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Translating climate forecasts into agricultural terms: advances and challenges

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ABSTRACT: Seasonal climate prediction offers the potential to anticipate variations in crop production early enough to adjust critical decisions. Until recently, interest in exploiting seasonal forecasts from dynamic climate models (e.g. general circulation models, GCMs) for applications that involve crop simulation models has been hampered by the difference in spatial and temporal scale of GCMs and crop models, and by the dynamic, nonlinear relationship between meteorological variables and crop response. Although GCMs simulate the atmosphere on a sub-daily time step, their coarse spatial resolution and resulting distortion of day-to-day variability limits the use of their daily output. Crop models have used daily GCM output with some success by either calibrating simulated yields or correcting the daily rainfall output of the GCM to approximate the statistical properties of historic observations. Stochastic weather generators are used to disaggregate seasonal forecasts either by adjusting input parameters in a manner that captures the predictable components of climate, or by constraining synthetic weather sequences to match predicted values. Predicting crop yields, simulated with historic weather data, as a statistical function of seasonal climatic predictors, eliminates the need for daily weather data conditioned on the forecast, but must often address poor statistical properties of the crop–climate relationship. Most of the work on using crop simulation with seasonal climate forecasts has employed historic analogs based on categorical ENSO indices. Other methods based on classification of predictors or weather types can provide daily weather inputs to crop models conditioned on forecasts. Advances in climate-based crop forecasting in the coming decade are likely to include more robust evaluation of the methods reviewed here, dynamically embedding crop models within climate models to account for crop influence on regional climate, enhanced use of remote sensing, and research in the emerging area of 'weather within climate.'

KEY WORDS: Yield forecasting · General circulation model · GCM · Crop simulation model · Stochastic weather generator · Calibration · Probabilistic forecasting

1. INTRODUCTION

Forecasts of climate fluctuations with a seasonal (i.e. several months) lead-time are possible because the atmosphere responds to the more slowly varying ocean and land surfaces, an example being climate fluctuations associated with the El Niño-Southern Oscillation (ENSO) in the tropical Pacific. Several climate prediction centers routinely issue probabilistic seasonal forecasts based on dynamic general circulation models (GCMs) that model the physical processes and dynamic interactions of the global climate system in response to sea and land surface boundary forcing. Probabilistic forecasts are obtained from ensembles of GCM integrations initialized with different atmospheric conditions. Periodic regional climate outlook forums in Africa and Latin America have issued seasonal climate forecasts targeting agriculture and other climate-sensitive sectors since 1997.

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By providing advance information early enough to adjust critical agricultural decisions, seasonal climate prediction appears to offer significant potential to contribute to the efficiency of agricultural management, and to food and livelihood security. However, there is a gap between the information that comes routinely from climate prediction centers and regional climate outlook forums, and the needs of farmers and other agricultural decision makers. Applications of climate forecasts within agriculture are concerned with impacts on production and environmental and economic outcomes, and not with climate fluctuations *per se*. 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, with uncertainties expressed in transparent, probabilistic terms. Market and food security early warning applications also need to translate climate information into production outcomes, but generally at a different spatial scale and lead time.

Stimulated in part by the socioeconomic consequences and widespread public awareness associated with the very strong 1997–1998 El Niño event, interest in agricultural application of seasonal climate prediction gained momentum in the late 1990s. Research efforts have used dynamic, process-oriented crop simulation models as a means of translating climate forecasts into crop yield prediction and as a basis for evaluating potential management responses. This work has depended heavily on analog methods based on categorical indicators of the ENSO (e.g. Jones et al. 2000, Meinke & Hochman 2000, Podestá et al. 2002, Everingham et al. 2003, Meinke & Stone 2005). Tropical Pacific sea surface temperatures (SSTs) or the Southern Oscillation Index (SOI) are classified into a small number of categories or 'phases.' Weather data from past years, with the same predictor category as the forecast period, are used as input to crop models. The set of simulated outcomes provides a probabilistic forecast. Through the 1990s, this work seldom attempted to incorporate operational dynamic climate forecasts, and borrowed little from the concurrent development of methodology for translating climate change scenarios (often based on the same GCMs used for seasonal forecasting) into estimates of agricultural impacts. Despite strong interest in using GCM-based seasonal forecasts for agricultural applications, progress has — until recently — been slow, due in part to limited accessibility of GCM results, methodological challenges related to the spatio-temporal scale mismatch between GCMs and crop model requirements, and concerns about characterizing and interpreting forecast probabilities.

The 1997–1998 El Niño also stimulated debate about the value of climate prediction to a range of societal problems. One concern was that limited predictability of crop yield response at the farm scale, early enough to allow farmers to modify critical pre-planting decisions, might be a fundamental constraint to the use of forecasts by risk-averse farmers (Barrett 1998, Blench 2003). The argument was based on 2 assumptions. (1) Variability of rainfall over small spatial scales implies that seasonal rainfall predictability is limited to regional spatial scales. (2) Because crop yield is not a simple function of seasonal total rainfall, the accumulation of errors going from seasonal climatic predictors (e.g. SSTs), to local seasonal means, to crop response, implies that predictions of effects such as crop response will be less accurate than predictions of climatic means. Recent research challenges these assumptions (Hansen 2005). Limited evidence suggests that much of the skill of regional seasonal forecasts holds up at a local scale (Gong et al. 2003), and that predictability of crop yield response can be as great or greater than predictability of seasonal climatic means (Cane et al. 1994, Hansen et al. 2004).

Our objective here is to survey progress in translating seasonal climate prediction into forecasts of agricultural production that are relevant to agricultural decision-making, through the integration of climate models with process-oriented agricultural simulation models. While most applications address crop or forage yields, relevant applications also include environmental quality impacts (Mavromatis et al. 2002, Zhang 2003). We highlight advances over the last decade, as well as key challenges and emerging opportunities facing us in the coming decade. Advances in the use of seasonal climate forecasts with agricultural simulation models contribute to (1) translating climate forecasts into more relevant information about impacts within the system being managed; (2) ex-ante assessment of benefit to motivate support and insights to target interventions; and (3) guiding management responses through the use of model-based systems that support discussion and decision-making (Hansen 2005).

2. THE CLIMATE–CROP MODEL CONNECTION PROBLEM

Operational seasonal climate forecasts are generally issued as averages in time (≥3 mo) and space. Because of the effect of spatial and temporal averaging on the random noise resulting from the chaotic nature of the atmosphere, the proportion of variability that is predictable at a seasonal lead-time due to boundary forcing tends to increase with increasing spatial and temporal scale up to a point. Furthermore, computational capacity limits the spatial resolution of GCMs used for seasonal prediction to a fairly coarse grid scale, currently on the order of 10 000 km^2.

Crop production is a function of dynamic, nonlinear interactions between weather, soil water and nutrient dynamics, management, and the physiology of the crop. Relating predicted climatic variations, averaged in space and time, to crop response is not straightforward. Crop response tends to be nonlinear and sometimes non-monotonic over a realistic range of environmental variability. Furthermore, crops do not respond to conditions averaged through the growing season, but to dynamic interactions between weather, soil water and nutrient dynamics, and the stage of crop development. In rainfed production systems, the interaction between rainfall and the soil water balance is particularly important. Crop characteristics, soil hydraulic and fertility properties, stresses, and management mediate sensitivity to weather conditions within the growing season. Finally, a range of interacting weather variables mediates many aspects of crop growth and development. To capture the dynamic, nonlinear interactions between weather, soil water and nutrient dynamics, and physiology and phenology of the crop, process-oriented crop simulation models typically operate on a daily time step and a spatial scale of a homogeneous plot (although sampling the heterogeneity of soil, weather and management inputs allows simulated results to be interpreted at a range of scales).

Global and regional dynamic climate models operate on sub-daily time steps, but the spatial averaging that occurs within grid cells distorts the temporal variability of daily weather sequences (Osborn & Hulme 1997). Any distortion of daily weather variability can seriously bias crop model simulations (Semenov & Porter 1995, Mearns et al. 1996, Riha et al. 1996, Mavromatis & Jones 1998a, Hansen & Jones 2000, Baron et al. 2005). One of the most serious effects is a tendency to over-predict frequency of wet days and under-predict their mean intensity (Mearns et al. 1990, 1995, Mavromatis & Jones 1998a, Goddard et al. 2001). The direction of resulting crop model error cannot be easily anticipated. On the one hand, when canopy cover is incomplete and evaporative demand is high, frequent low-intensity showers do not recharge soil water reserves in deeper layers, but favor increased evaporation from the soil surface, thereby increasing water stress (de Wit & van Keulen 1987). On the other hand, increasing the frequency of rainfall events tends to reduce the duration of dry periods between rain events, thereby reducing water stress (Carbone 1993, Mearns et al. 1996, Riha et al. 1996, Hansen & Jones 2000). Baron et al. (2005) suggested that millet in Sahelian West Africa can use only intermediate (10 to 30 mm d^{-1}) rainfall events efficiently, as smaller rainfall events are largely lost to soil evaporation while more intense rainfall is lost to runoff and drainage. Aggregating daily rainfall from 17 stations to a scale typical of GCMs resulted in the over-prediction of mean simulated yields by 28%, due to overestimation of rainfall efficiency associated with an increased proportion of intermediate rainfall events in the aggregated series.

3. ADVANCES IN METHODS FOR LINKING CLIMATE AND CROP MODELS

A range of methods for linking crop simulation models to seasonal climate forecast models have been advanced. We survey recent advances in methodology under 4 categories (Hansen & Indeje 2004): (1) crop simulation with daily climate model output, (2) use of synthetic daily weather conditioned on climate forecasts, (3) statistical prediction of crop response simulated with historic weather, and (4) classification and analog methods. The discussion includes some methods that have been developed for simulating agricultural impacts of GCM-based climate change scenarios, but that appear to have potential for yield prediction based on seasonal forecasts.

The applications include both field scales with a focus on farmer decisions, and regional scales that are relevant to food security early warning and market applications. Simulating crop response to weather at aggregate scales has progressed in 2 parallel directions. Process-oriented crop models that have been developed for field-scale applications can be scaled up by (1) representing heterogeneity of environment and management with spatial data sets, (2) probabilistic sampling of environmental variables, (3) calibration of model input parameters or (4) model outputs against reported crop data at the scale of interest (Hansen & Jones 2000). The alternative is to simulate aggregate crop response with models that are simplified to operate on a large spatial scale while maintaining enough complexity to capture the major components of yield responses to climate variability. Examples range from water-satisfaction indices based on simplified soil water balance (Frere & Popov 1979), to process-oriented models such as the General Large-Area Model (GLAM) designed to simulate annual crop yields at a GCM grid scale (Challinor et al. 2004, 2005).

3.1. Crop simulation with daily climate model output

Despite the tendency of GCMs to seriously distort daily variability, daily GCM output has been used as input to crop models with some success through either the calibration of yields simulated with raw GCM output, simple rescaling to correct GCM mean bias, or the application of a more sophisticated simultaneous correction of GCM rainfall frequency and intensity. Mavromatis & Jones (1998b) used uncorrected daily output from runs of the HadCM2 GCM as input to the CERES-Wheat model for studying potential impacts of climate change on regional winter wheat production in France. Yields simulated with GCM weather data approximated mean yields simulated with observed weather during the past century, and captured a yield trend associated with the recent trend in observed temperature, but under-represented year-to-year variability. Challinor et al. (2005) used daily meteorological variables from 9 seasonal hindcast runs from each of 7 GCMs as input to the GLAM crop model to predict groundnut yields over western India. Historic district groundnut yields aggregated to the GCM grid scale showed lowest overall prediction error when simulated yields were calibrated to observed district yields, regardless of whether mean bias in the GCM output was first corrected.

Studies (Mavromatis & Jones 1998a, Hansen & Jones 2000, Baron et al. 2005) have demonstrated the impact on day-to-day variability and crop simulation results, of aggregating daily weather data to a spatial scale typical of GCM grid cells and operational seasonal forecasts. Several approaches have been proposed to disaggregate GCM output and other area-averaged daily data sources (e.g. satellite rainfall estimates) to the scale of individual stations in a manner that corrects the biases. The simplest option for calibrating daily GCM output to match observed mean local climate is to apply a simple shift (e.g. Ines & Hansen 2006). An additive shift is appropriate for temperature and solar radiation. A multiplicative adjustment, e.g.

$$x'_i = x_{i,GCM}\bar{x}_{obs}/\bar{x}_{GCM} \quad (1)$$

is more appropriate for precipitation, as it preserves the sequence of zero values associated with dry days, where $x_{i,GCM}$ and x'_i refer to raw and calibrated GCM rainfall on day i, respectively, and $\bar{x}_{obs}$ and $\bar{x}_{GCM}$ are long-term mean observed and simulated rainfall, respectively, for a given time of year. However, because the multiplicative shift corrects total rainfall by adjusting intensity and not frequency, it cannot correct the observed tendency of GCMs to over-predict frequency and under-predict mean intensity (see Section 2).

Schmidli et al. (2006) and Ines & Hansen (2006) proposed calibrating both the frequency and intensity distribution of GCM rainfall. The tendency for GCM rainfall to be more frequent than observations can be corrected simply by calibrating a daily GCM rainfall threshold, such that the relative frequency of simulated rainfall above the threshold matches the long-term observed frequency for e.g. a given calendar month (Fig. 1a). Schmidli et al. (2006) used a simple multiplicative shift to correct the intensity distribution of daily GCM rainfall after calibrating frequency. To derive daily rainfall data for a maize simulation model at a semiarid location in Kenya, Ines & Hansen (2006) mapped the cumulative distribution of GCM rainfall $F_{GCM,m}(x)$, truncated below the calibrated threshold for month m, onto the distribution of observed daily rainfall $F_{obs,m}(x)$, using the transformation,

$$x'_i = F^{-1}_{obs,m}[F_{GCM,m}(x_i)] \quad (2)$$

for each ith day of GCM rainfall (Fig. 1b). The calibration, using a fitted gamma distribution for observed rainfall intensity, and either a gamma or empirical distribution of GCM rainfall intensity, substantially reduced biases of both mean and variance of monthly totals, frequency and mean intensity of GCM rainfall. Baron et al. (2005) demonstrated that disaggregating the spatial averages of daily rainfall from 17 stations (approximating the scale of a GCM grid cell) in Senegal to a network of 81 'virtual stations' corrected much of the bias in rainfall frequency and simulated millet yield that resulted from spatial aggregation. They used a spatial disaggregation algorithm based on a transformation of a multivariate Gaussian process to a shifted gamma rainfall distribution, designed to generate synthetic sets of rainfall that match a specified aerial average for a given day, but that have statistical properties (i.e. frequency, intensity distribution, spatial structure) that are consistent with observations at a set of stations within the area (Onibon et al. 2004).

Ines & Hansen (2006) found that using daily GCM rainfall calibrated to station data at a semiarid location

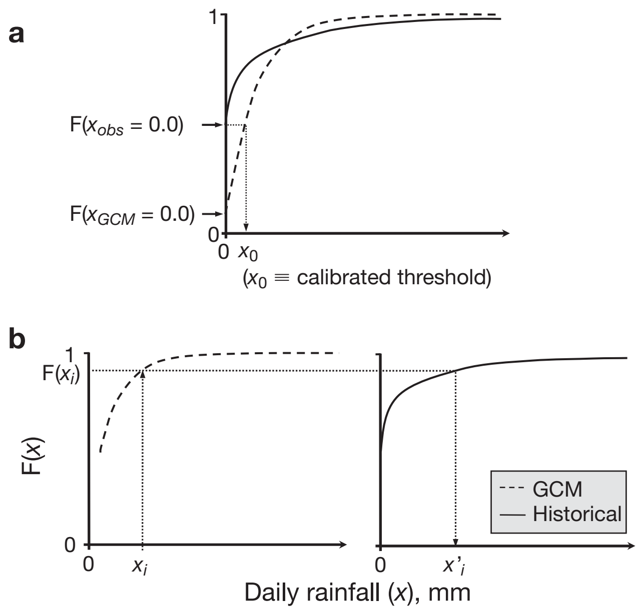

Fig. 1. Schematic representation of daily GCM bias correction: (a) frequency, (b) intensity (Ines & Hansen 2006). F: cumulative distribution function; x: daily rainfall amount; *obs*: historical observations; GCM: model simulations

in Kenya resulted in systematic under-prediction of simulated maize yields, even though the calibration largely corrected mean and variance of GCM monthly rainfall totals, frequency and intensity. They attributed the simulated yield bias to a tendency for the GCM rainfall to be more strongly autocorrelated than observed rainfall, resulting in excessive clustering of rainfall events and unrealistically long dry spells during the growing season. The potential utility of daily climate forecast model output for predicting crop response may therefore be limited more by the ability of GCMs to simulate rainfall with a realistic time structure than by biased simulation of rainfall frequency and intensity. However, there is some evidence from Northeast Brazil that a high-resolution climate model nested within GCM output fields can simulate daily rainfall with more realistic spell lengths than the underlying GCM (Sun et al. in press).

3.2. Synthetic weather conditioned on climate forecasts

Seasonal or sub-seasonal (e.g. monthly) climate forecasts can be disaggregated using a stochastic weather model 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. Two approaches have been advanced. The first, more common approach is to adjust the parameters of a stochastic generator in a manner that is consistent with the forecast. The second is to constrain the generated daily sequences to exactly match target monthly or seasonal means.

The input parameters of simple stochastic weather generators can be manipulated to reproduce predicted statistical properties of interest, such as means, variances, and the relative influence of the number of storms (i.e. frequency) and the type of storm (i.e. the intensity distribution) on total rainfall. Several studies of the behavior of stochastic weather models, motivated largely by climate change impact assessment, provide a solid foundation for using weather generators to produce synthetic daily sequences that are conditioned on seasonal forecasts (Wilks 1992, Katz 1996, Mearns et al. 1997). Methods for conditioning weather generator parameters on seasonal predictions or predictors include: estimating parameters from years with a particular categorical predictor value (Katz & Parlange 1993, Grondona et al. 2000, Katz et al. 2003), regressing parameters against a seasonal predictor (Woolhiser et al. 1993), predicting from GCM output fields using multivariate statistical downscaling (Cantelaube & Terres 2005, Feddersen & Andersen 2005, Marletto et al. 2005), and by sampling past years in proportion to forecast shifts from climatological tercile probabilities to estimate parameters (Wilks 2002). Conditioning precipitation parameters on seasonal forecasts requires either some assumption about the relative contribution of occurrence and intensity to target rainfall, or empirical estimation relating hindcasts to the historic rainfall frequency and intensity record. Because weather generators are stochastic, many replicates may be required to approximate target means or other statistics of interest with acceptable accuracy.

An alternative approach is to constrain the generated daily sequences to match target monthly values. A simple additive shift may be sufficient to constrain a generated series of temperatures to match a target monthly mean. For rainfall, this is accomplished by sampling and testing generated sequences until the total is sufficiently close to a target value, then correcting the generated sequence to exactly match the target (Hansen & Indeje 2004, Kittel et al. 2004, Hansen & Ines 2005). This approach requires no *a priori* assumption about the relative contribution of occurrence and intensity to target rainfall, but samples synthetic rainfall sequences that are consistent with the occurrence and intensity components of the weather generator, parameterized with historic data. It can, however, accommodate adjustments to parameters of the frequency and intensity processes. Hansen & Ines (2005) applied this approach to disaggregate observed monthly precipitation at sites in the Southeast USA, and both observed and hindcast precipitation at a site in Kenya, as input to the CERES-Maize model. Constraining generated monthly rainfall to match observations largely reproduced the cross-correlation between observed amount, frequency and mean intensity of rainfall more accurately than conditioning weather generator parameters on monthly rainfall, and required roughly an order of magnitude fewer realizations to approach the asymptotic maximum correlation with yields simulated with observed daily rainfall.

3.3. Statistical prediction of simulated crop response

The approaches discussed in Sections 3.1 & 3.2 involve conditioning crop model weather input data on the climate forecast. An alternative approach is to treat yields simulated with historic daily weather data as a statistical predictand, and condition the crop model output on the forecast. By bypassing the need to derive weather data inputs conditioned on the seasonal forecast, the use of a statistical model trained on crop model outputs eliminates one source of error. On the other hand, this approach is constrained to treating the seasonal forecast and its relationship to crop response as essentially static within a growing season. While our review focuses on forecasting using dynamic crop models, statistical prediction from GCM output fields has also been applied to remotely-sensed forage vegetation indices (Indeje et al. 2006) and de-trended crop production statistics (G. Baigorria, pers. comm.).

Crops tend to show non-linear, non-monotonic relationships with their environment over some range of variability, complicating direct statistical prediction. Other potential problems that violate assumptions of ordinary least-squares regression include residuals that are non-normally distributed, and residual variance that varies systematically with predictor. Approaches to dealing with these challenges include nonlinear regression, linear regression following normalizing transformation, generalized linear models, and non-parametric models.

As an example of nonlinear regression, Hansen & Indeje (2004) predicted simulated maize yields at a site in southern Kenya as a cross-validated function of the first principal component of GCM rainfall over the region. They chose a Mitscherlich function,

$$\hat{y} = a + b(1 - e^{-cx}) \quad (3)$$

based on its widespread use for modeling plant response to water and other growth factors. Diagnostics showed some evidence that residual variance varied systematically with the predictor—a mild violation of the assumptions of least-squares regression.

Where the relationship between predicted climate variations and simulated crop response is only weakly nonlinear, transforming the predictand and potentially the predictor may correct nonlinearity, non-normality of regression residuals and heterogeneity of residual variance sufficiently to permit ordinary linear regression. Hansen et al. (2004) used an optimal power series (Box & Cox 1964) transformation to normalize mildly-skewed simulated yield distributions before predicting district and state wheat yields, simulated with observed antecedent rainfall and historic within-season rainfall, as a linear function of a regional GCM rainfall predictor in northeastern Australia. Such data transformations may not handle non-monotonic crop–climate relationships or extreme departures from linearity and normality sufficiently to permit ordinary least-squares linear regression. Because aggregating in space smoothes year-to-year variability of crop yields and, by the Central Limit Theorem, reduces departures from normality, we hypothesize that linear regression, possibly with a normalizing transformation, may be more suited for yield forecasts at an aggregate scale than at a field scale. Generalized linear models (McCullagh & Nelder 1989), designed to extend the benefits of linear regression where data are not normally distributed, are a promising alternative that to our knowledge has not yet been applied to predicting crop yields in response to forecast seasonal climate variations.

3.4. Classification and analog methods

Several practical benefits account for the continued dominance of the historical analog approach for crop yield prediction described in Section 1 (Meinke & Stone 2005). The approach is easily adapted to any spatial or temporal scale for which historic data are available. If the predictors used provide any predictive information about higher-order variations beyond seasonal climatic means that influence crop response, analog years will incorporate that predictability into crop simulations. Distributions derived from analogs will account for any differences in dispersion, in addition to mean shifts associated with different states of ENSO. Finally and perhaps most important, distributions of outcomes simulated for the analog years associated with a given category provide an intuitive means of estimating and communicating forecast uncertainty in probabilistic terms.

The analog method also has important limitations. Confidence, artificial forecast skill and biased estimation of uncertainty are concerns in those cases when the number of categories and limited record length lead to small sample sizes within each category (Section 4.3). More important, analogs based on ENSO or other empirical indices do not necessarily capture the best that climate science or operational forecast systems have to offer. While statistical climate prediction models have generally approached their predictive limits, dynamic climate forecast models, which integrate global sea and land surface forcing, sometimes outperform the best statistical models, and are expected to improve with improvements in models, data assimilation, computer capacity and post-processing methods. Stone et al. (2000) proposed using the analog approach with GCM output fields classified into discrete categories by cluster analysis.

The analog method described above treats each past year falling within the given predictor category as equally probable. It is a special case of a more general set of methods based on classification of predictors or weather types. If there is a basis for predicting that the coming season is more likely to resemble some past years than others, we can use the predicted probabilities to derive a probability-weighted forecast distribution, or calculate weighted mean or other distribution statistics. The common method of issuing operational seasonal climate forecasts as shifted probabilities of each of the climatological terciles, can be used directly to assign weights to analog years or to resample past years in proportion to the forecast probabilities. For example, Everingham et al. (2002) and Bezuidenhout & Singles (2006) sampled analog years in proportion to tercile forecasts from the South African Weather Service to forecast sugarcane production.

The *k*-nearest neighbor (KNN) method selects and assigns probability weights to a subset of *k* past years based on their similarity, in predictor state space, to a given predictor state (Lall & Sharma 1996). Weights w_j of the *k* nearest neighbors, ordered on the basis of their similarity to the value of the current predictor vector, are calculated as:

$$w_j = (j \sum_{i=1}^{k} i^{-1})^{-1} \tag{4}$$

where *j* and *i* are indices of the given historic year and the other *k* nearest neighbor years, sorted by distance (i.e. closest = 1) from the current predictor vector. For all $j > k$, w_i is set to 0. Using the KNN method to sample past seasons showed comparable results to other methods that Hansen & Indeje (2004) tested for GCM-based maize prediction in Kenya. It has also been used successfully for predicting reservoir inflow from seasonal rainfall predictors in Northeast Brazil (DeSouza & Lall 2003). The KNN analog approach can also be applied on shorter time steps to probabilistically sample subsets of past weather observations based on the degree of similarity of current and historical values of a given feature vector that may include atmospheric indicators from SST-forced GCM outputs (Clark et al. 2004, Gangopadhyay et al. 2005). Appropriate selection criteria can preserve moments of the historical distribution, as well as observed spatial and temporal correlations and correlations among variables.

Weather classification works in the same way, except that historic data are clustered into discrete circulation patterns or 'weather types' identified e.g. by cluster analysis, that explain a substantial portion of the variability and spatial patterns of rainfall. The ability of a GCM, driven by SSTs, to produce daily regional circulation patterns with realistic frequency and seasonality provides a basis for re-sampling historic local rainfall observations based on similarity of circulation patterns simulated by a GCM and from reanalysis data used as a proxy for observed wind fields (V. Moron, pers. comm.). Moron proposed a 2-stage sampling procedure. To capture interannual variability, past seasons are sampled in proportion to their similarity to the current year based on the distance between principal components of GCM and reanalysis wind fields. Daily rainfall is then sampled randomly from the pool of days within the sampled past seasons with the same weather type that the GCM simulates. The process is repeated for the sequence of daily weather types that the GCM simulates through the season. The approach predicted a substantial portion of the year-to-year variability of rainfall characteristics (i.e. frequency, distribution of dry and wet spells, seasonal total) with encouraging skill and realism (V. Moron, pers. comm.). It appears to be a promising approach to conditioning daily weather data inputs on aspects of sub-seasonal variability that are predictable at a seasonal lead time, but it has not yet been tested for crop simulation.

Non-homogeneous hidden Markov models (NHMM) integrate weather classification with stochastic weather models (Section 3.2) (Hughes & Guttorp 1994, Charles et al. 1999, Hughes et al. 1999). Observed rainfall patterns are classified into discrete types. Transition between states in a NHMM is a Markov process, with transition probabilities conditioned on a given set of predictors. The NHMM is parameterized using daily sequences of spatial weather patterns, and is capable of representing the historic spatial structure in the weather patterns that it simulates. The NHMM has been applied to disaggregating seasonal rainfall predictions (Robertson et al. 2004, 2006), and to disaggregate rainfall data in space and time as input to a maize simulation model over the Southeast USA (Robertson et al. in press).

4. UNCERTAINTY IN CLIMATE-BASED CROP FORECASTING

Transparent presentation of uncertainty in probabilistic terms is crucial to appropriate application of advance information, particularly when risk aversion influences decisions. Underestimating the uncertainty of a forecast can lead to excessive responses that are inconsistent with a decision makers' risk tolerance, and can damage the credibility of the forecast provider, while overestimating uncertainty leads to underconfidence and lost opportunity to prepare for adverse conditions and take advantage of favorable conditions.

Climate variability and crop model (including input) error are the major sources of uncertainty in yield forecasting. One way to characterize the uncertainty associated with climate variability is to simulate yields with antecedent weather observations up to a given forecast date within the season for a current or hindcast year, and sample weather data for remainder of season from all other years (Fig. 2). The resulting distribution approximates the climatic component of uncertainty. Information about antecedent weather and its effect on stored soil moisture provides a degree of predictability of yields that increases as the forecast date advances through the growing season, and an increasing proportion of weather data is observed, rather than sampled. Several proposed and operational crop-forecasting systems integrate weather observations through the current date with sampling from climatology for the remainder of the growing season (Thornton et al. 1997,

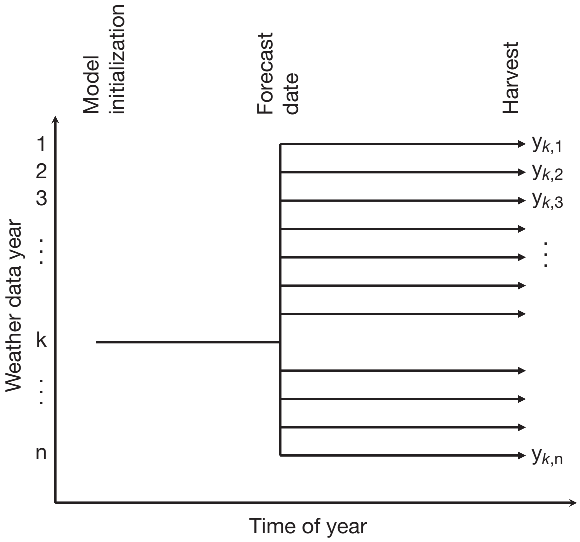

Fig. 2. Schematic of simulating yields y with antecedent weather data in year k and all other years of within-season weather data to characterize the climatic component of uncertainty in yield simulations at a given point within a growing season

Samba 1998, Bannayan et al. 2003, Lawless & Semenov 2005). Model error represents the remaining discrepancy between observed yields and yields simulated with observed weather.

A skillful seasonal climate forecast reduces the climatic component of uncertainty. Since the proportion of total uncertainty that is due to climate decreases through the growing season (Fig. 3a), the relative contribution of seasonal forecasts to overall predictability tends to be greatest early in the season, and to decrease as the season progresses and an increasing proportion of weather is observed, rather than predicted or sampled (Fig. 3b). On the other hand, reducing model error through e.g. improved measurement or calibration of model inputs, updating crop state variables based on remote sensing (see Section 5.2), or modeling additional yield-limiting factors, is likely to have a greater relative impact on overall uncertainty later in the growing season (Fig. 3c).

4.1. Deriving crop forecast distributions

Methods that have been developed for deriving and evaluating probabilistic climate forecasts are generally relevant to forecasts of agricultural impacts.

4.1.1. Forecast distributions from hindcast residuals

The first approach is to estimate a forecast distribution as the distribution of hindcast residuals, centered on the expected value of the current forecast. To illustrate, Fig. 4a shows a hypothetical 1960–2000 yield time series, derived from sampling a multivariate normal distribution, of observations (y) and hindcasts ($\hat{y}$) calibrated to observations by linear regression. Subtracting predictions from observations yields a time series of hindcast residuals

$$\varepsilon_i = y_i - \hat{y}_i \tag{5}$$

(Fig. 4b), which are then sorted to derive a residual distribution (Fig. 4c). The forecast distribution for the next year (2001) is obtained by adding its expected value, $\hat{y}$ = 1.9 Mg ha^{-1}, to each ε (Fig. 4d). The method accounts for the overall prediction error of the forecast system, and is generally applicable to statistical or dynamic forecast models.

The analog method discussed earlier (Sections 1 & 3.4) provides a simple, intuitively appealing way to derive

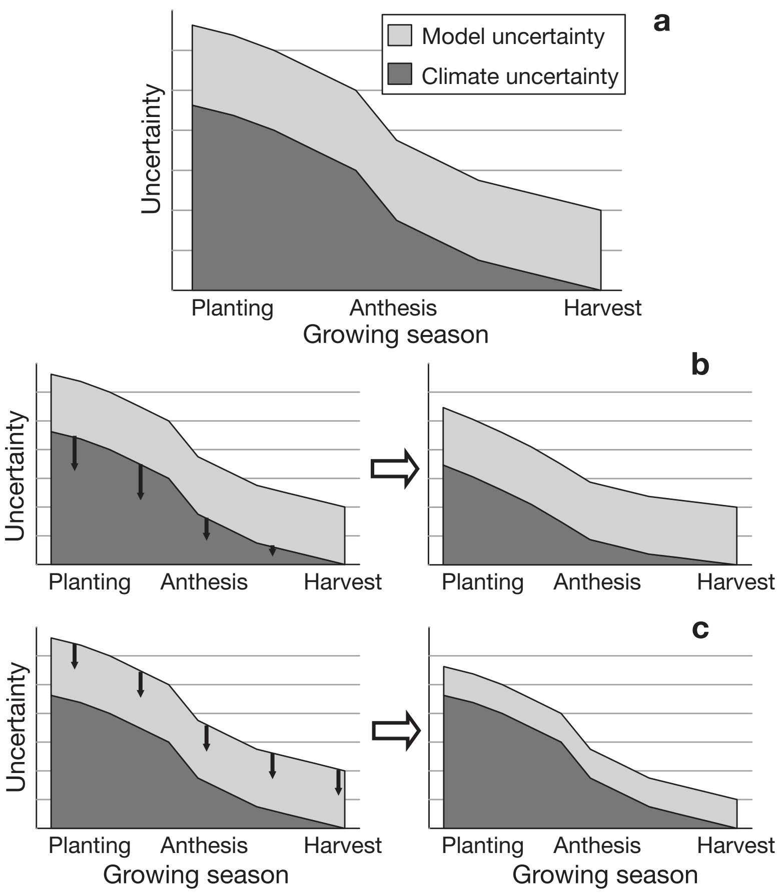

Fig. 3. Changing contribution of climatic and model uncertainty (a) through the growing season; and with impact of reducing (b) model and (c) climatic uncertainty

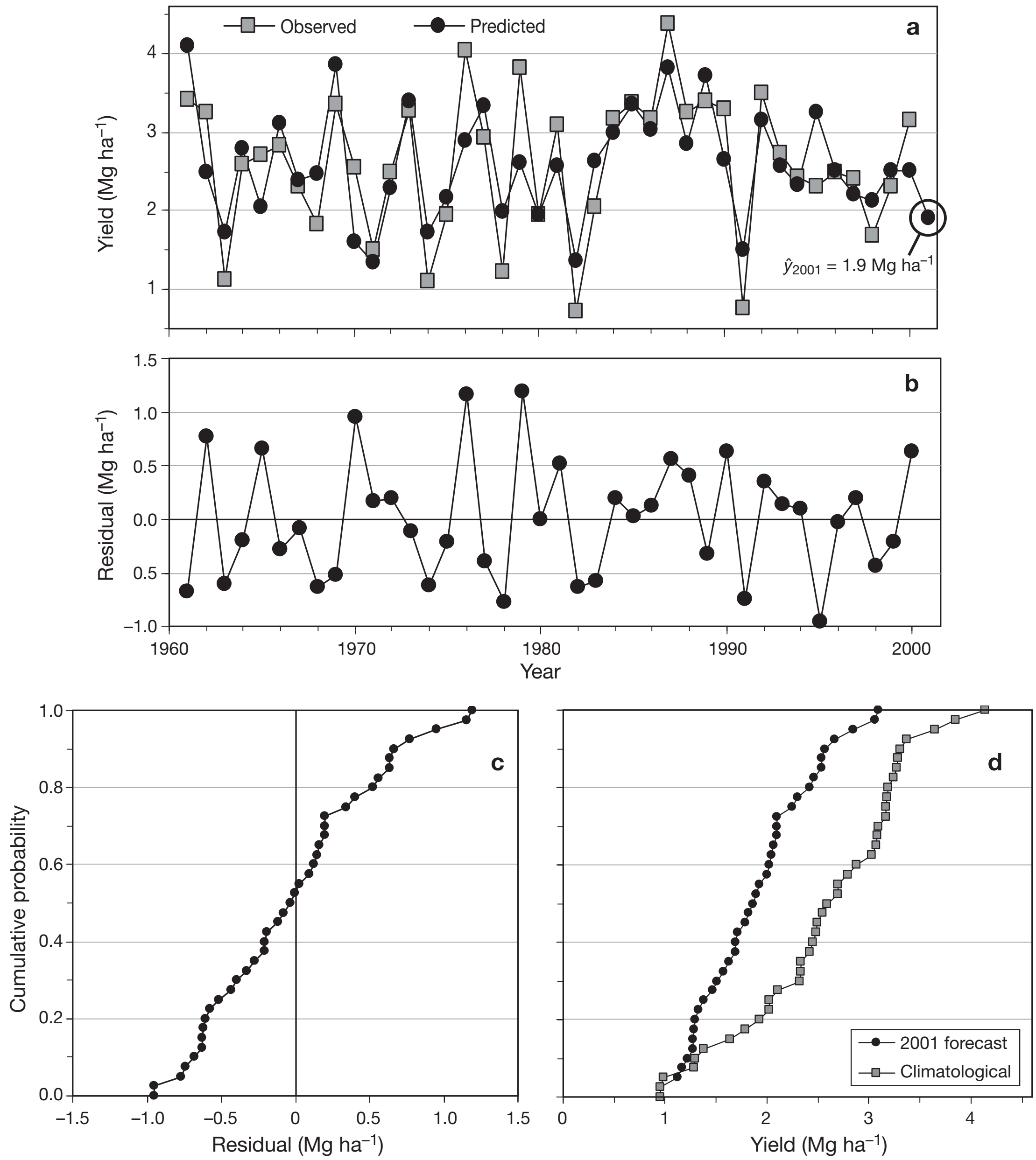

Fig. 4. Steps in deriving a probabilistic forecast from hindcast residuals: (a) synthetic time series of observations (y_i) and correlated, calibrated predictions ($\hat{y}_i$), (b) time series of residuals ($\varepsilon_i = \hat{y}_i - y_i$), (c) cumulative density function (CDF) of residuals and (d) CDF of 2001 forecast and climatology

probabilistic forecasts of climate variations and their agricultural impacts. Yields simulated with weather sampled from the set of past years falling within the category that corresponds to current conditions are taken as a forecast distribution. It is easy to show that distributions derived from historical analogs are a special case of residual-based distributions, which use the subset of residuals about the mean from those years that fall within the given predictor class. Hansen et al. (2004) compare cross-validated probabilistic wheat yield forecasts based on SOI phase analogs and regression from GCM predictors.

4.1.2. Forecast distributions from dynamic climate model ensembles

Initializing GCMs with different sampled atmospheric conditions improves skill and gives an indication of the uncertainty associated with initial conditions (Barnston et al. 2003, Palmer et al. 2004). The use of several different GCMs captures uncertainty associated with model structure and assumptions (Palmer et al. 2005). The spread of resulting predictions can be interpreted as a measure of forecast uncertainty, but must be calibrated before forecasts can be expressed as probability distributions at a local scale (Doblas-Reyes et al. 2005, Palmer et al. 2005). However, there is not yet a consensus about the most appropriate calibration method.

Probabilistic forecasting based on GCM ensembles can be extended to crop yield prediction. For example, Challinor et al. (2005) used daily output from each member of both single- and multiple-GCM ensembles to assess probabilistic forecasts of observed district-level groundnut yields and crop failure in western India. Cantelaube & Terres (2005) used monthly climatic means predicted from each ensemble member, statistically downscaled and disaggregated to daily values, using a stochastic weather generator (Feddersen & Andersen 2005) to produce probability density estimates of gridded and national wheat yields across Europe.

Although crop yield is a continuous quantity, the probability of yields falling below some threshold — a discrete event — may be more relevant than the magnitude of yields for applications related, for example, to food crisis response or crop insurance. In their study of groundnut yield forecasting in western India, Challinor et al. (2005) used a probabilistic, categorical skill metric (the relative operating characteristics [ROC] curve) to demonstrate skillful GCM-based predictions of crop failure. We extend their analysis to compare the predictability of extreme crop failure to more moderate failure. The inverted ROC (IROC) replaces the false alarm rate (i.e. crop failures that were forecast but not observed) used on the *x*-axis of the ROC curve with a false alarm ratio (i.e. fraction of incorrect failure forecasts), allowing events occurring with different frequencies to be compared (Lalaurette unpubl.). For any crop failure threshold, the nearer the intersection of the IROC curve and the no-bias line is to the point [0,1], the more skillful the forecast. Based on IROC curves (Fig. 5), simulation of crop yield failure is more skillful based on a 500 kg ha^{-1} than a 200 kg ha^{-1} threshold for both the multi-GCM ensemble and a single-GCM ensemble. Prediction skill at a 3 to 6 mo lead-time is significant for the higher yield threshold, which matches the yield below which the cost of groundnut cultivation exceeds its value (Rao et al. 2000).

4.2. Artificial skill and biased probabilities

The error of statistical forecast models tends to be smaller for the period used to calibrate the model than for predictions outside the calibration data. Artificial forecast skill and systematic underestimation of the dispersion of probabilistic forecasts are therefore inherent risks in statistical forecasting, including empirical calibration of dynamic forecast models. They are of particular concern for the analog method in those cases when the number of categories and limited record length lead to small sample sizes within each category. Robinson & Butler (2002) suggest that many studies that used analogs as a basis for prediction may have overestimated prediction skill (of climate or impacts) or the potential economic value of forecasts for particular decisions.

A simple numeric example illustrates the problem. To mimic an analog-based prediction system, we generated a series of 48 pairs of correlated (r = 0.64) random normal variates, arbitrarily selected one series as predictors and the other as predictands, and grouped sorted predictors into 3, 6, 12, and 16 equally-sized classes — a classification scheme that is analogous to classifying years into El Niño, Neutral and La Niña phases based on SST observations in the eastern tropical Pacific (Trenberth 1997). The proportion of variance in the predictand time series that the analogs explained is

$$r^2 = 1 - \sum_i (y_i - \hat{y}_i)^2 \Big/ \sum_i (y_i - \overline{Y})^2 \quad (6)$$

where y_i and $\hat{y}_i$ are the ith predictand and prediction, and $\overline{Y}$ is the mean of the predictand series. For each period i, $\hat{y}_i$ is taken as the mean of observations falling within the period's predictor class, either including period i, or with cross-validated estimates that omit y_i from the calculated mean. Unbiased estimation of forecast uncertainty requires that observations from the period being predicted do not influence the prediction. Cross-validation reduces this bias (Efron & Gong 1983, Michaelsen 1987). As expected, the proportion of variance that the analogs explain increases as the number of categories increases (Fig. 6). However, when the ith observation is excluded from the ith forecast through

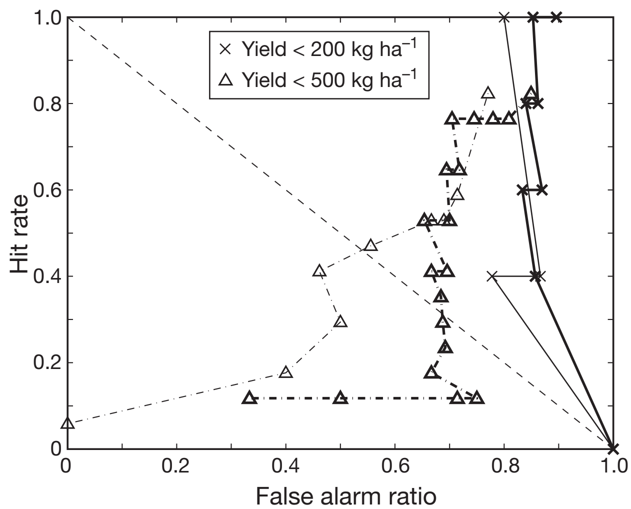

Fig. 5. Inverted relative operating characteristics (ROC) curve for the simulation of crop failure. Solid and dot-dashed lines — thick: multi-GCM ensemble, thin: single-GCM ensemble. Dashed line across graph: simulated crop failure occurrence equals observed climatology

cross-validation, increasing the number of categories decreases the proportion of variance predicted and hence the uncertainty that remains. The difference between cross-validated and non-cross-validated results is an indication of artificial skill and of bias in the dispersion of probabilistic forecasts (Michaelsen 1987, Meilke et al. 1997, Drosdowsky & Allen 2000), although more efficient methods are available for correcting prediction error bias (Kohavi 1995, Efron & Tibshirani 1997). Limiting bias when deriving and evaluating probabilistic climate-based crop forecasts in practice requires a combination of selection of credible predictors with a mechanistic basis, and conservative statistical methods such as independent validation and statistical hypothesis testing.

4.3. Year to year consistency of forecast uncertainty

Methods for deriving probabilistic forecasts—hindcast residuals, historical analogs and GCM ensemble distributions—differ in their ability to handle any changes in predictability from year to year. There is some evidence that predictability and hence the dispersion of forecast distributions changes over decadal time scales, and that GCM ensemble distributions can capture part of those variations (Grimm et al. 2005, Moron 2005). In other cases, analysis of GCM ensemble simulations show that variability of SST patterns influence climatic means but have little influence on the spread of seasonal mean atmospheric states (Kumar et al. 2000).

One source of apparent variation in predictability between years is the skewness of the underlying distributions. For strongly skewed variables, the magnitude of forecast residuals, and therefore the spread of a forecast distribution, tends to increase in the direction of skewness. To illustrate, ENSO phases significantly influence both the mean (by Kruskal-Wallis 1952 test) and variance (Levene's 1960 test) of December rainfall in Junin, Argentina (Fig. 7a). After applying a normalizing power series transformation (Box & Cox 1964) to reduce the positive skewness of the rainfall series, the mean separation remains, but variances are constant among ENSO phases (Fig. 7b). In this instance, the substantial differences in dispersion were an artifact of predicting a skewed distribution, and not an indication of fundamental shifts in predictability in different ENSO states. Although rainfall amounts tend to be positively skewed, the existence and direction of skewness of rainfed crop yields is difficult to anticipate, due to the generally concave nonlinearity of crop yield response to rainfall variability.

Hindcast residuals can account for the effects of skewness on forecast dispersion, for example by applying a normalizing transformation to the predictand and potentially the predictor time series, deriving a forecast distribution in transformed space, then applying an inverse transformation to put the forecast distributions into the original yield units (Hansen et al. 2004). GCM ensemble distributions seem to be the best way to account for any decadal changes in forecast uncertainty. Resolving the extent to which predictability of climatic variations and crop response change from year to year beyond the effect of skewness, and the degree to which GCMs can predict these variations, is beyond the scope of this review.

5. EMERGING ISSUES, OPPORTUNITIES, AND CHALLENGES

Methods for linking crop and climate models, and field and aggregate scales (see Section 3), and for evaluating probabilistic forecasts (see Section 4) are likely to see significant advances in the coming years. One of

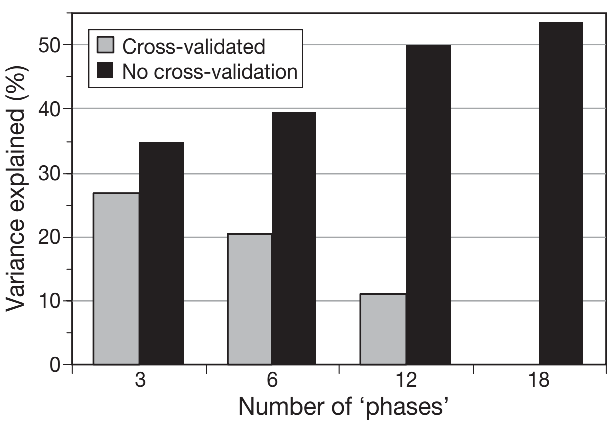

Fig. 6. Proportion of variance explained by a hypothetical analog prediction system with and without cross-validation. See Section 4.2 for description of 'phases'

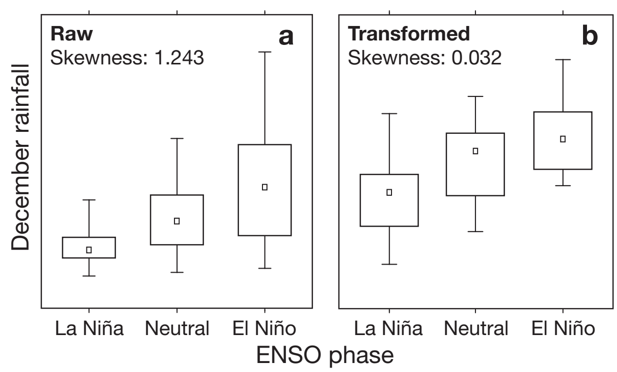

Fig. 7. Box plots and skewness of separation of means and variance of December rainfall in Junin, Argentina, by ENSO phase, (a) before and (b) after a normalizing Box-Cox transformation. ENSO influences means in both cases, and dispersion in the raw dataset ($p < 0.001$ in all cases)

the greatest immediate challenges is the near-absence of empirical comparison of the various methods. A comparison of stochastic disaggregation, nonlinear regression and weighted analog methods for simulating maize yields from GCM output at a single site in Kenya (Hansen & Indeje 2004) was inconclusive. Because of peculiarities of the various global and regional climate models; differences in the nature, spatial structure and predictability of climate variability among locations and seasons; and differences in crop sensitivity to within-season weather variability due to soil properties, crop characteristics and management, a great deal of empirical testing will be necessary before we can make any robust conclusions about the suitability of the various approaches. Areas that are likely to result in substantial future improvements in our ability to predict agricultural impacts of climate variations at a seasonal lead-time include: (1) expanded evaluation of alternative combined climate–crop forecasting methods, (2) embedding crop models within climate models, (3) enhanced use of remote sensing and spatial data, and (4) new avenues of climate prediction research.

5.1. Embedding crop models within climate models

It is increasingly apparent that vegetation can affect climate (Pitman et al. 1993, Lawrence & Slingo 2004, Osborne et al. 2004). At an aggregate scale, agricultural production influences the atmosphere by altering surface roughness, albedo, temperature, and moisture flux. Annual crops in particular have quite different seasonal cycles from natural vegetation. The methods described in Section 3 for translating climate forecasts into agricultural response account for the influence of climate on crops but do not allow any feedback from the crops to the climate. Dynamically integrating dynamic climate models with detailed crop and soil simulation models that replace existing land surface schemes would allow 2-way feedback between crops and climate within a growing season (Osborne 2004, Betts 2005). The challenge of matching the scale of the climate model grid would have to be addressed, either by scaling up a field-scale crop model to account for the heterogeneity within a grid cell (Hansen & Jones 2000), or by using a crop model that is optimized for the relatively coarse scale (Challinor et al. 2004). The primary benefit of such 2-way coupling would be improved prediction of local climate in the latter part of the season. Because of the biases that dynamic climate models show, we anticipate that yield predictions from fully coupled climate–crop models would require substantial calibration.

5.2. Enhanced use of remote sensing and spatial data

We anticipate that enhanced use of a range of spatial data sets from ground observations (e.g. soil surveys, crop management) and remote sensing (e.g. rainfall, vegetation indices) will contribute substantially both to the skill and to the spatial specificity of climate-based crop predictions in the coming years. Spatial databases are available or under development in many parts of the world for soil properties, land cover and stochastic weather generator parameters. Satellite remote sensing provides a great quantity of spatially explicit information about the land surfaces and atmosphere, at spatial resolutions that continue to improve with new sensors.

Remote sensing has the potential to make several contributions to climate-based crop forecasting. (1) Satellite rainfall estimates provide near-real-time information in locations where rainfall is not directly measured or rain gauge data are not accessible. Combined with soil and management information, spatially contiguous rainfall data offers the potential to simulate crop yields anywhere across the landscape (Thornton et al. 1997, Reed & Maidment 1999). (2) Remote sensing offers some potential to monitor cropped areas, planting dates and phenological stages (Ines & Honda 2005). (3) Remote sensing vegetation indices provide information about the state of the crop canopy that can be used to update the state variables of a crop simulation model during the growing season, calibrate model input parameters, or statistically correct final yield simulations (Bouman 1992, Delecolle et al. 1992, Moulin et al. 1998). The quality of remote-sensing data is expected to improve in the near future, given plans to launch improved sensors for precipitation (Tropical Rainfall Measuring Mission, TRMM; Advanced Microwave Scanning Radiometer for Eos, AMSR-E), soil moisture (AMSR-E; Soil Moisture and Ocean Salinity, SMOS) and vegetation (Moderate Resolution Imaging Spectroradiometer, MODIS).

Seasonal climate forecasts and remote sensing of the state of the crop complement each other. Remote sensing has the potential to reduce the crop model component of uncertainty by providing refined estimates of crop state variables up to the time of the forecast, while skillful seasonal forecasts reduce climatic uncertainty from the time of the forecast through the remainder of the season (see Section 4). Because this application of remote sensing applies only to crop forecasts made during the growing season, integrating remote sensing into climate-based crop forecasting may have greater value for food security and market applications than for farm-level applications.

5.3. New avenues of climate research

Climate prediction research has tended to focus on climatic means averaged in time over ≥3 mo periods, and over substantial spatial areas. Although this convention maximizes prediction skill by reducing non-covariant random variability, for agricultural applications it does so at the expense of relevance. With increased attention to forecast applications, particularly in agriculture, and growing awareness of the tradeoffs between skill and value, climate prediction research is paying increasing attention to downscaling in space and time.

Seasonal forecasts can, in principle, be calibrated and evaluated at a local scale, although attempts to quantify the effect on prediction skill have so far been few (e.g. Gong et al. 2003). Incorporating understanding of fine-scale climatic influences — such as orography, land–water interfaces, or land cover — into either statistical downscaling models or high-resolution, regional dynamic climate modeling is likely to further enhance prediction skill at the local scale that is relevant to farm impacts and decisions.

Although it is impossible to predict the timing of daily weather events through a season, it is reasonable to assume that the large-scale ocean–atmosphere interactions that give rise to predicable shifts in seasonal means may also influence higher-order statistics of synoptic weather events that are important to agriculture, such as the frequency and persistence of rainfall events, the distribution of dry spell durations, the timing of season onset and the probabilities of intense rainfall events or temperature extremes. For now, the predictability of these higher-order statistics at a seasonal lead-time remains largely unquantified. We anticipate that the emerging focus on what has been coined 'weather within climate' will gain momentum; lead to improvements in prediction of the higher-order weather statistics that determine agricultural impacts, and better characterization of predictability at finer spatial and temporal scales; and perhaps challenge the convention of presenting operational forecasts only as seasonal climatic means at an aggregate spatial scale.

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