha) indicate central tendency, and the probability of a negative VOI in any given year is 48%. A slight negative kurtosis indicates a flatter than normal distribution, implying a higher likelihood of extreme outcomes.

Figure 7 displays the interaction between climate and prices as sources of income variability. Price variability introduces positive skewness to the VOI histogram in figure 7. Because climate is favorable for crops in Pergamino, the mean or median yields are fairly close to their maximum potential, which explains the slight negative skew in figure 6. With variable prices, the VOI distribution in figure 7 has a longer right tail. The likelihood of a small VOI has increased slightly, since median VOI has decreased to \$5.32/ha (from \$6.16). At the same time, the increased likelihood of positive extreme events has raised the mean to \$10.70/ha (from \$6). The introduction of price variability also raises the standard deviation of the VOI distribution by 20%. The probability of a negative VOI in any given year at 48% remains the same as in the case of fixed prices.

Our use of long synthetic weather and price series has allowed us to generate probability distributions for economic returns and the value of ENSO information. At times a focus on central tendency may give a quite different perspective than one based on probability of occurrence. For example, we estimate that ENSO information can improve annual incomes in our study region between 1 and 9%, or $2 to $18 per ha. On the other hand, the probability that the value of ENSO information will be negative generally falls in the 45-50% range for the risk aversion levels we considered.

Each outcome we report has an associated probability of occurrence, a format most useful for decision makers but one that also usually has not been reported in the literature (Schimmelpfinnig 1996).

For many problems, especially those with nonlinear payoff functions, the probabilities of extreme events dominate decision-making (Patt, 1999). An increasing number of studies are focusing on extreme climatic events associated with ENSO (Gershunov, 1998; Cayan et al., 1999; Wolter et al., 1999). In contrast, less attention has been focused on ENSO's influence on extreme agricultural outcomes, probably because available historical records frequently are short. Our modeling approach produced a large number of outcomes, thus allowing exploration of extreme events.

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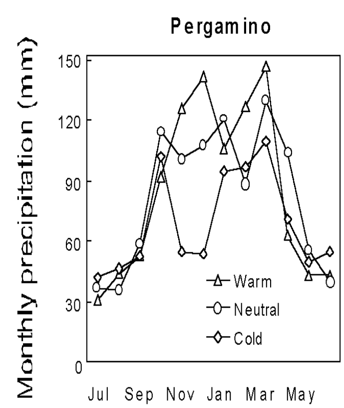

Figure 1: Mean monthly precipitation in Pergamino for each ENSO phase.

Nº	CROP	VARIETY	PLANTING DATE	NITRO KG/HA
1	Wheat	Oasis	Mid-June	60
2	Wheat	Isla Verde	Mid-July	60
3	Wheat	Oasis	Mid-June	100
4	Wheat	Isla Verde	Mid-July	100
5	Wheat	Oasis	Mid-June	140
6	Wheat	Isla Verde	Mid-July	140
7	Wheat / Soybean	Isla Verde / DM 48	Mid-July	60
8	Wheat / Soybean	Isla Verde / DM 48	Mid-July	100
9	Wheat / Soybean	Isla Verde / DM 48	Mid-July	140
10	Maize	DK 752	Sept. 10th	80
11	Maize	DK 752	Oct. 1st	80
12	Maize	DK 752	Oct. 20th	80
13	Maize	DK 752	Sept. 10th	120
14	Maize	DK 752	Oct. 1st	120
15	Maize	DK 752	Oct. 20th	120
16	Maize	DK 752	Sept. 10th	160
17	Maize	DK 752	Oct. 1st	160
18	Maize	DK 752	Oct. 20th	160
19	Sunflower	CF21-25	Oct. 20th	-
20	Soybean	A 5409	Early Nov.	
21	Soybean	DM 48	Early Dec.	

Table 1: Management Alternatives.

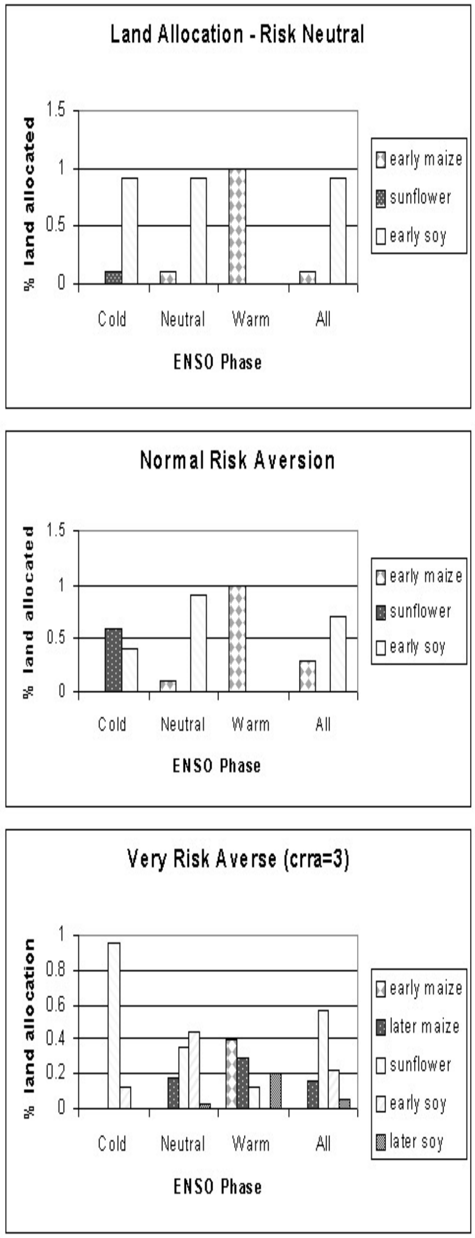

Figure 2. Optimal farm management by ENSO phase for neutral, normal and very high levels of risk aversion.

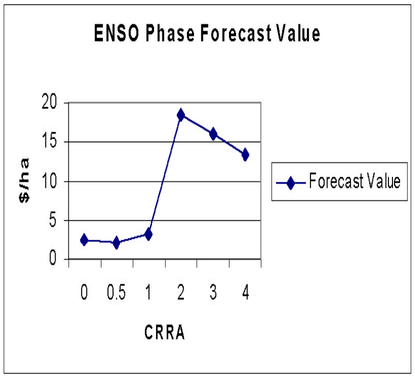

Figure 3: Value of information, by risk aversion level.

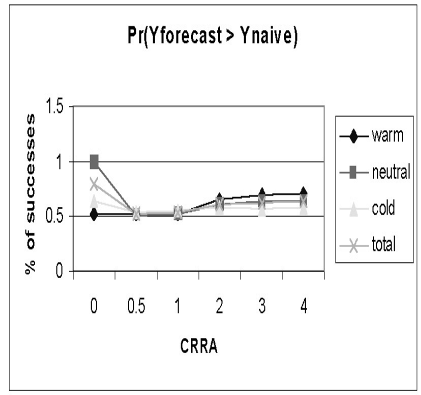

Figure 5: Probability of non-negative VOI, by CRRA and ENSO phase.

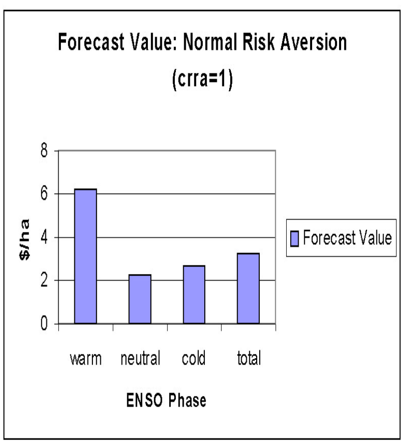

Figure 4: Value of information, by ENSO phase.

Table 2. Warm and Cold JMA ENSO Years between 1900 and 1999.

ENSO	Phase Years
Warm (22)	1902, 1904, 1905, 1911, 1913, 1918, 1925, 1929, 1930, 1940, 1951, 1957, 1963, 1965, 1969, 1972, 1976, 1982, 1986, 1987, 1991, 1997
Cold (25)	1903, 1906, 1908, 1909, 1910, 1916, 1922, 1924, 1938, 1942, 1944, 1949, 1954, 1955, 1956, 1964, 1967, 1970, 1971, 1973, 1974, 1975, 1988, 1998, 1999

Note: Years not listed are neutral.

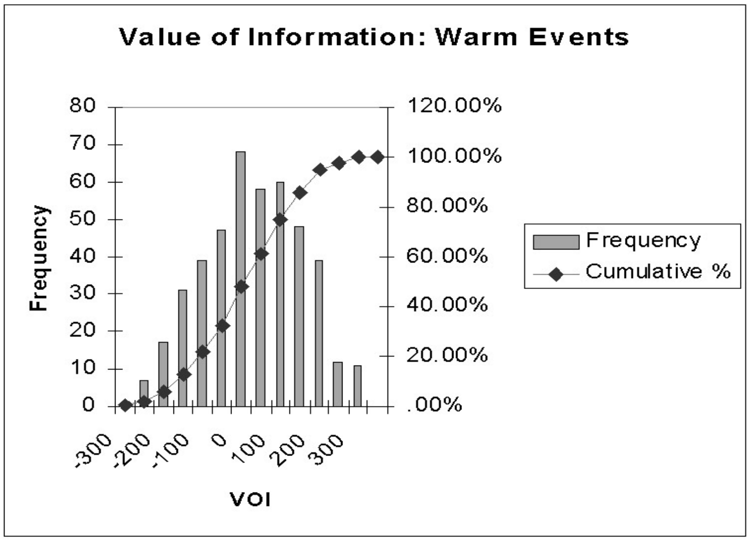

Figure 6: Value of information for warm events.

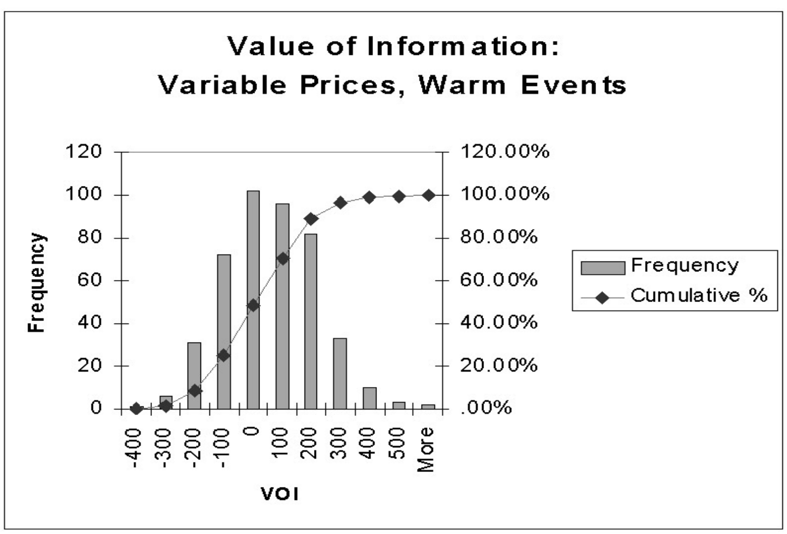

Figure 7: Value of information when prices vary.