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Research article

Small scale method for estimation of genetic coefficients of photoperiod-insensitive rice using generalized likelihood uncertainty estimation

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Abstract

Importance of the work: Genetic coefficients are important parameters for simulations of rice yield performance in crop growth models. Most genetic coefficients (GCs) are obtained from large experiments.
Objectives: To estimate the GCs of seven photoperiod-insensitive rice cultivars for four planting dates in a pot experiment.
Materials & Methods: Input data (soil, weather, management, plant parameters) were collected and used to calibrate the GCs of seven rice cultivars using the GLUE estimator in the DSSAT version 4.7 package. The data were collected from four planting dates: 1) 23 Nov 2019; 2) 23 Dec 2019; 3) 23 Jan 2020; and 4) 23 Feb 2020. The data from planting dates 1, 3 and 4 were used for calibration of the GCs, whereas the data from planting date 2 were used for evaluation of the GCs.
Results: Good prediction qualities of the model for most cultivars were indicated for days to anthesis and days to physiological maturity; however, there were poor prediction qualities for almost all cultivars for their biomass and grain weight.
Main finding: This information should be useful for further investigations of GCs in rice. Although the results were contrary to the initial hypothesis, the method showed promise for further use in rice modeling research if the method can be improved by experimental management, the use of suitable reference plants for each cultivar and running the model for an appropriate cycle. It was possible to obtain some reliable GCs from small-scale experiments, so the experiment should be improved to obtain better results. Further investigations should focus on the optimum scale and weather data specific to experimental sites.

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Introduction

Rice is an important cereal crop that feeds more than one-half of the world's population (Fairhurst and Dobermann, 2002). It is grown mostly in lowland areas under rain-fed and irrigated conditions (Rao et al., 2017). In Thailand, the central plain is the most important irrigated area for growing photoperiod-insensitive rice in two or more crops each year (Napasintuwong, 2019). A large number of new, high-yield cultivars are now available for farmers; consequently, the farmers in this region change the rice cultivars very often according to the demand for paddy price. However, selection of the most suitable cultivar is not easy because information on the yield performance of most of the released cultivars is not available for different growing seasons, soils and agronomic practices. It is also difficult for farmers and extension personnel to verify the correct cultivars because a large number of farm trials are required. Thus, the use of crop simulation models should be considered to evaluate cultivars best suited to specific growing conditions is possible and thereby eliminate the difficulty in selecting correct cultivars.

The identification of the correct cultivars for all growing environments is impossible using conventional methods because these require a large number of farm trials. The use of computer-based, crop simulation models can save time, labor and resources. The newest version of DSSAT (version 4.7.5) can simulate 42 crops (Hoogenboom et al., 2019). Rice researchers use the CSM-CERES-Rice option in DSSAT to study the responses of rice to climate change (Gupta and Mishra, 2019; Nasir et al., 2020), to forecast KDML 105 fragrant rice yield (Kaeomuangmoon et al., 2020), to manage nitrogen (Zhang et al., 2018) and for yield gap analysis (Phakamas, 2015). Therefore, the use of crop simulation models is very important in agriculture where it provides valid information for decision making. However, there are many limitations in adopting crop simulation models in agriculture.

The quality of the input data is very important in crop simulation models. CSM-CERES-Rice uses input information that includes management data (planting date, fertilization, watering, and plant population density), soil data (physical and chemical properties, soil color, drainage capacity, soil density, soil texture), and weather data (solar radiation, maximum temperature, minimum temperature, rainfall). These data are imported into the sub-model GLUE estimator (generalized likelihood uncertainty estimation) program in the DSSAT v4.7 program for evaluation (Hoogenboom et al., 2019). While the above data can be obtained with relative ease, the most problematic data are the genetic coefficients (GCs) of the crop cultivars.

The lack of valid GCs hinders the adoption of crop simulation models in agriculture. In general, determination of GCs has been carried out based on multi-location trials under a wide range of environments. Hoogenboom et al. (1999) suggested planting several cultivars in the same locations or using one planting date in multiple locations. These models, such as CSM-CERES-Rice in DSSAT for rice (Buddhaboon et al., 2018), need GCs as input data. However, large field experiments across different growing environments are required to obtain reliable GCs (Buddhaboon et al., 2018); consequently, GCs are not available for most newly released cultivars.

Only a few rice cultivars in Thailand have GCs available for crop simulation models, including: Chainat 1, Phitsanulok 2 and Pathum Thani 1 (Somchit, 2012; Buddhaboon et al., 2018;) and Suphanburi 1, Suphanburi 2, Suphanburi 3 and Pathum Thani 80 (Somchit, 2012). This problem could be expected in most rice-producing countries. Obtaining reliable genetic coefficients for all released rice cultivars is essential to provide useful information to farmers. This necessary information can be obtained by studying low-cost methods to obtain GCs.

In crop production, crop performance can be represented as a function of genetic + environment + (genetic × environment) factors. With the GCs obtained from experiments, crop simulation models can be used to assess crop performance across different environments and management practices (Stöckle and Kemanian, 2020). Therefore, suitable experiments with a smaller size might generate the suitable GCs that are similar to those generated from multi-environment trials. However, such information is not available for photoperiod-insensitive rice. The use of data from pot experiments to generate GCs is commonly practiced for greenhouse crops such as tomato (Lin et al., 2019), cucumber (Qiu et al., 2017), muskmelon (Baker and Reddy, 2001) and floral crops (Sarwar et al., 2013). However, it is very rare for such information to be available for field crops.

The question underlying the current research project was whether the GCs obtained from experiments smaller than the more commonly used large-scale experiments could accurately predict the phenology and growth of photoperiod-insensitive rice cultivars. Thus, the objective of the current study was to assess the GCs of popular rice cultivars cultivated in the central region of Thailand based on experimental plantings in pots. The information obtained could be used for further studies to obtain more reliable GCs of rice cultivars but at the lowest cost.

Materials and Methods

Experimental design and crop management

A 4×7 factorial experiment was undertaken in a pot experiment, with the treatments arranged in a completely randomized design with four repetitions. Four planting dates were assigned as factor A: 23 Nov 2019 (1), 23 Dec 2019 (2), 23 Jan 2020 (3) and 23 Feb 2020 (4). These dates were chosen because they were the planting dates for off-season rice in the central plain and the lower north of Thailand, as well as representing crops exposed to different weather conditions. Planting date 1 was exposed to low temperature and the crop had slow growth. Planting dates 2, 3 and 4 were exposed to a wide range of temperatures, and seven rice varieties (RD41, RD43, RD47, RD49, RD57, RD61, RD71) were assigned as factor B, where RD = Rice Department and odd number represent non-glutinous rice varieties. Therefore, the experiment had 28 treatments, with 5 pots for each experimental unit. As some plants died during the experiment, only four pots were used for each experimental unit, resulting in a total of 448 pots (plants).

All rice varieties were planted in seed beds for 25 d prior to transplanting. The pots (30.48 cm in diameter and 22.86 cm in height) were each loaded with 15 kg of soil collected from a rice field. Then, the pots were filled with water and maintained under water logging conditions for 15 d prior to transplanting. Mixed fertilizer (N–P–K, formula 15–15–15) was applied to each pot at the rate of 2.28 g prior to transplanting. Nitrogen fertilizer in the form of urea was applied to the crop in two doses (at tillering and panicle initiation) at the rate of 0.91 g per dose for each pot. The total fertilizer amounts applied to each pot, as recommended by the Rice Department (Rice Department, 2016), were 1.17 g for N, 0.034 g for P and 0.034 g for K (approximately 160.3 kg/ha, 46.8 kg/ha and 46.8 kg/ha, respectively). The fertilizer rates were calculated based on the surface area of the pot. One seedling was transplanted into each pot and water level was maintained at 10 cm above the soil surface until 1 wk before harvest. The pots were placed close together without spacing to mimic a rice crop planted in the field. A wire screen was installed over the experimental site to protect the crop from animal and insect pests; a door was installed at the site entrance.

Data collection

Soils at all planting dates were analyzed at the Soil Science Laboratory of the School of Agricultural Technology, King Mongkut's Institute of Technology Ladkrabang for physical and chemical properties prior to transplanting. The collected soil data consisted of: soil texture (silt, sand and clay), organic matter, pH, total carbon, total nitrogen, available phosphorus and exchangeable potassium (Table 1).

Meteorological data were kindly provided by the Bangna Agro-Meteorological Station, which was the nearest weather station. The collected meteorological data consisted of: maximum temperature and minimum temperature (both measured in degrees celcius), as shown in (Fig. 1) and daily rainfall (measured in millimeters). The daily solar radiation (in megajoules per square meter) was calculated using the minimum and maximum temperature (Phakamas et al., 2013). These input data were used in the model.

Table 1 Soil analysis before planting for seven cultivars of non-photosensitive rice

Soil property	Parameter
Sand (%)	35.48
Silt (%)	18.00
Clay (%)	46.52
Texture	Clay
pH	4.77
Organic matter (%)	2.71
Total carbon (%)	1.44
Total nitrogen (%)	0.12
Available phosphorus (ppm)	75.38
Exchangeable potassium (ppm)	190.30

ppm = parts per million

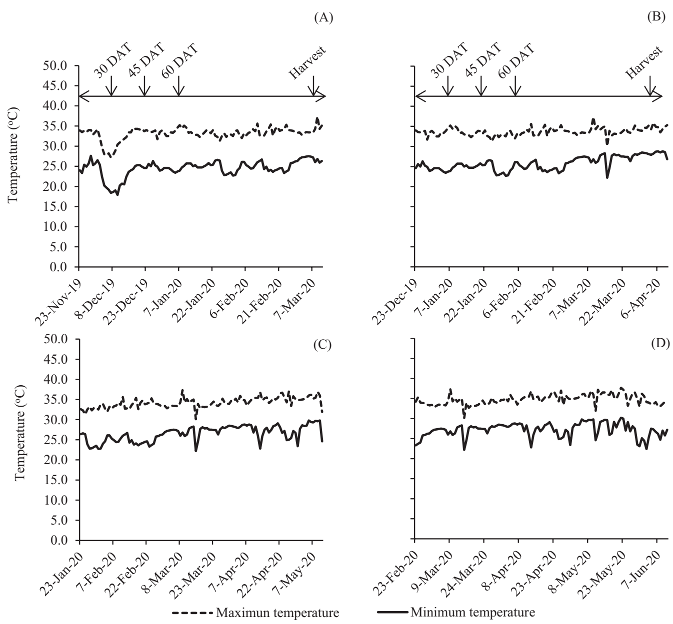

Fig. 1 Maximum and minimum temperatures during crop cycles: (A) planting date 1 (23 Nov 2019); (B) planting date 2 (23 Dec 2019); (C) planting date 3 (23 Jan 2020); (D) planting date 4 (23 Feb 2020)

The data for plant growth parameters were collected at 30 days after transplanting (DAT), 45 DAT and 60 DAT, while the yield data were collected at maturity, which differed among rice cultivars. At 30 DAT, 45 DAT and 60 DAT, one plant in each sampling unit was randomly chosen and measured for phenological and growth data. The sample was oven-dried and the plant dry weight without roots was determined. At harvest, the data were recorded for number of panicles and the plant was separated into straw (leaves and stem), unfilled seeds and filled seeds. All separated samples were oven-dried and the data were recorded for plant dry weight without roots. The harvest index (HI) and crop growth rate (CGR) were calculated using Equations 1 and 2:

$$\text{Crop growth rate} = \frac{1}{GA} \times \left[\frac{W_2 - W_1}{T_2 - T_1}\right] \quad \text{(Wolf and Carson, 1973)}$$

where GA is the land area and W_2 and W_1 are dry weights of plant at time T_2 and T_1, respectively.

$$\text{Harvest index} = \frac{\text{Economic yield}}{\text{Biological yield}} \quad \text{(Yoshida et al., 1972)}$$

where economic yield is the grain yield and total biological yield consists of all aboveground parts, both measured in tonnes per hectare.

Management information consisted of the planting date, population density and irrigation and fertilization data. The plant population density was calculated from the area of the pot. The data were used for evaluation of GCs.

Data analysis

Estimation of genetic coefficients (model calibration)

The GCs of the seven rice cultivars were estimated using the GLUE sub model available in the DSSAT v4.7 software (Hoogenboom et al., 2019). In general, IR64 has been used as a referent cultivar for non-photoperiod sensitive rice. The coefficients for vegetative growth have four values (P1, P2O, P2R, P5) and the coefficients for reproductive growth also have four values (G1, G2, G3, G4), according to Hoogenboom et al. (2011), as shown in Table 2. The rice GCs obtained in this step were further modulated in the next step. The complete definitions of the GCs for phenology (P1, P2O, P2R, P5) and growth genetic coefficients (G1, G2, G3, G4) have been described elsewhere (Buddhaboon et al., 2018). The definitions of these genetic coefficients are available in Table 2 (Hoogenboom et al., 2011).

Table 2 Genetic coefficients of seven rice cultivars estimated by the GLUE estimator in the DSSAT program

Genetic coefficient*		Cultivar name†						
		RD41	RD43	RD47	RD49	RD57	RD61	RD71
Phenology coefficient								
P1	Growing degree days (GDDs) from seedling emergence during which the rice plant is not responsive to changes in photoperiod.	419.0	348.8	402.3	405.9	412.5	423.5	403.1
P2R	Extent to which phasic development leading to panicle initiation is delayed for each hourly increase in photoperiod above P2O (GDDs)	120.3	112.5	110.2	109.7	118.1	89.0	121.9
P5	Time period from beginning of grain filling to physiological maturity (GDDs)	326.3	320.7	306.3	311.2	321.8	336.0	321.1
P2O	Critical photoperiod (hours)	10.7	10.5	10.1	10.9	10.9	10.5	10.8
Growth coefficient								
G1	Potential spikelet (spikelets/g of main culm)	50.2	50.6	51.1	55.5	56.2	58.1	58.7
G2	Single grain weight (g)	0.020	0.020	0.021	0.021	0.023	0.020	0.022
G3	Tillering coefficient	0.45	0.40	0.32	0.30	0.39	0.36	0.34
G4	Temperature tolerance coefficient	0.86	0.90	0.82	0.93	0.85	1.10	1.01

*Hoogenboom et al. (2011)

† Best set of genetic coefficients were obtained after using planting dates 1 (23 Nov 2019), 3 (23 Jan 2020) and 4 (23 Feb 2020) for calibration and planting date 2 (23 Jan 2020) for evaluation.

The data from planting dates 1 (23 Nov 2019), 3 (23 Jan 2020) and 4 (23 Feb 2020) were used for modulation of the GCs using the GLUE program. In modulating the genetic coefficient using GLUE, the program randomly calculated new coefficients within the data range specified by the maximum and minimum values of the specified coefficient (Buddhaboon et al., 2018). The program is able to modulate GCs for either vegetative growth (P1, P2O, P2R, P5) or reproductive growth (G1, G2, G3, G4) or for both groups at the same time. The developer of the program (Buddhaboon et al., 2018) recommend starting at 6,000 cycles (3,000 for vegetative coefficients and 3,000 for reproductive coefficients). The program was run for 15,000 cycles for RD41, RD49 and RD61 and for 12,000 cycles for RD43, RD47, RD57 and RD71 to obtain the most appropriate results.

Verification of the genetic coefficients (model evaluation)

The model was further validated to assess the ability of the GCs to predict the performance of rice cultivars for the studied traits, while the data from planting date 2 (23 Dec 2019) were used for evaluation of the model. The CSM-CERES-Rice model simulated the growth and development characters of rice using the input data obtained from calibration. The simulated growing conditions were identical to those for rice production.

The consistency of the simulated data and the observed data was determined based on the root mean square error (RMSE) and normalized root mean square error (RMSEn). Low values of these statistical parameters indicates a close association between the simulated values and the observed values. According to Rinaldi et al. (2003), RMSEn values lower than 10% indicate the best prediction of the model, values in the range 10–20% indicate good prediction, and values in the range 20–30% indicate acceptable prediction, while values greater than 30% indicated poor prediction. The RMSE and RMSEn were calculated using Equations 1 and 2:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (1)$$

where P_i is the simulated value for the i^{th} measurement and O_i is the observed value for the i^{th} measurement and n is the number of observations.

$$\mathrm{RMSEn} = \frac{\mathrm{RMSE} \times 100}{\overline{O}} \quad (2)$$

where $\overline{O}$ is the overall mean of the observed values.

Results and Discussion

Model calibration

The GCs of the seven non-photoperiod-sensitive rice cultivars were determined based on the GLUE program using the experimental data from the three planting dates (planting date 1, planting date 3 and planting date 4). The GCs were further adjusted using the GLUE program until the simulated results were obtained for both vegetative traits and reproductive traits. The estimated genetic coefficients of the seven rice cultivars are shown in Table 2.

For vegetative growth, P1 ranged between 348.8 in RD43 and 423.5 in RD61, P2R ranged between 89.0 in RD61 and 121.9 in RD71, P5 ranged between 306.3 in RD47 and 336.0 in RD61 and P2O ranged between 10.1 in RD47 and 10.9 in RD49 and RD57. The definitions of P1, P5, P2R and P2O are provided in Table 2.

For reproductive development, G1 ranged from 50.2 in RD41 to 58.7 in RD71, G2 ranged from 0.020 in RD41, RD43, and RD61 to 0.023 in RD57, G3 ranged from 0.30 in RD49 to 0.45 in RD41 and G4 ranged from 0.82 in RD47 and 1.10 in RD61. The definitions of G1, G2, G3 and G4 are provided in Table 2.

All G3 values were lower than 1, indicating that the rice cultivars had lower tiller numbers than the reference plant (IR64). Most rice cultivars had G4 values lower than 1, indicating that the environment for rice was cooler than for the normal rice-growing environment, except for RD61, which had a G4 value higher than 1.

The values of G4 were lower than 1.00 under low temperature conditions. However, the GLUE program was able to adjust the G3 values to the lower level in order that tillering and the panicle density of the simulated growth were close to the growth of the planted rice. Therefore, the differences between observed and predicted values for grain yield would not be too great (Vejpas et al., 2000).

Most cultivars had G4 values lower than 1.00, except for RD61 and RD71, which had G4 values of 1.10 and 1.01, respectively. The high G4 values in RD61 and RD71 resulted from the low and unstable temperatures during the crop cycle. With planting date 1, a sharp reduction in temperature to about 23.6 °C occurred for 1 wk at tillering. According to Gupta and O'Toole (1986), the optimum temperature range during tillering for Indica rice would be in the range 25–31°C. The average temperatures for the whole crop cycle for planting date 1 were in the range 24.9–33.3°C, while the optimum temperatures were in the range 27–32 °C (Summerfield et al., 1992). Low temperatures during panicle development would result in increased male sterility (Gunawardena et al., 2003), and high temperatures during this period would also result in increased male sterility (Matsui et al., 2000).

The G4 value is 1.00 for rice grown at the optimum temperature. However, the values can be higher than 1.00 for Japonica rice grown under temperatures higher than optimum and the values can be lower than 1.00 for Indica rice grown under temperatures lower than optimum (Hoogenboom et al., 2011).

G3 values indicate the tillering ability of rice cultivars compared to that of the reference plant (IR64), which has a G3 value of 1.0. Therefore, G3 values can be calibrated to obtain the optimum tillering ability of rice cultivars. Values higher than 1.0 indicate greater tillering ability than for IR64 and *vice versa*.

Days to panicle initiation (number of days after transplanting) were similar for all planting dates ranging being between 9 d in RD61 and 29 d in RD41, RD47, RD49 and RD57 (Table 3). For planting date 1, the model was able to simulate days to panicle initiation quite well for RD41, RD47, RD49 and RD57, with the RMSEn values in the range 0.0–5.5%. Acceptable simulated data were also obtained for RD43 and RD71 with RMSEn values in the range 18.1–20.4%. However, the simulated result for RD61 was disappointing as the RMSEn value was 58.8%.

For planting date 3, the simulated data followed a similar pattern of that for planting date 1, with good simulations being obtained for RD41, RD47, RD49, RD57, acceptable simulated data for RD43 and RD71 and poor simulated results for RD61. For planting date 4, four rice cultivars (RD41, RD47, RD49, RD57) had good simulated days to panicle initiation, one cultivar (RD43) had acceptable simulated days to panicle initiation and one cultivar (RD61) had poor simulated days to panicle initiation.

RD41 had the smallest RMSEn value, while RD61 had the largest across the three planting dates (planting dates 1, 3 and 4) of the calibration set. RD41 had a high P2R value of 120.3 and its prediction value for days to panicle initiation was 29 d which equaled its observed value. In contrast, RD61 had the lowest P2R value of 89.0, while its prediction value for days to panicle initiation was 29 d compared to the observed value of 9 d. The differences in RMSEn between the two extreme cultivars could have been due to the similar predictions by the model. According to Buddhaboon et al. (2018), the model should be run for 6,000 cycles (3,000 for vegetative coefficients and 3,000 for reproductive coefficients). However, to obtain the

Table 3 Observed (O) and simulated (S) values for days to panicle initiation, days to anthesis and days to physiological maturity of seven rice cultivars for planting dates 1 (23 Nov 2019) 3 (23 Jan 2020), and 4 (23 Feb 2020), which were used for genetic coefficient modulation (calibration)

Planting date	Cultivar	Days to panicle initiation*			Days to anthesis*			Days to physiological maturity*		
		O	S	RMSEn (%)	O	S	RMSEn (%)	O	S	RMSEn (%)
Planting date 1 (23 Nov 2019)	RD41	29	29	0.0	59	58	1.1	79	81	1.9
	RD43	19	27	18.1	49	56	9.4	69	78	9.5
	RD47	29	32	5.5	59	60	1.1	79	82	2.8
	RD49	29	27	3.7	59	56	3.5	79	78	0.9
	RD57	29	28	1.8	59	57	2.3	82	80	1.8
	RD61	9	29	58.8	39	61	34.3	61	86	29.0
	RD71	19	28	20.4	49	57	10.8	69	80	11.7
Planting date 3 (23 Jan 2020)	RD41	29	28	1.8	59	56	3.5	79	77	1.9
	RD43	19	25	13.6	49	53	5.4	69	74	5.3
	RD47	29	30	1.8	59	58	1.1	79	78	0.9
	RD49	29	25	7.4	59	53	7.1	79	73	5.7
	RD57	29	26	5.5	59	54	5.9	82	75	6.5
	RD61	9	27	52.9	39	58	29.6	61	83	25.5
	RD71	19	27	18.1	49	56	9.4	69	77	8.5
Planting date 4 (23 Feb 2020)	RD41	29	29	0.0	59	56	3.5	79	76	2.8
	RD43	19	26	15.9	49	53	5.4	69	73	4.2
	RD47	29	31	3.7	59	58	1.1	79	78	0.9
	RD49	29	27	3.7	59	54	5.9	79	74	4.8
	RD57	29	28	1.8	59	55	4.7	82	75	6.5
	RD61	9	29	58.8	39	61	34.3	61	86	29.0
	RD71	19	28	20.4	49	56	9.4	69	77	8.5

* = days after transplanting; RMSEn = normalized root mean square error

best results, the model was run for 15,000 cycles for RD41, RD49 and RD61 and for 12,000 cycles for RD43, RD47, RD57 and RD71. Different running cycles were required for different rice cultivars due to the differences in characteristics of the cultivars.

For days to anthesis, the model provided good simulations for six rice cultivars (RD41, RD43, RD47, RD49, RD57, RD71) for all planting dates (Table 3). For planting date 1, days to anthesis were in the range 39–59 days for the seven rice cultivars, while the simulated days to anthesis were in the range 56–61 d. The RMSEn values (1.1–10.8%) indicated there were good simulations by the model. However, the simulated result for RD61 was rather poor with an RMSEn value of 34.3%.

For planting date 3, the model predicted days to anthesis of six rice cultivars (RD41, RD43, RD47, RD49, RD57, RD71) quite well, similar to those for planting date 1. The observed values, predicted values and the RMSEn values were also in similar ranges to those for planting date 1. However, there was a poor simulated result for RD61 with an RMSEn value of 29.6%.

For planting date 4, the range of days to anthesis was similar to those for planting dates 1 and 3. However, the model simulated quite well six of the seven rice cultivars (RD41, RD43, RD47, RD49, RD57, RD71). The RMSEn values of these cultivars were in the range 1.1–9.4%. Only RD61 had a poor simulated value with an RMSEn value of 34.3%.

RD41 had the smallest RMSEn, whereas RD61 had the largest. The differences between these extreme cultivars for days to anthesis could have been due to differences in the growing degree days, similar to the differences in the days to panicle initiation, because the days to anthesis is a continuation of days to panicle initiation. Notably, the model predicted days to anthesis of RD61 that were greater than the observed values for all planting dates, but it predicted days to anthesis for RD41 rather well. The possible reason for the difference between these cultivars could have been due to differences in maturity. RD61 is an early maturing cultivar, whereas RD41 is late maturing.

For planting date 1 (23 Nov 2019), the model could predict days to physiological maturity for six rice cultivars (RD41, RD43, RD47, RD49, RD57, RD71) rather well (Table 3), with the differences between observed and predicted values in the range from 1 d for RD49 to 11 d for RD71. The RMSEn values for these cultivars were in the range 1.9–11.7%. However, the difference between observed value and predicted value for RD61 was wider than for the above cultivars (25 d) and its RMSEn value was 29.0%.

The differences between observed and predicted values for the seven rice cultivars for planting dates 3 and 4 followed a similar pattern as those for planting date 1. Good predictions were observed in six rice cultivars (RD41, RD43, RD47, RD49, RD57, RD71), with low differences in the range 0–7 d. Their RMSEn values were in the range 0.9–8.5%. However, the differences between observed values and predicted values for RD61 were wider than those of the above cultivars being 22 d for planting date 3 and 25 d for planting date 4, with RMSEn values of 25.5 and 29.0, respectively.

RD41 had the smallest RMSEn value and RD61 had the largest. When genetic coefficients (P5) were considered, RD61 had the highest growing degree days (336.0) indicating that it had the longest time for grain filling, whereas RD41 had growing degree days of 326.3. RD41 also had rapid vegetative growth, high tiller number, large plants, high days to anthesis and late maturity. However, the model simulated similar days to maturity for these cultivars.

For crop biomass, good simulations were obtained in two rice cultivars (RD61 and RD71) for planting date 1 (Table 4). The RMSEn values of these cultivars were low (2.9% for RD61 and 3.6% for RD71). Based on these low RMSEn values, the simulations of the other cultivars (RD41, RD43, RD47, RD49, RD57) were considered disappointing because of their rather high RMSEn values, ranging from 22.7% in RD57 to 75.8% in RD43. The observed values of biomass of the planting date 1 were in the range 3.97–7.57 t/ha and the simulated values were in the range 6.65–7.79 t/ha. Most predicted values of biomass were higher than the observed values except for RD71, which was lower than the observed value.

For planting date 3, the predictions of biomass were better than those for planting date 1. Five rice cultivars (RD41, RD47, RD49, RD57, RD61) had low RMSEn values in the range 3.0–10.6%. Only two cultivars (RD43 and RD71) had rather high RMSEn values of 34.0% and 22.0%, respectively.

For planting date 4, the predictions were also better than those for planting date 1. There were six cultivars (RD41, RD43, RD47, RD49, RD57, RD61) with low RMSEn values in the range 0.4–17.2%. Only one cultivar (RD71) had a high RMSEn value (36.2%). Planting date contributed the largest portion of total variation in biomass. Although all planting dates represented the growing period for off–season rice in irrigated lowland areas of the central plain and the lower north of the country, they had a wide variation in temperature from planting to harvest, as mentioned earlier. Planting date directly affected biomass accumulation.

Table 4 Observed (O) values and simulated (S) values for biomass and seed weight of seven rice cultivars for planting dates 1 (23 Nov 2019) 3 (23 Jan 2020), and 4 (23 Feb 2020), which were used for genetic coefficient modulation (calibration)

Planting date	Cultivar	Biomass (t/ha)			Seed weight (t/ha)		
		O ± SD	S	RMSEn (%)	O ± SD	S	RMSEn (%)
Planting date 1 (23 Nov 2019)	RD41	5.32 ± 0.18	7.13	34.0	2.12 ± 0.12	2.98	40.6
	RD43	3.97 ± 0.25	6.98	75.8	1.66 ± 0.15	3.02	81.9
	RD47	5.81 ± 0.17	7.71	32.7	2.38 ± 0.04	3.59	50.8
	RD49	4.62 ± 0.21	6.65	43.9	1.66 ± 0.16	3.28	97.6
	RD57	5.73 ± 0.65	7.03	22.7	2.33 ± 0.19	3.76	61.4
	RD61	7.57 ± 0.74	7.79	2.9	3.04 ± 0.05	3.77	24.0
	RD71	7.32 ± 0.56	7.06	3.6	3.21 ± 0.20	3.73	16.2
Planting date 3 (23 Jan 2020)	RD41	5.80 ± 0.24	6.06	4.5	2.18 ± 0.13	2.67	22.5
	RD43	4.47 ± 0.38	5.99	34.0	1.75 ± 0.26	2.66	52.0
	RD47	6.29 ± 0.20	6.48	3.0	2.44 ± 0.02	3.16	29.5
	RD49	5.14 ± 0.09	5.43	5.6	1.76 ± 0.05	2.75	56.3
	RD57	6.20 ± 0.70	5.57	10.2	2.38 ± 0.22	3.10	30.3
	RD61	7.75 ± 0.75	6.93	10.6	2.80 ± 0.13	2.87	2.5
	RD71	7.90 ± 0.88	6.16	22.0	3.36 ± 0.77	3.45	2.7
Planting date 4 (23 Feb 2020)	RD41	5.14 ± 0.26	5.12	0.4	2.13 ± 0.17	2.21	3.8
	RD43	3.89 ± 0.20	4.56	17.2	1.77 ± 0.08	1.93	9.0
	RD47	5.59 ± 0.41	5.70	2.0	2.35 ± 0.30	2.64	12.3
	RD49	4.49 ± 0.13	4.71	4.9	1.73 ± 0.04	2.30	32.9
	RD57	5.51 ± 0.50	5.01	9.1	2.30 ± 0.31	2.65	15.2
	RD61	7.34 ± 0.87	6.44	12.3	3.00 ± 0.11	2.24	25.3
	RD71	8.29 ± 0.50	5.29	36.2	4.37 ± 0.22	2.79	36.2

RMSEn = normalized root mean square error

For planting date 1, the model poorly simulated the seed weight of most rice cultivars, with only one rice cultivar (RD71) having a good prediction (Table 4), with a value of 16.2%.

The model poorly simulated the seed weight of six cultivars (RD41, RD43, RD47, RD49, RD57, RD61). The RMSEn values of these cultivars ranged between 24.0% for RD61 and 97.6% for RD49. The observed seed weights of the planting date 1 were in the range 1.66–3.21 t/ha, with the predicted seed weights in the range 2.98–3.77 t/ha.

In planting date 3, the simulations were better than those in planting date 1. The model was able to provide good predictions of seed weights for two rice cultivars (RD61 and RD71). The RMSEn values of these two cultivars were 2.5% and 2.7%, respectively. The model did not provide good predictions for the seed weights of five rice cultivars (RD43, RD49, RD57), with RMSEn values in the range 30.3–56.3%.

For planting date 4, the simulated results were somewhat better than those for planting date 1. Good simulations were obtained for four rice cultivars (RD41, RD43, RD47, RD57), whose RMSEn values were in the range 3.8–15.2%. The simulations of three rice cultivars (RD49, RD61, RD71) were not so good and their RMSEn values were in the range 25.3–36.2%.

Similar to biomass, planting date also contributed the largest portion of total variation in seed weight. Planting had a direct effect on the seed weight because the crop at different planting dates was exposed to different temperatures. For planting date 1, the crop was exposed to low temperatures during winter. For planting dates 2, 3 and 4, the crops were exposed to high temperatures but at different growth stages. A high temperature at grain filling had a large effect on the seed weight. The rice cultivars also showed differences in P5 values, indicating differences in times for seed filling.

Model evaluation

Comparison of the simulated data and observed data for days to panicle initiation could identified three groups of rice cultivars (Table 5). Group 1 (RD41, RD47, RD49, RD57) had good agreement between the simulated and observed data, with RMSEn values in the range 0.0–7.4%. Two rice cultivars (RD43 and RD71) were classified in Group 2 with intermediate agreement between simulated and observed data and having RMSEn values in the range 11.3–15.9%. Group 3 contained one cultivar (RD61) that had poor agreement between the simulated and observed data, with the highest recorded RMSEn value of 52.9%.

Table 5 Observed (O) and simulated (S) values for days to panicle initiation, days to anthesis and days to physiological maturity of seven rice cultivars for planting date 2 (23 Dec 19) used for adjustment of the genetic coefficient (evaluation)

Cultivar	Days to panicle initiation*			Days to anthesis*			Days to physiological maturity*		
	O	S	RMSEn (%)	O	S	RMSEn (%)	O	S	RMSEn (%)
RD41	29	27	3.7	59	56	3.5	79	78	0.9
RD43	19	24	11.3	49	53	5.4	69	75	6.3
RD47	29	29	0.0	59	59	0.0	79	80	0.9
RD49	29	25	7.4	59	54	5.9	79	75	3.8
RD57	29	26	5.5	59	55	4.7	82	77	4.6
RD61	9	27	52.9	39	59	31.2	61	84	26.7
RD71	19	26	15.9	49	55	8.1	69	77	8.5

* = days after transplanting; RMSEn = normalized root mean square error

Rice cultivars had different predicting abilities, as indicated by their RMSEn values. RD47 had the best prediction for panicle initiation, whereas RD61 had the poorest prediction for this parameter. Differences in predicting ability could have been due to differential responses to temperature and differences in the growing degree days of these cultivars.

Table 5 shows simulations of the seven rice cultivars for days to anthesis for an unrelated planting date (planting date 2). Notably the model was able to simulate days to anthesis quite well, and there were only small differences between observed data and simulated data. The RMSEn values were in the range 0.0–31.2%.

Similar to panicle initiation, RD47 had the lowest RMSEn for days to anthesis, while RD61 had the highest. The similarity in these two sets of results was due to the fact that days to anthesis is a continuation of days to panicle initiation.

Simulations of seven rice cultivars for days to physiological maturity for planting date 2 are shown in Table 5. The results were rather surprising as the simulated data were rather close to the observed data in six (RD41, RD43, RD47, RD49, RD47, RD71) of the seven cultivars. The RMSEn values of these cultivars were in the range 0.9–8.5%. However, there was a poor simulation result for RD61 with an RMSEn value of 26.7%.

RD41 and RD47 had the lowest RMSEn value for days to physiological maturity, whereas RD61 had the highest for this parameter. A possible reason for the poor predictions regarding RD61 could have been its early maturity. According to Mackill and Khush (2018), IR64 was used as a reference plant in this study and other rice modeling research notes it is a late maturing (117 d). This study used IR64 as a reference plant. This cultivar matures later than all the cultivars in this study. The use of a suitable reference plant might improve the results.

Biomass data for planting date 2 were simulated at 30 DAT, 45 DAT, 60 DAT and at harvest (Table 6). In general, the simulations of biomass was poor for earlier growth stages, especially at 30 DAT, while the simulations were better for later growth stages. However, most simulations were still poor, except for RD61, which showed good simulations at 45 DAT and 60 DAT with an RMSEn value of 6.5% for both growth stages.

At harvest, the observed values of biomass for the unrelated planting date (planting date 2) were in the range 4.07–8.93 t/ha, with the simulated values in the range 5.80–7.29 t/ha. RD47, RD57 and RD61 had the lowest differences between observed and predicted values, with RMSEn values in the range 1.5–15.4%. RD41, RD43, RD49 and RD71 had rather large differences between their observed and predicted values, with RMSEn values in the range 24.1–47.7%.

Most cultivars had higher simulated values than observed values, except for RD71, which had lower simulated value than observed values. Although there were differences in the predicting ability among the cultivars, only two cultivars (RD57 and RD61) showed good predictions for biomass. Poor model prediction could have been largely due to the complexity of the traits. Therefore, a larger scale of the experiment and a more deliberate experimental setup might improve the predictions.

Simulations of the crop growth rate data for planting date 2 were carried out at 30 DAT, 45 DAT, 60 DAT and at harvest (Table 6). Poor simulations were observed at 30 DAT, with the RMSEn values in the range 31.0–704.5%. Simulations improved at 45 DAT and 60 DAT; however, most simulations were still poor, except for RD61 with RMSEn values of 0.1% and 6.1% at 45 DAT and 60 DAT, respectively.

At harvest, all simulations were somewhat better than at 60 DAT, with the RMSEn values in the range 4.6–60.5%. The best simulations were observed for RD47 and RD61, with RMSEn values of 4.6% and 5.2%, respectively.

For planting date 2, the observed seed weights of seven rice cultivars were in the range 1.74–4.64 t/ha and the predicted seed weights were in the range 2.45–3.52 t/ha (Table 7). Good predictions of seed weight were obtained for the two rice cultivars RD41 and RD61, with RMSEn values in the range 18.1–19.9%.

Table 6 Observed (O) and simulated (S) values for biomass and crop growth rate at 30, days after transplanting (DAT), 45 DAT, 60 DAT and at harvest of seven rice cultivars for planting date 2 (23 Dec 19) used for adjustment of genetic coefficients (evaluation)

Time of sampling	Parameter	Cultivar						
		RD41	RD43	RD47	RD49	RD57	RD61	RD71
		Biomass (t/ha)						
30 DAT	O ± SD	0.24 ± 0.02	0.08 ± 0.01	0.22 ± 0.05	0.07 ± 0.02	0.12 ± 0.01	0.38 ± 0.13	0.16 ± 0.03
	S	0.54	0.62	0.57	0.53	0.54	0.50	0.50
	RMSEn (%)	125.0	675.0	159.1	657.1	350.0	31.6	212.5
45 DAT	O ± SD	1.06 ± 0.06	0.60 ± 0.14	1.65 ± 0.52	0.87 ± 0.23	0.89 ± 0.12	1.85 ± 0.19	0.93 ± 0.19
	S	2.08	2.21	2.20	2.01	2.05	1.97	1.97
	RMSEn (%)	96.2	268.3	33.3	131.0	130.3	6.5	111.8
60 DAT	O ± SD	3.29 ± 0.13	3.56 ± 0.31	3.68 ± 1.29	2.54 ± 1.15	2.35 ± 1.25	4.13 ± 1.35	4.03 ± 1.72
	S	4.50	4.51	4.55	4.26	4.38	4.40	4.40
	RMSEn (%)	36.8	26.7	23.6	67.7	86.4	6.5	9.2
Harvest	O ± SD	5.31 ± 0.21	4.07 ± 0.13	6.22 ± 0.17	4.59 ± 0.14	5.81 ± 0.23	7.18 ± 0.17	8.93 ± 0.33
	S	6.59	6.01	7.18	5.80	6.25	7.29	6.42
	RMSEn (%)	24.1	47.7	15.4	26.4	7.6	1.5	28.1
		Crop growth rate (g/m²/d)						
30 DAT	O ± SD	0.81 ± 0.06	0.28 ± 0.05	0.73 ± 0.15	0.22 ± 0.05	0.41 ± 0.03	1.26 ± 0.42	0.53 ± 0.09
	S	1.80	2.05	1.89	1.77	1.79	1.65	1.91
	RMSEn (%)	122.2	632.1	158.9	704.5	336.6	31.0	260.4
45 DAT	O ± SD	5.45 ± 0.51	3.43 ± 0.93	9.52 ± 3.37	5.36 ± 1.58	5.11 ± 0.73	9.80 ± 0.87	5.13 ± 1.39
	S	10.05	10.63	10.90	9.84	10.08	9.81	10.52
	RMSEn (%)	84.4	209.9	14.5	83.6	97.3	0.1	105.1
60 DAT	O ± SD	14.91 ± 1.20	19.79 ± 2.04	13.61 ± 7.63	11.14 ± 6.19	9.75 ± 7.72	15.26 ± 9.15	20.73 ± 10.53
	S	25.00	22.60	17.04	15.01	15.54	16.19	15.91
	RMSEn (%)	67.7	14.2	25.2	37.7	59.4	6.1	23.3
Harvest	O ± SD	4.48 ± 0.28	1.45 ± 1.07	5.64 ± 2.80	4.56 ± 2.83	7.21 ± 3.03	11.29 ± 4.37	14.01 ± 5.07
	S	1.77	1.17	5.38	3.43	3.89	10.70	5.55
	RMSEn (%)	60.5	19.3	4.6	24.8	46.0	5.2	60.4

RMSEn = normalized root mean square error

Table 7 Observed (O) and simulated (S) values for seed weight and harvests index (HI) of seven rice cultivars for planting date 2 (23 Dec 19) used for adjustment of genetic coefficient (evaluation)

Cultivar	O ± SD	S	RMSEn (%)
	Seed weight (t/ha)		
RD41	2.26 ± 0.19	2.71	19.9
RD43	1.89 ± 0.07	2.45	29.6
RD47	2.86 ± 0.20	3.49	22.0
RD49	1.74 ± 0.04	2.73	56.9
RD57	2.39 ± 0.26	3.26	36.4
RD61	2.98 ± 0.05	3.52	18.1
RD71	4.64 ± 0.21	3.37	27.4
	Harvest index		
RD41	0.39 ± 0.02	0.41	5.1
RD43	0.43 ± 0.02	0.41	4.7
RD47	0.43 ± 0.02	0.49	14.0
RD49	0.35 ± 0.01	0.47	34.3
RD57	0.39 ± 0.03	0.52	33.3
RD61	0.39 ± 0.01	0.48	23.1
RD71	0.50 ± 0.02	0.52	4.0

RMSEn = normalized root mean square error

However, the predictions for the other five cultivars (RD43, RD47, RD49, RD57, RD71) were not so good, as the RMSEn values of these cultivars were rather high in the range 22.0–56.9%.

The observed data for planting date 2 had the lowest harvest index (0.35) for RD49 and it was highest (0.50) for RD71, whereas the lowest harvest index for simulated data was 0.41 in RD41 and RD43 and the highest harvest index was 0.52 in RD57 and RD71 (Table 7). Good predictions for the harvest index were obtained with three rice cultivars (RD41, RD43, RD71), with RMSEn values in the range 4.0–5.1%. RD47 had an intermediate RMSEn value for the harvest index (14.0%), whereas RD49, RD57 and RD61 had high RMSEn values for the harvest index (34.3%, 33.3% and 23.1%, respectively).

Although there were differences in predicting ability among the cultivars, no cultivar had acceptable prediction. Predicting ability for grain weight was poorer than for biomass. This indicated that grain weight was more complex than biomass. Therefore, the use of data from a small experiment to predict biomass and grain weight of rice was not successful.

In this study, the model could only provide good predictions for the developmental characteristics of rice and not for yield performance. In another study, the CERES-Rice model was able to accurately predict the developmental stages of photoperiod insensitive rice cultivars (Jintrawet, 1995). However, the model was not able to provide good predictions of yield and total dry weight, and the predicted values were usually higher than observed values.

In another investigation, the CERES-Rice model predicted seed yields that were 0.2–0.3 t/ha (4–7%) higher than the observed yields (Tongyai, 1994). The inability of the model to provide correct predictions of yield and biomass could have been due to the large variation among the samples because experimental size was too small. In addition, the samples at harvest had dead and spoiled leaves that were not attached on the plants at sampling. These could have been the main reason for the differences between observed and predicted data (Buddhaboon et al., 2018).

A GC for a trait of a crop plant is a specific value that is unique to each genotype, environment and cultivar-environment interaction. In rice, genetic coefficients are generally determined based on multi-environmental trials. This practice hinders the usefulness of crop simulation models to simulate the newly released cultivars, because GCs of only a few cultivars are available. Breeding organizations should develop GCs of new cultivars as a part of regional yield trials by collecting additional data for use in the models. It is also possible to use genetic coefficients as plant data for registration requests. The question of this study was whether a small-sized experiment is sufficient to provide the crop data necessary for a generation of useful genetic coefficients.

Seven photoperiod-insensitive rice cultivars were evaluated for their GCs generated from an experiment in pots. The results for model calibration and evaluation were in similar patterns for both reproductive development and yield related traits. The model provided good predictions of days to anthesis and days to physiological maturity in most cultivars, except for RD61. Notably, RD61 had the lowest harvest maturity of 85–95 d, whereas RD71 and RD43 had harvest maturity periods that were less than 100 d. However, the predictions of days to panicle initiation were rather disappointing as the model poorly predicted RD43, RD61 and RD71. The model poorly predicted phenology of early and intermediate mature cultivars, but it better predicted the phenology of late maturing cultivars. The model did not provide good predictions for biomass and grain yield. The cultivars with good prediction for biomass were RD57 and RD61; however, neither of them had good prediction for grain weight, as all cultivars had RMSEn values higher than 10.

Good predictions for reproductive development traits could have been due to the fact that these traits are less complex than those for biomass and grain yield. The phenological traits in the current study had low levels of variation compared to other quantitative traits, such as biomass and grain yield. Therefore, a small experiment is sufficient to provide the correct genetic coefficients. However, biomass and grain yield are more complex traits, requiring a larger experiment to provide the correct GCs for good predictions. However, RD57 and RD61 predicted biomass well. RD57 is late maturing, while RD61 is early maturing. The common character of these cultivars was that they had rather high P1 values and P5 values. The evaluation data were in agreement with the calibration data, indicating that the GCs could be used to predict other planting dates. The information obtained in the current study should be useful for further investigations of GCs in rice. Although the results were contrary to the original hypothesis, the method showed promise for further use in rice modeling research if the method is improved. The improvement of research methodology should include experimental management, the use of a suitable reference plant for each cultivar and running the model for an appropriate cycle.

The knowledge learned from the experiment should be useful in improving the experiment in further studies. The experimental size was too small. Therefore, an increase in the experimental size might increase its predicting ability. The plant sample number should be larger and the data should be averaged over more plants. The containers were too small and the roots were confined at the bottom of the containers. Larger containers or cement containers should be more suitable for the experiment.

Conflict of Interest

The authors declare that there are no conflicts of interest.

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