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Linking weather generators and crop models for assessment of climate forecast outcomes

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ABSTRACT

Agricultural production responses to climate variability require salient information to support decisions. We coupled a new hybrid stochastic weather generator (combining parametric and nonparametric components) with a crop simulation model to assess yields and economic returns relevant to maize production in two contrasting regions (Pergamino and Pilar) of the Pampas of Argentina. The linked models were used to assess likely outcomes and production risks for seasonal forecasts of dry and wet climate. Forecasts involving even relatively small deviations from climatological probabilities of precipitation may have large impacts on agricultural outcomes. Furthermore, yield changes under alternative scenarios have a disproportionate effect on economic risks. Additionally, we show that regions receiving the same seasonal forecast may experience fairly different outcomes: a forecast of dry conditions did not change appreciably the expected distribution of economic margins in Pergamino (a climatically optimal location) but modified considerably economic expectations (and thus production risk) in Pilar (a more marginal location).

1. Introduction

The world faces the dual challenges of feeding a rapidly increasing 21st century population of perhaps 9 billion, while at the same time sustaining life support systems (National Research Council, 1999). Innovative environmental information will be central to this effort. The emerging ability to forecast regional climate is a hallmark achievement of the climate research community (Stern and Easterling, 1999) and creates exciting opportunities for agricultural decision-makers, who can use seasonal climate forecasts to mitigate unwanted impacts or take advantage of favorable conditions. By providing advance information with sufficient lead time to adjust critical agricultural (e.g., irrigation, weed control, planting, harvesting) decisions, seasonal forecasts have significant potential to contribute to the efficiency of agricultural management, and to food and livelihood security.

Adaptive responses to climate, however, require salient information to support decisions. If farmers are to benefit from seasonal climate forecasts, the information must be presented in terms of production outcomes at a scale relevant to their decisions (Baethgen et al., 2009). Agricultural outcomes of decisions are more relevant to stakeholders than raw climate information: a farmer is more interested in receiving likely distributions of crop yields or economic returns than a seasonal precipitation forecast. Unfortunately, still there is a gap between the information routinely produced by climate prediction centers and regional climate outlook forums, and the needs of farmers and other agricultural decision-makers (Hansen et al., 2006). A greater capacity is needed to convert raw climate information into distributions of relevant outcomes for agricultural risk assessment and management.

Outcomes resulting from the interaction of alternative management decisions and weather scenarios can be explored using process models simulating crop yields and other biophysical response variables. Models for various important crops in the Decision Support System for Agrotechnology Transfer (DSSAT) package (Jones et al., 2003) have been used to simulate processes in production systems that determine crop responses and crop performance, resource use and environmental impacts for different environments and management scenarios. More recently, the DSSAT models have been increasingly used to determine the potential impact of climate change on crop production and to

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provide management scenarios for adapting to climate variability (Alexandrov and Hoogenboom, 2000).

One impediment for linking effectively climate forecasts and crop simulations is a mismatch between the spatial and temporal scale of available seasonal forecasts and the daily weather input required by process-based models. Operational seasonal climate forecasts generally are coarse-grained in time ($\geq$3 months) and space. Nevertheless, seasonal or sub-seasonal (e.g., monthly) climate forecasts can be disaggregated using a stochastic weather generator to produce synthetic daily time series that capture the predictable, low-frequency components of seasonal or sub-seasonal variability, while reproducing important statistical properties of the high-frequency variability in the historic daily record (Alexandrov and Hoogenboom, 2000; Hoogenboom, 1999).

Stochastic weather generators are statistical models that create synthetic (i.e., simulated) series of daily weather from historical data. The statistical properties of synthetic series are intended to be similar to those of observed historical weather (or of other scenarios of interest, if different from climatology). Reviews of commonly used weather generators can be found in Wallis and Griffiths (1995) and Wilks and Wilby (1999); additional background is provided in the following section. Recently, Apipattanavis et al. (2007) developed a Semiparametric Weather Generator (SWG) that improves upon existing algorithms, while being easy and flexible to implement. Nevertheless, so far the SWG has not been applied to an agricultural question. The SWG uses a *k*-Nearest Neighbor (*k*-NN) resampling approach to generate weather sequences but also relies on a Markov chain to model the precipitation occurrence process. Thus, it captures well the wet and dry spell statistics and also all the distributional properties of the weather variables. The SWG can easily generate multiple daily weather series consistent with seasonal climate forecasts; this paper demonstrates such capability.

The overarching goal of this paper is to develop and validate a framework to assess possible responses to seasonal climate predictions in terms of outcomes (site-specific crop yields and economic returns) that are salient and relevant to decision-makers. The framework combines a semiparametric stochastic weather generator – to downscale seasonal climate forecasts into multiple, equally likely series of daily weather – and biophysical models to simulate crop yields. The simulated yields are then used to quantify net economic margins and production risks associated with alternative (dry, rainy) seasonal climate forecasts. As a case study, we simulate maize yields and economic profits in the Argentinean Pampas, a major world agricultural region.

2. Methodology

2.1. Weather generators

Several approaches have been proposed for the stochastic generation of weather variables. These approaches can be grouped into two main categories: parametric and nonparametric methods (Wilks and Wilby, 1999). Parametric weather generators also known as "traditional" weather generators typically use precipitation as the driving variable. Other variables such as maximum and minimum temperatures are generated by fitting a lag-1 Multivariate Autoregressive (MAR-1) model with dependent upon precipitation state (Richardson, 1981). Furthermore, the seasonal fluctuation of model parameters may be described by using Fourier series. An innovative approach to weather generation – based on fitting a generalized linear model – was introduced by Furrer and Katz (2007).

Some disadvantages of parametric approaches include: (1) the need for prior assumptions about the distributions of the historical data, (2) a large number of parameters must be fitted for each season (and this increases exponentially if simulations are conditioned on large scale climate indices), and (3) only linear relationships between the variables can be reproduced (Rajagopalan and Lall, 1999).

An attractive alternative to parametric approaches is the use of nonparametric methods, which are data-driven and do not require assumptions about the distributions of the variables of interest. They can provide a flexible framework, are parsimonious, and can be easily modified to do simulations based on particular climate states (Wilks and Wilby, 1999). One of the methods that has been routinely used and continuously modified is the *k*-Nearest Neighbor (*k*-NN) bootstrap approach (Bannayan and Hoogenboom, 2008). Rajagopalan and Lall (1999) extended the *k*-NN bootstrap method developed by Lall and Sharma (1996) for univariate time series resampling to multivariate data. Buishand and Brandsma (2001) and Yates et al. (2003) extended the *k*-NN bootstrap weather generator to multisite generation with good success. Furthermore, the *k*-NN approach was modified for conditional resampling on atmospheric indices and hydrologic time series (Beersma and Buishand, 2003; Mehrotra and Sharma, 2006).

The weather module in the DSSAT cropping system model generates daily weather data using the widely used WGEN and SIMMETEO (Richardson and Wright, 1984) weather generators. The main advantage of SIMMETEO in comparison to WGEN is that its input parameters can be estimated from monthly summaries instead of the daily data required for estimating the input parameters for WGEN (Geng et al., 1986, 1998). These parametric approaches have a long history of development but they suffer from several shortcomings. (1) The MAR framework requires normality of the data. If the data are not normally distributed, they have to be transformed to normality. With several variables and seasons (e.g., months), this transformation task can be quite difficult. (2) For the rainfall amounts potential non-normal features such as bimodality, if exhibited by the data, cannot be captured by the limited suite of PDFs.

2.1.1. The semiparametric weather generator

The Semiparametric Weather Generator (SWG) proposed by Apipattanavis et al. (2007) is a multivariate and multisite weather generator. SWG was developed for (i) improving the ability of the traditional *k*-NN model of Lall and Sharma (1996), Rajagopalan and Lall (1999) and Buishand and Brandsma (2001) to capture the historical wet day spell statistics by modifying the original algorithm to incorporate an additional Markov chain model; and (ii) adding to the modified model the capability of generating weather scenarios conditioned on seasonal climate forecasts currently issued operationally by many agencies around the world. Details on the algorithm and performance of the SWG are given in Apipattanavis et al. (2007); for the sake of completeness we briefly present the algorithm, abstracted from that paper.

SWG involves two steps combining parametric and nonparametric approaches. In an initial (parametric) step, a Markov chain is used to generate the precipitation state of the day (i.e., no rain, rain, or heavy rain) using the historical wet and dry spell statistics. In the second (nonparametric) step, a *k*-NN method is used to generate the suite of weather variables conditioned on the simulated precipitation state. The Markov chain correctly describes the spell statistics, whereas the *k*-NN bootstrap captures the distributional, cross-correlation, and lag-dependence statistics of the weather variables.

The SWG is quite flexible and can generate scenarios consistent with seasonal climate forecasts such as those operationally issued by organizations such as the International Research Institute for Climate and Society (IRI, www.iri.columbia.edu). The simulated conditional weather scenarios are useful for water and crop resource management at short time scales. We show these applications in subsequent sections of this paper. In addition to simulation conditioned on seasonal climate forecasts, the SWG can incorporate easily plausible climate trajectories such as a projected precipitation trend (Clark et al., 2004). In this case, SWG resamples the historical record according to the trend we wish to reproduce or simulate—wherein, each historical year is weighted according to its "closeness" (in terms of the conditioning variables) to the scenario for which weather sequences are to be generated. This technique was applied to generate weather sequences conditioned on a decadal trend for a location in Argentina for agricultural planning by Podestá et al. (2009).

2.2. The DSSAT crop models

The Decision Support System for Agrotechnology Transfer (DSSAT) is a package that facilitates the application of crop simulation models to agricultural decision-making and research (Jones et al., 2003). DSSAT is a collection of independent programs that operate together: the package includes primary modules for soil, weather, plant, soil–plant–atmosphere interface, and management components. In turn, the plant module incorporates models for 16 different crops (e.g., CROPGRO for soybean, Generic-CERES for maize and wheat, etc.).

DSSAT simulates growth and development of a crop growing on a uniform area of land under prescribed management and soil conditions. The programs contained in DSSAT allow users to simulate options for crop management over a number of years to assess the risks associated with each option. In this sense, computer experiments can be performed hundreds or even thousands of times for a given environment to determine how to best manage or control the system. The DSSAT helps decision-makers by reducing the time and human resources required for analyzing complex alternative decisions (Boote et al., 1998).

The information required for applying DSSAT package to different situations (e.g., crops, environments, etc.) includes a description of weather, soils, experiment conditions and measurements and genotypes (Tsuji et al., 1998). This information is provided through a database that includes: (a) daily weather series of minimum and maximum temperatures, solar radiation and precipitation for the location and years to be simulated, (b) values for a set of soil-related parameters (e.g., organic matter content for each layer, bulk density for each layer, etc.), (c) a definition of the crop management (e.g., sowing date, fertilization rate, etc.) and the conditions under which the experiment will be performed (e.g., simulation beginning date, soil water content at the beginning of the simulation, etc.), and (d) values for the "genetic coefficients" that describe physiological process and development differences among crop hybrids or varieties. Depending on the definition of this information it is possible simulating crop growth and development over a wide range of environments and management practices.

In this paper, we coupled the DSSAT package with daily synthetic weather series consistent with (a) historical climate data and (b) two different scenarios of predicted seasonal climate. In this way, we produced multiple realizations of crop yields (Fig. 1) that were used to estimate production and economic risks in two climatically contrasting regions of the Argentine Pampas. In the following section we describe this case study.

3. Case study

We tested the stochastic weather generator—crop modeling framework in the region of central-eastern Argentina known as the Pampas, one of the main cereal and oilseed producing regions in the world (Hall et al., 1992). We selected two specific locations with different agroecological characteristics: Pergamino (Buenos Aires Province, 33°56′S, 60°33′W) and Pilar (Córdoba Province, 31°41′S, 63°53′W) which respectively represent near-optimal and relatively marginal agricultural conditions.

Pergamino is in the most productive subregion of the Pampas and has a long agricultural history. In contrast, Pilar is in the northernmost semi-arid margin of the Pampas, and agriculture became widespread only in the last 20–30 years. Total annual rainfall and the annual precipitation cycle vary between the two locations (González and Barros, 1996). In Pergamino, median annual precipitation is 937 mm. Pilar represents drier conditions: median annual precipitation is 738 mm. In Pilar, the annual rainfall cycle has a marked winter minimum that, together with limited soil water storage, makes summer crops very dependent on spring precipitation. In contrast, the winter minimum in Pergamino is less marked. Currently, crop rotations in both sites include maize, soybean, and a wheat–soybean double crop (wheat followed by short-cycle soybean) and crop production technologies are similar in both locations. Contrasting agroecological conditions between sites let us use the integrated framework to explore interactions between the physical environment, climate scenarios, and crop behavior.

Because the vast majority of agriculture in the Pampas is rainfed, crop yields are highly sensitive to precipitation shortly before sowing and during crop development. Maize is particularly sensitive to water stress during flowering (a critical stage for definition of maize yield), which typically occurs around the end of December or beginning of January and coincides with the period with highest atmospheric water demand (Dardanelli et al., 1997). Because of the strong association between precipitation and yields, maize provides a good test-bed to explore the impacts of different climate scenarios on production outcomes. Consequently, we used the integrated framework to simulate maize yields for Pergamino and Pilar under different synthetic weather scenarios. In the following sections we provide details about the two main steps involved in the integrated framework: (a) the generation of synthetic weather series consistent with different seasonal scenarios, and (b) the simulation of multiple realizations of maize production outcomes.

3.1. Generation of synthetic weather series

3.1.1. Unconditional simulations

Quality-controlled records of daily precipitation, maximum and minimum temperatures, and solar radiation – estimated from relative sunshine or daily temperature range; see Podestá et al. (2004) – were available for 1931–2001 (71 years) in Pergamino and for 1941–2004 (64 years) in Pilar. These series were used as input to the weather generator in order to generate series consistent with the climatology (i.e., unconditioned series) or, alternatively, series conditioned on forecasted seasonal scenarios.

The SWG was used to produce daily synthetic series based on historical climate records for Pergamino and Pilar. For each location, we generated 100 realizations of daily weather sequences, each with the same length as the historical record (71 years for Pergamino, 64 for Pilar). That is, a total of 7100 (6400) synthetic weather years were generated for Pergamino (Pilar).

3.1.2. Simulations conditioned on seasonal climate forecasts

Seasonal climate outlooks with lead times of up to 12 months are currently disseminated for several regions of the world (Goddard et al., 2003; Mason et al., 1999). These forecasts are typically probabilistic and in a moving epoch format (e.g., 3 months). For instance the IRI, one of the most important agencies in the world producing seasonal forecasts, provides forecasts as percentage likelihood of A:N:B format where "A" is above-normal rainfall percent chance, "N" is near-normal rainfall percent chance

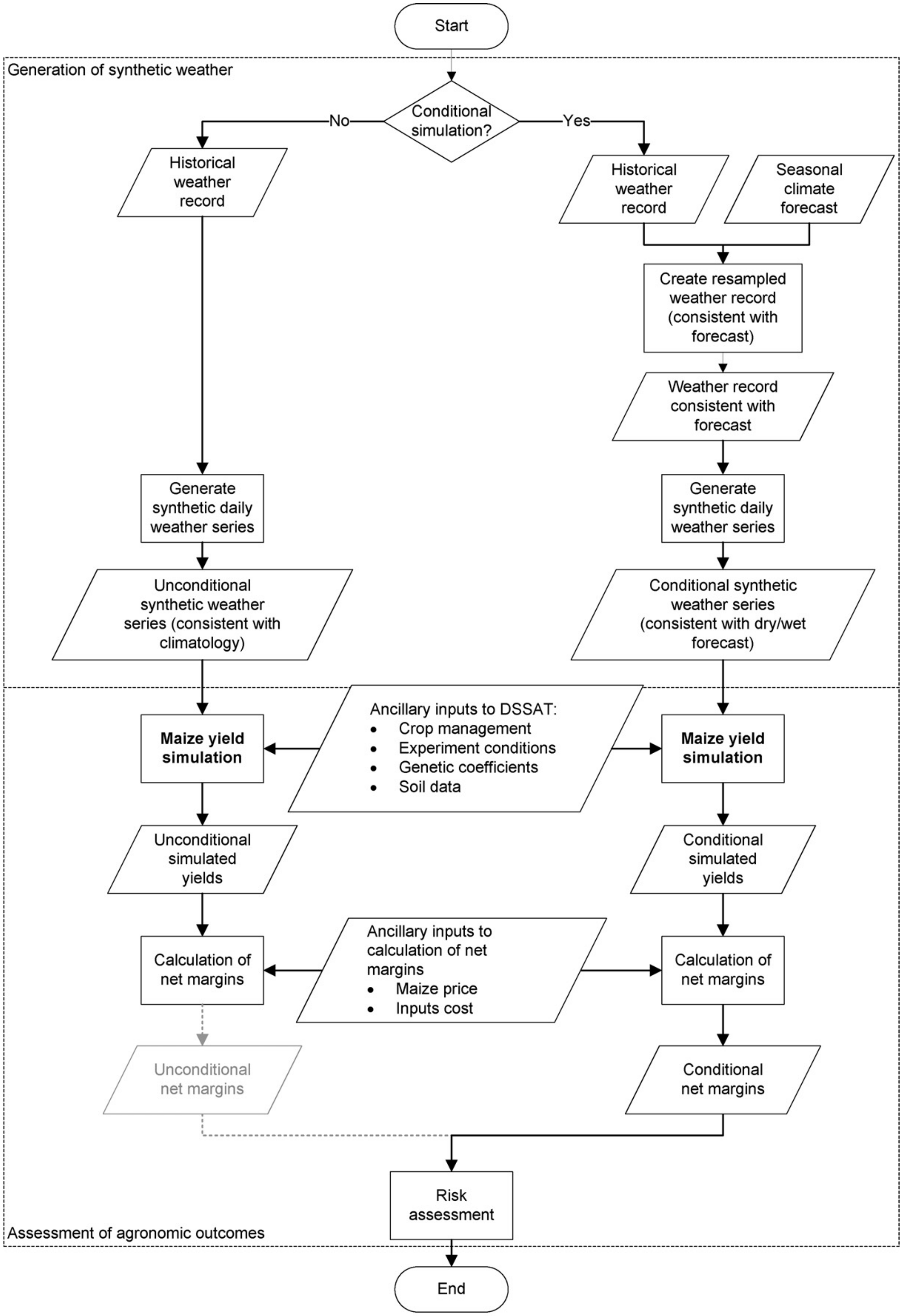

Fig. 1. Schematic diagram of the coupled SWG generator and DSSAT cropping system model.

and "B" is below-normal rainfall percent chance, with categories defined from terciles of climatological rainfall totals. The forecasts are provided for moving periods of 3 months. For example, over an area a forecast of "40:35:25" for precipitation in November–January means that there is a 40% chance of rainfall to be above-normal, 35% chance of rainfall to be near-normal, and 25% chance of below-normal precipitation in this period.

The model proposed by Apipattanavis et al. (2007) facilitates the generation of synthetic series conditioned on different climatic drivers (e.g., categorical seasonal forecasts, climatic indexes). The conditioning algorithm is based on weighted resampling of input historical years depending on the seasonal forecast (Yates et al., 2003). For the generation of synthetic series conditioned on an IRI forecast, first the historical years are classified into three categories—wet, normal, and dry based on the terciles of seasonal precipitation. Then, based on the example given in the previous paragraph, 40 years are randomly picked from the wet category, 35 from the normal and 25 years from the dry category. As a result of the conditional resampling a new input series of 100 years is obtained. Then, SWG is applied to this conditioned input pool of 100 years to generate synthetic series consistent with the seasonal forecast.

The procedure was used to generate 100 synthetic weather sequences for a cropping season conditioned on likelihood from two actual seasonal forecasts issued by IRI: (a) a seasonal forecast for December–January–February (DJF) 2003, anticipating wetter than normal conditions (45% of probabilities for the upper tercile and 25% of probabilities for the lower tercile), and (b) a seasonal forecast for December–January–February (DJF) 2004, anticipating drier than normal conditions (20% of probabilities for the upper tercile and 45% of probabilities for the lower tercile).

3.2. Simulation of maize production outcomes

3.2.1. Maize yields

The synthetic daily weather series were used as input to DSSAT in order to simulate maize yields (kg of grain per unit area). The Generic-CERES (Ritchie et al., 1998) within the DSSAT package simulates maize growth and development as a function of inputs such as soil characteristics, crop management, genetic information and daily weather. The Generic-CERES model has been calibrated and validated in the Pampas. The model has shown an average error of 17 and 20% in the prediction of maize and wheat yields at plot level under field conditions, while the differences between simulated and observed average yields (over a large number of cases under field conditions) were about 4.5% (Guevara et al., 1999; Mercau et al., 2001).

The combination of maize management options frequently used by farmers in each location was chosen as the typical or representative production system. Furthermore, a representative soil was selected for each region in consultation with local technical experts. Values of soil-related parameters (e.g., organic matter content) were available from soil charts produced by Argentina's Agricultural Research Institute (Instituto Nacional de Tecnología Agropecuaria, INTA). Crop simulation conditions were set to values frequently found in each region according to the information provided by local experts. Crop genetic coefficients and soil-related parameters were available from previous research in the study area (Mercau et al., 2001, 2007). All the climate series described in Section 3.1 were used to simulate maize production outcomes in Pergamino and Pilar using Generic-CERES. DSSAT-derived yields from the historical and synthetic weather data were then compared. Simulation outcomes using the historical climate records were used as a baseline to: (a) assess the performance of the SWG and WGEN synthetic weather generators and (b) quantify the relative impacts on maize yields of conditional weather scenarios (see below).

3.2.2. Calculation of maize economic margins

Once maize yields were simulated, we used a simple economic model to compute maize net margin per hectare for each climate scenario (Fig. 1). Net margin was computed as the difference between gross income and total costs. Gross income per hectare was the product of simulated yields and the median of 2002–2007 maize prices (80\$ ton^{-1}). Total costs included direct and indirect costs. Direct costs are those costs associated with maize production and, in turn, can be divided into fixed and variable costs. Fixed direct costs are independent of crop yields and include field labors, seeds and agrochemicals. Total fixed direct costs of 258\$ ha^{-1} and 200\$ ha^{-1} were assumed for Pergamino and Pilar, respectively. Variable direct costs depend on crop yields and include harvest (assumed as 6% of gross income for both locations), marketing (assumed as 8% of gross income for both locations) and grain transportation (a transportation price of 0.061\$ ton^{-1} and a distance to port of 100 km for Pergamino was assumed for Pergamino and a transportation price of 0.050\$ ton^{-1} and a distance to port of 400 km was assumed for Pilar). Indirect costs apply to the operation of the entire farm and are not associated with any specific crop; they include structure maintenance costs, management expenses, real estate taxes, and amortization of durable capital goods. The indirect costs were assumed to be 70\$ ha^{-1} for both locations. For all cited costs, values assumed are representative of the period 2002–2007.

Multiple realizations of maize net margins were used to quantify production risks under some of the climate scenarios. The cumulative probability distribution (CPD) of maize net margins was calculated for the conditioned climate scenarios (i.e., dry and wet scenarios) and for the historical climate record. The Kolmogorov–Smirnov (K–S) test was applied to assess differences among CPDs of net margins among the conditional climate scenarios. Based on the CPD we computed the probability of negative net margins (PNNM) to quantify risks to production associated with each climate scenarios. PNNM was computed as the proportion of realizations (for a given climate scenario) in which simulated net margins were negative (indicating that income received from maize production was lower than total costs).

4. Results and discussion

The results are divided into two parts. First, we assess the quality of unconditional simulated weather series in terms of maize yield statistics. Specifically, we assess the capability of the recently introduced hybrid weather generator (SWG) and the widely used WGEN algorithm (included in the DSSAT suite of crop models) to reproduce distributions of maize yields simulated with historical climate records. In a second part, we explore the impacts of conditional simulated weather (generated for both dry and rainy seasonal forecasts) on maize yields, net margins and economic risks.

4.1. Quality of unconditional weather scenarios

Distributional statistics of maize yields simulated using unconditional weather series produced with SWG and WGEN are shown in Fig. 2. The mean yields simulated with SWG are closer to the mean yields simulated using the historical climate series in both regions. Both generators overestimate the mean yield values in Pergamino (Fig. 2(a)). Conversely, in Pilar, the SWG tended to underestimate mean yields slightly, whereas WGEN overestimated mean yields (Fig. 2(c)).

The variability of maize yields was underestimated regardless of the weather generator used to simulate the climate series. In Pergamino, WGEN tended to reproduce better the variability

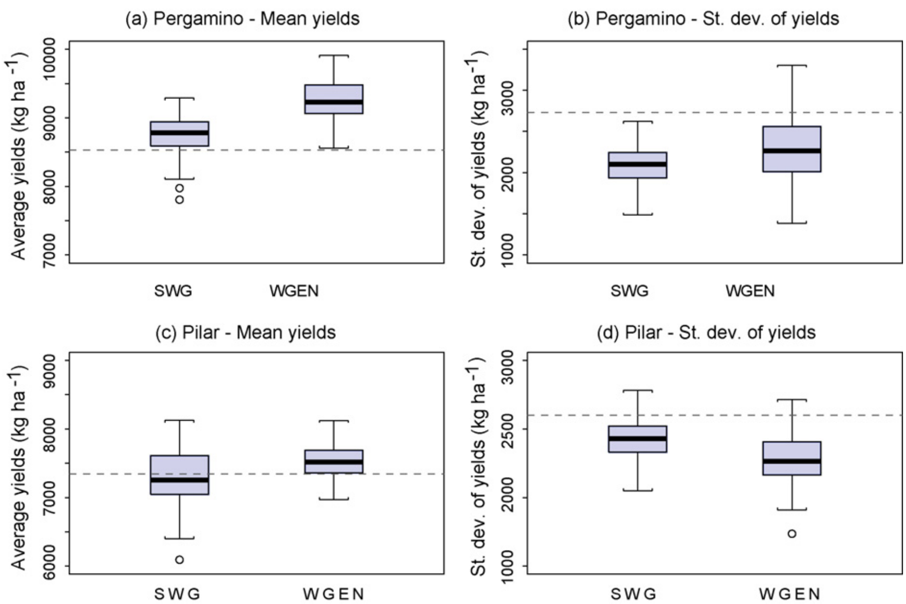

Fig. 2. Box plots of statistics of maize yields simulated using multiple realizations of climate synthetic series from SWG and WGEN generators: (a) distribution of mean yields for Pergamino, (b) distribution of standard deviations of yields for Pergamino, (c) distribution of mean yields for Pilar and, (d) distribution of standard deviations of yields for Pilar. The height of the boxes represents the interquantile range, the horizontal line inside the box corresponds to the median and the whiskers extend to the 5th and 95th percentile of the statistics. The dashed line in each panel indicates the maize yields simulated using the historical climate series for each location. Circles denote outliers, values beyond 1.5 times the interquartile range.

(Fig. 2(b)), whereas in Pilar SWG showed the better results (Fig. 2(d)). As the capability of the generators in reproducing the variability of maize yields differed between locations, we explored the multiple (100 realizations) maize yield distributions for each generator (Fig. 3). Empirical density functions were fitted to the historical and synthetic distributions of yields using the kernel density estimation procedure of Bowman and Azzalini (1997) and confidence intervals were constructed. Weather series from WGEN underestimated the frequency of low maize yields, mainly for Pergamino. That is, for low yields, the distribution of historical yields falls outside the 98% envelope of yields simulated with WGEN series. Conversely, when yields were simulated using SWG series, the frequency of low yields was closer to historical values although there was a tendency to underestimate the frequency of high yields.

As most farmers are moderately risk averse, they are primarily interested in the likelihood of low yields and/or economic outcomes. Therefore, simulations oriented to support decisions must be able to reproduce adequately the expected frequency of low values. Underestimating the frequency of low maize yields (as observed for WGEN) may lead to underestimation of production risks. As weather series generated by the SWG tended to reproduce better the probabilities of lower yields, this tool seems more appropriate to convert raw climate information into distributions of outcomes for agricultural risk assessment and management.

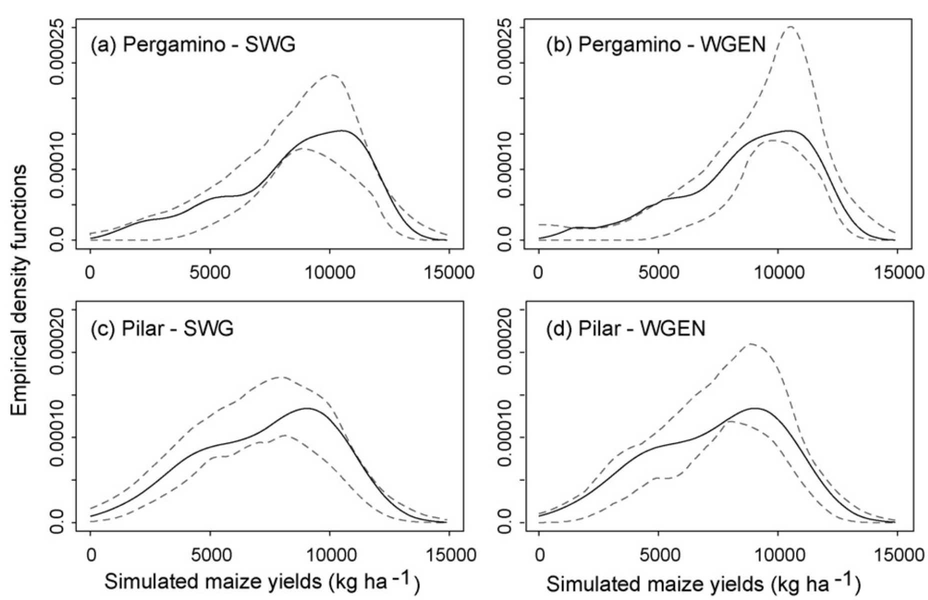

Fig. 3. The solid line represents an empirical density function (EDF) of simulated maize yields using the historical climate series for Pergamino (panels a and b) and Pilar (panels c and d). The dashed lines in each panel represent the 1st and 99th quantile of the EDFs estimated for maize yields simulated using multiple realizations of climate synthetic series from SWG (a and c) and WGEN (b and d) generators. Empirical densities were fitted to the historical and synthetic yields using the kernel density approach of Bowman and Azzalini (1997).

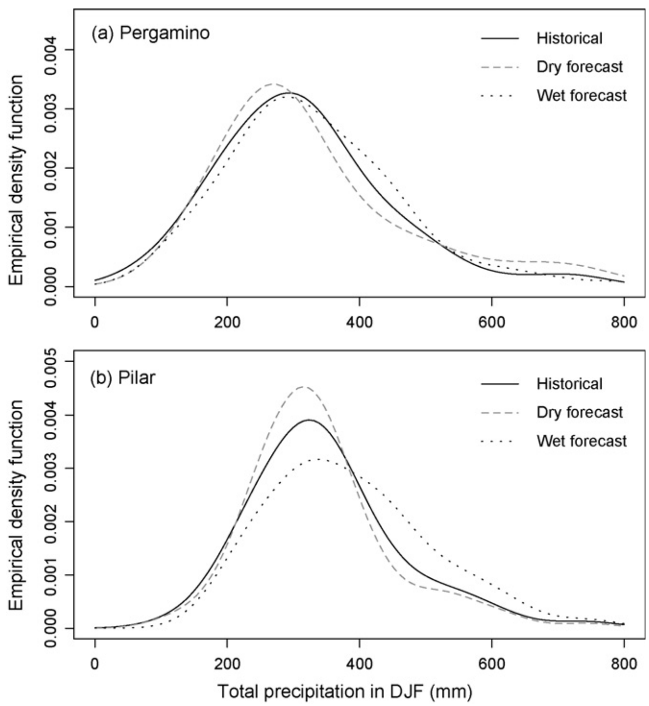

Fig. 4. Probability density functions (PDFs) of December–January–February total precipitation in (a) Pergamino and (b) Pilar for: (1) the historical climate record (solid black lines), (2) synthetic climate series consistent with a forecast of wetter than normal precipitation in December–January–February (dotted black lines), and (3) synthetic climate series consistent with a forecast of drier than normal precipitation in December–January–February (dashed grey lines). Empirical densities were fitted to historical and synthetic precipitation using the kernel density approach of Bowman and Azzalini (1997).

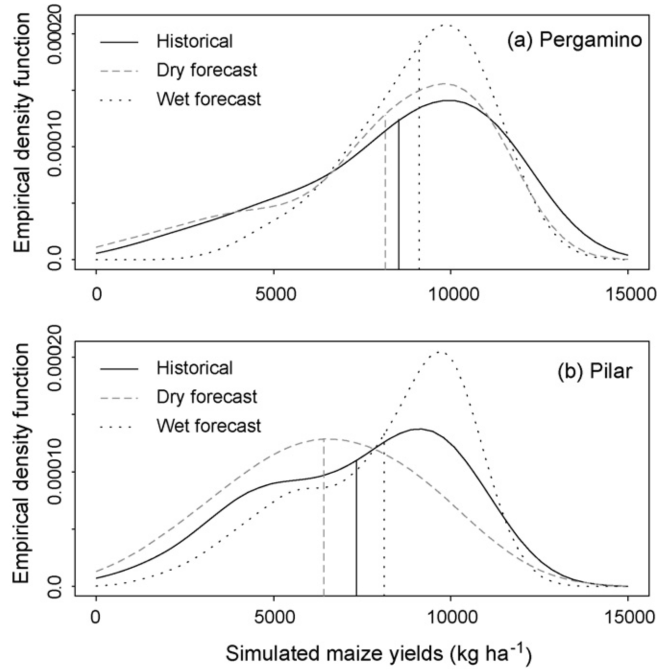

Fig. 5. Empirical probability density functions (PDFs) of simulated maize yields for Pergamino (a) and Pilar (b) using: (1) the historical climate record (solid lines), (2) the synthetic climate series consistent with a forecast of wetter than normal precipitation in December–January–February (dotted black lines), and (3) the synthetic climate series consistent with a forecast of drier than normal precipitation in December–January–February (dashed grey lines). The vertical lines represent the corresponding mean maize yields. Empirical densities were fitted using the kernel density approach of Bowman and Azzalini (1997).

4.2. Impacts of conditional weather scenarios—seasonal forecasts

Fig. 4 shows the empirical probability density functions (PDFs) of total December–January–February (DJF) precipitation from synthetic series conditioned on seasonal forecasts and the historical climate record. For both locations, the PDF of precipitation for synthetic series conditioned on the dry climate forecasts were shifted to the left of the historical PDF (i.e., DJF precipitation for the dry scenario is lower than for the historical). Conversely, the PDF of precipitation for synthetic series conditioned on the wet climate forecasts was shifted to the right of the historical PDF. This effect is more noticeable in the frequency of high precipitation values for Pilar. These results illustrate the capability of SWG to generate synthetic climate series consistent with seasonal climate forecasts.

Differences between simulated weather series conditioned on dry and wet seasonal forecasts induced changes in maize yields. The degree of change in maize yields was different for each seasonal forecast and location (Fig. 5). In Pergamino, the wet forecast led to a marked decrease in the frequencies of low maize yields ($<7000\ \mathrm{kg\ ha^{-1}}$) whereas the dry forecast did not significantly change maize yield distributions (Fig. 5(a)). In Pilar, both seasonal forecasts induced noticeable shifts in the PDFs of maize yields in relation with the historical distribution (Fig. 5(b)). The wet forecast led to a significant increase in maize yields, with a corresponding reduction in the frequency of low yields ($<7000\ \mathrm{kg\ ha^{-1}}$). Under the dry scenario, maize yields decreased markedly, with increases (decreases) in the proportion of low (high) yields (Fig. 5(b)).

Variations in maize yields between the different climate scenarios induced changes in economic outcomes. Fig. 6 shows

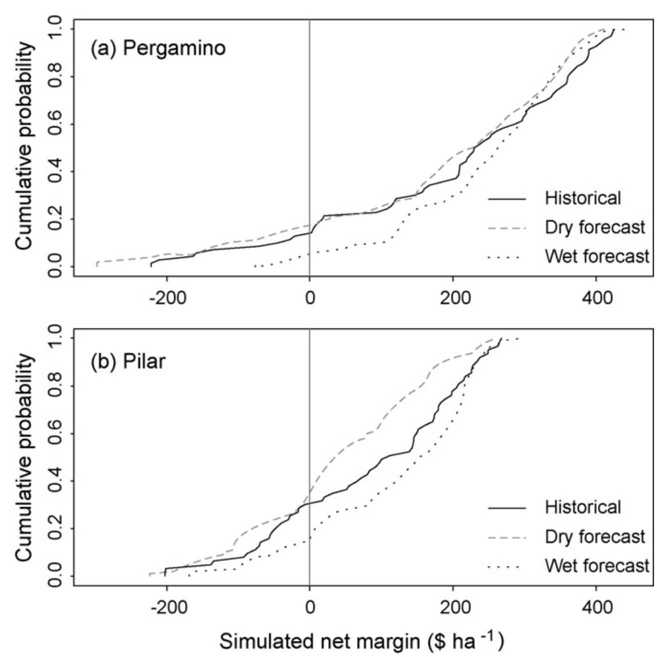

Fig. 6. Cumulative probability functions (CDF) of simulated net economic margins for Pergamino (a) and Pilar (b) for: (1) the historical climate record (solid lines), (2) the synthetic climate series consistent with a forecast of wetter than normal precipitation in December–January–February (dotted black lines), and (3) the synthetic climate series consistent with a forecast of drier than normal precipitation in December–January–February (dashed grey lines).

the Cumulative Density Functions (CDFs) of simulated net margins for Pergamino and Pilar and for the historical and conditioned scenarios. Differences among distributions were assessed using the *p*-values of Kolmogorov–Smirnov (K–S) tests. As for yields, in Pergamino, the CDF of net margins for the wet forecast was marginally different ($p = 0.16$) from the climatological distribution; the dry forecast distribution showed no statistical differences with the climatological margins. Conversely, in Pilar, the CDF of net margins changed significantly for the dry forecast ($p < 0.01$) but showed a limited difference for the wet forecast ($p = 0.21$); in both cases, differences were assessed against the climatological distribution of margins.

Seasonal forecasts involving even relatively small deviations from climatological probabilities of precipitation may have large impacts on the economic outcomes of crop production. For instance, in Pergamino, the median net margin increases more than 14% (from 233$ ha^{-1} to 266$ ha^{-1}) for the wet scenario (probability of above-normal precipitation is 0.45, instead of 0.33). In Pilar, the dry scenario (probability of below-normal precipitation is 0.45, instead of 0.33) is associated with a 65% decrease in median simulated net margins (from 112$ ha^{-1} to 39$ ha^{-1}).

In turn, changes in the distributions of net margins led to important differences in the production risks associated with each scenario. For instance, for a wet scenario, the probability of negative margins in Pergamino decreases to 1/3 of the historical averages. In Pilar, the historical probability of negative net margins in Pilar is around 30%. However, under the wet scenario this probability is halved.

Potential users of seasonal climate forecasts often complain that forecasts have coarse spatial resolution (i.e., the same deviations are predicted for large areas). For example, the same forecast of dry conditions (probability of below-normal DJF precipitation is 0.45) has widely different implications for our two target areas. For Pergamino, the distribution of simulated maize net margins is very similar for the dry and climatological scenarios (i.e., the dry forecast has no significant effects). In contrast, in Pilar the distribution of net margins under the dry scenario is considerably shifted to the left (i.e., lower probabilities of exceeding a given margin). Site-specific differences in the implications of the same forecast probably are tied to agroecological conditions in each region. Climate conditions in Pergamino are close to optimal for the production of maize; even under a small decrease in rainfall, results can be satisfactory. In contrast, production systems in Pilar already operate much closer to the limits of profitability than in Pergamino and have a slender buffer against climate hardships.

We stress that differences between forecasted scenarios are explored for only one crop (maize) and without changing the typical agronomic management. If different managements (including crop selection) were used for different forecasts, farmers might be able to mitigate negative results or take advantage of favorable conditions. The framework introduced here, which combines a semiparametric stochastic weather generator to downscale seasonal climate forecasts and crop simulation models, allows decision-makers to assess the likely outcomes of interactions between expected climate conditions and a range of management alternatives.

5. Conclusions

The increased recognition of the importance of climate on human systems has fostered a growing demand by decision-makers for reliable, quantitative climate information appropriate for use in assessments of climate variability and change, adaptation, impacts, and vulnerability (Bert et al., 2006). The linkage of stochastic weather generators and crop simulation models is useful to translate raw climate information into distributions of salient, relevant outcomes for agricultural risk assessment and management. Presenting expected outcomes of decisions in terms of distributions of crop yields or economic returns is more relevant to stakeholders than raw climate information such as a precipitation forecast.

Seasonal forecasts involving even relatively small deviations from climatological probabilities of precipitation may have large impacts on agricultural outcomes. A 12% change in the probability of a precipitation category (as explored here) may seem irrelevant to farmers, but conveying the likely agronomic or economic results of this shift may attract their attention considerably.

A frequent complaint from potential users of seasonal climate forecasts is that they have inadequate spatial resolution (i.e., the same deviations are predicted for large areas). Our results show that regions receiving the same seasonal forecast may experience fairly different outcomes. In particular, a given forecast may have much more serious implications for production systems in marginal regions that already operate much closer to the limits of profitability and have a slender buffer against climate hardships.

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