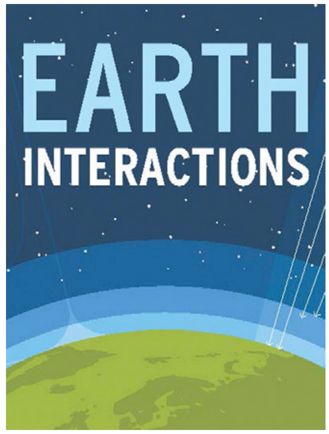

Calibration and Validation of the Hybrid-Maize Crop Model for Regional Analysis and Application over the U.S. Corn Belt

Xing Liu

Purdue University, West Lafayette, Indiana

Jeff Andresen

Michigan State University, East Lansing, Michigan

Haishun Yang

University of Nebraska–Lincoln, Lincoln, Nebraska

Dev Niyogi*

Purdue University, West Lafayette, Indiana

Received 13 January 2015; in final form 21 May 2015

---

* Corresponding author address: Dev Niyogi, Department of Agronomy and Department of Earth, Atmospheric, and Planetary Sciences, Purdue University, 915 W. State St., Lilly Hall 2420, West Lafayette, IN 47906.

E-mail address: climate@purdue.edu

DOI: 10.1175/EI-D-15-0005.1

ABSTRACT: Detailed parameter sensitivity, model validation, and regional calibration of the Hybrid-Maize crop model were undertaken for the purpose of regional agroclimatic assessments. The model was run at both field scale and county scale. The county-scale study was based on 30-yr daily weather data and corn yield data from the National Agricultural Statistics Service survey for 24 locations across the Corn Belt of the United States. The field-scale study was based on AmeriFlux sites at Bondville, Illinois, and Mead, Nebraska. By using the one-at-a-time and interaction-explicit factorial design approaches for sensitivity analysis, the study found that the five most sensitive parameters of the model were potential number of kernels per ear, potential kernel filling rate, initial light use efficiency, upper temperature cutoff for growing degree-days' accumulation, and the grain growth respiration coefficient. Model validation results show that the Hybrid-Maize model performed satisfactorily for field-scale simulations with a mean absolute error (MAE) of 10 bu acre^{-1} despite the difficulties of obtaining hybrid-specific information. At the county scale, the simulated results, assuming optimal crop management, overpredicted the yields but captured the variability well. A simple regional adjustment factor of 0.6 rescaled the potential yield to actual yield well. These results highlight the uncertainties that exist in applying crop models at regional scales because of the limitations in accessing crop-specific information. This study also provides confidence that uncertainties can potentially be eliminated via simple adjustment factor and that a simple crop model can be adequately useful for regional-scale agroclimatic studies.

KEYWORDS: Climatology; Regional effects; Land surface model; Agriculture; Crop growth

1. Introduction

This study stems from a regional, multi-institutional project titled "Useful to Usable (U2U): Transforming Climate Variability and Change Information for Cereal Crop." The U2U project seeks to develop decision support tools and climate resiliency–related resources for sustainable agriculture and improved profitability in the U.S. Corn Belt. One of the tasks underway is to develop historical and future agroclimatic assessments for U.S. Corn Belt (www.Agclimate4U.org) by understanding the impact of current and projected climate change on corn yields (Niyogi and Andresen 2011). To that end, the approach undertaken is to apply crop models for estimating regional crop yields.

A major limitation in applying crop models at large spatial scales is the difficulty in compiling required model input data, particularly for agronomic processes and management descriptors at regional scale. Therefore, a simple but reliable regional crop simulating system is desired to meet the increasing demand for regional agroclimatic assessments.

The Hybrid-Maize model (Yang et al. 2004) is selected for this study because it is simple, fast, and has relatively fewer input requirements compared to other crop models such as Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al. 2003), Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC) (Kiniry and Bockholt 1998), and the Erosion-Productivity Impact Calculator (EPIC) (Jones et al. 1991). This simplicity of crop model input is considered an advantage for developing large spatial-scale assessments. The Hybrid-Maize model has been tested and found to have reliable performance in simulating corn yield at a field scale (Yang et al. 2004, 2006a; Grassini

Table 1. Description of parameters used in the model sensitivity analysis (adapted from Yang et al. (2006b)).

Parameter	Description
*G*2	Potential number of kernels per ear
*G*5	Potential kernel filling rate (mg per day per kernel)
K	Light extinction coefficient (dimensionless)
FT	Fraction of leaf biomass that can be translocated as carbohydrate to grain each day
MF	Maximum fraction of leaf biomass at silking that can be translocated as carbohydrate to grain
EF	Efficiency of carbohydrate translocation from stem of leaf to grain, fraction
RD	Daily root death (turnover) rate in fraction of total root biomass
SDC	Stay green coefficient for controlling leaf senescence after silking (dimensionless)
LF	Senescent leaf area at maturity as a fraction of maximum LAI achieved at silking
UT	Upper temperature cutoff (°C) for GDD accumulation
TL	Threshold LAI above which leaf senescence due to light competition occurs
BAC	Biomass allocation coefficient for root at emergence, fraction
DS	Development stage at which the root system stops growing
EP	Empirical parameters that determine the relative contribution of a soil layer to water uptake (dimensionless)
LWS	Leaf water suction at permanent wilting point (cm)
RTT	Resistance of plant to transpiration (cm)
GRG	GDD requirement for germination
GRE	GDD requirement for emergence per centimeter of planting depth
MDE	Maximum days allowed from planting to emergence
RL, RS, RR, RG	Growth respiration coefficient of leaf, stem, root, and grain [g CH_2O g^{-1} dry matter (DM)]
MRL, MRS, MRR, MSR	Maintenance respiration coefficient for leaf, stem, root, and grain (g CH_2O g^{-1} DM)
MSR	Maximum (photosynthetic) assimilation rate (g CO_2 m^{-2} leaf h^{-2})
LUE	Initial light use efficiency [g CO_2 MJ^{-1} photosynthetically active radiation (PAR)]

et al. 2009). However, to date a regional-scale, multidecadal assessment of the Hybrid-Maize model is lacking.

Since the regions where the crop model will be applied have diverse environmental conditions, it is important to test, adjust, and validate model parameters. Sensitivity analysis is an effective tool for such a task (see Table 1 for a list of parameters used in the analysis). Sensitivity analysis can reveal which parameters are most highly influential to output variability (Hamby 1994). In addition, before applying the Hybrid-Maize model at a regional scale, validations and regional calibration are necessary to assess Hybrid-Maize's performance and understand what can be done to improve the large-scale simulation performance across the Corn Belt.

The first sensitivity analysis for the Hybrid-Maize model was conducted using a single representative scenario (Yang et al. 2004). This initial study was restricted to understand the impact of a few select parameters for a single site in Lincoln, Nebraska. Since the Hybrid-Maize model is a relatively new model that has not been widely used in the Corn Belt, there is a need to understand the sensitivity of simulated corn yields to different model variables and to validate the model performance at a regional scale. Therefore, the objective of this paper is to test the Hybrid-Maize model for its sensitivity over a range of parameters, validate, and calibrate it across the Corn Belt. This study is the first step for undertaking future

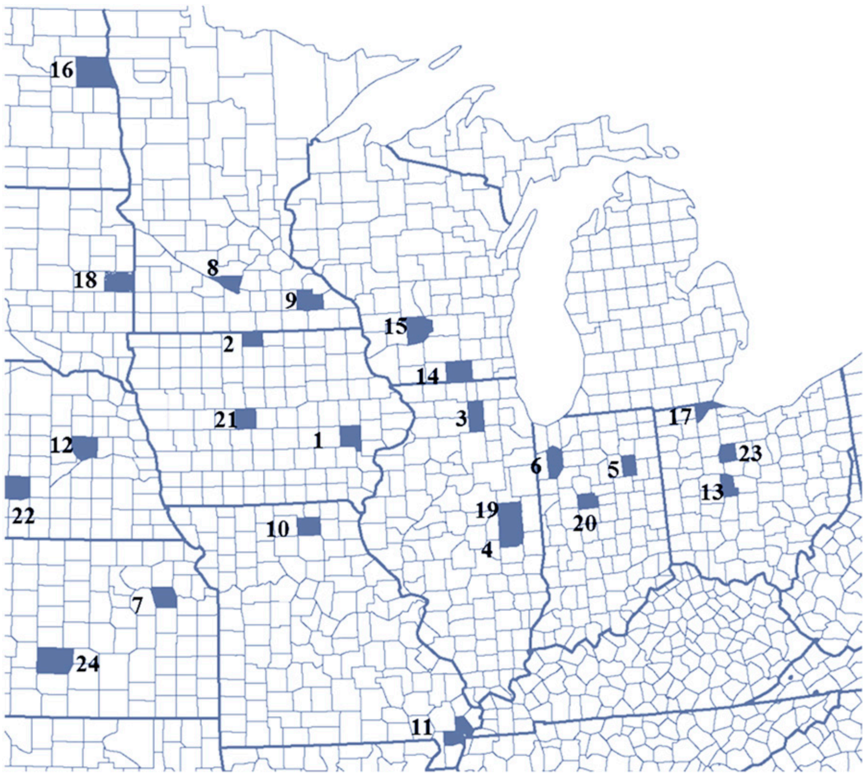

Figure 1. County-scale simulation sites.

research on developing a Hybrid-Maize–based crop–climate modeling system at larger regional spatial scales as part of the U2U project.

2. Materials and methods

2.1. Locations and data

We evaluated the Hybrid-Maize model at two spatial scales: county scale and field scale. The county-scale study included 24 counties (Figure 1) that considered a wide range of climatic conditions and crop yields across the Corn Belt. Data availability and accessibility are also taken into consideration when selecting these counties. Yield data for 18 counties (Figure 1, labeled 1–18) were used for model calibration, and data from an additional 6 counties (Figure 1, sites 19–24) were selected for testing the model yield adjustment factor, as described in section 3.

The 30 years (1981–2010) of daily weather data (minimum temperature, maximum temperature, and precipitation) were collected from the NOAA Daily Summaries Dataset (NOAA 2015) for a select location within each county of interest. Because of the lack solar radiation data at most weather stations, solar radiation was generated synthetically using the WeatherAid utility from the Hybrid-Maize crop simulation model package (Yang et al. 2005). County-level corn yield data were collected from USDA annual surveys (1981–2010) (USDA 2015). Yield data were detrended to a 30-yr average of each county to decrease the influence of technological advancements (e.g., Andresen et al. 2001; Hansen et al. 1998). The detrending approach assumed a linear trend and was applied here as is typically used in a variety of crop–climate studies (Hansen et al. 1998; Phillips et al. 1999). No assessments were done to assess spatial changes and only temporal trends were eliminated from the datasets.

The field-scale study included data from two sites at Bondville, Illinois (40.00°N, 88.29°W), and Mead, Nebraska (41.18°N, 96.44°W). Both sites are part of the AmeriFlux network (Baldocchi et al. 2001) that is operated for capturing the water, energy, and carbon fluxes over different natural ecosystems. Half-hourly meteorological data (2001–06) and seasonal yield data were obtained from the AmeriFlux data access portal (AmeriFlux 2015). The main reason to select the AmeriFlux sites is that the meteorological data and agronomic data were collected with a high level of accuracy. Additionally, solar radiation measurements are also available at these two sites, which provided an additional opportunity to test the model's overall performance at a field scale. The half-hourly weather dataset includes air temperature, precipitation, solar radiation, and relative humidity. Data were analyzed, paired, checked for consistency, extracted, and processed to daily weather input data for the crop model.

2.2. Model configuration

Our intent was to run and test the crop model with minimum requirements for crop and field management input and weather data. Required crop and field management input data include hybrid maturity [i.e., total growing degree-days (GDD) to maturity], planting date, and plant population. The model assumes optimal water management (i.e., nonwater limiting) for potential yield, and the corresponding meteorological input data required include daily minimum and maximum air temperature (°C) and daily solar radiation (MJ m^{-2}).

As stated, this study is motivated by the objective to assess the potential for applying the Hybrid-Maize crop model at regional scales. One of the limitations is the lack of ready access to regional cultivar information, soil data, and field management information. This lack of data is a critical consideration for our study, and we intend to use the model for contemporary and future climatic impacts on crop yield in a following study (Niyogi et al. 2015). We recognize that water stress and droughts can impact crop yields. The intent here is to explore if the model is run in its simplest configuration what biases emerge and if these biases can be reduced by a simple correction. Accordingly, the model was run with minimum input requirements under optimal water conditions and default agronomic characteristics. At the county scale, the planting date was set at 1 May, plant population at 31 600 per acre (78 000 per ha), 1389 GDD (10°C base) (i.e., 2500 GDD for 50°F base). For the field-scale studies at Bondville, Illinois, and Mead, Nebraska, 3 years of corn planting data and plant population are presented in Table 2. The model input data were prescribed by regional agronomists and climatologists, and with their advice, model runs were undertaken.

Table 2. Corn cropping information for two AmeriFlux field sites.

Sites	Year	Planting date	Plant density (×1000 per acre)
Bondville, Illinois	2001	19 Apr	32
	2003	16 Apr	32
	2005	22 Apr	32
Mead, Nebraska	2001	14 May	25
	2003	13 May	27
	2005	27 Apr	24

2.3. Sensitivity analysis scheme

The first set of analyses was conducted based on 30-yr (1981–2010) climate data for 18 county-scale sites (Figure 1, sites 1–18) and used a one-at-a-time (OAT) sensitivity approach (Niyogi et al. 1997). Three groups with a total of 29 model parameters were tested (Table 3), with changes prescribed at ±10%, ±20%, and ±30% of the default values. The results were presented as the relative percentage change of simulated yield to assess model sensitivity. The sensitivity

Table 3. Changes to the model input conditions in the crop model used for the OAT analysis. The parameter description is in Table 1.

Parameter	Default	−30%	−20%	−10%	10%	20%	30%
*G*2	675	472.5	540	607.5	742.5	810	877.5
*G*5	8.7	6.09	6.96	7.83	9.57	10.44	11.31
K	0.55	0.385	0.44	0.495	0.605	0.66	0.715
FT (10^{-3})	5.0	3.5	4.0	4.5	5.5	6.0	6.5
MF	0.15	0.105	0.12	0.135	0.165	0.18	0.195
EF	0.26	0.182	0.208	0.234	0.286	0.312	0.338
RD (10^{-3})	5.0	3.5	4.0	4.5	5.5	6.0	6.5
SDC	4	2.8	3.2	3.6	4.4	4.8	5.2
LF	0.7	0.49	0.56	0.63	0.77	0.84	0.91
UT	34	23.8	27.2	30.6	37.4	40.8	44.2
TL	4	2.8	3.2	3.6	4.4	4.8	5.2
BAC	0.35	0.245	0.28	0.315	0.385	0.42	0.455
DS	1.15	0.805	0.92	1.035	1.265	1.38	1.495
EP	4	2.8	3.2	3.6	4.4	4.8	5.2
LWS (10^{3})	17	11.9	13.6	15.3	18.7	20.4	22.1
RTT	9690	6783	7752	8721	10 659	11 628	12 597
GRG	15	10.5	12	13.5	16.5	18	19.5
GRE	6	4.2	4.8	5.4	6.6	7.2	7.8
MDE	25	18	20	23	28	30	33
RL	0.470	0.329	0.376	0.423	0.517	0.564	0.611
RS	0.520	0.364	0.416	0.468	0.572	0.624	0.676
RR	0.450	0.315	0.360	0.405	0.495	0.540	0.585
RG	0.490	0.343	0.392	0.441	0.539	0.588	0.637
MRL (10^{-3})	10.0	7.0	8.0	9.0	11.0	12.0	13.0
MRS (10^{-3})	6.0	4.2	4.8	5.4	6.6	7.2	7.8
MRR (10^{-3})	5.0	3.5	4.0	4.5	5.5	6.0	6.5
MRG (10^{-3})	5.0	3.5	4.0	4.5	5.5	6.0	6.5
MSR	7.0	4.9	5.6	6.3	7.7	8.4	9.1
LUE	12.5	8.8	10.0	11.3	13.8	15.0	16.3

index (SI) (Wallach et al. 2006) was used to study parameter sensitivity and was derived as

$$\mathrm{SI} = |[(O - O_{\mathrm{BC}})/(I - I_{\mathrm{BC}})] \times (\mathrm{I_{BC}}/\mathrm{O_{BC}})|, \tag{1}$$

where O is the output value, O_{BC} is the output value (yield) for the baseline scenario that uses the default parameter values, I is the input value, and I_{BC} is the original input value of the baseline scenario. The larger the SI, the more sensitive the yield output is to that parameter.

Because of the limitation of traditional sensitivity approaches in assessing the interaction between parameters, a global sensitivity analysis (Niyogi et al. 1997, 1999) was also undertaken. The 30-yr weather data for Johnson County, Iowa, were used in the model. Since the focus was on parameters that can possibly be calibrated at the regional scale, five parameters were selected based on the results of initial sensitivity analysis: the light extinction coefficient K, upper temperature cutoff for growing degree-days accumulation UT, threshold LAI above which leaf senescence due light competition occurs TL, initial light use efficiency (LUE), and a GDD10C requirement for germination GRG. The 10 corresponding interaction groups can be identified linking the two variable combinations as K + UT, K + TL, K + LUE, K + GRG, UT + TL, UT + LUE, UT + GRG, TL + LUE, TL + GRG, and LUE + GRG. For every interaction analysis, two parameters are changed each time, which results in a total of $2^5 \times 30 = 960$ factorial design simulations conducted for the five parameters. For each of these factorial combinations, sensitivity indices were calculated as

$$Y_{i+j} = Y_d + \alpha_i + \alpha_j + \alpha_{ij}. \tag{2}$$

The term Y_d is the result using default parameter values, α_i and α_j are the main effects of each parameter, and α_{ij} is the interaction effect between two parameters. As an example, for modified input, $Y_{K+\mathrm{LUE}}$ is the simulated yield, and $Y_{K+\mathrm{LUE}} = f(K, \mathrm{LUE})$. Similarly, Y_K is the simulated yield when only K is changed resulting in $Y_K = f(K)$; correspondingly, Y_{LUE} is the simulated yield when only LUE was changed, $Y_{\mathrm{LUE}} = f(\mathrm{LUE})$. For the different model-estimated yields, $\alpha_K = Y_K - Y_d$ is the main effect from parameter K. The equation $\alpha_{\mathrm{LUE}} = Y_{\mathrm{LUE}} - Y_d$ yields the main effect from parameter LUE; $\alpha_{K+\mathrm{LUE}} = Y_{K+\mathrm{LUE}} - Y_d - \alpha_K - \alpha_{\mathrm{LUE}}$ is the interaction effect for K and LUE. The total variability is calculated as

$$V_T = \sum V_i + \sum V_{ij}, \tag{3}$$

corresponding to the global result from the 960 simulations; v_i is the sum of squares of the main effect term for parameter i, and v_{ij} is the sum of squares on the interaction effect between parameters.

The main effect sensitivity index is defined as

$$s_i = V_i/V_T. \tag{4}$$

The interaction effect sensitivity index is defined as

$$S_{i+j} = V_{ij}/V_T. \tag{5}$$

The resulting total effect for the sensitivity index is

$$S_{i,T} = (V_i + V_{ij})/V_T. \tag{6}$$

For parameter LUE, $S_{LUE} = V_{LUE}/V_T$, the interaction effect sensitivity index between LUE and K is $S_{K+LUE} = V_{K+LUE}/V_T$, while the total effect for the sensitivity index of LUE is $S_{LUE,T} = (V_{LUE} + V_{LUE+K} + V_{LUE+UT} + \cdots)/V_T$.

2.4. Model validation and regional calibration

This study also assessed the simulated yields against National Agricultural Statistics Service (NASS)-reported county-scale yield data. The difference D_i between simulated yields and reported data were quantified using the mean absolute error (MAE):

$$D_i = Y_s - Y_a, \tag{7}$$

where Y_s is simulated yield data, and Y_a is the reported data. MAE was calculated as

$$\mathrm{MAE} = \sum_{i=1}^{N} |D_i|/N. \tag{8}$$

The advantage of using MAE is that it is easy to interpret and has the same unit as yield (Wallach et al. 2006).

The Hybrid-Maize model was developed to simulate the potential yield at field scale without accounting for yield losses from nutrient deficiencies, diseases, pests, and insects. To quantify the gap between the simulated potential yield and the actual yield, a regional calibration was applied for the county-scale study. After reviewing different model fits and bias correction approaches, a simple linear regression–based adjustment appeared to be sufficient. The adjustment factor is calculated as

$$Y_{iS2} = \partial_i Y_{iS1}, \tag{9}$$

where Y_{iS1} is the simulated potential yield, ∂_i is the adjustment factor, and Y_{iS2} is the simulated yield after the adjustment. After further tests, the constant in the linear regression analysis was set to zero. Although we realize that setting the constant to zero in the regression equation could limit the model calibration, it helped the process of obtaining an averaged adjustment factor for the entire Corn Belt. This simple approach was tested and allowed calibration of the model results to account for other environmental and agronomic as well as management decisions that are not available (or are difficult to obtain) as an input to the model.

3. Results and discussion

3.1. Sensitivity analysis

The sensitivity index results (Figure 2) suggest that the five most sensitive parameters are potential number of kernels per ear $G2$, potential kernel filling

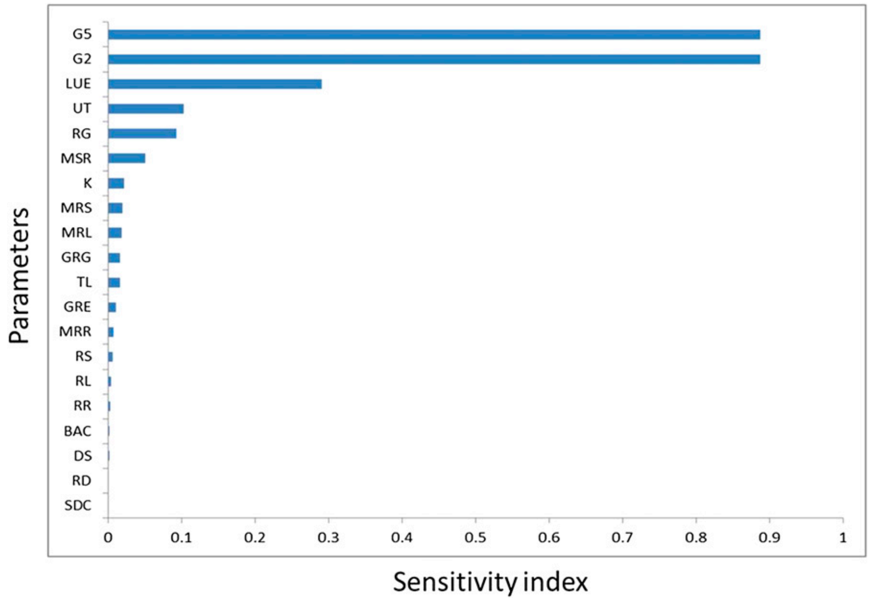

Figure 2. Yield sensitivity index of parameters (Table 1) in the Hybrid-Maize model based on OAT approach.

rate $G5$, initial LUE, upper temperature cutoff for growing degree-days accumulation UT, and growth respiration coefficient of grain RG. Both $G2$ and $G5$ are cultivar-specific genetic/management coefficients (see Table 1). The default values of $G2$ and $G5$ in this model are the mean values of common cultivars across the Corn Belt following Jones and Kiniry (1986). The relative changes for yield simulations (Figure 3) highlight the uncertainties of $G2$ and $G5$ specifications that can have the largest and almost equal impact on yield simulation.

For noncultivar-specific generic parameters group, the model is most sensitive to UT. It is noticeable that the model is more sensitive to lower UT values (<36°C) than for a higher UT (>36°C). This is because when using a lower UT (e.g., 27°C), compared to using the default value, the GDD accumulation in days that have maximum air temperatures higher than UT will be decreased. Similarly, when using higher UT (e.g., 40°C), GDD accumulation increases when the maximum air temperature is higher than default UT (e.g., 36°C). For the study region, during the growing season, the possibility of daily maximum temperature higher than a low UT is a realistic occurrence. Therefore, the accumulation of GDD will be impacted more when using low UT value.

Among the respiration and photosynthesis parameters, LUE, which relates to CO_2 assimilation, dominates model results. The SI for the simulated yield was significantly stable across the 30 years of climatic data. Climate variation appears to have a moderate impact on the sensitivity analysis results for the optimum parameter condition set in the model.

Among the 29 parameters we tested, simulation results were not sensitive to nine of the parameters (SI = 0) because of our experimental design of optimal water conditions. These nine parameters are fraction of leaf biomass that can be translocated

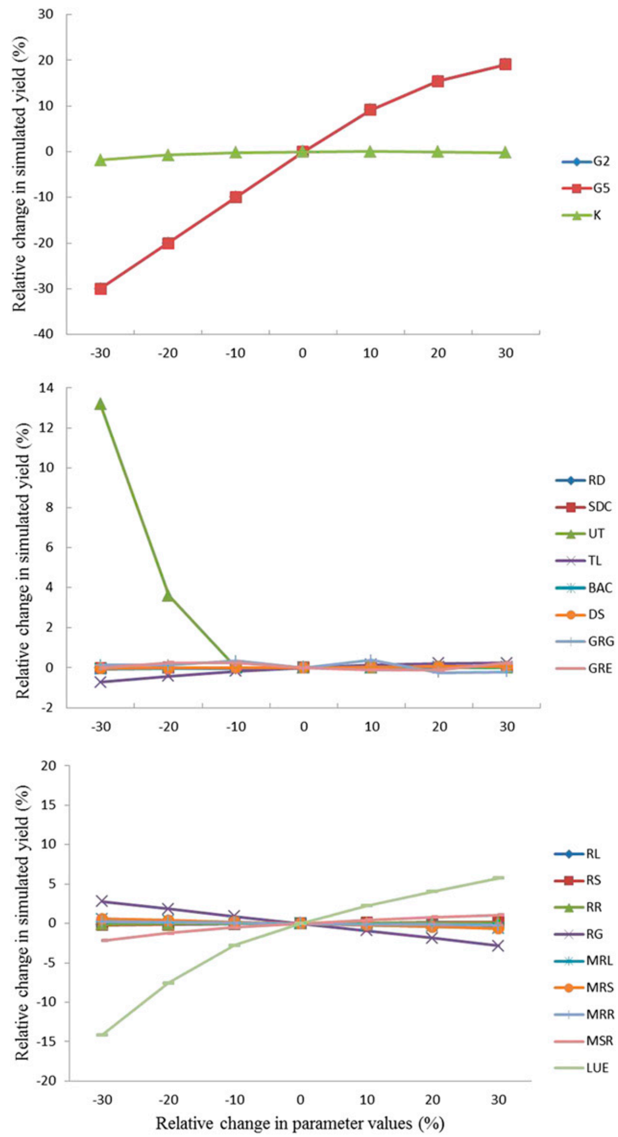

Figure 3. Average relative change in model-simulated yield corresponding to the relative change in parameter values of the Hybrid-Maize model across 18 Corn Belt counties over 30 years (1981–2010). (The lines of *G*2 and *G*5 in the first graph overlap each other.)

as carbohydrate to grain each day FT, maximum fraction of leaf biomass at silking that can be translocated as carbohydrate to grain MF, efficiency of carbohydrate translocation from stem of leaf to grain EF, senescent leaf area at maturity as a fraction of maximum LAI achieved at silking LF, empirical parameters that determine the relative contribution of a soil layer to water uptake EP, leaf water suction at permanent wilting point LWS, resistance of plant to transpiration RTT, maximum days allowed form planting to emergence MDE, and maintenance respiration coefficient for grain MRG.

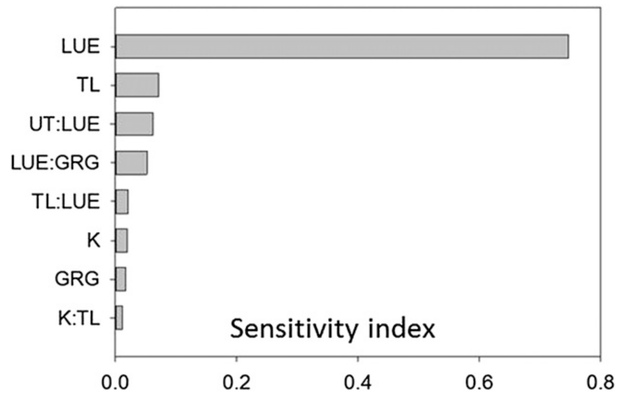

Figure 4. The eight largest sensitivity indices based on the factorial design.

Results of the OAT sensitivity analysis discussed above indicate that it is important to validate and calibrate the $G2$, $G5$, LUE, UT, and RG parameters. The goal of the broader project is to apply the model at the regional scale involving the entire U.S. Corn Belt with an aim to simulate corn yield under future climate scenarios. However, it has been a challenge to obtain the public database of the genetic and management parameters for the different cultivars for the whole region. Hence, building off the OAT sensitivity analysis results, an additional global sensitivity analysis based on a factorial design was conducted. Five parameters were selected: K, UT, TL, LUE, and GRG. In Figure 4, ignoring SI smaller than 1%, LUE has the largest SI value. Figure 5 shows LUE contributes the most to the total SI. Therefore, calibrating the LUE for different cultivar and subregion, which can possibly be aided by remote sensing data (Barton and North

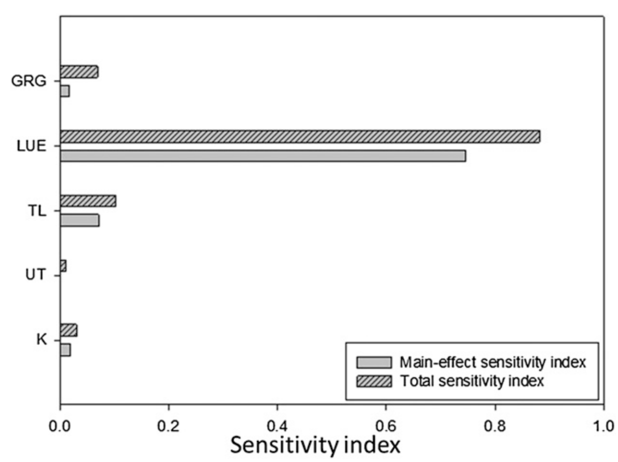

Figure 5. Main effect and total sensitivity indices based on the factorial design.

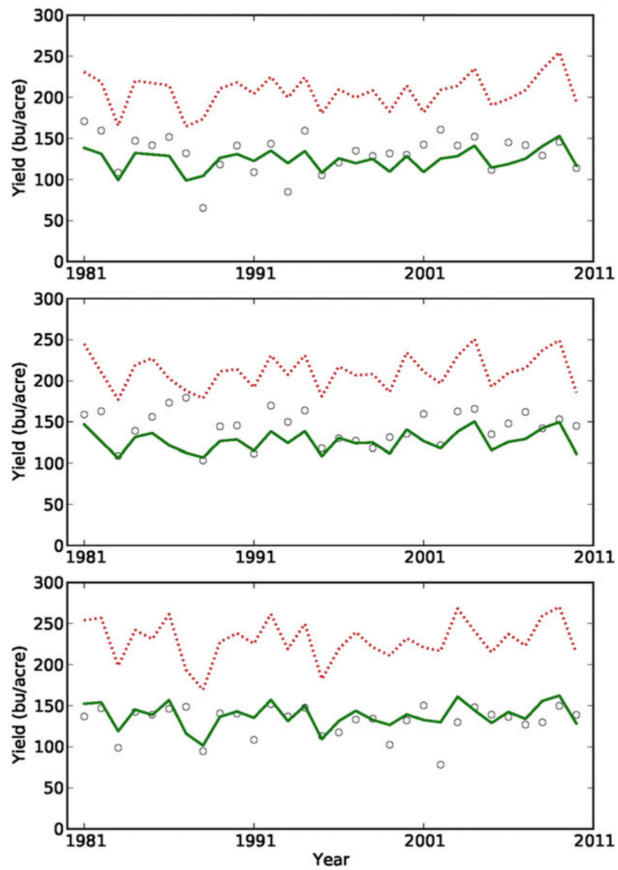

Figure 6. NASS-reported county corn yield and simulated yield before and after regression with survey data. (The selected three counties are 1) Johnson, Iowa; 2) Douglass, Illinois; and 3) Huntington, Indiana.) Open circles indicate observations, dashed lines indicate default value (before adjustment), and solid lines indicate model simulation yield with the adjustment factor of 0.6.

2001; Nichol et al. 2000), provides an encouraging avenue for regional-scale crop modeling.

3.2. Model validation at county and field scales

The model was validated at 18 counties for 30 years (1981–2010). The results (Figure 6) show a distinct offset with a similar, and consistent, trend between the model-simulated yield and the NASS survey–reported yield. While the results are qualitatively good, the average MAE for the 18 sites is large: 85 bu acre^{-1} (5.35 Mg ha^{-1}). There are two factors that help explain the gap between the model-simulated yield and the NASS survey–reported yield: (i) the Hybrid-Maize model simulates potential yield under

Table 4. Summary of measured (reported) and simulated corn yield at the two AmeriFlux field sites.

Sites	Year	Measured yield (bu $acre^{-1}$)	Simulated yield (bu $acre^{-1}$)
Bondville, Illinois	2001	168	165
	2003	192	182
	2005	164	145
	Mean	175	164
Mead, Nebraska	2001	139	128
	2003	123	140
	2005	145	146
	Mean	136	138

1 bu $acre^{-1}$ = 62.77 kg ha^{-1}

optimal conditions including lack of water stress, and (ii) the NASS survey data are the average yield data that includes different corn cultivars with different levels of agronomic management planted over a wide range of soils. However, the generally similar trends between simulated yield and surveyed (observed) yield indicate that the application of a regional calibration can help correct and narrow the gap between simulations and observations. This regional calibration we adopted is as discussed above [see Equation (9)]. At the field level, Table 4 shows that the 3-yr average simulated yield for Mead, Nebraska, is 136 bu $acre^{-1}$ (8.54 Mg ha^{-1}), while the 3-yr average measured yield is 138 bu $acre^{-1}$ (8.67 Mg ha^{-1}). The 3-yr average simulated yield in Bondville, Illinois, is 164 bu $acre^{-1}$ (10.30 Mg ha^{-1}), which is slightly lower than the 3-yr average measured yield data of 175 bu $acre^{-1}$ (10.99 Mg ha^{-1}). Average MAE of these two field sites is 10 bu $acre^{-1}$ (0.63 Mg ha^{-1}). The lower MAE at the field scale compared to the county scale could be because the two field sites were under optimal agronomic management, which helps the actual yield approach or even exceed the simulated potential yield.

3.3. Regional calibration

The difference between simulated and surveyed yield is reduced after conducting the regional calibration (Figure 6). The 18-county averaged MAE of the yield data after regression analysis lowers to 21 bu $acre^{-1}$ (1.31 Mg ha^{-1}). The MAE of each county before and after regional calibration is shown in Figure 7. The average adjustment factor of the 18 site county-scale study is 0.6 with a variance of 0.007. Therefore, if the Hybrid-Maize model is applied in simulating the county average corn yield, the model output could be calibrated by multiplying 0.6 to account for the simulated potential yield and surveyed (observed) yield.

To verify the robustness of this adjustment factor, we used six additional counties not considered in the regional calibration process. These counties include Champaign, Illinois; Clinton, Indiana; Boone, Iowa; Buffalo, Nebraska; Wyandot, Ohio; and Reno, Kansas (Figure 1, sites 19–24). The results (Table 5) indeed indicate that this 0.6 adjustment factor is not only convenient but also yields regionally representative yields at county scale. The averaged MAE of these six counties is 22 bu $acre^{-1}$ (1.37 Mg ha^{-1}).

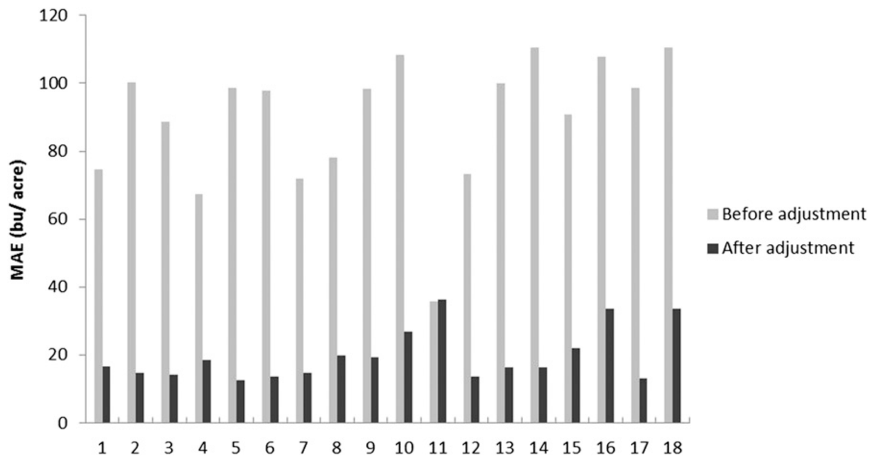

Figure 7. MAE (bu acre^{-1}) of 18 counties before and after applying the adjustment factor of 0.6 to convert potential to actual yield. Numbers on the *x* axis indicate locations corresponding to Figure 1.

4. Summary

This study is a building block for applying a relatively simple crop model, Hybrid-Maize, at regional scales. According to the results of two-level sensitivity analyses, yield simulations are sensitive to genetic and field management parameters such as potential number of kernels per ear $G2$ and potential kernel filling rate $G5$. The model results are also sensitive to initial light use efficiency (LUE). While obtaining regional crop genetic and field management parameters will be challenging, the LUE data are a promising option, particularly as more satellite products become accessible. The validation results indicate the Hybrid-Maize model has moderately good accuracy in simulating yield at the field scale. When validating the model at the county scale, there is a notable and generally consistent gap between the simulated and actual survey yield. After conducting a simple regional calibration with an adjustment factor of 0.6, the model bias was considerably lowered. Thus, the Hybrid-Maize simulation model shows good potential for regional applications using a limited set of input data to provide large-scale corn yield simulations. In future studies, the calibrated Hybrid-Maize model will be

Table 5. Average observed (reported) and simulated yield (bu acre^{-1}) for 1981–2010 for six additional counties not used in developing the regression estimate for the adjustment factor 0.6.

County, State	Observed (std dev)	Simulated (std dev)	MAE (bu acre^{-1})
Clinton, Indiana	146 (20)	132 (14)	22
Champaign, Illinois	145 (22)	126 (13)	20
Reno, Kansas	132 (14)	106 (13)	29
Buffalo, Nebraska	152 (11)	130 (14)	25
Wyandot, Ohio	129 (24)	140 (14)	19
Boone, Iowa	147 (18)	142 (19)	16

applied in a regional crop modeling using projected climatic data to assess how climate change and climate variability can impact corn yield in the U.S. Corn Belt.

Acknowledgments. Study benefitted from USDA/NIFA Grant U2U (2011-68002-30220) and Drought Trigger project through Texas A&M University (2011-67019-20042). We thank Prof. Roger Elmore at University of Nebraska–Lincoln for his comments and helpful suggestion on an earlier version of this paper. The study also benefitted from AmeriFlux data from Bondville, Illinois (PI: T. Meyers), and Mead, Nebraska (PI: A. Suyker).

References

AmeriFlux, 2015: AmeriFlux data archive. AmeriFlux, accessed 1 June 2014. [Available online at http://ameriflux.ornl.gov/.]

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, doi:10.2134/agronj2001.9351059x.

Baldocchi, D., and Coauthors, 2001: FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities. *Bull. Amer. Meteor. Soc.,* **82,** 2415–2434, doi:10.1175/1520-0477(2001)082<2415:FANTTS>2.3.CO;2.

Barton, C. V. M., and P. R. J. North, 2001: Remote sensing of canopy light use efficiency using the photochemical reflectance index: Model and sensitivity analysis. *Remote Sens. Environ.,* **78,** 264–273, doi:10.1016/S0034-4257(01)00224-3.

Grassini, P., H. S. Yang, and K. G. Cassman, 2009: Limits to maize productivity in western Corn-Belt: A simulation analysis for fully irrigated and rainfed conditions. *Agric. For. Meteor.,* **149,** 1254–1265, doi:10.1016/j.agrformet.2009.02.012.

Hamby, D. M., 1994: A review of techniques for parameter sensitivity analysis of environmental models. *Eur. J. Environ. Monit. Assess.,* **32,** 135–154, doi:10.1007/BF00547132.

Hansen, J. W., A. W. Hodges, and J. W. Jones, 1998: ENSO influences on agriculture in the southeastern United States. *J. Climate,* **11,** 404–411, doi:10.1175/1520-0442(1998)011<0404:EIOAIT>2.0.CO;2.

Jones, C. A., and J. R. Kiniry, 1986: *CERES-Maize: A Simulation Model of Maize Growth and Development*. Texas A&M Univeristy Press, 194 pp.

——, P. T. Dyke, J. R. Williams, J. R. Kiniry, V. W. Benson, and R. H. Griggs, 1991: EPIC: An operational model for evaluation of agricultural sustainability. *Agric. Syst.,* **37,** 341–350, doi:10.1016/0308-521X(91)90057-H.

Jones, J. W., and Coauthors, 2003: The DSSAT cropping system model. *Eur. J. Agron.,* **18,** 235–265, doi:10.1016/S1161-0301(02)00107-7.

Kiniry, J. R., and A. J. Bockholt, 1998: Maize and sorghum simulation in diverse Texas environments. *Agron. J.,* **90,** 682–687, doi:10.2134/agronj1998.00021962009000050018x.

Nichol, C. J., K. F. Huemmrich, T. A. Black, P. G. Jarvis, C. L. Walthall, J. Grace, and F. G. Hall, 2000: Remote sensing of photosynthetic-light-use efficiency of boreal forest. *Agric. For. Meteor.,* **101,** 131–142, doi:10.1016/S0168-1923(99)00167-7.

Niyogi, D., and J. Andresen, 2011: Useful to Usable (U2U): Transforming climate variability and change information for cereal crop producers. *2011 Fall Meeting,* San Francisco, CA, Amer. Geophys. Union, Abstract GC13A-0960.

——, S. Raman, and K. Alapaty, 1997: A dynamic statistical experiment for atmospheric interactions. *Environ. Modell. Assess.,* **2,** 307–322, doi:10.1023/A:1019021729938.

——, ——, and ——, 1999: Uncertainty in the specification of surface characteristics, Part II: Hierarchy of interaction-explicit statistical analysis. *Bound.-Layer Meteor.,* **91,** 341–366, doi:10.1023/A:1002023724201.

——, X. Liu, J. Andresen, Y. Song, A. K. Jain, O. Kellner, E. S. Takle, and O. C. Doering, 2015: Crop models can capture the impacts of climate variability on corn yield. *Geophys. Res. Lett.,* **42,** 3356–3363, doi:10.1002/2015GL063841.

NOAA/National Centers for Environmental Information (NCEI), 2015: Global Historical Climatology Network-Daily (GHCN-D). NOAA/NCEI, accessed 11 May 2014. [Available online at http://www.ncdc.noaa.gov/cdo-web/search?datasetid=GHCND.]

Phillips, J., B. Rajagopalan, M. Cane, and C. Rosenzweig, 1999: The role of ENSO in determining climate and maize yield variability in the U.S. Cornbelt. *Int. J. Climatol.,* **19,** 877–888, doi:10.1002/(SICI)1097-0088(19990630)19:8<877::AID-JOC406>3.0.CO;2-Q.

USDA/NASS, 2015: Quick Stats. USDA, accessed 22 April 2014. [Available online at http://quickstats.nass.usda.gov/.]

Wallach, D., D. Makowski, and J. W. Jones, Eds., 2006: *Working with Dynamic Crop Models: Evaluation, Analysis, Parameterization, and Applications.* 1st ed. Elsevier Science, 462 pp.

Yang, H. S., A. Dobermann, J. L. Lindquist, D. T. Walters, T. J. Arkebauer, and K. Cassman, 2004: Hybrid-Maize: A maize simulation model that combines two crop modeling approaches. *Field Crops Res.,* **87,** 131–154, doi:10.1016/j.fcr.2003.10.003.

——, ——, K. G. Cassman, and D. T. Walters, 2005: Weather Aid: A software for weather data management. University of Nebraska–Lincoln.

——, ——, ——, and ——, 2006a: Features, applications, and limitations of the Hybrid-Maize simulation model. *Agron. J.,* **98,** 737–748, doi:10.2134/agronj2005.0162.

——, ——, K. Cassman, D. T. Walters, and P. Grassini, 2006b: *Hybrid-Maize: A Simulation Model for Corn Growth and Yield.* University of Nebraska–Lincoln, 95 pp.