Land allocation conditioned on El Niño-Southern Oscillation phases in the Pampas of Argentina

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Abstract

The El Niño-Southern Oscillation (ENSO) contributes to the vulnerability of crop production to climate variability in the Pampas region of Argentina. Predictability of regional climate anomalies associated with ENSO may provide opportunities to tailor decisions to expected climate, either to mitigate expected adverse conditions or to take advantage of favorable conditions. Model analysis was used to explore the potential for tailoring land allocation among crops to ENSO phases at the farm scale in two sub-regions of the Pampas. The model identifies as a function of risk preferences and initial wealth the crop mix that maximizes expected utility of wealth at the end of a 1-year decision period based on current costs and prices, and crop yields simulated for each year of historical weather. The model reproduced recent land allocation patterns at the district scale under moderate risk aversion, and predicted increasing diversification with increasing risk aversion. Differences in land allocation among ENSO phases were consistent with known climate response to ENSO, and crop response to water availability. Tailoring land allocation to ENSO phase increased mean net farm income between US$5 and $15 ha⁻¹ year⁻¹ relative to optimizing the crop mixture for all years, depending on location, risk aversion and initial wealth. The relationship between potential value of ENSO information and risk aversion was not monotonic, and differed between locations. Crop mix and information value also varied with crop prices and initial soil moisture. There are potential financial benefits of applying this approach to tailoring decisions to ENSO phases. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Climate prediction; El Niño-Southern Oscillation; Risk; Expected utility

1. Introduction

Climate variability is the major source of agricultural production risk in Argentina. The Pampas, the main agricultural region in Argentina, is characterized by high interannual variability of rainfall (CV = 28%) and rainfed crop production (Hall et al., 1992). Climate risk increases toward the western part of the region due to an east–west gradient (1000–600 mm year⁻¹) in precipitation. The CV of crop yields in the western districts ranges from 11% for sunflower to 20% for soybean. Median crop losses (i.e. planted area that is not...
harvested) range from 15% for wheat to 35% for sunflower. Farmers’ aversion to income risk leads to conservative management strategies that reduce mean productivity (Keating et al., 1991; Kingwell, 1994; Thornton and Wilkens, 1998).

The El Niño-Southern Oscillation (ENSO) accounts for much of the interannual variability of the climate of the Pampas (Kiladiz and Diaz, 1989; Halpert and Ropelewski, 1992; Ropelewski and Halpert, 1996). The ENSO phenomenon involves two extreme phases characterized by anomalously warm and cold surface waters in the eastern tropical Pacific. During cold events, maximum temperatures and solar irradiance tend to be higher, and minimum temperature and rainfall tend to be lower than normal. Warm events show an opposite but weaker influence. ENSO influences crop yields in the region through its influence on precipitation, temperatures and solar irradiance (Magrin et al., 1998; Podesta et al., 1999). While maize, soybean and sorghum yields tend to be lower than normal during cold events, sunflower yield shows a weaker and opposite response. Maize is the most responsive of the major field crops to increases in rainfall during warm events (Podestá et al., 1999).

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. Crop management and land allocation among alternative crops are the most important options available to farmers for managing climate risk (Muchow and Bellamy, 1991; Kingwell, 1994; van Noordwijk et al., 1994). Most applications of ENSO-based climate forecasts for managing risk have focused on management of individual crops (Hansen et al., 1996; Marshall et al., 1996; Meinke et al., 1996; Phillips et al., 1998). Attempts to use ENSO information to optimize land allocation decisions have generally been at regional, rather than farm, spatial scales (Adams et al., 1995; Solow et al., 1998).

The objective of this study is to explore the potential for managing climatic risk at a farm scale by tailoring land allocation among crops to ENSO phases in the Argentine Pampas. We accomplish this through model analysis of representative farms at two locations differing in rainfall, soils and present cropping patterns, and by analysis of the sensitivity of optimal crop mix and information value to factors that vary among farms (i.e. risk preferences, initial wealth, soil, climate) and between years (i.e. crop prices, initial conditions). The research tests three hypotheses under conditions appropriate to the Pampas region. First, optimal land allocation among crops differs among ENSO phases for a given physical and economic environment. Second, optimizing crop mix based on ENSO phase information increases mean farm income. Third, the physical and economic environment and farmers’ aversion to risk influence the optimal crop mix and potential value of ENSO information.

2. Land allocation model

Expected utility theory provides a quantitative framework for characterizing decision makers’ preferences among risky outcomes (Pratt, 1964; Robison et al., 1984; Hardaker et al., 1997). Non-linearity of a utility function $U$ of, for example, wealth $W$ accounts for risk attitudes. Increasing $U$ implies that the decision maker prefers more wealth to less. A concave utility function accounts for aversion to risk by giving low wealth greater weight than higher wealth. In other words, the expected utility of wealth is less than the utility of expected wealth. Aversion to risk is quantified by the curvature rather than the scale of $U$. For a given expected wealth, risk aversion can be expressed by a coefficient of absolute $R_a$,

$$R_a(W) = -U''(W)/U'(W),$$

or relative risk aversion ($R_r$),

$$R_r(W) = W/R_a(W) = -WU''(W)/U'(W),$$

where $U'$ and $U''$ are the first and the second derivatives of $U$ with respect to wealth. Theory predicts that decision makers seek to maximize the expected value of $U$ for the distribution of expected outcomes.
We assume that farmers allocate land to cropping enterprises in a way that maximizes the expected utility of wealth at the end of a 1-year planning period:

$$W_F = W_0 + \Pi,$$

where $W_0$ is initial wealth and $\Pi$ is risky farm net income during the year. The power function,

$$U(W_F) = W_F^{1-R_a}/(1 - R_a),$$  \hspace{1cm} (1)

used in this study implies constant relative risk aversion. Under this assumption, $R_a$ decreases as $W_0$ increases. Decisions are sensitive to additive changes in $W_0$ but insensitive to scale (i.e. proportional changes in $W_0$ and $\Pi$) (Pope and Just, 1991).

Empirical evidence supports the implication of Eq. (1) that wealthier farmers are less averse to risk than poorer ones (Young, 1979; Lins et al., 1981; Pope and Just, 1991; Chavas and Holt, 1990).

We assume that prices are known but weather is unknown at decision time. Farmers in the region have access to international future prices prior to planting, and can fix their prices by contract. This initial approach allowed us to isolate climate from price risks in our analysis. Effects of price variability were examined as a part of a sensitivity analysis (see below). Distributions of net income from each crop enterprise were calculated from constant crop prices (means for 1986–97) and input costs, and from yields simulated for each year of historical weather data within a particular category. Net farm income $\Pi$ (US$) that would result from weather year $i$ is calculated as:

$$\Pi_i = \sum_{j=1}^{m} x_j \pi_{ij} - C - T_i,$$  \hspace{1cm} (2)

$$\pi_{ij} = Y_{ij} P_j - c_j,$$  \hspace{1cm} (3)

where $x_j$ is land area (ha) allocated to crop $j$, $Y_{ij}$ and $\pi_{ij}$ are yield (Mg ha$^{-1}$) and gross margin (US$ ha^{-1}$) from crop $j$, $P_j$ and $c_j$ are price (US$ Mg^{-1}$) and fixed production costs (US$ ha^{-1}$) for crop $j$, $C$ is fixed farm costs (US$) and $T_i$ is income tax liability (US$). Variable crop production costs are factored into $P$.

For given expected weather conditions, optimal land allocation is determined by maximizing expected utility of wealth at the end of the decision period:

$$\max_x \mathbb{E}(U(W_F)) = \sum_{j=1}^{n} U(W_0 + \sum_{j=1}^{m} x_j \pi_{ij} - C - T_i)/n$$  \hspace{1cm} (4)

subject to:

$$Ax \leq b,$$

$$x \geq 0,$$

where $U_i$ is utility (Eq. (1)) for weather year $i$, $A$ is a matrix of technical coefficients, $x$ is the vector of areas allocated to each cropping system, and $b$ is a vector of farm resource constraints (Lambert and McCarl, 1985; Chavas and Holt, 1990). In this case, $b$ is the total farm size (a scalar) and $A$ becomes a vector of ones to relate land allocated to each crop to available land. Although this fairly standard formulation is flexible enough to handle a variety of linear constraints such as availability of labor or equipment, we consider only non-negativity and farm size constraints to land allocation.

The potential value $V$ of ENSO information can be expressed as the difference in expected economic returns to optimal decisions conditioned on ENSO phases and returns to optimal decisions based on the historical climatology (Thornton and MacRobert, 1994; Solow et al., 1998; Wilks and Wolfe, 1998), or:

$$V = (\sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{n} \Pi_{ik}^*)/n,$$  \hspace{1cm} (5)

where $\Pi_{ik}^*$ is farm income in year $j$ of ENSO phase $i$ given optimal crop mix for phase $j$, and $\Pi_{ik}$ is farm income in weather year $k$ given crop mix optimized for all $n$ weather years in the historical record. For ease of comparison, we express $V$ on a ha$^{-1}$ basis.
3. Approach

3.1. ENSO phases

ENSO events were categorized based on 5-month running means of spatially averaged sea surface temperature (SST) anomalies in the region of the tropical Pacific Ocean between 4°N–4°S and 90°–150°W. A crop year (preceding July to current June) was classified as a warm (cold) event if the SST anomalies were \( \geq 0.5 \)°C (\( \leq -0.5 \)°C) for at least six consecutive months including the October–December quarter (Sittel, 1994; Trenberth, 1997). The SST index is based on observed data for the period 1949 to the present. For years before 1949, the index was derived from reconstructed monthly mean SST fields (Meyers et al., 1999). The period from 1931 includes 13 warm events (1940, 1951, 1957, 1963, 1965, 1969, 1972, 1976, 1982, 1986, 1987, 1991 and 1997) and 15 cold events (1938, 1942, 1944, 1949, 1954, 1955, 1956, 1964, 1967, 1970, 1971, 1973–1975 and 1988).

3.2. Case study farms

We applied the land allocation model to representative farms at two locations in the Pampas. Hall et al. (1992) provide a thorough description of regional climate, soils and cropping systems. Pergamino is in the climatically favorable eastern humid region, where the dominant crops are maize, wheat and soybean. Santa Rosa is in the drier, climatically marginal western region, where yields are more variable due to years with water deficits. More drought-tolerant crops—wheat, sunflower and sorghum—dominate in this region. In both regions, wheat is sown in June and July, maize and sunflower in October and November, and soybean from mid-November through December. Dominant soils include Typic Hapludolls and Ustipsamets in Santa Rosa, and Vertic Argiudolls and Typic Hapludolls in Pergamino. Fig. 1 shows mean monthly precipitation by ENSO phase at each location.

Assumptions about the case study farms (Table 1) were based on information from AACREA (Asociacion Argentina de Consorcios Regionales de Experimentacion Agricola). Livestock is an important component of farming systems near Santa Rosa. However, because this study focuses on crop production, calculations of income, taxes and initial wealth were based only on that portion of the farm devoted to crops.

Initial wealth is defined as liquid assets, estimated at 60% of the recent value of crop land. This definition is based on the assumption that a farmer will not sacrifice future income potential by selling crop land, but can borrow up to 60% of land value. We assumed that the farmer owns his land, and does not carry debt on facilities or equipment beyond their salvage value. Production
costs for each crop were estimated using technical assumptions made by AACREA (1998) and historical input prices provided by SAGPyA (Secretaria de Agricultura, Ganaderia, Pesca y Alimentacion). Variable production costs include: (1) harvest costs equal to 8% of crop value; (2) trading costs equal to 10% of value for maize, 8% for soybean, 7% for wheat and 6% for sunflower; and (3) transportation costs. Trading costs include a 2% tax on gross income, drying costs, discounts for weed seed presence and 3% trader commission. Fixed farm costs include administration costs and property taxes. Income tax $T_i$ was calculated for each weather year $i$ as:

$$T_i = \begin{cases} 
  b(\Pi_i - a) + c & \Pi_i > a \\
  0 & \Pi_i \leq a 
\end{cases}$$

where $a$, $b$ and $c$ are tabulated values designed to provide an incrementally progressive marginal tax rate. Mean farmgate prices (Table 2) were estimated from historical prices (1986–97) at the Rosario port for all crops at Pergamino and for maize and soybean in Santa Rosa. Wheat and sunflower prices at Santa Rosa are based on prices for the same period at the Bahia Blanca port. The sunflower price includes an 8% premium for oil content.

### 3.3. Crop simulation

Dynamic, process-level crop simulation models have proven useful for quantifying the interactions between weather variability, management and the physical environment. They were used in this study to estimate distributions of crop yields due to historical climate variability for given soils 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. Careful regional calibration and validation of these models has been performed at INTA (Instituto Nacional de Tecnologia Agropecuaria)
INTA researchers provided characteristic parameter values calculated for the dominant agricultural soils and commonly used crop cultivars in the Pampas (Meira, Magrin and Travasso, personal communication). Daily weather data for the 1931–97 period (rainfall, maximum and minimum temperature, bright sunshine duration and limited periods of solar irradiance) for Pergamino and Santa Rosa are from the Servicio Meteorologico Nacional, and have undergone extensive quality checking (Podestá, University of Miami, personal communication). Solar irradiance $H$ (MJ m$^{-2}$ day$^{-1}$) was estimated from bright sunshine duration ($S$) using the Ångström (1924) equation, with monthly $a$ and $b$ coefficients calculated by robust regression (Lanzante, 1996). When both $H$ and $S$ were missing (26% of days at Santa Rosa, 25% at Pergamino) $H$ was generated stochastically using an adaptation of WGEN (Richardson and Wright, 1984) that incorporates the stochastic solar irradiance model described by Hansen (1999). Typical management practices for each crop and location (Table 3) are based on data provided by the farmer organizations, AACREA and FAA (Federacion Agraria Argentina). Simulated sowing was conditioned on soil conditions, and occurred as soon after the dates in Table 3 as soil water content in the top 10 cm exceeded 50% of plant-extractable soil water holding capacity, and soil temperature exceeded 5°C for wheat, 12°C for maize and 14°C for sunflower and soybean.

Soil conditions at sowing vary among years, and have important effects on simulated yields. This is particularly important for deep soils with high water holding capacity, such as those in the Pampas region. Average initial soil conditions were calculated from continuous long-term (1931–97) sequences simulated for each cropping system.

### Table 2
Mean and standard deviation of farmgate pricesa (US$ Mg$−1) for field crops (1986–97)

<table>
<thead>
<tr>
<th>Crop</th>
<th>Harvest period</th>
<th>Pergamino</th>
<th>Santa Rosa</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>$S$</td>
<td>Mean</td>
</tr>
<tr>
<td>Maize</td>
<td>Apr.–Jun.</td>
<td>97</td>
<td>26</td>
</tr>
<tr>
<td>Soybean</td>
<td>May–Jul.</td>
<td>221</td>
<td>58</td>
</tr>
<tr>
<td>Wheat</td>
<td>Dec.–Feb.</td>
<td>110</td>
<td>34</td>
</tr>
<tr>
<td>Sunflower</td>
<td>Feb.–May</td>
<td>180</td>
<td>35</td>
</tr>
</tbody>
</table>

a Source: SAGPyA, archives.

### Table 3
Management assumptions used for crop simulations

<table>
<thead>
<tr>
<th>Crop</th>
<th>Cultivar</th>
<th>Planting Datea</th>
<th>Density (m$^{-2}$)</th>
<th>$N$ Fertilizera</th>
<th>Amount (kg ha$^{-1}$)</th>
<th>Cultivar</th>
<th>Planting Dateb</th>
<th>Density (m$^{-2}$)</th>
<th>$N$ Fertilizerb</th>
<th>Amount (kg ha$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maize</td>
<td>‘DK 752’</td>
<td>1 Oct.</td>
<td>8.0</td>
<td>40</td>
<td>60</td>
<td>‘DK 752’</td>
<td>1 Oct.</td>
<td>5.5</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>Soybean</td>
<td>‘A 5435’</td>
<td>1 Nov.</td>
<td>25.0</td>
<td>–</td>
<td>0</td>
<td>‘DM 4700’</td>
<td>1 Nov.</td>
<td>25.0</td>
<td>–</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>‘A 5435’</td>
<td>20 Dec.</td>
<td>30.0</td>
<td>–</td>
<td>0</td>
<td>‘DM 4700’</td>
<td>15 Dec.</td>
<td>30.0</td>
<td>–</td>
<td>0</td>
</tr>
<tr>
<td>Wheat</td>
<td>‘Oasis’</td>
<td>5 Jun.</td>
<td>200.0</td>
<td>0</td>
<td>75</td>
<td>‘Pigue’</td>
<td>1 Jul.</td>
<td>250.0</td>
<td>–</td>
<td>0</td>
</tr>
<tr>
<td>Sunflower</td>
<td>‘Conti 3’</td>
<td>1 Oct.</td>
<td>5.0</td>
<td>–</td>
<td>0</td>
<td>‘Conti 3’</td>
<td>10 Oct.</td>
<td>4.0</td>
<td>–</td>
<td>0</td>
</tr>
</tbody>
</table>

a Target date. Simulations permitted delayed sowing due to unfavorable soil temperature and water content for all crops, and preceding wheat maturity date for double-cropped soybean.
b Days after planting.
Simulated soil water, NO₃⁻ and NH₄⁺ contents on 31 March, averaged across years and cropping systems, were used as initial conditions for the crop simulations used to optimize land allocation. The 31 March initialization date for soil water and N-balance simulations is based on the assumption that soil water content is predictably low shortly after the summer crop harvest. Starting soil simulations early captures the effect of recharge from rain during the fallow from 31 March to sowing.

3.4. Optimization

The first step in calculating optimal land allocation was to simulate yields for each cropping system and every year of weather data. Gross margins from each crop enterprise (Eq. (3)) were then calculated from constant production costs (Table 1) and prices (Table 2), and yields simulated for each weather year. Eq. (4) was then solved by constrained nonlinear optimization to identify the set of areas (x) allocated to each crop enterprise that maximized expected utility. This study used the generalized reduced gradient algorithm (Lasdon et al., 1978) included in the Microsoft (1997) Excel spreadsheet software. Because the utility function (Eq. (1)) is always concave for \( R_e > 0 \), the procedure is expected to always identify the global maximum (Lambert and McCarl, 1985). However, we used several random starting values of x to ensure that the solution identified was the global optimum. The optimization loop iteratively adjusted x subject to constraints, calculated \( \Pi_i \) (Eq. (2)) and \( U(\Pi_i) \) (Eq. (1)) for each weather year \( i \), then calculated the current value of the objective function as the average utility among weather years.

We repeated the optimization procedure for all 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 \( V \) of ENSO information (Eq. (5)).

3.5. Sensitivity analyses

3.5.1. Risk preferences and initial wealth

The optimization problem (Eqs. (1)–(4)) was solved for typical farms at Santa Rosa (600 ha) and Pergamino (630 ha) for four levels of relative risk aversion (\( R_e = 0.0, 1.0, 2.0 \) and 3.0) representing risk-neutral and slightly, moderately and very risk-averse decision makers (Hardaker et al., 1997). Three levels of initial wealth were considered for Pergamino (\( W_0 = \$1386, \$1108 \) and \( \$831 \) ha⁻¹) and Santa Rosa (\( \$521, \$417 \) and \( \$312 \) ha⁻¹) based on the ability to borrow up to 60% of land value, and 20 and 40% reductions from that maximum. The reduced levels of \( W_0 \) account for indebtedness.

3.5.2. Sensitivity to factors that vary among years

Crop prices and soil conditions, water and nitrogen content at sowing, vary among years and influence gross margins of individual crop enterprises. To test the influence of these factors on optimal land allocation and information value, the land allocation model was solved for a moderately risk-averse farmer (\( R_e = 2 \) and \( W_0 = 1108 \)) at Pergamino using different crop prices and different initial soil conditions. Sensitivity of optimal crop mix and information value to price variability was explored by solving the land allocation model using crop prices for individual years from 1986–97. Sensitivity of optimal crop mix and information value to soil conditions variability was tested using information, derived from simulation, that attempted to capture crop and climate effects during the preceding growing season and fallow on soil water and nitrogen content at sowing. We analyzed sensitivity to these factors by comparing yields and optimization results simulated using average soil initial conditions derived for each preceding cropping system. Soil water, NO₃⁻ and NH₄⁺ contents by soil layer were averaged for all years as described previously from long-term sequential simulations for wheat, the wheat–soybean double crop, and the mean among summer crops (i.e. maize, sunflower, soybean). We repeated the procedure using soil initial conditions derived for each preceding ENSO phase.

4. Results and discussion

Crops included in the optimal crop mix differed between the two locations. For moderate risk
aversion ($R_r = 2; W_0 = \text{US}\$812 \text{ ha}^{-1}$ at Pergamino and \text{US}\$417 \text{ ha}^{-1}$ at Santa Rosa), the model predicted optimal farm land allocation for all years that was quite similar to the actual allocation of land among cropping systems in the districts corresponding to each location (Alippe, unpublished report; Cascardo et al., 1988) (Fig. 2). Under the assumption of risk neutrality, all land was allocated to the cropping system with the highest mean net return (Table 4). The predicted increase in diversification among crop enterprises with increasing aversion to risk is consistent with other studies (Patten et al., 1988; Kingwell, 1994). As risk aversion increased from neutrality to $R_r = 3$, simulated mean income decreased from \text{US}\$128 to \text{US}\$117 \text{ ha}^{-1}$ in Pergamino and from \text{US}\$13 to \text{US}\$4 \text{ ha}^{-1}$ in Santa Rosa, while the standard deviation of income decreased from \text{US}\$154 to \text{US}\$109 \text{ ha}^{-1}$ in Pergamino and from \text{US}\$135 to \text{US}\$44 \text{ ha}^{-1}$ in Santa Rosa. This pattern of increased diversification and decreasing variability of farm income with increasing risk aversion can be explained by the imperfect correlation of yields and, therefore, of gross margins, among crop enterprises (Table 4). A mixture of risky strategies will have a lower overall risk (expressed by standard deviation $S$) than the weighted average of risk of the individual strategies if their cross-correlation is less than one (van Noordwijk et al., 1994). Overall risk of the mixture decreases as income correlation among crop enterprises decreases.

The very low mean income simulated for Santa Rosa suggests that crop production should not be feasible in that region given historical climate conditions. The ratio of cultivated to grazed land has increased in recent decades. Viglizzo et al. (1995) attribute this trend primarily to an increasing trend in precipitation (Fig. 3A). Simulations showed a trend toward increasing yields and farm income due to changes in climate at Santa Rosa. Mean farm income simulated for a moderately risk-averse farmer ($R_r = 2, W_0 = \text{US}\$417 \text{ ha}^{-1}$) increased from \text{US}\$19 \text{ ha}^{-1}$ for the period 1940–70 to \text{US}\$43 \text{ ha}^{-1}$ for 1971–97 (Fig. 3B). The trend in simulated income helps to explain the observed
changes in land use, and reconciles the current feasibility of crop production with the extremely low long-term mean simulated income. We chose to base our analyses of farm-scale land allocation on the entire weather series (1931–97) to ensure adequate representation of warm and cold events. The implications of this decision on current land use decisions needs further research.

4.1. Optimal land allocation conditioned to ENSO

Fig. 4 shows optimal land allocation among cropping systems predicted for Pergamino and Santa Rosa for varying levels of risk aversion. The differences in optimal crop mix among ENSO phases can be explained by differences in crop tolerance to water availability, and are consistent with known effects of ENSO on rainfall in this region (Fig. 1). Precipitation tends to be low during cold events and high during warm events in the critical period from November to December when grain number is determined in maize (Hall et al., 1992; Cirilo and Andrade, 1994) and sunflower (Cantagallo et al., 1997). Rainfall is less influenced by ENSO during pod formation in soybean (February), when the crop is most susceptible to water shortage (Sinclair et al., 1994). The optimal crop mix for the cold phase was dominated by crops that either tolerate water stress (i.e. sunflower in Santa Rosa) or avoid periods of water shortage during critical development stages (i.e. wheat and soybean in Pergamino). In Pergamino, the majority of land was allocated to maize in the warm phase. Under conditions of ample rainfall and average prices (Table 2), maize is generally the most profitable crop in the region.

4.2. Influence of risk aversion

Under the assumption of risk neutrality, the optimization procedure usually selected the monoculture with the highest mean gross margin for
each ENSO phase (Table 4; Fig. 4A, D). The exception was the cold phase in Pergamino, where the optimal crop mix included both wheat and soybean. Monocultures are expected when risk neutrality is assumed (Mjelde et al., 1996, 1997). However, the progressive marginal tax rate in Argentina reduces the marginal value of increasing income and, therefore, has the same effect as risk aversion (Hardaker et al., 1997). Simulated gross margins of the two crops were quite similar on the average, but negatively correlated (Table 4). The influence of risk aversion on the value of ENSO information differed between the two locations (Fig. 5). At Pergamino, $V$ increased monotonically with increasing $R_\gamma$ for the range considered. However, at Santa Rosa, $V$ decreased as $R_\gamma$ increased above 1.0. Favorable climate conditions and relatively greater initial wealth and mean income in Pergamino generally favored strategies that take advantage of the greater climatic differences among ENSO phases that occur in Pergamino. In contrast, the more adverse climatic conditions in Santa Rosa favored strategies that protect farmers from extremely low incomes. The decrease of $V$ with increasing $R_\gamma$ reflects the high probability of negative net incomes in all ENSO phases, and the similarity of strategies to avoid economic loss among ENSO phases. Furthermore, lower initial resource endowment and mean income results in greater absolute risk aversion for a given relative risk aversion in Santa Rosa than in Pergamino. These results support the lack of monotonic relationship between risk aversion and the value of information predicted by Hilton (1981). Mjelde and Cochrane (1988) also found a negative relationship between risk aversion and climate information value when crop management strategies were optimized for adverse climate conditions, and a positive relationship when climatic conditions were more favorable.

4.3. Influence of prices

The possible effect of prices on optimal crop mix and the value of ENSO information were explored by optimizing land allocation for different observed commodity prices for a moderately risk-averse farmer ($R_\gamma = 2$, $W_0 = 1108$) at Pergamino.
Changes in relative prices (Table 5) can favor or exclude crops from the set of feasible options (see examples in Fig. 6). An increase in the price of one crop relative to the others (e.g. maize in 1989, Fig. 6A) can reduce the feasibility of the alternatives and decrease differences in optimal crop mix among ENSO phases. The resulting loss of flexibility reduces the potential value of ENSO information. This was the case for 1987–90, 1996 and 1997 price scenarios. The relatively high soybean prices in 1987, 1988 and 1997 favored monocultures for all ENSO phases, resulting in an ENSO information value of zero (Table 5). In contrast, the balance of commodity prices in 1992 (Fig. 6B) enhanced the value of ENSO information by favoring differences in optimal crop mix among ENSO phases. The greatest absolute benefit from tailoring land allocation to ENSO phases came from 1994 prices (Fig. 6C), when high sunflower prices compensated for its relatively low productivity.

These results illustrate the important effect of relative prices of alternative crops on optimal land allocation. Relative pricing can limit the potential benefit of ENSO information in particular years. Decision support applications of this type of optimization model should, therefore, always be based on the most current price expectations.
4.4. Sensitivity to soil initial conditions

Simulated mean initial (31 March) extractable soil water and mineral N contents were sensitive to the preceding crop (Table 6). The preceding ENSO phase influenced initial soil water, but not N. Simulated crop yields responded significantly to the different initial conditions (Table 6). Among the crops considered, maize was the most sensitive and sunflower the least sensitive to different initial soil conditions due to previous ENSO phase. Initial soil conditions also influenced optimal land allocation for any single year. Maize and soybean tended to dominate the optimal crop mix when initial soil water contents were high (i.e. following wheat monoculture or warm events) at Pergamino, while drier initial conditions (i.e. following wheat–soybean) tended to favor the wheat–soybean double crop (data not shown).

Both mean income for the crop mix optimized without considering ENSO and the potential value of ENSO information were quite sensitive to differences in initial soil conditions (Table 6). With the exception of initial conditions associated with the wheat–soybean double crop, initial conditions influenced mean income and information value in the same direction. The relatively high information value following the double crop suggests that ENSO information might help farmers avoid important losses associated with growing soybean after wheat during a cold event (data not shown). These results highlight the sensitivity of initial soil conditions to conditions in the preceding

Table 5
Historical price scenarios (1986-97) and corresponding predicted ENSO information value for a moderately risk-averse farmer at Pergamino

<table>
<thead>
<tr>
<th>Year</th>
<th>Relative crop price a</th>
<th>Information value (US$ ha⁻¹)</th>
<th>% b</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maize</td>
<td>Soybean</td>
<td>Wheat</td>
</tr>
<tr>
<td>1986</td>
<td>0.87</td>
<td>0.81</td>
<td>0.68</td>
</tr>
<tr>
<td>1987</td>
<td>0.89</td>
<td>1.15</td>
<td>0.79</td>
</tr>
<tr>
<td>1988</td>
<td>1.08</td>
<td>1.48</td>
<td>1.08</td>
</tr>
<tr>
<td>1989</td>
<td>1.50</td>
<td>1.34</td>
<td>1.20</td>
</tr>
<tr>
<td>1990</td>
<td>0.90</td>
<td>0.72</td>
<td>1.30</td>
</tr>
<tr>
<td>1991</td>
<td>0.84</td>
<td>0.77</td>
<td>0.47</td>
</tr>
<tr>
<td>1992</td>
<td>0.84</td>
<td>0.82</td>
<td>0.93</td>
</tr>
<tr>
<td>1993</td>
<td>0.83</td>
<td>0.92</td>
<td>1.01</td>
</tr>
<tr>
<td>1994</td>
<td>0.93</td>
<td>0.94</td>
<td>0.96</td>
</tr>
<tr>
<td>1995</td>
<td>0.88</td>
<td>0.79</td>
<td>0.98</td>
</tr>
<tr>
<td>1996</td>
<td>1.46</td>
<td>1.04</td>
<td>1.64</td>
</tr>
<tr>
<td>1997</td>
<td>0.97</td>
<td>1.22</td>
<td>0.97</td>
</tr>
</tbody>
</table>

a Prices relative to observed mean prices for 1986–97.

b ENSO information value relative to mean income for the optimal crop mix without using ENSO information.
growing season, and confirm the importance of assumptions about initial soil water content for obtaining reliable yield simulations. Marshall et al. (1996) indicated that improved initial soil conditions may increase the potential benefit of climate forecasts to Australian wheat farmers.

5. Conclusions

The simple model presented in this paper identifies optimal land allocation by maximizing the expected value of nonlinear utility of wealth associated with a given distribution of simulated

Table 6

<table>
<thead>
<tr>
<th>Factor</th>
<th>Initial soil *</th>
<th>Mean simulated</th>
<th>Information value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Water (mm)</td>
<td>N (kg ha⁻¹)</td>
<td>Crop yield (Mg ha⁻¹)</td>
</tr>
<tr>
<td>Previous crop</td>
<td></td>
<td></td>
<td>Maize</td>
</tr>
<tr>
<td>Wheat</td>
<td>210</td>
<td>168</td>
<td>7.9a</td>
</tr>
<tr>
<td>Summer crops</td>
<td>134</td>
<td>57</td>
<td>6.0b</td>
</tr>
<tr>
<td>Wheat–soybean</td>
<td>78</td>
<td>41</td>
<td>4.7c</td>
</tr>
<tr>
<td>Previous ENSO phase</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Warm</td>
<td>174</td>
<td>77</td>
<td>7.0a</td>
</tr>
<tr>
<td>Neutral</td>
<td>124</td>
<td>73</td>
<td>6.3ab</td>
</tr>
<tr>
<td>Cold</td>
<td>105</td>
<td>76</td>
<td>5.7b</td>
</tr>
</tbody>
</table>

* Mean simulated extractable soil water and mineral N on 31 March.

* Means for a given crop followed by different letters differ significantly (p = 0.05) by Tukey’s multiple comparison test.

* Obtained for land allocation optimized without using ENSO information.

* ENSO information value relative to mean income for the optimal crop mix without using ENSO information.
The model proved useful in accomplishing our objective of exploring the potential benefits of tailoring farm land allocation to ENSO phases, and is a step toward the practical application of ENSO-based climate prediction to farm-scale land allocation decisions. The ability of the optimization model to predict actual land use practices at a district scale strengthens confidence in the validity of the approach, input data and assumptions. Results of this exploratory study complement previous studies that focused either on optimizing management for a single crop or cropping patterns at regional scale, and suggest that the optimization model has potential as a farm decision support tool. The structure of the model is readily adapted to consider other constraints or objectives that may be relevant to particular farms. Further research is necessary to explore implications of other farm constraints (e.g. labor and machinery capacity) and crop management tailored to ENSO phase on the potential value of ENSO information.

Predicted optimum land allocation varied among ENSO phases in a manner that was consistent with known influences of ENSO on precipitation and differences in sensitivity to water availability among crops. Results suggest that tailoring land allocation among crops to ENSO phases can increase mean farm income by 9% in average and up to 20%. However, optimal crop mix and resulting financial benefits are quite sensitive to factors that vary among location, farm characteristics and years. In particular, effects of risk aversion on potential ENSO information value was nonmonotonic and influenced by location. Changes in prices and risk aversion within plausible ranges can constrain the value of ENSO information by restricting the feasibility of alternative crop enterprises. Except for the previous crop scenario wheat–soybean, initial soil water content affect crop yields, land allocation and forecast value proportionally to net mean income. For these reasons, decision support applications of this type of model should be updated each year based on current price expectations and soil water content, and consider the characteristics and environment of each farm. We emphasize the importance of using locally validated crop models and high quality historical weather records in order to obtain reliable results from the optimization model.

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References


