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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