Evaluating DSSAT and APEX Models for Simulating Corn Yield under Different Nitrogen Supplies

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Abstract.

Nitrogen (N) is a critical yield-limiting factor for corn (Zea mays L.). However, over-application of N fertilizers is a common problem in the US Midwest, leading to many environmental problems. It is crucial to develop precision N management (PNM) strategies to improve corn N management. With increased availability of spatial and temporal datasets including remotely sensed images, land cover maps, digital soil surveys, gridded weather datasets and county scale crop yield reports, there is an increasing interest in evaluating grain yield and N management using crop growth model simulations. The objective of this study was to calibrate and evaluate DSSAT and APEX models to estimate corn yield under different N supplies in Minnesota. Six site-years of N rate experimental data conducted in Minnesota were used to calibrate and evaluate the models, including the maturity date, yield, aboveground biomass, harvest index, aboveground biomass N uptake, and grain N uptake. The models were calibrated based on data from 2014 and 2015. Then an independent model validation was conducted using the data in 2016. The preliminary results showed that the models simulated the growth duration, biomass, yield, plant N uptake, and grain N uptake reasonably well.

Keywords.
Corn, Yield, Nitrogen management, Environment impacts, Model Ensemble.

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Introduction

Plant nutrient management has traditionally relied on farmers' knowledge of field conditions and soil nutrients like nitrogen (N), phosphorous (P), and potassium (K). Precision agriculture, which has been developed over the past forty years, enhances this by using remote sensing technologies, big data analysis, smart machinery, and GPS to optimize fertilizer use by matching soil nutrient supply with crop demand. Nitrogen is a critical yield-limiting factor for crop production, with environmental losses occurring through leaching, denitrification, and volatilization. Improving N management is crucial for protecting water resources and reducing greenhouse gases. Over and under fertilization of N in corn production affects the farmer’s profitability and the environment (Cummings et al., 2021). Precision N management (PNM) has the potential to increase N use efficiency by reducing N losses while maintaining crop yields.

Minnesota, located in the Midwest, is known for its varied land, with forests, prairies, and many lakes. Agriculture, especially with major crops including corn, soybeans, wheat, and sugar beets, is important for the state's economy. Corn is the most widely grown crop in Minnesota that need large amounts of N(Bierman et al., 2012). In Minnesota, most of the N contributions come from soil organic matter, fertilizer, manure and legume crops. High N fertilizer input for corn fields can cause large environmental losses and pollution. Climate change results in higher temperatures and unpredictable precipitation leading to rapid changes in N-related soil temperature and soil water movement. Precision N management (PNM) can improve N use efficiency by synchronizing N supply and crop N demand in space and time, which can minimize negative environmental impacts and maintain or increase crop yield (Shao et al., 2023).

With increased availability of spatial and temporal datasets including remotely sensed images, land cover maps, digital soil surveys, gridded weather datasets and county scale crop yield reports, crop models are increasingly used to simulate yield, N management and cycle at a larger scale (Manivasagam and Rozenstein, 2020). Process-based crop models that simulate crop growth in response to soil, water, nutrient, and weather dynamics have been identified as a tool to predict and explain the complex interactions between soil-crop processes. Crop models are commonly used in spatial simulations for yield gap and yield potential analysis (Liu et al., 2021), fertilizer management (Yan et al., 2020), irrigation water management (Kothari et al., 2019b), and climate impact on yield (Adhikari et al., 2016). The typical input data requirements include crop type, N applications, weather conditions, soil properties and management practices, which will reflect the spatial diversity of soil, climate and cultivar in regional scales.

The goal of this paper is to calibrate and evaluate the DSSAT and APEX crop models to estimate yield under different N supplies.

Materials and methods

Experimental sites and data collection

A total of 49 corn grain yield responses to added N fertilizer trials were collected from 2014 to 2016 in eight U.S. Midwest states (Iowa, Illinois, Indiana, Minnesota, Missouri, Nebraska, North Dakota, and Wisconsin) as part of a public–industry partnership (Kitchen et al., 2017; Ransom et al., 2020, 2021). For 49 site-years, each site-year followed a standardized protocol for plot research implementation. The experiment was conducted in a randomized complete block design with two application timings (all at planting or the majority sidedressed), 16 N application treatments (single application at-planting: 0, 45, 90, 135, 180, 225, 270, and 315; split application: 45+45, 45+90, 45+135, 45+180, 45+225, 45+270, 90+90, and 90+180 kg N ha^{-1}), and four replications at each site. The data collected from 2014 to 2016 for 49 site-years include site characterization, field measurements, management records, and weather (Kitchen et al., 2017).

Among the eight states, 6 site-years located in Minnesota state were selected in this study for model calibration and evaluation (Table 1). Minnesota is the leading state in corn cultivation within the United States, with a significant portion of its agricultural land devoted to this crop. At the national level, Minnesota ranks among the top five states contributing to corn production. The crop observed data extracted for crop models include the yield, aboveground biomass, harvest index, aboveground biomass, nitrogen uptake, and grain nitrogen uptake.

Crop model, weather and soil data

Two crop models (CERES-Maize and APEX) are used to simulate corn yield and quantify their uncertainties. CERES-Maize is a model embedded in Decision Support System For Agro-technology Transfer (DSSAT) to specifically simulate corn growth and development (Hoogenboom et al., 2021). It can simulate corn growth and development process with a daily time step based on genetic coefficients, environments, and management. DSSAT is internationally recognized comprehensive crop model that is developed to simulate biophysical processes in agricultural systems, particularly as it relates to the economic and ecological outcomes of management practices in the face of climate risk. It is also being used to explore options and solutions for food security, climate change adaptation and mitigation and carbon trading problem domains (Zhen et al., 2022; 2023).

APEX models were developed by the core team spans three agencies: Texas A&M AgriLife Research, USDA Agricultural Research Service, and USDA Natural Resources Conservation Service. The Agricultural Policy / Environmental eXtender (APEX) model was developed to simulate land management impacts for small-medium watersheds and heterogeneous farms. It can be configured for land management strategies such as irrigation, drainage, furrow diking, buffer strips, terraces, waterways, fertilization, manure management, lagoons, reservoirs, crop rotation and selection, pesticide application, grazing, and tillage (Wang et al., 2012).

The crop models need daily weather data. The daily climate data consisted of maximum and minimum temperature, precipitation and solar radiation. For experimental sites, historical observed weather data from 1990 to 2023 (33 years long) was obtained from the Iowa Environmental Mesonet (http://mesonet.agron.iastate.edu/). The crop models also require soil profile data in different soil layers in the top 200 cm. Soil information for the dominant soils on each experimental field across Minnesota will be obtained from the USDA Soil Survey Geographic Database (SSURGO) at 30-m resolution (USDA-NRCS, 2023).

Statistical indices for model performance

To evaluate the model performance and accuracy for simulating maturity dates and yields, statistical indicators including coefficient of determination (R^2), root mean square error (RMSE), and normalized root mean square error (NRMSE) were computed from observed (O_i) and simulated (S_i) values.

$$R^2 = 1 - \sum (O_i - S_i)^2 / \sum (O_i - O_a)^2,$$

$$RMSE = [(\sum (O_i - S_i)^2) / n]^{0.5},$$

$$NRMSE = RMSE / O_a \times 100,$$

Where O_i is the ith observation value, S_i is the ith simulation value, O_a is the average value of a series observations and n is the sample number.

The genetic coefficients were adjusted recursively through the “trial and error” method to maximize the coefficient of determination (R^2) of the linear regression and minimize the root mean square error (RMSE) and normalized root mean square error (NRMSE) to find the best agreement between the simulated and measured field observations (Wang et al., 2021).

Results

The ability of the models to simulate corn growth duration was assessed by comparing the simulated and observed values of maturity dates. The model simulated the maturity dates reasonably well for calibration years in 2014 and 2015, with an overall R^2 value of 0.99, RMSE value of 12 days, and NRMSE value of 0.09 (Fig. 1). The model generated good simulations of yield and biomass with the R^2 value of 0.41 and 0.36, respectively. The biomass and grain N uptake were also simulated well by the crop model with high R^2, and lower model errors indicated by RMSE and NRMSE.

The calibrated model was evaluated for the independent year 2016. Evaluation of the model indicated that the simulated corn maturity dates agreed well with observed values, which was indicated by a R^2 value of 0.99 and values of RMSE, NRMSE of 12 days, 9%, respectively (Fig. 2). The evaluation results also confirmed a good yield and biomass simulation for independent year 2016 with higher R^2 (0.67 and 0.72, respectively). The simulation of biomass and grain N uptake were reasonably well with the R^2 value of 0.75 and 0.67, respectively.

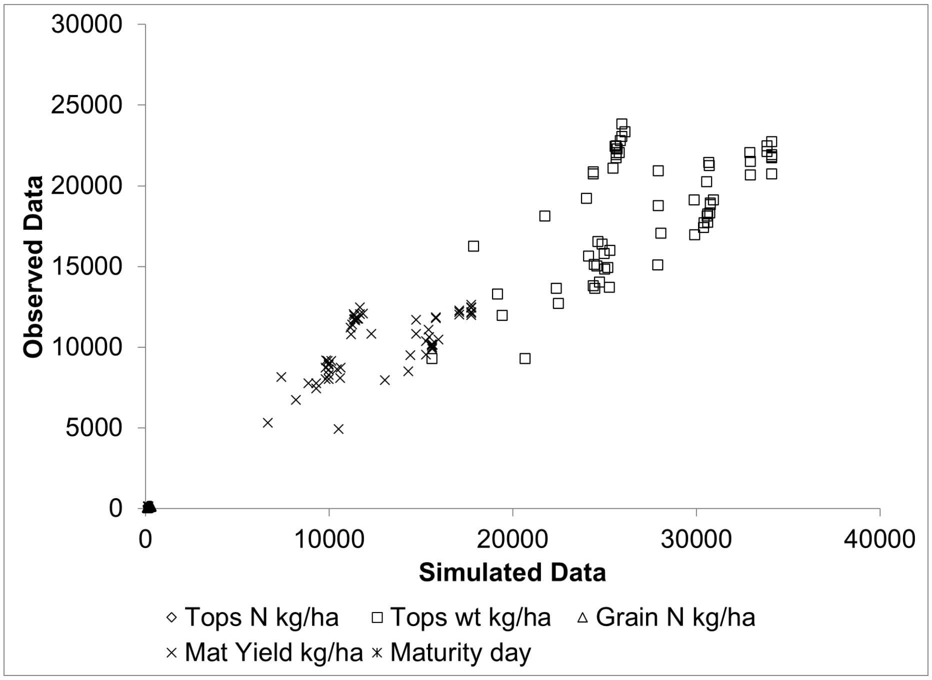

Fig. 1. Calibration results in the years 2014 and 2015 for the crop model in simulating the maturity date, yield, aboveground biomass, aboveground biomass nitrogen uptake, and grain nitrogen uptake.

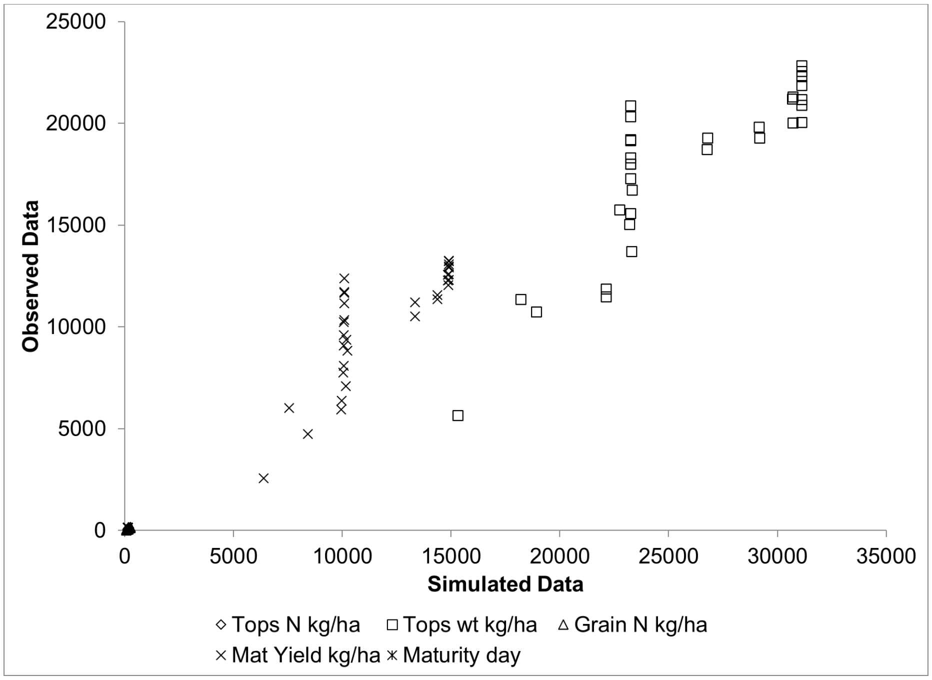

Fig. 2. Validation results in the year 2016 for the crop model in simulating the maturity date, yield, aboveground biomass, aboveground biomass nitrogen uptake, and grain nitrogen uptake.

Table 1. Description of 6 site-years distributed in Minnesota state.

Sites	Latitude, longitude	Hybrid	Soil type	Water treatments	Experimental Years	References
NewRichland	43.92° N, 93.51° W	P9917AMX	Canisteo-Glencoe and Webster clay loam	Dryland	2014	
StCharles	44.07° N, 92.02° W	P9917AMX	Seaton silt loam	Dryland	2014	
NewRichland	43.88° N, 93.55° W	P0157AMX	Webster clay loam and Nicollet clay loam	Dryland	2015	Kitchen et al., 2017; Ransom et al., 2020, 2021
StCharles	44.07° N, 92.02° W	P0157AMX	Seaton silt loam, ridge phase	Dryland	2015	
Becker	45.39° N, 93.89° W	P0157AMX	Hubbard-Mosford complex	Irrigation	2016	
Waseca	44.11° N, 93.64° W	P0157AMX	Cordova clay loam	Dryland	2016	

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