A linked-modeling framework to estimate maize production risk associated with ENSO-related climate variability in Argentina

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Received 2 August 2000; received in revised form 28 November 2000; accepted 1 December 2000

Abstract

A risk assessment framework is presented to characterize the vulnerability of agricultural production systems to El Niño-southern oscillation (ENSO)-related climate variability. The framework was applied to current maize production systems in two locations (Pergamino and Pilar) in the Pampas of central-eastern Argentina. Climatic, agronomic, and economic models were linked to produce probability distributions of farm-level yields and net returns by ENSO phase. Generally, an enhanced chance of higher (lower) simulated maize yields existed during warm (cold) ENSO events. However, regional differences existed: the effect of warm events on yields was more marked in Pilar, but Pergamino showed a proportionally stronger response to cold events. The modeling framework allowed the exploration of outcomes of high and low scenarios of soil water availability at planting time and ENSO phase. High initial soil water availability in Pilar offset increased yield risks from dry conditions associated with cold ENSO events. Fluctuations of output prices were shown to have considerable influence on the risk associated with ENSO-related climate variability. Despite these general results, there was considerable overlap in yields and net returns for the various ENSO phases. This overlap has significant implications for the adoption of ENSO forecasts in agriculture. The risk assessment framework developed here is a necessary precursor to risk management studies that prescribe or describe possible responses to expected climate scenarios. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: El Niño-southern oscillation; Climate impacts; Maize; Crop yield; Maize

1. Introduction

The El Niño-southern oscillation (ENSO) phenomenon, the result of a two-way interaction between the ocean and the atmosphere in the tropical Pacific Ocean, is the major single source of climate variability on seasonal-to-interannual scales in many parts of the world (Trenberth, 1997). The phenomenon involves two extreme phases: El Niño years or warm events (so named because of warm sea surface temperatures in the tropical Pacific Ocean), and cold events, referred to as La Niña years; years which do not fall in the extreme phases are referred to as “neutral”.

ENSO events have a strong influence on crop yields and economic results of farming enterprises in many regions. Links between ENSO and crop yields have been shown for the United States (Carlson et al., 1996;
Phillips et al., 1999; Mjelde et al., 1997; Legler et al., 1999), Australia (Nicholls, 1985), northeastern Brazil (Rao et al., 1997), and southern Africa (Phillips et al., 1998).

Recent improvements in understanding interactions between the tropical oceans and the atmosphere and the ability to monitor both have made it possible to forecast, with moderate skill, ENSO events with a lead time of months to a year (Latif et al., 1998). The forecasting capability may allow the mitigation of negative effects of ENSO-related climate variability or the exploitation of favorable conditions (Stern and Easterling, 1999). A necessary precursor to management of climate risk, however, is the characterization of the vulnerability of regional agricultural production to ENSO-related climate variability.

Useful descriptions of associations between ENSO and crop yields can be derived from statistical analyses of historical data. This approach, however, has limitations. Firstly, 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. Secondly, 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. Thirdly, 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 (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).

The goal of this work is to develop a risk assessment framework for the characterization of agricultural vulnerability to ENSO-related climate variability. This framework is based on the linkage of climatic, agronomic, and economic components. 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. Each outcome has an associated probability of occurrence. This is a result most relevant to policy/risk analysts, but which has not been reported in the literature very often (Schimmelpfennig, 1996).

The risk assessment framework is illustrated for current maize production 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 (Magrin et al., 1998; Podestá et al., 1999 and references therein).

2. The study area

To compare the vulnerability of maize production systems to ENSO-related climate variability in different environments we selected two locations in the Argentine Pampas: Pergamino (33°56’S, 60°33’W) and Pilar (31°41’S, 63°53’W). These sites respectively represent near-optimal and relatively marginal conditions for growing maize.

Pergamino is located 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 soil is a typical Argiudoll (Paruelo and Sala, 1993). Characteristic crop rotations include maize, soybean, and a wheat–soybean relay. Pilar is in the semi-arid Pampas. The predominant soil is a silty loam entic haplustoll (Dardanelli et al., 1997). Rotations typically include maize or sorghum and soybean.

Total annual rainfall and the annual precipitation cycle vary between the two locations (Prohaska, 1976; González and Barros, 1996). In Pergamino, median annual precipitation is 937 mm. Pilar represents drier conditions: median annual precipitation is 738 mm. The annual rainfall cycle has a clear maximum in late spring and summer and a marked winter minimum. The winter rainfall minimum in Pergamino is less marked than in Pilar. Median
Table 1
Median monthly precipitation (in millimeter) in Pergamino and Pilar by ENSO phase, September–March

<table>
<thead>
<tr>
<th>Month</th>
<th>Pergamino</th>
<th>Pilar</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Warm</td>
<td>Neutral</td>
</tr>
<tr>
<td>September</td>
<td>41.9</td>
<td>40.9</td>
</tr>
<tr>
<td>October</td>
<td>92.1</td>
<td>97.6</td>
</tr>
<tr>
<td>November</td>
<td>129.5</td>
<td>103.6</td>
</tr>
<tr>
<td>December</td>
<td>92.6</td>
<td>105.7</td>
</tr>
<tr>
<td>January</td>
<td>85.6</td>
<td>104.6</td>
</tr>
<tr>
<td>February</td>
<td>129.8</td>
<td>68.1</td>
</tr>
<tr>
<td>March</td>
<td>133.1</td>
<td>135.0</td>
</tr>
</tbody>
</table>

*Statistics derived from historical precipitation series for 1931–1996. Columns labeled “K–W P” show the probability values of Kruskal–Wallis tests of differences in the central tendency of monthly precipitation among all ENSO phases. Probability values <0.05 are indicated with an asterisk.

monthly precipitation by ENSO phase (defined as in Podestá et al., 1999) for both locations is shown in Table 1 for September–March, the period spanning the maize growth cycle. Table 1 also shows probability values for Kruskal–Wallis tests of differences in the central tendency of monthly total precipitation among ENSO phases.

Values in Table 1 confirm previous reports of a marked ENSO signal during November–December in southeastern South America (Grimm et al., 2000; Montecinos et al., 2000). For these months, warm (cold) ENSO events tend to be wetter (drier) than neutral years. However, we stress that there is significant inter-event (i.e., within-phase) variability in the precipitation signature (statistics not shown); the lack of statistical significance of differences among phases for November in Pilar may reflect this.

3. The approach

The risk assessment framework involves linked climatic, agronomic, and economic components. 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 maize yields by ENSO phase. In the economic component, simulated maize yields are combined with stochastically generated maize prices and information on production costs to obtain frequency distributions of economic net returns for each ENSO phase. Each component is described in more detail below.

3.1. Climatic component

Obtaining long-term daily weather data as input to agricultural risk assessment 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) to generate long synthetic daily weather series (maximum and minimum temperature, total precipitation, solar radiation) for each ENSO phase and location.

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.

Precipitation is the variable most likely to influence maize yields in rainfed production systems in Argentina. ENSO-conditional precipitation generation was described in detail by Grondona et al. (2000).
For each month, the “best” model of the precipitation process was objectively selected from a range of parameterization schemes, from “simple” (common parameters for all ENSO phases) to “full” models (a parameter set for each ENSO phase). We used historical daily weather data from January 1931 to June 1996 to fit generator parameters and select the “best” model for each month and location. Conditional models tended to be selected when an ENSO signal was present in the historical rainfall data. Simple, more parsimonious models were preferred when no ENSO signal was apparent (e.g., during winter months). The modified stochastic weather generators successfully captured differences among ENSO phases in precipitation processes in the Pampas (various diagnostics are presented in 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. Agronomic component

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. CERES-Maize, a model within the DSSAT suite (Jones et al., 1998), was used to simulate maize growth. CERES-Maize has been validated in numerous locations and soils in Argentina for different planting dates, 11 hybrids, and different nitrogen fertilization rates. Errors in predicted yields were consistently <15% of observed yields for the range of 5.0–13.5 t ha⁻¹ (Guevara and Meira, 1995; Guevara et al., 1998; Meira et al., 1999). Further, the model has been used successfully in several decision-support studies in the region of interest (Paruelo and Sala, 1993; Messina et al., 1999) and in many parts of the world. The crop model was run for 990 cropping cycles for each ENSO phase. Details on the crop simulations are provided below.

A central objective was to explore ENSO impacts on current maize production systems. The first step, therefore, was to define a set of typical or modal management practices at each of the study locations through extensive interactions with local technical experts and farmers. Modal management defined for each location is shown in Table 2.

We simulated the cultivar DK 752 (De Kalb) in both locations. In the 1998–1999 season, 80% of the bags of maize seed sold in Argentina corresponded to this cultivar (A. Cirilo, pers. comm.). It is a modern hybrid with an intermediate cycle. We used the following genetic coefficients: $P_1 = 247; P_2 = 0.303; P_5 = 775; G_2 = 865; G_3 = 7.01; PHINT = 45$.

The planting dates (Table 2) reflect differences in rainfall patterns between locations. In Pergamino, typically there is enough soil water to sow maize in early September. Such early planting is not feasible in Pilar, however, due to its drier winter and consequently lower soil water during early spring. Instead, maize

<table>
<thead>
<tr>
<th>Management practice</th>
<th>Pergamino</th>
<th>Pilar</th>
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<tbody>
<tr>
<td>Irrigation</td>
<td>Rainfed, no irrigation</td>
<td>Rainfed, no irrigation</td>
</tr>
<tr>
<td>Cultivar</td>
<td>DeKalb DK 752</td>
<td>DeKalb DK 752</td>
</tr>
<tr>
<td>Planting date</td>
<td>10 September</td>
<td>Adaptive: (a) mid-to-late October or (b) early December, depending on soil water availability</td>
</tr>
<tr>
<td>Row spacing</td>
<td>70 cm</td>
<td>70 cm</td>
</tr>
<tr>
<td>Planting density</td>
<td>7.0 plants m⁻²</td>
<td>6.0 plants m⁻²</td>
</tr>
<tr>
<td>Fertilizer application</td>
<td>(a) 60 kg ha⁻¹ of diammonium phosphate (15% N) at planting; (b) 120 kg ha⁻¹ of urea (46% N), 40 days after planting</td>
<td>(87 kg ha⁻¹ of urea (46% N), 30 days after planting</td>
</tr>
</tbody>
</table>
sowing in Pilar follows an adaptive scheme: planting occurs around mid-to-late October if there is enough soil water, or in early December otherwise. According to local farmers, November planting dates are mostly avoided because they expose the crop to frequently occurring droughts in January coinciding with the very sensitive maize flowering period. The higher planting density and larger fertilizer amounts used in Pergamino reflect the higher expected yields and net returns, resulting primarily from greater precipitation during the crop cycle.

Results from the crop models are sensitive to the way in which precipitation is partitioned into infiltration and runoff. An adequate representation of this process is required to ensure realistic results, and thus meaningful risk estimates. The DSSAT models perform this partition using the USDA’s Soil Conservation Service (SCS) Curve Number Method (USDA, 1972). The partition is controlled by a parameter called CN2. Model results can be very sensitive to variations in CN2 (Favis-Mortlock and Smith, 1990). The CN2 value is not only a function of soil and management, but also varies with precipitation amount and intensity (Hawkins, 1975; Boughton, 1989), characteristics that vary seasonally. The use of a single CN2 value may introduce significant errors when the simulated interval encompasses periods with different rainfall regimes. Crop simulations were split so that recharge of the soil water profile during fall and winter was controlled by a “winter” CN2 (or CN2_w), while the cropping season used a “summer” CN2_s. Values of CN2_w and CN2_s were estimated for each location by simultaneously fitting (a) the simulated soil water to available soil water measurements (Guevara and Meira, unpublished data), and (b) variety-trial data of expected mean yields for the maize variety used (Guevara and Meira, unpublished data).

The optimal values of CN2_w and CN2_s for each location are shown in Table 2. These values are consistent with values tabulated by the SCS (USDA, 1972) for fallow and row crops grown in soils having some impediments to infiltration (an argillic horizon in Pergamino, and surface crusting in Pilar). Although the difference between CN2_w = 82 (83) and CN2_s = 84 (85) for Pergamino (Pilar) may seem insignificant, simulated infiltration during spring thunderstorms may differ by up to 14% according to which of these CN2 values is chosen.

In Pergamino, each simulated cycle involved a set of two consecutive model runs. The first run encompassed the period from 31 March to 9 September and used the estimated CN2_w value. This run performed the water-balance simulation necessary to capture interannual variability of precipitation and soil water availability prior to planting. The second model run (from 10 September to physiological maturity) simulated the crop growth cycle based on CN2_s and using the simulated water in the soil profile at the end of the first model run as an initial condition.

The adaptive management followed by farmers in Pilar presented an additional implementation challenge: the DSSAT models include a simple form of automatic selection of a planting date that is incompatible with the method used in Pilar. Within a user-specified time window, the models will plant the crop on the first date that meets specified soil water and soil temperature criteria. However, it is not possible to exclude a range of dates (e.g., to prevent November planting in Pilar while allowing planting during October and December). We solved this problem by performing an additional model run per simulated cycle (i.e., a total of three) in Pilar. The first run, using CN2_w, encompassed the period from 3 April to 9 October; this was analogous to the first model run for Pergamino. A second run began on 10 October (the first possible planting date) and used CN2_s. In the second run, planting conditions were evaluated for each day until a suitable planting date was found (but excluding November). Conditions on this date became initial conditions for the third run. The third and final model run (from planting to physiological maturity) simulated the crop growth cycle. The various simulation runs are summarized in Table 3.

### 3.3. Economic component

While our focus is on ENSO-induced risk, output price variability is frequently the largest source of risk to agricultural producers, thus its consideration is essential to a thorough risk assessment. To explore the effects of output price variability on the economic performance of the maize enterprise, we generated a simulated distribution of maize prices, consistent with historical variability. Maize prices were randomly drawn for each simulated cropping cycle (independent of ENSO phase, see Appendix A) and used, together
Table 3
Characteristics of the crop simulation runs at each location

<table>
<thead>
<tr>
<th></th>
<th>Pergamino</th>
<th>Pilar</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Winter” simulation</td>
<td>31 March–9 September, CN2 = 82</td>
<td>3 April–9 October, CN2 = 83</td>
</tr>
<tr>
<td>“Summer” simulation</td>
<td>10 September — maturity, CN2 = 84</td>
<td>(a) 9 October — planting date. (b) Planting date — maturity; CN2 = 85 for both (a) and (b)</td>
</tr>
<tr>
<td>Initial water conditions (at start of fallow)</td>
<td>Model-derived estimate from Messina et al. (1999)</td>
<td>Soil water measurements from 10 experiments in four different years from Ferreyra (1998)</td>
</tr>
<tr>
<td>Initial N conditions (planting date)</td>
<td>Local expert estimate based on soil N measurements</td>
<td>Local expert estimate based on soil N measurements</td>
</tr>
<tr>
<td>Constraints used to optimize CN2w and CN2s</td>
<td>(a) Estimate of mean water content on 1 October, based on soil water content measurements (Guevara and Meira, unpublished data). (b) Mean harvest yield from variety trials (Guevara and Meira, unpublished data). (c) Expert estimate of fallow efficiency</td>
<td>(a) Median water content measurements from seven experiments in three different years (Dardanelli, unpublished data). (b) Mean harvest yield in field experiments (Cantarero, Salas, pers. comm.)</td>
</tr>
</tbody>
</table>

with simulated yields and information on production costs, to simulate economic net returns of the maize enterprise in both locations.

A realistic distribution of maize prices 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 maize prices after deregulation was too short for an adequate description of price variability. For that reason, we followed a three-step approach to generate maize prices.

First, we used a 1950–1998 series of average maize prices received by US farmers (National Agricultural Statistical Service, available at http://usda.mannlib.cornell.edu/data_sets/crops/92152) to characterize historical variability. The rationale was that the US accounts for a major proportion of the world maize trade (Mjelde et al., 2000), thus playing an important role in driving global prices for this commodity. The US prices were (a) converted to US dollars per dry ton (assuming average marketing moisture of 15.5%), and (b) 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 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 percentage of their corresponding low-frequency trend component values) were computed. Most subsequent analyses focused on relative residuals for April, May, and June, when the bulk of the Argentine maize harvest is marketed.

In a second step, maize prices were stochastically generated for the US. We fitted an empirical density function to the 147 historical residuals for April–June using a kernel filter (Bowman and Azzalini, 1997) with bandwidth selected following Sheather and Jones (1991). The empirical density distribution was then sampled to generate 2970 simulated relative price residuals (one per simulated maize yield). The 1996–1998 mean deflated maize price ($100.37 per ton) was used to convert simulated relative residuals into absolute simulated US prices.

In the final step, an association was established between recent (1994–1998) maize prices in the US and Rosario, Argentina, where most of the maize produced in both study locations is traded. Daily maize prices in Rosario from Argentina’s Bolsa de Cereales (grain exchange) were aggregated into monthly averages, adjusted for average marketing moisture (14.5%), and deflated to 1998 Argentine pesos using Argentina’s CPI. An exchange rate of 1 Argentine peso (1998) = 1 US dollar was assumed. A linear regression was fitted to US and Rosario 1994–1998 prices. The fitted equation was

$$P_r = (P_u \times 1.145) - 15.352,$$  

where $P_r$ is the maize price in Rosario (in 1998 US dollars per dry ton) and $P_u$ is the price in the US (same
units as $P_r$). The standard deviation of residuals in the regression was $12.67$ per ton, and $r^2 = 80.5\%$. The regression equation was used to convert the simulated US prices into simulated prices in Rosario.

A series of 2970 simulated prices was generated for Rosario (Fig. 1). We stress that the distribution in Fig. 1 is not a historical price distribution. Rather, it is a simulated distribution approximately centered on average 1998 prices (median: $98.0$ per ton) and with a variability range consistent with the historical record.

To estimate production costs and net returns, input costs were assumed constant. This was supported by the results of Brescia et al. (1998), who found input costs to be much less variable than other sources of risk. Input usage was assumed independent of crop price, because data availability did not allow us to model the association between these variables. The independence assumption makes our approach a conservative, first-order description of climatic risk to maize production. Production costs were computed following Messina et al. (1999). Net returns for each year were calculated by multiplying the simulated yield and output price, and subtracting fixed and variable costs.

3.4. Computation of risk curves

Our ultimate objective was to assess the risk for cropping outcomes (yields and net returns) from ENSO-related climate variability and other factors. Here, we propose an approach to quantify outcome risk for various scenarios. The approach is based on comparing the chances of exceeding a given yield or income during a scenario of interest with the corresponding chances for a reference scenario. The scenarios for which risk is estimated may include a single factor (e.g., warm or cold ENSO events) or a combination of factors (e.g., warm ENSO events and high maize prices).

A reference set of outcomes must be defined for each scenario of interest. For example, to estimate risk associated with ENSO phase, the reference set includes the simulated outcomes for the 990 neutral years. The empirical probability of exceedance function (EPEF) of the variable of interest (yield or economic return) is computed for both the reference set ($EPEF_r$) and the scenario of interest ($EPEF_i$). A risk factor (RF) curve is computed as

$$RF_i = \log_{10} \left( \frac{EPEF_i}{EPEF_r} \right).$$

(2)

The logarithm is taken so that RF values are proportionally similar for EPEF ratios greater or lower than one. The reference level (indicating no shift in probability with respect to the reference set) is 0. For a given scenario, if $RF < 0$ for the entire range of outcomes, the crop is at risk, as the probability of exceeding any given outcome is lower than what would be expected for the reference set. Conversely, if $RF > 0$ for all outcomes, the scenario shows a favorable effect, because the probability of exceeding any outcome is greater than for the reference. To compare RF curves, we focus our discussion on four “reference quantiles”, the 10-, 33-, 66-, and 90-percentiles (noted as $q_{10}$, $q_{33}$, $q_{66}$, and $q_{90}$) for the reference set. These quantiles define outcomes (i) “much below normal” (outcomes $< q_{10}$), (ii) “below normal” (outcomes $< q_{33}$), (iii) “above normal” (outcomes $> q_{66}$), and (iv) “much above normal” (outcomes $> q_{90}$).

4. Results

4.1. Yields and ENSO phase

There were significant differences among ENSO phases in the central tendency of simulated maize yields in both locations. In Pergamino, the median...
yield for cold events (5768 kg ha\(^{-1}\)) was about 30% lower than for either warm or neutral events (median yields: 8096 and 8146 kg ha\(^{-1}\), respectively). Pairwise Wilcoxon tests showed no significant differences in the central tendency of yields between warm and neutral years (\(P = 0.815\)). However, for both of these phases, the central tendency of yields was significantly higher than for cold events (\(P \ll 0.001\) for both tests). In Pilar, the median yield for warm years (6246 kg ha\(^{-1}\)) was about 9% higher than the median for neutral years (5712 kg ha\(^{-1}\)), which in turn was about 23% higher than the median yield for cold events (4655 kg ha\(^{-1}\)). Unlike Pergamino, the increase in Pilar yields during warm events was statistically significant. Wilcoxon tests showed significant differences between all pairs of ENSO phases.

Histograms of Pergamino simulated yields have a longer left tail for warm and neutral years (Fig. 2). In Pergamino, yields are close to their maximum potential and favorable climate conditions may not enhance yields much, whereas the depression of yields associated with unfavorable conditions is more noticeable. Huff and Neill (1982) observed a similar pattern for maize yields in the US Corn Belt (another favorable maize-growing region). In Pilar, the yield distributions do not show marked peaks, although low (high) yields are more frequent during cold (warm) events (Fig. 2).

Risk curves were estimated for yields during warm and cold ENSO events. The reference set included the simulated yields for neutral years. In Pergamino, the RF curve for the warm ENSO phase is close to zero for most yields, suggesting fairly similar yield distributions for warm and neutral years (Fig. 3a). Only for above-normal yields (>\(q_{66}\)) the warm phase curve shows values >0. The probability of exceeding \(q_{90}\) is 16% higher for warm ENSO events than for neutral years. That is, warm ENSO events introduce a small shift in the probability of high yields. In contrast, the curve for cold events shows a much steeper slope below the zero reference line. This indicates a very strong effect of cold events: the probabilities of exceeding \(q_{33}\), \(q_{66}\) and \(q_{90}\) are, respectively, 0.42, 0.24 and 0.12 times the corresponding probabilities for neutral years. For Pilar (Fig. 3b) the warm events curve differs from that of Pergamino, as it shows a positive effect of warm events for the entire range of yields. The probabilities of exceeding \(q_{33}\) and \(q_{66}\) are 1.13 and 1.26 times the corresponding probabilities for neutral years. As in Pergamino, the cold phase has more marked effects than the warm phase. The probabilities of exceeding

Fig. 2. Histograms of simulated maize yields for Pergamino and Pilar. C, N and W indicate cold, neutral and warm events.
4.2. Initial soil water conditions and yield risks

Soil water content at the time of planting may influence the final yield of a crop (Meyer et al., 1991; Messina et al., 1999). Adequate pre-season soil water availability decreases a crop’s vulnerability to climate during the growth cycle. In Pergamino, e.g., October–February evapotranspiration exceeds precipitation in 50% of the years; the crop’s success, therefore, will depend to a large degree on initial soil water availability (Rebella and de Zeljкович, 1980).

Soil water conditions at planting were derived from the sets of CERES runs described above. In Pergamino, median initial soil water availability (ISWA, integrated over a depth of 210 cm) was fairly similar for all ENSO phases (median values were 212, 226 and 229 mm for warm, neutral, and cold events). In Pilar, ISWA values were lower than in Pergamino (median values: 106, 110 and 104 mm for warm, neutral and cold events). This reflects differences in winter precipitation, as maximum soil water holding capacities over 210 cm are very similar for both locations (315 mm in Pilar, 310 mm in Pergamino).

We estimated RF as a function of both ENSO phase and ISWA level. The reference set was defined as the yields for neutral years and medium ISWA values. The medium ISWA category (values in the central third of the distribution) included values between 201 and 245 mm in Pergamino; corresponding boundaries for Pilar were 92 and 124 mm. The risk curves are shown in Fig. 4. There are two curves per ENSO phase, corresponding to low and high ISWA scenarios; medium ISWA scenarios are not shown to focus attention on extreme situations.

Generally, high initial soil water reduced yield risks associated with ENSO events, whereas low initial water scenarios enhanced risks. In Pergamino (Fig. 4a) high ISWA and warm events result in significantly higher probabilities of exceeding the reference yields for the entire range of values. The ratios of probabilities for \( q_{33} \), \( q_{66} \) and \( q_{90} \) were 1.26, 1.51 and 2.20.

That is, if the crop starts with abundant water supplies, the probability of exceeding the upper decile is more than twice that for the reference set. On the other hand, if ISWA is in the low category, any beneficial influence of warm events is lost: in the central part of the distribution (\( q_{33} \) and \( q_{66} \)), the probabilities of exceeding reference yields are only about two-thirds
Fig. 4. Yield risk curves for ENSO phase and initial soil water availability (ISWA) classes for: (a) Pergamino and (b) Pilar. Note that there are two curves for warm events (black lines, filled triangles), respectively, for low (curve noted L) and high (curve noted H) ISWA values. Correspondingly, there are two lines for cold ENSO events (grey lines, inverted open triangles), one per ISWA scenario. The four vertical dashed lines indicate, from left to right, $q_{10}$, $q_{33}$, $q_{66}$ and $q_{90}$. The scale on the right $y$-axis indicates the ratio of cumulative probabilities (i.e., the antilog of the risk factor).

of the reference (neutral years, medium soil water). A similar pattern is observed for cold events. The yield risk increase is somewhat moderated by high ISWA, even though high initial water conditions cannot offset entirely the negative effects of dry conditions during the growth cycle. For $q_{33}$ and $q_{66}$, RFs are only about half of those for the cold phase alone (Fig. 3a). The combination of low initial soil water and cold events is particularly damaging. Even at the low end of the yield range (where differences in risk usually are not very noticeable) the effects are marked. The probability of exceeding $q_{10}$ is only one third than that of the reference set. The probability of exceeding $q_{66}$ is only 2% of the reference probability, and the probability of exceeding $q_{90}$ is zero.

In Pilar (Fig. 4b), high ISWA markedly enhances the decrease in risk for warm events. The probabilities of exceeding $q_{66}$ and $q_{90}$ are 1.80 and 2.56 times those for the reference set. In contrast, low ISWA cancels any positive effects of warm events and increases yield risk. Perhaps the most interesting result is that high ISWA values may cancel negative effects of cold events in Pilar. The risk curve for this case is always above zero, indicating a decrease in risk in relation to the reference set. That is, a high supply of moisture at the beginning of the growth cycle significantly reduces the vulnerability of the crop to ENSO-related water shortages in Pilar. In contrast, low ISWA and cold events increase yield risk significantly: probabilities of exceeding $q_{66}$ and $q_{90}$ are only 0.28 and 0.13 of the reference probabilities. The yield risk for this combination of conditions is 2–4 times higher than for cold events alone. An important corollary of these results is that they illustrate the importance of monitoring soil water availability at the time of planting.

4.3. Yields and precipitation during flowering

The timing of phenological stages crucial in defining yield (e.g., flowering) may help explain the influence of ENSO-related climate anomalies. Numerous references suggest that maize yield under rainfed conditions is strongly influenced by precipitation around its flowering period (Rebella and de Zeljkovich, 1980; Huff and Neill, 1982; Kaufmann and Snell, 1997; Travasso et al., 1999). Simulated flowering dates for each location are shown in Table 4. Because ENSO effects on temperature are not significant, the timing of flowering is very similar among all ENSO phases, thus statistics are presented for pooled data. For Pilar, dates are shown separately for early- and late-planting opportunities. For completeness, Table 4 shows also the dates of physiological maturity. In both locations, simulated dates for all phenological stages are consistent with those observed in the field.

To explore the association between yield and rainfall around maize flowering, we computed the Spearman rank correlation coefficient (to allow for non-linear associations) between yields and precipitation in the
Table 4
Simulated dates of flowering and physiological maturity for Pergamino and Pilar

<table>
<thead>
<tr>
<th></th>
<th>Pergamino</th>
<th>Pilar</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Flowering date</td>
<td>Maturity date</td>
</tr>
<tr>
<td></td>
<td>Early planting</td>
<td>Late planting</td>
</tr>
<tr>
<td>$P_{0.10}$</td>
<td>1 December</td>
<td>22 January</td>
</tr>
<tr>
<td>Median</td>
<td>12 December</td>
<td>2 February</td>
</tr>
<tr>
<td>$P_{0.90}$</td>
<td>23 December</td>
<td>15 February</td>
</tr>
</tbody>
</table>

*The median date and the 10- and 90-percentiles ($P_{0.10}$ and $P_{0.90}$, respectively) are shown for each stage. In Pilar, early planting (between 13 October and 3 November) was possible in about 35% of the simulated years; in the remaining years, late planting was on 3–4 December. Dates are not separated by ENSO phase because they did not differ significantly among phases.

4.3.1. Maize prices and net returns risk

Net returns from the maize enterprise are influenced by ENSO phase. However, because stochastic output prices were generated independently of ENSO phase (see Appendix A), any differences in net returns among phases are being driven solely by yields. For this reason, results of associations between ENSO phase and net returns are very similar to those shown above for yields and will not be discussed.

Interesting results arise when the influence of ENSO and output price scenarios on profitability of the maize enterprise are considered jointly. The approach was similar to that used to explore the combined effects of ISWA and ENSO phase. Maize price categories were defined by dividing the distribution of all stochastically generated prices into terciles. The medium price category included values from $94.6 to $101.3 per ton. The reference set included net returns for neutral years and medium maize prices. Risk curves are shown in Fig. 5.

The interesting issue is how maize prices interact with ENSO-related climate variability to enhance or moderate risks on net returns. In Pergamino, warm events and high prices enhance significantly the chances of above normal and much above normal net returns. The probability of exceeding $q_{66}$ is 50% higher than for the reference set; for $q_{90}$ the probability is over three times higher than for the reference set. Low price scenarios during warm events, in contrast, increase considerably risk on net returns. Probability of exceeding $q_{66}$ falls to about one-third of that for the reference set; the corresponding value for $q_{90}$ is only about 20% of the reference. Readers should remember that the effect of warm ENSO events alone

31-day period around the simulated flowering dates ($P_f$). The correlation was 0.553 for Pergamino and 0.535 for Pilar; both values were highly significant ($P \ll 0.001$).

There was significant variability in $P_f$ among ENSO phases. In Pergamino (where median flowering date was 12 December), median $P_f$ values were 111, 90 and 44 mm for warm, neutral and cold events, respectively. That is, median precipitation during flowering was almost three times higher for warm events than for cold events. The synchrony between the timing of the strongest ENSO signal (cf. Table 1) and the critical flowering period may explain the strong association between maize yields and ENSO phase in Pergamino, especially the marked yield decreases during cold events.

In Pilar, $P_f$ did not vary much among ENSO phases: median values for early plantings were 121, 119 and 105 mm for warm, neutral, and cold events, respectively. The corresponding values for late plantings were 101, 99 and 84 mm. The planting dates in Pilar result in median flowering dates in early January (early planting) or early February (late planting), when the ENSO signal is less distinct. Historical January precipitation does not show significant differences among ENSO phases (Table 1). This probably decreases yield risk from cold events in comparison to Pergamino. At the same time, enhanced rainfall during November–December associated with warm events (Table 1) may result in adequate accumulation of water in the soil. This may explain the positive effect of warm events on simulated yields, even though precipitation during flowering is not very different between warm and neutral years.
did not show very marked effects on Pergamino yield or net return risks. For cold events, high prices do not offset the negative effects of climate, but decrease risk considerably. For high prices, probabilities of exceeding \( q_{66} \) are about one half of the reference, and for \( q_{90} \), the probability of exceeding the reference is zero.

In Pilar, warm events and high prices make the chance of exceeding \( q_{66} \) to be 30% higher than reference. Remarkably, the probability of exceeding \( q_{90} \) is almost 2.8 times as high as reference. Previously, we noted that beneficial effects of warm events were more marked in Pilar than in Pergamino. This is particularly apparent in the curve for low prices: probabilities of exceeding \( q_{33} \) and \( q_{66} \) are 93 and 61% of reference, whereas for Pergamino the corresponding values were lower (65 and 34%). Cold events enhance risks for most of the net return distribution even with high prices, but above \( q_{90} \) the curve crosses the zero line. Cold events and low prices are associated, as expected, with high risk: chances of exceeding \( q_{66} \) and \( q_{90} \) are only 32 and 4% of reference. Still, these risk factors are not as high as for Pergamino, the corresponding numbers were 2 and 0%.

In summary, we have found differences in risk between scenarios and locations. Pergamino, because of its higher yields and more intensive production systems (with correspondingly higher production costs), seems to be more sensitive to price risk than Pilar; this appears to be true for both low and high price scenarios.

5. Discussion

We developed a risk assessment framework to characterize the vulnerability of regional agricultural production to ENSO-related climate variability. The framework was applied to current maize production systems in the Pampas of central-eastern Argentina, yielding probability distributions of agronomic and economic impacts by ENSO phase at the farm-level.

Generally, there was an enhanced chance of higher (lower) maize yields during warm (cold) ENSO events. This was associated with a tendency towards higher (lower) precipitation during November–December of warm (cold) events (Grimm et al., 2000; Montecinos et al., 2000). Modeling results confirmed the effects of ENSO-related variability on maize yields previously shown by historical analyses (e.g., Podestá et al., 1999). In this study, however, ENSO impacts were
characterized for present production systems (i.e., current management practices and genetic materials).

There were regional differences in the ENSO impact on maize yields. Pergamino generally did not show significantly enhanced outcomes during warm events, except for the upper tails of outcome distributions. In contrast, cold events had much stronger and consistent negative effects. The Pergamino results are linked to the strong coincidence between the timings of maize flowering (crucial in defining yield) and the strongest ENSO signal (in particular, dry conditions during cold events). Pilar showed clearly enhanced yields and net returns during warm events, but a less negative effect of cold events than in Pergamino. These results are consistent with those discussed in Magrin et al. (1998) and Messina et al. (1999) using historical data. Such results may be partly due to differences in the production potential of both regions. In an optimal region such as Pergamino, yields are close to the crop’s potential and there is not much chance for improvement (except during unusually favorable years), whereas bad climatic conditions can decrease yields significantly. In a relatively marginal region such as Pilar, on the other hand, the opportunities to benefit from favorable climatic conditions may be greater, hence the clearer signal of warm events. The lower sensitivity to cold events in Pilar may be partially explained by the climate-adaptive management currently followed by farmers in that location. If soil water content is not sufficient, planting is delayed. The delayed planting (which in our simulations takes place in about 2 of 3 years) shifts maize flowering to late January or early February, when the ENSO signal is less marked or even reverses. Water deficits associated with cold events, therefore, are less likely during flowering.

For many problems, especially those with non-linear 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 (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. We found that focusing on central tendencies or extreme events may yield quite different perspectives. For example, the central tendency (median) of simulated yields for cold events was about 71% of the median for neutral years in Pergamino. This suggests a relatively strong effect of cold ENSO events. However, when attention was focused on the upper tail of the yield distribution, the effects of cold events were highly magnified. The probability of yields in the upper decile was only 12% of the corresponding probability for neutral years.

The model-based risk assessment framework allowed us to explore the interaction between various scenarios of soil water availability at planting time and ENSO phase. This would have been difficult to achieve with historical records. Soil water availability at the time of planting is an important diagnostic quantity that provides useful context for a forecast of a given ENSO phase and thus assists the interpretation of the forecast’s implications on expected maize yields and net returns. Output prices were shown to have considerable influence on the risk associated with ENSO-related climate variability. Changes in risk arising from various price scenarios strongly highlight the need to interpret a climate forecast within the context of other factors (Pulwarty and Redmond, 1997; Messina et al., 1999). For example, given the very low agricultural commodity prices in recent years, we wonder what the impact on Argentine agriculture would have been if the cold ENSO event of 1998–1999 had been associated with prevalent dry conditions throughout the Pampas. As it turned out, precipitation was fairly close to normal and overall production was only slightly affected. We stress that cold events with relatively normal precipitation are quite possible (albeit somewhat less probable). The implications of inter-event variability are discussed in more detail below.

The differential impacts of ENSO-related climate variability between the two study locations influences the usefulness of ENSO forecasts. For locations such as Pergamino, near the crop’s potential yield, forecasts of a poor growing season may be more useful than forecasts for good years. For relatively marginal sites like Pilar, on the other hand, forecasts of favorable years may be used as a basis to increase inputs to capitalize on favorable conditions and thus may be more relevant (Phillips et al., 1998). These conclusions, however, contrast with perceptions revealed by a survey of farmers in the Pergamino region (Letson
et al., 2000). When asked about ENSO impacts on their regional climate, surveyed farmers were more knowledgeable about the effects of warm ENSO events than about the usually more pronounced (and negative) effects of cold events. This may be due to the remembered effects of recent warm and cold events.

An important finding from our simulation studies is the considerable amount of overlap in yields and net returns for the various ENSO phases (despite the statistically significant differences in central tendencies of outcomes). The overlap of outcomes among ENSO phases has significant implications for the adoption of ENSO forecasts in agriculture. Firstly, clearly it poses a greater burden on climate forecasters, who need to produce not only a forecast of an ENSO event (from which likely regional conditions could be derived), but rather a forecast of expected climate conditions in the region of interest. Phillips et al. (1998) reached a similar conclusion for ENSO effects on agriculture in Zimbabwe. In the near future, ENSO is likely to remain the main source of predictability for climate in the study region. Nevertheless, a challenge is to improve our understanding of both regional modulation to forcing by conditions in the tropical Pacific Ocean and factors other than ENSO influencing the regional climate. Secondly, the inter-event variability may influence the willingness of decision makers to use ENSO-related climate forecasts. Agricultural stakeholders may not be willing to follow a climate-adaptive management (admittedly, another level of difficulty in an already complex decision making environment) if they do not perceive clear differences in both the climate conditions and agricultural outcomes expected.

The risk assessment framework developed in this work is a necessary precursor to risk management studies that prescribe or describe possible management responses to various expected climate scenarios. The framework of linked models used here can be a valuable decision support tool for decision making at the farm level (where it can be used to manage inputs to an agricultural system for maximum profit given a particular climate forecast). With minor changes to allow for differences in the definition of ENSO years and the timing of cropping/simulation seasons, the methodology can be applied to any location where vulnerability of the agricultural sector to ENSO needs to be studied.

Acknowledgements

This work was supported by grants from NOAA’s Office of Global Programs, the National Science Foundation (Methods and Models for Integrated Assessment) and the Inter-American Institute for Global Change Research (IAI) to a Consortium of Florida Universities (University of Miami, University of Florida, Florida State University). CEPROCOR (Córdoba, Argentina) provided additional financial support for RAF’s visit to Miami. We thank P. Salas (INTA Manfredi) and M. Cantarero (Univ. Nacional de Córdoba) for their assistance in defining typical management practices in Pilar. J. Granda (INTA Manfredi) helped define the economic components of maize production costs in Pilar. The historical climate data used to fit the stochastic weather generators were provided by Argentina’s Servicio Meteorológico Nacional.

Appendix A. Maize prices and ENSO phase

An important assumption in the stochastic generation of maize prices was that price of this commodity is independent of ENSO phase. This assumption was supported by an exploratory analysis of the historical US data, as the Argentine price series encompassed only a few ENSO events. US monthly relative price residuals were aggregated into quarterly averages to reduce intra-seasonal variability. Average price residuals for the April–May–June (AMJ) quarter (when the bulk of the Argentine harvest is marketed) were then binned by ENSO phase. We note that AMJ prices correspond to what in the ENSO literature has been called “year 1” or “year (+)” of an event (cf. Grimm et al., 2000). For example, prices for April–June 1998 were binned as corresponding to the 1997–1998 warm ENSO event. The period 1950–1998 included 12 warm events, 12 cold events, and 25 neutral years.

Boxplots of AMJ residuals by phase (not shown) suggested that the central tendency of maize prices was slightly higher (lower) during cold (warm) events. The medians of AMJ relative residuals were −0.57, 2.78 and 7.22% for warm, neutral and cold years, respectively. Such differences in US maize prices between ENSO phases would be consistent with reported trends for above-normal (below-normal) yields.
in the US Corn Belt during “year 0” of warm (cold) events (Carlson et al., 1996; Phillips et al., 1999). Nevertheless, a Kruskal–Wallis test showed no statistically significant differences in the central tendency of AMJ relative price residuals among all ENSO phases ($P = 0.244$). A Wilcoxon test exploring price differences only between warm and cold events showed significance only at $P = 0.160$.

An ENSO signal has been reported for prices of other agricultural commodities such as soybean futures (Keppene, 1995). Nevertheless, when Keppene focused on maize, the ENSO signal was not significant. He speculated that the lack of association was due to the US Government’s support and regulation of the maize market. Less active governmental intervention in agricultural commodities’ markets may imply that the ENSO signal may become more apparent in the future. Until now, however, our assumption of independence between prices and ENSO phase is supported by historical data.

References


