Evaluation of a Process-Based Agro-Ecosystem Model (Agro-IBIS) across the U.S. Corn Belt: Simulations of the Interannual Variability in Maize Yield

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Received 8 July 2003; accepted 17 September 2003

ABSTRACT: A process-based terrestrial ecosystem model, Agro-IBIS, was used to simulate maize yield in a 13-state region of the U.S. Corn Belt from 1958 to 1994 across a 0.5° terrestrial grid. For validation, county-level census [U.S. Department of Agriculture (USDA)] data of yield were detrended to calculate annual yield residuals. Daily atmospheric inputs from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis were used in conjunction with the Climate Research Unit's (CRU's) monthly climate anomaly dataset at 0.5° resolution and a weather generator to drive the model at a 60-min time step. Multiple simulations were used to quantify model sensitivity to hybrid selection (defined by growing degree-day requirements), planting date, and soil type. The

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calibration of raw yields and model capability to replicate interannual variability were tested.

The spatial patterns of simulated mean bias error (mbe) of raw yields were largely unresponsive to variations in soil texture, optimum hybrid choices, and planting dates typical for the region. Simulated 15-yr mean yields had a significant bias that was higher than observations, with an mbe of 0.97 Mg ha^{-1} and a root-mean-squared error (rmse) of 1.75 Mg ha^{-1}. Simulations of interannual maize yield variability appeared to have a relatively weak response to changes in soil type and were more responsive to a planting date than a hybrid selection.

The correlation (r^2) between observed and simulated yield residuals within individual 0.5° grid cells ranged from 0.0 to 0.6, and increased as additional scenarios of land management decisions within 0.5° grid cells were taken into account. The correlations appeared to have a weak but significant relationship to a reported harvested area ($r^2 = 0.36$). Model simulations produced a larger absolute magnitude of interannual variability than observations (positive and negative simulated yield residuals over the region averaged 18% and −21%, compared with 13% and −17% for observations), but spatial patterns were consistent. It was determined that the impact of irrigation on maize yield in the western Great Plains must be properly accounted for in future modeling scenarios to capture the increase (36%) in mean yields and significantly decreased interannual variability compared to rain-fed maize for future sensitivity studies.

KEYWORDS: Yield, Model validation, Interannual variability

1. Introduction

At the scale of individual farms or plots, crop simulation models have been used to study the interactions between soil, vegetation, the atmosphere, and human management, using varying degrees of numerical sophistication—ranging from highly *mechanistic* to purely *empirical*, and often a blend of the two (Montieth, 1996; Ritchie and Alagarswamy, 2002). While previous work has contributed significantly toward the creation and advancement of crop modeling tools (Jones and Kiniry, 1986; Sharpley and Williams, 1990; Acock and Trent, 1991; Haskett et al., 1995), the models themselves are typically not applied across larger regions, where some key policy decisions become more relevant (Moen et al., 1994; Chipanshi et al., 1999; Jagtap and Jones, 2002). For example, Monteith (Monteith, 1996) suggested that while the scientific literature contains numerous investigations using crop models within individual fields or farms, very few have been used to dictate land management decision making across a large landscape. While land use policies are implemented by individuals, decision making is frequently based upon large-scale (e.g., county, crop reporting district, and state) regional assessments, occasionally guided by model projections.

Some of the most important questions currently posed in agricultural research are how cropping systems and land management might be affected by future large-scale climate changes (Doering et al., 2002; Reilly et al., 2002). The threat of perturbations to mean climate and variability related to such phenomena as the El Niño–Southern Oscillation (ENSO; Carlson et al., 1996; Mauget and Upchurch,

1999) or rising CO_2 in the atmosphere (Houghton et al., 2001) is particularly important to the central United States, because corn and soybean production in this area constitutes a large proportion of the global supply. The United States produces approximately 40%–45% of the world's corn supply and is responsible for 70% of the total global exports, but does so on only 20% of the total global acreage devoted to corn [U.S. Department of Agriculture (USDA), 2003]. Currently, U.S. soybean production accounts for 43% of the global total and is responsible for 33% of the world exports. Therefore, changes in the frequency of extreme weather events across the central United States could be particularly disruptive, or even catastrophic, to global agricultural productivity and the economy (Rosenzweig and Parry, 1994; Legler et al., 1999; Southworth et al., 2000; Reilly et al., 2002).

An important consideration is that localized regions of the U.S. Corn Belt may respond differently to climate change. Simulation models offer one means to examine the interactions between crop growth, management decisions (e.g., planting date, hybrid), soil conditions, and seasonal weather patterns, and how these vary across large landscapes. However, before we can suggest how agricultural systems might respond to future climate changes, we need to use our knowledge of previous conditions to assess whether models can replicate what has already occurred. The scale at which this is done is just as important; otherwise, there can be little validity or truth applied to forecasts of future crop behavior and response.

There have been relatively few regional-scale modeling efforts that have coupled crop simulation models with gridded input datasets of past climate to assess model performance and help identify biases or uncertainties in predictive capabilities (e.g., Easterling et al., 1996; Easterling et al., 1998; Jagtap and Jones, 2002). This has generally been due to the lack of spatial and temporal data (e.g., weather, soils, management, cultivar, economics) that is needed to drive crop simulation models across larger scales. To bypass this deficit of spatially explicit information in model validation or climate change studies, researchers have defined agricultural regions according to crop reporting districts and have simulated crop responses to climate change for "representative farms" in the district, which include a typical soil type, hybrid, and varied management scenarios, using a representative micrometeorological station for daily weather data (Haskett et al., 1997; Chipanshi et al., 1999; Southworth et al., 2000; Southworth et al., 2002; Andresen et al., 2001). Model driver and input data therefore exemplify conditions for an "average" farm in a larger region.

Other researchers have combined well-tested crop models with gridded output from global and regional climate models [e.g., the regional climate model (RegCM) of Mearns et al., 1999] to analyze the impact of future climate change on crop productivity (Mearns et al., 1992, Mearns et al., 1999). This approach has been hindered by the fact that the general circulation model (GCM) climate change scenarios provide information on mean changes in precipitation or temperature at coarse temporal and spatial resolution with little confidence in the prediction of changes to future climate variability (Reilly et al., 2003). Generally, processes and interactions between the biosphere and atmosphere that are not simulated by GCMs drive local climate variability, which is important to agricultural production (Reilly et al., 2003). While comprehensive studies by Easterling et al. (Easterling et al., 1998) and Mearns et al. (Mearns et al., 2001) have examined how the spatial scale of input climate data affects simulations of crop yield, our understanding of model capabilities to predict interannual variability is limited, and thus confidence in projections of future climate change impacts on agriculture is low (Reilly et al., 2002; Reilly et al., 2003).

According to Doering et al. (Doering et al., 2002) and Reilly et al. (Reilly et al., 2002), the impacts of changing climate variability on agriculture is potentially more important than changes in mean climate because farm management adaptation is more likely to occur with respect to changing mean climate. Interannual climate variability presents the most significant risks and challenges at the farm level (Pfeifer et al., 2002), and climate change will likely be observed and experienced through changes in extreme events and variability rather than changes in mean quantities (Reilly et al., 2002). Even though the importance of climate variability to agriculture has been realized, we still have an inadequate understanding of whether models designed for the individual farm can be applied to the regional scale and represent the impact of spatial heterogeneity of climate variability on crop yield (Doering et al., 2002).

Based on the preceding arguments, it is contended that comparisons of simulated and observed (e.g., census data) interannual crop yield variability must take place over terrestrial grids, at a resolution similar to GCM output, to lend validity to future projections of crop behavior. To address this idea, in this study a regional-scale crop modeling effort evaluated the capabilities of a process-based terrestrial ecosystem model [called the Integrated Biosphere Simulator (IBIS); Foley et al., 1996; Kucharik et al., 2000) recently adapted to simulate the dominant U.S. Corn Belt agroecosystems: maize, soybean, and spring and winter wheat (Kucharik and Brye 2003; Donner and Kucharik, 2003). The main objective of this study was to examine the ability of the model to capture previous spatial and temporal corn yield variability in a 13-state region of the U.S. Midwest and Great Plains.[1] Simulations of corn rather than soybean were conducted for two primary reasons: 1) harvested acreage has been much greater and covered a longer period of time, allowing for a more diverse sampling of varied climate conditions and impacts on interannual yield variability; 2) the model used in this study has been sufficiently tested for corn at smaller watershed scales (Donner and Kucharik, 2003) and the individual field scale (Kucharik et al., 2001; Kucharik and Brye, 2003). Specific questions to address were

- Can a process-based terrestrial ecosystem model be used at a coarse resolution (0.5° latitude by 0.5° longitude) to predict regional differences in maize yield due to varied combinations of soil type, climate regimes, and land management?
- Can the model capture the observed spatial patterns and magnitude of interannual yield variability?
- Which model drivers (or simulated processes) impart the most influence on simulated output?

[1] In this study, the 13-state Corn Belt region was ND, SD, NE, KS, MN, IA, IL, MO, WI, MI, IN, OH, and KY.

2. Materials and methods

2.1. Study region

The geographic region delineated for this case study was between 36.25° and 49.25°N latitude and -79.75° and -104.25°W longitude. The 1958–94 period was used to compare simulated and reported maize yields. Approximately 80% of the total U.S. acreage in corn production is within this region, with Iowa and Illinois composing approximately 30% of the U.S. acreage and approximately 40% of the total U.S. corn production alone (USDA, 2003). Highly fertile silt loam soils are common throughout the region and the average growing season length ranges from 130 in the north to 210 days across the south. The annual precipitation ranges from 800 to 1200 mm across a large portion of the region, but decreases rapidly below the 508-mm threshold (20 in.) across Kansas, Nebraska, and the Dakotas, where irrigation has been a common management practice since the 1950s.

2.2. USDA county-level maize yield data

The National Agricultural Statistics Service (NASS), coordinated by the USDA (more information available online at http://www.usda.gov/nass), was used to compile county-level maize yield data for the 1910–2001 period. The yield data used in this analysis were the reported average of total production of irrigated and nonirrigated corn per unit land area (reported in bushels per acre). The USDA data in raw form were not directly comparable because of resolution differences (i.e., county boundaries were assigned using 5-min resolution versus the simulated 0.5° grid), and because simulated output does not account for the large gains in yield since the 1950s due to technological advances and improvements in management. Two transformations were therefore applied to the USDA county-level data so 0.5° grid cell–simulated output could be directly compared with observations.

First, the county-level data were detrended using single spectrum analysis (SSA), a data-adaptive filter that can be used with shorter time series with significant interannual variations and that is generally more powerful than simple linear regression (Dettinger et al., 1995; Schlesinger and Ramankutty, 1994; Botta et al., 2002). This allowed for the low-frequency trends (e.g., due to technology, genetics, management) to be separated from high-frequency variability, generally attributed to weather variability. The two most significant modes (eigenvectors) of low-frequency (long term) variability were used to “detrend” each county’s yield data record. The first two modes generally accounted for 70%–80% of the total variability and included both technological changes and shorter-period (~5 yr) climate trends. This allowed for a calculation of a trend-adjusted yield for each year of each county’s continuous data records. The percent deviation from the trend (yield residual) for each year was calculated as

$$(Y_o - T_{\mathrm{SSA}})/(T_{\mathrm{SSA}})100.0,$$

where Y represents the actual county yield and T represents the trend-adjusted yield. Second, the raw USDA yield data, detrended yield values, and percent deviations were aggregated to a 0.5° spatial grid using an area-weighting approach (Jagtap and Jones, 2002). The 0.5° grid cell values were the sum of the weighted

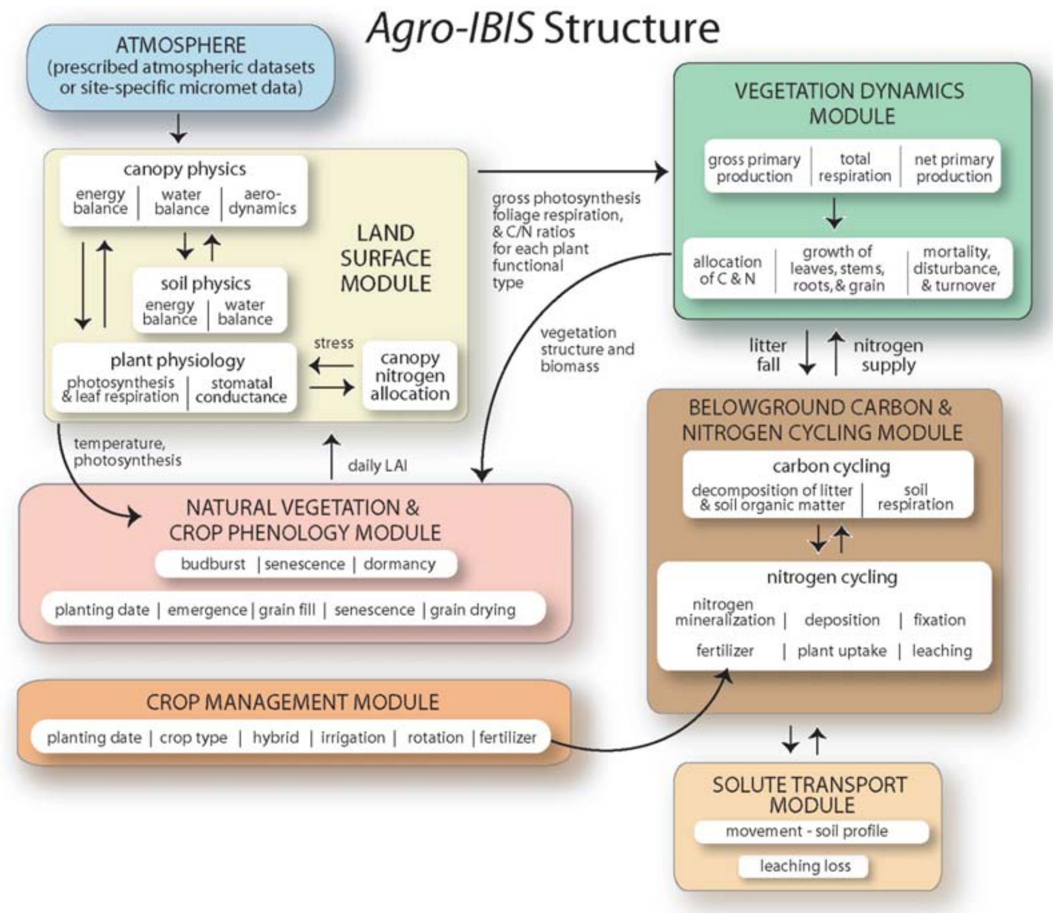

Figure 1. Schematic of Agro-IBIS, an altered version of the IBIS of Foley et al. (Foley et al., 1996) and Kucharik et al. (Kucharik et al., 2000). Agro-IBIS incorporates managed agroecosystems using crop phenology, crop management (e.g., fertilizer, tillage, irrigation, hybrid selection), and a mechanistic solute transport submodel (Kucharik and Brye, 2003).

quantities; the fraction of 0.5° grid cell area occupied by each respective county multiplied by each quantity were summed together.

2.3. Agro-IBIS model description

An updated, U.S. agricultural version of the IBIS model, called Agro-IBIS (Figure 1), includes representations of land surface and soil physics (energy, water, and momentum exchange between soil, vegetation, and the atmosphere), canopy physiology (canopy photosynthesis, conductance, and respiration), terrestrial carbon balance (net primary productivity, soil respiration, organic matter decomposition), crop phenology (leaf emergence and growth, grain fill, and senescence), solute transport (i.e., leaching of inorganic nitrogen fertilizer), and management options such as fertilizer application, planting and harvest date, cultivar selection [i.e., growing degree days (GDDs) required to reach silking and physiological maturity], and irrigation (Kucharik et al., 2000; Kucharik and Brye, 2003).

IBIS uses a short 60-min time step to simulate the rapid exchange of energy, carbon, water, and momentum between soils, vegetative canopies, and the atmosphere. The model can be driven either by site-specific meteorological data or by gridded climate datasets. This version of the model uses a lower-canopy vegetation layer for corn, six soil layers (successive thicknesses of 10, 15, 25, 50, 50, and 100 cm) to a depth of 2.0 m, and a three-layer thermodynamic snow model (Kucharik et al., 2000). The mechanistic corn growth model uses physiologically based representations of C_4 photosynthesis (Farquhar et al., 1980; Collatz et al., 1992), stomatal conductance (Ball et al., 1986), and respiration (Amthor, 1984). Soil moisture and leaf-nitrogen stress functions are used to reduce the maximum photosynthetic capacity ($V_{\max}$) of the plant. Leaf area expansion is simulated by multiplying leaf biomass carbon by the specific leaf area (SLA) using a daily time step. The partitioning of dry matter assimilated to the various carbon pools (leaf, stem, root, grain) changes according to crop phenological stage (Penning de Vries et al., 1989).

Some examples of model output are crop yield, harvest index, daily leaf area index (LAI), root growth and turnover, total plant N uptake, net N mineralization, evapotranspiration, and soil surface CO_2 flux (Kucharik and Brye, 2003). An appendix found in Kucharik and Brye (Kucharik and Brye, 2003) provides a more detailed description of the Agro-IBIS crop models. Additionally, the reader is referred to extensive summaries in Donner and Kucharik (Donner and Kucharik, 2003) and Kucharik and Brye (Kucharik and Brye, 2003), which qualitatively compare Agro-IBIS and its structure to other well-documented crop models such as CERES-Maize (Crop Environment Resource Synthesis), Erosion-Productivity Impact Calculator (EPIC) and DRAINMOD-N.

Agro-IBIS simulations of carbon (yield, harvest index, total dry matter accumulation, and LAI), nitrogen (N leaching, net N mineralization, plant N uptake, and grain N removal), and water cycling have been previously validated in optimally fertilized and unfertilized corn agroecosystems in southern Wisconsin for a 6-yr field experiment from 1995 to 2000 (Kucharik and Brye, 2003). Previous regional-scale calibration and validations for mean corn and soybean yields have also occurred for the Upper Mississippi drainage basin (S. Donner and C. J. Kucharik 2003, unpublished manuscript) for the 1985–94 period. A precision agricultural version of the model [called the Precision Agricultural Landscape Modeling System (PALMS)] has also been developed to simulate water balance, farm runoff, crop yield, and nitrogen cycling at a 5-m resolution scale within individual fields (C. Molling 2002, personal communication). Extensive model validation has also occurred with field observations at the same scale.

2.4. Soil texture inputs and assignment of soil properties

The dominant soil texture [chosen from 11 possible categories based upon percent sand, silt, and clay; Campbell and Norman (1998)] for each soil layer in each 0.5° grid cell was derived from the State Soil Geographic (STATSGO) 1-km resolution dataset (Miller and White, 1998). This dataset was previously aggregated to a 0.5° terrestrial grid. From the assignment of a textural category in each grid cell and each soil layer, the porosity, field capacity, wilting point, saturated air-entry potential and hydraulic conductivity, and moisture release curve "b" (Campbell and Norman, 1998) coefficient are obtained from a lookup table (Campbell and Norman, 1998). At the soil surface, contributions of soil moisture are used in combination with snow and vegetative properties to determine the surface albedo (Kucharik et al., 2000).

2.5. Climate data input

Monthly climate anomaly data (deviations from a 1961–90 average for temperature, precipitation, relative humidity, solar radiation, and wind speed) from the Climate Research Unit's (CRU's) 1901–95 dataset (CRU05; New et al., 1999; New et al., 2000) at 0.5° resolution were used to drive a statistical weather generator (Richardson, 1981; Geng et al., 1986) and to generate daily to interannual variability for a 50-yr model spinup period from 1901 to 1957. An independent comparison of the Vegetation–Ecosystem Modeling and Analysis Project (VEMAP; Kittel et al., 1995) monthly climate dataset with the CRU05 data yielded no significant differences at 0.5° resolution. The model was initialized in year 1 with 50% (volumetric) soil moisture and isothermal soil temperatures of 10°C. Hourly weather data were subsequently calculated using additional statistical equations, but for this initial 57-yr spinup period, the daily weather data were not meant to resemble the actual daily series of weather for any grid cell. The model spinup was necessary to bring the model to equilibrium and to determine the annual average growing season GDD (base 8°C). Total annual GDD were summed for each grid cell using the following equation:

$$\mathrm{GDD} = T_{\mathrm{avg}} - 8.0,$$

where T_{avg} is the daily average (average of maximum and minimum) air temperature (2 m), and the daily summation of GDD is between a minimum of 0.0° and maximum of 30.0°C (McMaster and Wilhelm, 1997).

The GDD accumulated between the average last spring and first fall freezes (using 0.0°C as a temperature threshold) was used to compute the growing season GDD and the average growing season length to help determine an appropriate hybrid (e.g., GDD required to silking and physiological maturity) and appropriate crop relative maturity (CRM) ratings for each 0.5° grid cell. A 30-yr running average GDD is recomputed for each simulation year using the current year's daily temperature data and a 30-yr average *e*-folding time.

For maize yield simulations during the 1958–94 evaluation period, daily atmospheric inputs from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (which includes air temperature, temperature range, wind speed, precipitation rate, and cloud fraction) were used in conjunction with the CRU monthly climate anomaly dataset and the weather generator to produce hourly data. The NCEP–NCAR data are available at T62 (~209 km) resolution and were previously bilinearly interpolated to 0.5° resolution (Lenters et al., 2000). Because some previous studies have questioned the realism and quality of the model-derived NCEP–

NCAR precipitation dataset (Kalnay et al., 1996; Lenters et al., 2000), these data were only used to simulate daily weather anomalies throughout the case study period (1958–94), but when combined with the CRU05 dataset, they statistically preserved the CRU05 monthly anomalies. The combination of the two datasets offers a means to preserve monthly weather anomalies for all variables, as well as incorporate realistic daily and hourly weather events that are essential to more realistic simulations of crop growth and automatic management decisions (e.g., planting dates, killing frosts, etc.). Thus, crop yield simulations were only compared with reported data for the 1958–94 time period in this case study. All simulations were performed with a static atmospheric CO_2 concentration of 365 ppm.

2.6. Experimental model runs

Agro-IBIS corn yield simulations were carried out on a 0.5° (latitude by longitude) terrestrial grid encompassing the study region, all covering the 1958–94 time period. Model simulations assumed that maize crops were grown in each grid cell (100% cover) of each simulation year (e.g., continuously), were rain fed (no irrigation), and were not nutrient (e.g., nitrogen) limited. Thus, simulated interannual yield variability during the 1958–94 period only reflected the impacts of weather, hybrid, planting date, and soil-type variations. Simulated corn yield was previously calibrated to represent the 1990 levels of technology (Donner and Kucharik, 2003). Although varied row spacing, planting density, hybrid resistance to pests and disease, and soil erosion are important to yield variations at the individual farm level, they were not accounted for in this case study. Agro-IBIS allows for either prescribed or optimum (automatic) selection of a spring planting date and hybrid in terms of the GDD required to reach silking and physiological maturity based on local climate (0.5° grid cell).

Jagtap and Jones (Jagtap and Jones, 2002) and Moen et al. (Moen et al., 1994) suggested that to properly simulate an *average* yield over a larger heterogeneous region, the output of several independent simulations should be averaged based on the known distribution of soils, climatic conditions, cultivars planted, planting dates, and other management typical for the region of study. The finest, regional-scale resolution data available for validation, and that which is heavily relied upon for other planning and policy purposes, is the USDA county-level yield information (USDA, 2003). County-level yields represent an aggregated average yield resulting from varied soils, weather, cultivars and management, and impacts of disease and pests. Here, numerous model simulations were used to quantify model sensitivity to hybrid selection, planting date, and soil type (Moen et al., 1994). Table 1 lists the format of model simulations, with the approach of using multiple combinations of soils, cultivars, and planting dates being similar to previous protocol discussed by Moen et al. (Moen et al., 1994) and Jagtap and Jones (Jagtap and Jones, 2002).

2.6.1. Control run

In a control run (CR), optimum planting date and cultivar selection (GDD required to silking and maturity) were automatically determined for each grid cell by model

Table 1. Summary of Agro-IBIS model simulations of maize over the study region from 1958 to 1994.

Simulations	Description
Control run	Optimum planting date and hybrid selection automatically determined by algorithms for each grid cell independently CRM ratings of 73–135 based on Pioneer-brand maize Soil texture was the dominant class as a function of depth from STATSGO database
Soil-type sensitivity	Planting date and hybrid selection automatically determined by algorithms Same soil texture at each grid cell and each soil depth implemented Soil types simulated: silt loam, sandy loam, clay loam, sand, and clay
Planting date sensitivity	Hybrids from the GDD (growing degree day base 8°C) sensitivity tests were planted at three varied dates: 1) Automatic planting date from control run (related to soil temperature) 2) 15 days earlier than the control run date 3) 15 days later than the control run date Soil texture was the dominant class as a function of depth from STATSGO database
GDD (hybrid) sensitivity	Three hybrids were planted at each grid cell (in combination with planting date tests): 1) Automatic GDD requirement from control run (related to soil temperature) 2) Control run hybrid −150 GDD 3) Control run hybrid +150 GDD Soil texture was the dominant class as a function of depth from STATSGO database

algorithms. Optimum crop planting occurs when 10-day running averages of daily mean 2-cm soil temperature and minimum air (2 m) temperatures reach thresholds required to plant ($T_{avg} \geq 9°C$; $T_{min} \geq 4°C$). In addition, planting cannot take place before 1 April based on the typical growing season across the eastern United States, with a latest possible planting date of 15 June. The GDDs to physiological maturity are used to calculate the GDD requirements for silking [grain fill initiation in Agro-IBIS; Kucharik and Brye (2003)] based on linear relationships for Pioneer-brand corn grown in the U.S. Corn Belt for CRM ratings from 73 to 134 (Figure 2). The minimum and maximum GDDs for hybrids were bounded by 950 GDD (CRM ~70–75) and 1700 GDD (CRM ~120–125), respectively, required to physiological maturity. The GDDs needed to physiological maturity are based on 30-yr running mean GDD accumulations (base 8°C) between the last freeze (0°C) in spring and first freeze in fall, inclusive.

2.6.2. Soil textural changes

Five subsequent simulations were used to quantify the impact of soil textural type on yield variability, assuming optimum planting dates and hybrid selection, which is identical to the approach used in the CR. In each run, the soil textural profile was assigned (each depth) the same soil textural type in each grid cell. The five soil textural types used were clay loam, sandy loam, silt loam, clay, and sand. An ensemble average of simulated crop yield was calculated for each 0.5° grid cell from these five simulations to compare with the CR to assess 1) whether the ensemble averaging helped to improve the overall agreement with observed

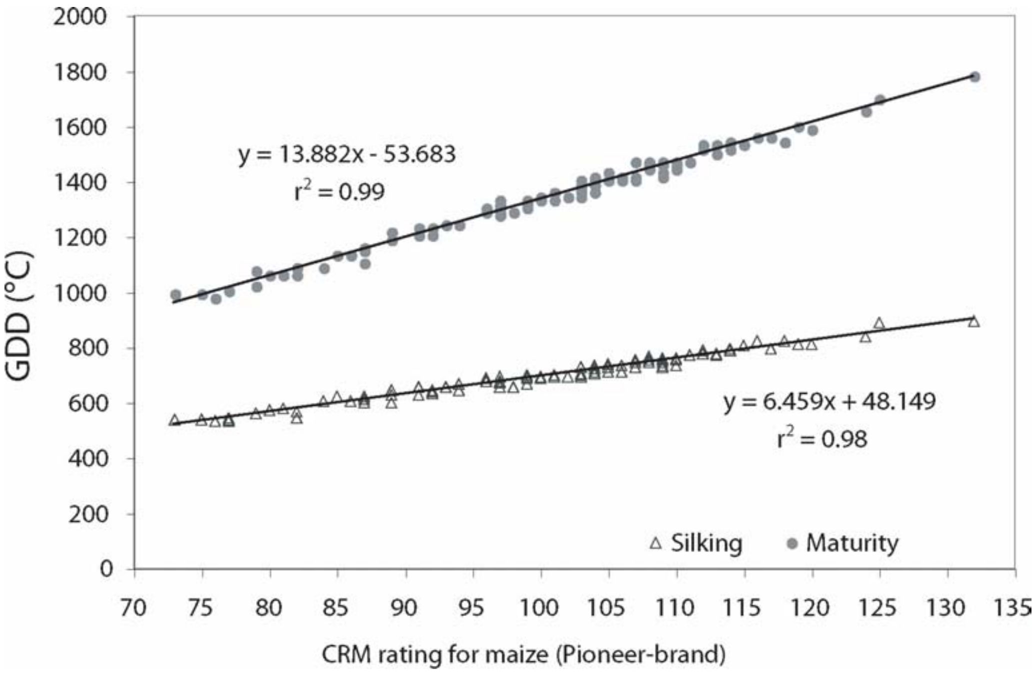

Figure 2. Relationship between GDDs (°C) necessary to reach the silking stage and physiological maturity and the CRM rating for Pioneer-brand corn hybrids grown in the U.S. Corn Belt.

interannual maize yield variability, and 2) simulated crop growth sensitivity to soil textural changes.

2.6.3. Changes in planting date and hybrid selection

A factorial combination of model runs consisting of three planting dates and three different hybrids (i.e., GDD requirements for phenological stages) was used to gauge whether accounting for a wider range in farm management at each 0.5° grid cell improved the CR results, and which management choices produced the largest impact. The dominant soil texture from the CR was assumed in these model runs. An ensemble average yield value for each year (for each 0.5° grid cell) was calculated using the nine independent model run results. Three planting date scenarios were performed independently for each simulation year: 1) the automatic date from the CR, 2) 15 days earlier than the CR planting date, and 3) 15 days later than the CR planting date. The three hybrids (varied GDD requirements for silking and maturity) were 1) the automatic calculation outlined in the CR, 2) the CR hybrid minus 150 GDD, and 3) the CR hybrid with an additional 150 GDD.

2.7. Statistical analysis and validation

Simple linear regression was used to assess continental-scale model calibration by quantifying the relationship between simulated versus observed 15-yr mean yields for each grid cell using the CR output. Because Agro-IBIS had been previously calibrated to simulate maize yield experiencing current (late 1990s) levels of technology, and the climate driver datasets used only allowed simulations to be carried through 1994, the 1980–94 simulated mean yield for each 0.5° grid cell was compared with observation (USDA) averages for the 1987–2001 period. The raw spatial differences (mean bias error) were used to diagnose potential limitations of the modeling approach across a large continental scale.

Because simulations did not account for changes (trends) in maize yield over time due to changes in technology and management, simulated and observed raw yields could not be directly compared. Therefore, annual simulated yield residuals were calculated as the percent deviation from the mean yield rather than in terms of absolute yield (e.g., kilograms per hectare) over the entire simulation period for each grid cell. Direct comparisons of simulated and observed yield residuals, as percent deviation, were subsequently performed. While it has been observed that the magnitude of interannual corn yield variability is approximately proportional to observed mean values, there is some evidence for decadal-scale changes in the average percent deviations from the trend line (Naylor et al., 1997), which may or may not be attributed to weather. Once the complete time record of residuals was formed for simulations and observations at each 0.5° grid cell, linear regression analysis (i.e., simulated yield residual versus observed yield residual) was used to characterize the slope, intercept, and coefficient of determination (r^2). The f statistic (F ratio) was used to test for the significance level (p value) of the correlation. A bias error and average percent negative and positive deviations were also used to assess localized regions where simulated and observed yield residuals were in agreement to better understand whether simulated processes or driver datasets were the primary cause of disagreement.

3. Results and discussion

3.1. Continental-scale yield calibration and validation

In two previous studies (Kucharik and Brye, 2003; Donner and Kucharik, 2003), Agro-IBIS was calibrated so that simulated average maize yield across the Upper Mississippi basin region was representative of late 1990s productivity. Figure 3 depicts a 15-yr simulated mean maize yield (the average is for the last 15 yr of the model control run) for each grid cell compared to the corresponding 1987–2001 observed yield average. Of the 1044 total 0.5° grid cells simulated, 168 grid cells in Nebraska, Kansas, Oklahoma, and Colorado were removed from the regression analysis because they had a significant fraction of irrigated agricultural land area in maize ($> 50\%$). The regression analysis for the 876 remaining grid cells dominated by rain-fed agriculture suggested that the model produced a slight positive bias for yields greater than 5 Mg ha^{-1}, but underpredicted corn yield at lower values. The regression analysis produced a coefficient of determination of $r^2 = 0.46$. The average yield bias of simulations aggregated over the entire study region (excluding those grid cells designated as dominated by irrigation) was 0.97 Mg ha^{-1}, with an rmse of 1.75 Mg ha^{-1}. Thus, the rmse was 24% of the simulated average yield over the region for the 15-yr period.

Figure 4 shows the spatial distribution of mbe between simulated (control run) and observed maize yield. Simulated yield averages were neither consistently

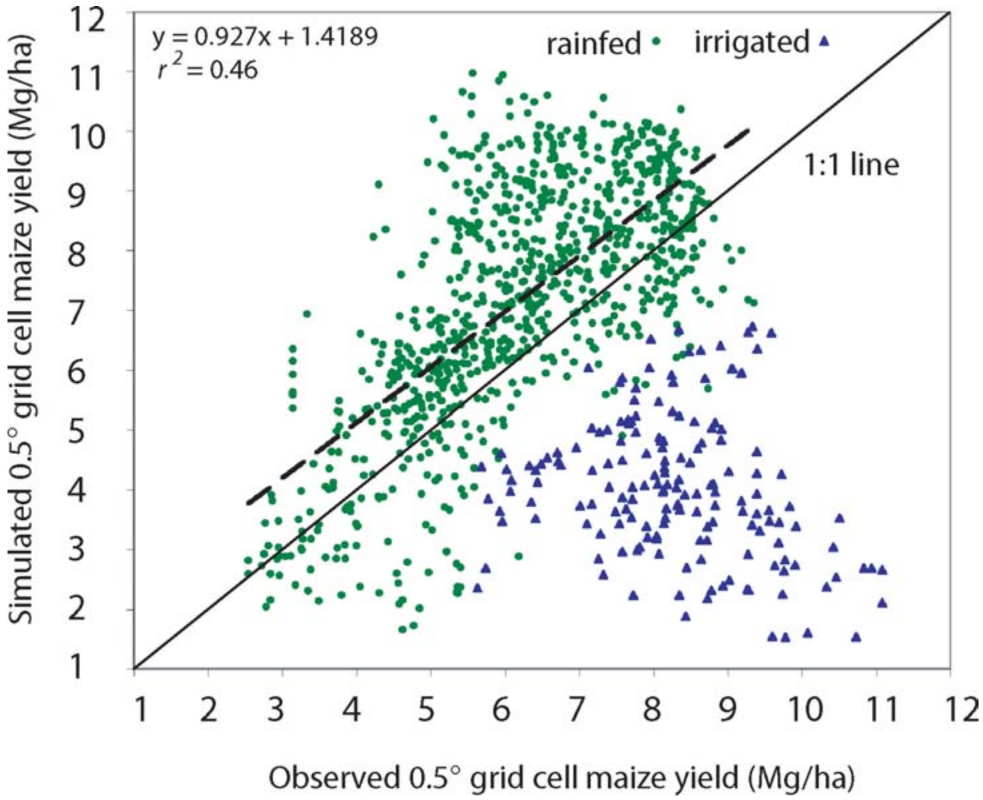

Figure 3. Relationship between 15-yr mean observed (USDA) maize yield (1987–2001) for each 0.5° grid cell plotted against the corresponding simulated mean yield for the 1980–94 period. The grid cells designated as highly irrigated (grid cells in KS, CO, OK, and NE; blue triangles) were removed from the regression analysis (denoted by the dashed line). The solid line corresponds to the 1:1 line.

higher nor lower across the entire study region. There was no clear pattern of consistent model bias throughout the Dakotas, Minnesota, Iowa, Missouri, Wisconsin, Illinois, and Indiana, where differences were generally centered around 0 Mg ha^{-1}, and ranged from −2 to 2 Mg ha^{-1} in both north–south and east–west directions. Two smaller regions, however, had significantly greater differences between simulated and observed yield. Within the eastern portions of the study region across Michigan, Ohio, Indiana, and Kentucky, the mean differences approached 4–5 Mg ha^{-1} in some grid cells (Figure 4). The region with the highest level of error was contained in Nebraska, Kansas, Oklahoma, and Colorado. Because model simulations were performed without irrigation management, simulated yields were 8 Mg ha^{-1} lower than observations in some grid cells. In many counties across these states, greater than 65% of the agricultural land area is irrigated (USDA, 2003).

It was clear that the impacts of irrigation across the far western states in the region have had a significant impact on mean maize yields since the 1950s, and this

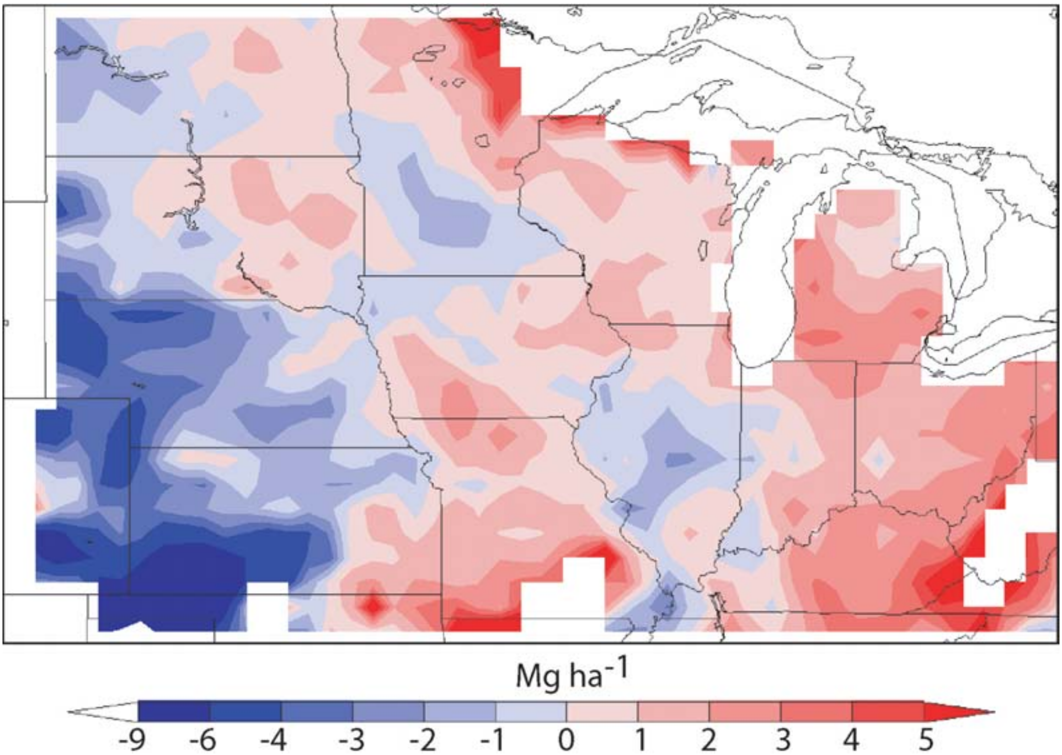

Figure 4. Difference (mbe) between simulated and observed 15-yr average maize yield (results show the simulated – observed value, in Mg ha^{-1}) across the study region.

is deserving of a more detailed analysis, but that was beyond the scope of this study. Nonetheless, a simple study of the impact of irrigation on maize yield was performed to better understand model capabilities for dryland agriculture in the Great Plains. The simulated average (nonirrigated) aggregated yield for all 0.5° grid cells in the state of Nebraska (91 total) was calculated separately and compared to the observed state averages for irrigated and nonirrigated maize for the 1987–2001 period. The simulated 15-yr (1980–94) state average (5.5 Mg ha^{-1}) was 3.8 Mg ha^{-1} (41%) lower than the corresponding observed state average for irrigated maize (9.31 Mg ha^{-1}). The corresponding difference between mean observations of irrigated and nonirrigated (5.98 Mg ha^{-1}) corn in Nebraska was 3.3 Mg ha^{-1}, or 36% lower in nonirrigated fields. Thus, the average discrepancy between simulated and observed nonirrigated corn yield in Nebraska was only 8% (0.48 Mg ha^{-1}). This suggests that the simulated impact of soil moisture stress on mean yield was satisfactory in the far western portions of the region.

The suite of simulations performed in addition to the control run (CR; Table 1) suggested that regional climate patterns produced by the CRU05 and NCEP 0.5° climate databases and the weather generator within the Agro-IBIS model were more influential in contributing to spatial patterns of error between simulated and observed yield averages than the underlying soil type, planting date, or hybrid chosen. While the raw differences between simulated and observed yield for each grid cell changed for the array of various hybrids planted, soil types chosen, or planting dates, the patterns of mbe were similar to the CR, regardless of the results of individual simulation results or ensemble averages (e.g., average of all simulations including varied soil types, planting dates, and hybrids).

Thus, three conclusions can initially be drawn from this part of the analysis. First, the Agro-IBIS model captured lower reported yields across the western Great Plains for nonirrigated, dryland corn even though the model was originally calibrated for regions farther to the east (Kucharik and Brye, 2003; Donner and Kucharik, 2003). This suggests that the model satisfactorily captured the impact of simulated water (soil moisture) stress on maize phenology and grain fill. Second, irrigation has played a large role in agriculture in many portions of the Corn Belt, and further model investigations could be used to determine the amount of water that would be necessary to maintain current yields in the event of future drier climatic conditions. Finally, it appears that the climate input datasets themselves impacted the pattern of simulated yields, regardless of the type of soil, hybrid, or planting date at any individual location.

3.2. Simulated interannual variability of maize yield across regional landscapes

The suite of model simulations (Table 1) was used to assess whether the spatial and temporal variability of maize yield and the magnitude of deviations across the Corn Belt could be captured with the model and simulation protocol. One objective was to evaluate whether automatic (optimum) planting and hybrid-type selection (within given typical ranges as determined by model algorithms based on climate) were feasible to use in future analyses that examine how cropping systems might react to future climate change scenarios. Some previous studies have assumed that decision making (i.e., planting date, hybrid selection) remains static through time in the event of future climate changes. In reality, if climate change occurs slowly enough, farmers will likely be able to adapt to these changes. It is likely that planting date or selection of hybrids according to GDD requirements for crops will change concurrently.

The second objective was to better understand where model failure occurs, which driver (e.g., soils or climate) or decision making (e.g., hybrid choice and planting date) is the model most responsive to, and what limitations are introduced as a derivative of the modeling approach. The overall goal was to determine whether the model simulations of spatial and temporal corn yield variability were improved by averaging multiple model runs that accounted for an array of management decisions and varied soil types.

3.2.1. Regression analysis of simulated and observed yield residuals: 1958–94

For the 37-yr time series at each grid cell, maize yield residuals for observations (percent deviation from the SSA trend line) and simulations (percent deviation from each grid cell's 1958–94 mean value) were subjected to linear regression analysis and an F ratio was used to test for the significance of the linear relationship. This analysis was first done to the CR, subsequently for ensemble combinations of varied soil types, hybrids, and planting dates, and then for the ensemble average of the nine potential combinations of three planting dates and three hybrid types. For all simulations, except the series of tests that varied soil texture, the dominant soil texture from the aggregation of the STATSGO dataset (as in the CR) was used as model input. Table 1 details the framework of individual simulations.

Figure 5a shows the resulting coefficient of determination (r^2) value from observed yield residuals regressed against the CR-simulated yield residuals. In general, the predictive capabilities of the model were most robust through Missouri, central Illinois, and Indiana where r^2 values of 0.4 and greater were common. Another area of similar levels of agreement existed from southeast North Dakota southward into eastern Nebraska and western Iowa. However, lower correlations were noted in adjacent areas of high cropland density including north-central Iowa, central Wisconsin, and the western regions of the Great Plains. The poor correlations over western Nebraska and Kansas were expected because irrigation was not included in this particular set of model runs.

3.2.2. Impact of contrasting soil types

The absolute, positive change (increasing) in r^2 values (compared to the CR) for the soil ensemble average set of simulations is depicted in Figure 5b. For each of the five simulations, the same soil type was assumed to be uniform across the study region at all soil depths while optimum hybrid selection and planting date were similarly chosen as in the CR. The results depicted in Figure 5b suggest that simulations of raw yield and interannual maize yield variability were only minimally responsive to the prescribed changes to grid cell soil texture. Small increases to the r^2 for simulated yield residuals regressed against observations were noted, but this only occurred in 44% of all grid cells. Thus, within the majority (56%) of all grid cells, the correlation decreased from the formation of an ensemble yield average via this exercise. Only regions in southeast Ohio and Kentucky saw significant (r^2 increased by 0.3) improvement due to the inclusion of more than one dominant soil texture.

The weak model response to soil variations was in agreement with the study of Easterling et al. (Easterling et al., 1998), where greatly contrasting soils types imposed at a similar grid cell resolution (0.5° and greater) had little effect on simulated yields using the EPIC model across a portion of the Great Plains. While Agro-IBIS uses a mechanistic soil physics routine to simulate soil water movement, it appears that climate and management decisions have a more dominant impact on yield where they are more limiting than the underlying soil type. However, the pattern of sensitivity depicted in Figure 5b suggests that regions in the southeast portion of the study area that receive more precipitation than the western regions were the most responsive to changing soil texture.

3.2.3. Ensemble average results of varied planting dates and hybrids

It has been previously hypothesized that correlation between simulated and observed yield residuals (at 0.5° resolution) would increase from the formation of

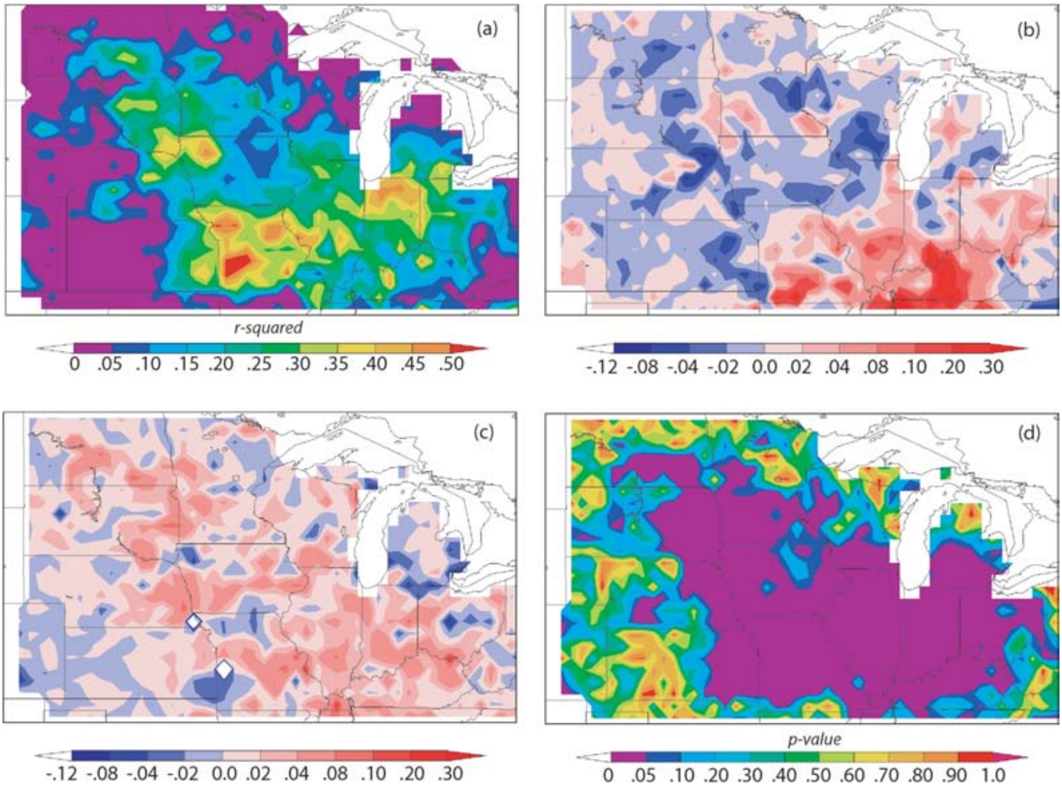

Figure 5. (a) The r^2 value (coefficient of determination from linear regression analysis) between observed (USDA, irrigated and nonirrigated) and control run simulations (Agro-IBIS, nonirrigated) of annual percent maize yield deviations (residuals) for the 1958–94 time period at 0.5° resolution. (b) Absolute change in r^2 value [cf. the control run in (a)] for an ensemble average of five model runs that used varied the grid cell soil type across the study region (sand, sandy loam, silt loam, clay loam, clay). Regions shaded in blue (red) correspond to grid cells where the ensemble average decreased (increased) the correlation [relative to results of the control run in (a)]. (c) Absolute change in r^2 value [cf. the control run in (a)] for an ensemble average of nine model runs that varied planting date and hybrids (GDD to reach silking and physiological maturity) across the study region using the dominant soil type from the CR. Regions shaded in blue (red) correspond to grid cells where the ensemble average decreased (increased) the correlation [relative to results of the control run in (a)]. (d) Depiction of regions where the correlation between interannual yield residuals (observed vs simulated) was statistically significant (p value ≤ 0.05) for the results of the ensemble average of nine model runs that varied planting date and hybrid (refer to Table 1).

ensemble yield averages of model simulations that represented a larger array of potential management decisions at the farm level. Based on the relatively weak response of simulated maize yield to soil type, the dominant soil texture derived from aggregation of the STATSGO dataset was used for all additional sensitivity tests. Initially, the agreement (coefficient of determination, r^2) between simulated and observed yield residuals was studied for each individual hybrid planted and for an ensemble average of all hybrids studied (Table 1) within each grid cell at the optimum (e.g., control run) planting date. Subsequently, the improvement in r^2 was studied for the ensemble average of three planting dates while planting the optimum maize hybrid. Finally, the aggregation of the nine possible combinations of planting dates and changing hybrids was studied. The results are briefly summarized here.

Results suggested that yield simulations were more responsive to variations in planting date (optimum ±15 days and equal weighting used to form the average resulting yield for each year) over a month in spring than the planting of three different hybrids (optimum ±150 GDD). For the hybrid ensemble, r^2 values positively increased in 51% of all grid cells. The average (absolute) change in r^2 was 0.005 over all grid cells, and 0.017 for those having a positive increase (relative to the CR). For the planting date ensemble, r^2 values positively increased in 59% of all grid cells. The average increase in r^2 was 0.009 across all grid cells and 0.021 for those having a positive change (relative to the CR), respectively. Thus, the improvement in correlation between observed and simulated yield residuals over the 37-yr period was minimal for each of these separate ensemble averages.

The factorial combination of three planting dates and three hybrid choices at each grid cell was used to represent nine potential land management choices at the farmer level. Figure 5c shows the absolute (positive, increasing) change in r^2 values (cf. the control run) for the ensemble yield averaging of these nine model simulations (Table 1), while keeping the underlying soil type assigned to each grid cell (dominant, STATSGO) the same. The average increase in r^2 across all grid cells was 0.011, and in 59% of the grid cells that showed a positive change, the average increase in r^2 was 0.026. Some individual grid cells showed an increase of 0.1 or greater in r^2 values, but there was no apparent systematic pattern of change. Figure 5d depicts geographically where the results were statistically significant (p value ≤ 0.05).

The observed pattern of statistical significance (both r^2 and p value) appeared to be related to USDA total maize-harvested area or cropland density (Ramankutty and Foley, 1998), with the exception of regions in western Nebraska and Kansas. Model results in these regions were not expected to produce statistically significant agreement with observed yield residuals because of the impact of irrigation. Figures 6a and 6b illustrate statistical relationships between the grid cell–harvested area (the average over the 37-yr period 1958–94 was used) and the corresponding grid cell r^2 and p values, respectively. When these individual grid cell statistical measures were regressed against the grid cell–harvested area, a modest ($r^2 = 0.35$) but significant ($p < 0.0001$) relationship was noted. These data suggested that simulated and observed yield residuals achieved greater correlation as grid cell cropland density (e.g., maize-harvested area) increased.

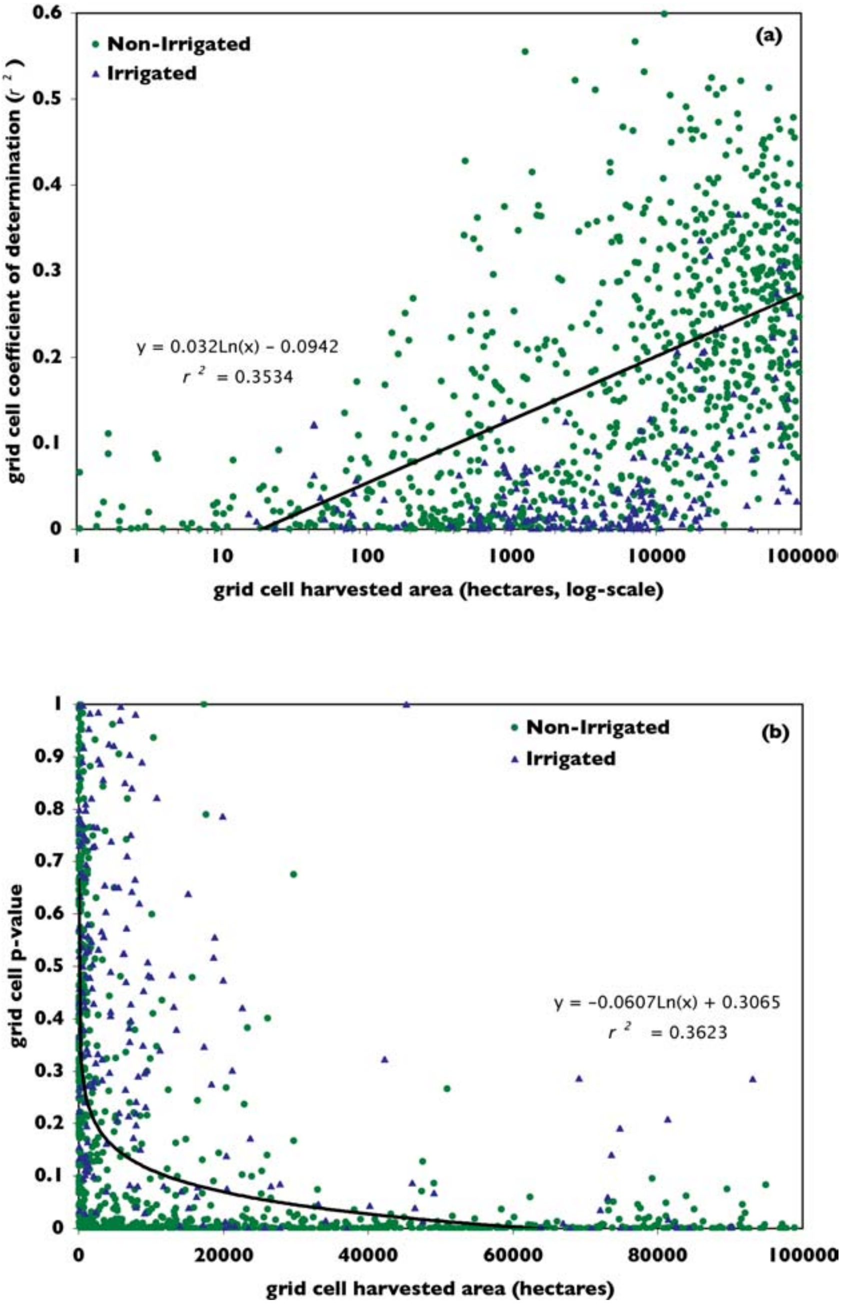

Figure 6. Relationship between grid cell average harvested area (for 1958–94) and the resulting (a) coefficient of determination (r^2) and (b) level of significance (*p* value) from the linear regression of observed and simulated yield residuals for the nine-run ensemble average (1958–94). The linear regression (relationship between reported grid cell–harvested area and r^2 or *p* value) drawn on the graph is for nonirrigated points exclusively.

Intuitively, this result may not be surprising. Any 0.5° grid cell (~2000 km^2) that has a high cropland density to support the reported data would produce a more representative average for the area than a grid cell with a lower density of farms. Additional cropped land area increases the likelihood that yield extremes are averaged out, thereby approximating more closely what model simulations represent, the average conditions within a 0.5° grid cell. Reported yield within grid cells that contain lower cropland density on the perimeter of the core Corn Belt region would be influenced more by extreme variations in weather that are not characterized by the model, skewing the results. Moreover, the very reason that these regions have a lower cropland density is because they are either not well suited for agriculture at the present time or have different land use purposes and land cover (Ramankutty and Foley, 1998). The only region that appears to significantly dismiss the harvested area–residual correlation theory is from north-central Iowa into south-central Minnesota, which had consistently low r^2 values. Surprisingly, regions of central Missouri that have a low maize cropland density compared to the rest of the Corn Belt (Donner, 2003) have the highest level of correlation between simulated and observed yield residuals. The north-central Missouri region is also subjected to a large degree of summertime precipitation variability (CV ~63% for July 1958–94) compared to other regions east of the 508-mm annual precipitation line.

3.2.4. Examples of varied correlation at grid cells

To better illustrate a wide range of yield variability and model capabilities in the Corn Belt, a series of four individual grid cells were used (Figures 7a–7d) for closer analysis. The four grid cells represent locations with high or low correlation between observed and simulated yield residuals (an ensemble average of nine model runs), a range of maize cropland density during the study period, and large variations in July precipitation amount and interannual variability, which has been shown previously to be highly correlated with maize yield (Thompson, 1986; Thompson, 1988). Figures 7a,b depict grid cells with high correlation ($r^2 > 0.5$), but are located in regions that have significant differences in July precipitation variability (CVs were 63% and 36%, respectively) with similar amounts of average harvested acreage (11 400 and 8300 ha, respectively). For these grid cells, the yield interannual variability appears highly correlated to both amount and variability of July precipitation.

The data shown in Figure 7c are for a grid cell located within 1° latitude and 1° longitude of the grid cell in Figure 7b; thus, it has approximately the same degree of precipitation variability, but roughly 25% of the harvested area (2739 ha). The corresponding correlation is weak (0.05) and insignificant ($p = 0.17$), suggesting the lower amount of harvested land area may be producing a yield that is less representative of a potential average if maize was grown on more land area within that grid cell. Figure 7d illustrates a case in which the harvested area (11 233 ha) is approximately equal to the example in Figure 7a, but is located in a region (west-central Nebraska) where irrigation is heavily used. While the CV of July precipitation CV was 52% during the period, the reported average yield deviations were −9.5% and 7.5% for years when yield residuals were negative and positive,

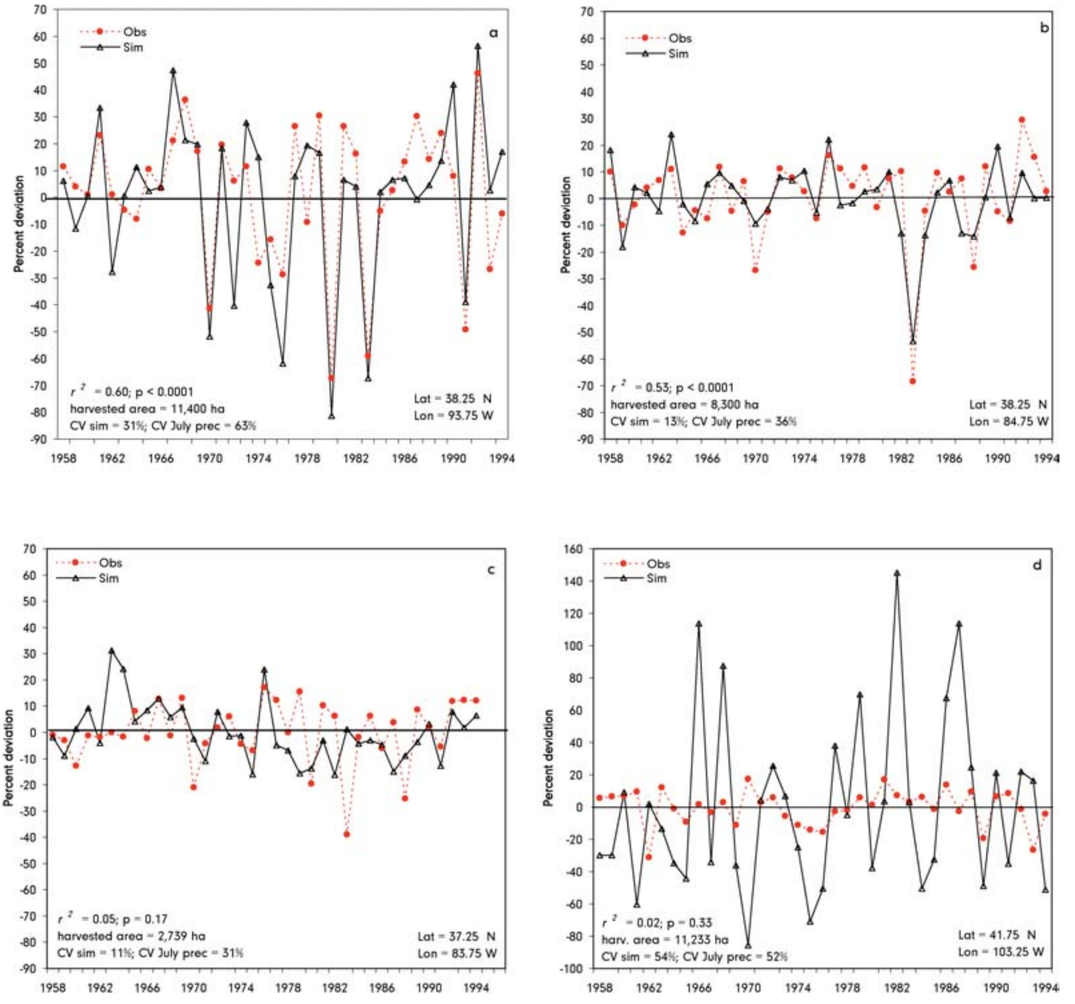

Figure 7. Comparison of observed and simulated (ensemble average of nine model simulations) yield residuals (percent deviation) for four individual grid cells with varied Jul precipitation, average harvested area, and degree of correlation. Grid cells were located at (a) 38.25°N, –93.75°W; (b) 38.25°N, –84.75°W; (c) 37.25°N, –83.75°W; and (d) 41.75°N, –103.25°W.

respectively. The simulated average variability for this grid cell in Nebraska was –40.8% and 43.1% for negative and positive yield residuals, respectively. This clearly shows how irrigation has not only helped to boost yields, but virtually eliminated large variations in maize yield.

3.3. Spatial patterns of average negative and positive percent deviations across the region: Observed versus simulated

Three of the model sensitivity experiments (control run, varied soil texture, and ensemble average) were used to better understand how changing model inputs and simulated farmer decision making impacted spatial patterns of interannual yield magnitude. Independent average percent deviations from the trend line for county-level census data were divided into two categories for each grid cell: years that were above the trend line or having a positive deviation and those below the trend line (negative deviation). Similar statistics and averages were calculated for simulated yield, only deviations were based on using the 37-yr grid cell yield average as a baseline. This resulted in an average positive and average negative percent deviation for simulated and observed yield at each grid cell for the 1958–94 time period.

The ensemble average of the nine factorial simulations (three planting dates and three hybrids chosen) had average negative deviations of −3% to −10% in the far southeastern portions of the region, and −35% to −45% over the far western regions (North Dakota, South Dakota, Nebraska, and Kansas; Figure 8a). This simulated pattern is a function of the variability and magnitude of growing season precipitation and temperature stress on plant growth. The same analysis using USDA county-level data depicted variability that was less in magnitude than simulations, particularly in Wisconsin, Indiana, Illinois, Missouri, and Iowa (Figure 8a). The impact of irrigation use has generally decreased the average annual negative deviations from the trend to 0% to −10% across the dry regions of Nebraska and western Kansas. This is up to a factor of 5 lower than the typical average annual simulated negative deviations of −40% to −50%.

The simulated average annual positive deviations from the 37-yr mean were 5% to 15% less (in absolute magnitude) than negative departures over the eastern two-thirds of the study region (Figure 8b). However, in drier regions where simulated yields were relatively low on average, good weather years (e.g., above-average precipitation) had a much larger impact on maize yields compared to the period mean. For the CR, the average percent positive and negative yield residuals for all grid cell years averaged for the region were 20.6% and −22.3%, respectively. The frequency of occurrence of positive versus negative yield deviations for all years and grid cells in CR simulations was 51.9% and 48.1%, respectively. This same general response appears within the observation record for nonirrigated regions in that there is a higher frequency (55.7%) of positive yield residuals, and their average magnitude over the 37 yr for the 868 nonirrigated grid cells was lower (12.8%) than negative deviations (−17.2%; Table 2). Therefore, it appears that simulations satisfactorily captured the observed geographic patterns and frequency of positive versus negative deviations for yield residuals, except that absolute variability for CR simulations was significantly higher (~60%) than USDA data (Table 2).

The ensemble average of simulated yield residuals for multiple "farm-level" management decision making (e.g., ranges in planting date and hybrid choice) was hypothesized to decrease the magnitude of interannual variability because a larger array of management possibilities could be taken into account. The results reported in Table 2 suggest that as a higher number of management scenarios were simulated and combined to calculate interannual variability, the variability decreased, and the difference in magnitude between reported and simulated variability also diminished. The ensemble averaging of the factorial combinations of three planting dates and three characteristic hybrids for each grid cell decreased

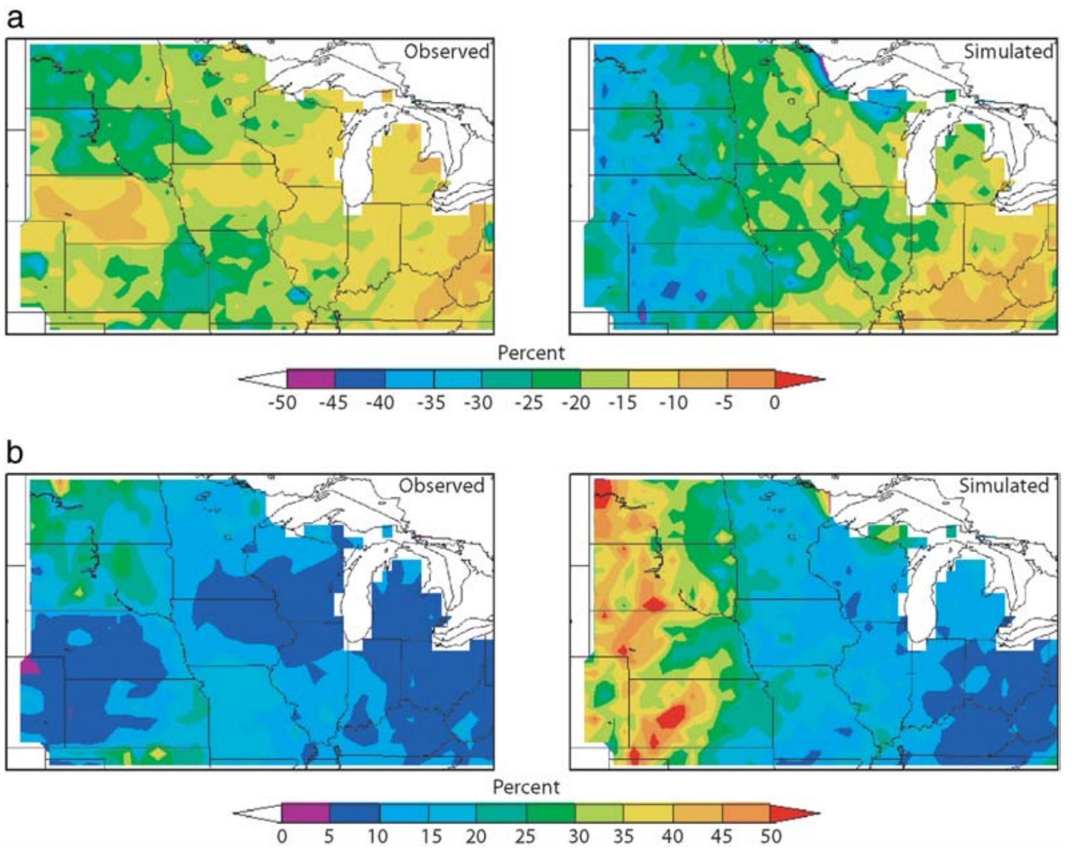

Figure 8. (a) The 37-yr (1958–94) mean value of yield residuals (average percent deviation) for years when the observed or simulated maize yield (for each case treated individually) was less than (negative deviation) the expected maize yield (i.e., annual SSA trend value for observations; 37-yr mean value of simulations for each grid cell).(b) The 37-yr (1958–94) mean value of yield residuals (average percent deviation) for years when the observed or simulated maize yield (for each case treated individually) was greater than (positive deviation) the expected maize yield (i.e., annual SSA trend value for observations; 37-yr mean value of simulations for each grid cell).

the study region average positive and negative deviations by approximately 10% (relative to the CR), but were still higher in magnitude than the observations (39% and 21% higher relative to observations for positive and negative deviations, respectively; Table 2). However, the frequency of grid cell years with deviations greater than the 37-yr simulated average yield increased to 53.4%, up from 51.9% for the CR. This suggested that additional simulations that accounted for a larger range of management scenarios decreased the frequency of grid cell years that had below-average yield. It was noted that when model response to varied hybrids planted versus planting dates were studied separately (ensemble averages for three separate runs for each; Table 2), planting date variations had a larger impact on

Table 2. Summary of average corn yield residuals (percent deviation from the average) for all grid cells during the 1958–94 period for particular simulation cases and observations. Heavily irrigated values are for grid cells in SD, NE, KS, OK, and CO. The frequency denotes the total percentage of all reported years that had positive and negative yield residuals.

	Nonirrigated*				Irrigated**			
Scenario/case	Positive (%)	Frequency (%)	Negative (%)	Frequency (%)	Positive (%)	Frequency (%)	Negative (%)	Frequency (%)
Control run	20.6	51.9	−22.3	48.1	37	47	−34.5	53.0
Varied soil ensemble avg	20.7	51.9	−22.4	48.1	37.4	47.5	−33.8	52.5
Hybrid ensemble (three runs)	19.2	52.8	−21.5	47.2	36.5	47.2	−32.7	52.8
Planting date ensemble (three)	19.0	52.6	−21.1	47.4	36.6	47.2	−32.7	52.8
Planting date and hybrid ensemble (nine)	18.1	53.4	−20.8	46.6	34.7	47.5	−31.5	52.5
Observations (USDA)	12.8	55.7	−17.2	44.3	10.4	51.1	−15.3	48.9

* Number of 0.5° cells = 876; USDA data included maize yield for both irrigated and nonirrigated cropland
** Number of 0.5° cells = 168; USDA data included maize yield for both irrigated and nonirrigated cropland

decreasing absolute variability. The average of the five simulations that used contrasting soil types had a negligible effect on the overall average variability across the entire study region (while using the other CR methodology: optimum planting date and hybrid choice). Unlike the other ensemble averages of multiple runs of varied planting dates or hybrids, there was a slight increase (0.1%) in interannual variability over the study region compared to the CR (Table 2). This is further supporting evidence of large-scale yield simulations having minimal response to changes in soil texture.

Figures 9a and 9b depict the 37-yr grid cell average simulated and observed yield residuals (as percent deviations). For both negative and positive yield residuals, the best linear regression fit falls on the simulation side of the 1:1 line, supporting the overall bias of greater variability in simulations. Furthermore, model simulations better represent the distribution of grid cell 37-yr-average positive yield residuals ($r^2 = 0.49$) than negative deviations ($r^2 = 0.24$). This may suggest that the model is able to better represent interannual yield variability in good weather years. Several hypotheses may help to explain the apparent increased difficulty in simulating below-average yields: 1) negative deviations are larger in magnitude than positive deviations, have more scatter, and have a multitude of factors that can contribute to lower than average yields; 2) the model's representation of heat and soil moisture stresses imparted on maize may be difficult to generalize across large continental scales due to differences in hybrid responses to heat and water stress; and 3) the model does not account for diseases and pests that contribute to below-average yields. Additionally, it is hypothesized that to improve simulations of average yields at a 0.5° grid cell resolution and decrease the bias of higher absolute interannual variability, more than one weather time series (combination of monthly and daily datasets) should be implemented. While monthly and daily (time step) gridded input climate datasets at 0.5° resolution are sufficient for simulating natural vegetation responses over months or

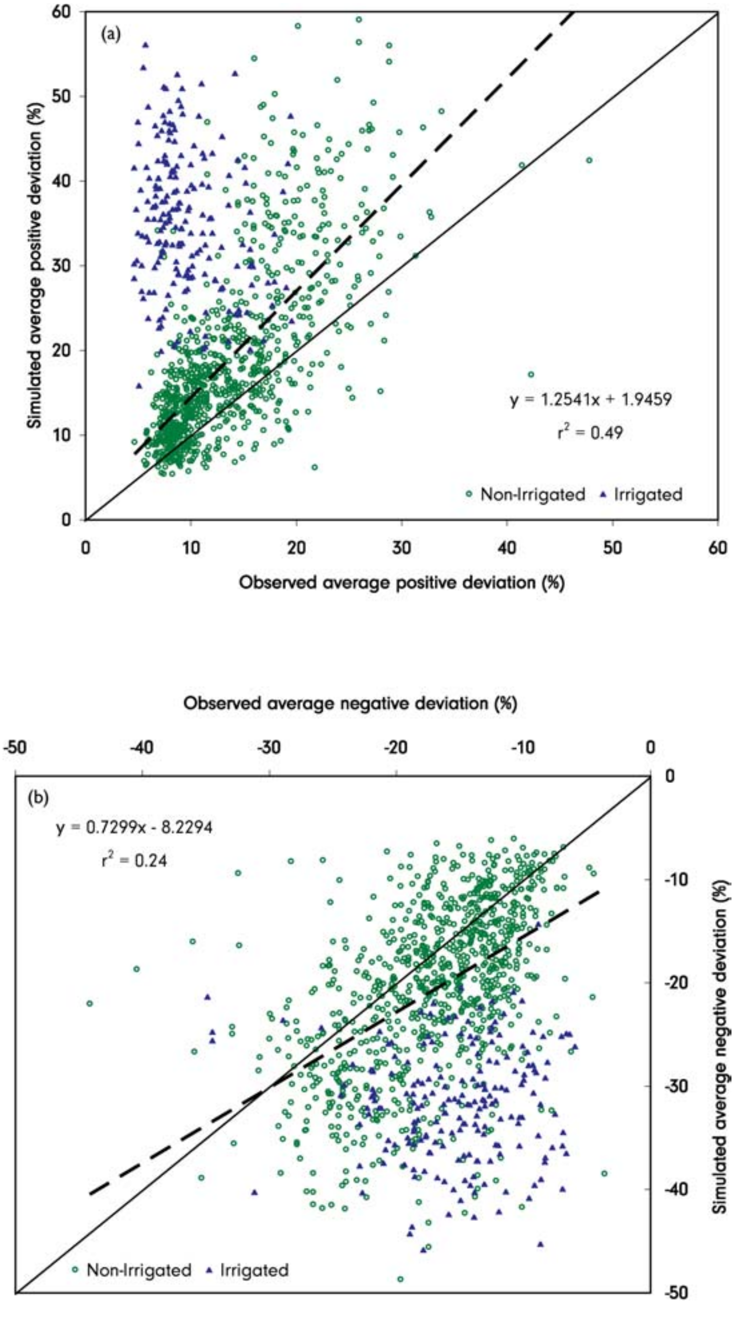

Figure 9. Relationship between each grid cell average (for 1958–94) observed and simulated (ensemble average of nine simulations) (a) positive and (b) negative deviations (yield residuals). The linear regression drawn (dashed line) on the graph is for nonirrigated points exclusively. A 1:1 line (solid) is shown for comparison.

years, cropping systems are much more dynamic by nature because of human management. Besides variations of management across small distances, atmospheric variables, particularly precipitation, can vary significantly across a 2000 km^2 region, leading to an array of yields. The problematic nature in landscape ecology of scaling from the farm level to a 0.5° grid cell obviously surfaces in this study. If additional statistical time series of varied weather conditions about mean values were used to simulate growing season conditions within a grid cell, the simulated variability would likely be decreased.

For grid cells that were designated as being heavily dominated by irrigation practices, the differences between simulated and observed yield residuals were significantly higher, and the variability is generally twice as large as in nonirrigated grid cells. Table 2 reports the average simulated and observed positive and negative deviations for the 168 grid cells classified as heavily irrigated. In general, two obvious differences surface: first, the frequency of simulated positive deviations were less than negative deviations; and second, they are larger in magnitude. This was not the case for observations. While ensemble averaging helped to decrease the magnitude of variability in these grid cells, the absolute difference between simulations and observations was still high at 234% and 106% for positive and negative deviations, respectively. Because it was suspected that the model has a more difficult time simulating the impact of stresses on crop growth under stressful growing conditions and dry regions, a subset of these 168 grid cells was used for closer analysis to gauge model performance.

The USDA county-level data for the state of Nebraska was divided into average maize yields produced on irrigated (approximately 65% of the total agricultural land base) and nonirrigated land for the 1958–2001 period. The SSA was used to detrend the reported nonirrigated and irrigated maize yields separately for each county. As the first part of the assessment, model calibration for nonirrigated maize was assessed using the 1987–2001 state average yields. Second, the entire time record for 1958–94 was used to assess model capability in reproducing interannual yield variability based on detrended county-level observations. Simulated averages for the entire state of Nebraska were formulated using a subset of the 91 grid cells located within the state boundaries for this analysis.

The average observed positive and negative yield deviations for nonirrigated maize, calculated as the average of the 91 grid cells, were 18.5% and −19.7% during the 37-yr study period, respectively. On irrigated land, the corresponding deviations were only 5.6% and −7.4%. Observed deviations above and below the SSA occurred 52.7% and 47.3% of the time, respectively. The average simulated positive and negative yield deviations, calculated as the average of the 91 grid cells, were 30.2% and −29.1% during the 37-yr study period, respectively. Simulated deviations above and below the period average occurred 49% and 51% of the time, respectively. These results for Nebraska suggest the following: 1) the model appears capable of simulating mean yields in dry regions, 2) variability was significantly higher in simulations (48% and 63% higher for negative and positive departures, respectively), and 3) the simulation of "single-point" weather time series for an entire grid cell likely introduces variability that becomes more significant under more stressful conditions to plant growth.

4. Conclusions

The primary conclusions of this study are as follows.

- Spatial patterns of simulated yield mbe (for a 15-yr average) associated with current model calibration were largely unresponsive to variations in soil texture, and optimum hybrid choices and planting dates typical for the U.S. Corn Belt.
- Simulated average maize yields associated with the current model calibration for contemporary (1990s) levels of technology had an mbe of 0.97 and an rmse of 1.75 Mg ha^{-1} across the entire region.
- The impacts of irrigation on maize yields in the western Great Plains must be properly accounted for in future modeling studies to capture increases (36%) to overall productivity, water usage, and decreased interannual variability compared to rain-fed maize.
- Simulated interannual maize yield variability demonstrated a weak response to changes in soil type.
- The correlation between observed and simulated annual yield residuals generally increased as additional combinations of management scenarios within 0.5° grid cells were taken into account.
- The correlation between observed and simulated yield residuals appeared to have a weak ($r^2 = 0.36$) but significant ($p < 0.0001$) relationship to reported harvested area, demonstrating that the quality of observations (and land area over which they are averaged) was important to the assessment of model capabilities.
- Model simulations produced a larger absolute magnitude of interannual variability, on average, for the entire region during the study period. For designated nonirrigated grid cells, the average annual percent positive and negative deviations from the mean yield for simulations were 18% and –21%, respectively. For observations, the average positive and negative yield residuals (deviation from the trend line) were 13% and –17%, respectively, when averaged over all nonirrigated grid cells in the region.
- The difference in the absolute magnitude between simulated and observed interannual variability was greater in more limiting growing conditions, such as those found in Nebraska.
- The use of a single time series of weather conditions for 0.5° grid cells might be partially responsible for the higher degree of simulated interannual yield variability.
- The spatial patterns of simulated interannual variability appeared consistent with observations, and collectively, simulations and observations suggest that deviations above the trend line are more frequent than negative deviations. As an increasing number of combinations of planting date and hybrid choice were simulated, the overall interannual variability decreased within grid cells.

This exercise demonstrated the difficulty associated with using a model at relatively coarse resolution across large scales to simulate corn production and interannual variability. The results suggested that accounting for a wider range of relevant land management possibilities within a 0.5° grid cell ultimately leads to a reduction of overall absolute variability of simulated crop yield. This conclusion contradicts the belief that when varied management is superimposed on weather, yield variability can escalate (Kaufmann and Snell, 1997).

A variety of factors have likely contributed to the presented differences between simulated and observed yield variability in this study. On the modeling side, several simplifications are necessary when using a terrestrial grid that covers the Corn Belt at a 0.5° resolution; accounting for all possible farm-level decision making is difficult, if not impossible. For example, the impacts of tillage, row spacing, crop rotations, pest and disease, and economic factors that influence farm-level decisions were not accounted for in simulations. Other within-field processes such as surface compaction and crusting and water routing are unable to be characterized within a 0.5° grid cell, but obviously influence productivity. On the data input side and approach, the use of a dominant soil series and representative average weather time series are likely contributing causes to model error. Future model testing could examine whether using an array of weather conditions and soils superimposed on management options within a 0.5° grid cell improved results. In actuality, this type of approach is more representative of how average county-level crop yield is impacted.

The impact of nitrogen fertilization on simulated yield also deserves mention here. The model simulations assumed that plant growth was not impacted by changes in nitrogen availability through time, which is an obvious over-simplification of reality. Previous modeling work performed with Agro-IBIS over the Upper Mississippi basin (Donner and Kucharik, 2003) and at an agricultural field site in southern Wisconsin (Kucharik et al., 2001; Kucharik and Brye, 2003) highlighted two important points in regard to simulated nitrogen cycling and crop yield by Agro-IBIS. First, in years when weather conditions led to environmental conditions that were far from optimal for crop growth (e.g., the 1988 drought or the excessive 1993 spring rains and flooding conditions), nitrogen fertilizer application had a relatively minimal (5%–15%) impact on simulated crop yield. Second, at the individual field scale where components of the complete nitrogen cycle were measured over a 6-yr period, Agro-IBIS failed to replicate the observed magnitude of interannual variability in nitrogen cycling. In general, the model had difficulty in capturing extreme fluctuations in net nitrogen mineralization and leaching, which have a direct impact on available plant nitrogen for uptake.

Observations of corn yield variability at the agricultural study site in Wisconsin showed that the coefficient of variation (CV) was 23% in optimally fertilized fields (180 kg N ha^{-1}) and 15% in unfertilized plots (0 kg N ha^{-1}) over the 6-yr study, suggesting that nitrogen fertilizer dependency slightly increased yield variability. However, Agro-IBIS produced CVs that were 18% and 22% for optimally fertilized and unfertilized scenarios, respectively, which suggests that accounting for nitrogen fertilizer decreased the interannual variability. Therefore, it is hypothesized that accounting for nitrogen fertilizer and the impacts of nitrogen cycling on crop growth in this study would have caused simulated interannual variability to decrease, at least in regions where corn is able to thrive without irrigation. In the future, continued investigation of the impacts of a variety of nitrogen management scenarios on yield variability in both simulations and field experiments would appear to be a necessary step to continued model validation, as well as important to assessing trade-offs between agricultural production; food security; and contamination of lakes, rivers, and oceans as well as groundwater reservoirs (Donner and Kucharik, 2003).

The definitive outcome of this research was that while the Agro-IBIS model produced satisfactory results, the protocol used for scaling model simulations from the farm level to a much larger scale (such as a 0.5° grid cell) still needs much refinement. The most important factors to consider are how to account for varied land management and weather variability across a 2000 km^2 grid cell, and how these factors are influenced by soil type and other resources available to individual farmers. As Kaufmann and Snell (Kaufmann and Snell, 1997) point out, most models that are in the same genre as Agro-IBIS fail to account for social determinants and their impacts on yield. The author argues that more diverse and readily accessible farm-level data at the county level, such as varied management used, could help in such model evaluation exercises.

It is argued that before it becomes common practice to use GCM output to drive crop models across large, regional terrestrial grids, model predictive capabilities should be tested by using gridded datasets of previous climate as a surrogate for potential future climate variability. If models are unable to characterize or recreate past spatial and temporal yield variability, then it is unlikely that their response to future climate changes can be regarded as valid. Furthermore, if studies of climate change impacts on crop yield are desired in the future, the corresponding model structure should allow for human decision-making adaptation, such as planting and harvest date or hybrid selection to change gradually over time.

Confidence in these models can be increased, however, by using additional data sources currently available from a variety of sources, and by focusing on more than just the careful simulation of yield. Many crop models are capable of simulating complete carbon, nitrogen, and water balance at short time intervals, and therefore outpace the collection of measurements needed for extensive spatial (e.g., gridded) validation (Monteith, 1996). However, detailed carbon, nitrogen, and water budget observations are available at individual sites [e.g., Ameriflux or Free Air-CO_2 Enrichment (FACE) research experiments], and therefore model validation can be performed at the individual site level for those purposes. There is also much promise to use large-scale, high temporal and spatial resolution (~30–250 m) remotely sensed data from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat to assess model simulated plant phenology, LAI, biomass, and net primary productivity, but these data are only available for a historically short time frame, and therefore need to be coupled with all other available ground data to better understand the role of climate variability and changing atmospheric chemistry on potential future crop structure and function.

As a parting thought, the potential usage of a crop model such as Agro-IBIS, however, goes beyond studies of evaluating crop yield response to environmental change. It is argued that such models have a significant unexplored dimension to add to integrated assessment studies of the past and future impacts of agricultural production on the environment. Agricultural land use has transformed the landscape and has been the primary driver to the significant disruption of natural biogeochemical cycling (Houghton et al., 2001). Only recently has the impact of agricultural land use change been incorporated into large-scale carbon cycling studies. However, it is done in a rudimentary fashion nonetheless; with a few exceptions, a majority of terrestrial ecosystem models do not explicitly simulate cultivated ecosystem processes and management decisions and their impact on biogeochemical cycling (McGuire et al., 2001).

The ultimate hope is that the modeling approach presented in this study will be used as a benchmark for future model validation as managed ecosystems are added to other terrestrial ecosystem models. As higher-resolution (e.g., 30 m–1 km) model driver datasets become available and computer power increases, this type of modeling tool could be used to further our understanding of how to best manage our current farmland base to maximize food production and minimize environmental losses, particularly in the face of changes in climate variability.

Acknowledgments. The author gratefully acknowledges helpful comments by Jon Foley on an earlier version of the manuscript, and two anonymous reviewers for valuable guidance used in improving the final product. Special thanks are given to Mary Sternitzky who graciously helped with the creation of figures. This research was supported by a grant through the Office of Science, Biological and Environmental Research Program (BER), U.S. Department of Energy, through the South-Central Regional Center of the National Institute for Global Environmental Change (NIGEC) under Cooperative Agreement Number DE-FC03-90ER61010.

References

Acock, B., and A. Trent, 1991: The soybean crop simulator, GLYCIM: Documentation for the modular version 91. Department of Plant, Soil, and Entomological Sciences, University of Idaho, Moscow, Idaho, 242 pp.

Amthor, J.S., 1984: The role of maintenance respiration in plant growth. *Plant Cell Environ.,* **7,** 561–569.

Andresen, J.A., G. Alagarswamy, C.A. Rotz, J.T. Ritchie, and A.W. LeBaron, 2001: Weather impacts on maize, soybean, and alfalfa production in the Great Lakes region, 1895–1996. *Agron. J.,* **93,** 1059–1070.

Ball, J.T., I.E. Woodrow, and J.A. Berry, 1986: A model predicting stomatal conductance and its contribution to the control of photosynthesis under different environmental conditions, in *Progress in Photosynthesis Research*, edited by J. Biggins, Martinus Nijhoff, Netherlands, 221–224.

Botta, A., N. Ramankutty, and J.A. Foley, 2002: Long-term variations of climate and carbon fluxes over the Amazon basin. *Geophys. Res. Lett.,* **29,** 1319, doi:10.1029/2001GL013607.

Campbell, G.S., and J.M. Norman, 1998: *An Introduction to Environmental Biophysics,* 2nd ed., Springer-Verlag, New York, 286 pp.

Carlson, R.E., D.P. Todey, and S.E. Taylor, 1996: Midwestern corn yield and weather in relation to extremes of the Southern Oscillation. *J. Prod. Agric.,* **9,** 347–352.

Chipanshi, A.C., E.A. Ripley, and R.G. Lawford, 1999: Large-scale simulation of wheat yields in a semi-arid environment using a crop-growth model. *Agric. Syst.,* **59,** 57–66.

Collatz, G.J., M. Ribas-Carbo, and J.A. Berry, 1992: Coupled photosynthesis–stomatal conductance model for leaves of C_4 plants. *Aust. J. Plant Physiol.,* **19,** 519–538.

Dettinger, M.D., M. Ghil, C.M. Strong, W. Weibel, and P. Yiou, 1995: Software expedites singular-spectrum analysis of noisy time series. *Eos Trans. AGU,* **76(2),** 12, 14, 21.

Doering, O.C., J.C. Randolph, J. Southworth, and R.A. Pfeifer, 2002: Conclusions, in *Effects of Climate Change and Variability on Agricultural Production Systems*, edited by O.C. Doering et al., Kluwer Academic Publ., Boston, 265–271.

Donner, S., 2003: The impact of cropland cover on river nutrient levels in the Mississippi River Basin. *Global Ecol. Biogeogr.,* **12,** 341–355.

Donner, S., and C.J. Kucharik, 2003: Assessing the impacts of climate variability and land management on crop yield and nitrate flux across the Upper Mississippi Basin. *Global Biogeochem. Cycles,* **17,** 1085, doi:10.1029/2001GB001808.

Easterling, W.E., X. Chen, C. Hays, J.R. Brandle, and H. Zhang, 1996: Improving the validation of model simulated crop yield response to climate change: An application to the EPIC model. *Clim. Res.,* **6,** 263–173.

Easterling, W.E., A. Weiss, C.J. Hays, and L.O. Mearns, 1998: Spatial scales of climate information for simulating wheat and maize productivity: The case of the US Great Plains. *Agric. For. Meteorol.,* **90,** 51–63.

Farquhar, G.D., S. von Caemmerer, and J.A. Berry, 1980: A biogeochemical model of photosynthetic CO_2 assimilation in leaves of C3 species. *Planta,* **149,** 78–90.

Foley, J.A., I.C. Prentice, N. Ramunkutty, S. Levis, D. Pollard, S. Sitch, and A. Haxeltine, 1996: An integrated biosphere model of land surface processes, terrestrial carbon balance and vegetation dynamics. *Global Biogeochem. Cycles,* **10,** 603–628.

Geng, S., F.W.T. Penning de Vries, and I. Supit, 1986: A simple method for generating daily rainfall data. *Agric. For. Meteorol.,* **36,** 363–376.

Haskett, J.D., Y.A. Pachepsky, and B. Acock, 1995: Estimation of soybean yields at county and state levels using GLYCIM: A case study for Iowa. *Agron. J.,* **87,** 926–931.

Haskett, J.D., Y.A. Pachepsky, and B. Acock, 1997: Increase of CO_2 and climate change effects on Iowa soybean yield, simulated using GLYCIM. *Agron. J.,* **89,** 167–176.

Houghton, J.T., Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson, (Eds.), 2001: *Climate Change 2001: The Scientific Basis,* Cambridge Univ. Press, New York, 881 pp.

Jagtap, S.S., and J.W. Jones, 2002: Adaptation and evaluation of the CROPGRO-soybean model to predict regional yield and production. *Agric. Ecosyst. Environ.,* **93,** 73–85.

Jones, C.A., and J. R. Kiniry, (Eds.), 1986: *CERES-Maize: A Simulation Model of Maize Growth and Development*, Texas A&M Univ. Press, College Station, 194 pp.

Kalnay, E., et al., 1996: The NCEP/NCAR 40-Year Reanalysis Project. *Bull. Am. Meteorol. Soc.,* **77,** 437–471.

Kaufmann, R.K., and S.E. Snell, 1997: A biophysical model of corn yield: Integrating climatic and social determinants. *Amer. J. Agric. Econ.,* **79,** 178–190.

Kittel, T.G.F., et al., 1995: The VEMAP integrated database for modelling United States ecosystem/vegetation sensitivity to climate change. *J. Biogeogr.,* **22,** 857–862.

Kucharik, C.J., and K.R. Brye, 2003: IBIS yield and nitrate leaching predictions for Wisconsin maize agroecosystems receiving varied N-fertilizer. *J. Environ. Qual.,* **32,** 247–268.

Kucharik, C.J., J.A. Foley, C. Delire, V.A. Fisher, M.T. Coe, S.T. Gower, J. Lenters, C. Molling, J.M. Norman, and N. Ramankutty, 2000: Testing the performance of a dynamic global ecosystem model: Water balance, carbon balance, and vegetation structure. *Global Biogeochem. Cycles,* **14,** 795–825.

Kucharik, C.J., K. R. Brye, J. M. Norman, J. A. Foley, S. T. Gower, and L. G. Bundy, 2001: Measurements and modeling of carbon and nitrogen cycling in agroecosystems of southern Wisconsin: Potential for SOC sequestration during the next 50 years. *Ecosystems,* **4,** 237–258.

Legler, D.M., K.J. Bryant, and J.J. O'Brien, 1999: Impact of ENSO-related climate anomalies on crop yields in the US. *Climatic Change,* **42,** 351–375.

Lenters, J.D., M.T. Coe, and J.A. Foley, 2000: Surface water balance of the continental United States, 1963–1995: Regional evaluation of a terrestrial biosphere model and the NCEP/NCAR reanalysis. *J. Geophys. Res.,* **105,** 22,393–22,425.

Mauget, S.A., and D.R. Upchurch, 1999: El Nino and La Nina related climate and agricultural impacts over the Great Plains and Midwest. *J. Prod. Agric.,* **12,** 203–215.

Mearns, L.O., C. Rosenzweig, and R. Goldberg, 1992: Effect of changes in inter-annual climatic variability on CERES-Wheat yields: Sensitivity and $2 \times CO_2$ general circulation model studies. *Agric. For. Meteorol.,* **62,** 159–189.

Mearns, L.O., T. Mavromatis, E. Tsvetsinskaya, C. Hays, and W. Easterling, 1999: Comparitive responses of EPIC and CERES crop models to high and low spatial resolution climate change scenarios. *J. Geophys. Res.,* **104,** 6623–6646.

Mearns, L.O., W. Easterling, C. Hays, and D. Marx, 2001: Comparison of agricultural impacts of climate change calculated from high and low resolution climate change scenarios: Part I. The uncertainty due to spatial scale. *Climatic Change,* **51,** 131–172.

McGuire, A.D., and Coauthors, 2001: Carbon balance of the terrestrial biosphere in the twentieth century: Analyses of CO_2, climate, and land-use effects with four process-based ecosystem models. *Global Biogeochem. Cycles,* **15,** 183–206.

McMaster, G.S., and W.W. Wilhelm, 1997: Growing degree-days: One equation, two interpretations. *Agric. For. Meteorol.,* **87,** 291–300.

Miller, D.A., and R.A. White, 1998: A conterminous United States multilayer soil characteristics dataset for regional climate and hydrology modeling. *Earth Interactions*, 2. [Available online at http://EarthInteractions.org.]

Moen, T.N., H.M. Kaiser, and S.J. Riha, 1994: Regional yield estimation using a crop simulation model: Concepts, methods, and validation. *Agric. Syst.,* **46,** 79–92.

Monteith, J.L., 1996: The quest for balance in crop modeling. *Agron. J.,* **88,** 695–697.

New, M., M. Hulme, and P.D. Jones, 1999: Representing twentieth century space–time climate variability. Part I: Development of a 1961–1990 mean monthly terrestrial climatology. *J. Clim.,* **12,** 829–856.

New, M., M. Hulme, and P.D. Jones, 2000: Representing twentieth entury space–time climate variability. Part II: Development of 1901–1996 monthly grids of terrestrial surface climate. *J. Clim.,* **13,** 2217–2238.

Penning de Vries, F.W.T., D.M. Jansen, H.F.M. Ten Berge, and A. Bakema, 1989: Simulation of ecophysiological processes of growth in several annual crops. Centre for Agricultural Publishing and Documentation (Pudoc), Wageningen, Netherlands, Simulation Monographs 29, 271 pp.

Pfeifer, R.A., J. Southworth, O.C. Doering, and L. Moore, 2002: Climate variability impacts on farm-level risk, in *Effects of Climate Change and Variability on Agricultural Production Systems,* edited by O.C. Doering et al., Kluwer Academic Publ., Boston, 179–191.

Ramankutty, N., and J.A. Foley, 1998: Characterizing patterns of global land use: An analysis of global croplands data. *Global Biogeochem. Cycles,* **12,** 667–685.

Reilly, J., et al., 2002: *Agriculture: The Potential Consequences of Climate Variability and Change for the United States*, Cambridge Univ. Press, New York, 136 pp.

Reilly, J., et al., 2003: US agriculture and climate change: New results. *Climatic Change,* **57,** 43–69.

Richardson, C.W., 1981: Stochastic simulation of daily precipitation, temperature, and solar radiation. *Water Resour. Res.,* **17,** 182–190.

Ritchie, J.T., and G. Alagarswamy, 2002: Overview of crop models for assessment of crop production, in *Effects of Climate Change and Variability on Agricultural Production Systems*, edited by O.C. Doering et al., Kluwer Academic Publ., Boston, 43–68.

Rosenzweig, C., and M. Parry, 1994: Potential impacts of climate change on world food supply. *Nature,* **367,** 133–139.

Schlesinger, M.E., and N. Ramankutty, 1994: An oscillation in the global climate system of period 65–70 years. *Nature,* **367,** 723–726.

Sharpley, A.N., and J.R. Williams, 1990: EPIC—Erosion/Productivity Impact Calculator: 1. Model documentation. U.S. Department of Agriculture Technical Bull. *No. 1768,* 235 pp.

Southworth, J., J.C. Randolph, M. Habeck, O.C. Doering, R.A. Pfeifer, D.G. Rao, and J.J. Johnston, 2000: Consequences of future climate change and changing climate variability on maize yields in the Midwestern United States. *Agric. Ecosyst. Environ.,* **82,** 139–158.

Southworth, J., R.A. Pfeifer, M. Habeck, J.C. Randolph, O.C. Doering, J.J. Johnston, and D.G. Rao, 2002: Changes in soybean yields in the midwestern United States as a result of future changes in climate, climate variability, and CO_2 fertilization. *Climatic Change,* **53,** 447–475.

Thompson, L.M., 1986: Climatic change, weather variability, and corn production. *Agron. J.,* **78,** 649–653.

Thompson, L.M., 1988: Effects of changes in climate and weather variability on the yields of corn and soybeans. *J. Prod. Agric.,* **1,** 20–27.

USDA, 2003: National Agricultural Statistics Service Historical Data. [Available online at http://www.nass.usda.gov:81/ipedb/.]