Improving the Precision of Maize Nitrogen Management using Crop Growth Model in Northeast China

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Abstract. *The objective of this project was to evaluate the ability of the CERES-Maize crop growth model to simulate grain yield response to plant density and N rate for two soil types in Northeast China, with the long-term goal of using the model to identify the optimum plant density and N fertilizer rate for specific site-years. Nitrogen experiments with six N rates, three plant densities and two soil types were conducted from 2015 to 2017 in Lishu county, Jilin Province in Northeast China. The CERES-Maize model was calibrated for 2015 and 2016, and evaluated for 2017 experiments. Results indicated that the model provided good estimations of yield across plant densities and N rates for the calibration years (R^2=0.83 for black soil and R^2=0.89 for sandy soil) and evaluation year (R^2=0.91 for black soil and R^2=0.95 for sandy soil), respectively. The calibrated model was then run using weather data from 1965 to 2017 for 15 different N rates, and 7 different plant densities to determine the optimum N rate and plant density for two soil types in different weather conditions. Model analysis indicated that the optimum plant density for black soil was 5.1-6.6, 7.3-9.2, and 8.3-8.4×10^4 ha^{-1} for dry, normal and wet years, respectively. For sandy soil, the optimum plant density was 3.0-3.9, 4.5-7.3, and 5.2-6.7 ×10^4 ha^{-1} for dry, normal and wet years respectively. For the optimum N rate, the value was 183-209, 231-239, and 220-228 kg ha^{-1} for dry, normal and wet years, respectively, for black soil. The optimum N rate was 171-186, 216-224, and 229-285 kg ha^{-1} for sandy soil for dry, normal and wet years, respectively. We concluded that the CERES-Maize model was able to simulate maize growth and yield, and could be used as a tool to assist precision plant density and N management for different soil types and weather conditions in Northeast China.*

Keywords. *Precision crop management, Optimum plant density, Optimum N rate, Soil-specific*

management, Weather-specific management

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Introduction

Maize is among the top three most important cereal crops for food, animal feed, and bio-fuel in the world (Lashgari et al. 2011; Chen et al. 2011; Grassini and Cassman 2012). Plant density and N fertilizer application are often considered the most important crop management practices to improve grain yield and nitrogen (N) use efficiency (NUE) during intensive maize production (Tollenaar and Lee 2002; Lee and Tollenaar 2007; Majaivana 2016). Precision crop management has the potential to increase crop productivity and quality, while reducing N leaching by optimizing the plant density and N fertilizer application for site-specific management (Mulla 1996; Mulla and Miao 2016).

Maize (Zea mays) is one of the main field crops grown in Northeast China, but the yield varies substantially from year to year due to weather conditions (Ahmed et al. 2007; Cabas et al. 2010), and from site to site due to soil type variations, changes in cultivars and adoption of soil and crop management practices (Liu et al. 2011). Crop growth models such as DSSAT (Jones et al., 2003), which integrates the effects of soils, weather, management, genetics, and pests on daily growth, have been used for optimizing planting density, fertilizer, irrigation, pest management, and site-specific farming applications (Cabrera et al. 2007; Jones et al. 2003; Lobell et al. 2006; Batchelor et al. 2002). The objectives of this study were to: (1) calibrate and evaluate the CERES-Maize model in Northeast China; and (2) use the calibrated CERES-Maize model to simulate maize yield over 53 years of continuous maize production to identify the optimum plant density and N fertilizer rate for different soil types and weather conditions.

Materials and methods

Study sites

The study site was located at the Lishu Experiment Station, China Agricultural University (43.3°N, 124.1°E), located in Lishu County, Jilin Province. This area is a typical rain–fed spring maize region in Northeast China, where annual average precipitation is 556 mm, 70%–80% of which occurred between June and September. It has a mean temperature of 6.6 ℃, with maximum temperatures of more than 29.7 ℃ in July and minimum temperatures below -31.8 ℃ in November. The soil at the two study locations were classified as Black Soil, equivalent to typical Haploboroll and sandy soil, equivalent to typical Cryopsamments according to USDA Soil Taxonomy.

Experiment design

The experiments were conducted from 2015 to 2017, and consisted of six N rates (0, 60, 120, 180, 240, 300 kg ha^{-1}) and three plant densities (5. 5, 7.0, 8.5 $\times 10^4$ plants ha^{-1}). A randomized complete block design was used with three replicates. Each plot area was 108 m^2. Phosphorus (90 kg ha^{-1} P_2O_5) and potassium (90 kg ha^{-1} K_2O) fertilizer was applied before sowing. One third of the N fertilizer was applied before sowing, and the remainder was applied at the V8 stage.

Harvest procedures

Maize was harvested after physiological maturity. Yield was estimated from 100 sub samples of each 108 m^2 per treatment in the center of the plot to avoid border effects. Grain was shelled by hand and separated from stove and cores. Grain was weighed using a digital scale and moisture content taken immediately to correct yields to 0% moisture content. After harvest, weather data including daily maximum and minimum temperature, rainfall, and sunshine hours were collected from the local weather station. Sunshine hours were converted to daily solar radiation.

Model calibration and validation

The years 2015 and 2016 were used for model calibration. Six cultivar coefficients (Table 1) were estimated in order to calibrate the model for the plant density and N management treatments. The CERES-Maize model calibration involved making systematic adjustments to development and growth cultivar coefficients to minimize error between simulated and measured yield. After calibration for data collected in 2015 and 2016, the model was evaluated using data collected in 2017.

After calibration and validation, the model was used to estimate the long term optimum plant density and N rate for maize in this area for each soil type. Weather data for 1965-2017 from the Lishu Weather Station were used to simulate the yield response to 8 different plant densities ranging from 3 to 10 $\times 10^4$ ha^{-1} in increments of 10^4 ha^{-1}, and 15 different N rates ranging from 0 to 300 kg ha^{-1} in increments of 20 kg ha^{-1}.

Statistical analysis

The 53 years were classified into dry years (< 386.4 mm), normal years (386.4 - 528.1 mm), and wet years (> 528.1 mm) based on the rainfall data using SPSS 18.0 (SPSS Inc., Chicago, Illinois, USA).

The relationship between simulated yield and plant density was fit using the linear-plus-plateau: $y = a + bx$, $x < x_0$ (Eq. 1); $y = a + bx_0$, $x \geq x_0$ (Eq. 2). In these equations, y represented corn yield (either observed or simulated in t/ha), x was the plant density, a was the intercept, b was the linear coefficient, and x_0 was the N rate at the join point. The PROC NLIN procedure in SAS (Version 8.0, SAS, 2013).

The relationship between simulated yield and N rate was fit using the quadratic-plus-plateau: $y = a + bx + cx^2$, $x < x_0$ (Eq. 3); $y = a + bx_0 + cx_0^2$, $x \geq x_0$ (Eq. 4). In these equations, y represented corn yield (either observed or simulated), x was the N fertilizer rate, a was the intercept, b was the linear coefficient, c was the quadratic coefficient, and x_0 was the N rate at the join point. The PROC NLIN procedure in SAS (Version 8.0, SAS, 2013).

Results

Model calibration and validation

The model cultivar coefficients that gave the best fit between simulated and measured yield for calibration years of 2015 and 2016 are shown in Table 1, while simulated and measured yields for the two soil types are shown in Fig. 1a and 1c. The model gave an R^2 of 0.82 and 0.89 for black soil and sandy soil respectively. The model gave good results across two years, three plant densities and six N rates for both soil types. The cultivar coefficients calibrated for 2015 and 2016 were used to simulate the experiments consisting of two soil types, three densities, and six N rates treatments for the evaluation year 2017. The results of the validation year are shown in Fig. 1b and 1d. The R^2 was 0.91 and 0.95 for black soil and sandy soil respectively. These results indicated that the CERES-Maize model was able to simulate N-yield response at two different soil types, three plant densities and six N rates very well in Northeast China.

Long term optimum planting density

Plant density is a major factor in determining the ability of the crop to capture light and generate yield (Majaivana et al. 2016). Optimum plant density allows the plants to maximize light use and nutrients to maximize yield (Ayman and Samier 2015). Figs. 2 and 3 show the simulated yield average over 53 seasons for seven different plant densities under low (60 kg ha^{-1}), medium (180 kg ha^{-1}), and high (300 kg ha^{-1}) N fertilizer rates. The results of the simulation gave optimum plant densities for different N fertilizer rates under different weather conditions. For the 53 year average and normal rainfall years for black soil (Figs. 2a and 2c), the optimum plant densities increased significantly with an increase in N fertilizer rates (7.4, 8.3 and 9.0 $\times 10^4$ plants ha^{-1} for the long term average years and 7.3, 8.3 and 9.2 $\times 10^4$ plants ha^{-1} for normal years under low, medium and high N fertilizer rates treatment respectively). However, there was no significant difference in optimum plant density (about 8.3 $\times 10^4$ plants ha^{-1}) under different N fertilizer rates treatment for wet years (Fig. 2d). For dry years (Fig. 2b), the optimum plant densities were lower than normal and high rainfall years (6.6, 5.1 and 6.1 $\times 10^4$ plants ha^{-1} under low, medium and high N fertilizer rate treatments, respectively) for all three N fertilizer rate treatments.

For the sandy soil, the simulated yield averaged over 53 seasons for seven different plant densities under low, medium, and high N fertilizer rates are shown in Fig. 3. There were different optimum plant densities for different weather conditions. Compared with black soil, sandy soil had a lower optimum plant density for different types of rainfall years. There were no differences in optimum plant densities between the medium and high N rates for normal rainfall years (about 5.5 $\times 10^4$ plants ha^{-1}) (Fig. 3a) and dry years (about 3.9 $\times 10^4$ plants ha^{-1}) (Fig. 3b), respectively. For the normal rainfall years (Fig. 3c) and wet rainfall years (Fig. 3d), the optimum plant density had higher values for a medium N rate than the low and high N rates. Meanwhile, the normal years had higher values for plant density than wet years under medium N and high N rates.

Table 1 Six cultivar coefficients in CERES-Maize calibrated for the 2015 and 2016 seasons

Cultivar Coefficient	Definition	Calibrated Value
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8 deg. C) during which the plant is not responsive to changes in photoperiod.	250.0
P2	Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours).	0.400
P5	Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8 deg.C).	950.0
G2	Maximum possible number of kernels per plant.	800.0
G3	Kernel filling rate during the linear grain filling stage and under optimum conditions (mg/day).	8.00
PHINT	Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.	42.00

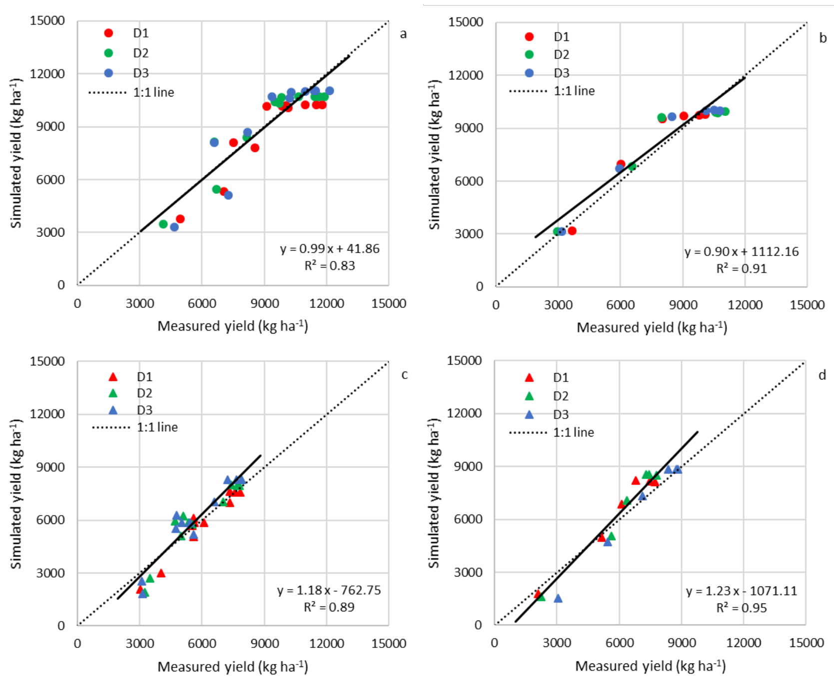

Fig. 1 Relationship between simulated and measured yield for calibration years (a: black soil, c: sandy soil) and validation year (b: black soil, d: sandy soil)

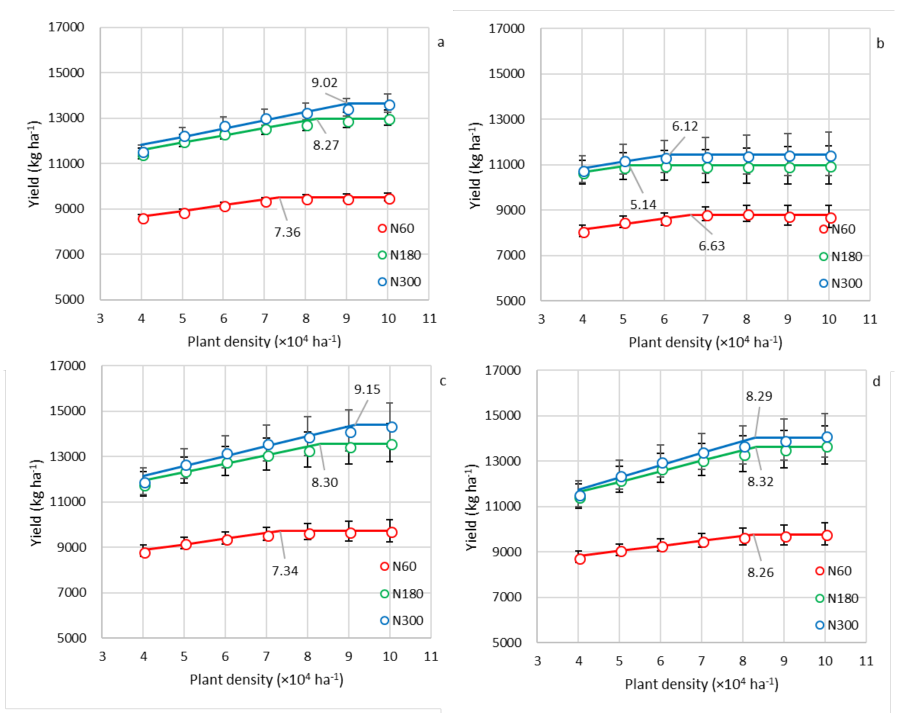

Fig. 2 Simulated optimum plant density under different N rates and weather conditions (a: 53 year average , b: dry years, c: normal years, d: wet years) for the black soil

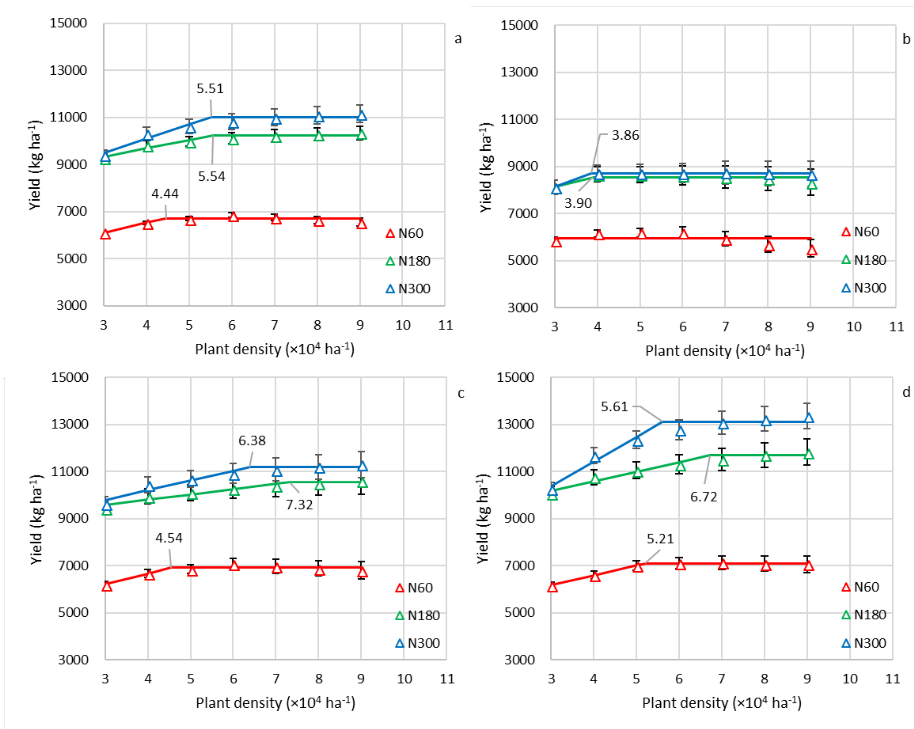

Fig. 3 Simulated optimum plant density under different N rates and weather conditions for (a: 53 year average, b: dry years, c: normal years, d: wet years) on sandy soil

Long term optimum N rate

Determining the optimum N rates is critical to maximizing crop economic yields (Majaivana et al. 2016). Improving optimum N rate recommendations is critical for profitable corn production and for reducing N losses to the environment (Morris et al. 2018). Figs. 4 and 5 show the simulated yield averaged over 53 seasons for fifteen different N rates under low (5×10^4 plants ha^{-1}), medium (7×10^4 plants ha^{-1}), and high (9×10^4 plants ha^{-1}) plant densities for black soil and low (3×10^4 plants ha^{-1}), medium (5×10^4 plants ha^{-1}), and high (7×10^4 plants ha^{-1}) plant densities for sandy soil. The results of the simulation gave optimum N rate for different plant densities under different weather conditions. For the long term average (Fig. 4a) and wet years for black soil (Fig. 4d), the optimum N rate was the same value at different plant densities (about 220-228 kg ha^{-1}), while it had a slightly larger value under normal years (about 231-239 kg ha^{-1}) (Fig. 4c). Nevertheless, there were no significant differences in optimum N rate among different plant densities for the 53 year average, normal year, or wet year. Under dry years (Fig. 4b), optimum N rate was lower (209 kg ha^{-1}, 194 kg ha^{-1}, and 183 kg ha^{-1} for low, medium, and high plant densities) than other types of year.

For the sandy soil in Fig. 5, there were differences in optimum N rates for the different weather seasons. The optimum N rates had similar values for the 53 year average (Fig. 5a) and normal years (Fig. 5c) (211, 224-233, and 216-227 kg ha^{-1} under low, medium, and high plant density). Compared with black soil, sandy soil had similar optimum N rate for dry years (Fig. 5b), while it had a higher optimum N rate (283 and 282 kg ha^{-1}) under medium and high plant density for wet years (Fig. 5d).

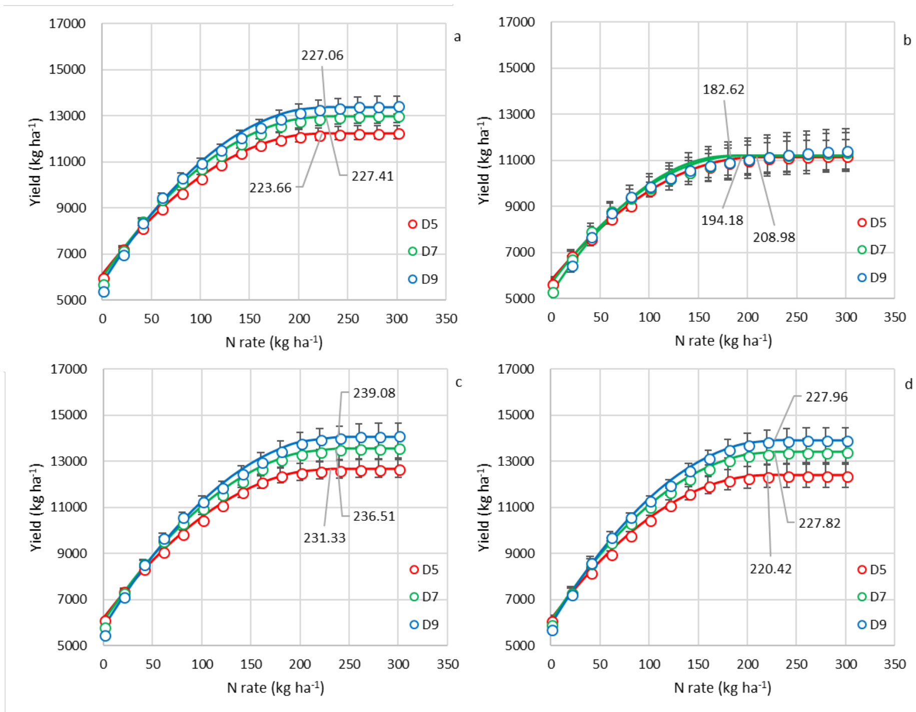

Fig. 4 Simulated optimum N rate under different plant densities and weather conditions (a: 53 year average, b: dry years, c: normal years, d: wet years) for black soil

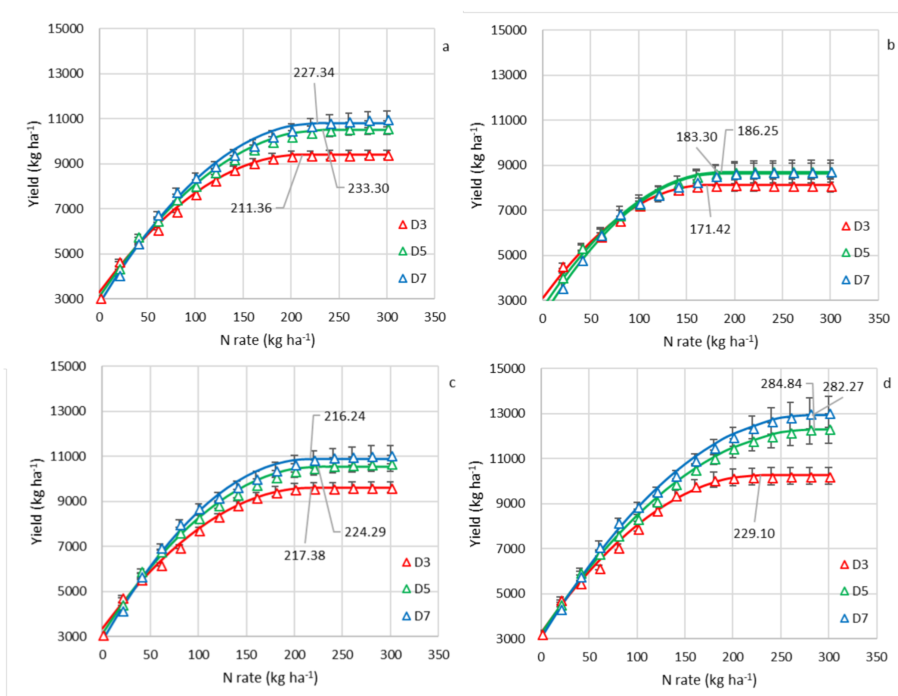

Fig. 5 Simulated optimum N rate under different plant densities and weather conditions (a: average year, b: dry year, c: normal year, d: wet year) for sandy soil

Conclusions

The results of this study indicated that the CERES-Maize model provided good estimates of yield across plant densities and N rates for both the calibration and evaluation years. Model simulation analysis indicated that the optimum plant density for black soil was 5.1-6.6, 7.3-9.2, and 8.3-8.4×10^4 ha^{-1} for dry, normal and wet years, respectively. For sandy soil, the optimum plant density was 3.0-3.9, 4.5-7.3, and 5.2-6.7 ×10^4 ha^{-1} for dry, normal and wet years respectively. For N rate, the optimum value was 183-209, 231-239, and 220-228 kg ha^{-1} for dry, normal and wet years, respectively, for black soil. The optimum N rate was 171-186, 216-224, and 229-285 kg ha^{-1} for sandy soil in dry, normal and wet years, respectively. We concluded that the CERES-Maize model was able to simulate maize growth and could be used as a useful tool to assist precision plant density and N management across different soil types and weather conditions in Northeast China.

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