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Climatic information and decision-making in maize crop production systems of the Argentinean Pampas

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Abstract

In many places, predictions of regional climate variability associated with El Niño Southern Oscillation (ENSO) phenomenon offer the potential to improve farmers' decision-making, i.e., mitigate negative impacts of adverse conditions or take advantage of favorable conditions. However, various conditions must be met for a forecast to result in enhanced decision-making. First, information has to be relevant to, and compatible with production decisions. Second, alternative options must exist for a given decision and these should result in different outcomes under different climate conditions. Third, decision-makers should be able to evaluate the outcomes of alternative actions. In this paper, we explored these conditions as part of a case study targeting maize production systems in the Argentine Pampas. The decision-making process was described via "decision maps" that (a) characterized the main decisions involved in maize production systems and their timing, (b) identified decisions sensitive to climate, and (c) provided a realistic set of options for each decision under different seasonal climate scenarios. Then, we used crop simulation models to assess the outcomes of tailoring crop management

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to predicted climate conditions. We found differences between the options selected by regional advisors for each climate scenario and those that maximized average profits in the simulation exercise. In particular, differences were most noticeable in preferred nitrogen fertilization rates. While advisors tended to lower fertilization in response to a forecast of dry spring conditions, associated with La Niña events, the simulation exercise showed a consistent drop in maize yields and profits with low N rates even in La Niña years. Advisors and producers' aversion to risk can be determining these differences, since the analysis showed that the probability of negative economic results are minimized under their decision rule. The procedure was effective to meet some of the conditions required to use climate information and to determine the value of incorporating ENSO-related information to effectively improve the maize decision process. However, results suggest that better knowledge of farmers decision rules are necessary when the value of using climatic information is estimated and interpreted.

Keywords: ENSO; Maize; Argentine pampas; Decision map; Value of climate information

1. Introduction

Climate variability is one of the main sources of uncertainty and risk in many agricultural systems around the world. Indeed, agriculture has been described as the most weather-dependent of human activities (Oram, 1989), and most production decisions directly or indirectly involve a consideration of this factor. Because farmers usually do not know what climate to expect in the following growing season, they have evolved conservative cropping strategies that not only may fail to capitalize fully on beneficial conditions but also frequently buffer poorly against negative effects (Jones et al., 2000; Hansen, 2002; Meinke and Stone, in press).

The El Niño-Southern Oscillation phenomenon (ENSO) is the major single source of climatic variability on seasonal-to-interannual scales in many parts of the world (Trenberth and Stepaniak, 2001; Goddard et al., 2001). This phenomenon results from the two-way interaction between the ocean and atmosphere in the tropical Pacific Ocean. ENSO involves two extreme phases: warm events, also known as "El Niño" years, and cold events, referred to as "La Niña"; those years which do not fall in these extreme phases are labeled as "Neutral" (Trenberth, 1997). Links between ENSO-related climate variability and agricultural outcomes have been shown in many agricultural regions (Dilley, 1997; Hsieh et al., 1999; Hammer et al., 2001; Hansen et al., 1996; Naylor et al., 2001; Amissah-Arthur et al., 2002; Gimeno et al., 2002). There are indications that ENSO also may influence prices of globally traded agricultural commodities (Chapman et al., 2000; Letson and McCullough, 2001).

Advances in understanding and observations of the oceans and atmosphere have made it possible to predict with moderate skill ENSO-related sea surface temperature (SST) anomalies some months in advance (Latif et al., 1998; Goddard et al., 2001). Predicted SSTs and atmospheric general circulation models are subsequently used to predict seasonal-mean precipitation and temperature in many regions (Mason et al., 1999; Goddard et al., 2003). The emerging capability to predict regional climate and its consequences on agricultural production systems offers the potential to improve farmers' decision-making, allowing them to mitigate adverse conditions or, alternatively, take advantage of favorable conditions (Hammer et al., 2001; Hansen, 2002; Meinke and Stone, in press).

The availability of climate forecasts, regardless of how accurate and well communicated is not sufficient to ensure that agricultural incomes will rise or production costs will fall (Jones et al., 2000; Hansen, 2002). Several conditions have been proposed by previous studies as necessary for climate forecasts to result in improved outcomes, regardless of the specific application sector, or the temporal and spatial scales of the application (Lamb, 1981; Sonka et al., 1987; Everingham et al., 2002; Hansen, 2002; Meinke and Stone, in press). Here we present some of these conditions, stressing that the list discussed is not exhaustive by any means. First, information has to be relevant to, and compatible with production decisions. In part, this is a function of the existence of entry points for climate information into the decision-making process (Jones et al., 1999b). Second, alternative options must exist for a given decision. Examples of possible alternative actions include land allocation among various farm activities (Messina et al., 1999) or the specific management of a crop (Meinke and Stone, 1997; Jones et al., 2000). Furthermore, the alternative actions should show an interaction with expected climate scenarios. That is, a given action should result in different outcomes under different climate conditions. Third, decision-makers ideally should be able to evaluate the outcomes of alternative actions. Crop models and simulation approaches provide a way to explore the consequences of a broad range of decisions (Hammer, 2000; Meinke et al., 2001). Fourth, the forecasts must have useful accuracy (but note that usefulness depends on the specific application) and appropriate lead-time and geographical and temporal resolutions (Hansen, 2002; Hartmann et al., 2002; Podestá et al., 2002). Finally, decision-makers must be willing and able to modify their actions in response to climate information. This depends not only on the individual decision-maker's willingness to adopt climate-adaptive management in an already complicated decision environment, but also on the economic, institutional, and cultural context in which farmers make decisions (Eakin, 2000). Similar conditions have been proposed by several other authors.

In this work we explore some of the previously listed conditions for the effective use of seasonal-to-interannual climate information and forecasts in agricultural production. Specifically, we study decision-making processes in maize production systems in the Argentine Pampas of central-eastern Argentina, one of the most productive agricultural areas in the world (Hall et al., 1992).

The Pampas show a strong ENSO signal, particularly in the southern spring–summer, coinciding with the growing season of the most valuable crops (Ropelewski and Halpert, 1987, 1989, 1996; Vargas et al., 1999; Grimm et al., 2000). During these months, warm (cold) ENSO events tend to be wetter (drier) than neutral years. In Neutral years, precipitation tends to be very close to climatological values (as these years account for about half of the historical record). ENSO-related climate variability influences yields of important crops in the Pampas (Podestá et al., 1999; Jones et al., 2000; Travasso et al., 2003). In particular, maize yields showed the closest association with ENSO. Warm ENSO events had a positive effect on yields of this crop: above-normal maize yields (those in the upper third of the historical distribution after removing trends due to technological changes) were twice as likely during warm events as by chance alone. A similar but opposite pattern was observed during cold events: low maize yields (in the lower third of the historical distribution) occurred twice as frequently as expected by chance (Magrín et al., 1998; Podestá et al., 1999).

Because the vast majority of agriculture in the Pampas is rainfed, the link between ENSO and maize yields seems to be mediated by coincidence in the timing of ENSO-related precipitation anomalies with sensitive periods shortly before or during crop development. For instance, maize flowering (that occurs in December/early January in the study area) is extremely critical in defining maize yield, and sensitivity to water availability during this period is high (Hall et al., 1981, 1992). Because of the strong associations between ENSO and expected regional climate and yields, maize production systems provide a good test-bed to explore the use of climate information and forecasts in agricultural decision-making.

The overarching objective of the paper is to evaluate the potential for incorporating ENSO-related climate information to support farm-level decisions during the cropping cycle in maize crop production systems of the Argentine Pampas. Specific objectives of the paper are (i) to characterize the decision-making process in a Pampean maize production system; (ii) to assess the outcomes of various technological options under different expected climate scenarios; and (iii) to evaluate the possible impacts of using climate information on maize yields and economic results. The paper is organized as follows. First, we build a decision map identifying production decisions that are sensitive to climate information and describe how these decisions are made in response to expected climate conditions. Then, we use crop simulation models to evaluate the outcomes of a realistic set of alternatives for each climate-sensitive decision. Finally, we quantify the effects on yields and economic returns of incorporating seasonal climatic forecasts into decision-making in maize production in the Pampas.

2. The study area

The geographic focus of this study is the Pampas of central-eastern Argentina (Hall et al., 1992). A large proportion of Argentina's considerable crop production originates in this region. We focus on the area around Pergamino (33°56′ S, 60°33′ W) in the Rolling Pampas, the most productive subregion of the Pampas where maize production is concentrated (Hall et al., 1992; Paruelo and Sala, 1993). The predominant soils in this region are typical Argiudolls and Hapludolls (Paruelo and Sala, 1993). Although soils are fertile, phosphorus fertilizer is applied as starter and there are high responses to nitrogen fertilizer, particularly if $N\text{-}NO_3$ content at sowing is low (Satorre, 2001). Median annual precipitation in Pergamino is 937 mm, with maxima in fall and late springsummer, and a winter minimum. The high water demand by maize during its late spring–early summer growth (about 6 mm day^{-1}), together with relatively limited soil water storage capacity, make maize yield heavily dependent on precipitation at this time (i.e., soil moisture storage is insufficient to satisfy the crop's needs).

Agricultural production systems in Argentina have changed markedly in the last 20 years (Satorre, 2002). In the study region, the traditional mixed crop – cattle rotation gave way to continuous agriculture (Hall et al., 1992). Typical crop rotations include maize, followed by soybean, and a wheat–soybean relay (Solari, 2002). However, in recent years, this rotation has been somewhat replaced by an increasing trend towards monoculture of soybeans, mostly because soybeans have lower production costs, simpler management, and more stable yields than those of maize (the other major summer crop). About half of the cropped area in the Pampas is currently planted with soybeans (Satorre, 2002), and there are increasing concerns about the sustainability and resilience of such a system. Effective use of climate information may foster enhanced management and higher gross margins for maize, thus providing incentives to improve crop diversity, and reducing the overall vulnerability of agriculture in the Pampas.

3. Methods

3.1. Development of a decision map for maize production

The effective use of climate information in agricultural production requires that this information be relevant to production decisions (Jones et al., 1999b). To determine relevance, a first step is to identify the existence of entry points for climate information into the decision-making process. Towards this goal, we built a "decision map" for a maize production system in Pergamino that characterized (a) the main decisions required in maize production systems and their timing, (b) the climatic conditions that affect each decision, and (c) a realistic set of appropriate options for each decision under different seasonal climate scenarios. The climate-sensitive decisions involved in maize production were described through simplified schematic models or influence diagrams (Burns and Clemen, 1993; Morgan et al., 2002). Influence diagrams are analytical tools that facilitate the identification and selection of variables used in conceptual or simulation models (Jones et al., 1998a).

An initial version of the decision map was developed based on the regional literature and the authors' knowledge of production practices in the study area. The draft decision map then was discussed and validated in focus groups with eight technical consultants who are active in the study region and have considerable influence on decisions taken by farmers. Consultants also were presented with a broad range of management options and were asked to select a particular management combination for each ENSO phase, based on their experience. The maps were also validated to a limited extent (due to limited resources) by 16 farmers and other stakeholders.

3.2. Simulation of maize yields and economic profits under various climatic scenarios

Regionally adapted and locally tested crop simulation models allow decision-makers to assess the outcomes of a wide range of decision alternatives under different climate scenarios. We used the Ceres-Maize model within the DSSAT v3.5 (Jones et al., 1998b; Ritchie et al., 1998). This model has been calibrated and validated in several production environments, including the Pampas (Guevara et al., 1999; Mercau et al., 2001). The model has shown an average error of 17% in the prediction of yield maize under field conditions (Mercau et al., 2001). The information required to run the model includes daily weather series, soil parameters and initial conditions, crop genetic coefficients, and a description of selected crop management. Except for the daily weather sequences, all information required was available from previous research in the Pergamino area (Mercau et al., 2001).

Obtaining long-term daily weather data as input to crop models is often difficult or expensive. 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 weather generator based on the approach described by Richardson (1981); see also reviews in Semenov et al., 1998 and Wilks and Wilby, 1999) to generate long synthetic series of daily weather variables (maximum and minimum temperature, precipitation, solar radiation) for each ENSO phase. Unlike previous approaches, our generator was parameterized conditionally on ENSO phase (Grondona et al., 1999). That is, model parameters were estimated separately for warm and cold ENSO events and neutral years in the historical record (January 1931 to June 1996) for Pergamino. ENSO phases were defined for a July-to-June "ENSO year" according to sea surface temperature (SST) anomalies in the tropical Pacific Ocean between 4° N–4° S and 90° W–150° W (see Podestá et al., 1999 for details). The ENSO-conditional stochastic weather generator produced synthetic daily weather that was used as input to simulate 990 maize cropping cycles for each ENSO phase. A major advantage of the modeling approach is that probability distributions of a large number of simulated yields and gross margins (in this case, 990 outcomes for each ENSO phase) can be incorporated into risk assessment or decision-support tools. Furthermore, the large number of simulations allows the exploration of ENSO influence on extreme (much above or below normal) outcomes, a difficult approach with historical series that are typically short and do not reflect current production technology.

We defined 24 different management combinations that encompassed the options selected by consultants in the focus groups, and that are frequently used by maize producers in the study region. The options considered included (a) two maize hybrids (DK 752, long cycle; DK 615, short cycle), (b) two planting dates (early planting on 15 September; late planting on 15 October), (c) two planting densities (7 and 8 plants m^{-2}) and (d) three fertilization levels (50, 100, and 150 kg of N ha^{-1}). Because the model is unable to simulate insect or disease damage and weed competition, crop protection factors were not included in the simulations. However, it is recognized that climatic information can also affect crop disease, pest or weed management decisions. Soil water availability and nutrient conditions at sowing time were set to values frequently found in the region: 50 kg N ha^{-1} and 100% of available water.

Yields were simulated for each of the 24 crop management combinations and the three ENSO phases using synthetic weather data for 990 maize cropping cycles (i.e., a total of $24 \times 3 \times 990 = 71{,}280$ simulated cropping cycles). Net returns for each cycle were calculated by multiplying the simulated yields times a constant output price (output price = market grain price minus 19% export tax charged by the Argentine Government at sale) and subtracting fixed and variable costs. The assumed maize price ($83\ \$\ \mathrm{mg}^{-1}$) was slightly higher than the historical average for 1980–2001 (Márgenes Agropecuarios Magazine, 2003). Fixed costs included seed, fertilizer, herbicides and labor, while the variable costs included harvest and marketing expenses. Input costs were obtained from local literature (Márgenes Agropecuarios Magazine, 2003).

The yields and gross margins of the 24 management combinations simulated for each ENSO phase were subjected to ANOVA. When a significant F ($P < 0.05$) was obtained in the ANOVA, the means of management combinations were compared using a "t" test (Least Significant Difference – LSD, $P = 0.05$). Maximum average yields or gross margins were used to identify the near-optimal crop management among the various options.

3.3. Estimation of the economic value of climate information

Climate information and forecasts in many countries often are provided and subsidized by the public sector. Estimates of the economic value of climate information and forecasts therefore can help justify public investments in such technology. At the scale of individual decision-makers, it is difficult to justify the use of climate information if it does not add perceptible value to current decision-making.

Researchers have used a variety of approaches to estimate the value of climate information and forecasts (Mjelde et al., 1998; Solow et al., 1998; Messina et al., 1999; Hammer et al., 2001; Chen et al., 2002; Adams et al., 2003; Meza and Wilks, 2003; Meza et al., 2003). Some have used Bayesian decision theory to simulate ideal forecast responses (Johnson and Holt, 1997; Stern and Easterling, 1999). This approach shows how a rational decision-maker will adjust prior expectations of seasonal climate in response to predicted climate conditions, considering how good this forecast tends to be (Kite-Powel and Solow, 1994). The expected value of forecast information is the difference in the outcomes of optimal actions for two different contexts: (a) the decision-maker is assumed to have only historical climate information (i.e., no forecasts are available) and (b) the decision-maker is empowered with the predictive climate information under evaluation (Hilton, 1981; Mjelde et al., 1988).

To derive an initial estimate of the value of seasonal forecasts we compared (a) the management combination that maximized simulated average profits for each ENSO phase with (b) the management selected by technical advisors for Neutral years. We assume the management selected for Neutral years is representative of the preferred management in the absence of any climate information because total precipitation during Neutral years is very similar to the climatological totals for the study region.

Research that estimates value of information by simulating optimal forecast responses can provide useful insights, but actual decisions frequently deviate from those of models typically used in economic modeling (e.g., maximization of subjective expected utility). An alternative and complementary approach relies on observed or elicited decisions, where the emphasis is on how forecasts are actually interpreted and applied, rather than ideal responses (Stern and Easterling, 1999; Stewart et al., 1997; Stewart et al., 2004). For this reason, we derived a second estimate of forecast value by comparing the results from the consensus managements selected by technical advisors (a) for each extreme ENSO phase (i.e., Niños or Niñas) and (b) the management selected by technical advisors for Neutral years.

4. Results and discussion

4.1. Decision map for a maize production system

Decisions involved in maize production were divided into three major groups and their timing and factors influencing them were described (Table 1). The first group-included decisions related to the assignment of land among various possible farm activities (i.e., crops), including maize. The second group involved decisions about maize production technology (hybrid selection, planting date, crop density, fertilizer amount and timing, weed and pest control strategies). Finally, a third group of decisions was linked to marketing strategies for the crop (Table 1). Decisions in Table 1 that were influenced by expected or realized climate conditions were considered as entry points for climate information and ENSO forecasts. These decisions were arranged into various decision maps (Figs. 1–5).

The first group of decisions involves the assignment of land among various farm activities (i.e., crops). Some of these decisions are initially made in early March, well before sowing of any crop. Nevertheless, the decisions are often revised in response to various factors (Table 1) up to the period preceding planting of summer crops (September–November). How many hectares are sown under the various crops is determined, to a great extent, by the expected gross margin of alternative commodities and by farm (soil moisture at sowing and/or harvest, soil quality, in-farm labor constraints, etc.) and farmer characteristics (production objectives, economical and financial situation, etc.; see more details in Table 1). Information about climate conditions that might affect crop yields plays an important role in this group of decisions (Fig. 1). Expected climate during September (when maize sowing starts), December (maize flowering) and March (maize harvest) may affect the land assignation to maize. For example, expected weather during maize flowering may influence the area assigned to maize: farmers may increase maize area if rain during this critical crop period is expected to be higher than normal, which will allow high yields although depending of the perception of the influence of the expected climate on yield (risk aversion). Moreover, this decision may be revised in response to actual weather conditions at sowing (i.e., during September). If September is too rainy, depending on soil attributes (e.g., soil drainage capacity) that determine soil condition at sowing (e.g., soil excessively wet at sowing), a farmer may decide to maintain the amount

Table 1
Decision groups, its components, intervention periods and influencing factors identified in maize crops planning

Component of decision	Period of decision	Influencing factors
Land assignment		
Proportion of maize in the farm	From March to October	**Enterprise-related:** (i) *Expected weather scenario at flowering* (its influence on yields) (ii) Production costs (iii) Output prices (iv) Agricultural policies (i.e. export taxes) **Farm-related:** (i)*Field soil and road condition at harvest* (ii)*Expected weather scenario at sowing* (soil moisture at sowing via its influence on soil condition; i.e. excessively wet or dry) (iii) Soil quality (chemical and physical characteristics) (iv) Rotation scheme (v) Operative restrictions (machinery availability)
Proportion of other crops		**Farmer-related:** (i) Aversion to risk (ii) Production and profit objectives (iii) Economic and financial situation of the firm (iv) Farmer knowledge and access to technical advice (v) Household characteristics and additional income
Production technologies		
Sowing date	From July to October	(i) *Likelihood of low soil temperatures at sowing and late frosts* (ii) *Expected weather scenario at sowing* (its influence on soil condition; i.e. excessively wet or dry) (iii) *Expected weather scenario at flowering* (its influence on yields) (iv) *Expected weather conditions at harvest* (its influence on soil condition) (v) Type of crop (commodity or specialty) (vi) Labor/machinery availability (vii) Production objectives (i.e. risk diversification, high yield potential)
Maize genotype	From July to October	(i) *Expected weather scenario at flowering* (its influence on expected yields) (ii) *Expected weather conditions at harvest* (its influence on soil condition) (iii) Production objectives (i.e. risk diversification, high yield potential, low cost production, etc.) (iv) Seed cost (v) Weed problems (vi) Sowing date (vii) Pest problems
Crop density	From July to October	(i) *Expected weather scenario at flowering* (its influence on expected yields) (ii) Production technologies (iii) Soil quality (chemical and physic characteristics)
Rate and time of fertilizer application	From July to November	(i) *Expected weather scenario at flowering* (its influence on expected yields) (ii) Soil available N at sowing (iii) Crop price and fertilizer cost (iv) Labor/machinery availability (v) Soil quality (Chemical and physic characteristics) (vi) Risk aversion (vii) Genotype and potential yield
Weed control	From March to November	(i) Infestation level (ii) type of weed (iii) Genotype (iii) Herbicide cost and grain price (iv) Treatment efficacy (v) Easiness of management (vi) Labor/machinery availability
Commercialization strategies		
Grain storage time of sale mechanism	From August to May	**Farm-related:** (i) *Expected weather conditions at harvest* (its influence on soil condition) (ii) *Climatic conditions in other agricultural areas* (iii) Expected market performance (iv) Economic and tax restrictions (v) Offer production. **Farmer-related:** (i) Risk aversion (ii) Farmer's managerial ability

Climate conditions influencing each decision are in italics and at the beginning of the list.

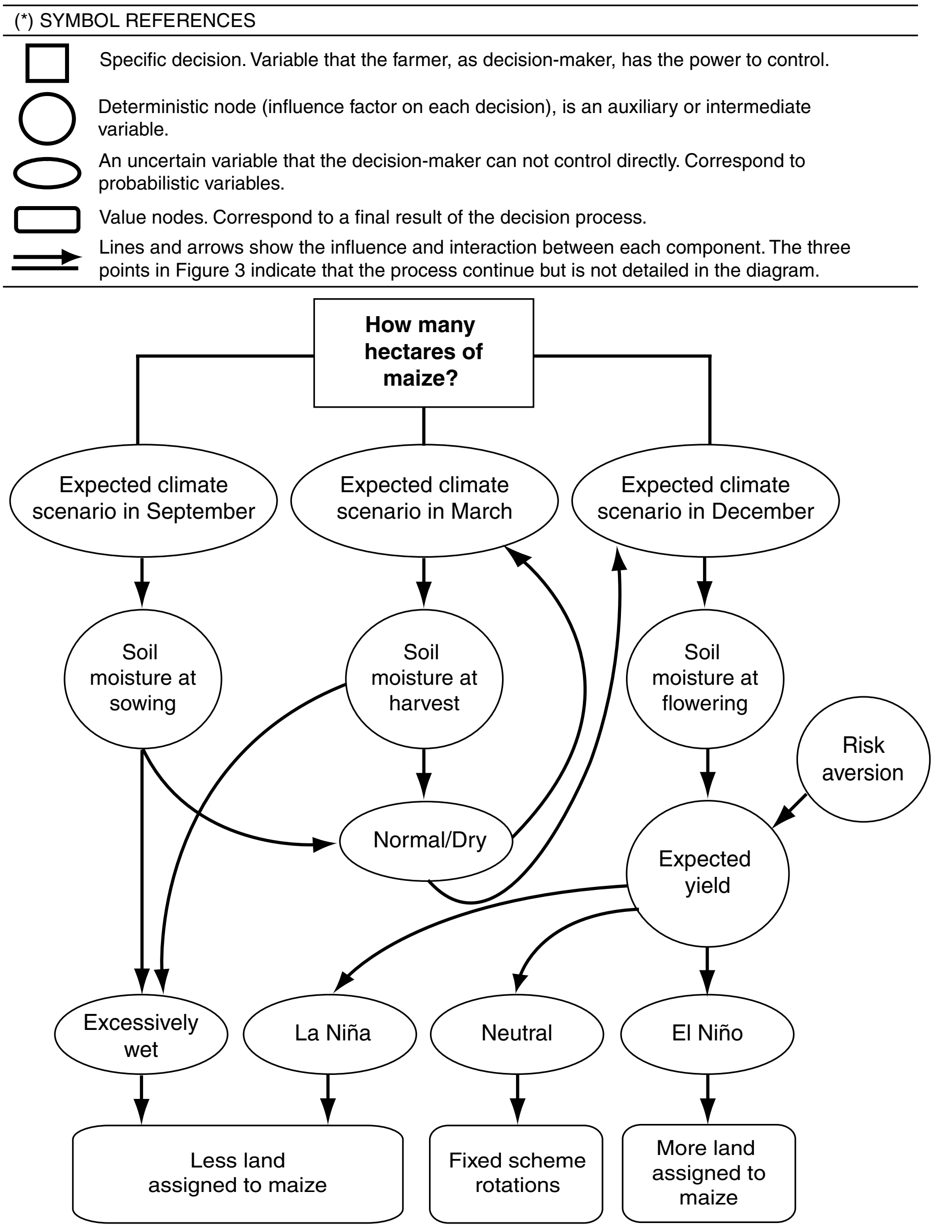

Fig. 1. Conceptual diagrammatic representation of climate influences on land assignment to crops within an ideal farm in the Pampas. Symbol references are: (*)

of land assigned to maize and change production techniques (i.e., sowing is delayed) or, alternatively, if inadequate conditions persist after the end of October, the maize area may be reallocated among other crops such as soybeans. This complex pattern

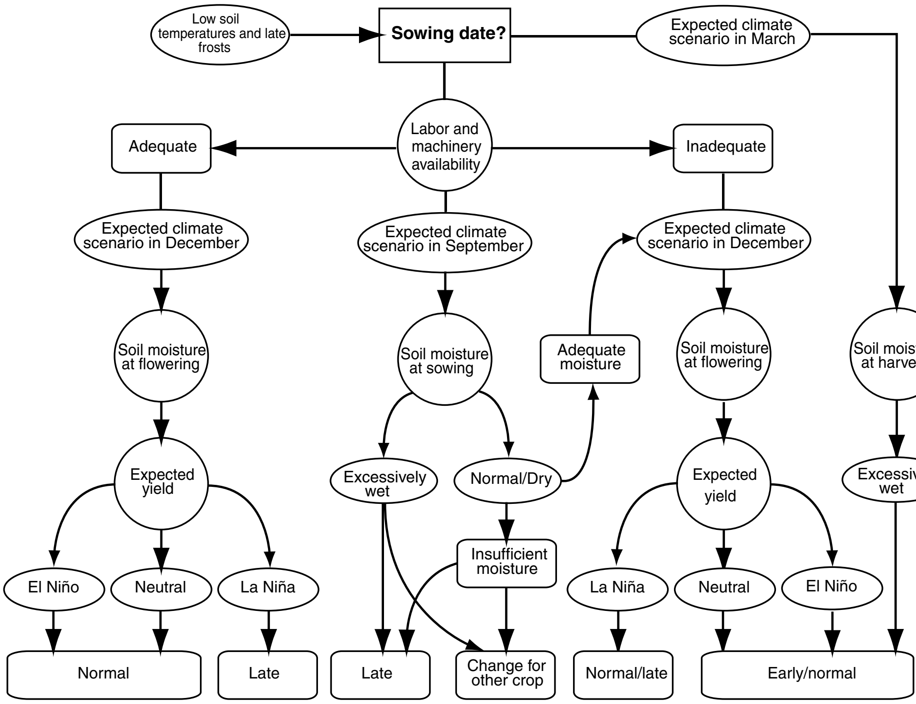

Fig. 2. Conceptual diagrammatic representation of climate influences on deciding sowing date for maize crops within an ideal farm in the Pampas.

illustrates the dynamic, iterative nature of decisions, which are subject to continuous revisions in response to updated information.

The second group of decisions involves various maize management alternatives that define a specific level of cropping technology. Decisions in this group can be further divided into those related to (a) crop establishment, (b) crop nutrition, and (c) crop protection. Crop establishment decisions involve issues such as: Which hybrid will be sown? Which sowing density will be used? When will sowing begin? Crop nutrition decisions may be summarized as: Which fertilizer will be applied? How much fertilizer will be used? When will fertilization be applied? Finally, in maize production systems, crop protection decisions are relatively simple and mostly related to weed control: i.e., which herbicide will be used? When will the herbicide be applied? At which rate will herbicide be applied (Table 1)? Decisions related to crop establishment, nutrition and protection span several months, usually from March (prior to sowing of winter crops) to November (after maize sowing). Many factors may influence the production technology applied to a particular maize field (see details in Table 1). Farm-related factors, such as soil attributes and conditions (soil fertility, moisture at sowing or harvest, etc.), farmer characteristics, (e.g., production objectives or aversion to risk), and production system characteristics (pest and weed problems, cost of seed and agrochemicals) influence the decisions associated with the crop

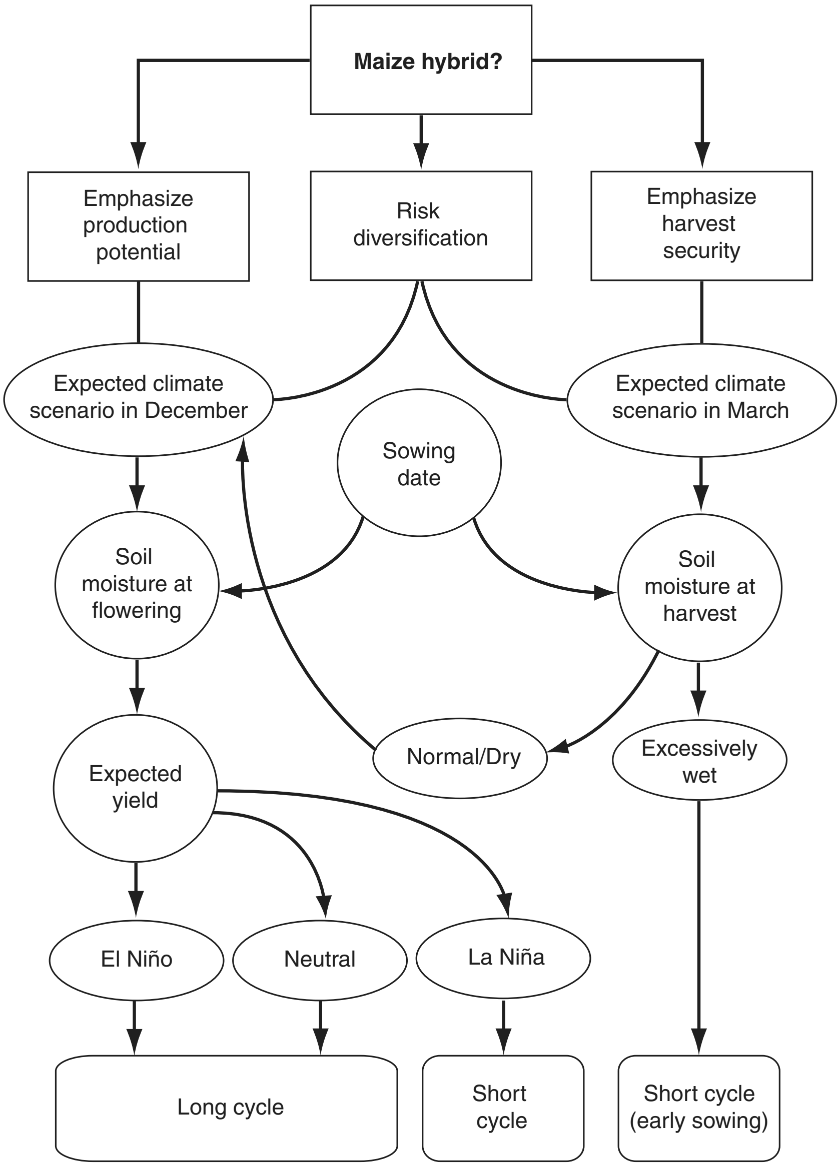

Fig. 3. Conceptual diagrammatic representation of climate influences on deciding maize hybrid choice.

production technology (see more details in Table 1). However, climate may also influence some of these decisions (Table 1; Figs. 2–5). For example, farmers may decide to sow maize early (15 September) if climate conditions at crop flowering are expected to be wetter than normal. Conversely, a late sowing date may be selected if conditions during flowering are expected to be drier than normal, as frequently

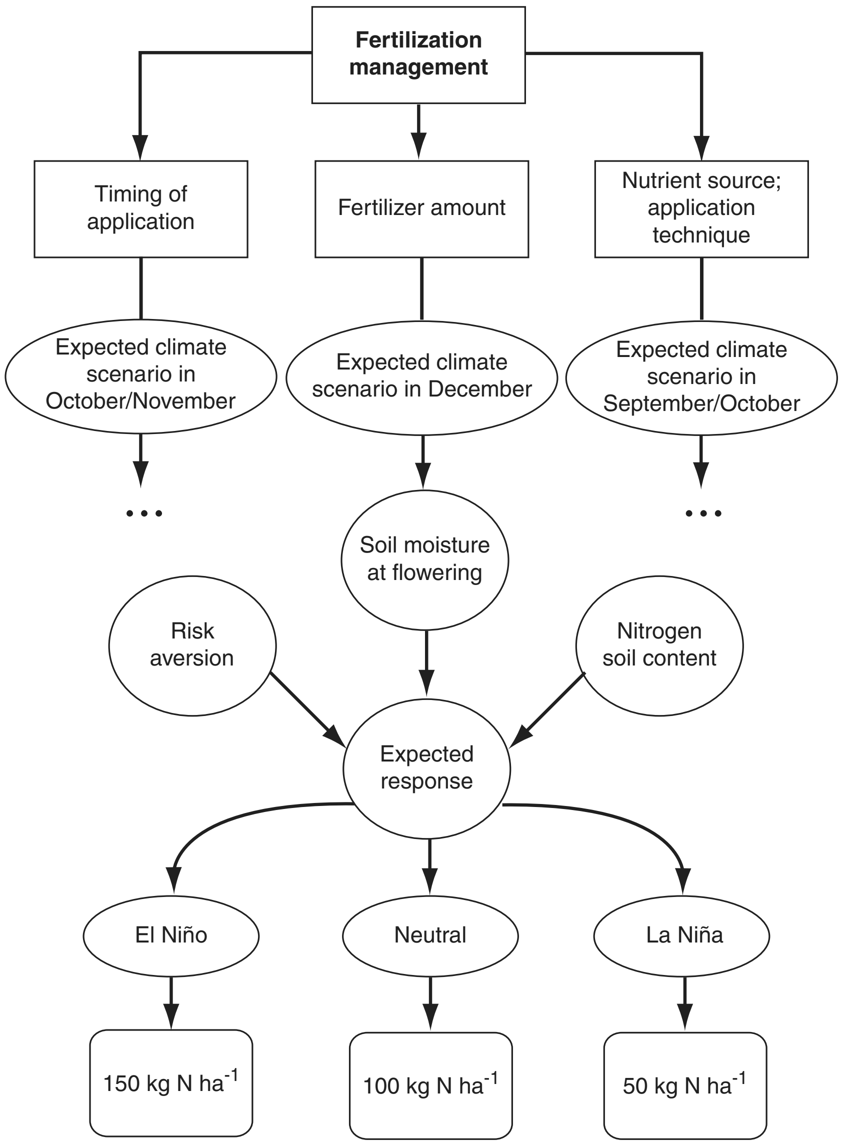

Fig. 4. Conceptual diagrammatic representation of climate influences on deciding maize nitrogen fertilizer management.

occurs during a La Niña event (Fig. 2). The rationale for late sowing is that more water may be stored in the soil prior to sowing and the critical flowering period will take place in January, thus escaping water stress likely earlier in the cycle.

The third group of decisions includes marketing decisions, such as when to sell the crop production, whether financial instruments like options or futures are used, etc. This group of decisions is generally made from the time just prior to sowing (August)

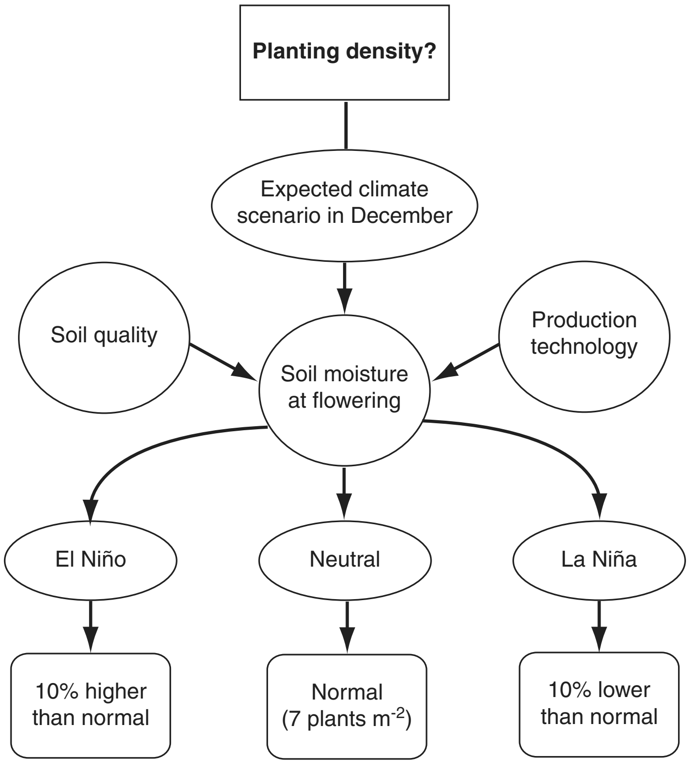

Fig. 5. Conceptual diagrammatic representation of climate influences on deciding maize sowing density.

to after harvest (May). Factors such as the amount of production obtained, expected performance of markets, economic restrictions, and farmer managerial style affect the final commercialization strategy (see more details in Table 1). It appears that climate information affects decisions in this group only slightly. Since Argentine maize production is insufficient to influence global maize prices, local climate outlooks play a minor role in influencing decisions such as purchase of futures or options. On the other hand, information on climate conditions in major production regions such as the US Corn Belt, which shows a mild ENSO signal (e.g., Phillips et al., 1999), may be relevant to decisions by farmers in the Pampas. On-farm bulk grain storage is not very common in the study region. However, weather conditions at harvest may affect the decision to increase on-farm storage of grains. For this purpose, field storage on large plastic bags has become a common practice in the region, greatly increasing farmers' flexibility to decide when to sell, and reducing costs by avoiding peak demand for grain transportation.

4.2. Climate-dependent management selected by experts

Technical consultants in the study region were asked to select preferred management combinations for each ENSO phase, based on their experience and expectations of climate. The elicitation was performed prior to simulating outcomes of the different management options.

Our interactions clearly showed that agricultural advisors consider climate information at various stages of the maize production cycle. Most decisions (or at least initial realizations of decisions) are made in the March–September period previous to maize sowing. Climate-influenced decisions suggested by local advisors are mainly based on expectations of rainfall shortly before and during maize flowering. However, climate conditions during September (sowing) and March (harvesting) were also relevant to some of the decisions (Table 1, Figs. 1–5). The focus groups performed with technical advisors to validate and revise our preliminary decision maps confirmed that they perceive potential benefits in adopting different management strategies depending on expected climate during sensitive crop periods. The willingness to adopt a climate-adaptive management is one of the necessary conditions for deriving benefits from climate information.

The consensus preferred management for "El Niño" events (for which higher than normal precipitations in November–December are more likely) involved early (mid-September) sowing of the long-cycle DK-752 hybrid at a high density of 8 plants m^{-2}, and fertilizing it with 150 kg of N ha^{-1}. Conversely, the consensus management selected by technical advisors for La Niña years (when below-normal precipitations in November–December are more likely) involved less intensive strategies: late sowing (mid-October) of the intermediate-short-cycle hybrid DK-615 at a low density of 7 plants m^{-2}, and fertilized with only 50 kg N ha^{-1}. Preferred management for neutral years (also considered the preferred management in the absence of climate forecasts) involved early sowing of the hybrid DK 752, low density (7 plants m^{-2}), and an intermediate fertilization rate (100 kg of N ha^{-1}).

4.3. Simulated outcomes of management options

There were significant ($P < 0.05$) overall differences among ENSO phases in simulated maize yields and economic results (Table 2). Averaging all management options, the expected yield and gross margin for cold ENSO events (8.34 mg ha^{-1} and 269 \$ ha^{-1}) were lower than for either neutral (9.74 mg ha^{-1} and 338 \$ ha^{-1}) or warm events (9.80 mg ha^{-1} and 341 \$ ha^{-1}). These results are consistent with the ENSO signal on rainfall in the Pergamino area: average rainfall for La Niña during November–December, a critical period for yield determination in maize, is lower than for either El Niño or Neutral years (Podestá et al., 2002).

Crop management options that maximized average simulated maize yield and economic returns differed among some of the ENSO phases (Table 2). During the El Niño and Neutral years, the same management combination maximized both average yield and profits: early sowing of hybrid DK 752, high planting density, and high N fertilizer rates. Nevertheless, yields and gross margins for other managements that also involved high N application but either early sowing/low density or late sowing/high density did not differ significantly ($P < 0.05$). The high water availability to the crop during its mid–growing season associated with El Niño contributes to

Table 2
Simulated grain yield (mg ha^{-1}) and gross margin (\$ ha^{-1}) for various maize crop management combinations under three ENSO phases

Combination of management				ENSO phase					
				Neutral		Niños		Niñas	
Hybrid	Planting date	Density	kg N ha^{-1}	Yield (mg ha^{-1})	Gross margin (\$ ha^{-1})	Yield (mg ha^{-1})	Gross margin (\$ ha^{-1})	Yield (mg ha^{-1})	Gross margin (\$ ha^{-1})
DK 752	15-Sep	7 pl m^{-2}	50	8.71	315	8.79	318	7.32	246
			100	10.05	356	10.11	360	8.40	275
			150	10.77	368	10.81	370	8.96	279
		8 pl m^{-2}	50	8.81	312	8.88	316	7.36	241
			100	10.12	353	10.19	356	8.41	268
			150	**10.96**	**370**	**11.02**	**373**	9.05	276
	15-Oct	7 pl m^{-2}	50	8.64	311	8.71	314	7.53	256
			100	9.98	353	10.03	356	8.67	289
			150	10.69	364	10.72	366	9.22	**292**
		8 pl m^{-2}	50	8.73	308	8.81	312	7.57	251
			100	10.04	349	10.10	352	8.68	282
			150	10.88	366	10.93	369	**9.32**	290
DK 615	15-Sep	7 pl m^{-2}	50	8.57	308	8.64	311	7.61	260
			100	9.91	349	9.96	352	8.50	280
			150	10.57	358	10.62	361	8.99	281
		8 pl m^{-2}	50	8.69	306	8.76	310	7.67	256
			100	10.01	347	10.07	351	8.54	275
			150	10.81	363	10.87	366	9.14	281
	15-Oct	7 pl m-2	50	8.34	296	8.43	301	7.53	256
			100	9.65	337	9.72	340	8.38	274
			150	10.25	342	10.30	345	8.74	268
		8 pl m^{-2}	50	8.45	294	8.54	299	7.37	241
			100	9.73	333	9.80	337	8.43	270
			150	10.46	346	10.52	348	8.88	268
		Mean		9.74	338	9.81	341	8.34	269
		LSD		0.10	5.1	0.11	5.4	0.15	7.3

The numbers in bold show the maximum maize yield and gross margin under each weather scenario (see text for details). The LSD row shows the least significant difference ($P < 0.05$) for comparisons between treatments.

higher yields in dry land crop farming systems of the pampas, particularly if plant density and N fertilization are increased (Royce et al., 2001).

During La Niña events, different management combinations led to maximization of either average simulated yields or economic returns. Highest average yields were obtained with late planting of hybrid DK 752 at high density, and high N applications (Table 2). This combination, however, was not significantly different from another one that was identical except for a lower planting density. The yield response to increased N fertilization was significant ($P < 0.05$) under any crop management option (Table 2). In contrast to the maximization of average yields, maximizing average economic returns involved late sowing of hybrid DK 752, low planting density, and 150 kg of N ha^{-1} (Table 2). This economic result was not significantly different from that obtained under other management combinations that involved the same hybrid and late planting date, but higher planting density or less N applications (100 kg N ha^{-1}).

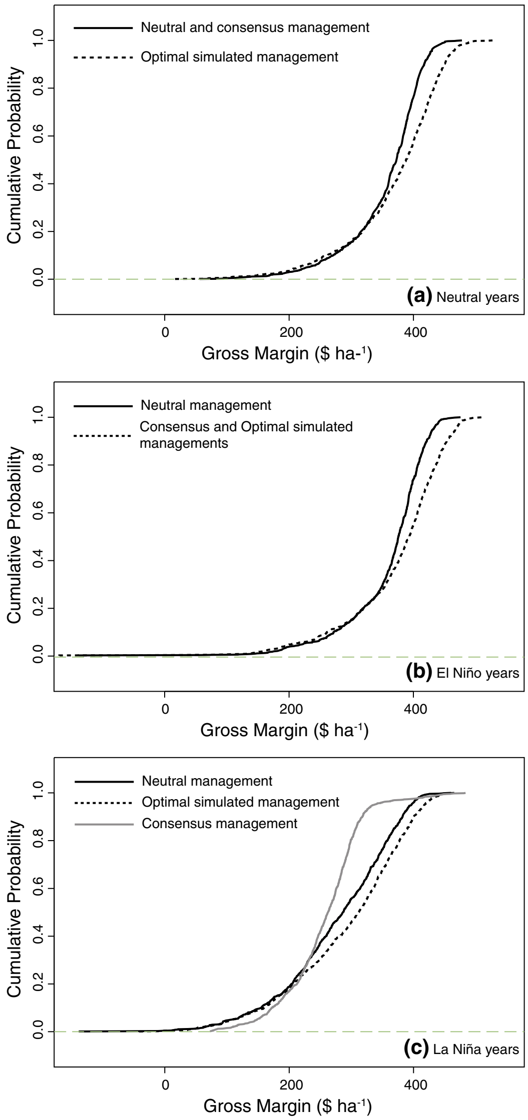

Fig. 6. Cumulative probability distributions for simulated gross margins obtained under various combinations of ENSO phases and crop management strategies. Strategies compared are those resulted from managing crops as suggested from the decision map (*Consensus Management*, with incorporation of climate information) applying the resulting *Optimal Simulated* management as resulted from crop simulations, and the single strategy suggested for *Neutral* scenarios (ignoring climate information) in each ENSO phase presented, (a) Neutral; (b) El Niño; and (c) La Niña.

There were differences between the model-identified managements that maximized average yields and economic results and the consensus management selected by technical advisors for a given ENSO phase. The consensus management for Neutral years involved lower fertilization rates and plant densities than those suggested by the simulations (Figs. 2–5). However, this consensus strategy produces higher margins only in about 1/6 of the years (Fig. 6a). In contrast, during El Niño events the management that maximized average simulated yields and economic returns coincided with the management selected for this phase by regional advisors, and it was better than the management for Neutral years (Figs. 2–5 and 6b).

During La Niña years, high simulated average returns involved intermediate or high N applications (100 or 150 kg ha^{-1}). These results differed from the management recommended by regional advisors for this ENSO phase, which involved a lower fertilization rate (50 kg N ha^{-1}). Because in the study region fixed production and structural costs are very high, management decisions tend to emphasize higher yields and overall profit maximization, instead of maximization of the efficiency in the use of a single input such as fertilizer. At first glance, the difference between simulated and expert management choices may suggest the need for research on maize fertilization guidelines in the region, and their interaction with climate conditions. However, since low fertilization rates produced higher profits in the worst yielding La Niña years (the lowest 25%; Fig. 6(c)) these results may be suggesting, on one hand, a high-risk aversion on the part of the technical advisors or, on the other hand, an incomplete knowledge of climate conditions during La Niña that may tend to overemphasize the likelihood of dryness. If the latter is true, this suggests the need for interventions that improve farmers' knowledge of their local climate and its variability.

Our results on fertilization during La Niña events contrast with recent findings by Royce et al. (2001), who suggested that only 58 kg N ha^{-1}were necessary to maximize economic yields of maize in Pergamino during La Niña years. As simulation experiments involve several assumptions about initial soil conditions, soil parameters and crop genetic coefficients, different results may be obtained even when the same model and quite similar weather records (the synthetic series were shown to be consistent with historical records) are used. Differences in assumptions may explain the divergence between our results and those published by Royce et al. (2001). However, there are evidences in the literature that maize response to fertilization may be similar under dry and wet years (e.g., Vanotti and Bundy, 1994a,b), supporting the idea that, under La Niña conditions, intermediate or high amounts of fertilizer would not

Table 3
Simulated gross margins ($ ha^{-1}) obtained from managing maize crops (i) as the consensus for neutral scenarios (ignoring climate information); (ii) applying the consensus management to each ENSO phase (with incorporation of climate information); and (iii) applying optimal management in each ENSO phase as resulted from crop simulations

ENSO Phase	Management			LSD
	Neutral or average	Consensus	Optimal simulated	
Neutral	357	357	371	7.4
El Niño	360	373	373	5.9
La Niña	275	256	292	6.8
Mean	330	329	345	

only increase average yields but also economic returns, as predicted from our simulations.

4.4. Value of climate information

During the El Niño years, the management combination preferred by technical advisors also maximized both simulated average yield and profits. Adopting this management is expected to generate an average benefit of 13.6 $\$$ ha^{-1} with respect to adopting the consensus management for neutral years (Table 3). During La Niña events, simulated management combinations that led to maximization of either average yield or economic returns differed from the consensus management selected by advisors for this phase. Adopting the consensus La Niña management would lead to an average loss of 19 $\$$ ha^{-1} with respect to adopting the consensus management for neutral years; since better results would come out from adopting combinations with higher N applications (e.g. those corresponding to "Niño and Neutral management") (Table 3). Adopting the optimal simulated management in La Niña years would earn a benefit of 16.8 $\$$ ha^{-1} with respect to apply the simulated optimal neutral management and an extra 35.8 $\$$ ha^{-1} with respect to the consensus management proposed in the decision map for La Niña years. Moreover, in Neutral years higher economic yields were obtained from applying the consensus management suggested for El Niño years instead of "Neutral management" (Table 3).

Nitrogen fertilization rate appeared to be a decision sensitive to climate information. Moreover, the results obtained pointed out that nitrogen management was a key factor to increase yield and economic returns in maize under various climatic scenarios. As mentioned above, it is well known that farmers are risk averse; therefore they usually tend to minimize losses adopting conservative strategies. Our results show that, under the management suggested by the advisors, negative economic results are minimized (Fig. 6(c)). However, according to our simulated results, reducing fertilizer input may lead to low average yield and economic benefits in maize, even under La Niña years, which are usually associated to low rainfall. The contrasting result between the optimal management identified from the decision map and the one identified from simulation points out the importance of the interaction between a risk-averse decision criterion (reducing N costs) and the agronomic response to climate information, particularly in La Niña events. This sort of interactions partially explain why climate information may be reluctantly used; according to our results there may be no positive effect of using climate information under La Niña years if nitrogen rates are reduced; i.e. those who ignore climate information, by maintaining invariably a crop management strategy, would capture average better yields and economic results, although with a higher risk of failure (Fig. 6(c)).

5. Conclusions

The goal of this paper was to explore some of the conditions required for the effective use of seasonal-to-interannual climate information and forecasts in agricultural decision-making. Although five conditions were listed in Section 1, here we addressed in detail only the first three.

As a first condition, climate information has to be relevant to, and compatible with production decisions. However, it is important to distinguish between information that is desired and information that will influence viable decisions (Hansen, 2002). Our interactions with stakeholders in the Argentine Pampas showed that climate information influences directly or indirectly several decisions in a maize production system. There was strong consensus among technical advisors and farmers that the climate conditions most relevant for management decisions in maize productions systems in the study region were (a) rainfall in the period just before and during maize flowering (November–December) and (b) rainfall during harvest (March). Several "entry points" involving these climate situations exist in the decision maps.

The second condition states that alternative options must exist for a given decision. Argentine agriculture underwent major changes since the 1990s, when stable economic conditions fostered a steep increase in use of fertilizers, agrochemicals, and genetically modified varieties (especially for soybeans) (Estefanell, 1997; Satorre, 2002). These modern technologies offer a wide range of management options that allow flexible response to climate information (Hammer, 2000). A set of management options consistent with current practices in the region was identified and incorporated into the decision maps. The iterative and participatory elicitation process, which involved local researchers, technical advisors, and a limited number of farmers, ensured that our description of decisions and options in maize production systems was realistic.

As a third condition, decision-makers had to be able to evaluate the outcomes of alternative actions. Regionally validated and tested crop growth models were used to explore the outcomes of a set of decision alternatives under various climate scenarios. The modeling exercise highlighted divergences between options selected to maximize average profits by local experts and the simulation results. These differences were most apparent in nitrogen fertilization rates. Technical advisors tended to select lower fertilization rates in response to a forecast of dry spring conditions associated with La Niña events. In contrast, the simulations showed that low doses of N would lead to a consistent drop in maize yields and profits, even in most La Niña years. Low N rates resulted in higher average profits only when the worst yielding years (the lowest 25%) were considered separately. This result suggests either a high risk aversion by the technical advisors or an incomplete knowledge of the local climatology. Indeed, this finding is highly consistent with a tendency of agricultural decision-makers to overestimate the probabilities of adverse climatic conditions (Sherrick et al., 2000). This is an issue that should be addressed in future efforts to communicate climate information.

The remaining conditions we submitted for effective use of climate information were not explored in detail in this work. Nevertheless, we address them briefly for the sake of completeness. The fourth condition involved seasonal climate forecasts with useful accuracy, and appropriate lead-time and spatial/temporal resolution. Rainfall during October–December (maize flowering) has good predictability and shows a statistically significant association with the occurrence of extreme phases of the ENSO phenomenon (Goddard et al., 2003). Predictions of expected rainfall during this period, therefore, not only are feasible but also highly relevant to management decisions. Unfortunately, predictability during maize harvest (March) seems low at present (Goddard et al., 2003).

The fifth condition addressed the decision-makers' willingness to modify their actions in response to climate information. Because it is implemented through iterative adjustments of many interrelated decisions, effective use of seasonal climate forecasts imposes intensive demands on management skill (Hansen, 2002). Our interactions with stakeholders generally showed a favorable disposition to include climate information as part of the decision-making process. Nevertheless, previous work in the region (Letson et al., 2001) showed a marked distinction between "a favorable disposition" and actual changes in management in response to climate predictions. Our results suggest that seasonal climate information can enhance average economic returns of the maize enterprise. As profit is a powerful incentive in commercial agriculture, the prospect of enhanced returns may stimulate further use of climate forecasts.

Agricultural use of seasonal climate prediction remains a new and developing technology. Many of the conditions necessary for the effective use of climate forecasts appear to be present in maize production systems in the Argentine Pampas. However, in this work we explored in detail only the climate-sensitive decision points, and the outcomes of a realistic set of alternatives for each decision. Future work should consider a realistic description of the farmers' goals and the context in which they operate, as it may involve both opportunities and constraints for the use of climate information.

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