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Exploring management strategies to improve maize yield and nitrogen use efficiency in northeast China using the DNDC and DSSAT models

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ABSTRACT

Process-based models are valuable tools for simulating crop production, estimating agronomic efficiency and developing optimum management practices to achieve sustainable agriculture. However, a comparison of the DeNitrification-DeComposition (DNDC) and Decision Support System for Agrotechnology Transfer (DSSAT) models has not been previously used to optimize management practices for spring maize in northeast China. The objectives of this study were to evaluate the performance of the DSSAT and DNDC models in simulating maize growth and soil C & N dynamics and analyse their weaknesses and strengths based on a 7-year spring maize study in northeast China; and to explore the optimal management practices for improving maize production and nitrogen use efficiency under 20-year climate variability. Both DNDC and DSSAT exhibited "good" to "excellent" performance in simulating maize yield, above-ground biomass and plant N uptake for ecological intensification with N fertilizer (EI-N) and farmers' practice with N fertilizer (FP-N) treatments based on percent bias (PBIAS) of −10.5–4.2%, a normalized root mean squared error (nRMSE) of 7.5–17.2%, a Nash-Sutcliffe efficiency (NSE) of 0.17–0.77 and a d index of agreement (d) of 0.81–0.94. Both models showed "fair" to "good" performance in the same simulation for EI without N fertilizer (EI-N0) and FP without N fertilizer (FP-N0) treatments, but the maize yield simulation was better for the DSSAT model. In addition, the two models provided "fair" performance for N-fertilized treatments to "poor" performance for N-unfertilized treatments in simulations of soil organic carbon (0–0.20 m) and mineral N (0–0.30 m), but the simulations were better for the DNDC model. Sensitivity analyses indicated that the optimum yield and agronomic efficiency were achieved at a planting date of late April to early May, a fertilizer N application rate of 180–210 kg N ha^{-1} with two timing splits in the DNDC and DSSAT model and a planting density of 7 seeds m^{-2} in the DSSAT model. This study suggests that comparing the management scenarios of multiple dynamic models is more beneficial to develop best management practices for improving crop production and fertilizer use efficiency.

1. Introduction

The demand for global agricultural production has greatly increased with the rising population worldwide and is likely to continue increasing in the future (FAO, 2009; Godfray et al., 2010). More intensified cropping with large amounts of fertilizer input has been conducted to obtain higher yields. However, the excessive and imbalanced application of fertilizers has resulted in low nutrient use efficiency and high environmental risks (e.g., greenhouse gas emissions, water contamination) (Gu et al., 2015; Xu et al., 2016). Thus, modern sustainable agriculture is facing the challenge of balancing crop production and environmental effects. Ecological intensification (EI) is an effective approach for sustainable agriculture that is essential to meet these challenges.

The principle of EI is to satisfy the anticipated increase in food demand while minimizing the negative effects on the environment by integrating ecological management practices (Cassman, 1999). EI technology emphasizes efficiently using inputs (e.g., fertilizer, pesticide), optimizing agronomic management practices (e.g., sowing dates, planting density, irrigation, tillage, rotation) and minimizing the effects on the environment (e.g., greenhouse gas emissions, nitrate leaching) (Hochman et al., 2013; Petersen and Snapp, 2015). In recent decades,

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many field experiments have demonstrated the co-benefit of EI practices under different climate conditions and crop systems. For example, optimized planting density and fertilizer N input improved maize yield and N use efficiency in Mozambique (Roxburgh and Rodriguez, 2016), and adopted heterotic hybrids plus the use of herbicide and fertilizer increased maize yield by 32% from the 1990s to the 2000s in the United States (Flavell, 2010).

In northeast China, excessive fertilization and inappropriate management practices in maize fields have resulted in low agronomic nutrient efficiency and high environmental risks (Xu et al., 2014a, 2016). It has been reported that changes in planting date could lead to 15–35% variations in maize yields (Yao et al., 2015). Increasing plant density can contribute to high yield, but blind increases often reduced maize yield due to the dense canopy and weak stems, which may cause plant lodging (Zhang et al., 2014, 2017). Tillage is an essential management practice in crop production, but its influence on crop growth is complex, which is related to soil quality (e.g., soil moisture, soil temperature and soil nutrient availability) (Zhang et al., 2015a; Liu et al., 2018). Therefore, optimizing agronomic managements based on the EI concept is essential to exploring best management practices for obtaining high maize production and agronomic efficiency in northeast China.

Process-based models such as the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003), Simulateur mulTIdisciplinaire pour lesCultures Standard (STICS) (Brisson et al., 2003), Agricultural Production Systems Simulator (APSIM) (Keating et al., 2003), Root Zone Water Quality Model (RZWQM2) (Ma et al., 2012), DeNitrification-DeComposition (DNDC) (Li et al., 2012), and daily time step versions of the CENTURY ecosystem model (DayCent) (Parton et al., 1998) are widely used in agroecosystems to evaluate the effects of agricultural management practices on crop growth and nutrient dynamics (Dutta et al., 2017; Li et al., 2018; Plaza-Bonilla et al., 2018; Qi et al., 2011, 2013); develop useful tools for farmers or policy applications (Li et al., 2015; Zhang et al., 2015b; He et al., 2016; Malik et al., 2019); and assess climate change impacts on crop production and environment risks as well as explore potential adaptation measures (He et al., 2018a, 2018b; Ngwira et al., 2014). Sensitivity analysis is an effective approach for the applications of crop and soil models to explore optimal management strategies (e.g., fertilizer application rate, planting date, planting density and irrigation) for improving crop growth and minimizing environmental risk under current and future climate change (He et al., 2016, 2018a, 2018b; Qi et al., 2013; Zhang et al., 2015). For example, He et al. (2016) conducted sensitivity analysis of the DSSAT model to simulate the response of maize/wheat yield and N leaching to different input parameters (e.g., fertilizer application rate, planting date, planting density) under various Canadian climate; Zhang et al. (2015b) employed the DNDC model to optimize management practices in North China for maintaining maize yield and reducing N leaching including the improvements of fertilizer application rate and timing, tillage depth and irrigation; and Qi et al. (2013) verified that the CERES-Wheat module incorporated in RZWQM2 model well simulated crop yield under various planting dates and planting densities for spring wheat in the Northern Great Plain of the United States.

The DNDC model is a well-established tool used to predict C and N cycling in agroecosystems, and it has the capacity to simulate crop growth by specifying N requirements for C biomass accumulation (Li et al., 2012; Gilhespy et al., 2014; Dutta et al., 2017; Smith et al., 2019). The DSSAT model includes widely used crop simulation models (CSMs), which can systematically simulate the crop growth stages with genotypic differences represented by cultivar-specific genetic coefficients (Jones et al., 2003; Hoogenboom et al., 2012). The DNDC and DSSAT models have been well applied separately to simulate maize growth, soil water movement and nutrient cycling under different field management practices in northeast China (Liu et al., 2013, [CSL STYLE ERROR: reference with no printed form.]; Yang et al., 2011). However, a comparison of the DNDC and DSSAT models has not been previously used to simulate spring maize growth and soil processes and optimize management practices in order to improve maize production and agronomic efficiency in northeast China. This information gap has limited any further applications of the DNDC and DSSAT models for regional management improvement and forecasting. The objectives of this study were: (1) to calibrate and evaluate the DNDC and DSSAT models using measured crop yield, above-ground biomass, N uptake, soil organic carbon (SOC) and mineral N based on a 7-year spring maize study conducted in northeast China; (2) to identify the performances and report weaknesses of the two models for simulating spring maize growth and soil C & N dynamics, and most importantly (3) to optimize management practices including the planting date, planting density, tillage depth, and fertilizer N rate and timing to improve maize yield and N use efficiency in northeast China.

2. Materials and methods

2.1. Field experiment

A field experiment was conducted from 2009 to 2015 in Liufangzi County, Jilin Province (43°35′N and 124°54′E), in the Corn Belt of China. The average air temperature of the growing season (May – September) was 18.9 °C, with an average seasonal precipitation of 423 mm (Fig. A. 1). The basic soil physical and chemical properties at the beginning of the field experiment are listed in Table A. 1. A split plot experimental design with four replications was used. The main plots consisted of ecological intensification and farmers' practice, and the split plots consisted of different nitrogen fertilizer rates. The four treatments consisted of ecological intensification with nitrogen fertilizer (EI-N), farmers' practice with nitrogen fertilizer (FP-N), ecological intensification without nitrogen fertilizer (EI-N0) and farmers' practice without nitrogen fertilizer (FP-N0). The fertilizer application rates were 180 kg N ha^{-1}, 75 kg P_2O_5 ha^{-1} and 90 kg K_2O ha^{-1} in the EI-N treatment, which was recommended based on expected yield response to fertilizer and target agronomy efficiencies of applied N and the concept of ecological intensification management; additionally, the N rate was increased to 200 kg N ha^{-1} in 2015. Half of the N rate was applied as basal fertilizer and half was applied at the jointing stage from 2009 to 2011. Then, the N rate was applied at the sowing, jointing and tasselling stages at ratios of 1/4:2/4:1/4, respectively, from 2012 to 2015, and all P_2O_5 and K_2O were applied as basal fertilizers. Meanwhile, the FP-N treatment received a fertilizer supply of 251 kg N ha^{-1}, 145 kg P_2O_5 ha^{-1} and 100 kg K_2O ha^{-1} as basal fertilizer from 2009 to 2015, representing an average fertilizer rate applied based on farmers' practice in northeast China (Xu et al., 2014a, b; 2016). All other practices of the EI-N0 and FP-N0 treatments were the same as those in the EI-N and FP-N treatments. In this study, the conventional tillage with fall mouldboard ploughing (0.20 m depth) was conducted before snowing. Maize was planted at seeding rate range from 5.0 to 6.5 seeds m^{-2} with 60 cm row space. The SOC contents (0–0.20 m) were measured at harvest from 2009 to 2015 using dichromate oxidation method (Kalembasa and Jenkinson, 1973). Detailed measurements of maize yield, N uptake and soil mineral N can be referred to Zhao et al. (2016). Management practice, planting/harvest date and cultivar information is shown in Table 1.

2.2. DNDC and DSSAT model descriptions

2.2.1. DNDC model

The DNDC model was initially developed to simulate the biogeochemical cycles of carbon and nitrogen in agroecosystems (Li et al., 1992, 1994). It has been widely used to estimate crop growth, soil C and N dynamics, greenhouse gas emissions and the soil water cycle under various management practices and climatic conditions (Gilhespy et al., 2014). The first component of the DNDC model consists of soil, climate, crop growth and decomposition sub-models, which are related

Table 1
The basic management information for spring maize from 2009 to 2015 at experimental site.

Treatment	Year	Cultivar information	Planting date	Harvest date	Planting density	Tillage depth	N fertilizer application (kg N ha^{-1})		
			(day of year)	(day of year)	(seed m^{-2})	(m)	Basal	Jointing	Tasseling
EI (FP)[a]	2009	Pioneer335 (Pioneer335)	124	271	6.0 (6.0)	0.20	90 (251)	90	-
	2010	Pioneer335 (Pioneer335)	129	273	6.5 (5.0)	0.20	90 (251)	90	-
	2011	Pioneer335 (Jidong33)	117	267	6.5 (5.0)	0.20	90 (251)	90	-
	2012	Pioneer335 (Lvyu4117)	122	268	6.5 (5.0)	0.20	45 (251)	90	45
	2013	Pioneer335 (Lvyu4117)	121	273	6.5 (5.0)	0.20	45 (251)	90	45
	2014	Pioneer335 (Lvyu4119)	120	273	6.5 (5.0)	0.20	45 (251)	90	45
	2015	Nonghua101(Lvyu4119)	119	273	6.5 (5.0)	0.20	50 (251)	100	50

[a] The content within the brackets represents the detail information for the FP treatment. EI: ecological intensification; FP-N: farmers' practice.

to four ecological factors (climate, soil, vegetation and anthropogenic activity) that can predict daily crop growth (e.g., water demand, root respiration, N uptake and growth of grain, stem and root), soil environmental conditions (e.g., temperature, moisture, potential evapotranspiration, pH, oxidation-reduction potential) and the soil carbon pool dynamic (e.g., deposition rate, dissolved organic C concentration). The second component consists of denitrification, nitrification and fermentation sub-models, which are used to simulate the impacts of soil and environmental conditions on soil microbial activity to predict the emissions of trace gases, including dinitrogen (N_2), nitrous oxide (N_2O), nitric oxide (NO), carbon dioxide (CO_2), ammonia (NH_3), and methane (CH_4), from the plant-soil system (He et al., 2018; Li et al., 2012; Uzoma et al., 2015).

2.2.2. DSSAT model

The DSSAT model is a software application program, and the current version of DSSAT v4.6 is integrated with widely used Cropping System Models, a soil water balance module, and two soil nitrogen and organic matter modules (the CERES- and CENTURY-based soil models) (Hoogenboom et al., 2012). The CSMs can simulate the growth of over 40 different crops for field and fallow fields. The CENTURY-based soil model was selected to simulate the soil N and C dynamics in our research due to its more realistic simulations under a long-term field study (Gijsman et al., 2002). The soil water balance module is based on the Ritchie equation to calculate daily soil water changes (Tsuji et al., 1998; Hoogenboom et al., 2012). The DSSAT model has been widely used to simulate crop growth, soil water balance, soil carbon and soil nitrogen dynamics under different crop systems, management practices and climatic conditions (Ngwira et al., 2014; Li et al., 2015; He et al., 2016, 2018b; Malik et al., 2019).

2.3. Model initialization and cultivar calibration

The DNDC and DSSAT models must be initialized and parameterized before the models can be used to simulate crop growth, soil C and N dynamics. The required input information for the DNDC and DSSAT models includes daily meteorological data (e.g., maximum, minimum temperature (°C), precipitation (mm) and solar radiation (MJ m^{-2})); soil property data (e.g., initial bulk density, texture, field water capacity, pH, organic carbon, nitrate and ammonium N content); and crop management information (e.g., cropping system, planting time, tillage, fertilization and irrigation). In this study, local meteorological data were obtained from the Gongzhuling weather station during the field experiment. The annual and seasonal temperature, precipitation and solar radiation based on daily data from 2009 to 2015 are shown in Fig. A. 1. The initial soil properties for each soil layer at the experimental site and the crop management practices (e.g., planting and harvest dates, fertilizer application rates and timing) used for our modelling study are shown in Table 1 and Table A. 1, respectively.

The DNDC model includes a crop growth sub-model (Li et al., 1994), which has been successfully studied to simulate crop growth worldwide and reported its ability in capturing the water and N stresses (Dutta et al., 2017; He et al., 2018; Smith et al., 2019; Zhang et al., 2015). Plant growth for a specific cultivar is characterized by empirical growth curves specifying N requirements for C biomass accumulation and is driven by the accumulation of growing degree days. The model calculates water and N demand for crop growth based on several physiological parameters (e.g., maximum biomass production and its portioning fractions to shoot and roots, the C/N ratio of plants, the accumulative temperature for maturity and water requirement). Crop parameters include the maximum biomass production (kg C ha^{-1} yr^{-1}), biomass fraction (ratio of grain, leaf, stem and root), biomass C/N ratio, thermal degree days for maturity (°C) and water demand (g water g^{-1} dry matter) (He et al., 2018; Smith et al., 2019).

In the CSM-CERES-Maize model, maize growth is controlled by physiological growth stages, which are governed by thermal time (growing degree days), depending on the stages (Jones et al., 2003). Three cultivar coefficients (P1, P2, P5) determine the critical phenology stages, such as the anthesis date and maturity date. Two cultivar coefficients (G2, G3) determine grain filling, and one cultivar coefficient determines leaf phenology (PHINT) (Jones et al., 2003; Hoogenboom et al., 2012). Five cultivars were selected, including Pioneer335, Nonghua101, Jidong33, Lvyu4117 and Lvyu4119, which were calibrated for the EI and FP treatments in the DNDC and DSSAT models (Table A. 2, 3). In this study, the cultivar parameters were calibrated using measured dry maize yield, above-ground biomass and plant N uptake based on a 'Trial and Error' method and the statistics of root mean square error (RMSE) to find the best agreement between the simulated and measured values. The fertilized treatments (EI and FP) were used for model calibration and the unfertilized treatments (EI-N0 and FP-N0) were used for validation across all the experiment years (2009–2015) including both the humid and dry years. The calibrated DNDC and DSSAT models were then used to simulate the soil organic carbon and mineral nitrogen dynamics.

2.4. Model performance statistics

Model simulation performance was estimated by comparing the simulated and measured maize yield, above-ground biomass, plant N uptake, nitrogen use efficiency, soil organic C and soil mineral N distribution. Four deviation statistics were employed to provide an integrated evaluation: percent bias (PBIAS), the normalized root mean squared error (nRMSE), Nash-Sutcliffe efficiency (NSE) and the index of agreement (d) (Nash and Sutcliffe, 1970; Willmott, 1982; Moriasi et al., 2007). The deviation statistics were calculated using Eqs. (1)–(4):

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n} (M_i - S_i)}{\sum_{i=1}^{n} (M_i)} \times 100 \tag{1}$$

$$\mathrm{nRMSE} = \frac{\sqrt{\sum_{i=1}^{n} (S_i - M_i)^2/n}}{\bar{M}} \times 100 \tag{2}$$

Table 2
The parameter levels for sensitivity analysis at Liufangzi, Jilin, China.

Levels	Planting date (day of year)	Planting density (seed m^{-2})	Tillage depth (m)	N application rate (kg N ha9^{-1})	N application ratio Basal	Jointing	Tasseling
1	03-Apr (93)[a]	3	0	0	1	–	–
2	10-Apr (100)	4	0.05	30	1/2	1/2	–
3	17-Apr (107)	5	0.10	60	1/3	2/3	–
4	24-Apr (114)	6	0.20	90	2/3	1/3	–
5	01-May (121)	7	0.30	120	1/3	1/3	1/3
6	08-May (128)	8		150	1/4	2/4	2/4
7	15-May (135)	9		180	1/4	1/4	2/4
8	22-May (142)	10		210	2/4	1/4	1/4
9	29-May (149)			240			
10				270			
11				300			

[a] The content within the brackets represents the day of year.

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (S_i - M_i)^2}{\sum_{i=1}^{n} (M_i - \bar{M})^2} \tag{3}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (S_i - M_i)^2}{\sum_{i=1}^{n} (|S_i - \bar{M}| + |M_i - \bar{M}|)^2} \tag{4}$$

where S_i is the simulated value, M_i is the measured value, i = 1, …, n is the number of measured values and $\bar{M}$ is the mean of the measured values.

The PBIAS indicates the average tendency of the simulated data to underestimate (negative value) or overestimate (positive value) the measured data (Moriasi et al., 2007). The nRMSE shows the relative size of the average difference without units, and this statistic is unbounded (Priesack et al., 2006). The NSE ($-\infty$ to 1) is a normalized measure that determines the relative magnitude of model residuals compared to the measured variance (Moriasi et al., 2007). The index of agreement (d) ($0 \le d \le 1$) is intended to be a descriptive measure, and it is both a relative and bounded measure (Willmott, 1982; Krause et al., 2005). Therefore, using different indicators to estimate the model performance can ensure the accuracy of model simulation based on previous studies. In this study, we consider a "fair" agreement between the simulated and measured data when PBIAS was within < ± 25% and < ± 70% for N (Moriasi et al., 2007). An agreement is said to be "excellent" when the nRMSE is ≤10%, "good" when 10 < nRMSE ≤ 20%, "fair" when 20% < nRMSE ≤ 30%, and "poor" when nRMSE > 30% (He et al., 2018; Liu et al., 2013). The NSE criteria should be project-specific so as to increase the efficiency of evaluation based on previous studies (Motovilov et al., 1999; Moriasi et al., 2007; Yang et al., 2014; Waseem et al., 2017; Abebe and Gebremariam, 2019). In our study, we consider "perfect" model performance when NSE value = 1.0, "good" performance when 0.5 < NSE < 1, "fair" performance when 0.0 ≤ NSE ≤ 0.5, and "poor" performance when NSE < 0.0. A value of d ≥ 0.9 is considered "excellent" agreement, 0.8 ≤ d < 0.9 is considered "good" agreement, 0.7 ≤ d < 0.8 is considered "fair" agreement, and d < 0.7 is considered "poor" agreement when comparing the simulated and measured values (He et al., 2018; Liu et al., 2013).

Additionally, data were compared using the paired-*t* test from IBM SPSS 19.0 software to determine whether the differences between measured and simulated values were statistically significant at $p < 0.05$.

2.5. Sensitivity analysis

Sensitivity analysis is a fundamental tool in the use and understanding of simulation models as it can be used to indicate the variation range of the output variable after changing one input parameter value within the specific boundaries while keeping all other inputs at their default values (Misra and Rose, 1996; Bert et al., 2007; Li et al., 2015; He et al., 2016). In this study, the sensitivity analyses of the DNDC and DSSAT models were used to explore best management practices including the planting date, planting density, tillage depth and fertilizer rate and times (Table 2). A 20-year historical weather data (1996–2015) was used to explore the best management practices for improving maize yield and nutrient use efficiency (Fig. A. 1). The planting date in the sensitivity analysis ranged from 3 April (93) to 29 May (149) with a 7-day interval based on farmers' practices in northeast China (Xu et al., 2014a, 2014b; Zhao et al., 2015). The sensitivity level of the planting density ranged from 3 to 10 seeds m^{-2} (Zhang et al., 2014, 2017), with a 1 seed m^{-2} interval conducted only by the DSSAT model as the DNDC model is incapable of adjusting planting density. The tillage depth was conducted to encompass 0, 0.05, 0.10, 0.20 and 0.30 m (Zhang et al., 2015b; Piao et al., 2016). The fertilizer N application rate was set to vary from 0 to 300 kg N ha^{-1} with a 30 kg N ha^{-1} interval (Niu et al., 2013; Xu et al., 2014a,b, 2016; Wang et al., 2016). The fertilization time was considered according to three main growth stages: basal, jointing and tasselling. The ratios of two-splitting fertilizer were 1/2:1/2, 1/3:2/3 and 2/3:1/3 and at basal and 1/3:1/3:1/3, 1/4:2/4:1/4, 2/4:1/4:1/4 and 1/4:1/4:2/4 for three-splitting, respectively. More detailed information is listed in Table 2. All input parameters of sensitivity analysis are based on the default values from current farmers' practice in northeast China, the default cultivar, planting date, planting density, tillage depth and fertilizer rate are Pioneer335, 1 May, 6.0 seeds m^{-2}, 0.20 m and 251 kg N ha^{-1}, respectively.

2.6. Nitrogen use efficiency

The nitrogen use efficiency parameters included the agronomic efficiency of N (AEN, kg kg^{-1}), the partial factor productivity of N (PFPN, kg kg^{-1}) and the recovery efficiency of N (REN, %), which were calculated using Eqs. (5)–(7):

$$\mathrm{AEN} = \frac{GY_N - GY_{N0}}{N_{rate}} \tag{5}$$

$$\mathrm{PFPN} = \frac{GY_N}{N_{rate}} \tag{6}$$

$$\mathrm{REN} = \frac{U_N - U_{N0}}{N_{rate}} \times 100 \tag{7}$$

where GY_N is the maize yield (kg ha^{-1}) for the EI-N and FP-N treatments, and GY_{N0} is the maize yield (kg ha^{-1}) for the EI-N0 and FP-N0 treatments; U_N is the plant N uptake at maturity (kg N ha^{-1}) for the EI-N and FP-N treatments and U_{N0} is the plant N uptake at maturity (kg N ha^{-1}) for the EI-N0 and FP-N0 treatments. N*rate* is the fertilizer N application rate (Xu et al., 2016).

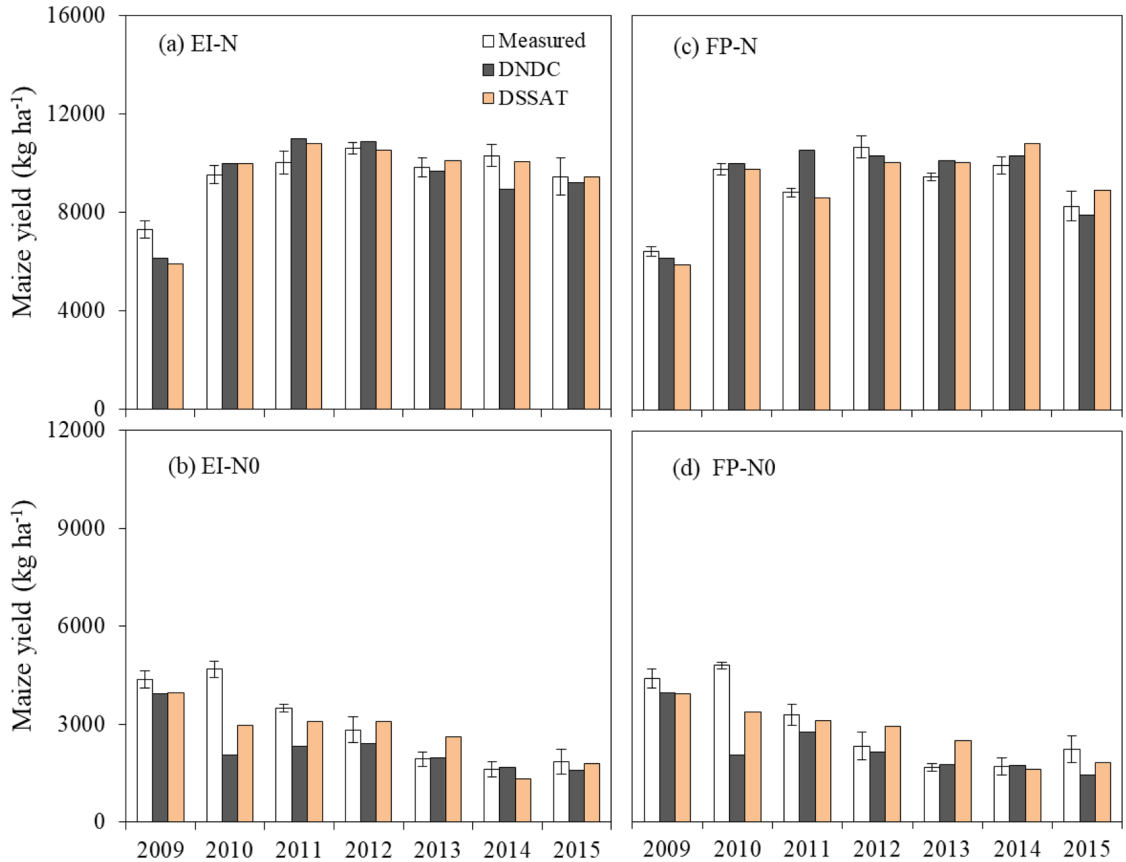

Fig. 1. Measured and simulated maize yield from 2009 to 2015 for (a) ecological intensification with nitrogen fertilizer (EI-N), (b) EI without nitrogen fertilizer (EI-N0), (c) farmers' practice with nitrogen fertilizer (FP-N) and (d) FP without nitrogen fertilizer (FP-N0). Bars are standard deviations (n = 4).

3. Results and discussion

3.1. Model calibration and evaluation

3.1.1. Crop growth

Calibration of the DNDC and DSSAT model indicated that "good" to "excellent" agreement between the simulated and measured maize yields and above-ground biomass for the EI-N and FP-N treatment based on the values of −7.0% ≤ PBIAS ≤ 1.9%, 11.3% ≤ nRMSE ≤ 7.5%, 0.32 ≤ NSE ≤ 0.77, and 0.88 ≤ d ≤ 0.94 (Fig. 1 and A. 2, 3, Table 3). Both models underestimated maize yields for the EI-N treatment and overestimated maize yields for the FP-N treatment, but there was no significant difference between the simulated and measured data. These results demonstrated that the DNDC and DSSAT models matched well between the simulated and measured maize yields and above-ground biomass of the N-fertilized (EI-N and FP-N) treatments. For plant N uptake, both the models showed "good" agreement, with the −10.5% ≤ PBIAS ≤ 4.2%, 11.4% ≤ nRMSE ≤ 17.2%, 0.17 ≤ NSE ≤ 0.63 and 0.81 ≤ d ≤ 0.89 between the simulated and measured data under N-fertilized treatments (Fig. 2, Table 3). Overall, the N use efficiency was calculated based on the successfully calibrated N uptake in the DNDC and DSSAT models (Table 4, Fig. A. 4). Compared to the measured plant N uptake, the DNDC model underestimated the N uptake for the FP-N treatments ($p > 0.05$); in contrast, the DSSAT model significantly ($p < 0.05$) overestimated the N uptake. A similar finding reported by Liu et al. (2012) indicated that the over-prediction of the N uptake of maize in the DSSAT model might be due to an overestimation of N mineralization rate. In addition, the plant N uptake would decrease

Table 3
Statistics of model calibration and evaluation between the measured and simulated maize yield and nitrogen uptake at Liufangzi, Jilin, China.

Variable	Treatment	Measured	Simulated		PBIAS[a] (%)		nRMSE (%)		NSE		d		Paired *t* test (*p*)	
			DNDC	DSSAT	DNDC	DSSAT	DNDC	DSSAT	DNDC	DSSAT	DNDC	DSSAT	DNDC	DSSAT
Maize yield ($kg\,ha^{-1}$)	EI-N[b]	9582	9400	9552	1.9	0.3	9.1	7.5	0.32	0.53	0.88	0.92	0.28	0.82
	EI-N0	2938	2279	2696	22.4	8.3	38.4	26.0	0.02	0.55	0.71	0.83	0.01	0.09
	FP-N	9043	9328	9145	−3.2	−1.1	9.5	7.7	0.59	0.73	0.91	0.94	0.07	0.12
	FP-N0	2916	2256	2775	22.6	4.8	39.1	25.1	0.10	0.63	0.72	0.86	0.01	0.32
Nitrogen uptake ($kg\,N\,ha^{-1}$)	EI-N	171	164	179	4.2	−5.0	11.7	12.5	0.55	0.48	0.86	0.87	0.06	0.06
	EI-N0	42	48	47	−15.1	−12.2	42.7	32.3	0.22	0.55	0.70	0.82	0.06	0.05
	FP-N	175	171	193	2.4	−10.5	11.4	17.2	0.63	0.17	0.89	0.81	0.31	0.09
	FP-N0	44	48	53	−9.5	−20.4	45.2	30.3	0.32	0.70	0.70	0.90	0.27	0.00

[a] PBIAS: percent bias; nRMSE: normalized root mean square error; NSE: Nash-Sutcliffe efficiency; d: index of agreement.
[b] EI-N: ecological intensification with nitrogen fertilizer; EI-N0: EI without nitrogen fertilizer; FP-N: farmers' practice with nitrogen fertilizer; FP-N0: FP without nitrogen fertilizer.

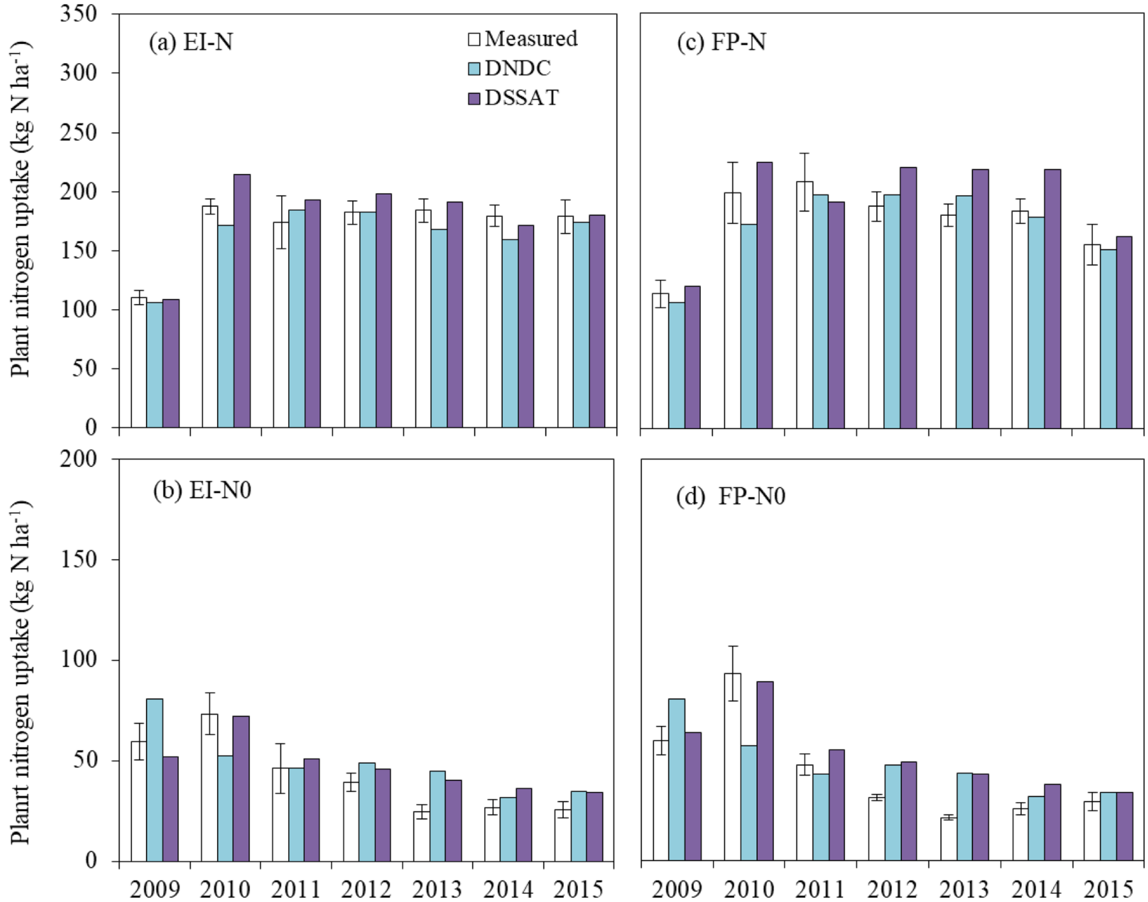

Fig. 2. Measured and simulated plant nitrogen uptake from 2009 to 2015 for (a) ecological intensification with nitrogen fertilizer (EI-N), (b) EI without nitrogen fertilizer (EI-N0), (c) farmers' practice with nitrogen fertilizer (FP-N) and (d) FP without nitrogen fertilizer (FP-N0). Bars are standard deviations (n = 4).

when the value of the N stress coefficient for changes in concentration with growth stage (CTCNP2) increased by 20–60% in the DSSAT model. However, the influence of a high CTCNP2 coefficient could reduce the sensitivity of crop growth to the fertilizer N rate. The long-term simulation of plant N uptake and soil N mineralization rate under excessive fertilization should be considered in further development of the DSSAT model.

The DNDC and DSSAT model produced "fair" to "good" agreement between the simulated and measured maize yields, above-ground biomass and plant N uptake under the EI-N0 and FP-N0 treatments with $-20.4\% \le PBIAS \le 22.6\%$, $0.02 \le NSE \le 0.70$ and $0.70 \le d \le 0.90$; however, nRMSE > 30% in all cases except for maize yields in the DSSAT model. Nevertheless, the DSSAT model showed better performance than the DNDC model in simulating maize yields (Figs. 1, 2 and A. 2, 3, Table 3). The DNDC model did not capture the changes in inter-annual yields under N-unfertilized treatments partially due to the underestimated N mineralization rate and N availability from the dissolved inorganic N pools under N stress conditions, which resulted in low yield and N uptake, particularly under continuous N deficiencies (Sansoulet et al., 2014; Zhang et al., 2017b). Another possible factor was the incomplete consideration of the soil organic carbon decomposition and mineralization when sudden cessation of fertilization occurred in the model simulation (Zhang et al., 2017b). Long-term field experiment with high quality datasets should be conducted in the model development to understand the impact of nutrient deficiency on crop growth and soil nutrient dynamic cycling.

Table 4
Statistical of model calibration and evaluations between the measured and simulated agronomic efficiency of N (AEN), partial factor productivity of N (PFPN) and recover efficiency of N (REN) at Liufangzi, Jilin, China.

Treatment	Variable	Measured	Simulated		PBIAS[a] (%)		nRMSE (%)		NSE		d		Paired *t* test (*p*)	
			DNDC	DSSAT	DNDC	DSSAT	DNDC	DSSAT	DNDC	DSSAT	DNDC	DSSAT	DNDC	DSSAT
EI-N[b]	AEN (kg kg^{-1})	43.0	43.0	36.4	7.9	15.3	22.8	21.4	0.33	0.42	0.81	0.85	0.06	0.05
	PFPN (kg kg^{-1})	52.5	51.5	50.9	1.9	3.0	9.1	7.1	0.40	0.64	0.89	0.93	0.28	0.82
	REN (%)	70.3	63.4	71.5	9.7	−1.8	19.7	15.5	0.53	0.71	0.88	0.91	0.01	0.62
FP-N	AEN (kg kg^{-1})	28.9	28.5	25.1	1.4	16.6	17.4	23.1	0.75	0.55	0.92	0.86	0.69	0.05
	PFPN (kg kg^{-1})	36.0	37.5	35.0	−4.0	2.8	9.1	6.8	0.60	0.78	0.92	0.94	0.08	0.47
	REN (%)	52.1	49.4	55.5	5.1	−6.7	16.7	18.5	0.70	0.64	0.93	0.90	0.10	0.05

[a] PBIAS: percent bias; nRMSE: normalized root mean square error; NSE: Nash-Sutcliffe efficiency; d: index of agreement.
[b] EI-N: ecological intensification with nitrogen fertilizer; EI-N0: EI without nitrogen fertilizer; FP-N: farmers' practice with nitrogen fertilizer; FP-N0: FP without nitrogen fertilizer.

In addition, the two models significantly underestimated the maize yield in 2009 (a dry year) compared to the measured data (Fig. 1). This might be due to the overestimation of the actual evapotranspiration of the crop in the DSSAT model (Eitzinger et al., 2004; Sau et al., 2004) which resulted in water stress later in the growing season. The increased gap between the potential and actual evapotranspiration rate resulted in an increased water stress levels which limited crop biomass accumulation (Eitzinger et al., 2004). López-Cedrón et al. (2008) indicated that the DSSAT model underestimated the maize yield partially because that the simulated water extraction was earlier than field experiment under water deficit condition. In the DNDC model, the inaccurate simulation of root distribution and soil water content under dry conditions could affect the crop growth mainly due to its inability to simulate a heterogeneous soil profile and no water table (Uzoma et al., 2015; Smith et al., 2019).

3.1.2. Soil organic carbon

The SOC contents at soil depths of 0–0.20 m from 2009 to 2015 were simulated using the DNDC and DSSAT models (Fig. 3). The statistical values were PBIAS ≤ 1.2%, nRMSE < 10% and NSE > 0, although d < 0.7 for N-unfertilized treatments, overall provided "fair" agreement between the simulated and measured data in the DNDC model for all treatments. The results were consistent with other studies which reported that the DNDC model simulated well the SOC contents (Zhang et al., 2006; Chen et al., 2015; Zhang et al., 2017b). The model slightly overestimated the SOC content under N-fertilized treatment, which was probably due to the stimulation in C mineralization associated with microbial activity under N sufficient conditions. The DSSAT model provided a "fair" simulation for SOC under the EI-N and FP-N treatments, with the PBIAS ≤ 2.1%, nRMSE ≤ 7.6%, NSE > 0 and d > 0.7. However, the model underestimated ($p > 0.05$) the SOC content for the EI-N0 and FP-N0 treatments, with the PBIAS ≤ 2.8%, nRMSE < 10%, NSE < 0 and d < 0.7. The underestimation of SOC might be associated with the flows of carbon from one pool to another accompanied by the amount of N which was proportional to the C:N ratio of the decomposing material. Additional N needed for adding C to the recipient pool was obtained by immobilizing some inorganic N from the surrounding soil under N deficiency condition (Porter et al., 2010). Similar studies indicated that the DSSAT model underestimated the soil organic carbon content under N deficiency conditions (De Sanctis et al., 2012; Liu et al., 2017). Li et al., 2015 demonstrated that the low initial topsoil C/N ratio contributed to rapidly increase SOC using the DSSAT model.

3.1.3. Soil mineral nitrogen

The soil mineral nitrogen contents at soil depths of 0–0.30 m from 2009 to 2015 were simulated in the DNDC and DSSAT models (Fig. 4). For the EI-N0 and FP-N0 treatments, the results from both models showed "poor" agreement between the simulated and measured soil mineral nitrogen contents based on statistical values PBIAS > 50%, nRMSE > 30%, NSE < 0 and d < 0.7. For the EI-N and FP-N treatment, the DNDC and DSSAT models showed "fair" performance in simulating soil mineral N content compared to the measured values, with 3.2% ≤ PBIAS ≤ 45.0%, 0.27 ≤ NSE ≤ 0.60 and 0.71 ≤ d ≤ 0.88, although nRMSE > 30%. Both models underestimated soil mineral nitrogen content for all treatments, but there was no significant difference between the simulated and measured data under the EI-N and FP-N treatments in the DNDC model. The changes in soil mineral nitrogen content were related to the actual N uptake by crop, which was affected by soil N supply and water availability during the growing season in the

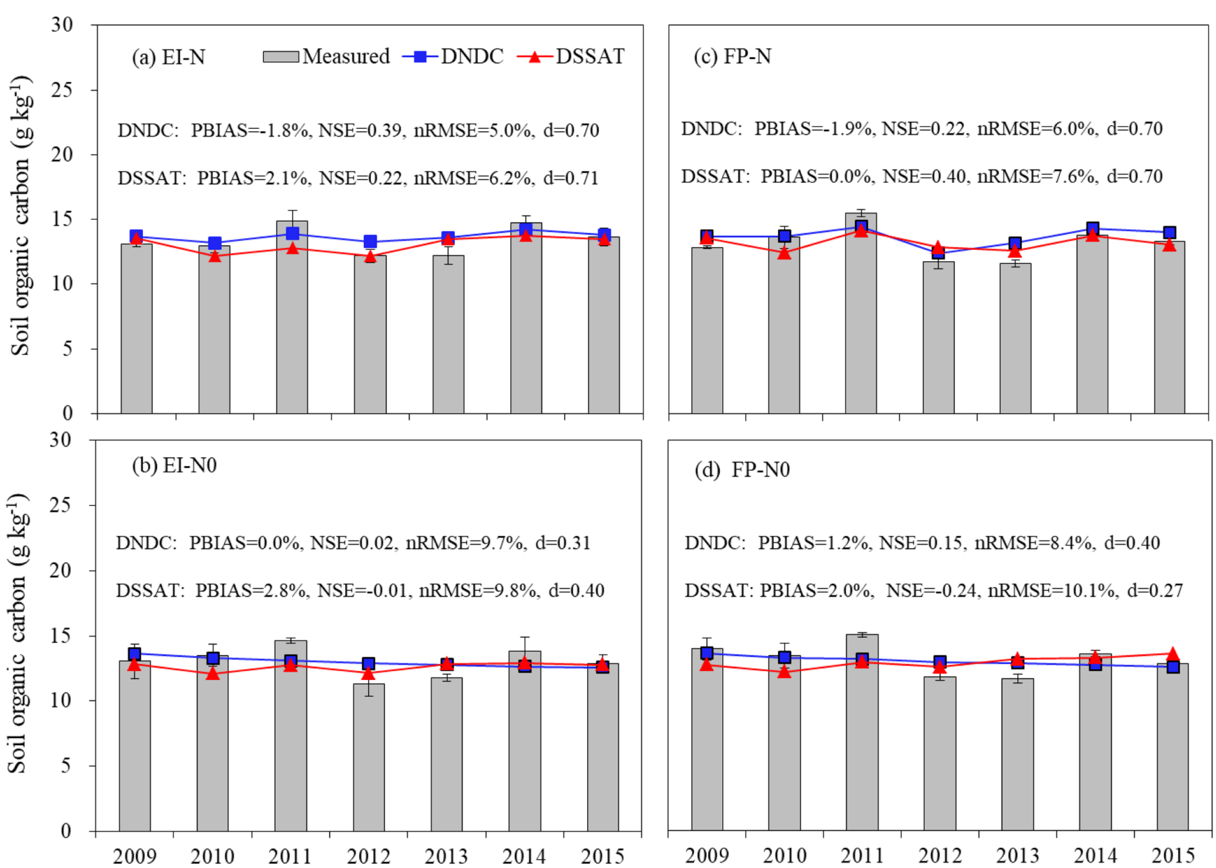

Fig. 3. Measured and simulated soil organic carbon content (0–0.20 m) from 2009 to 2015 for (a) ecological intensification (EI-N), (b) EI without nitrogen fertilizer with nitrogen fertilizer (EI-N0), (c) farmers' practice with nitrogen fertilizer (FP-N) and (d) FP without nitrogen fertilizer (FP-N0). Bars are standard deviations (n = 4).

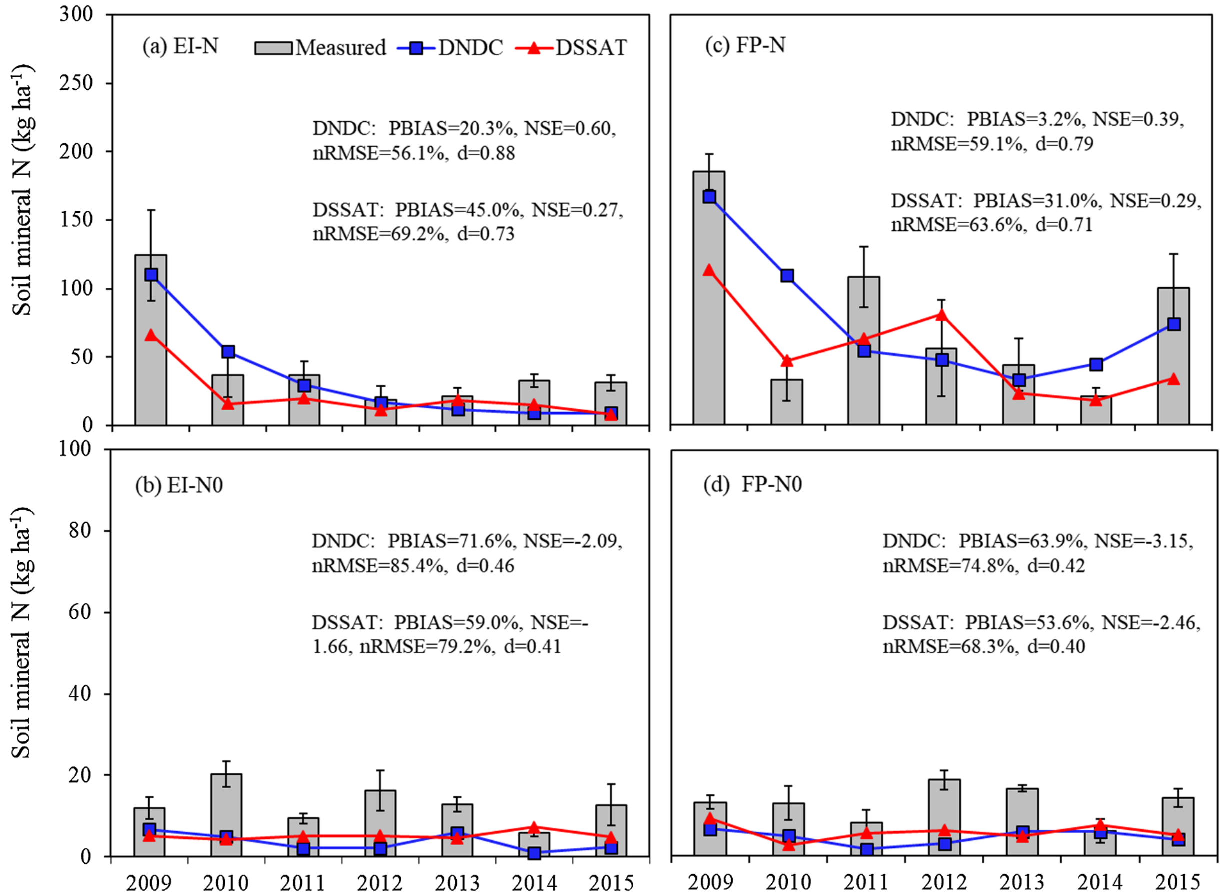

Fig. 4. Measured and simulated soil mineral N content (0–0.30 m) from 2009 to 2015 for (a) ecological intensification with nitrogen fertilizer (EI-N), (b) EI without nitrogen fertilizer (EI-N0), (c) farmers' practice with nitrogen fertilizer (FP-N) and (d) FP without nitrogen fertilizer (FP-N0). Bars are standard deviations (n = 4).

model simulation (Sansoulet et al., 2014; Yakoub et al., 2017). The DSSAT model underestimated the soil mineral nitrogen content for the FP-N treatment partially due to the overestimation of crop N demand under N-sufficient conditions. Moreover, both the models underestimated soil mineral N content for N-unfertilized treatments, which might be due to the underestimation of the amount of the mineralized nitrogen under N deficiency; similar results were reported by Liu et al. (2011) and Liu et al. (2014). Liu et al. (2014) showed that the DSSAT model underestimated the simulated soil inorganic nitrogen content, mainly because the model could not accurately account for the soil mineral N content below a depth of 0.30 m, whereas the model reasonably captured the soil mineral N trajectory during the whole growth period (Liu et al., 2011; Yang et al., 2011). It was also found that the DNDC model poorly estimated the soil mineral nitrogen content (0–0.30 m) using field experiment data, which was associated with the poor structure in the soil water balance module (He et al., 2018a). The complexity of soil N dynamics led to a large uncertainty in simulating the soil mineral N content. The imprecise simulations of soil mineral N fluctuations for different soil layers are mainly due to the flaws in the soil water balance module, particularly under extreme weather conditions or nutrient stress, which needs to be better characterized in the model. Additionally, the inaccurate estimation of the immobilization-mineralization processes also could result in the model error (Brilli et al., 2017).

3.2. Sensitivity analysis for maize yield and agronomic efficiency

Sensitivity analyses of the DNDC and DSSAT models were conducted to explore best management practices, including the planting date, planting density, tillage depth, and fertilizer N application rate and time (Table 2). The simulation results were observed with the response curves of the maize yield to the values of different management practices (Fig. 5 and A. 5). The simulated average maize yield was 9434 and 9252 kg ha^{-1} for the DNDC and DSSAT models based on default value, respectively. Based on the sensitivity analysis, the planting date, planting density, fertilizer N application rate and fertilizer split had a greater influence on maize yield than did the tillage depth.

3.2.1. Fertilizer N application rate and time

There was a curvilinear increase in the maize yield when the fertilizer N rates ranged from 0 to 300 kg N ha^{-1}, and the average maximum yields (9434 and 9236 kg ha^{-1}) were observed at 240 kg N ha^{-1} as basal fertilizer in both the DNDC and DSSAT models (Fig. 5a). Although the simulated maize yield showed a slight increase when the fertilizer N rate exceeded 240 kg N ha^{-1} in the DSSAT model, there was no significant difference. The increased crop yield and N uptake values decreased when nitrogen fertilizer application exceeded crop N demand based on patterns of diminishing returns, leading to low nitrogen use efficiency (Chen et al., 2014). The difference in simulated maize yield between the DNDC and DSSAT models was found at a low fertilizer N rate, which may be due to the different responses of yield to nitrogen supply in maize growth for the two models. The yields were more sensitive to N stress in the DNDC model compared to the DSSAT model, which was consistent with the response of simulated yields under N-unfertilized conditions.

Previous studies showed that the temporal synchronicity between crop N demand and soil N availability could be improved via fertilizer N application times at the crop growth stages (Xu et al., 2016; Wang et al., 2016). The sensitivity of the DNDC and DSSAT model showed that the simulated maximum maize yield with higher N use efficiency was

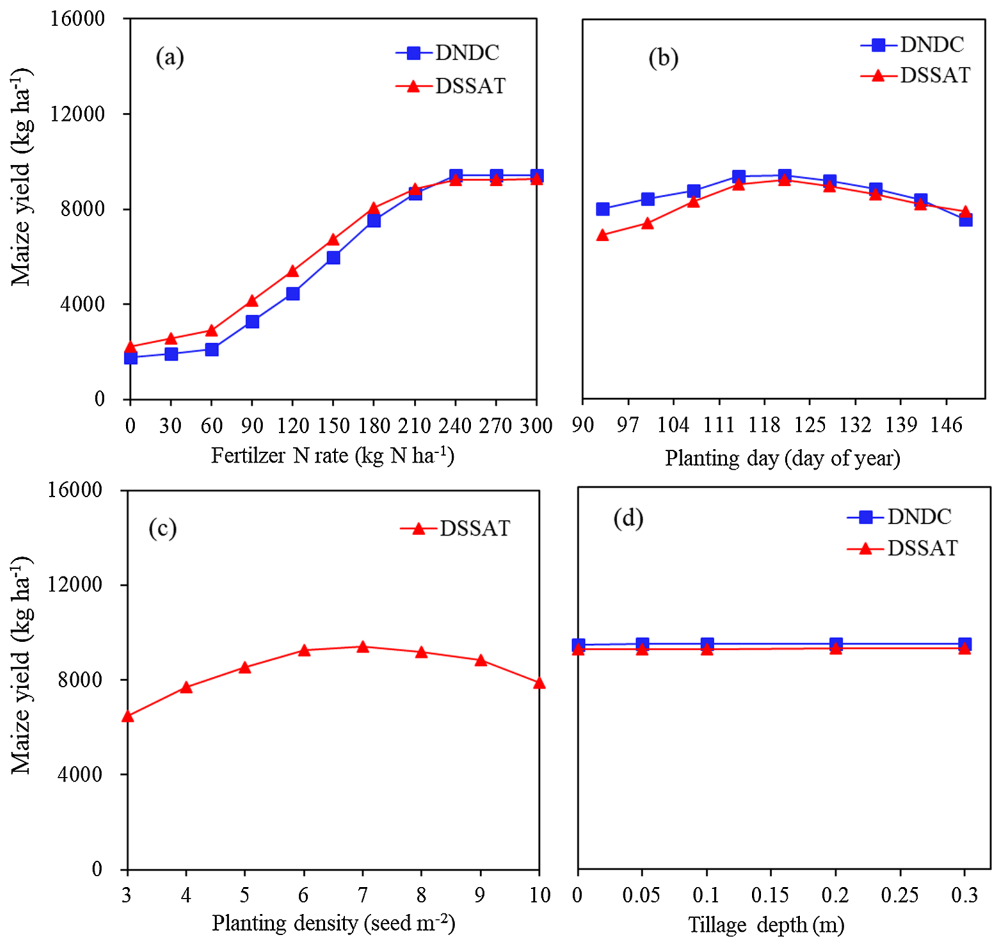

Fig. 5. Sensitivity of maize yields to (a) fertilizer application rate, (b) planting date, (c) planting density and (d) tillage depth in the DNDC and DSSAT model at Liufangzi, Jilin, China.

Table 5
Recommendations of field management practices based on the sensitivity analyses of the DNDC and DSSAT models at Liufangzi, Jilin, China.

Model	Index	Default Values	Nitrogen fertilizer application and times (kg N ha^{-1}) (Basal) 240	(Basal: jointing) 210 (1/3:2/3)	(Basal: jointing: tasselling) 210/240 (1/4:2/4:1/4)	Planting date (day of year) 121	Planting density (seed m^{-2}) 7	Combined optimization
DNDC	Grain yields (kg ha^{-1})	9434	9434	9449	9435	9434	–	9449
	AEN (kg kg^{-1})[a]	30.5	31.9	36.6	36.5	30.5	–	36.6
	PFPN (kg kg^{-1})	37.6	39.3	45.0	44.9	37.6	–	45.0
	REN (%)	52.1	52.8	56.6	56.9	52.1	–	56.6
DSSAT	Grain yields (kg ha^{-1})	9252	9236	9243	9217	9252	9420	9466
	AEN (kg kg^{-1})	28.0	29.2	33.4	29.1	28.0	28.6	34.4
	PFPN (kg kg^{-1})	36.9	38.5	44.0	38.4	36.9	37.5	45.1
	REN (%)	55.7	56.0	59.2	56.7	55.7	57.4	61.2

[a] AEN: agronomic efficiency of N; PFPN: partial factor productivity of N; REN: recover efficiency of N.

obtained at 210 kg N ha^{-1} when the fertilizer N applied with two- or three-time splitting compared to the default fertilizer application as basal (251 kg N ha^{-1}), except for three-time splitting at 240 kg N ha^{-1} in the DSSAT model (Table 5, Fig. A. 5). For different splitting, the N split ratio of 1/3:2/3 and 1/4:2/4:1/4 for both models performed slightly better than other split ratio. In both models simulation, the high maize yield would achieve at 210 kg N ha^{-1} (Fig. A. 5), but there were no statistical differences at 180–210 kg N ha^{-1} range with splitting especially in the DSSAT model. These results indicated that split application of fertilizer N with lower N application rates could obtain equal or higher maize yields than single fertilization. The excessive application of fertilizer N as basal fertilizer had a negative impact on nitrogen uptake and transport and posed an environmental risk (e.g., NO_3^- leaching and greenhouse gas emissions) (Xu et al., 2016; He et al., 2016). The potential yields did not increase when fertilizer N application was delayed until the silking stage, even though it had a response between N application and crop N demand (Scharf et al., 2002). Therefore, based on our model sensitivity analysis, the optimal fertilizer N application for maize was 180–210 kg N ha^{-1} with two-time splitting (1/3 as basal fertilizer; 2/3 at jointing stage). Previous studies have also indicated that fertilizer N application with two or three-time splitting based on the nutrient demand of maize growth would be recommended versus a high fertilizer N application rate as basal fertilizer with low nitrogen use efficiency common in current farmers' practice in northeast China (Yang et al., 2011a; Niu et al., 2013; Xu et al., 2014a,b, 2016). Niu et al. (2013) reported that the nitrogen application was 225 kg N ha^{-1} with a two timing splits for spring maize based on field experimental data at current cultivation levels or 300 kg N ha^{-1} with three-time splitting at high-yielding cultivation levels in northeast China. Yang et al., 2011 reported that the fertilizer N application rate ranged from 200 to 240 kg N ha^{-1} with two-time splitting in the DSSAT model in northeast China. These results indicate that reasonable nitrogen fertilizer management is conducive to reducing the amount of nitrogen fertilizer and increasing crop productivity and nutrient uptake.

3.2.2. Planting date

The planting date showed a non-linear effect on maize yield (Fig. 5b). Both models indicated the maximum yield would obtain on day 121 (1 May), but there was no significant difference between day 114 and 121. If the planting date was advanced or delayed 14–28 days, the maize yield decreased by approximately 6.2–19.6% in the DNDC model and 7.3–25.3% in the DSSAT model. The different effects of planting dates on maize yield between the DNDC and DSSAT models were mainly due to the differences in mechanisms of simulating crop phenology. In the DNDC model, crop growth was characterized by empirical growth curves specifying N requirements for C biomass accumulation and driven by the accumulation of thermal degree days (Gilhespy et al., 2014), whereas in the DSSAT model, the crop growth was controlled by phenologically defined growth stages based on growing degree days and daily intercepted photosynthetically active radiation (Jones et al., 2003; Hoogenboom et al., 2012). Meteorological factors (e.g., temperature, precipitation) could affect the maize yield (Zhao et al., 2015). Early planting with low temperature most likely reduced the leaf number and internode length of crops, resulting in lower crop production (Tsimba et al., 2013). In addition, low air temperature led to lower soil temperature, which could affect seed emergence (Yang et al., 2011b). In contrast, late planting under high temperatures reduced the photosynthetic activity of crops (Otegui et al., 1996). Tsimba et al. (2013) also demonstrated that delaying the planting date made crops susceptible to water stress more than advancing the date. In this study, the precipitation in September was 15–94% lower than that in August in the growing season. These results demonstrated that the recommended planting date ranged from late April to early May.

3.2.3. Planting density

The sensitivity analysis of the DSSAT model showed that maize yield was sensitive to the planting density within a varying range (Fig. 5c). The maize yield increased when the planting density changed from 3 to 7 seeds m^{-2}, whereas it gradually decreased with the increase in the planting density due to plant lodging and the low photosynthetic efficiency (Zhang et al., 2014, 2017). The maximum yield was observed at a planting density of 7 seeds m^{-2} and increased by 2.3% along with a higher AEN, PFPN and REN in the DSSAT model compared to the default values (Table 5). These results demonstrated that the current planting density should be improved to obtain a higher maize yield. In this study, the maize planting density was lower than other countries (e.g., 7–9 seeds m^{-2} in the corn belt of U.S.) (Qi et al., 2011a,b; Balboa et al., 2019) depending on different cultivars, soil and climate. Previous studies indicated that the maize yield increased with the increase of planting density, but decreased when the planting density exceeded 7.5 seeds m^{-2} in northeast China (Zhang et al., 2014). This might be due to the kernel number and thousand kernel weight per maize ear decreased with increasing planting density (Zhang et al., 2014) and the high logging percentage would increase with high density when excess 8.25 seeds m^{-2} (Zhang et al., 2017).

3.2.4. Tillage

There was no significant linear relationship between the tillage depth and maize yield in the DNDC and DSSAT models based on the sensitivity analyses (Fig. 5d). Tillage-involved factors influencing crop growth are complex and include soil moisture, temperature and nutrient availability. However, maize yield was little affected by tillage depth in our modelling study, partially due to that the models did not adjust some soil properties overtime (e.g., bulk density) (Brilli et al., 2017). Maize yields were not affected by tillage depth in our modelling study which was in agreement with He et al., 2018; Liu et al., 2013, who reported little or no change in maize yields between no tillage and conventional tillage in the DSSAT model in northeast China and the DNDC model in Canada. Thus, the effects of tillage depths on maize growth need to be better characterized in the DNDC and DSSAT models for future improvement. More factors should be considered when exploring the effect of tillage on crop yield, such as rooting depth effect and the change of soil physical and chemical properties under different tillage (Corbeels et al., 2016).

3.2.5. Combination of optimized management practices

Maize yield and nitrogen use efficiency further increased when all optimized management practices were combined (Table 5). Compared to the default data, the maize yield, AEN, PFPN and REN increased by 2.3%, 6.5 and 6.0 kg kg^{-1}, 8.2 and 7.4 kg kg^{-1}, and 9.9 and 8.7% when optimal management practices were combined in the DSSAT and DNDC model, respectively (Table 5). Niu et al. (2013) reported that the combined improvement of maize genotype management and agronomic management would have a more positive impact on maize productivity in northeast China. In addition, Zhang et al. (2015b) reported that the DNDC model optimized critical agronomic and environmental N rates for maize growth in North China. These results indicated that integrated optimal management practices could have the potential to further improve crop yield and N agronomic efficiency.

4. Conclusions

The DNDC and DSSAT models were used to investigate the impacts of ecological intensification management and farmers practices on maize growth and soil C & N dynamics and to explore best management strategies to improve maize production with high NUE in northeast China. Both models overall indicated “good” performance in simulating maize yield, above-ground biomass and N uptake based on the statistical evaluations. The DSSAT model showed better simulations in maize yield under the N-unfertilized treatments compared to DNDC modelling, but the two models performed poorly in simulating maize growth and soil nutrient dynamics under dry conditions, mainly due to the flaws in the soil water balance module. In addition, the DNDC and DSSAT models showed “fair” performances in simulating soil organic carbon (0–0.20 m) and mineral nitrogen (0–0.30 m) for the N-fertilized treatments, but “poor” performances for N-unfertilized treatments which was partially attributed to underestimated mineralization rate under N stress conditions. The sensitivity analyses indicated that the maize yield and nitrogen use efficiency could be further improved by adjusting the planting date, planting density, fertilizer application rates and times. This study suggests that optimizing management practices based on modelling approach can be useful for policy decision in planning best management practices in an effort to improve nutrient use efficiency and maintain a crop sustainable production footprint.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2019.104988.

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