

# Predicting crop yields and soil-plant nitrogen dynamics in the US Corn Belt

Sotirios V. Archontoulis<sup>1</sup>  | Michael J. Castellano<sup>1</sup> | Mark A. Licht<sup>1</sup>  |  
 Virginia Nichols<sup>1</sup> | Mitch Baum<sup>1</sup> | Isaiah Huber<sup>1</sup> | Rafael Martinez-Feria<sup>1,2</sup> |  
 Laila Puntel<sup>1,3</sup> | Raziel A. Ordóñez<sup>1</sup> | Javed Iqbal<sup>1,3</sup> | Emily E. Wright<sup>1</sup> |  
 Ranae N. Dietzel<sup>1</sup> | Matt Helmers<sup>4</sup> | Andy Vanloocke<sup>1</sup> | Matt Liebman<sup>1</sup> |  
 Jerry L. Hatfield<sup>5</sup> | Daryl Herzmann<sup>1</sup> | S. Carolina Córdova<sup>1,6</sup> | Patrick Edmonds<sup>1</sup> |  
 Kaitlin Togliatti<sup>1</sup> | Ashlyn Kessler<sup>1</sup> | Gerasimos Danalatos<sup>1</sup> | Heather Pasley<sup>1</sup> |  
 Carl Pederson<sup>4</sup> | Kendall R. Lamkey<sup>1</sup> 

<sup>1</sup>Department of Agronomy, Iowa State University, Agronomy Hall, Ames, IA, USA

<sup>2</sup>Department of Earth and Environmental Science, Michigan State University, East Lansing, MI, USA

<sup>3</sup>Department of Agronomy and Horticulture, University of Nebraska-Lincoln, Lincoln, NE, USA

<sup>4</sup>Department of Agricultural and Biosystems Engineering, Iowa State University, Elings Hall, Ames, IA, USA

<sup>5</sup>USDA-ARS, National Laboratory for Agriculture and the Environment, Ames, IA, USA

<sup>6</sup>Kellogg Biological Station, Michigan State University, East Lansing, MI, USA

## Correspondence

Sotirios V. Archontoulis, Department of Agronomy, Iowa State University, Agronomy Hall, Ames, IA, USA.  
 Email: sarchont@iastate.edu

## Funding information

National Science Foundation, Grant/Award Numbers: #1830478, #1842097; U.S. Department of Agriculture, Grant/Award Numbers: 2019-67019-29404, IOW10480, IOW04414; Foundation for Food and Agriculture Research, Grant/Award Number: #534264; Iowa Soybean Association; Iowa State University; Iowa crop improvement association

Assigned to Associate Editor Carlos Messina.

## Abstract

We used the Agricultural Production Systems sIMulator (APSIM) to predict and explain maize and soybean yields, phenology, and soil water and nitrogen (N) dynamics during the growing season in Iowa, USA. Historical, current and forecasted weather data were used to drive simulations, which were released in public four weeks after planting. In this paper, we (1) describe the methodology used to perform forecasts; (2) evaluate model prediction accuracy against data collected from 10 locations over four years; and (3) identify inputs that are key in forecasting yields and soil N dynamics. We found that the predicted median yield at planting was a very good indicator of end-of-season yields (relative root mean square error [RRMSE] of ~20%). For reference, the prediction at maturity, when all the weather was known, had a RRMSE of 14%. The good prediction at planting time was explained by the existence of shallow water tables, which decreased model sensitivity to unknown summer precipitation by 50–64%. Model initial conditions and management information accounted for

**Abbreviations:** APSIM, Agricultural Production Systems sIMulator; RRMSE, relative root mean square error.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited and is not used for commercial purposes.

© 2020 The Authors. *Crop Science* published by Wiley Periodicals, Inc. on behalf of Crop Science Society of America

one-fourth of the variation in maize yield. End of season model evaluations indicated that the model simulated well crop phenology ( $R^2 = 0.88$ ), root depth ( $R^2 = 0.83$ ), biomass production ( $R^2 = 0.93$ ), grain yield ( $R^2 = 0.90$ ), plant N uptake ( $R^2 = 0.87$ ), soil moisture ( $R^2 = 0.42$ ), soil temperature ( $R^2 = 0.93$ ), soil nitrate ( $R^2 = 0.77$ ), and water table depth ( $R^2 = 0.41$ ). We concluded that model set-up by the user (e.g. inclusion of water table), initial conditions, and early season measurements are very important for accurate predictions of soil water, N and crop yields in this environment.

## 1 | INTRODUCTION

Predicting crop growth and soil processes has the potential to provide timely information for management recommendations (Hansen & Indeje, 2004). Such information can improve profitability, environmental quality and marketing decisions (Brandes et al., 2016; Johnson et al., 2016). Current efforts to forecast seasonal crop yields include field surveys, expert judgement, remote sensing, statistical models, and process-based simulation models (Basso et al., 2013; Feng et al., 2019; Hammer et al., 1996; Prasad et al., 2006; Ines et al., 2013). There are trade-offs among approaches in terms of accuracy, explanatory power, and desired scale and resolution (Basso & Liu, 2019). Farmer-based surveys are helpful but rely on voluntary participation and their information is restricted to events of the past. Remote sensing and statistical models are descriptive (Atzberger, 2013; Lobell et al., 2015) and offer limited insight on belowground processes that are key to environmental performance. In contrast, process-based models offer a way to understand and explain the underlying crop and soil processes driving yield and environmental outcomes, but this comes at the cost of extensive input data requirements (Basso et al., 2012; Puntel et al., 2018). Successful yield forecasting approaches using crop models in the United States (Morell et al., 2016; Togliatti et al., 2017) and Australia (Carberry et al., 2009), have shown potential to couple explanatory with predictive power to evaluate adaptive management strategies (Jones et al., 2017).

Predicting yield and soil-crop dynamics during the growing season faces the challenge of capturing weather-related uncertainty and its interaction with the variability of soil properties, crop genetics, and management practices (Tollenaar et al., 2017). Therefore, the success in forecasting yields via crop simulation methods depends on the capability of the model to accurately represent dynamic processes (van der Velde et al., 2012), and the quality and availability of data inputs (Hansen et al., 2004).

Although the algorithms behind crop models continue to be refined to improve the representation of biophysical pro-

cesses, knowledge gaps still limit their use (Keating et al., 2003; Li et al., 2019; Rötter et al., 2018). This is particularly evident when predictions are made under extreme weather scenarios or in environments with specific characteristics such as shallow water tables or soil constraints (Wang & Smith, 2004). Crop models are generally capable of accurately simulating the effect of water deficits on soil-crop-atmospheric processes, but less accurate when simulating excessive water impacts (Rosenzweig et al., 2002; Shaw & Meyer, 2015; Warren et al., 2015). For example, Li et al. (2019) showed that many maize (*Zea mays* L.) models overestimated yields in situations with excessive precipitation due to the lack of excess moisture yield loss mechanisms. Others have shown that inclusion of waterlogging routines improved the overall model capability to predict production and environmental outcomes (Ebrahimi-Mollabashi et al., 2019). Excessive moisture is most damaging in poorly drained soils with shallow water tables, which are present in a large portion of cropland in the US Midwest (Fan et al., 2013; Rizzo et al., 2018).

Continuous development and testing of field-scale agronomic crop models with experimental data can improve our understanding of fundamental science, identify gaps in model function, and improve current forecasting methods to better account for extreme events (Peng et al., 2018). To this end, we used a multi-location-year dataset that included many measurements of the crop-soil system. Data were collected during the first four years of the Forecast and Assessment of Cropping sysTemS (FACTS) project (Archontoulis & Licht, 2016). This project aimed to develop and test a methodology to perform in-season forecasts of maize and soybean [*Glycine max* (L.) Merr.] yields and other important aspects of the system, related to crop management and environmental performance such as soil N availability and crop N uptake at 10 locations in Iowa, USA. In this paper, we: (1) describe the methodology used to perform forecasts of yield and crop-soil dynamics and improvements made to the model; (2) evaluate model prediction accuracy, error and uncertainty; and (3) identify inputs that are key in forecasting yields, soil water and N dynamics, and discuss lessons learned over four years.

## 2 | MATERIALS AND METHODS

### 2.1 | Field experiments, management, and weather conditions

We set up 10 experimental locations with maize and soybean crops across Iowa, USA (Figure 1). Experiments covered a range of weather conditions, management practices, soil drainage systems, and soil properties. Over a 4-yr period, 2015–2018, we collected data from 94 unique site-year-crop-management combinations (hereafter test plots; 56 test plots with maize and 38 with soybean; Supplemental Table S1). Each test plot was replicated three times and the size of each replication ranged from 300 to 4,000 m<sup>2</sup>, depending on location and treatments. Crops were grown under typical management practices at each location. In some locations, we added treatments to study cropping system response to planting date, N-fertilization rate, and subsurface drainage (Supplemental Table S1). Maize and soybean crops were grown in rotation and both crop phases were present in each year with one exception of a central Iowa location, in which maize was grown in monoculture. Eight of the ten locations had shallow water tables that fluctuated from 30 to 300 cm below the soil surface (Ebrahimi-Mollabashi et al., 2019; Nichols et al., 2019). The existence of shallow water tables is very common in the US Corn Belt. For reference, 55%, 61% and 56% of the land in Iowa, Illinois, and Indiana, respectively, has shallow water tables (Supplemental Figure S1). Three locations had subsurface tile drainage at 1.1 m depth (Figure 1; Supplemental Table S1). Irrigation was applied in one location (Muscatine, very sandy soil; Supplemental Table S2). In all other locations, crops were rainfed. Soil organic matter and plant available water differed across locations (Figure 1; Supplemental Table S2).

Planting dates and cultivars across the test plots varied among locations (Figure 1b). On average, maize was planted on May 5 and soybean a week later. We used seven maize hybrids (range 101–115 day maturity) and 12 soybean varieties (range 1.8–3.6 maturity group) across the 94 test plots (Figure 1b; Supplemental Table S1). Each cultivar was used for two years and in at least two locations. Target plant densities averaged 8.6 plants m<sup>-2</sup> for maize and 36 plants m<sup>-2</sup> for soybean (Figure 1b). Row spacing was 76 cm with the exception of two soybean test plots, which was 38 cm. N-fertilization for maize was 166 kg N ha<sup>-1</sup> in most of the trials following Iowa State University recommendations for a maize-soybean rotation (Sawyer et al., 2006). In four locations we studied variable N-rates to maize, including zero and excessive (336 kg N ha<sup>-1</sup>; Supplemental Table S1). No N fertilizer was applied to soybean except few test plots (see Supplemental Table S1) in which we experimented with a high-input management system. The timing of N fertilizer application to maize varied by location, from two weeks

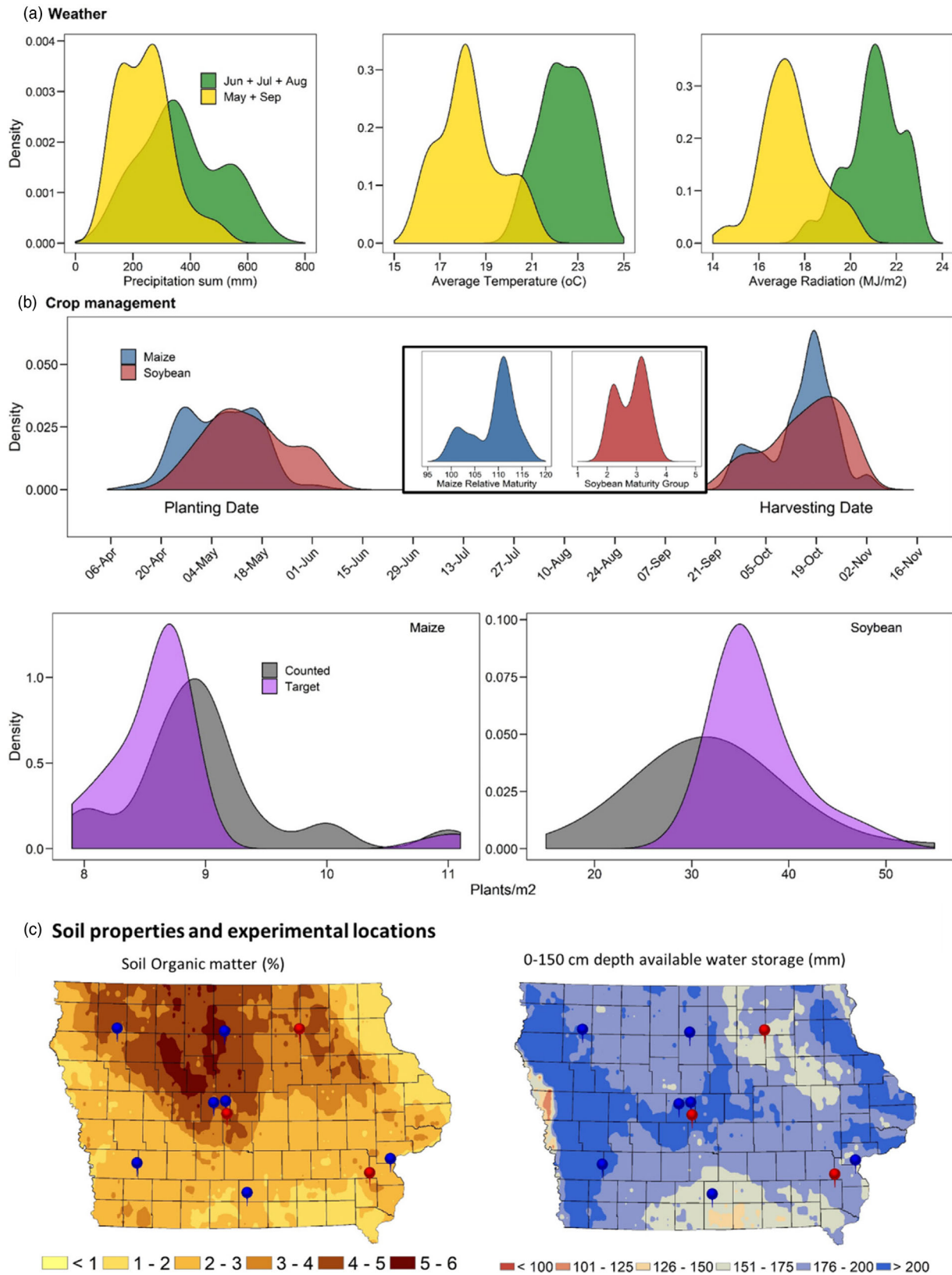
before planting to two weeks after planting. N fertilizer was either broadcasted (urea-N) or injected (urea ammonium nitrate). Phosphorus, potassium, and sulfur fertilizers were applied in the fall or spring following Iowa State University recommendations and annual 15 cm soil sampling (Mallarino et al., 2013). The target was to maintain Mehlich 3 soil test P and K levels in the higher end of the optimal soil test category (P, 16–20 ppm; K, 86–120 ppm). Sulfur applied at a rate of 34 kg S ha<sup>-1</sup> as ammonium sulfate. Tillage operations varied by location and crop. Typically, a disc tillage system was used to incorporate maize stover in the fall and field cultivators were used for seedbed preparation and to incorporate fertilizers in the spring. Herbicides, insecticides, fungicide and manual weeding were applied as needed to keep the plots free of weeds, pests, and diseases.

Field trials were set up next to fully automated weather stations (Iowa Environmental Mesonet, 2019). Crops experienced a range of weather conditions across locations and years (Figure 1a). The average summer temperature (June, July, and August) varied from 18–24 °C while the summer precipitation varied from 146–630 mm (Figure 1a). Compared to 35-year weather record, the 2015 summer was wet and cool, the 2016 summer was dry and warm in the first half and wet and cool in the second half, the 2017 summer was warm and dry, while the 2018 summer was warm and wet. Additional weather information by location and year is provided in Supplemental Table S3.

### 2.2 | Soil and crop measurements

All of the replicated test plots were outfitted with 5TM soil moisture and temperature sensors (METER Group Inc., Pullman, WA, USA) at two depths (15 and 45 cm), except few test plots in Kanawha and McNay. In addition, water tables monitoring wells were installed in all sites except Muscatine. Wells consisted of 5-cm diameter slatted polyvinyl chloride (PVC) pipes, outfitted with CTD-10 sensors (METER Group Inc., Pullman, WA, USA). Initially, two water table wells were installed to a depth of 1.8 m at the borders of each experiment. In 2017, wells were re-installed inside the plots to a deeper depth (2.8 m) and we also increased the number of wells to a total of 38 across all test plots. Data were recorded hourly during the growing season and in some cases during the fallow period using EM50 dataloggers.

Soil nitrate and ammonium were measured in all test plots (1370 with 3 replications for 4,110 samples). In 2015, measurements were taken every week from April to November at 0–30 cm depth. In 2016 and 2017, we added a second depth (30–60 cm) and decreased the frequency of measurements to every other week. In 2018, the same two-depth protocol was maintained but fewer samples were collected compared to 2017. Each time, eight soil cores were taken from every



**FIGURE 1** (a) Weather conditions including precipitation, temperature, and radiation during two periods (June, July, August versus May and September). (b) Crop management including planting and harvesting dates, cultivars life cycle and plant populations for 56 maize and 38 soybean trials. (c) Soil properties including soil organic matter and available water from SSURGO. Colored symbols in (c) indicate experimental locations; red refers to soils with subsurface tile drainage and blue to soils without. Additional weather, management, and soil data are provided in Supplemental Tables S1–S3

replication and soil samples were homogenized into one sample. Then, the sample was extracted in 2 M potassium chloride (5:1 solution/soil ratio) and passed through a Whatman filter paper #1. Nitrate plus nitrite and ammonium concentrations in the filtrate were measured in microplates using the Griess–Ilosvay reaction with vanadium (III) chloride as a reducing agent and the Berthelot reaction, respectively (Hood-Nowotny et al., 2010). Gravimetric soil moisture was determined from these samples to scale the N concentrations to mass N dry soil and test the moisture sensors.

Crop growth and development were measured in all test plots approximately every two weeks. Crop measurements included destructive plant sampling (1 m<sup>2</sup> each time) and non-destructive assessments of crop staging and population density. In total, we collected 1,922 (644 with 3 replications) biomass samples. In each sample, we measured dry biomass and partitioning to different organs (green and yellow leaves, stems, cobs, husk, shank and kernels for maize; and green and yellow leaves, stems, pod walls and seeds for soybean), organ N and C concentration, green leaf area, and number of kernels per ear. Leaf area index, specific leaf area index, and tissue N uptake were calculated from these data. During biomass sampling, we also measured root depth in years 2016 and 2017 from all test plots and in year 2018 from central Iowa test plots (Ordóñez, Castellano, Hatfield, Helmers et al., 2018; Ebrahimi-Mollabashi et al., 2019). Crop staging was assessed using the V/R system for maize and soybean (Fehr & Caviness, 1977; Ritchie & Hanway, 1982). In addition to staging, total and actual maize leaf number and soybean node and pod numbers were counted. Combine grain yields were determined by harvesting 4–8 middle rows from each replicated test plot using the Harvest Master weight bucket.

Additional measurements included N<sub>2</sub>O and CO<sub>2</sub> emissions from the soil surface (12 test plots), residue decomposition (8 test plots), evapotranspiration (4 test plots), soybean N-fixation (8 test plots; Córdova et al., 2019), leaf area profiles along the main stem (8 test plots), water flow and N leaching to tile drainage (15 test plots), vertical root mass and length distributions and root C and N concentrations in 36 test plots (Ordóñez, Castellano, Hatfield, Licht et al., 2018; Nichols et al., 2019). Measurements were used to check, improve and calibrate various APSIM routines (see below). In this manuscript, we present model performance against sensors, soil and crop data.

### 2.3 | General description of the APSIM software platform

We used the Agricultural Production Systems sIMulator (APSIM; Holzworth et al., 2014) version 7.7 in the first year and version 7.8 in subsequent years. The following modules were used: maize and soybean crop models (Keating

et al., 2003), SWIM soil water model (Huth et al., 2012), soil N and carbon model (Probert et al., 1998), residue model (Probert et al., 1998; Thorburn et al., 2001), soil temperature 2 (Campbell, 1985) and various management rules to account for tillage and other management operations. The crop models simulate biomass production based on a combined radiation and water use efficiency concept. The SWIM soil water model uses the Richards equation to simulate water balance processes including simulation of shallow water tables and tile drainage (Malone et al., 2007). The soil N model simulates soil organic carbon mineralization, immobilization, and inorganic N fluxes including nitrification, denitrification, nitrous oxide emissions, N leaching, and urea fertilizer hydrolysis. The decomposition of crop residue influences soil-water-N-temperatures modules in APSIM. Information flow passes from one module to another on a daily basis to account for feedbacks among various soil, crop, and atmospheric processes (for additional information, see [www.apsim.info](http://www.apsim.info)).

### 2.4 | APSIM model set up and calibration

We set up the model to simulate a water- and N-limited production situation. Each simulation started on January 1 to allow time for the soil water balance to reach an equilibrium. Starting values for surface residue (amount and carbon to nitrogen, C to N, ratio), root mass in the soil and C to N ratio, soil nitrate, and water by layer were derived by simulating the previous cropping year and extracting the values on December 31 in the first year and by field measurements in subsequent years or combination of both. Soil organic matter values by layer to 1.2-m depth were derived from baseline measurements taken in every location (6 replications per location) and then SSURGO (Soil Survey Staff, 2019) data was used to develop a 2.5-m soil profile per location (Supplemental Table S2). The model uses three soil organic matter pools, a fast decomposing, a slow decomposing and an inert pool that does not decompose. Because the size of each pool depends on carbon inputs (crop, management, soil properties, and weather conditions interactions), a 10-yr spin-up simulation was run to derive these fractions in a manner similar to that used by Dietzel et al. (2016). The values are shown in Supplemental Table S2.

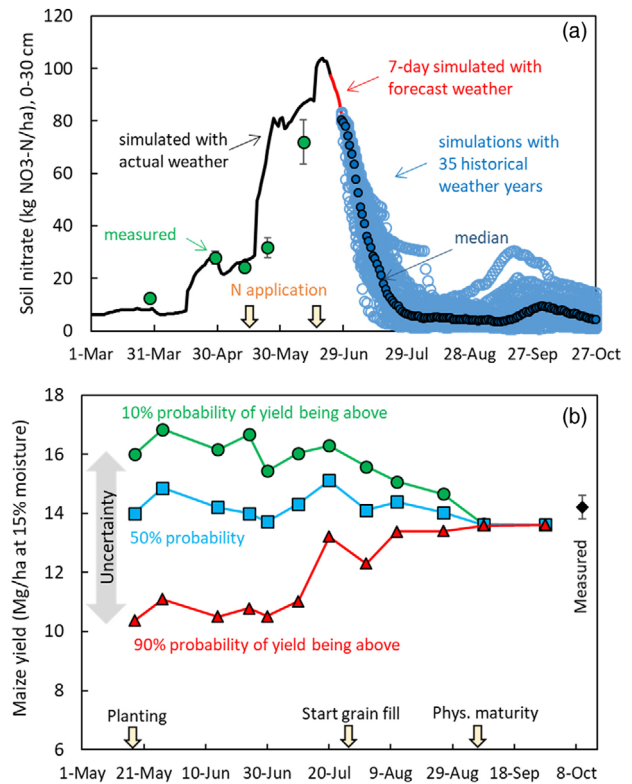
Soil hydrological parameters including drained upper limit, drained lower limit, and saturation by layer were initially taken from SSURGO and subsequently calibrated using data from moisture and water table sensors (see values in Supplemental Table S2). The air-dry lower limit and runoff parameters were estimated similar to Archontoulis et al. (2014). The XF parameter, which reflects soil constraints to root growth, was set to 1 (no limitation) in all sites except McNay, which has a clay pan from 30–80 cm soil depth and XF was set to 0.7 to constrain root penetration in these soil layers. The 0.7 value

better matched root depth observations over time in this location. The KL parameter that reflects the ability of the crop to extract water was set to  $0.08 \text{ day}^{-1}$  from 0 to 0.8 m and then decreased exponentially to 0.03 at 1.5-m depth, similar to Hammer et al. (2009). Saturated hydraulic conductivity by layer was estimated using Saxton and Rawls (2006) equations that use the inputs soil organic matter and texture (Supplemental Table S2).

Knowing that the experimental locations have a shallow water table (Supplemental Figure S1), we used the SWIM model, which has the capacity to simulate fluctuating water tables (Huth et al., 2012). The simulation of the water table was implemented by using a constant head bottom boundary condition that reflected the average water table depth by location (see values in Supplemental Table S4 and implementation details in Ebrahimi-Mollabashi et al., 2019). SWIM model hydraulic conductivity and matric potential at field capacity parameters were calibrated using water table and moisture data and values ranged from 0.1 to 0.3 mm per day and  $-100$  to  $-300$  cm, respectively.

In the crop models, we made changes to the crop parameter files and source code, which were guided by measurements and literature. The changes are listed in Supplemental Tables S4 and S5, including default and new values per crop. In brief, in the maize crop model, we increased the radiation use efficiency parameter (Soufizadeh et al., 2018), decreased the root front velocity (Ordóñez, Castellano, Hatfield, Helmers et al., 2018), decreased the leaf appearance rates, and decreased the critical maize grain N concentration (Ciampitti & Vyn, 2012). In the soybean model, we increased the node senescence parameter to slow down senescence (Archontoulis et al., 2014b; Wu et al., 2019), decreased the potential fixation rate (Córdova et al., 2019), decreased the root front velocity (Ordóñez, Castellano, Hatfield, Helmers et al., 2018), decreased the critical grain N concentration (Balboa et al., 2018) and the pod N concentration. In addition, we decreased the fraction of dry matter allocated to pods at the early reproductive stages and decreased stem and leaf N concentrations at late reproductive stages. In both crop models, we added a new function in the source code to inhibit root front velocity when a layer is nearly saturated with water (see Ebrahimi-Mollabashi et al., 2019). This new function is incorporated into release version 7.9.

In the soil N model, we added a new function in the source code to constrain denitrification beyond a certain depth (user-defined; 1-m depth was used). This modification was necessary because the inclusion of water table stimulated unrealistically high denitrification rates from the subsoil. That was due to the way that the denitrification equation was previously programmed in APSIM (see details in Martinez-Feria et al., 2018). This change improved simulation of the N leaching to tile drainage. In the residue model, we used the default settings with the exception of one change in the soybean



**FIGURE 2** (a) In-season prediction of soil nitrate on 26 June 2016, that includes measured data, simulated data using actual weather, predicted data using 7-day forecasted weather, predicted using a range of historical data and the median value that was used as the predictor. (b) In-season yield prediction showing 90%, 50% (median) and 10% probabilities of yield being above as well as measured yield. This information was publicly available via <https://crops.extension.ia.state.edu/facts/> and was updated every two weeks. Data from the central Iowa, Kelley location, maize crop, year 2016 are displayed in the above panels (see also Supplemental Table S1, ID #10)

residue surface cover (from 0.0002 to  $0.0004 \text{ ha kg}^{-1}$ ). This change was supported by field measurements (residue cover and soil moisture) and resulted in better simulation of soil water dynamics.

## 2.5 | Prediction protocol

To predict yields and soil water-N dynamics during the growing season we used a synthetic weather file that included: observed weather data up to a certain date, forecasted weather data for 7 days, and historical weather data from then on (Figure 2a; see also Togliatti et al., 2017). In 2015 we used the Weather Research and Forecasting model (Skamarock et al., 2008) for forecasted weather data while in subsequent years NDFD (National Digital Forecast Database) and CFS (Climate Forecast System) forecasted weather data. Starting at planting time, we run the models every other week to predict yields, soil nitrate and

water, crop staging, and crop water and N uptake. Portions of the results (measurements and simulations) were displayed in a publicly available website (Archontoulis & Licht, 2016; <https://crops.extension.iastate.edu/facts/>). Both actual and benchmarking predictions (e.g. percent yield or soil N above or below normal with normal being a 35-yr average) were provided in the website. The overall workflow is illustrated in Supplemental Figure S2. At the end of each forecast season, we used the modeling framework to answer *what-if* farmers' questions, e.g. what-if I had planted a week earlier or used a higher seeding rate or N-rate.

Early in the growing season (June) we adjusted the model, if needed, to ensure leaf number, leaf area index, crop biomass, soil water, and soil N followed the measurements (Figure 2a; Supplemental Figure S3). In most cases, when the model simulations did not follow the measurements, the errors were due to the incorrect simulation of emergence or incorrect initial N or residue amount inputs. When we implemented a fix in the initial conditions, we re-run the simulations from planting time. No changes to model source code or crop parameter values were made during the forecast period except some ad-hoc modifications as needed to account for herbicide damage to leaf canopy in soybeans or hail damage to both crops. In these cases, we decreased photosynthesis for a few days via modifying radiation amount for the period of the event. After each growing season, we used all the measured data for a comprehensive systems evaluation of the modules. As new information became available, we improved the modules year-by-year to better represent the system. The process of improvement is still in progress.

## 2.6 | Statistical indices to assess model performance

To evaluate in-season yield predictions we calculated the relative root mean square error (RRMSE) and created  $y = ax$  (measured versus simulated) graphs from which we determined the  $R^2$  and the slope of the plot. The RRMSE is a measure of the error,  $R^2$  is a measure of predictive ability, while the slope is useful to identify systematic bias in predictions. The above indices were calculated for each yield prediction during the season, from planting to harvesting. As explained above, in each forecast a synthetic weather file consisting of 35 years was used, which resulted in 35 yield predictions. The median yield was used as the predicted yield and the actual yield at harvest time as the measured yield (Figure 2; Supplemental Figure S2).

To estimate the uncertainty that is associated with the unknown weather during the season (Figure 2b), we calculated the standard deviation of the median prediction. The standard deviation was divided by the mean yield to create a normalized index to compare the two crops.

To evaluate end-of-season model performance we calculated RRMSE,  $R^2$ , root mean square error (RMSE), and modeling efficiency (ME). Equations can be found in Archontoulis and Miguez (2015).

## 2.7 | Sensitivity analysis

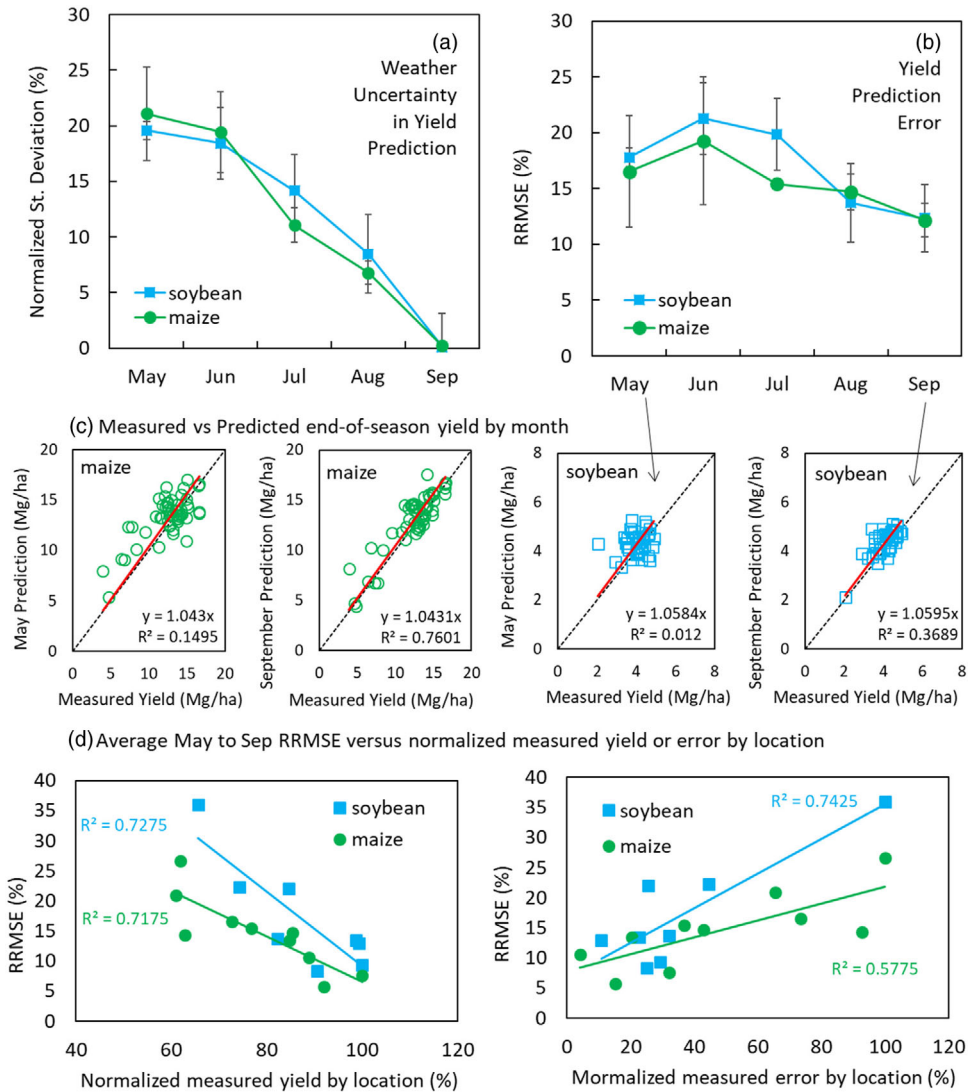
To gain a deeper understanding of the factors determining yield prediction at planting time as well as other important variables we performed a sensitivity analysis of APSIM inputs including weather, management, crop cultivar parameters, initial conditions, and soil conditions. This analysis reflects all the decisions that a user has to make while performing in-season predictions (see Supplemental Table S7).

We classified the factors into known (e.g. weather from January 1 to April 30), partially known (e.g. cultivar life cycle duration), and unknown (e.g. growing season weather). Within each category, we defined factors (e.g. rain) and different levels within each factor. In total 28 factors were defined per crop (Supplemental Table S7). We used different ranges per factor to best represent reality. For example, the range of precipitation from January to April was from 83 to 393 mm and derived from analysis of 35-yr data from central Iowa. This range reflects a  $\pm 65\%$  variation from the median value that was 241 mm. Then we defined different levels within that range ( $-65$ ,  $-35$ ,  $-15$ ,  $+15$ ,  $+30$ ,  $+65\%$ ) and by using the climate control script available in APSIM we ran 35 years of simulation for each level. All other inputs were held constant. A second example is the maize thermal time parameter from silking to physiological maturity. This information is available in 'seed bag tags' but is not precise. Therefore, we included a  $\pm 10\%$  variation in this parameter. For a maize hybrid with a grain fill period thermal time of  $800\text{ }^\circ\text{C-d}$ , a 10% variation ( $720$  to  $880\text{ }^\circ\text{C-d}$ ) is approximately 5–8 d deviation in this region.

We performed a one-factor-at-a-time sensitivity analysis (Lenhart et al., 2002). A baseline scenario was constructed for central Iowa using average values for each parameter (Supplemental Table S7). A single parameter was varied from a feasible minimum and maximum value (Supplemental Table S7). Sensitivity of grain yield, soil nitrate and other variables were assessed using a relative sensitivity index (Hamby, 1994). Data analysis and visualization were conducted in R version 3.5.1 (R Core Team, 2013), which was expanded with the packages *readxl* (Wickham & Bryan, 2018) and *tidyverse* (Wickham, 2017).

## 2.8 | Sensibility analysis of yield response to summer precipitation

In addition to model testing against in-season data, a robust model should also predict known yield response to external factors such as management practices or soil and weather



**FIGURE 3** (a) Weather uncertainty during the growing season expressed as normalized standard deviation of 35 weather-year predictions. Data are averages across 56 (maize) and 38 (soybean) predictions that encompass different management, years, and locations (Supplemental Table S1). Standard deviations are shown with error bars. (b) Relative root mean square error (RRMSE) during the growing season for 56 maize and 38 soybean predictions. (c) Measured versus median predicted yield in May and September. (d) Correlations between season average RRMSE and normalized average measured yield or measured error across the 10 locations. In (d), the 100% maize and soybean yields are 15.2 and 4.4 Mg/ha respectively, and the 100% measured error for maize and soybean is 4.2 and 1.2 Mg/ha, respectively. Measured error reflects the variability from replication to replication

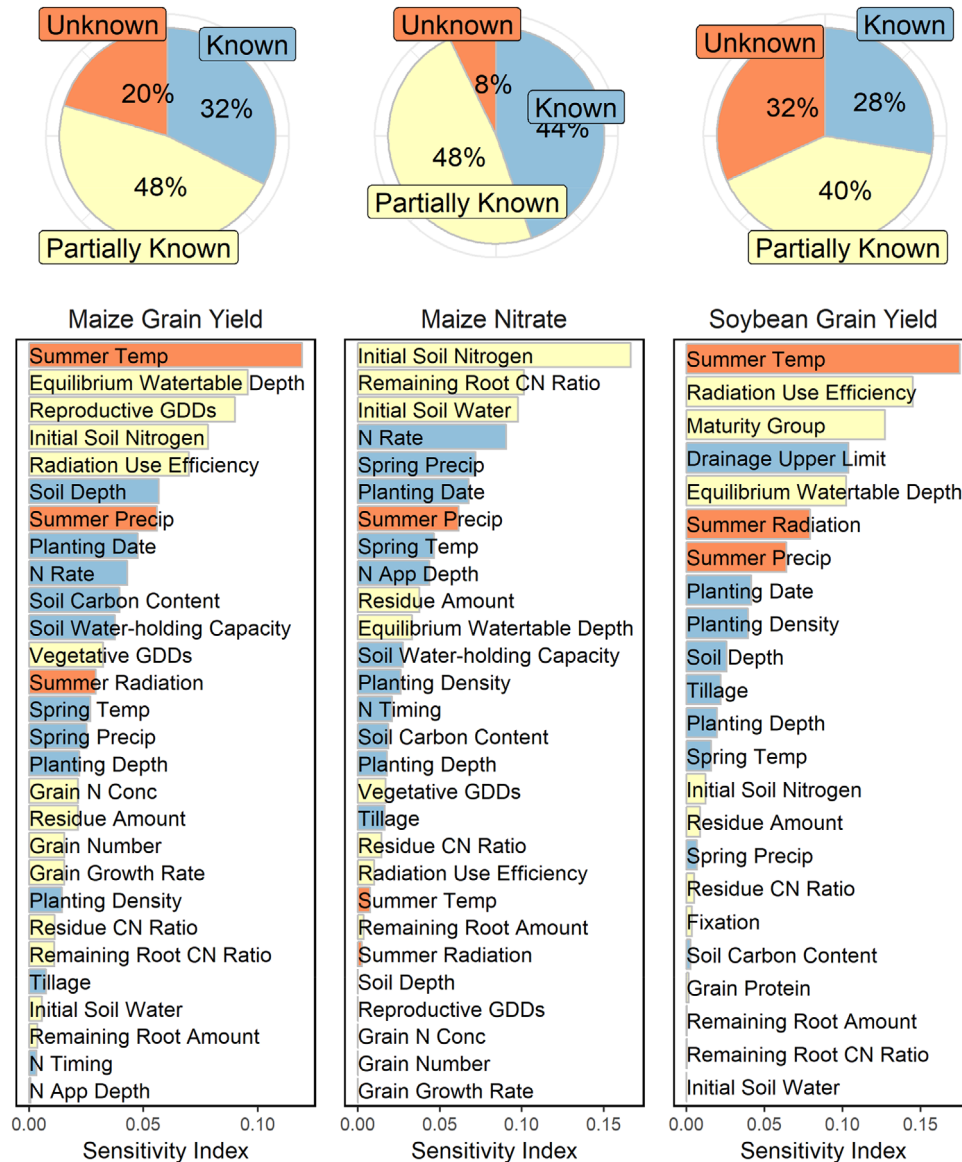
factors. We tested yield response to summer precipitation, with and without water table influence. We enabled simulation of water table and impacts on yields, by appropriately setting subsoil parameters (Supplemental Table S2), bottom boundary conditions (Supplemental Table S4), and adding a new function into the model to inhibit root growth in soil layers saturated with water (Supplemental Tables S5 and S6). For the analysis, we used a central Iowa location, typical management, and cultivars for this region, and we ran the model for 38 historical years. Simulated yields were compared to county yield data for the Boone County, Iowa (NASS, 2019). In this comparison, we removed the effect of management and genetics from the historical crop NASS yield increase.

## 3 | RESULTS

### 3.1 | Yield prediction during the growing season

Across locations, the weather uncertainty in yield prediction (standard deviation of the median prediction) was highest early in the season (~20%) and decreased towards physiological maturity to 0% (Figure 3a). Within locations, the growing season weather uncertainty was highest in the southern locations, particularly in the south-central location for both crops (Supplemental Figure S4).





**FIGURE 4** Sensitivity analysis of different variables and parameters associated with grain yield and soil N prediction at planting time. The ranges of values explored are provided in Supplemental Table S6. Variables and parameters were separated into known, partially known and unknown

The RRMSE (error between median prediction and measured yield) decreased much less compared to the uncertainty during the growing season, from 20% at planting to 14% at physiological maturity (Figure 3b). In general, the RRMSE slightly increased during June and July and then decreased during August. We observed variability in these trends from location to location as indicated by the error bars in Figure 3b. The variability in RRMSE across locations was explained by the yield of each location and also by the yield measurement error. The higher the yield or the lower the measurement error, the lower the RRMSE for both crops (Figure 3d-e). This shows better model performance in high yielding environments and uniform field experiments (less within field variability). For reference, across years and management, the highest maize yield was obtained in the irrigated Muscatine

location (southeast Iowa) and the highest soybean yield in the rainfed Sutherland location (northwest Iowa). The highest measurement error was obtained in McNay (southcentral Iowa) for both crops.

The yield prediction accuracy in May (planting time) was only surpassed by the yield prediction accuracy in September (physiological maturity; Figure 3d). To understand this, we performed a sensitivity analysis to determine the factors contributing to yield prediction at planting time (Figure 4). Results indicated that 32% of the maize yield variability was explained by known factors, 48% by partially known factors, and only 20% by unknown factors at planting time (Figure 4; Supplemental Table S7). Summer temperature (weather factor), equilibrium water table depth (soil factor), and thermal time during reproductive phase (crop-factor) explained most

**TABLE 1** Summary analysis of APSIM model performance against in-season experimental data. The corresponding graphs are provided in Supplemental Figures S7–S26. N, number of replicated data; Slope, the “a” from the  $y = ax$  regression;  $R^2$ , from the  $y = ax$  regression; ME, modeling efficiency ( $\infty$  to 1; 1 is best); RMSE, root mean square error (a measure of model error with unit); RRMSE, relative root mean square error (0 to  $\infty$ ; 0 is best; values are presented as %)

Variable name	Unit	Range	n	Slope	$R^2$	ME	RMSE	RRMSE	Figure
<i>Maize</i>									
Root depth	cm	15–170	151	1.14	0.847	0.720	23.2	22.9	S7
Leaf number	–	3–21	565	1.00	0.897	0.920	1.69	11.5	S8
Leaf area index	m <sup>2</sup> /m <sup>2</sup>	0–7	326	0.84	0.667	0.674	1.07	39.7	S9
Biomass accumulation	Mg/ha	0–34	380	1.02	0.940	0.956	1.98	16.8	S10
Grain accumulation	Mg/ha	0–16	238	0.94	0.845	0.867	1.73	22.6	S11
Leaf N concentration	%	0.6–5.5	358	0.90	0.590	0.759	0.68	21.9	S12
Plant N uptake	kg N/ha	0–321	373	1.04	0.846	0.830	3.55	24.1	S13
Grain N uptake	kg N/ha	0–220	184	0.88	0.821	0.793	2.42	27.8	S14
<i>Soybean</i>									
Root depth	cm	0–160	135	1.04	0.759	0.701	22.9	25.5	S15
Node number	–	2–22	200	0.91	0.855	0.852	2.20	20.9	S16
Leaf area index	m <sup>2</sup> /m <sup>2</sup>	0–7.5	219	1.09	0.793	0.737	1.02	32.7	S17
Biomass accumulation	Mg/ha	0–11.5	270	0.97	0.923	0.931	0.85	21.2	S18
Seed + pod accumulation	Mg/ha	0–7.9	185	0.93	0.942	0.869	0.16	28.3	S19
Leaf N concentration	%	1–7	234	0.98	0.330	0.516	0.78	18.0	S20
Plant N uptake	kg N/ha	0–350	255	0.99	0.900	0.910	2.95	22.5	S21
Seed + pod N uptake	kg N/ha	0–345	162	0.99	0.873	0.870	36.9	28.4	S22
<i>Both crops</i>									
Soil moisture @ 15 cm	mm/mm	0.1–0.55	22500	0.98	0.425	0.33	0.04	16.6	S23
Soil temperature @ 15 cm	°C	0–30	22500	0.93	0.934	0.890	2.34	13.9	S24
Soil nitrate (0-30,30-60 cm)	kg N/ha	0–345	1370	0.85	0.773	0.775	19.6	70.8	S25
Water table depth	cm	0–250	3245	0.99	0.416	0.479	32.8	23.7	S26

of the variability in maize yield at planting time. Management and initial conditions together accounted for nearly one-fourth of the variation in maize yield. Among these, only the weather is unknown at planting. Soil and crop factors at planting are known or partially known. Thus, the low RRMSE of maize yield at planting is explained by the low share of the unknown factors to the total yield variability. Similar results were obtained for the soybean yield prediction at planting time (Figures 3 and 4).

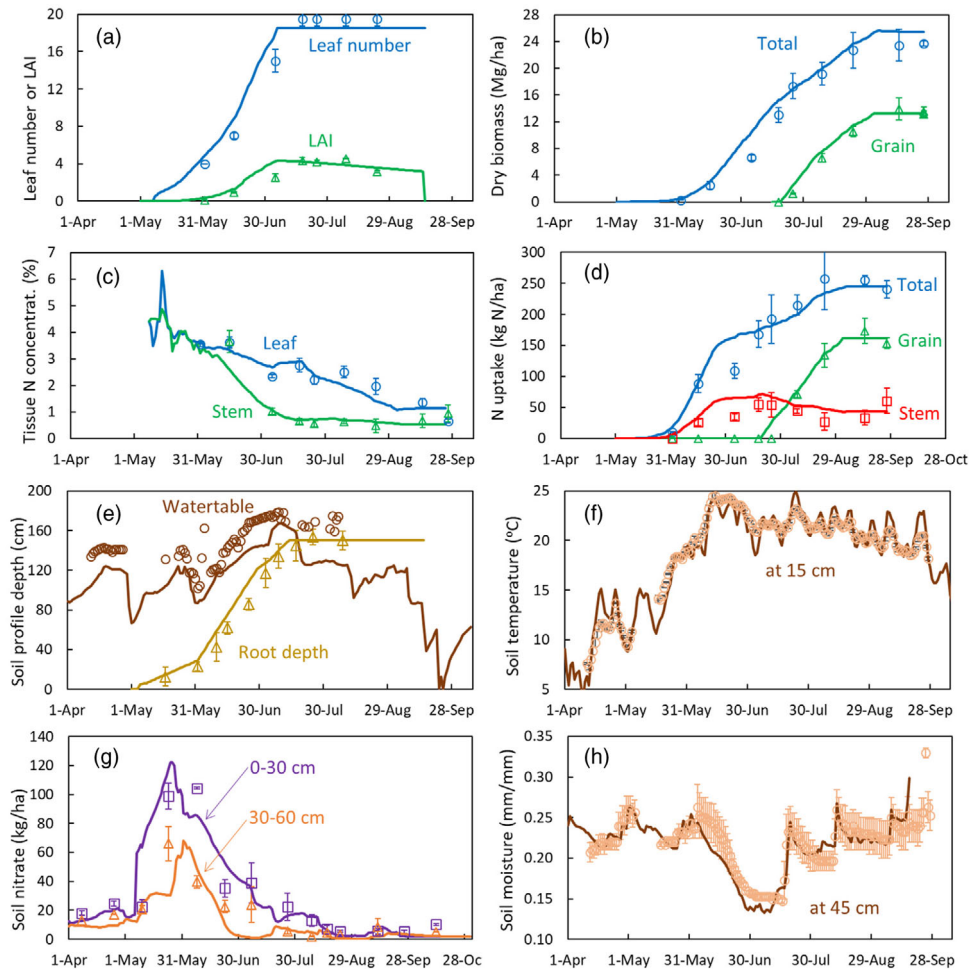
In the case of soil nitrate prediction in maize (0–30 cm depth; average of multiple predictions during summer time), we found that the contribution of unknown factors was only 8%. This shows that the model is even less sensitive than maize yield to the unknown weather during the season, which is an encouraging result for model use to assist in-season N management decisions. For soil N prediction, the model was most sensitive to initial conditions, namely initial soil nitrate, initial soil water, and previous crop roots CN ratio, which are all partially known factors (Figure 4; Supplemental Table S7).

The sensitivity analysis revealed four additional major results. First, different model output variables have different sensitivities to model input variables or parameters (see also

Supplemental Figure S5 for phenology and crop N uptake results). Second, depth to water table was more important than summer precipitation for prediction of crop yield and N uptake. Third, model initial conditions on 1 January (water and nitrate in the soil profile, residue amount and CN ratio, and previous crop roots amount and CN) accounted for 13, 37, and 25% of the total sensitivity in maize yield, soil nitrate and N uptake predictions, respectively. The soybean model predictions were less sensitive to initial conditions than maize. Fourth, management information such as N-rate, N-timing, N-application depth, planting depth, plant density, and tillage accounted for 10, 22, and 16% of the total sensitivity in maize yield, soil nitrate, and N uptake predictions, respectively.

### 3.2 | Evaluating model performance in simulating soil and crop variables

The model performed well in simultaneously simulating many crop and soil variables as indicated by the slope of the  $y = ax$  regression that averaged at  $0.98 \pm 0.07$  and other statistical indices presented in Table 1. The corresponding graphs are



**FIGURE 5** Measured (points) versus simulated (lines) leaf number and leaf area index (a), total aboveground biomass and grain yield accumulation (b), leaf and stem nitrogen concentration (c), total, stem and grain N uptake (d), depth to the water table and root depth (e), soil temperature (f), soil nitrate (g) and soil moisture (h) for one of the 94 datasets. This example refers to Boone location, year 2016, maize crop, early planted treatment (see ID #8 in Supplemental Table S1)

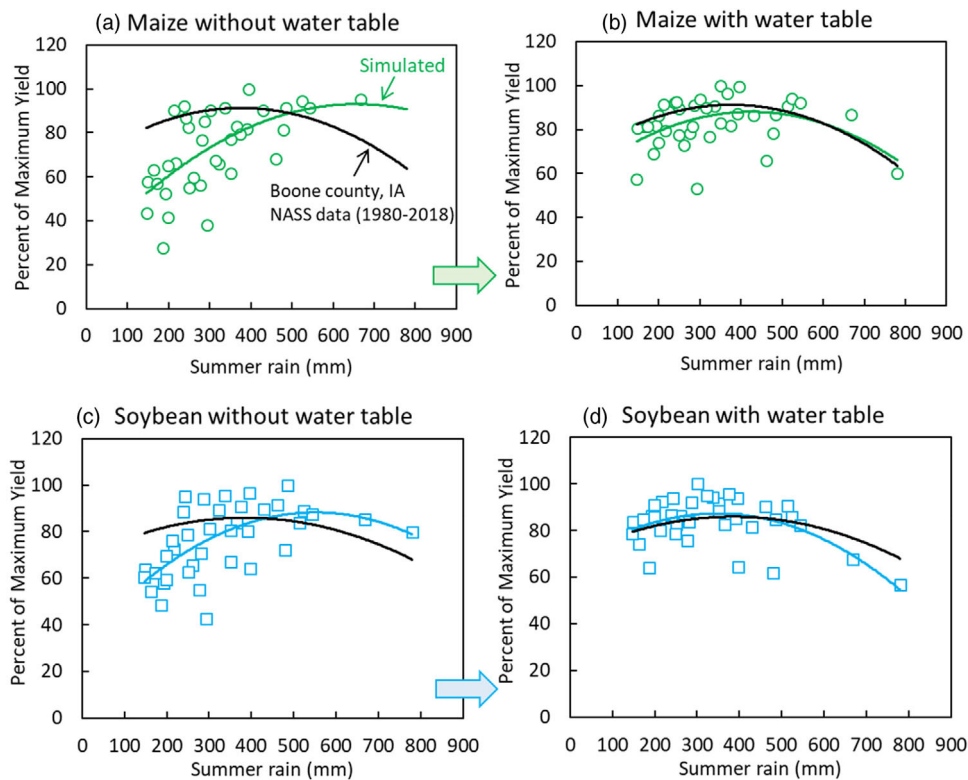
provided in supplementary materials (Supplemental Figures S7–S26), while for one of the 94 test plots the time series results are presented in Figure 5. Across all test plots, the mean RRMSE was 25% and it was lowest in leaf number prediction and highest in soil N prediction (Table 1). The leaf number is simple to predict because it is mainly driven by temperature and crop parameters. On the other hand, soil N is complex to predict because it depends on many soil-crop processes, and measurements have large uncertainty and error. In terms of  $R^2$  and ME, the simulation of soil moisture and water table depth had the lowest values compared to crop variables such as biomass production (Table 1). Note that we ran the model assuming uniformity among replications.

Our systems analysis revealed that an over- or under-estimation of one crop variable had cascading effects on other variables. For example, Figure 5 shows that APSIM overestimated maize leaf number on 7 July 2016. This resulted in an overestimation in leaf area index, biomass production, and total N uptake on that date. Either the model

did not capture well a phenomenon that occurred prior to that date or there was a measurement error. This example shows how such multi-faceted data can stimulate systems thinking and further improvements to the model and detection of measurement errors.

### 3.3 | The impact of water table on yield prediction

The inclusion of the water table in the simulation process coupled with waterlogging functions provided a yield credit in dry years (precipitation <300 mm) and a yield penalty in wet years (precipitation >500 mm; Figure 6). Overall simulations including the water table improved maize and soybean yield response to summer precipitation compared to the simulations without the water table (Figure 6). In wet years, the yield penalty caused by the inhibition of root depth and also by increased N loss from the system (see Supplemental Figure



**FIGURE 6** Simulated maize and soybean yield response to summer precipitation in central Iowa with and without including water table impacts on the simulation process. Black line refers to the normalized NASS yield data for this county, which were used as benchmark

**TABLE 2** Simulated yields (0% moisture) with and without water table in central Iowa, Boone county

Simulation	Average yield (1980-2018)		Coefficient of variation	
	Maize	Soybean	Maize	Soybean
	Mg/ha		%	
With water table	13.02	3.87	13	12.1
Without water table	11.70	3.43	26	19.6

S6). In dry years, the yield credit caused by the water uptake from the deep soil layers (data not shown). On average, the simulations including the water table increased mean simulated yields over 38-yr period by 12% and decreased year-by-year yield variability by 50% in both crops (Table 2).

## 4 | DISCUSSION

### 4.1 | Ten lessons learned by performing in-season yield and soil N predictions

First, it is critical that crop models include waterlogging functions and being able to simulate shallow water table in Iowa and similar temperate humid regions with shallow water tables, which account for >100 million ha of the global arable land (Fan et al., 2013; Schultz et al., 2007; Supplemental Figure S1); otherwise, predictions will be mostly accurate in aver-

age weather years (Figure 6). This was particularly noticeable in years 2016 and 2017 in central Iowa in which crops did not receive precipitation for almost 30 days during critical growth periods (Supplemental Table S3) and still produced high yields. Previous simulation analysis indicated that the water table provided a yield benefit of 26% in maize and 17% in soybean (see details in Archontoulis et al., 2017). Rizzo et al. (2018) reached a similar conclusion about the contribution of water table to yield and yield stability across the Corn Belt. In this study, we made significant progress to improve understanding and simulation of water table fluctuations across different soil types. The inclusion of water table improved yield response to precipitation (Figure 6; Supplemental Figure S5); something that was recently found to be a limitation in many crop models (Li et al., 2019; Kimball et al., 2019). In general, the simulation of water table in crop models has not received attention in the past, but current results suggest that it should be prioritized for even better prediction of

soil-crop processes in the US Corn Belt. Yet, several knowledge gaps still remain. For example, how do we set up sub-soil hydrological parameters across the landscape? How deep should a soil profile be defined to enable accurate simulation of a water table? Besides root growth, what other processes are affected by the water table and in which direction? Answers to the above questions can help guide improvements to the prediction accuracy and scalability of crop models to simulate regional scale impacts.

Second, many different factors affect yield and soil-plant N predictions (see sensitivity analysis; Figure 4; Supplemental Figure S5). Some of these factors, especially initial conditions, are typically ignored in data collection protocols, but are important and, once integrated with other model inputs, account for a large share of the total variance. By quantifying more inputs to the model, prediction accuracy will increase. Future measurement protocols should consider a systems approach like the one we followed in this project (and not just measuring one trait, e.g. yield or leaf N) towards developing datasets that can support enhancements or development of better prediction models.

Third, the accuracy of the management information is very important for accurate model predictions as it accounted for 10–26% of the total sensitivity in maize yield, soil nitrate and crop N uptake predictions at planting. For reference, we found a 3% and 14% deviation between target plant population (used as model inputs to predict yields at planting) and measured plant counts later in the season for maize and soybean crops, respectively (Figure 1). Lowering this deviation is beneficial for modeling (Figure 4a; Supplemental Figure S4).

Fourth, if the model accurately predicts early-season trajectories (Figure 2a; Supplemental Figure S3), the chances for an accurate end-of-season prediction are high. If not, the chances for an accurate prediction are very low. Thus, attention should be placed early in the season on how the model is performing in terms of biomass and leaf area index simulation as well as soil nitrogen and water. Coupling simulation models with remote sensing, soil-plant sensors or field observations, can improve predictive ability (Anderson et al., 2019; Lawes et al., 2019).

Fifth, although we expected the RRMSE to decrease during the season as more weather information became available, this was not the case; in contrast, the median yield prediction at planting was the second most accurate prediction after the prediction at physiological maturity (Figure 3). Similar results were found by Puntel et al. (2018) in central Iowa who ran the APSIM model without reset for 20 years. The June and July yield predictions were sensitive to short-term weather variability and were, in general less accurate (Figure 2b). We believe the relatively low RRMSE and thus high prediction accuracy in May is due to the low share of the unknown factors (summer weather) to the total yield sensitivity in this region (Figure 4). Of particular note is the ranking of the summer pre-

cipitation in the sensitivity analysis (Figure 4; Supplemental Figure S5); it was below the ranking of the water table depth. This suggests that the water table depth is a more important determinant of grain yield than the summer precipitation in this environment. This agrees with Williams et al. (2008) who analyzed 12 county-level climatic, edaphic, and topographic environmental characteristics and found the depth to the water table and soil organic matter to explain most of the yield variability in Iowa. However, in environments without water table influence, we believe the yield will be more sensitive to the growing season precipitation, and perhaps the uncertainty and RRMSE of the yield prediction at planting time will be higher than that observed in this study (Hammer et al., 1996; Nosetto et al., 2009). To test this, we reran the sensitivity analysis but without including water tables (data not shown). We found that water tables decrease model's sensitivity to summer precipitation by 50% in maize yield prediction (sensitivity index decreased from 0.12 to 0.06) and by 64% in soybean yield prediction (sensitivity index decreased from 0.17 to 0.06). Thus, the water table buffers the crop to variation in summer precipitation and reduces model sensitivity to unknown summer weather.

Sixth, in addition to existing model algorithm enhancements (e.g. maize N dynamics, Soufizadeh et al., 2018; grain growth dynamics, Messina et al., 2019) equal emphasis should be placed on adding new functions into the models to account for non-biophysical factors such as herbicide or hail damage. In this study, we had issues with temporal foliage damage caused by herbicides applied to soybeans. Once we implemented an ad-hoc fix, the model matched experimental observations and increased accuracy. More universal rules and specific measured data are needed to better model such phenomena. Inclusion of such small modifications to simulation platforms will greatly increase applicability of today's crop models to real-world conditions.

Seventh, we noticed that model prediction accuracy increased in high-yielding locations and also in locations with low measurement error (less yield variability from replication to replication; Figure 3). This is because APSIM can capture weather and soil water/nitrogen related growth limiting factors but not all of the limiting factors that are probably evident in low yielding locations, and thus the obtained gradient in prediction accuracy across yielding environments. To address the yield variability from plot to plot (note that some plots were big, i.e. >1,000 m<sup>2</sup>), running the model for every replication or by including sub-field variability may be a better approach towards increasing prediction accuracy. Of course, this comes with additional computation cost and need for more precise inputs and better characterization of the environments.

Eighth, consistent with Togliatti et al. (2017), the short-term weather forecast (Supplemental Figure S2) added little value to end-of-season yield predictions but did add value in

planning short-term field operations. The long-term weather forecast from the CFS model (6-month) was quite variable with rapid changes from day to day (data not shown), and thus its use was constrained to represent one of the 35 weather historical years used in the ensemble approach (Figure 2). Recently Puntel et al. (2018) found that the more historical weather years included in the ensemble, the higher the prediction accuracy, with a minimum of 20 years for accurate yield predictions in this region. Similar results have been reported for different environments (Grassini et al., 2015).

Ninth, the dissemination of yield, phenology, soil water and N predictions in a publicly available website during the growing season indicated two times more web visits in June than in August. Thus, early-season crop model predictions are the most valuable for US farmers because this time period coincides with important management decisions and also with high market prices due to weather uncertainty. Between, actual predictions and benchmarking predictions (e.g. percent yield or soil N above or below normal with normal being a 35-yr average), the benchmarking approach was easier for the users to interpret and extrapolate results to their own operations. The what-if model scenario analysis (after crop harvest), which was presented at extension conferences, generated significant discussion and interest by the farmers (Archontoulis et al., 2016). Over the 4-yr period, we learned that the what-if questions and interests that farmers had after crop harvest were different every year and driven by the main yield limiting factors that occurred during the growing season. For instance, in 2016, the scenarios were around crop management. In 2017, a dry year, the scenarios were around water stress. In 2018, a wet year, the scenarios were around N rate, timing and leaching.

Tenth, the APSIM software platform was found to account for and simulate well the most important soil and crop processes (Table 1; Supplemental Figures S7–S26). Presumably, that is because of the evolution of crop models over the past decades to be more soil-centric and thus broader in the science they contain and the problems to which they can be applied (Keating & Thorburn, 2018). Of particular note is the flexibility that this platform offers to set up various management options and simulate water tables. We made improvements to APSIM models and identified other processes that may benefit from further improvements (see above section on water tables). We found that the model simulated biomass and yields more accurately ( $R^2 = 0.84\text{--}0.94$ ) than leaf area index and leaf N concentration ( $R^2 = 0.33\text{--}0.79$ ; Table 1). The latter could be evidence that both model processes may require further improvements, although it should be noted that the measurement error is high because is difficult to accurately separate senesced from green portions within leaves.

## 4.2 | How does our approach compare with those of others?

We simulated a water- and N-limited production situation and accounted for water table impacts. Thus, our approach is very complex but also comprehensive as it accounts for many different aspects of the cropping system. For reference, previous maize yield predictions in the US Corn Belt using the Hybrid-maize model considered only water-limited situations without accounting for water tables (Morell et al., 2016). Compared to Australia's wheat yield predictions (Carberry et al., 2009) using the APSIM model, our approach was similar, but had two key differences: (1) we started the model approximately four months prior to planting (1 January) and not at planting time; and (2) we included a weather forecast component in addition to the current and historical weather. Our choice to start the model on 1 January and not at planting was to reduce the model sensitivity to initial conditions. Initializing the model at previous crop harvest (approximately 15 October) or even running the model sequentially without initialization are other options to explore in the future.

Compared to remote sensing and machine learning yield prediction approaches, the benefit of our approach is that in addition to crop yields, the model can provide actual data on soil water and N (for different soils depths) that cannot be predicted by remote sensing. Most importantly, simulation models can be used to conduct what-if scenario analyses to learn from the past (see ninth lesson in Section 4.1 above) to better design the future. In contrast to commercial N decision tools such as Adapt-N (Sela et al., 2016) and others (FieldView, Encirca), our aim was not to make specific input recommendations but instead to provide useful data to stakeholders to make informed decisions.

In the future, the whole system can be re-designed to address specific management questions, provide scenarios for preplant decisions, and regional scale forecasts. For the preplant decisions, a recent study found that coupling APSIM with machine learning (creation of a meta-model) to be a more cost-, time-, and scale-effective approach than using crop modeling alone (Shahhoseini et al., 2019). Lastly, in the future the destructive measurements can be replaced with real-time sensing of soil and crop conditions to inform model initial conditions.

## 5 | CONCLUSIONS

This manuscript laid the groundwork for future forecasting and research applications of the APSIM model in the US Corn Belt by providing a comprehensive evaluation of many crop and soil processes included in the model and by developing prediction protocols. Of importance was the good prediction

of grain yield at planting time and of soil N dynamics throughout the growing season. Together these two aspects can assist growers with N management decisions. More accurate predictions will likely result from improving the quality of data inputs to the model (especially initial conditions and precision of management data as together accounted for nearly one-fourth of the variation in maize yield), further enhancing model algorithms, and including sub-field variability. Links between crop modeling and remote sensing and soil-plant sensors can assist in this direction. Lastly, in this region, the existence of a shallow water table had a substantial influence on yield and soil N predictions, and more research is needed in this area to fully understand and predict water table impacts. Thus, model set up becomes very critical to accurately predict crop and environmental aspects in the US Corn Belt.

## ACKNOWLEDGEMENTS

This work was sponsored by Iowa Soybean Association, Foundation for Food and Agricultural Research (Grant #534264), Iowa Crop Improvement Association, NSF (#1830478, #1842097), USDA (2019-67019-29404), USDA Hatch projects (IOW10480, IOW04414), Iowa Nutrient Reduction Center, Iowa State University Plant Sciences Institute, Department of Agronomy, and Agriculture and Natural Resources Extension. We thank Dean Holzworth and Neil Huth from CSIRO for their support with the APSIM model, Iowa State University students (Alyssa Waldschmidt, Gretchen Kooyenga, Ben Ng, Oluwakorede Olugbenle, Emily Marrs, Jenny Jensen, Jake Smith, Caitlin Cervac) and farm managers (Josh Sievers, Ryan Rusk, Terry Tuttle, Matt Schnabel, Ken Pecinovsky, Mike Fiscus, Nathan Meyer, Myron Rees, Cody Schneider, Dominic Snyder, Gary Thompson, John Beckman) for assistance with data collection and managing the field experiments. We also thank the APSIM Initiative for making the software publicly available and for ensuring software quality.

## ORCID

Sotirios V. Archontoulis 

<https://orcid.org/0000-0001-7595-8107>

Mark A. Licht  <https://orcid.org/0000-0001-6640-7856>

Kendall R. Lamkey 

<https://orcid.org/0000-0001-8510-8798>

## REFERENCES

- Anderson, II, S. L., Murray, S. C., Malambo, L., Ratcliff, C., Popescu, S., Cope, D., ... Thomasson, J. A. (2019). Prediction of maize grain yield before maturity using improved temporal height estimates of unmanned aerial systems. *The Plant Phenome Journal*, 2, 190004. <https://doi.org/10.2135/tppj2019.02.0004>
- Archontoulis, S. V., & Miguez, F. E. (2015). Nonlinear regression models and applications in agricultural research. *Agronomy Journal*, 107, 786–798. <https://doi.org/10.2134/agronj2012.0506>
- Archontoulis, S. V., & Licht, M. (2016). A web platform for Forecasting and Assessment of Cropping sysTEms (FACTS). Integrated Crop Management Newsletter, Iowa State University. Retrieved from <http://crops.extension.iastate.edu/facts/>
- Archontoulis, S.V., Licht, M., Castellano, M., Dietzel, R., VanLoocke, A., Ordonez, R., ... Helmers, M. (2016). Understanding the 2016 yields and interactions between soils, crops, climate and management. In Proceedings of the 28<sup>th</sup> ICM conference (pp. 13–17). November 30–December 1, 2016. Ames, IA: ICM.
- Archontoulis, S. V., Miguez, F. E., & Moore, K. J. (2014b). A methodology and an optimization tool to calibrate phenology of short-day species included in the APSIM PLNAT model: Application to soybean. *Environmental Modeling and Software*, 62, 465–477. <https://doi.org/10.1016/j.envsoft.2014.04.009>
- Archontoulis, S. V., Miguez, F. E., & Moore, K. J. (2014). Evaluating APSIM maize, soil water, soil nitrogen, manure and soil temperature modules in the Midwestern United States. *Agronomy Journal*, 106, 1025–1040. <https://doi.org/10.2134/agronj2013.0421>
- Archontoulis, S. V., Licht, M., Castellano, M., Ordóñez, R. A., Iqbal, J., Martinez-Feria, R., ... Helmers, M. (2017). Water availability, root depths and 2017 crop yields. In Proceedings of the 29<sup>th</sup> ICM conference (pp. 25–33). November 29–30, 2017. Ames, IA: ICM.
- Atzberger, C. (2013). Advances in remote sensing of agriculture: Context description, existing operational monitoring systems and major information needs. *Remote Sensing*, 5, 949–981. <https://doi.org/10.3390/rs5020949>
- Balboa, G. R., Sandras, V., & Ciampitti, I. (2018). Shifts in soybean yield, nutrient uptake and nutrient stoichiometry: A historical systems-analysis. *Crop Science*, 58, 43–54. <https://doi.org/10.2135/cropsci2017.06.0349>
- Basso, B., & Liu, L. (2019). Seasonal crop yield forecast: Methods, applications, and accuracies. *Advances in Agronomy*, 154, 201–255. <https://doi.org/10.1016/bs.agron.2018.11.002>
- Basso, B., Cammarano, D., & Carfagna, E. (2013). Review of crop yield forecasting methods and early warning systems. In Proceedings of the First Meeting of the Scientific Advisory Committee of the Global Strategy to Improve Agricultural and Rural Statistics. Rome, Italy: FAO.
- Basso, B., Chou, T. Y., Chihyuan, C., & Meiling, Y. (2012). i-Salus: New web based spatial systems for simulating crop yield and environmental impact. In Proc. Inter. Conf. Precision Agriculture. Indianapolis: International Society of Precision Agriculture.
- Brandes, E., McNunn, G. S., Schulte, L. A., Bonner, I. J., Muth, D. J., Babcock, B. A., ... Heaton, E. A. (2016). Subfield profitability analysis reveals an economic case for cropland diversification. *Environmental Research Letters*, 11, 014009. <https://doi.org/10.1088/1748-9326/11/1/014009>
- Campbell, G. S. (1985). *Soil physics with BASIC. Transport models for soil-plant systems. Vol. 14*. Amsterdam, The Netherlands: Elsevier Science Publishers B.V.
- Carberry, P. S., Hochman, Z., Hunt, J. R., Dalgliesh, N. P., McCown, R. L., & Whish, J. P. M. (2009). Re-inventing model-based decision support with Australian dryland farmers. 3. Relevance of APSIM to commercial crops. *Crop and Pasture Science*, 60, 1044–1056. <https://doi.org/10.1071/CP09052>

- Ciampitti, I. A., & Vyn, T. J. (2012). Physiological perspectives of changes over time in maize yield dependency on nitrogen uptake and associated nitrogen efficiencies: A review. *Field Crops Research*, *133*, 48–67. <https://doi.org/10.1016/j.fcr.2012.03.008>
- Córdova, S. C., Castellano, M. J., Dietzel, R., Licht, M., Togliatti, K., Martínez-Feria, R., & Archontoulis, S. V. (2019). Soybean nitrogen fixation dynamics in Iowa. *Field Crops Research*, *236*, 165–176.
- Dietzel, R., Liebman, M., Ewing, R., Helmers, M., Horton, R., Jarchow, M., & Archontoulis, S.V. (2016). How efficiently do corn- and soybean-based cropping systems use water? A systems modeling analysis. *Global Change Biology*, *22*, 666–681.
- Ebrahimi-Mollabashi, E., Huth, N. I., Holzwoth, D. P., Ordóñez, R. A., Hatfield, J. L., Huber, I., ... Archontoulis, S. V. (2019). Enhancing APSIM to simulate excessive moisture effects on root growth. *Field Crops Research*, *236*, 58–67.
- Fan, Y., Li, H., & Miguez-Macho, G. (2013). Global patterns of groundwater. *Science*, *339*, 940–943.
- Fehr, W. R., & Caviness, C. E. (1977). Stages of soybean development. Special Report 87. Retrieved from <http://lib.dr.iastate.edu/specialreports/87>
- Feng, P., Wang, B., Liu, D. L., Waters, C., & Yue, Q. (2019). Incorporating machine learning with biophysical model can improve the evaluation of climate extremes impacts on wheat yield in south-eastern Australia. *Agricultural and Forest Meteorology*, *275*, 100–113. <https://doi.org/10.1016/j.agrformet.2019.05.018>
- Grassini, P., van Bussel, L. G. J., Van Wart, J., Wolf, J., Claessens, L., H. Yang, ... van Ittersum, M. K., & Cassman, K.G. (2015). How good is good enough? Data requirements for reliable crop yield simulations and yield-gap analysis. *Field Crops Research*, *177*, 49–63. <https://doi.org/10.1016/j.fcr.2015.03.004>
- Hamby, D. M. (1994). A review of techniques for parameter sensitivity analysis of environmental models. *Environmental Monitoring and Assessment*, *32*, 135–154. <https://doi.org/10.1007/BF00547132>
- Hammer, G. L., Holzworth, D. P., & Stone, R. C. (1996). The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability. *Australian Journal of Agricultural Research*, *47*, 717–737. <https://doi.org/10.1071/ar9960717>
- Hammer, G. L., Dong, Z., McLean, G., Doherty, A., Messina, C., Schussler, J., ... Cooper, M. (2009). Can changes in canopy and/or root system architecture explain historical maize yield trends in the US Corn Belt? *Crop Science*, *49*, 299–312. <https://doi.org/10.2135/cropsci2008.03.0152>
- Hansen, J. W., Potgieter, A., & Tippett, M. (2004). Using a general circulation model to forecast regional wheat yields in North-east Australia. *Agricultural and Forest Meteorology*, *127*, 77–92. <https://doi.org/10.1016/j.agrformet.2004.07.005>
- Hansen, J. W., & Indeje, M. (2004). Linking dynamic seasonal climate forecasts with crop simulation for maize yield prediction in semi-arid Kenya. *Agricultural and Forest Meteorology*, *125*, 143–157. <https://doi.org/10.1016/j.agrformet.2004.02.006>
- Holzworth, D. P., Huth, N. I., deVoil, P. G., Zurcher, E. J., Herrmann, N. I., McLean, G., ... Keating, B. A. (2014). APSIM-evolution towards a new generation of agricultural systems simulation. *Environmental Modelling & Software*, *62*, 327–350.
- Hood-Nowotny, R., Umana, N. H. N., Inselbacher, E., Oswald-Lachouani, P., & Wanek, W. (2010). Alternative methods for measuring inorganic, organic, and total dissolved nitrogen in soil. *Soil Science Society of America Journal*, *74*, 1018–1027. <https://doi.org/10.2136/sssaj2009.0389>
- Huth, N. I., Bristow, K. L., & Verburg, K. (2012). SWIM3: Model use, calibration, and validation. *Transactions of the American Society of Agricultural Engineers*, *55*, 1303–1313. <https://doi.org/10.13031/2013.42243>
- Ines, A. V., Das, N. N., Hansen, J. W., & Njoku, E. G. (2013). Assimilation of remotely sensed soil moisture and vegetation with a crop simulation model for maize yield prediction. *Remote Sensing of Environment*, *138*, 149–164. <https://doi.org/10.1016/j.rse.2013.07.018>
- Iowa Environmental Mesonet. (2019). *Iowa Ag Climate Network*. Ames, IA: Iowa State University. <https://mesonet.agron.iastate.edu/agclimate/>
- Johnson, M. D., Hsieh, W. W., Cannon, A. J., & Davidson, A. (2016). Crop yield forecasting on the Canadian prairies by remotely sensed vegetation indices and machine learning methods. *Agricultural and Forest Meteorology*, *218–219*, 74–84. <https://doi.org/10.1016/j.agrformet.2015.11.003>
- Jones, J. W., Antle, J. M., & Basso, B. (2017). Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agricultural Systems*, *155*, 269–288. <https://doi.org/10.1016/j.agry.2016.09.021>
- Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., ... Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy*, *18*, 267–288. [https://doi.org/10.1016/s1161-0301\(02\)00108-9](https://doi.org/10.1016/s1161-0301(02)00108-9)
- Keating, B. A., & Thorburn, P. J. (2018). Modeling crops and cropping systems – Evolving purpose, practice and prospects. *European Journal of Agronomy*, *100*, 163–176. <https://doi.org/10.1016/j.eja.2018.04.007>
- Kimball, B. A., Boote, K. J., Hatfield, J. L., Ahuja, L. R., Stockle, C., Archontoulis, S., ... Williams, K. (2019). Simulation of maize evapotranspiration: An inter-comparison among 29 maize models. *Agricultural and Forest Meteorology*, *271*, 264–284. <https://doi.org/10.1016/j.agrformet.2019.02.037>
- Lawes, R. A., Oliver, Y. M., & Huth, N. I. (2019). Optimal nitrogen rate can be predicted using average yield and estimates of soil water and leaf nitrogen with infield experimentation. *Agronomy Journal*, *111*, 1–10.
- Lenhart, T., Eckhardt, K., Fohrer, N., & Frede, H. G. (2002). Comparison of two different approaches of sensitivity analysis. *Physics and Chemistry of the Earth, Parts A/B/C*, *27*, 645–654. [https://doi.org/10.1016/S1474-7065\(02\)00049-9](https://doi.org/10.1016/S1474-7065(02)00049-9)
- Li, Y., Guan, K., Schnitkey, G. D., DeLucia, E., & Peng, B. (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. *Global Change Biology*, *25*, 2325–2337. <https://doi.org/10.1111/gcb.14628>
- Lobell, D. B., Thau, D., Seifert, C., Engle, E., & Little, B. (2015). A scalable satellite-based crop yield mapper. *Remote Sensing of Environment*, *164*, 324–333. <https://doi.org/10.1016/j.rse.2015.04.021>
- Mallarino, A. P., Sawyer, J. E., & Barnhart, S. K. (2013). *A general guide for crop nutrient and limestone recommendations in Iowa*. PM 1688. Ames, IA: Iowa State Univ. Ext. and Outreach.
- Malone, R. W., Huth, N., Carberry, P. S., Ma, L., Kaspar, T. C., Karlen, D. L., ... Heilman, P. (2007). Evaluating and predicting agricultural management effects under tile drainage using modified APSIM. *Geoderma*, *140*, 310–322. <https://doi.org/10.1016/j.geoderma.2007.04.014>



- Martinez-Feria, R., Castellano, M., Dietzel, R., Helmers, M., Liebman, M., Huber, I., & Archontoulis, S. V. (2018). Linking crop- and soil-based approaches to evaluate system nitrogen-use efficiency and tradeoffs. *Agriculture, Ecosystems & Environment*, *256*, 131–143. <https://doi.org/10.1016/j.agee.2018.01.002>
- Messina, C., Hammer, G., McLean, G., Cooper, M., van Oosterom, E., Tardieu, F., ... Gho, C. (2019). On the dynamic determinants of reproductive failure under drought in maize. *In Silico Plants*, *1*. <https://doi.org/10.1093/insilicoplants/diz003>
- Morell, F. J., Yang, H. S., Cassman, K. G., Wart, J. V., Elmore, R. W., & Licht, M. (2016). Can crop simulation models be used to predict local to regional maize yields and total production in the US Corn Belt? *Field Crops Research*, *192*, 1–12. <https://doi.org/10.1016/j.fcr.2016.04.004>
- NASS. (2019). Surveys. National Agricultural Statistics Service, USDA. <https://www.nass.usda.gov/Surveys/>
- Nichols, V., Ordóñez, R. A., Castellano, M. J., Liebman, M., Hatfield, J. L., Helmers, M., ... Archontoulis, S. V. (2019). Vertical distribution of maize and soybean roots in Iowa, USA. *Plant and Soil*, *444*, 225–238.
- Nosetto, M. D., Jobbágy, E. G., Jackson, R. B., & Sznajder, G. A. (2009). Reciprocal influence of crops and shallow ground water in sandy landscapes of the Inland Pampas. *Field Crops Research*, *113*, 138–148. <https://doi.org/10.1016/j.fcr.2009.04.016>
- Ordóñez, R. A., Castellano, M., Hatfield, J., Helmers, M., Licht, M., Liebman, M., ... Archontoulis, S. V. (2018). Corn and soybean root front velocity and maximum depth in Iowa, USA. *Field Crops Research*, *215*, 122–131. <https://doi.org/10.1016/j.fcr.2017.09.003>
- Ordóñez, R. A., Castellano, M., Hatfield, J., Licht, M., Wright, E., & Archontoulis, S. V. (2018). A solution for sampling position errors in maize and soybean root mass and length estimates. *European Journal of Agronomy*, *96*, 156–162. <https://doi.org/10.1016/j.eja.2018.04.002>
- Peng, B., Guan, K., Chen, M., Lawrence, D. M., Pokhrel, Y., Suyker, A., & Lu, Y. (2018). Improving maize growth processes in the community land model: Implementation and evaluation. *Agricultural and Forest Meteorology*, *250–251*, 64–89. <https://doi.org/10.1016/j.agrformet.2017.11.012>
- Prasad, A. K., Chai, L., Singh, R. P., & Kafatos, M. (2006). Crop yield estimation model for Iowa using remote sensing and surface parameters. *International Journal of Applied Earth Observation and Geoinformation*, *8*, 26–33. <https://doi.org/10.1016/j.jag.2005.06.002>
- Probert, M. E., Dimes, J. P., Keating, B. A., Dalal, R. C., & Strong, W. M. (1998). APSIM's water and nitrogen modules and simulation of the dynamics of water and nitrogen in fallow systems. *Agricultural Systems*, *56*, 1–28. [https://doi.org/10.1016/s0308-521x\(97\)00028-0](https://doi.org/10.1016/s0308-521x(97)00028-0)
- Puntel, L. A., Sawyer, J. E., Barker, D. W., Thorburn, P. J., Castellano, M., Moore, K. J., ... Archontoulis, S. V. (2018). A systems modeling approach to forecast corn economic optimum nitrogen rate. *Frontiers in Plant Science*, *9*, 436. <https://doi.org/10.3389/fpls.2018.00436>
- R Core Team. (2013). *R: A language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing. <http://www.R-project.org>.
- Rizzo, G., Edreira, J. R., Archontoulis, S. V., Yang, H., & Grassini, P. (2018). Do shallow water tables contribute to high and stable maize yields in the US Corn Belt? *Global Food Security*, *18*, 27–34. <https://doi.org/10.1016/j.gfs.2018.07.002>
- Ritchie, S. W., & Hanway, J. J. (1982). How a Corn Plant Develops. Special Report No. 48. Ames, IA: Iowa State University of Science and Technology, Cooperative Extension Service.
- Rosenzweig, C., Tubiello, F. N., Goldberg, R., Mills, E., & Bloomfield, J. (2002). Increased crop damage in the US from excess precipitation under climate change. *Global Environmental Change*, *12*, 197–202. [https://doi.org/10.1016/s0959-3780\(02\)00008-0](https://doi.org/10.1016/s0959-3780(02)00008-0)
- Rötter, R. P., Appiah, M., Fichtler, E., Kersebaum, K. C., Trnka, M., & Hoffmann, M. P. (2018). Linking modelling and experimentation to better capture crop impacts of agroclimatic extremes—A review. *Field Crops Research*, *221*, 142–156. <https://doi.org/10.1016/j.fcr.2018.02.023>
- Sawyer, J., Nafziger, E., Randall, G., Bundy, L., Rehm, G., & Joern, B. (2006). *Concepts and rationale for regional nitrogen guidelines for corn*, PM2015. Ames, IA: Iowa State University Extension.
- Saxton, K. E., & Rawls, W. J. (2006). Soil water characteristic estimates by texture and organic matter for hydrologic solutions. *Soil Science Society of America Journal*, *70*, 1569–1578. <https://doi.org/10.2136/sssaj2005.0117>
- Sela, S., Van Es, H. M., Moebius-Clune, B. N., Marjerison, R., Melkonian, J., Moebius-Clune, D., ... Gomes, S. (2016). Adapt-N outperforms grower-selected nitrogen rates in northeast and midwestern United States strip trials. *Agronomy Journal*, *108*, 1726–1734. <https://doi.org/10.2134/agronj2015.0606>
- Shahhoseini, M., Martinez-Feria, R., Hu, G., & Archontoulis, S. V. (2019). Maize yield and nitrate loss prediction with machine learning algorithms. *Environmental Research Letters*, *14*, 124026.
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Wang, W., & Powers, J. G. (2008). *A description of the Advanced Research WRF version 3*. NCAR Technical Note. Boulder, CO: University Corporation for Atmospheric Research.
- Shaw, R. E., & Meyer, W. S. (2015). Improved empirical representation of plant responses to waterlogging for simulating crop yield. *Agronomy Journal*, *107*, 1711–1723. <https://doi.org/10.2134/agronj14.0625>
- Soil Survey Staff. (2019). *Soil survey geographic (SSURGO) database*. Washington, DC: USDA Natural Resources Conservation Service. [https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2\\_053627](https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_053627)
- Soufizadeh, S., Munaro, E., McLean, G., Massignam, A., van Oosterom, E. J., Chapman, S. C., ... Hammer, G. L. (2018). Modelling the nitrogen dynamics of maize crops – enhancing the APSIM maize model. *European Journal of Agronomy*, *100*, 118–131. <https://doi.org/10.1016/j.eja.2017.12.007>
- Schultz, B., Zimmer, D., & Vlotman, W. (2007). Drainage under increasing and changing requirements. *Irrigation and Drainage*, *56*, 3–22. <https://doi.org/10.1002/ird.372>
- Thorburn, P. J., Probert, M. E., & Robertson, F. A. (2001). Modelling decomposition of sugarcane surface residues with APSIM-Residue. *Field Crops Research*, *70*, 223–232.
- Togliatti, K., Archontoulis, V. S., Dietzel, R., Puntel, L. A., & Van-Loecker, A. (2017). How does inclusion of weather forecasting impact in-season crop model predictions? *Field Crops Research*, *214*, 261–272. <https://doi.org/10.1016/j.fcr.2017.09.008>
- Tollenaar, M., Fridgen, J., Tyagi, P., Stackhouse, P. W. Jr., & Kumudini, K. (2017). The contribution of solar brightening to the US maize yield trend. *Nature Climate Change*, *7*, 275–278. <https://doi.org/10.1038/NCLIMATE3234>
- van der Velde, M., Tubiello, F. N., Vrieling, A., & Bouraoui, F. (2012). Impacts of extreme weather on wheat and maize in France: Evaluating regional crop simulations against observed data. *Climatic*

- Change*, 113, 751–765. <https://doi.org/10.1007/s10584-011-0368-2>
- Wang, E., & Smith, C. J. (2004). Modelling the growth and water uptake function of plant root systems: A review. *Crop Pasture Science*, 55, 501–523.
- Warren, J. M., Hanson, P. J., Iversen, C. M., Kumar, J., Walker, A. P., & Wullschleger, S. D. (2015). Root structural and functional dynamics in terrestrial biosphere models evaluation and recommendations. *New Phytologist*, 205, 59–78. <https://doi.org/10.1111/nph.13034>
- Wickham, H. (2017). tidyverse: Easily install and load the ‘Tidyverse’. R package (Version 1.2.1).
- Wickham, H., & Bryan, J. (2018). readxl: Read excel files. R package (Version 1.1.0).
- Williams, C. L., Liebman, M., Edwards, J. W., James, D. E., Singer, J. W., Arritt, R., & Herzmann, D. (2008). Patterns of regional yield stability in association with regional environmental characteristics. *Crop Science*, 48, 1545–1559. <https://doi.org/10.2135/cropsci2006.12.0837>
- Wu, Y., Wang, E., He, D., Liu, X., Archontoulis, S., Huth, N., ... Yang, W. (2019). Combine observation data and modeling to quantify cultivar differences of soybean. *European Journal of Agronomy*, 111, 125940. <https://doi.org/10.1016/j.eja.2019.12.5940>

## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

**How to cite this article:** Archontoulis SV, Castellano MJ, Licht MA, et al. Predicting crop yields and soil-plant nitrogen dynamics in the US Corn Belt. *Crop Science*. 2020;1–18. <https://doi.org/10.1002/csc2.20039>