Contributions of historical changes in sowing date and climate to U.S. maize yield trend: An evaluation using large-area crop modeling and data assimilation

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Abstract

The consequences of changes observed in climate and management to yield trends in major crop-producing regions have implications for future food availability. We present an assessment of the impacts of historical changes in sowing date and climate to the maize yield trend in the U.S. Corn Belt from 1980 to 2006 by using large-area crop modeling and a data assimilation technique (i.e., the model optimization based on the Markov chain Monte Carlo method). Calibrated at a regional scale, the model captured the major characteristics of the changes reported in yield as well as the timing and length of maize growth periods across the Corn Belt. The simulation results using the calibrated model indicate that while the climate change observed for the period likely contributed to a decreasing yield trend, the positive contribution from the reported shift to an earlier sowing date offset the negative impacts. With the given spread in the assessment results across previous studies and in this study, the conclusion that the negative impacts of climate change on U.S. maize yield trend more likely derive from a decreasing trend in growing-season precipitation than to an increasing trend in temperature.

Key words: Data assimilation, Historical climate change, Large-area crop model, Sowing date.

1. Introduction

The consequences of past climate change on crop yield trends in major crop-producing regions are inconclusive. A major approach to investigating these impacts includes regression analyses that use yield trend as a dependent variable and growing season temperature and/or precipitation as independent variables (e.g., Kucharik and Serbin, 2008; Lobell and Asner, 2003; Lobell and Field, 2007; Lobell et al., 2013). Though useful, these analyses have limited value in explaining the underlying mechanisms.

Recently, process-based large-area crop models (Challinor et al., 2004; Iizumi et al., 2009; 2013a) or agro-ecosystem models (Kucharik, 2003) have become feasible. These models are useful when simulating crop yield on a regional scale and allow researchers to evaluate the consequences of past changes in climate and management on regional yield trends in a process-based manner (Sacks and Kucharik, 2011; Twine and Kucharik, 2009).

However, to evaluate such consequences reliably, an intensive calibration of a complex crop model is needed. Data assimilation techniques, including the Markov chain Monte Carlo (MCMC) method, are suitably to fitting a complex model to observations (e.g., Iizumi et al., 2009; 2013a; Makowski et al., 2002). In this study, we intensively calibrated a large-area crop model (called PRYSBI-1.1) by using the MCMC method and quantified the contributions of historical changes in sowing date and climate on regional crop yield trends.
for the period 1980–2006, for which we used maize yield in the U.S. Corn Belt as an example (Fig. 1). The area is a major crop-producing region—about 42% of the world’s maize production in 2009 (FAO, 2010) was produced in the region—and several studies have suggested the different impacts of past changes in sowing date and climate on yield trends (Kucharik and Serbin, 2008; Lobell and Asner, 2003; Sacks and Kucharik, 2011). Estimates from an approach independent of those used in previous studies (i.e., large-area crop modeling combined with data assimilation on a regional scale) can therefore provide more robust conclusions for the issue.

2. Materials and Methods

2.1 Large-area crop model

The Process-Based Regional-Scale Yield Simulator with Bayesian Inference version 1.1 (PRYSBI-1.1) is a process-based large-area crop model designed based on the Soil and Water Assessment Tool (Neitsch et al., 2005). The current version of the PRYSBI-1.1 model consists of submodels for growth and development, dry matter production, yield formation, soil water balance, nitrogen dynamics, and the management of sowing, irrigation, nitrogen, and crop residual operations (see Appendix for details). For this study, we calibrated 22 parameters (Table A1) important to determining a crop’s characteristics related to developmental rate, radiation-use efficiency, response to elevated CO₂ concentration, and tolerance to several abiotic stresses on a scale of 1.125° (≒120 km) in latitude and longitude. These parameters appeared in the growth processes that are likely sensitive to climatic conditions, including an altered climate, and were thus selected for calibration.

2.2 Model inputs

Table A2 presents a summary of the model inputs. The PRYSBI-1.1 model requires daily maximum and minimum temperatures, precipitation, solar radiation, relative humidity, and wind speed. Japanese reanalysis data (Onogi et al., 2007) were used as the weather inputs. Soil data were assigned for six soil layers after regridding. Values of CO₂ concentration data used were identical across the grid cells, but changed year by year. We used annual country nitrogen data from the Food and Agriculture Organization (FAO, 2010). Identical values were used across the grid cells. The locations where maize was grown were specified by using the crop-specific harvested area map of Monfreda et al. (2008). The annual country irrigation data from FAO (2010) were used in a manner similar to that described for nitrogen, though the locations with irrigation facilities were specified by using the irrigated area map of Siebert et al. (2005). Historical maize sowing dates from the U.S. Department of Agriculture (USDA,
2.3 Calibration method

The MCMC method (Hastings, 1970; Metropolis et al., 1953) was used to calibrate the crop model, for which parameter values distributed within a known possible range (represented by a uniform distribution; Table A1) were updated by using calibration data to form a posterior distribution of a parameter value according to Bayes’s theorem:

\[
p(\theta | D) = \frac{\pi(D | \theta) p(\theta)}{\int \pi(D | \theta) p(\theta) d\theta},
\]

where \( p(\theta | D) \) is the posterior probability distribution of parameter \( \theta \) under a given data \( D \), \( \pi(D | \theta) \) is the likelihood function, \( p(\theta) \) is the prior probability distribution of parameter \( \theta \), and the denominator on the right-hand side is the normalizing constant.

The likelihood function was specified as:

\[
\pi(\theta) = \prod_{i=1}^{6} \pi_i(\theta),
\]

\[
\pi_i(\theta) = \left(2\pi \sigma_i^2\right)^{-\frac{N}{2}} \exp\left[-\frac{1}{2\sigma_i^2} \left(\mathbf{Y}_i - \mathbf{\hat{Y}}_i\right)^T \left(\mathbf{Y}_i - \mathbf{\hat{Y}}_i\right)\right],
\]

where \( N \) is the sample size, and \( \mathbf{Y}_i \) and \( \mathbf{\hat{Y}}_i \) are the vectors of the calibration data and model outputs, respectively. The variances of error (\( \sigma_i^2 \)) were estimated in parallel to other parameters of the crop of interest. The suffix \( i \) denotes the \( i \)-th metric number of the calibration data (Table A3). The error distribution was assumed to be a multivariate normal distribution with the nondiagonal elements of the variance–covariance matrix equal to zero.

The MCMC method was performed following the procedures described in Iizumi et al. (2009). The iterations of 1,000,000 Monte Carlo steps with three parallel Markov chains were conducted. We selected the single set of parameter values showing the maximal value of likelihood across the sample paths of parameter values and used for analysis. Therefore, the MCMC method was used not for the derivation of the posterior distributions of parameters for uncertainty analysis, but the optimization of parameters.

2.4 Calibration data

The data summarized in Table A3 were arranged to fit a grid size of 1.125° and used for calibration. The crop data included the reported data on yield and dates of silking and harvesting, as well as the yield ratio of the elevated and ambient CO2 levels in 2004 observed at the Free-Air CO2 Enrichment site in Champaign, Illinois (Leakey et al., 2006).

The total leaf area index (TLAI) and net primary productivity (NPP) for maize were estimated from data from the National Oceanic and Atmospheric Administration’s Advanced Very High Resolution Radiometer Normalized Difference Vegetation Index (Iizumi et al., 2013b). Since these data were bimonthly and in 8 km resolution, the harvested area weighted-mean values were computed to match the grid size of the data to that of the model. The truncation of TLAI and NPP values less than the thresholds (0.4 m² m⁻² and 300 kg ha⁻¹ day⁻¹, respectively) were performed to remove data for the non-growing season.

2.5 Simulation experiments

To isolate the respective contributions of the histori-

<table>
<thead>
<tr>
<th>Name</th>
<th>Sowing date</th>
<th>Climate</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTRL</td>
<td>Fixed sowing date (the date in 1980)</td>
<td>Detrended climate</td>
</tr>
<tr>
<td>SOW</td>
<td>Historical sowing date</td>
<td>Detrended climate</td>
</tr>
<tr>
<td>CLIM</td>
<td>Fixed sowing date (the date in 1980)</td>
<td>Historical climate change</td>
</tr>
<tr>
<td>REAL</td>
<td>Historical sowing date</td>
<td>Historical climate change</td>
</tr>
<tr>
<td>SOW-T</td>
<td>Historical sowing date</td>
<td>Historical temperature change, but detrended climate for other climatic variables</td>
</tr>
<tr>
<td>SOW-P</td>
<td>Historical sowing date</td>
<td>Historical precipitation change, but detrended climate for other climatic variables</td>
</tr>
<tr>
<td>SOW-S</td>
<td>Historical sowing date</td>
<td>Historical solar radiation change, but detrended climate for other climatic variables</td>
</tr>
</tbody>
</table>
cal changes in sowing date and climate to yield trend, four simulation experiments (Table 1) were conducted that used the calibrated crop model: (1) no historical changes in either sowing date or climate (CTRL); (2) historical shift to an earlier sowing date without climate change (SOW); (3) historical climate change without any shift of sowing date (CLIM); and (4) historical changes in both sowing date and climate (REAL). For the CTRL and CLIM experiments, the observed sowing date in 1980 was used for all years. For the CTRL and SOW simulations, we used detrended climate data, of which the linear trend was calculated for each month and climatic variable for the period 1980–2006 and removed from the daily weather inputs.

To isolate the impacts of the historical trend in temperature on yield trend, we performed the simulation experiment with the historical shift to an earlier sowing date and temperature trend, but without trends for other climatic variables (SOW-T). Similar setups were used for the SOW-P and SOW-S simulations, which intended to isolate the respective contributions of the trends in precipitation and solar radiation.

3. Results

3.1 Reliability of the calibrated model outputs

Figure 2 presents the correspondence between the two samples (i.e., the calibration data and calibrated model simulation) to demonstrate the reliability of the

![Fig. 2](https://example.com/fig2.png)

**Fig. 2.** Pearson’s correlation coefficients between the simulated and calibration data for (a) the maize silking date, (b) harvesting date, (c) yield with trend, and (d) detrended yield from 1980 to 2006, and (e-h) the corresponding root-mean-square errors (RMSEs). A black dot indicates that the correlation value is significant ($p < 0.05$). The number in the lower right of each panel indicates the harvested area weighted-mean value of the correlation (or RMSE) and its spatial variation (in parentheses).
model outputs. The harvested area weighted-mean correlation value for the silking date was 0.88 \( (p < 0.01) \) (Fig. 2a). The correspondence between the two samples for the harvesting date was lower than that for the silking date, but still reliable (Fig. 2b). The root-mean-square error (RMSE) was 7.5 days for the silking date (Fig. 2e) and 13.2 days for the harvesting date (Fig. 2f).

The correlation values for the yield with the trend (Fig. 2c) were higher in areas where maize was more densely grown (see Fig. 1); the area-mean correlation value was 0.62 \( (p < 0.01) \). For the detrended yield (the first differences of the simulated and reported yield time series were calculated independently), higher correlation values appeared in the central Corn Belt (Fig. 2d) with a RMSE of 1.6 t ha\(^{-1}\) (Fig. 2h).

3.2 Changes in the timing and length of maize growth periods

The sowing date for the Corn Belt became significantly earlier, with a harvested area weighted-mean slope value of \(-4.3\) days decade\(^{-1}\) (Fig. 3a), which indicates that the sowing date became earlier by 12 days from the period from 1980 to 2006. By contrast, shifts in the timings of the silking and harvesting dates (\(-8\) and \(-10\) days for the period, respectively) were smaller than that of the sowing date (Fig. 3b and c). These unequal shifts between the sowing and silking dates prolonged the vegetative growth period (VGP; sowing to silking) by 4 days for the period (Fig. 3d). However, the changes in the reproductive growth period (RGP; silking to harvesting) of 1 day (Fig. 3e) and whole growth period (WGP; sowing to harvesting) of 2 days (Fig. 3f) were smaller than those in the VGP.

3.3 Changes in climate during maize growth periods

Figure 4 presents the linear trends in mean temperature, precipitation, and solar radiation during the maize growth periods (VGP, RGP, and WGP) during the 27-

![Phenology](image1.png)

![Growing period](image2.png)

**Fig. 3.** Linear trends from 1980–2006 for (a) the sowing date, (b) silking date, (c) harvesting date, (d) vegetative growth period, (e) reproductive growth period, and (f) whole growth period. A black dot indicates that the trend is significant \( (p < 0.05) \) based on the Mann-Kendall rank test (Mann, 1945). The number in the lower right of each panel indicates the harvested area weighted-mean trend and its spatial variation (in parentheses).
year period. An decreasing temperature trend during the VGP was observed throughout most of the Corn Belt (Fig. 4a), whereas an increasing temperature trend during the RGP was observed in quite a few parts of the area (Fig. 4b). The WGP temperature trend encompassed the mixed features of VGP and RGP temperature trends (Fig. 4c). Geographical patterns somewhat similar to those of the temperature trends were found for solar radiation trends (Figs. 4g–i). Parallel to increased solar radiation, significantly decreased precipitation appeared in the southwestern part of the area for all growth periods (Fig. 4d–f).

3.4 Contributions of sowing date and climate changes to yield trend

Figure 5 depicts the contributions of the historical changes in sowing date and climate to the maize yield trends across the Corn Belt derived from the simulation experiments. The contribution of the shift to an earlier sowing date can be quantified by taking the difference between the CTRL and SOW experiments. Similarly, the contribution of the historical climate change can be quantified by comparing the CTRL and CLIM experiments.

On a harvested area weighted-mean basis, the yield trend was +0.81 t ha\(^{-1}\) decade\(^{-1}\) (+2.2 t ha\(^{-1}\) for the study period) when the sowing date and climate were considered (Fig. 5f). (The reported increasing yield trend was accurately captured by the model, though the simulated value was underestimated by 36% compared to the yield trend of +1.26 t ha\(^{-1}\) decade\(^{-1}\) derived from the reported data; figure not shown.) The simulated yield trend was +0.90 t ha\(^{-1}\) decade\(^{-1}\) (+2.41 ha\(^{-1}\)) for the condition with the historical sowing date change and without climate change (Fig. 5b), while it was +0.65 t ha\(^{-1}\) decade\(^{-1}\) (+1.8 t ha\(^{-1}\)) for the condition with the historical climate change and without the sowing date change (Fig. 5d). The experiment results showed that the shift to an earlier sowing date increased the yield trend by 20% ( = 0.15 / 0.75 x 100) compared to results from the CTRL experiment (Fig.

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**Fig. 4.** Linear trends from 1980–2006 for (a–c) mean temperature, T; (d–f) precipitation, P; and (g–i) solar radiation, S for the vegetative, reproductive and whole growth period (VGP, RGP, and WGP), respectively. A black dot indicates that the trend is significant (p < 0.05) based on the Mann-Kendall rank test (Mann, 1945). The number in the lower right of each panel indicates the harvested area weighted-mean trend and its spatial variation (in parentheses).
By contrast, the historical climate change effectively decreased the yield trend by 13% (Fig. 5e), and the positive effects of the shift to an earlier sowing date offset the negative impacts of the climate change and further increased the yield trend by 8% (Fig. 5g).

### 3.5 Contributions of change in each climatic variable to yield trend

Figure 6 presents the contributions of the historical change in each climatic variable (i.e., the growth period’s mean temperature, precipitation, and solar radiation) to the yield trend. On a harvested area weighted-mean basis, if the historical change in the precipitation was considered (the SOW-P experiment), the yield trend (0.84 t ha\(^{-1}\) decade\(^{-1}\); Fig. 6) was found to decrease by 7% ([0.84-0.90] / 0.90×100) relative to the yield trend from the SOW experiment (0.90 t ha\(^{-1}\) decade\(^{-1}\)). The corresponding impact on the yield trend...
was −4% (0.86 t ha\(^{-1}\) decade\(^{-1}\)) and +1% (0.91 t ha\(^{-1}\) decade\(^{-1}\)) for the temperature trend and solar radiation trend, respectively. These results suggest the relative importance in the study area of the decreasing precipitation trend to the yield trend.

### 4. Discussion

The calibrated PRYSBI-1.1 large-area crop model was able to follow the major characteristics of maize phenology and yield associated with the technology-driven shift to earlier maize sowing dates reported in Kucharik (2006) (e.g., the development of genotypes tolerant of suboptimal temperatures, planting equipment improvements, and the adoption of time-saving management practices such as conservation tillage), which ensured that the analysis using the model outputs was valid for the calibrated area and period. Although larger errors were found for the harvesting date, the calibrated model simulations captured the prolonged VGP and small change in the RGP, both of which were reported by a previous study that used state-level crop statistics data (Sacks and Kucharick, 2011). The errors observed in harvesting date probably arose because the actual harvesting in the area occurs after several weeks of drying subsequent to physiological maturity (Sacks and Kucharick, 2011), for which the model did not account.

Results show that the impact of solar radiation change on yield trend was smaller than that of precipitation change (Fig. 6). Also, trends in July–August (JA) precipitation and solar radiation can better explain variation in the yield trends across the grid cells (represented by the coefficient of determination value) compared to the JA temperature trend (Fig. 7). The JA interval roughly corresponds to the occurrence of maize silking (USDA, 1994) or early RGP even after the shift to an earlier sowing date. Therefore, it is likely that decreased growing-season precipitation (and RGP precipitation in particular; Figs. 4e and 7b), not increased temperature during the RGP (Figs. 4b and 7a), contributes significantly in lowering the yield trend in the area (Fig. 6). The change in RGP solar radiation running parallel to decreased precipitation (Fig. 4h) positively contributed to the yield trend (Fig. 7c), though its impact was likely far less than that due to changes in precipitation and temperature. The relative importance of growing-season precipitation to the yield trend in the area revealed by analysis is consistent with the results of previous studies that use agro-ecosystem models (Kucharik and Serbin, 2008; Twine and Kucharik, 2009) or regression analysis (Kucharik and Serbin, 2008). However, our results differ from those of other studies using regression analysis (Lobell and Asner, 2003), which showed that...
yield trends more strongly depended upon temperature than precipitation.

Our results suggest that the shift to an earlier sowing date contributed to the yield trend more than historical climate change. This finding contradicts that of a previous study that used the agro-ecosystem model (Sacks and Kucharik, 2011), which concluded that the shift to longer season cultivars (and increases in irrigation and fertilizer application) instead of the shift to an earlier sowing date was responsible for the yield trend. Because differences in crop modeling can be a primary cause of uncertain simulated impacts on crop yield due to climate change (Rosenzweig et al., 2013), the differences observed in the simulated contributions of the sowing date and climate change on yield trend between this and previous studies may not be surprising. However, the large-area crop modeling combined with the data assimilation technique used in this study is an approach independent of those used in previous studies (i.e., regression analysis or site-calibrated agro-ecosystem modeling). Our conclusion that the maize yield trend in the U.S. Corn Belt is lower more due to decreased precipitation than temperature is strengthened by being consistent across the two independent approaches. A multi-model ensemble approach (Rosenzweig et al., 2013) would therefore be preferable for further studies regarding this issue, for it can offer higher credence than any analysis using a single model.

5. Conclusion

This study evaluated how historical changes in sowing date and climate have contributed to the maize yield trend in the U.S. Corn Belt from 1980 to 2006 by using a large-area crop model and a data assimilation technique. Our results indicate that, for the yield trend during the last few decades, the benefit of the shift to an earlier sowing date outweighs the negative impacts of climate change. The negative impacts on the yield trend were thus entirely offset on a regional scale. The negative impacts of climate change on the yield trend are more likely due to decreased growing-season precipitation than to temperature.

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Appendix

A1. Large-area crop model description

Here we briefly describe the crop growth processes modeled in version 1.1 of the Process-Based Regional-Scale Yield Simulator with Bayesian Inference (PRYSBI-1.1). This large-area crop model was originally developed for irrigated paddy rice in Japan (Iizumi et al., 2009) and modified for upland crops based on the Soil and Water Assessment Test (Iizumi et al. 2013a; Neitsch et al., 2005). Figure A1 shows the schematic overview of the model.

A2. Growth and development

Changes in the crop growth stage, leaf area, canopy height, and root depth were calculated in daily time steps. The fraction of the growing season \( f_{GDD} \) (i.e., the current growing degree-day \( GDD_i \)) divided by the total growing degree-days to maturity \( TGDD \); see Table A1) was calculated to determine the occurrence of phenological events (Hasegawa et al., 2008):

\[
f_{GDD, t} = \frac{\sum_{i=1}^{t} GDD_i}{TGDD}, \quad (A1)\]

\[
GDD_i = \begin{cases} 
(T_i - T_b) \cdot PE_t & T_i > T_b \\
0 & T_i \leq T_b
\end{cases}, \quad (A2)
\]

\[
PE_t = \begin{cases} 
1 - \exp(DL_t \cdot DL_{tr}) & DL_t \leq DL_{tr} \\
1 & DL_t > DL_{tr}
\end{cases}, \quad (A3)
\]

where \( T_i \) is the daily mean temperature, \( T_b \) is the crop-specific base temperature (10 °C for maize), \( PE_t \) is the photoperiod effect, \( DL_t \) is the day length, and \( DL_{tr} \) is the threshold day length (Table A1). The subscript \( t \) denotes time on a daily basis. The value of \( f_{GDD, t} \) is defined as 0 at sowing, 0.55 at the initiation of reproductive growth (silking), and 1 at maturity. Its value at silking was determined by a statistical analysis using state-level maize progress reports from Iowa, U.S., and observed weather data in the area.
Table A1. Abbreviations, units, definitions, relevant equations (or text), priors, posteriors (90 %-interval), and sources of biophysical and physiological parameter values for the maize calibrated for this study.

<table>
<thead>
<tr>
<th>Abbr.</th>
<th>Unit</th>
<th>Definition</th>
<th>Equation</th>
<th>Prior</th>
<th>Posterior</th>
<th>Reference(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TGDD</td>
<td>℃ days</td>
<td>Total growing degree-days required for maturity</td>
<td>Eq. (A1)</td>
<td>(1000, 2573)</td>
<td>(2572, 2574)</td>
<td>Ko et al. (2009)</td>
</tr>
<tr>
<td>DLtr</td>
<td>hours</td>
<td>Threshold day length</td>
<td>Eq. (A3)</td>
<td>(6.24, 17.9)</td>
<td>(17.8, 17.9)</td>
<td>Hasegawa et al. (2008)</td>
</tr>
<tr>
<td>fGDD2</td>
<td>fraction</td>
<td>Fraction of the growing period that corresponds to the second point of the maximum LAI curve</td>
<td>Text related to Eq. (A4)</td>
<td></td>
<td>0.391 (0.390, 0.392)</td>
<td>Lokupitiya et al. (2009)</td>
</tr>
<tr>
<td>fGDD, sen</td>
<td>fraction</td>
<td>Fraction of growing season at which senescence becomes the dominant growth process</td>
<td>Eq. (A6)</td>
<td>(0.7, 0.9)</td>
<td>0.527 (0.526, 0.528)</td>
<td>Steduto and Hsiao (1998)</td>
</tr>
<tr>
<td>LAImax</td>
<td>m²/m²</td>
<td>Maximum leaf area index (LAI)</td>
<td>Eq. (A7)</td>
<td>(2, 4)</td>
<td>2.74 (2.73, 2.75)</td>
<td>Christy and Williamson (1985)</td>
</tr>
<tr>
<td>fb</td>
<td>-</td>
<td>1st shape coefficient of the maximum possible LAI given the nitrogen status of the crop</td>
<td>Eq. (A7)</td>
<td>(0.1, 1.0)</td>
<td>0.795 (0.793, 0.796)</td>
<td>Hasegawa et al. (2008)</td>
</tr>
<tr>
<td>fc</td>
<td>-</td>
<td>2nd shape coefficient of the maximum possible LAI given the nitrogen status of the crop</td>
<td>Eq. (A7)</td>
<td>(1, 5)</td>
<td>1.03 (1.02, 1.04)</td>
<td>Hasegawa et al. (2008)</td>
</tr>
<tr>
<td>hmax</td>
<td>m</td>
<td>Maximum canopy height</td>
<td>Eq. (A8)</td>
<td>(0.79, 1.65)</td>
<td>(1.64, 1.66)</td>
<td>Stewart et al. (1998)</td>
</tr>
<tr>
<td>RUEamb</td>
<td>kg ha⁻¹ (MJ m⁻² day⁻¹)⁻¹</td>
<td>Radiation-use efficiency (RUE) at ambient CO₂ (376 ppm)</td>
<td>Eq. (A12)</td>
<td>(30, 45)</td>
<td>46.1 (46.0, 46.2)</td>
<td>Stockle et al. (1992); Lobell et al. (2003)</td>
</tr>
<tr>
<td>RUEe/RUEamb</td>
<td>fraction</td>
<td>Ratio of the RUE at ambient CO₂ to the RUE at elevated CO₂ (550 ppm)</td>
<td>Text related to Eq. (A12)</td>
<td>(1.05, 1.07)</td>
<td>(1.06, 1.08)</td>
<td>Leakey et al. (2006)</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Table A1. (Continued.)</th>
<th>Definition</th>
<th>Equation</th>
<th>Prior</th>
<th>Posterior</th>
<th>Reference(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta RUE_{dcl}$ (kg ha$^{-1}$·(MJ m$^{-2}$·day$^{-1}$)$^{-1}$·kPa$^{-1}$)</td>
<td>Rate of decline in the RUE per unit increase in vapor pressure deficit (VPD)</td>
<td>Eq. (A13)</td>
<td>(3, 20)</td>
<td>11.7 (11.5, 11.8)</td>
<td>Neitsch et al. (2005)</td>
</tr>
<tr>
<td>$vpd_0$ kPa</td>
<td>Threshold VPD above which the crop will exhibit reduced RUE</td>
<td>Eq. (A13)</td>
<td>(0, 3)</td>
<td>2.51 (2.49, 2.52)</td>
<td>Stockle and Kiniry (1990)</td>
</tr>
<tr>
<td>Stress factor for growth</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>$T_o$ °C</td>
<td>Optimal temperature</td>
<td>Eq. (A15)</td>
<td>(20, 30)</td>
<td>23.5 (23.4, 23.6)</td>
<td>Stewart et al. (1998)</td>
</tr>
<tr>
<td>$f_{\text{iso}, \text{tr}}$ -</td>
<td>Threshold fraction of actual nitrogen content to optimal value</td>
<td>Eq. (A18)</td>
<td>(0, 1)</td>
<td>0.319 (0.315, 0.320)</td>
<td>Neitsch et al. (2005)</td>
</tr>
<tr>
<td>Yield formation</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>$c_{\text{highT}}$ -</td>
<td>Curvature coefficient of harvest index for high temperature stress</td>
<td>Eq. (A23)</td>
<td>(0.2, 1)</td>
<td>0.619 (0.615, 0.620)</td>
<td>Nakagawa et al. (2003)</td>
</tr>
<tr>
<td>$T_{\text{highT}, \text{tr}}$ °C</td>
<td>Threshold high temperature at which the harvest index is 50% of the maximum value</td>
<td>Eq. (A23)</td>
<td>(30, 40)</td>
<td>33.9 (33.8, 34.0)</td>
<td>Singletary et al. (1994); Nakagawa et al. (2003)</td>
</tr>
<tr>
<td>$c_{\text{lowT}}$ -</td>
<td>Curvature coefficient of harvest index for low temperature stress</td>
<td>Eq. (A24)</td>
<td>(0.1, 1)</td>
<td>0.871 (0.869, 0.872)</td>
<td>Horie et al. (1995)</td>
</tr>
<tr>
<td>$T_{\text{lowT}, \text{tr}}$ °C</td>
<td>Threshold low temperature at which the harvest index is 50% of the maximum value</td>
<td>Eq. (A24)</td>
<td>(15, 22)</td>
<td>15.4 (15.3, 15.5)</td>
<td>Horie et al. (1995)</td>
</tr>
<tr>
<td>$c_W$ -</td>
<td>Curvature coefficient of harvest index for water stress</td>
<td>Eq. (A25)</td>
<td>(5, 20)</td>
<td>15.7 (15.6, 15.8)</td>
<td>Neitsch et al. (2005)</td>
</tr>
<tr>
<td>$W_{\text{tr}}$ -</td>
<td>Threshold water stress level at which the harvest index is 50% of the maximum value</td>
<td>Eq. (A25)</td>
<td>(0.1, 0.9)</td>
<td>0.299 (0.296, 0.300)</td>
<td>Neitsch et al. (2005)</td>
</tr>
</tbody>
</table>
The canopy height and leaf area were controlled by the maximum leaf area development curve:

\[ f_{\text{LAI max},t} = \frac{f_{\text{GDD},t}}{f_{\text{GDD},t} + \exp(l_1 - l_2 \cdot f_{\text{GDD},t})}, \quad (A4) \]

where \( f_{\text{LAI max},t} \) is the fraction of the maximum leaf area index (LAI) that corresponds to a given fraction of the growing season, and \( l_1 \) and \( l_2 \) are the shape coefficients. The values of \( l_1 \) and \( l_2 \) were calculated by analytically solving Eq. (A4) for \( l_1 \) and \( l_2 \), respectively, by using two known points for the fractions of LAI and the growing season, \( (f_{\text{LAI}}, f_{\text{GDD}}) \) and \( (f_{\text{LAI}}, f_{\text{GDD}}) \), as described in Neitsch et al. (2005) (see Table A1 for \( f_{\text{GDD}} \)).

The daily increment of leaf area \( (\Delta \text{LAI}) \) in the initial growth stage was calculated as follows:

\[ \Delta \text{LAI}_t = \left( f_{\text{LAI max},t} - f_{\text{LAI max},t-1} \right) \cdot \text{LAI}_{\text{max}} \cdot \left[ 1 - \exp\left( 5 \cdot (\text{LAI}_{t-1} - \text{LAI}_{\text{max},t-1}) \right) \right]^{\frac{1}{\gamma_t}}, \quad (A5) \]

where \( \text{LAI}_{\text{max},t} \) is the maximum LAI adjusted for the crop nitrogen content and \( \gamma_t \) is the stress factor (see Section A4). The daily total LAI was updated by \( \text{LAI}_t = \text{LAI}_{t-1} + \Delta \text{LAI}_t \). When the maximum LAI was reached, the LAI remained constant until leaf senescence began. LAI began to decline when leaf senes-
sence became the dominant growth process:

\[ \text{LAI}_t = \text{LAI}_{\max} \frac{\left(1 - \frac{f_{GDD,t}}{f_{GDD,sen}} \right)}{\left(1 - \frac{f_{GDD,sen}}{f_{GDD,sen}} \right)} f_{GDD,t} > f_{GDD,sen}, \]

where \( f_{GDD,sen} \) (Table A1) is the fraction of the growing season at which leaf senescence begins.

\( \Delta \text{LAI} \) was decreased by non-optimal temperature and by shortages of water and nitrogen, whereas the maximum LAI was assumed to be limited by nitrogen alone:

\[ \text{LAI}_{\max,t} = \text{LAI}_{\max} \cdot \left(1 - f_b \cdot \exp\left(-f_c \cdot \text{strs}_{N,t} \right) \right), \]

where \( \text{LAI}_{\max,t} \) and \( \text{LAI}_{\max} \) are the maximum LAI at a limited and optimal crop nitrogen content, respectively; \( \text{strs}_{N,t} \) is the nitrogen stress factor; and \( f_b \) and \( f_c \) are the shape coefficients (Table A1).

The canopy height \( (h_t) \) was assumed to increase with increasing LAI up to a maximum canopy height, \( h_{\max} \) (Table A1):

\[ h_t = h_{\max} \cdot \frac{\text{LAI}_t}{\text{LAI}_{\max,t}}. \]

The fraction of total biomass in the roots \( (f_{\text{root},t}) \) was calculated with references to Jones (1985):

\[ f_{\text{root},t} = 0.4 - 0.2 \cdot f_{GDD,t}. \]

The modeled root depth \( (z_{\text{root},t}) \) varied linearly from 10 mm at emergence to the maximum root depth \( (z_{\text{root,max}} = 950 \text{ mm}; \text{Kramer and Boyer, 1995}) \) when \( f_{GDD} = 0.4 \). This was based on the equation described in Neitsch et al. (2005):

Table A2. List of PRYSBI1.1 model inputs used for this study.

<table>
<thead>
<tr>
<th>Element</th>
<th>Data name</th>
<th>Original resolution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weather</td>
<td>JRA-25/JCDAS</td>
<td>1.125° × 1.125°</td>
<td>Onogi et al. (2007)</td>
</tr>
<tr>
<td></td>
<td>ISLSCP-II global soil characteristics</td>
<td>1° × 1°</td>
<td>Hall et al. (2006)</td>
</tr>
<tr>
<td>Nitrogen</td>
<td>Reported nitrogen input</td>
<td>Country</td>
<td>FAO (2010)</td>
</tr>
<tr>
<td>Cropland</td>
<td>Global harvested area map</td>
<td>0.083° × 0.083°</td>
<td>Monfreda et al. (2008)</td>
</tr>
<tr>
<td>Irrigation</td>
<td>Reported irrigation input</td>
<td>Country</td>
<td>FAO (2010)</td>
</tr>
<tr>
<td></td>
<td>Global irrigation map</td>
<td>0.083° × 0.083°</td>
<td>Siebert et al. (2005)</td>
</tr>
<tr>
<td>CO₂</td>
<td>CDIAC reported [CO₂]</td>
<td>Site (Mauna Loa,</td>
<td>Keeling et al. (2009)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Hawaii, U.S.)</td>
<td></td>
</tr>
<tr>
<td>Sowing date</td>
<td>Reported sowing date</td>
<td>State</td>
<td>USDA (2010)</td>
</tr>
</tbody>
</table>

1 Abbreviations are as follows: JRA-25/JCDAS, Japanese 25-yr Reanalysis/Japan Meteorological Agency Climate Data Assimilation System; CDIAC, Carbon Dioxide Information Analysis Center; ISLSCP-II, International Satellite Land-Surface Climatology Project, Initiative II; FAO, United Nations Food and Agriculture Organization; and USDA, U.S. Department of Agriculture.

2 The bottom depth of each soil layer corresponds to 20, 100, 300, 600, 1000, and 1500 mm.

3 In the simulations, we assumed that 30 % of the nitrogen input was supplied in the surface two soil layers 1 day before sowing; nitrogen was supplied in the surface layer to meet crop nitrogen demand if the nitrogen stress factor \( (\text{strs}_{N,t}) \) the previous day was below 0.8; and the nitrogen supply was stopped if the total amount of supplied nitrogen for a growing period exceeded the FAO data value.

4 In the simulations, the irrigation water was intermittently put into the surface soil layer, although the irrigation input per operation was limited to less than 30 % of its yearly value, and the irrigation operation was conducted only when there were more than five consecutive dry days and where there was still irrigation water remaining for the year (a dry day was defined as a day with precipitation < 1 mm d⁻¹).
\[ z_{\text{root}, t} = \begin{cases} 2.5 \cdot f_{\text{GDD}, t} \cdot z_{\text{root max}} & f_{\text{GDD}, t} \leq 0.4 \\ z_{\text{root max}} & f_{\text{GDD}, t} > 0.4 \end{cases} \]  

(A10)

**A3. Dry matter production**

The daily maximum increase in crop biomass (\( \Delta \text{bio}_t \)), which included roots, was calculated as follows:

\[ \Delta \text{bio}_t = RUE_t \cdot PAR_t \cdot r_t, \]  

(A11)

where \( RUE_t \) is the radiation-use efficiency (RUE), \( PAR_t \) is the photosynthetically active radiation intercepted by the leaf, and \( r_t \) is the stress factor (see Section A4). The daily total crop biomass (\( \text{bio}_t \)) was incremented as \( \text{bio}_t = \text{bio}_{t-1} + \Delta \text{bio}_t \).

The RUE value was sensitive to variations in the atmospheric carbon dioxide ([CO$_2$]) concentration and vapor pressure deficit (VPD) (Stockle and Kiniry, 1990; Stockle et al., 1992). The following adjustment of the RUE for elevated [CO$_2$] was performed annually as described in Neitsch et al. (2005):

\[ RUE_i = \frac{100 \cdot \text{CO}_2}{\text{CO}_2 + \exp(r_1 - r_2 \cdot \text{CO}_2)}, \]  

(A12)

where \( r_1 \) and \( r_2 \) are the shape coefficients, which though determined in the same manner as \( l_1 \) and \( l_2 \) for the maximum leaf area development curve, are calculated by comparing two known points for RUE at ambient and elevated CO$_2$ to the two corresponding CO$_2$ concentrations: \( \langle RUE_{\text{amb}}, \text{CO}_2_{\text{amb}} \rangle \) and \( \langle RUE_{\text{hi}}, \text{CO}_2_{\text{hi}} \rangle \). \( RUE_{\text{hi}} \) is given by \( RUE_{\text{amb}} \times RUE_{\text{hi}} / RUE_{\text{amb}} \) (Table A1). The adjustment of RUE for VPD (\( \text{vpd}_t \)) was performed by using a daily time step as described in Neitsch et al. (2005):

\[ \text{RUE}_t = \begin{cases} \text{RUE}_{\text{vpd} = 1 - \Delta \text{RUE}_{\text{del}} \cdot (\text{vpd}_t - \text{vpd}^*_t)} & \text{vpd}_t > \text{vpd}^*_t \\ \text{RUE}_{\text{vpd} = 1} & \text{vpd}_t \leq \text{vpd}^*_t \end{cases} \]  

(A13)

where \( \text{RUE}_{\text{vpd} = 1} \) is the RUE at a VPD of 1 kPa, \( \Delta \text{RUE}_{\text{del}} \) is the rate at which RUE declines, and \( \text{vpd}^*_t \) is the threshold VPD above which crops exhibit reduced RUE (Table A1).

**A4. Stress factors for crop growth**

Daily increments in the leaf area and biomass were reduced by several stresses, including non-optimal temperature and shortages of water and nitrogen. The stress factor that most limited crop growth (\( r_t \)) is specified as follows:

\[ r_t = \min(\text{strs}_{T,t}, \text{strs}_{W,t}, \text{strs}_{N,t}), \]  

(A14)

where \( \text{strs}_{T,t}, \text{strs}_{W,t}, \text{strs}_{N,t} \) are stress factors for temperature, water, and nitrogen, respectively, and take values of 1 under optimal conditions and approach 0 when the crop is substantially stressed.

The temperature stress was calculated by using the optimal temperature, \( T_o \) (Neitsch et al., 2005; Table A1):

\[ \text{strs}_{T,t} = \begin{cases} 0 & T_t \leq T_b \\ \exp \left[ -0.1054 \cdot \left( T_o - T_b \right)^2 \right] & T_b < T_t \leq T_o \\ \exp \left[ -0.1054 \cdot \left( T_o - T_b \right)^2 \right] \cdot \left( 2 \cdot T_o - T_b \right) & T_o < T_t \leq 2 \cdot T_o - T_b \\ 0 & T_t > 2 \cdot T_o - T_b \end{cases} \]  

(A15)

**Table A3.** Types, sources, variables, and notes for calibration data (see Appendix for abbreviations).

<table>
<thead>
<tr>
<th>Type</th>
<th>Source</th>
<th>Variable</th>
<th>Model</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Silking date (2)</td>
<td>Yearly, 1980–2009</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Harvesting date (3)</td>
<td>Yearly, 1980–2009</td>
<td></td>
</tr>
<tr>
<td>Free-Air CO$_2$</td>
<td>Leakey et al. (2006)</td>
<td>Yields at 550 and 376 ppm [CO$_2$] (4)</td>
<td>Yearly, 2004</td>
<td></td>
</tr>
<tr>
<td>Enrich experiment</td>
<td>Iizumi et al. (2013b)</td>
<td>LAI (5)</td>
<td>Yearly, 1980–2009</td>
<td></td>
</tr>
<tr>
<td>Remote sensing</td>
<td></td>
<td>NPP (6)</td>
<td>Bi-monthly, 1982–2006</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Aboveground biomass</td>
<td></td>
</tr>
</tbody>
</table>
Water stress was given as the ratio of actual to potential transpiration \( \frac{E_{a,t}}{E_{p,t}} \): \[ strs_{W,t} = \frac{E_{a,t}}{E_{p,t}} \quad \text{(A16)} \]

The potential transpiration and evaporation were calculated by the Penman–Monteith equation (Allen et al. 1989), whereas the actual transpiration was calculated by a one-dimensional soil–water balance model that simulates major potential pathways of water movement, including canopy storage, infiltration, percolation, evapotranspiration, lateral subsurface flow, and surface runoff (Neitsch et al., 2005). (See Neitsch et al. [2005] for a more detailed description of the soil–water balance model.

Nitrogen (N) stress was calculated by comparing the actual and optimal crop nitrogen contents:

\[ strs_{N,t} = \frac{\varphi_{n,t}}{\varphi_{n,t} + \exp(s_{n1} - s_{n2} \cdot \varphi_{n,t})} \quad \text{(A17)} \]

where \( \varphi_{n,t} \) is a scaling factor and \( s_{n1} \) and \( s_{n2} \) are the shape coefficients (\( s_{n1} = 3.535 \) and \( s_{n2} = 0.02597 \); Neitsch et al., 2005). The scaling factor was calculated as follows:

\[ \varphi_{n,t} = \begin{cases} 200 \cdot \left( \frac{bio_{N,a,t}}{bio_{N,p,t}} - f_{\text{bio, tr}} \right) & \frac{bio_{N,a,t}}{bio_{N,p,t}} \geq f_{\text{bio, tr}} \\ 0 & \frac{bio_{N,a,t}}{bio_{N,p,t}} < f_{\text{bio, tr}} \end{cases} \quad \text{(A18)} \]

where \( bio_{N,p,t} \) and \( bio_{N,a,t} \) are the optimal and actual crop nitrogen content, respectively, and \( f_{\text{bio, tr}} \) is the threshold fraction (Table A1). The crop N uptake and soil N cycle were calculated by using the dynamic

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**Fig. A1.** Schematic diagram of the modeled crop growth processes in the PRYSBI1.1 large-area crop model with an emphasis on the calibrated parameters.
nitrogen model described in Neitsch et al. (2005), which accounts for the N supply from inorganic and organic N fertilizer, crop residue, and rainfall, as well as accounts for losses due to volatilization, denitrification, and crop uptake.

A5. Yield formation

When the crop reached maturity (\(f_{\text{GDD}} = 1\)), the crop yield (\(Y\)) was calculated by multiplying the above-ground biomass (\(\text{bio}_{\text{ag}, t} = \text{bio}_{e} (1 - f_{\text{root}, t})\)) by the technical coefficient (\(\gamma\)) and the harvest index (HI):

\[
Y = HI \cdot \text{bio}_{\text{ag}, t} \cdot \tau .
\]  

(A19)

The technical coefficient was modeled as a logistic function to account for factors that improve yield, but not considered in the model (e.g., the introduction of genetically modified organisms, increased HI due to improved cultivars, higher planting density, and more effective pest control):

\[
\tau = \tau_{\text{min}} + \frac{\tau_{\text{max}} - \tau_{\text{min}}}{1 + \exp[a \cdot (yr - yr_{\text{tr}})]},
\]  

(A20)

where \(\tau_{\text{min}}\) and \(\tau_{\text{max}}\) are the minimum and maximum technical coefficients (1 and 1.2), respectively; \(a\) is the shape coefficient; and \(yr_{\text{tr}}\) is the threshold year (Table A1). The harvest index was calculated as follows:

\[
HI = HI_{\text{max}} \cdot \gamma,
\]  

(A21)

where \(HI_{\text{max}}\) is the time-constant maximum HI at ideal growing conditions and \(\gamma\) is the stress factor for HI.

The overall stress factor for HI (\(\gamma\)) was obtained by multiplying the high and low temperature stress factors and the water stress factor for HI (\(\gamma_{\text{hiT}}, \gamma_{\text{lowT}},\) and \(\gamma_{W}\), respectively):

\[
\gamma = \gamma_{\text{hiT}} \cdot \gamma_{\text{lowT}} \cdot \gamma_{W}.
\]  

(A22)

The effects of high and low temperatures on HI were calculated as follows (Nakagawa et al., 2003; Singletary et al., 1994):

\[
\gamma_{\text{hiT}} = \frac{1}{1 + \exp[c_{\text{hiT}} \cdot (T_{\text{max}} - T_{\text{hiT}, \text{tr}})],
\]  

(A23)

\[
\gamma_{\text{lowT}} = \frac{1}{1 + \exp[c_{\text{lowT}} \cdot (T_{\text{lowT, tr}} - T)]},
\]  

(A24)

where \(c_{\text{hiT}}\) and \(c_{\text{lowT}}\) are the shape coefficients for high and low temperature stress, respectively; \(T_{\text{max}}\) and \(T\) are the daily maximum and mean temperatures, respectively, averaged over the course of the beginning of the reproductive growth period (0.55 < \(f_{\text{GDD}} < f_{\text{GDD, sen}}\)), and \(T_{\text{hiT, tr}}\) and \(T_{\text{lowT, tr}}\) are the threshold high and low temperatures, respectively (Table A1). The effect of water shortage on HI was calculated similarly:

\[
\gamma_{W} = \frac{1}{1 + \exp[c_{w} \cdot (\text{W}_{\text{tr}} - \text{strs}_{W})]},
\]  

(A25)

where \(c_{w}\) is the shape coefficient for water stress, \(\text{strs}_{W}\) is the water stress factor averaged over the course of the beginning of the reproductive growth period, and \(\text{W}_{\text{tr}}\) is the threshold for water stress.

References


