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Evaluation and application of the ORYZA rice model under different crop managements with high-yielding rice cultivars in central China

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ABSTRACT

ORYZA version 3, as the successor to ORYZA2000, is an ecophysiological model that can simulate rice growth and development for targeted yield with different nitrogen (N) fertilizer rates and planting densities in a given rice production system. Currently, there is little published information on the application of ORYZA (v3) and ORYZA2000 in simulating high-yielding rice cultivars under different N rates and planting density schemes in central China. This paper combines field experimentation with ORYZA (v3) to calibrate the crop growth characteristics of widely grown high-yielding inbred and hybrid rice cultivars. The calibrated model was applied to simulate yields under different N rates, planting densities, and seedlings per hill, using historical weather data from 1986 to 2015. ORYZA (v3) reliably simulated the dynamics of crop biomass and leaf area index, and seasonal yield, with relatively small normalized root mean square error ($RMSE_n$) and high adjusted linear correlation coefficient (R^2), but slightly over-estimated leaf N concentration. Scenario analyses indicated that the maximum differences in simulated yields were 72.1 kg ha^{-1} due to planting density, 112.8 kg ha^{-1} due to seedlings per hill, and 3266.2 kg ha^{-1} due to N rates. The simulations demonstrated that further field experiments are crucial in investigating the effects of rice genotype, N management and their interactions on yield for optimal crop management.

1. Introduction

Rice (*Oryza sativa* L.) is one of the most important staple food crops and feeds more than half of the world's population (Fan et al., 2016). Its production must be increased by 70% by 2050 to meet the growing demand for food accompanying population growth and economic development (Godfray et al., 2010). The productivity of transplanted rice, however, is threatened by environmental degradation and labor scarcity (Peng, 2014, 2016). An increase in rice production must be achieved using existing cropland under the pressures of less anthropogenic resource and labor inputs to maintain the sustainability of agroecosystems and social development. Crop genetic improvements and management technology innovations have contributed significantly to increased crop production in past decades (Gregory and George, 2011). It is imperative to develop crop management that is less dependent on heavy agronomic input but still achieves the potential of high-yielding rice cultivars.

Among plant nutrients, nitrogen (N) is the most important in determining crop yield, and fertilizer N is the major source in modern agricultural systems (Mae, 1997). Thus, almost every farmer applies N to obtain desirable yields (Peng et al., 2010). In China, the average N application rate in rice production is approximately 180 kg ha^{-1}, which is higher than that in most countries and as much as 75% above the global average. This value can reach 300 kg ha^{-1} in some parts of China (Roelcke et al., 2004; Peng et al., 2010). As indicated by Li et al. (2010), the N rate applied to rice crops still shows an increasing trend. However, excessive use of N has not only greatly decreased economic return from applied N but has also placed a heavy economic burden on farmers (Zhang, 2007). Moreover, over-application of N often induces lodging and pest damage, resulting in a reduction in rice yield and quality (Cu et al., 1996). Overuse of N may contribute to soil acidification (Guo et al., 2010), water pollution (Diaz and Rosenberg, 2008), and increased emissions of N_2O (Smil, 1999). Further increases in N application to croplands are unlikely to be effective as a method for increasing crop yield (Tilman et al., 2011).

Suitable planting density and seedlings per hill are critical for achieving optimal tiller density and high grain yield (Ghosh and Singh, 1998). However, labor scarcity in agricultural production and rising production costs for crop seed and labor have resulted in a desire for a lower planting density (Peng, 2016). Planting density can exert a great

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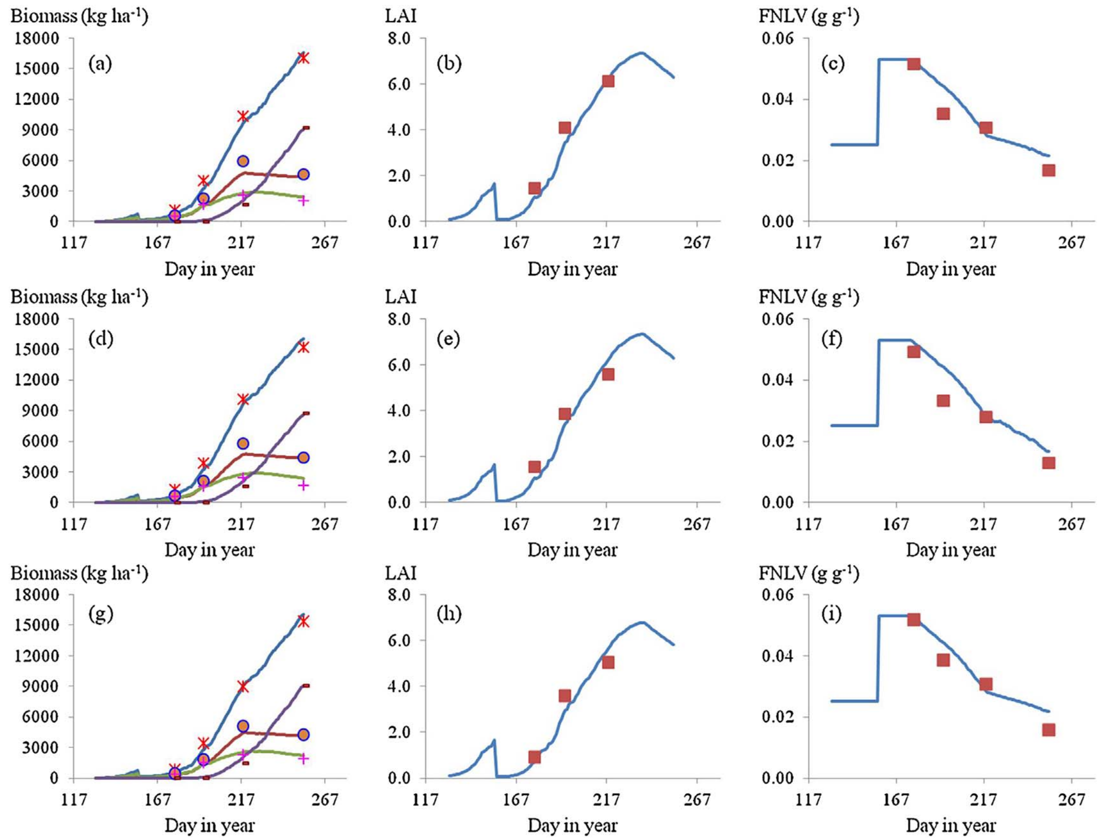

Fig. 1. Simulated (lines) and measured biomass of the whole crop (Ж), green leaves (+), stems (●), and panicles (−), leaf area index (LAI) and leaf N concentration (FNLV) of inbred rice in farmers' practice (a, b, and c), low N input (d, e, and f), and low planting density (g, h, and i) in Dajin County, Wuxue City, Hubei Province, China in 2014 (calibration data set). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

impact on reasonable population structure and has close links to rice yield (Sabeti et al., 2012). High planting density can result in large yield losses due to an excessive number of tillers, a great proportion of ineffective tillers, and higher spikelet sterility (Kabir et al., 2008). In general, appropriately-reduced planting density can promote individual tillering and crop growth, while less productive ears can affect the population structure as well as yield (Shimono, 2011). Meanwhile, widening row spacing resulting from decreased planting density can improve lodging resistance (Yang et al., 2009) and total seasonal light exposure of plants (Lin et al., 2009) and, thus, increase yield. Planting density is of great significance in adjusting canopy structure, improving yield, and decreasing production costs. Therefore, it appears vital to optimize the planting density for high-yielding rice cultivation.

Several factors have been investigated in a series of field experiments conducted under several site-specific climate-management conditions (Clerget et al., 2016; Pampolino et al., 2007). Crop growth simulation models are useful tools for extrapolating the results of field experiments, and examining the effects of different crop management practices across different seasons and environments with the simulation model representing complex interactions of crop genotype, management factors, and climatic conditions (Amiri et al., 2011). Furthermore, adequately calibrated and validated crop models also provide a systems approach and a fast alternative method for evaluating crop management systems that can utilize advanced technologies of agricultural production (Saseendran et al., 2008). ORYZA (v3) is a simulation model developed for simulating the growth and development of rice in agricultural research (Li et al., 2017) and is an improvement over its ancestor ORYZA2000 (Bouman et al., 2001). A number of studies using ORYZA2000 have been conducted with many rice genotypes under many management practices, including various N management, water management, seedling age, CO_2 concentration, temperature, sowing date, and planting density, across different rice production regions in the Philippines (Li et al., 2013b), India (Sudhir-Yadav et al., 2011), Indonesia (Boling et al., 2004), Iran (Amiri et al., 2011), and China (Bouman et al., 2007). As indicated by Li et al. (2013b, 2016, 2017), the predicted growth and yield of ORYZA2000 and ORYZA (v3) are influenced by environmental condition, crop management, and cultivar characteristics. Central China is one of the most important rice-producing regions in China, and its rice production accounts for 54.0% of the national total production (NBSC, 2016). Until now, there had been no case-study on the application of ORYZA2000 or ORYZA (v3) with high-yielding rice cultivars under different N and planting density schemes for the region.

The objectives of this study were to (a) calibrate and evaluate the performance of ORYZA (v3) for high-yielding inbred and hybrid cultivars grown in central China under different crop management practices, and (b) apply ORYZA (v3) to investigate yield response to planting density, seedlings per hill, and N application rates.

2. Materials and methods

2.1. Field experiment

The field experiments were conducted in Dajin County, Wuxue City, Hubei Province, China (29°51′N, 115°33′E, 23 m altitude) in the middle seasons from May to October of 2014 and 2015. The experiments were laid out as a split-plot design with four replications consisting of crop management practices as the main plot and cultivars as the subplot. The three crop management practices included in this study were farmers' practice (FP), low N input (LN), and low planting density (LD). The subplot size was 30 m^2. The 25-day-old seedlings were transplanted at a hill spacing of 13.3 × 30.0 cm for FP and LN, and 20.0 × 30.0 cm for

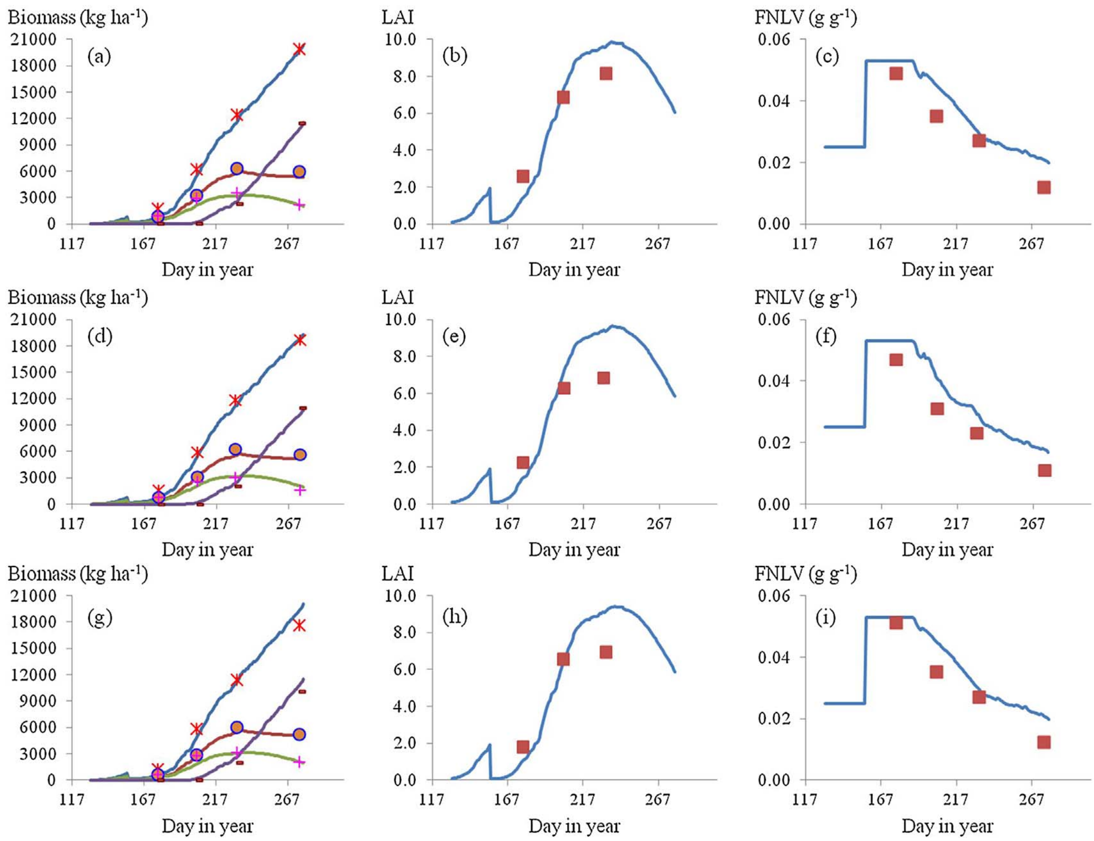

Fig. 2. Simulated (lines) and measured biomass of the whole crop (Ж), green leaves (+), stems (●), and panicles (−), leaf area index (LAI) and leaf N concentration (FNLV) of hybrid rice in farmers' practice (a, b, and c), low N input (d, e, and f), and low planting density (g, h, and i) in Dajin County, Wuxue City, Hubei Province, China in 2014 (calibration data set). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

LD, with two seedlings per hill. An N rate of 180 kg ha^{-1} (basal: mid-tillering: panicle initiation = 4: 3: 3) was applied to FP and LD, and 90 kg ha^{-1} (basal: mid-tillering = 6: 4) was applied to LN. Phosphorus (40 kg P ha^{-1}) and Zinc (5 kg Zn ha^{-1}) were applied and incorporated in all plots one day before transplanting. Potassium (100 kg K ha^{-1}) was split equally at basal and panicle initiation. Other management was the same for all plots and followed local standard practices. Two widely planted local high-yielding rice cultivars, Huanghuazhan (indica inbred) and Yangliangyou 6 (indica hybrid), were used in the experiments.

During the experimental period, 12 hills were randomly collected from each subplot at mid-tillering, panicle initiation, heading, and physiological maturity stages. Each sample was separated into sheath and stem, green leaf, and panicle. Green leaf area was measured with a leaf area meter (LI-3100, LI-COR, Lincoln, NE, USA) at mid-tillering, panicle initiation, and heading stages. Dry weights were determined by oven-drying at 80 °C to constant weight. Rice yield was measured from a 5-m^2 area in each subplot and was expressed as grain weight at 14% moisture content. Leaf N concentration (FNLV) was determined by an Elemental analyzer (Elementar vario MAX CNS/CN, Elementar Trading Co., Ltd, Germany). Weather data were retrieved from a meteorological station within 1 km of the experimental field.

2.2. ORYZA (v3) model

2.2.1. Model introduction

A detailed description of the model along with the program source code is given by Bouman et al. (2001). The model assumes that the rice crop is well protected against diseases, pests, and weeds, and consequently, the model does not consider yield reduction due to these factors. ORYZA2000 is a rice model using empirical- and physiological-based equations to describe the physiology, phenology, and growth of the rice plant. The model follows the daily calculation scheme for the rates of dry matter production of the plant organs and the rate of phenological development from emergence until harvest. By integrating these rates over time, dry matter production is simulated throughout the growing season, and final yield is calculated. The daily canopy assimilation rate is calculated by integrating instantaneous rates of leaf photosynthetic assimilation over depth within the canopy, over the time of one day. The daily dry matter accumulation is obtained after subtraction of maintenance and respiration requirements. The dry matter produced is partitioned among various plant organs. For the aboveground part, the accumulated dry matter is distributed to the stem, leaf, and panicle as a function of the phenological development stage, which is tracked as a function of daily mean temperature and photoperiod. Leaf area grows exponentially as a function of thermal time at the relative leaf growth rate when the canopy has not yet closed. Then, leaf area grows linearly and is calculated from the increase in leaf weight times a specific leaf area (Bouman et al., 2001). ORYZA (v3) is a new version of ORYZA2000 that fully couples the interaction of water and nitrogen, and incorporates new sub-modules for quantifying soil temperature, carbon, and nitrogen daily dynamics (Li et al., 2017).

2.2.2. Model calibration and validation

A large number of parameters have been set in ORYZA (v3). During the simulation, this model requires inputs of management practices, soil properties, and weather data in addition to field observations on crop growth parameters. The required management practices are plant spacing or plant population, transplanting depth, nursery duration, fertilizer application, and irrigation amount and timing. Soil properties required are volumetric soil water content at saturation, field capacity and wilting point, depth of puddled soil, and saturated hydraulic

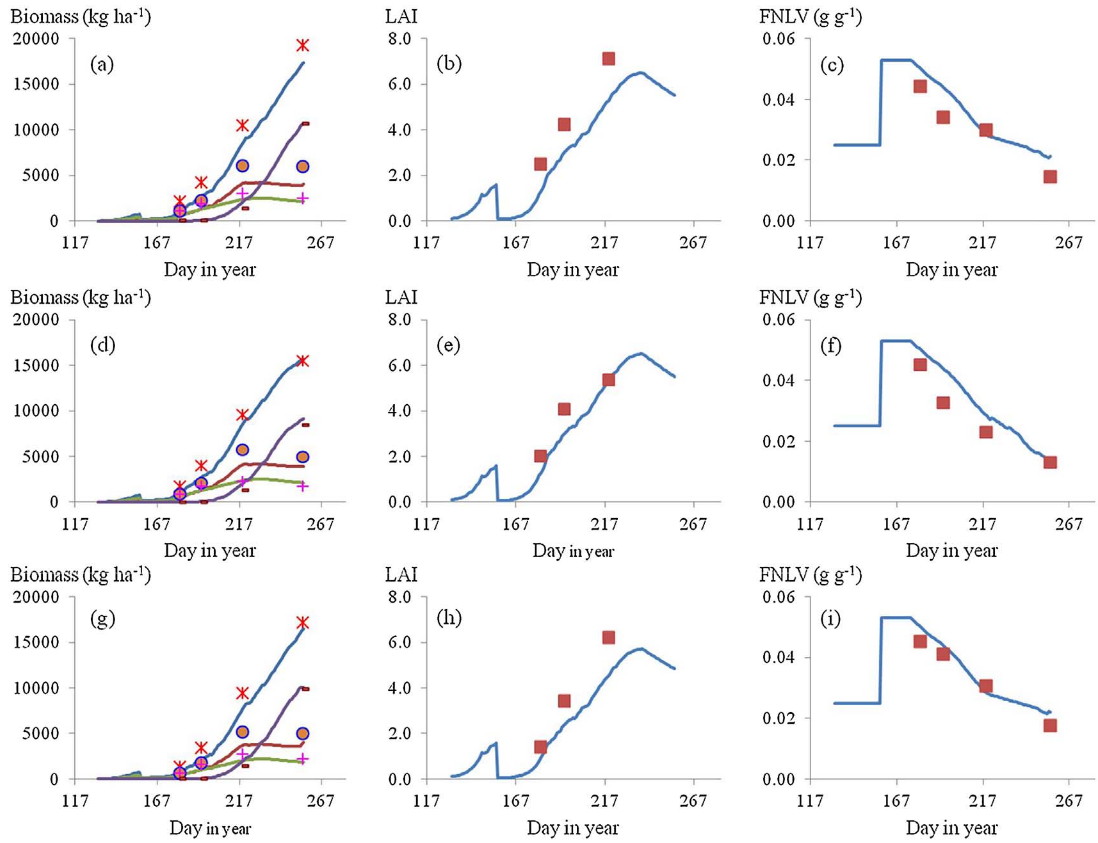

Fig. 3. Simulated (lines) and measured biomass of the whole crop (Ж), green leaves (+), stems (●), and panicles (−), leaf area index (LAI) and leaf N concentration (FNLV) of inbred rice in farmers' practice (a, b, and c), low N input (d, e, and f), and low planting density (g, h, and i) in Dajin County, Wuxue City, Hubei Province, China in 2015 (validation data set). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

conductivity of each soil layer. The weather data include the radiation, minimum and maximum air temperatures, vapor pressure, wind speed, and precipitation during the growing season. The crop parameters include those for phenological development and many related to the process of crop growth. However, most can be set as default values, except for the parameters reflecting rice heredity and cultivar characteristics, such as development rates, partitioning factors of the assimilate, relative leaf growth rate, specific leaf area, leaf death rate, and the fraction of stem reserves, which are calibrated using experimental data following the procedure of Li et al. (2009).

ORYZA (v3) was calibrated with data from 2014 and validated with data from 2015. ORYZA (v3) was parameterized for two high-yielding rice cultivars, starting with the standard crop parameters for cultivar IR72 and following the procedures described by Bouman and van Laar (2006) and Li et al. (2009) using the AutoCalibration tool as in the studies of Zhang et al. (2016) and Li et al. (2016). The complete experimental data from one crop management that represent potential production conditions and two calibration programs, DRATES and PARAM, built in the ORYZA (v3) model, were used to provide initial values of rice genetic parameters. The phenological development and the fractions of total dry matter partitioned to the leaves, stems, and panicles parameters and values used for the parameterization of ORYZA (v3) for the two rice varieties are shown in supplementary Tables S1 and S2.

We used a combination of graphical presentations and statistical measurements to evaluate the performance of the model in predicting aboveground biomass, leaf area index (LAI), and FNLV. We calculated the intercept (α), slope (β), and adjusted correlation coefficient (R^2) of the linear regression, root mean square error (RMSE), normalized root mean square error ($RMSE_n$), and Student's *t*-test of means assuming unequal variance P(t) between simulated and measured values. RMSE and $RMSE_n$ characteristics are common tools to test the goodness-of-fit of simulation models (Bouman et al., 2001):

$$RMSE = \left(\sum_{i=1}^{n} (P_i - O_i)^2/n\right)^{0.5}$$

$$RMSE_n = 100 \times \left(\sum_{i=1}^{n} (P_i - O_i)^2/n\right)^{0.5} / O_{mean}$$

where P_i is the simulated value, O_i is the measured value, and n is the number of measurements. Ideally, the α, RMSE and $RMSE_n$ should be near 0, and the P(t) should be greater than 0.05, while the β and R^2 should be near 1.0. Model predictions are good if RMSE and $RMSE_n$ are comparable to the standard deviation and coefficient of variation of observation (Gaydon et al., 2017)

2.3. Scenario analyses

ORYZA (v3) was employed to estimate the effects of planting density, seedlings per hill, N application rates, and the interaction among them on the yield of high-yielding rice cultivars in central China. For scenario analyses, the emergence date was set to the 130th day of the year with transplanting of the seedling age of 25 d, as in the field experiment. Planting density ranging from 15 to 40 hills m^{-2} and seedlings per hill ranging from 1 to 5 were tested in the scenarios analysis. The model was run using three N application rates (0, 90, and 180 kg N ha^{-1}) on the same clay soil as the field experiment, using weather data from 30 different rice growing seasons (1986–2015) from the National Meteorological Information Center of the China Meteorological Administration. The simulations were run from one day before emergence until physiological maturity in each season.

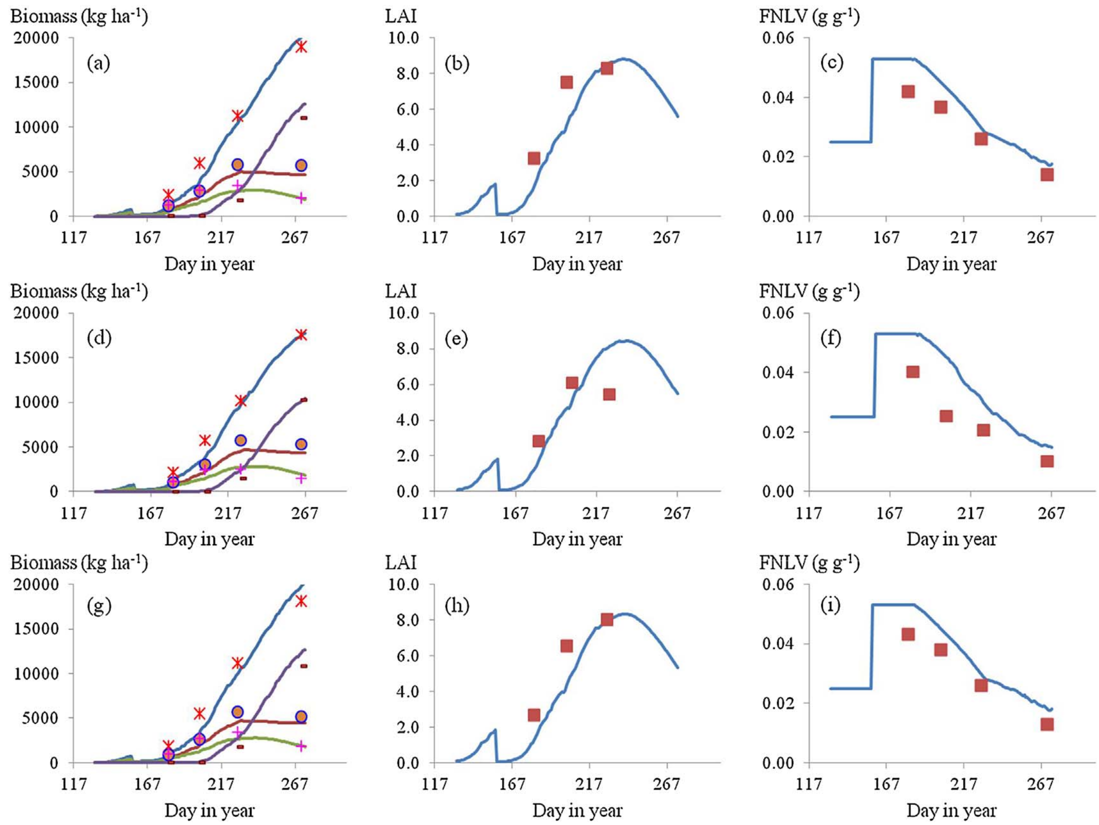

Fig. 4. Simulated (lines) and measured biomass of the whole crop (Ж), green leaves (+), stems (●), and panicles (−), leaf area index (LAI) and leaf N concentration (FNLV) of hybrid rice in farmers' practice (a, b, and c), low N input (d, e, and f), and low planting density (g, h, and i) in Dajin County, Wuxue City, Hubei Province, China in 2015 (validation data set). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Results

3.1. Calibration and validation of ORYZA (v3)

ORYZA (v3) was calibrated using data from the 2014 growing season, and data from the 2015 growing season was used for model validation of crop growth parameters of yield, biomass, LAI, and FNLV under different crop management practices. Examples of graphical comparisons of simulated and measured LAI, FNLV, and biomass of the whole crop and crop organs over time are provided in Fig. 1 for inbred rice and Fig. 2 for hybrid rice in the calibration data set. These comparisons in the validation data set are shown in Figs. 3 and 4 for inbred and hybrid rice, respectively. There was a satisfactory agreement between simulated and measured biomass, LAI, and FNLV. The simulated LAI was slightly over-estimated for hybrid rice at the heading stage in the calibration set (Fig. 2), and simulated FNLV slightly exceeded the measurement for hybrid rice in both the calibration and validation data sets (Figs. 2 and 4). Despite the over-estimation of LAI and FNLV for hybrid rice, the dynamics in biomass of whole crop, panicles, green leaves, and stems for two cultivars, and LAI and FNLV for inbred rice were simulated accurately throughout the growing season.

The scatter diagrams of simulated against measured variables for two cultivars and crop management practices are provided in Figs. 5 and 6 for the calibration and validation data sets, respectively. Most of the simulated biomass parameters, LAI, and FNLV values were near the 1:1 line, and showed a close agreement between simulated and measured values. This was also supported by a strong correlation between simulated and observed data with the determination of coefficient (r^2) being greater than 0.85 much of the time. Simulated LAI and FNLV for inbred and hybrid rice in the validation set were found both below and above the 1:1 line (Figs. 5 and 6), respectively, which indicated a general under-estimation and over-estimation of LAI and FNLV for inbred and hybrid rice, respectively. The goodness-of-fit parameters between simulated and measured crop variables are presented in Table 1 for the calibration data set and in Table 2 for the validation data set. Student's *t*-test suggested that the majority of simulated crop variables were not significantly different from measured values with 99% confidence in the calibration data set (Table 1). The adjusted linear correlation coefficient (R^2) between simulated and measured values was at least 0.72, except for green leaf biomass of hybrid rice in the validation set (Tables 1 and 2). $RMSE_n$ values for total biomass, stem biomass, panicle biomass, green leaf biomass, LAI, and FNLV ranged from 7% to 34% (Tables 1 and 2). The slopes (β) of the biomass variables, LAI, and FNLV were close to 1 and the intercept (α) values were reasonable, showing a close fit between simulated and measured data. The results were better for inbred rice than for hybrid rice, especially for crop biomass variables and FNLV. The discrepancy between simulated and measured LAI and FNLV was larger than for crop biomass variables, as reflected by higher $RMSE_n$. Nevertheless, for crop biomass variables, RMSE and $RMSE_n$ were 1–3 times higher than the mean SE and CV of measured data in the calibration data set, respectively, and 2–4 times higher in the validation data set, respectively. The simulation was less accurate for LAI and FNLV, with RMSE and $RMSE_n$ being three times greater than SE and CV for LAI, respectively, and four times greater than SE and CV values for FNLV, respectively,

Measured grain yield ranged from 8531 to 10441 kg ha^{-1} in 2014, and simulated values ranged from 8426 to 10370 kg ha^{-1} in the calibration set (Table 1). In the validation set, measured and simulated grain yield ranged from 9878 to 10738 kg ha^{-1} and 9856 to 10918 kg ha^{-1}, respectively. The simulated yield was not significantly different from the measured yield. RMSE and $RMSE_n$ were nearly equal to the mean SE and CV of the measurements, respectively, except for hybrid rice in the validation set (Tables 1 and 2). ORYZA (v3) simulated yield relatively accurately at a high yielding level over a range from

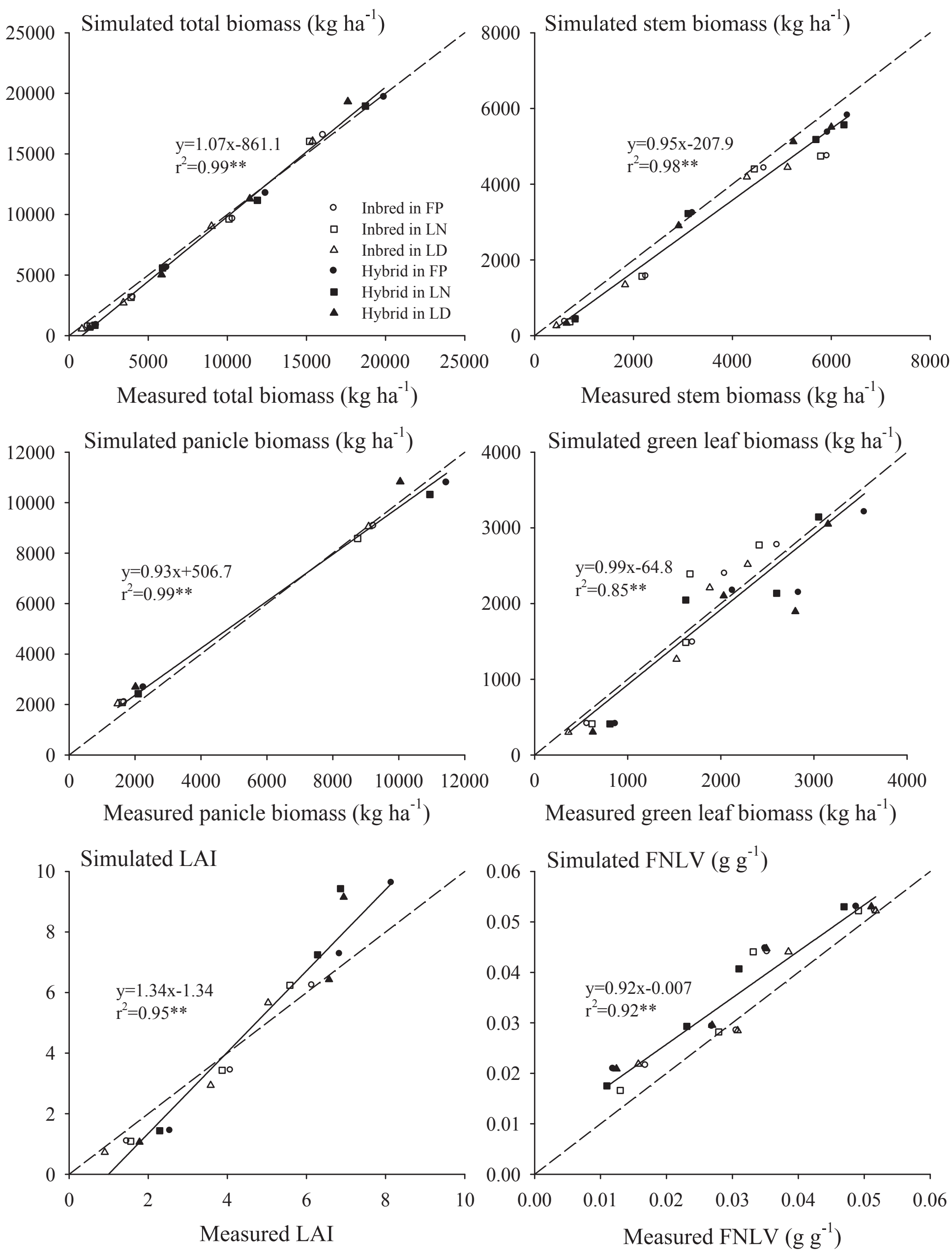

Fig. 5. Correlation between simulated and measured total biomass, stem biomass, panicle biomass, green leaf biomass, leaf area index (LAI), and leaf N concentration (FNLV) of inbred and hybrid rice for the 2014 calibration data set. Short dash lines are the 1:1 relationship. FP, LN, and LD indicate farmers' practice, low N input, and low planting density, respectively. ** indicates significance at $p \leq 0.01$ (LSD test). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

8000 to 11000 kg ha^{-1} of measured data.

3.2. Scenario analyses

The cumulative probability distribution of grain yield for inbred and hybrid rice cultivars at three N application rates (0, 90, and 180 kg ha^{-1}), both simulated using 30 years of weather data, are shown in Fig. 7. The median (with 50% probability of exceedance) of simulated grain yield, respectively, for the 0, 90, and 180 kg N ha^{-1} rates was 5731.2, 8183.3, and 8886.9 kg ha^{-1} for inbred rice and 6985.7, 9800.9, and 10414.3 kg ha^{-1} for hybrid rice. Across N rates, the simulated grain yield for the hybrid rice cultivar was, on average, 18% higher than that of the inbred rice cultivar. ORYZA (v3) simulated similar grain yield trends at three N rates for both inbred and hybrid rice, simulating higher grain yields with increasing N fertilization. Yield difference across years was larger at a high N rate, and yield varied between 7565 and 12437 kg ha^{-1} at 180 kg N ha^{-1}, from 7322 to 11010 kg ha^{-1} at 90 kg N ha^{-1}, and from 5191 to 7444 kg ha^{-1} without N applied. The difference in simulated yields under the same N rate over the years was mainly due to differences in temperature and solar radiation, but high N rates enhanced the variation.

The average simulated grain yields over 30 years of inbred and hybrid rice under various planting densities and seedlings per hill in three N applied rates are provided in Fig. 8. The yields were largely influenced by the N application rate for both inbred and hybrid rice. The simulated yields were5758, 8125, and 8887 kg ha^{-1} for inbred rice at 0, 90, and 180 kg N ha^{-1}, respectively, and they were 6919, 9624, and 10390 kg ha^{-1} for hybrid rice at 0, 90, and 180 kg N ha^{-1}, respectively. Hybrid rice yields were consistently higher than inbred rice yields, and the difference in yields between the two cultivars became larger with an increase in N application rate. Scenario analyses suggested that yield response to N application declined with a further increase in N application rate to over 100 kg ha^{-1}.

Combined analysis of variance using simulated grain yield under different N rate, planting density, and seedlings per hill indicated that N rate had a greater effect on grain yield than other factors for both

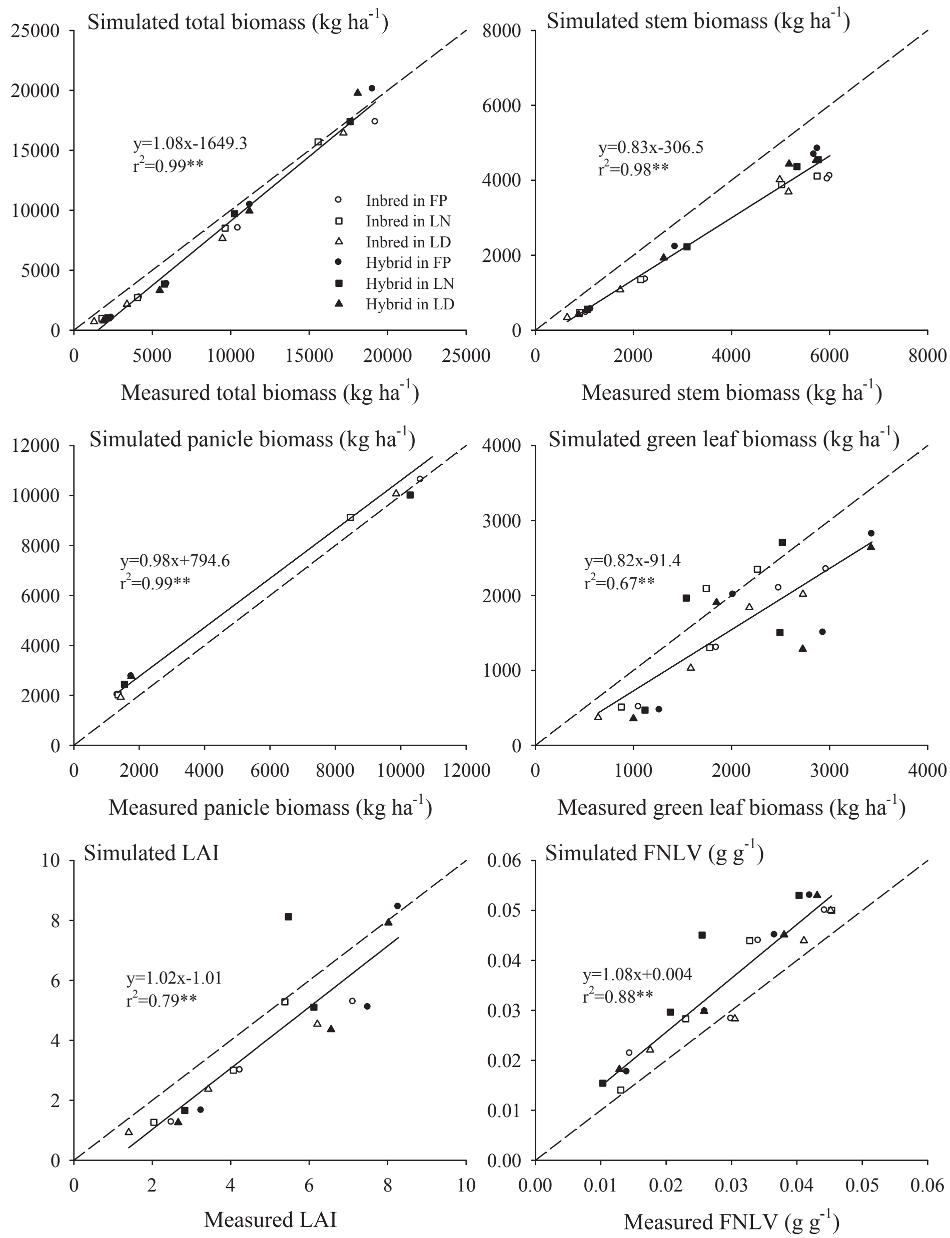

Fig. 6. Correlation between simulated and measured total biomass, stem biomass, panicle biomass, green leaf biomass, leaf area index (LAI), and leaf N concentration (FNLV) of inbred and hybrid rice for the 2015 validation data set. Short dash lines are the 1:1 relationship. FP, LN, and LD indicate farmers' practice, low N input, and low planting density, respectively. ** indicates significance at $p \leq 0.01$ (LSD test). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

inbred and hybrid rice cultivars (Table 3). The results of scenario analyses showed that the difference in grain yields across planting densities was relatively small, as well as seedlings per hill. On average, across N application rates and cultivars, yields ranged between 8214 and 8286 kg ha^{-1} varying planting density, and they ranged from 8194 to 8307 kg ha^{-1} varying seedling per hill. However, the interaction of genotype, planting density, and seedlings per hill on yield was observed in this study. The simulated yield gradually declined with the increase in planting density at each seedling per hill. The yield also decreased with the increased seedlings per hill in each planting density. The yield difference across seedlings per hill declined with the increase in planting density without N applied, while this difference became larger with increased planting density under N applied condition. The hybrid rice was more sensitive to increased planting density than the inbred rice.

4. Discussion

There are many studies on calibration and validation of ORYZA2000 under various management practices on rice growth and development around the world (Bouman et al., 2007; Li et al., 2015), but there has been little research on the evaluation and application of ORYZA2000 under different crop management practices with high-yielding cultivars in central China. In addition, there had previously been no published evaluation of ORYZA (v3) performance. The current study used the ORYZA (v3) simulation model to determine crop variables under FP, LN, and LD with widely planted local high-yielding inbred and hybrid rice cultivars followed by a scenario analysis on rice yield under various N application rates, planting densities, and seedlings per hill using historical weather data of 30 years.

Confidence in the capacity of a model to respond sensibly in simulating crop response to changes in agronomic practice factors is vital to its successful application in crop management. Therefore, a powerful technique was investigated to evaluate model performance and determine whether acceptable performance has been achieved (Gaydon et al., 2017). As indicated by these authors, when the RMSE value between simulated and observed values is lower than the standard deviation within the observed values, it essentially demonstrates that the model can simulate the observed behavior within the bounds of experimental uncertainty. In this study, RMSEs of the simulated biomass

Table 1
Evaluation results for ORYZA (v3) simulations of crop growth variables over the entire growing season for inbred and hybrid rice in the calibration data set.

Cultivar	Crop variable	N	Xmea (SD)	Xsim (SD)	P(*t*)	α	β	R^2	RMSE	$RMSE_n$ (%)	SE	CV (%)
Inbred	Total biomass (kg ha^{-1})	12	7567 (5846)	7339 (6312)	0.21	−815	1.078	1.00	613	8	254	11
	Biomass of stems (kg ha^{-1})	12	3185 (2064)	2702 (1925)	0.00	−226	0.919	0.97	595	19	140	11
	Biomass of green leaves (kg ha^{-1})	12	1608 (739)	1702 (942)	0.31	−265	1.224	0.92	312	19	82	12
	Biomass of panicles (kg ha^{-1})	6	5307 (4076)	5484 (3747)	0.25	607	0.919	1.00	355	7	114	7
	Leaf area index (m m^{-2})	9	3.58 (1.90)	3.43 (2.22)	0.40	−0.68	1.148	0.96	0.5	14	0.22	15
	Leaf N concentration (g g^{-1})	12	0.033 (0.013)	0.036 (0.013)	0.02	0.005	0.941	0.91	0.005	16	0.001	7
	Grain yield (kg ha^{-1})	3	8531 (348)	8426 (226)	0.40	−3293	1.403	0.83	175	2	117	3
Hybrid	Total biomass (kg ha^{-1})	12	9547 (6773)	9228 (7250)	0.15	−962	1.067	0.99	758	8	297	7
	Biomass of stems (kg ha^{-1})	12	3914 (2265)	3596 (2169)	0.00	−129	0.952	0.99	406	10	112	7
	Biomass of green leaves (kg ha^{-1})	12	2172 (996)	1919 (1036)	0.04	−192	0.972	0.87	438	20	113	11
	Biomass of panicles (kg ha^{-1})	6	6468 (4782)	6623 (4414)	0.58	692	0.917	0.99	605	9	199	6
	Leaf area index (m m^{-2})	9	5.36 (2.43)	5.90 (3.61)	0.27	−1.87	1.448	0.95	1.39	26	0.27	11
	Leaf N concentration (g g^{-1})	12	0.030 (0.014)	0.036 (0.013)	0.00	0.009	0.925	0.96	0.007	23	0.001	7
	Grain yield (kg ha^{-1})	3	10441 (105)	10330 (384)	0.56	7631	0.272	1.00	254	2	181	3

The standard error and coefficient of variation of the measured crop variables were also given.
N, number of data pairs; Xmea, mean of measured values; Xsim, mean of simulated values; SD, standard deviation; P(*t*), significance of paired *t*-test, P(*t*) > 0.01 means that simulated and measured values are the same at 99% confidence level; α, intercept of linear relation between simulated and measured values; β, slope of linear relation between simulated and measured values; R^2, adjusted linear correlation coefficient between simulated and measured values; RMSE, absolute root mean square error; $RMSE_n$, normalized root mean square error (%); SE, standard error of measured variables; CV, the coefficient of variation of measured variables.

Table 2
Evaluation results for ORYZA (v3) simulations of crop growth variables over the entire growing season for inbred and hybrid rice in the validation data set.

Cultivar	Crop variable	N	Xmea (SD)	Xsim (SD)	P(*t*)	α	β	R^2	RMSE	$RMSE_n$ (%)	SE	CV (%)
Inbred	Total biomass (kg ha^{-1})	12	8197 (6381)	7038 (6391)	0.00	−1136	0.997	0.99	1296	16	462	13
	Biomass of stems (kg ha^{-1})	12	3466 (2177)	2409 (1670)	0.00	−230	0.761	0.99	1184	34	210	14
	Biomass of green leaves (kg ha^{-1})	12	1846 (728)	1481 (742)	0.00	−239	0.932	0.84	467	25	155	16
	Biomass of panicles (kg ha^{-1})	6	5509 (4583)	5961 (4383)	0.01	697	0.955	1.00	520	9	291	10
	Leaf area index (m m^{-2})	9	4.04 (1.93)	2.99 (1.72)	0.00	−0.46	0.856	0.93	1.17	29	0.36	18
	Leaf N concentration (g g^{-1})	12	0.031 (0.012)	0.035 (0.013)	0.00	0.003	1.040	0.90	0.006	19	0.002	11
	Grain yield (kg ha^{-1})	3	9878 (758)	9856 (913)	0.86	1803	0.819	0.98	167	2	125	2
Hybrid	Total biomass (kg ha^{-1})	12	9258 (6331)	8435 (7323)	0.04	−2223	1.151	0.99	1405	15	258	6
	Biomass of stems (kg ha^{-1})	12	3757 (2025)	2943 (1805)	0.00	−397	0.889	1.00	849	23	94	7
	Biomass of green leaves (kg ha^{-1})	12	2193 (858)	1635 (873)	0.01	−47	0.767	0.57	806	37	162	13
	Biomass of panicles (kg ha^{-1})	6	6186 (4932)	7096 (4944)	0.02	944	0.994	0.98	1074	17	122	6
	Leaf area index (m m^{-2})	9	5.63 (2.23)	4.85 (2.89)	0.17	−1.36	1.102	0.72	1.65	29	0.49	14
	Leaf N concentration (g g^{-1})	12	0.028 (0.012)	0.036 (0.014)	0.00	0.004	1.165	0.92	0.009	34	0.002	13
	Grain yield (kg ha^{-1})	3	10738 (602)	10918 (1231)	0.67	5410	0.488	1.00	546	5	157	3

The standard error and coefficient of variation of the measured crop variables were also given.
N, number of data pairs; Xmea, mean of measured values; Xsim, mean of simulated values; SD, standard deviation; P(*t*), significance of paired *t*-test, P(*t*) > 0.01 means that simulated and measured values are the same at 99% confidence level; α, intercept of linear relation between simulated and measured values; β, slope of linear relation between simulated and measured values; R^2, adjusted linear correlation coefficient between simulated and measured values; RMSE, absolute root mean square error; $RMSE_n$, normalized root mean square error (%); SE, standard error of measured variables; CV, the coefficient of variation of measured variables.

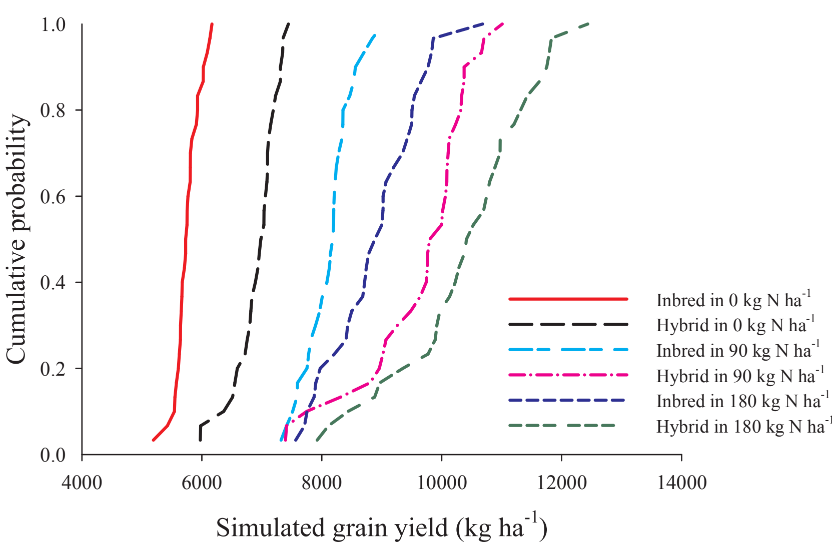

Fig. 7. Cumulative probability distribution of simulated grain yield for inbred and hybrid rice cultivars using historical weather data from 1986 to 2015 under 0, 90, and 180 kg N ha^{-1} rates.

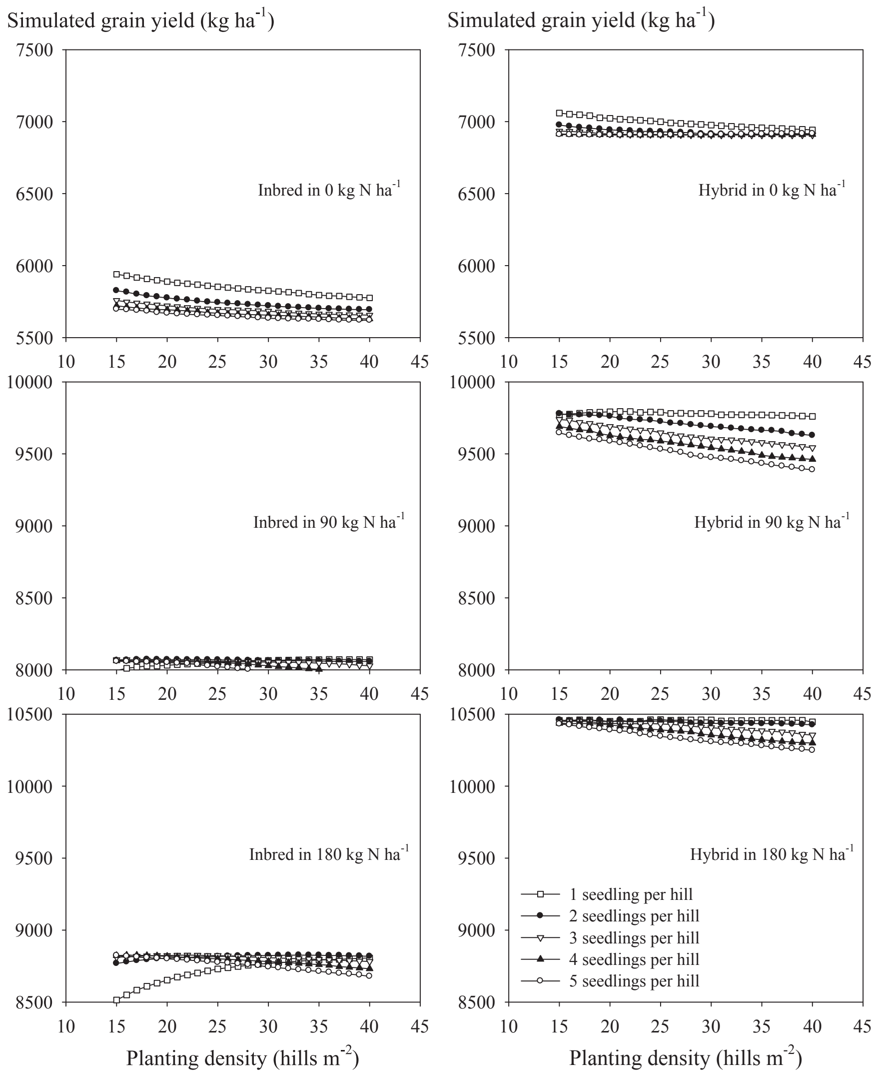

Fig. 8. Average simulated grain yield of 30 years for inbred and hybrid rice with different planting density and seedlings per hill under 0, 90, and 180 kg N ha^{-1} rates.

Table 3
Analysis of variation (F values) for simulated grain yield under different nitrogen rate, planting density, and seedlings per hill for inbred and hybrid rice cultivars.

Source of variation	Inbred (Huanghuazhan)	Hybrid (Yangliangyou 6)
Nitrogen (N)	368093**	716187**
Planting density (D)	3.75**	23.62**
Seedlings per hill (S)	75.55**	500.62**
N × D	2.08**	3.53**
N × S	79.8**	81.23**
D × S	1.42*	NS

Levels of significance indicated: NS = not significant.
* Significant at p ≤ 0.05.
** Significant at p ≤ 0.01.

of the whole crop, panicles, stems, and green leaves, and LAI were much lower than observed experimental standard deviations of these crop variables in both calibration and validation data sets. Apparently, for our purposes, the ORYZA (v3) model performed well in reproducing various measured crop variables under different crop management practices for both high-yielding inbred and hybrid rice.

Simulated and measured yield matched quite well, which was apparent by the lower RMSE than standard deviation, except for hybrid rice in the calibration data set. The ORYZA (v3) model simulated yields relatively accurately for inbred and hybrid rice under different N rate and planting density schemes at a high yielding level over a range of 8531–10738 kg ha^{-1} of measured data. Previous study has indicated that prediction of crop performance at the end of the season is usually more accurate than in-season prediction (Artacho et al., 2011). We concluded that the ORYZA (v3) satisfactorily simulated crop performance for both in-season and end of the season. The results of this study suggested that ORYZA (v3) can simulate crop growth and yield accurately with high-yielding rice cultivars in central China. However, simulated FLNV was slightly less accurate than those of crop biomass variables and yield, which was coincident with the findings of Jing et al. (2008). This may be due to the limited accurate information on soil organic matter and indigenous soil N supply across different soil layers in this study, as plant N status is greatly impacted by N availability in the soil-plant system (Cassman et al., 1996). The simulation of LAI using ORYZA2000 has been relatively poor, and LAI values were typically over-estimated, especially at a low N fertilizer application rate (Bouman and van Laar, 2006). Similarly, ORYZA (v3) over-estimated LAI for hybrid rice in all schemes in the calibration data set and LN in the validation data set, but the results were more accurate than those of ORYZA2000 (Li et al., 2017). The simulation of LAI was more accurate for inbred rice than for hybrid rice, and it could be a result of the better fit in the simulation of LAI for the short-duration rice cultivar (Larijani et al., 2011); crop growth duration of inbred rice was shorter than hybrid rice in this study (data not shown). The difficulty of modeling LAI is well known, and simulation error in LAI has also been reported by others using ORYZA2000 and many other models (Sailaja et al., 2013).

Scenario analyses indicated that median simulated yields were 6358.5, 8992.1, and 9650.6 kg ha^{-1} at a 0, 90, and 180 kg N ha^{-1} rate, respectively. Yields were comparable to those reported by others with similar N rate for the tested cultivars in this study (Yao et al., 2012). The simulated yields for inbred and hybrid rice strongly responded to an N rate less than 100 kg ha^{-1}, but there was no significant yield increase with further N application. The average N rate in a paddy field in China is much higher than the global average, but N use efficiency in China is largely less than other countries (Peng et al., 2010). Therefore, it is essential to optimize N management to increase N use efficiency, which agrees with the results given by the scenario analyses in this study. N productivity (e.g. the ratio of grain yield to N application rate) also decreased with an increase in N rate over 100 kg ha^{-1} in scenario analyses. N use efficiency and optimal N management strategy of high-yielding rice cultivars need to be further determined by a combination of field experiments, ORYZA modeling, and economic analysis. The decreasing yield with increasing planting density and seedling density indicated by scenario analysis was presumably due to the high density, which intensified the contradiction among individuals and resulted in size degradation (Li et al., 2013a). However, the minor effects of planting density and seedling per hill on yield implies that the current arrangements of planting density and seedling per hill in farmers' practice are suitable for high-yielding rice cultivars in central China. Therefore, field experiments are still required to investigate the effects of genotype, N management, and their interactions on yield.

5. Conclusions

The rice simulation model ORYZA (v3) adequately simulated the growth and development of high-yielding inbred and hybrid rice cultivars under three different crop management practices in central China. ORYZA (v3) simulated yield relatively accurately at a high-yielding level over a range of 8531–10738 kg ha^{-1} of measured data, with the simulated yield ranging from 8426 to 10918 kg ha^{-1}. ORYZA (v3) performed well in simulating biomass of the whole crop and of green leaf, stem, and panicle, and leaf area index but consistently slightly over-estimated leaf N concentration across various N and planting density treatments. More research is needed to identify the causes of the over-estimation of leaf N concentration and to incorporate these into ORYZA (v3). The scenario analyses using historical weather data from the last 30 years indicated that the N application rates had greater impacts on rice yield than planting densities and seedling per hill. The simulation demonstrated that further field experiments are crucial to investigate the effects of rice genotype, N management, and their interactions on yield for optimal crop management.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.fcr.2017.07.010.

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