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Performance of the CSM–MANIHOT–Cassava model for simulating planting date response of cassava genotypes

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ABSTRACT

Selecting the appropriate genotypes for particular planting dates may help increase cassava productivity. The CSM–MANIHOT–Cassava model is a new tool to support decision making for crop management. However, it is important to explore the potential of a model prior to any application. The objective of this study was to evaluate the CSM–MANIHOT–Cassava model in simulating the performance of cassava genotypes for different planting dates. An experiment with four cassava genotypes and eight planting dates was conducted on the experimental farm of the Faculty of Agriculture at Khon Kaen University, Thailand, under optimum conditions. The data for soil and weather conditions, crop management, and crop traits were recorded. The cultivar parameters were determined using experimental data for three planting dates, while the remaining five planting dates were used for model evaluation. A scenario analysis for different planting dates using historical weather data from 2003 to 2018 was also conducted. The calibration results showed a good agreement between simulated and observed phenology and crop traits. Model evaluation based on the d-index showed a good agreement between simulated and observed total crop, stem, and storage root dry weights with values above 0.8 for almost all four genotypes and five planting dates. The model provided acceptable outputs for final total crop dry matter and storage root yield. The results from both the scenario analysis with the CSM–MANIHOT–Cassava model and the actual experiment classified Kasetsart 50 and CMR38–125–77 as one out of the top two genotypes based on final total crop biomass, demonstrating the potential of the model to help identify promising cassava genotypes.

1. Introduction

Cassava (*Manihot esculenta* Crantz.) is a significant economic crop in many parts of the world. It is widely used as a staple for human food and animal feed as well as for industrial purposes (Howeler, 2014). The demand for cassava has increased with the rise in the global population growth. Thailand is one of the most important cassava producers for the world market (Office of Agricultural Economics, 2018). However, the average fresh storage root yield of cassava is about 23.1 t ha^{-1} (FAO, 2017), which is lower than its potential yield (Howeler, 2013). In Thailand, cassava can be grown all year round with a growing season duration that ranges from 8 to 12 months. Weather conditions during the growing season cause different responses in development and growth, and ultimately affect yield and starch content of cassava (Irikura et al., 1979; Keating et al., 1982a, 1982b; Janket et al., 2018, 2020; Vongcharoen et al., 2018, 2019; Mahakosee et al., 2019; Phoncharoen et al., 2019a, 2019b; Santanoo et al., 2019). Recommendations for suitable cassava genotypes for specific planting dates would require multiple experiments. However, the information can be obtained at lower cost using crop simulation models that can generate the responses of crops for various environments and management scenarios following thorough model evaluation (Jones et al., 2003; Tsuji et al., 1998).

A total of 18 crop models have been developed for cassava, but only eight include an algorithm that simulates the effect of photoperiod on

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growth and development, thus allowing them to be applicable to regions other than the tropics (Fukai and Hammer, 1987; Matthews and Hunt, 1994; Matthews and Lawson, 1997; Mithra et al., 2013; Tironi et al., 2017; de Araújo Visses et al., 2018; Hoogenboom et al., 2019a; Moreno-Cadena et al., 2020, 2021). However, only three of these models are in the public domain and can be readily downloaded for evaluation and testing. This includes the "Simanihot" model (Tironi et al., 2017) and the CSM–CROPSIM–Cassava and the CSM–MANIHOT–Cassava model of the Decision Support System for Agrotechnology Transfer (DSSAT; Hoogenboom et al., 2019a, 2019b). Gabriel et al. (2014) compared the performance of three different cassava models, i.e., the original GUMCAS model, a modified version of the GUMCAS model (Simanihot), and the CSM–CROPSIM–Cassava for cassava production in four subtropical sites in southern Brazil. Ezui et al. (2018) proposed an alternative model, called LINTUL–Cassava, on the basis of light interception and light use efficiency. This model has been developed solely using experimental data from West Africa for better understanding of cassava growth, development, and yield under drought condition. Ezui et al. (2018) recommended that further testing and adaptation is needed prior to implementation as a decision support system for cassava production.

In previous research, the CSM–CROPSIM–Cassava model was calibrated for application in Thailand (Keawmuangmoon and Jintrawet, 2014; Kumsueb and Jintrawet, 2020). The Cropping System Model (CSM)–MANIHOT–Cassava model is an improved version of CSM–CROPSIM–Cassava model that contains many new processes that are specifically targeted for biomass and root growth of cassava (Moreno-Cadena et al., 2020). Therefore, the CSM–MANIHOT–Cassava model was selected for this study, as it is the best cassava model of the DSSAT crop modelling ecosystem (Hoogenboom et al., 2019a) and applicable to different environmental conditions and crop management scenarios.

The CSM–MANIHOT–Cassava model is a dynamic crop model that simulates growth, development, and yield (Moreno-Cadena et al., 2020). It has been incorporated into the Cropping System Model (Jones et al., 2003) of DSSAT (www.dssat.net) and can be used as an innovative tool for strategic and tactical analysis (Thornton and Hoogenboom, 1994; Tsuji et al., 1998). The model is physiologically based and simulates daily photosynthesis, biomass partitioning, growth, and crop development as a function of weather conditions, soil characteristics, management practices, and plant genetics (Hoogenboom et al., 2019b).

The CSM–MANIHOT–Cassava model in DSSAT provides the opportunity for researchers to determine the impact of different weather conditions during the crop growing season on phenological events, growth, and yield (Hoogenboom et al., 2019a, 2019b). Input data for the DSSAT crop simulation models include daily weather data, soil surface and profile characteristics, crop management, and cultivar or genetic parameters (Tsuji et al., 1994; Hoogenboom et al., 2012). Kaweewong et al. (2013) described the ability of the cassava model to capture the response of the genotype Kasetsart 50 grown under different nitrogen fertilizer rates. Until now, the model has not been evaluated for common cassava genotypes that are grown in Southeast Asia. Prior to the application of a model for the identification of suitable genotypes for different planting dates, the performance of the model must be evaluated. The goal of this study, therefore, was to evaluate the performance of the CSM–MANIHOT–Cassava model for simulating the response of genotypes to different planting dates for common cassava environments in Southeast Asia.

2. Materials and methods

2.1. The CSM–MANIHOT–Cassava model

In this study the CSM–MANIHOT–Cassava model of DSSAT Version 4.7.5 (Hoogenboom et al., 2019b) was used. A detailed description of the crop growth and development processes of the model is presented in Moreno-Cadena et al. (2020). The model calculates daily assimilate by multiplying the solar radiation intercepted and the solar radiation use efficiency. Biomass partitioning prioritizes the growth of leaves, stems, and fibrous roots with additional assimilates going to the storage roots, referred to as spill–over strategy. The actual growth of nodes and fibrous roots is reduced when the daily assimilation is less than the amount required to satisfy the potential growth. Leaf formation is explained by a saturation growth rate, where the interval between the appearance of new nodes increases. The node was used as the basic growth unit for cassava and includes both the leaf and internode section of stem. The nodal growth rate is represented by a logistic function based on node age and the cumulative number of leaves when the node appears. The size of leaf increases as the crop ages and leaf size reaches a maximum value when the cumulative thermal age of the crop is 900–degree days (°Cd). The function for cassava development in the model is driven by accumulated thermal time with different cardinal temperatures for the process of forking, and for potential size, age, and growth of leaves. The CSM–MANIHOT–Cassava model represents the indeterminate growth and development of cassava, which does not have critical phenological phases. The model also does not simulate a distinct physiological maturity compared to cereal crops.

2.2. Field experiments

In this study four cassava genotypes, i.e., Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77, were used. They were grown under irrigated conditions at the research farm of the Faculty of Agriculture, Khon Kaen University, Thailand (16° 28′ N and 102° 48′ E, 195 m above sea level). There were a total of eight planting dates, including four that are representative of the warm growing season, i.e., 20 April, 25 May, and 30 June 2015 and 19 May 2016, and four that are representative of the cool growing season, i.e., 5 October, 10 November, and 15 December 2015 and 3 November 2016. For each planting date, the experiment was laid out in a randomized complete block design (RCBD) with four replications. The plot size was 28 m × 7 m for the planting dates in 2015 and was 20 m × 7 m for the planting dates in 2016. Additional information with respect to land preparation, planting details and crop management practices can be found in Phoncharoen et al. (2019a, 2019b).

The soil profile characteristics prior to planting were obtained by collecting soil samples at depths of 0–15, 15–30, 30–45, 45–60, 60–75, 75–90, and 90–105 cm. Soil pH (1:1 H_2O) was determined using a pH meter. Organic matter was measured by Walkley and Black method (wet oxidation), and organic carbon was calculated using the following relationship: organic matter = 1.724 × organic carbon (Nelson and Sommers, 1996). Total nitrogen was analyzed with the Kjeldahl method (Bremner, 1965). Soil ammonium and nitrate concentrations were determined using flow injection techniques (Tecator, 1984). The percentage of sand, silt, and clay were measured using the hydrometer method. The core sampling method was used to determine bulk density (Table A1). Soil hydrological properties such as saturated water content (SAT), drained upper limit of soil water content (DUL), and lower limit of plant extractable plant extractable water (LL) were computed (Gijsman et al., 2002; Ma et al., 2009; Hoogenboom et al., 2019b). The soil root growth factor (SRGF) was also evaluated using a function in DSSAT (data not shown) (Calmon et al., 1999a, 1999b; Hoogenboom et al., 2019b).

Plant development data of cassava or forking dates were obtained from ten sampled plants per experimental plot. The forking dates were recorded when at least 50 % of the plants in each plot showed forking on the top of the main stem. Crop growth traits were recorded from six sampled plants per plot every 30 days, starting at 30 days after planting (DAP) until 360 DAP for the six planting dates in 2015 and at 30, 90, 120, 180, 240, 270, 300, and 360 DAP for the two planting dates in 2016. In addition, 18 plants per plot were also sampled to determine final performance at 360 DAP. The individual plant organs were separated from the sampled plants, such as leaves, petiole, stem, and storage root, and all crop organs were subsampled (about 10 % of the total fresh

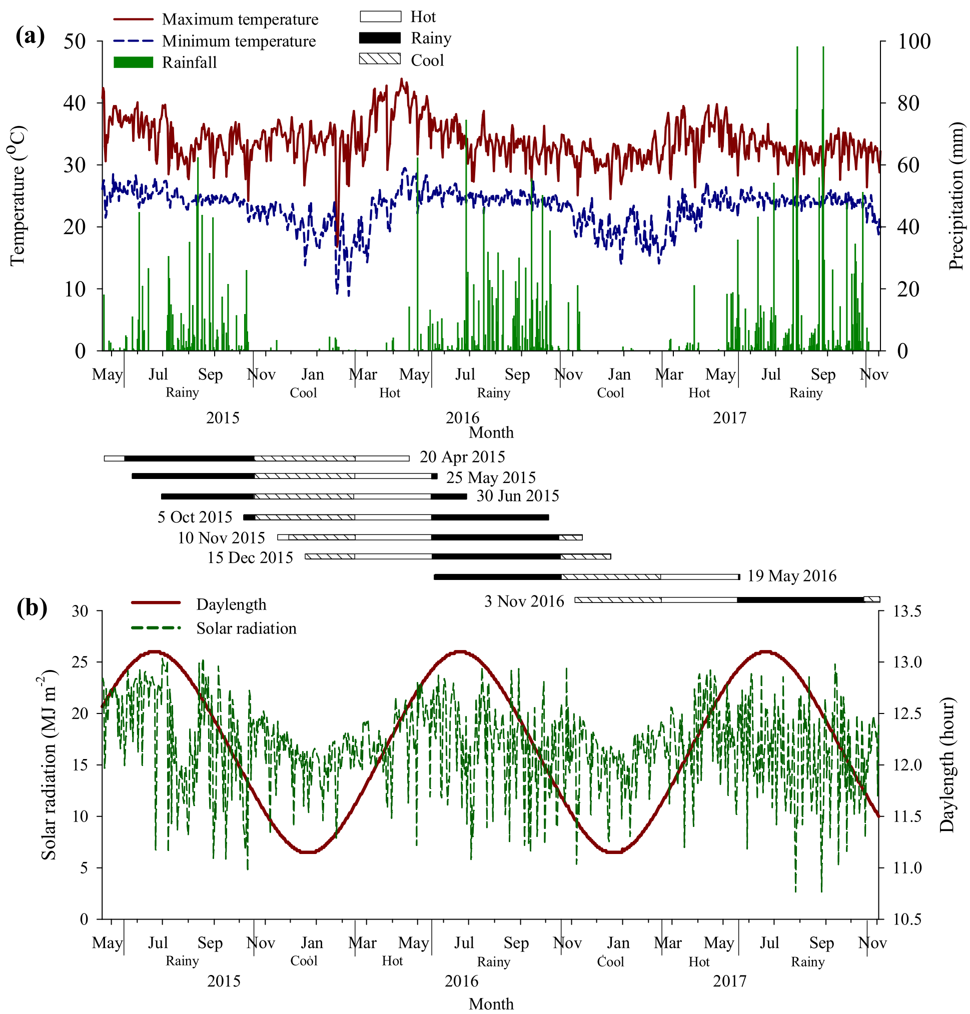

Fig. 1. Daily maximum and minimum temperature and daily total rainfall (a) and daily total solar radiation and daylength (b) from 20 April 2015 until 3 November 2017 recorded at the weather station of Khon Kaen University, Khon Kaen, Thailand.

Table 1
Calibrated genetic parameters for the four cassava genotypes.

Genetics input file	Genetic parameter	Definition	Genotype				CV (%) [a]
			Kasetsart 50	Rayong 9	Rayong 11	CMR38–125–77	
Cultivar	B01ND	Duration from planting to first forking (thermal units)	510	1650	250	300	97.1
	B12ND	Duration from first forking to second forking (thermal units)	330	1	615	505	74.1
	B23ND	Duration from second forking to third forking (thermal units)	260	1	240	175	70.0
	BR1FX	Branch number per fork at fork 1 (#)	3.0	1.0	3.5	3.5	43.3
	BR2FX	Branch number per fork at fork 2 (#)	2.0	1.0	2.7	2.5	37.0
	BR3FX	Branch number per fork at fork 3 (#)	2.5	1.0	2.0	1.5	36.9
	BR4FX	Branch number per fork at fork 4 (#)	2.0	1.0	1.5	1.5	27.2
	LAXS	Area/leaf at maximum area/leaf (cm^2)	945	655	690	710	17.6
	SLAS	Specific leaf lamina area when crop growing without stress (cm^2 g^{-1})	230	230	252	245	4.6
	LLIFA	Leaf life, from full expansion to start senescence (thermal units)	1460	2300	1400	1250	29.5
	LPEFR	Leaf petiole fraction (fraction of lamina + petiole)	0.33	0.33	0.33	0.33	0.0
	LNSLP	Slope for leaf production (#)	1.49	1.38	1.52	1.40	4.7
	NODWT	Node weight for the first stem of the shoot before branching at 3400 °Cd (g)	20.2	17.3	17.5	17.1	8.1
	NODLT	Mean internode length for the first stem of the shoot before branching when is lignified (cm)	4.5	4.0	2.5	4.0	23.1
Ecotype	PARUE	PAR conversion factor, standard (g dry matter MJ^{-1})	1.60	1.67	1.65	1.65	1.8
	KCAN	PAR extinction coefficient (#)	0.50	0.56	0.43	0.51	10.7
	PPS1	Photoperiod sensitivity for phase 1 (% drop for 10 h pp. change)	0.00	0.00	0.02	0.01	127.7

[a] Coefficient of variation (CV) = (standard deviation / mean) × 100.

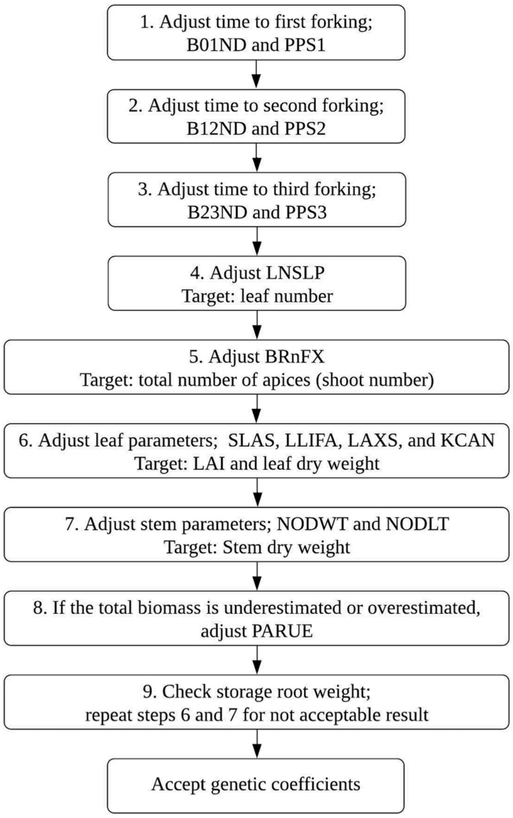

Fig. 2. The optimization sequence for calibration of the genetic parameters of the CSM–MANIHOT–Cassava model for different genotypes (see description of the cultivar parameters in Table 1).

weight of each organ). The subsampled leaves were used to measure the leaf area by using a leaf area meter (LI–3100, LI–Cor, Inc., USA). Subsamples of all plant organs were oven dried at 80 °C to a constant weight to determine dry biomass of the individual plant organs. The leaf area index (LAI) was calculated as the ratio of total leaf area to plant cover ground area.

Daily maximum and minimum temperature, total solar radiation, and total precipitation were recorded with an automatic weather station (WatchDog 2000; Spectrum Technologies, Inc., Lincoln, NE, USA) (Fig. 1). The Khon Kaen province has been identified as a tropical wet or savanna climate with a monthly precipitation of less than 60 mm during the cool season (Kottek et al., 2006). Based on the recorded data during the period of April 2015 to November 2017, the daily minimum temperature ranged from 8.9 °C (8 February 2016) to 29.5 °C (15 April 2016) and the daily maximum temperature from 16.8 °C (25 January 2016) to 43.9 °C (11 April 2016). Daily solar radiation varied from 2.7 MJ m^{-2} (27 July 2017) to 25.4 MJ m^{-2} (19 August 2015). The total rainfall per year during 2015, 2016, and 2017 were 839.9, 1120.6, and 1431.1 mm, respectively.

2.3. Model calibration

To determine the genetic parameters for the four cassava genotypes, one data set from the warm season planting, i.e., May 2015, and two planting from the cool season, i.e., December 2015 and November 2016, were used for model calibration. The genetic parameters that represent crop development and growth for the four cassava genotypes include 14 cultivar parameters and 3 ecotype parameters (Table 1). For model calibration, the information of soil, weather, and management were converted into DSSAT format files following standard procedures (Hoogenboom et al., 2019b). The development and growth of each cassava genotype were first simulated for the three different planting dates with the default genetic parameters that were available for the CSM–MANIHOT–Cassava model. The approach that was used to optimize the genetic parameters started with the parameters related to development and followed by the ones that describe the growth as it is recommended by Hoogenboom et al. (2019b) and described in Fig. 2. The simulations were repeated using the sensitivity analysis tool to adjust the genetic parameters until the simulated and observed values were in good agreement. The phenological parameters that relate to the dates of the first forking level (B01ND), the second forking level (B12ND), and the third forking level (B23ND) were adjusted. The calibration was then continued for the other parameters that relate mainly to cassava growth, i.e., branch number per fork (BR1FX, BR2FX, BR3FX, and BR4FX), maximum leaf area (LAXS), specific leaf area (SLAS), leaf life (LLIFA), leaf petiole fraction (LPEFR), slope for leaf production (LNSLP), node weight of the first stem of the shoot before forking (NODWT), and internode length of the first stem of the shoot before branching (NODLT). To optimize results, the ecotype parameters that define the photosynthetically active radiation (PAR) conversion factor (PARUE), PAR extinction coefficient (KCAN), and photoperiod sensitivity (PPS1) were adjusted.

The accuracy of the genetic parameters was determined by comparing the simulated values of forking date, crop biomass, and LAI with their corresponding observed values and with the statistical parameters. The values for index of agreement (d-index) were calculated following Eq. 1 (Willmott, 1982). The root mean square error values (RMSE, Eq. 2) were also computed, and the values of normalized root mean square error (*n*RMSE) were then determined as the percentage of the RMSE values divided by observed means (Eq. 3) (Wallach and Goffinet, 1989). The equations for the statistical parameters are as following:

$$\text{d-index} = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i'| + |O_i'|)^2}\right] \tag{1}$$

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

$$n\text{RMSE} = \frac{\text{RMSE x 100}}{\bar{O}} \tag{3}$$

where n is the number of observations, P_i and O_i are simulated and observed values, respectively, $P'_i = P_i - \bar{O}$ and $O'_i = O_i - \bar{O}$ ($\bar{O}$ is the mean of the observed variable).

The d-index values range from 0 to 1, with 1 indicating a perfect fit. A low *n*RMSE value indicates a good agreement between simulated and observed values. Agreement is considered to be perfect when the *n*RMSE value is less than 10 %; good if the *n*RMSE value is more than 10 % and less than 20 %; moderate between 20–30 %; and poor if the *n*RMSE value is more than 30 % (Yang et al., 2014; Andarzian et al., 2015; Li et al., 2015).

2.4. Model evaluation

Evaluating the model is an important aspect for demonstrating its capability and potential for application (Tsuji et al., 1998). In this study, the five remaining plantings, i.e., April, June, October, and November 2015 and May 2016, were used. The genetic parameters of the four cassava genotypes that were obtained during model calibration were used as input for the model. The simulated values were compared with the corresponding observed values. The d-index and *n*RMSE were also used to explain the agreement between the observed and simulated data. Model evaluation based on relative performance (ranking) of each cassava genotype for different planting dates was also conducted. Following evaluation, the CSM–MANIHOT–Cassava model was used for determining the interaction between planting data and local

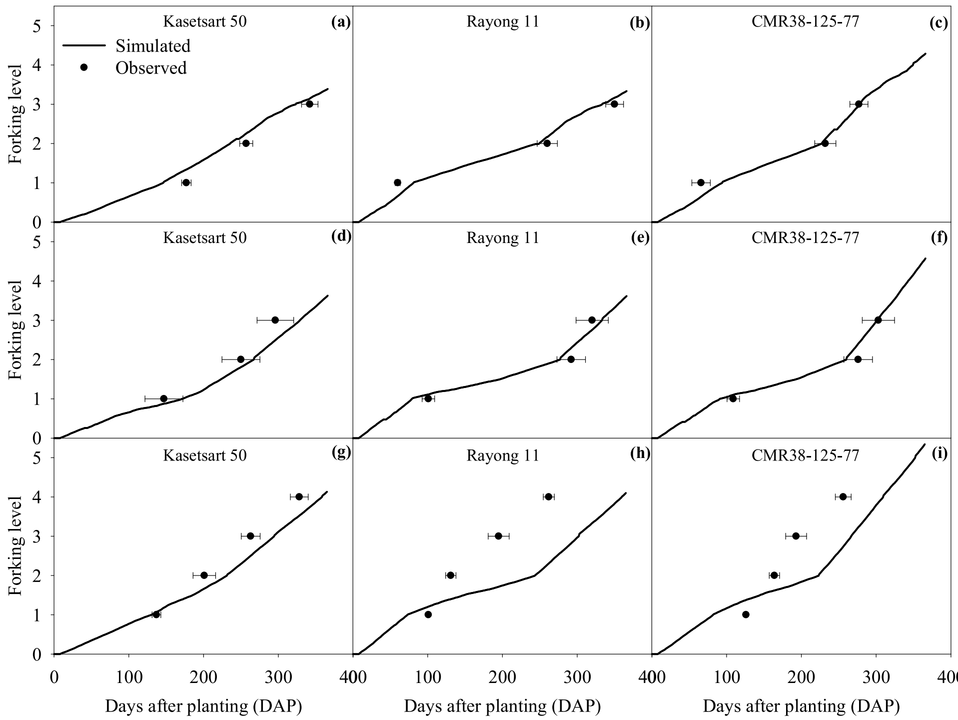

Fig. 3. Simulated (lines) and observed (symbols) forking dates for model calibration for the cassava genotypes Kasetsart 50, Rayong 11, and CMR38–125–77 planted on 25 May 2015 (a–d), 15 December 2015 (e–h), and 3 November 2016 (i–l).

environmental conditions, using the seasonal analysis approach (Thornton and Hoogenboom, 1994). The performance of the four cassava genotypes was simulated with 15–years of historical weather data, i.e., 2003–2018, and for different planting dates under irrigated conditions, using the detailed crop management practices explained in Phoncharoen et al. (2019a, 2019b).

3. Results

3.1. Model calibration

The genetic parameters were adjusted until a good agreement between simulated and observed forking date, dry weight, and LAI was achieved. To obtain a better fit between the simulated and observed time to first forking, second, and the third forking levels, the values of PPS1 were adjusted for the genotypes Rayong 11 and CMR38–125–77 (Table 1). The variation of this parameter among the four genotypes was large as indicated by the coefficient of variation (CV) of 127.7 %. The values of B01ND, B12ND, and B23ND were adjusted for the forking genotypes Kasetsart 50, Rayong 11, and CMR38–125–77. The results from the calibration showed a close agreement between simulated and observed forking date for the genotypes Kasetsart 50, Rayong 11, and CMR38–125–77 for the May and December 2015 plantings (Fig. 3) with d-index values ranging from 0.95 to 0.99 and *n*RMSE varying from 10.8–16.1 % (Table 2). A good agreement for the forking date for the genotype Kasetsart 50 was recorded for the November 2016 planting with a d-index of 0.96 and a *n*RMSE of 15.4 % (Table 2; Fig. 3h and i). However, there were some discrepancies between the simulated and observed values for the genotypes Rayong 11 and CMR38–125–77 for the second, third, and the fourth forking dates, ranging from 50 to 112 days (Fig. 2h and i). The genotype Rayong 9 did not show any forking during the experimental period, so it was considered as a non–forking genotype using a high value for B01ND and no value for B12ND and B23ND as compared to the other three genotypes (Table 1). These discrepancies resulted in large differences among the four genotypes (high CV value) for the genetic parameters B01ND, B12ND, and B23ND that are associated with the forking traits.

The PARUE is one of the main genetic parameters that affects biomass growth. This parameter was adjusted to improve the simulated values for total crop dry weight with calibrated values of 1.60, 1.67, 1.65, and 1.65 g MJ^{-1} for Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77, respectively (CV = 1.8 %) (Table 1). The genetic parameters of BR1FX, BR2FX, BR3FX, and BR4FX define the number of branches per fork for each forking level and affect leaf growth. For these four genetic parameters, the differences among genotypes were rather large with CV values ranging from 27.2–43.3 % and with a higher variation for the first forking level. The parameters of KCAN, LAXS, SLAS, LLIFA, LPEFR, and LNSLP are used to describe leaf growth, and these genetic parameters were adjusted to achieve a better agreement between simulated and observed values for leaf dry weight and LAI, which indirectly contributes to storage root growth. The CV values for these four genetic parameters ranged from 0.0–29.5 %. Increasing the value for the genetic parameter NODLT slightly increased the simulated stem dry weight, while the genetic parameter NODWT related directly with the proportion of biomass allocation between the stem and storage root. The value for NODWT ranged from 17.1–20.2 g per node. The CV values for NODLT and NODWT were 23.1 and 8.1 %, respectively.

The simulated and observed dry matter for total crop biomass, leaf, stem, and storage root for the four cassava genotypes for May and December 2015 and November 2016 plantings are shown in Fig. 4. There was a good agreement between the simulated and observed total crop biomass for the genotypes Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77 for these three planting dates with values for the d-index that ranged from 0.95 to 1.00, and *n*RMSE that ranged from 10.1–28.9 % (Table 2 and Fig. 4). Total crop dry weight of the genotype Rayong 9 for the May and December 2015 and November 2016 plantings were simulated accurately with a d-index of 0.99, 0.99, and 0.98, respectively, and with *n*RMSE values of 15.3, 13.4, and 18.7 %, respectively (Table 2; Fig. 4b, f, and j). The model was able to simulate stem and storage root dry weights accurately for all genotypes for the May and December 2015 plantings, with good d-index values ranging from 0.86 to 0.99 and values for *n*RMSE ranging from 14.4–42.4 %

Table 2
The values of d-index and normalized root mean square error (*n*RMSE) (%) for crop traits for the four cassava genotypes and eight planting dates.

Planting date	Crop Trait	Genotype							
		Kasetsart 50		Rayong 9		Rayong 11		CMR38–125–77	
		d-index	*n*RMSE	d-index	*n*RMSE	d-index	*n*RMSE	d-index	*n*RMSE
May[a] 2015	Forking	0.97	13.0	–	–	0.98	11.9	0.99	10.8
	Total[c]	0.96	23.2	0.99	15.3	0.99	16.6	0.96	23.0
	Leaf[c]	0.87	30.7	0.89	31.7	0.94	22.8	0.87	37.1
	Stem[c]	0.86	42.4	0.89	38.1	0.90	37.9	0.87	40.1
	Storage root[c]	0.93	39.4	0.99	14.4	0.97	30.7	0.96	30.5
	LAI	0.74	46.6	0.88	36.6	0.84	38.6	0.85	40.0
December[a] 2015	Forking	0.95	16.1	–	–	0.98	11.6	0.98	12.1
	Total[c]	1.00	10.1	0.99	13.3	0.99	14.7	0.99	12.6
	Leaf[c]	0.90	32.5	0.94	27.4	0.92	33.3	0.89	40.8
	Stem[c]	0.97	25.5	0.98	20.3	0.99	15.4	0.99	17.1
	Storage root[c]	0.96	24.6	0.97	26.5	0.96	25.4	0.94	31.3
	LAI	0.90	33.5	0.89	38.3	0.90	40.8	0.87	45.0
November[a] 2016	Forking	0.96	15.4	–	–	0.67	44.4	0.75	36.6
	Total[c]	0.95	28.9	0.98	18.7	0.97	24.2	0.97	23.6
	Leaf[c]	0.69	70.3	0.86	34.6	0.69	60.0	0.68	70.3
	Stem[c]	0.98	21.0	0.95	39.7	0.97	28.5	0.92	53.7
	Storage root[c]	0.74	61.5	0.83	49.2	0.70	69.8	0.68	70.3
	LAI	0.67	52.0	0.74	32.3	0.54	63.7	0.56	55.9
April[b] 2015	Forking	0.98	12.3	–	–	0.95	20.8	0.91	30.6
	Total[c]	0.94	29.4	0.94	28.0	0.95	27.4	0.98	18.2
	Leaf[c]	0.66	54.8	0.83	41.6	0.70	53.5	0.72	56.8
	Stem[c]	0.75	59.9	0.83	46.6	0.81	50.0	0.81	47.9
	Storage root[c]	0.98	21.1	0.96	26.4	0.97	27.6	0.91	51.8
	LAI	0.71	50.0	0.85	41.7	0.74	52.4	0.76	54.4
June[b] 2015	Forking	0.86	36.9	–	–	0.93	17.3	0.80	32.7
	Total[c]	0.95	33.7	0.97	24.7	0.95	30.6	0.98	20.0
	Leaf[c]	0.87	36.6	0.63	64.6	0.89	33.2	0.68	65.8
	Stem[c]	0.99	17.0	0.90	50.1	0.93	43.7	0.94	36.6
	Storage root[c]	0.89	55.4	0.95	30.3	0.85	50.5	0.93	34.7
	LAI	0.86	38.2	0.62	70.7	0.87	36.7	0.65	71.2
October[b] 2015	Forking	0.98	10.6	–	–	0.95	16.2	0.96	15.6
	Total[c]	0.95	32.6	0.97	27.7	0.98	20.4	0.99	16.2
	Leaf[c]	0.86	36.1	0.70	53.6	0.81	42.2	0.70	58.0
	Stem[c]	0.92	54.0	0.94	42.9	0.97	33.2	0.95	40.3
	Storage root[c]	0.91	40.2	0.95	31.7	0.94	34.6	0.95	29.8
	LAI	0.82	45.2	0.63	63.2	0.73	55.4	0.64	66.3
November[b] 2015	Forking	0.99	9.9	–	–	0.94	18.9	0.93	23.9
	Total[c]	0.98	17.6	0.99	11.9	0.99	14.9	0.99	13.0
	Leaf[c]	0.83	39.6	0.82	40.3	0.86	35.4	0.69	57.2
	Stem[c]	0.95	31.4	0.98	21.9	0.99	16.4	0.99	16.4
	Storage root[c]	0.92	36.3	0.97	23.6	0.97	24.3	0.93	35.2
	LAI	0.83	41.0	0.82	43.2	0.86	36.9	0.66	60.0
May[b] 2016	Forking	0.81	35.8	–	–	0.80	34.3	0.92	19.1
	Total[c]	0.96	25.0	0.94	28.9	0.90	39.5	0.92	33.1
	Leaf[c]	0.51	82.0	0.71	49.9	0.71	54.5	0.72	55.4
	Stem[c]	0.98	16.7	0.82	68.7	0.97	23.1	0.97	22.1
	Storage root[c]	0.79	54.5	0.68	65.7	0.67	74.0	0.72	60.9
	LAI	0.44	99.6	0.72	50.5	0.66	66.7	0.58	80.8

[a] Model calibration.
[b] Model evaluation.
[c] Dry weight (kg ha^{-1}).

(Fig. 4a–h). However, stem dry weight was overestimated for the genotype CMR38–125–77 for the November 2016 planting with a d-index of 0.92 and a *n*RMSE of 53.7 % (Table 2 and Fig. 4l). The model showed a good simulation for leaf dry weight for all four cassava genotypes for the May and December 2015 plantings (Fig. 4a–h); the values for the d-index were moderate to high (0.87–0.94), and the *n*RMSE values ranged from 22.8–40.8 % (Table 2). The simulated leaf dry weight for the November 2016 planting was higher than the observed values during the late growing period (between 300–360 DAP), which resulted in lower values for the d-index (0.68–0.69) and higher values for *n*RMSE (60.0–70.3 %) for the genotypes Kasetsart 50, Rayong 11, and CMR38–125–77 (Table 2; Fig. 4i–l). The simulated values for LAI showed a similar pattern as leaf dry weight for the four cassava genotypes for the May and December 2015 and November 2016 plantings with the d-index ranging from 0.54 to 0.90 and *n*RMSE ranging from 33.6–63.7 % (Table 2 and Fig. 5).

3.2. Model evaluation

3.2.1. Model evaluation based on actual performance of cassava genotypes

The CSM–MANIHOT–Cassava model was evaluated with the data sets obtained from the different planting dates in April, June, October, and November 2015 and May 2016. Cassava phenology was accurately simulated for all five planting dates based on the statistical indices with d-index values ranging from 0.80 to 0.99, and values for *n*RMSE ranging from 9.9–34.3 % (Table 2 and Fig. 6).

The comparison between simulated and observed data with respect to crop traits of the four cassava genotypes are shown in Fig. 7. The model performed well for simulated crop biomass accumulation with high d-index values for all five planting dates (Table 2). There were small differences between simulated and observed values for the genotype CMR38–125–77 for all five planting dates with high d-index values (0.92–0.99) and low values for *n*RMSE (13.0–33.1 %) (Table 2 and

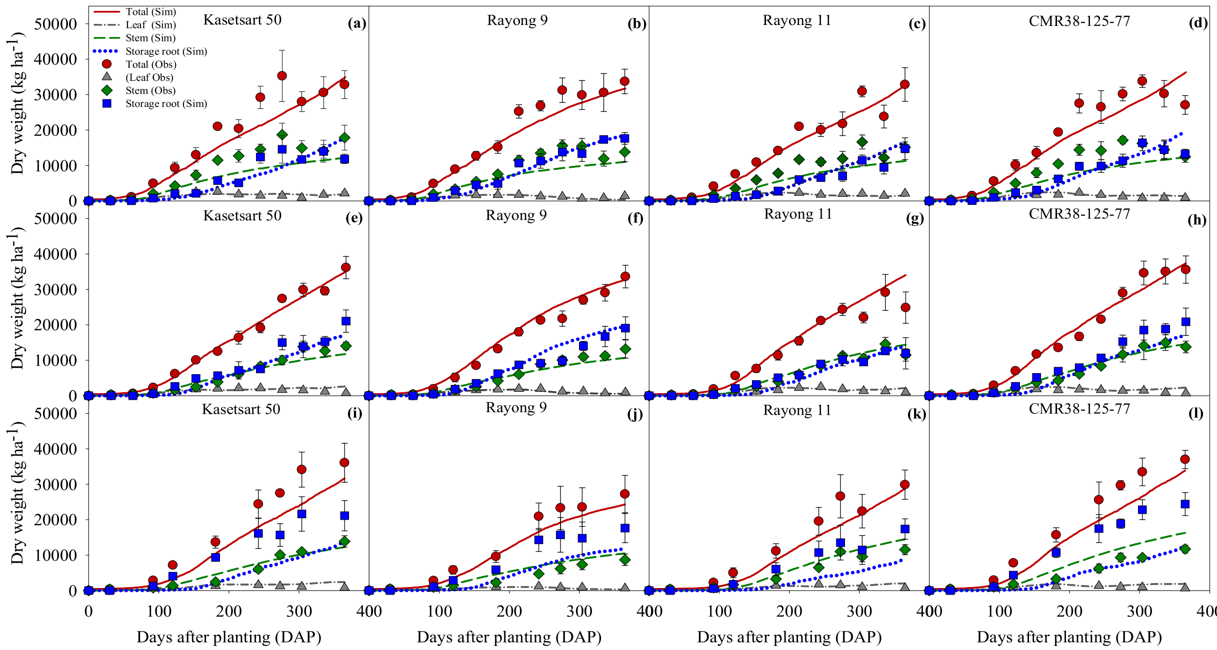

Fig. 4. Simulated (lines) and observed (symbols) values for model calibration for total, leaf, stem, and storage root dry weights for the cassava genotypes Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77 planted on 25 May 2015 (a–d), 15 December 2015 (e–h), and 3 November 2016 (i–l).

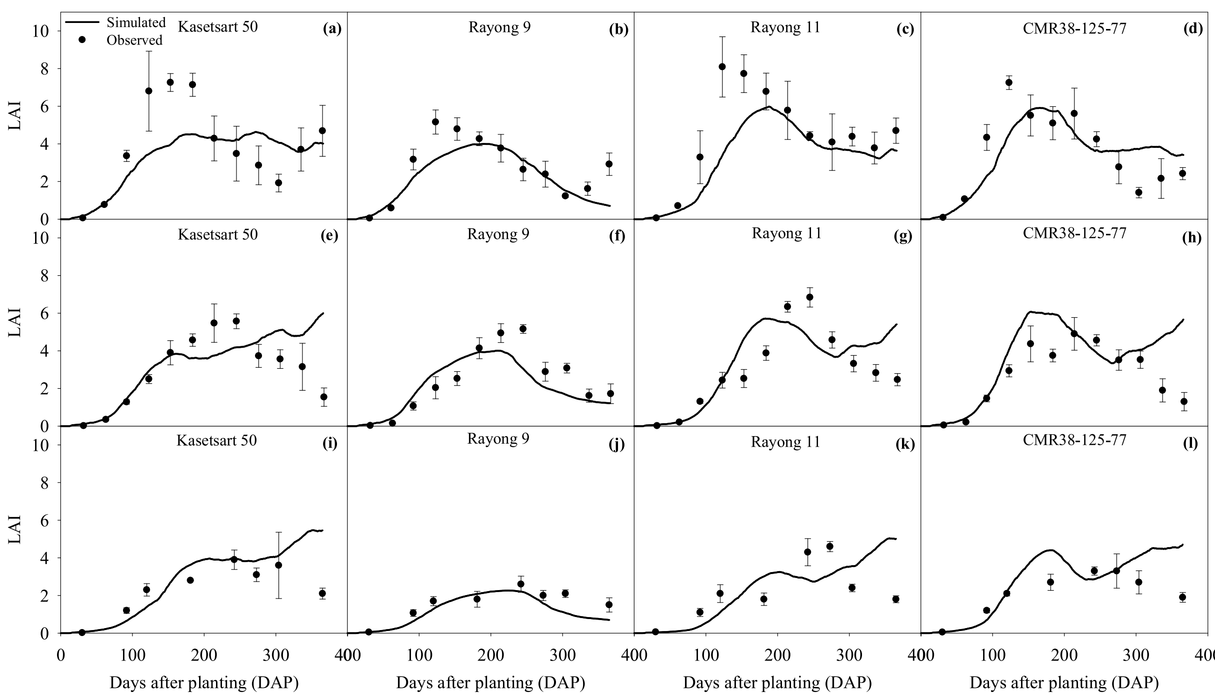

Fig. 5. Simulated (lines) and observed (symbols) leaf area index (LAI) for model calibration for the cassava genotypes Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77 planted on 25 May 2015 (a–d), 15 December 2015 (e–h), and 3 November 2016 (i–l).

Fig. 7d, h, l, p, and t). Although the model underestimated total dry weight for the planting of May 2016, the simulated values for crop dry weight are still within the observed variation from 300–360 DAP, except for the genotype Rayong 11 (Fig. 7q, r, and t). Good simulations for storage root dry weight were achieved for almost all genotypes and planting dates, except for the May 2016 planting (Fig. 7q–t). Simulated and observed storage root dry weights for the genotype Rayong 9 were in good agreement based on the high values for the d-index (0.95–0.97) and moderate values for *n*RMSE (23.6–31.7 %) for most planting dates, except for the May 2016 planting (Table 2; Fig. 7b, f, j, n, and r). A good fit between simulated and observed stem dry weights was found for almost all cases (the combination between genotypes and planting dates) with d-index values ranging from 0.90 to 0.99 and *n*RMSE values ranging from 16.4–54.0 %, except for all genotypes for the April 2015 planting, which underestimated the stem weight, and for the genotype Rayong 9 for the May 2016 planting, which showed overestimated results (Table 2; Fig. 7a–d and r). The model simulated the stem dry weight for the genotype Rayong 11 well for the November 2015 planting, which had a high d-index (0.99) and low *n*RMSE (16.4 %) (Table 2 and Fig. 7o). The model performed moderately well for leaf dry weight and LAI for

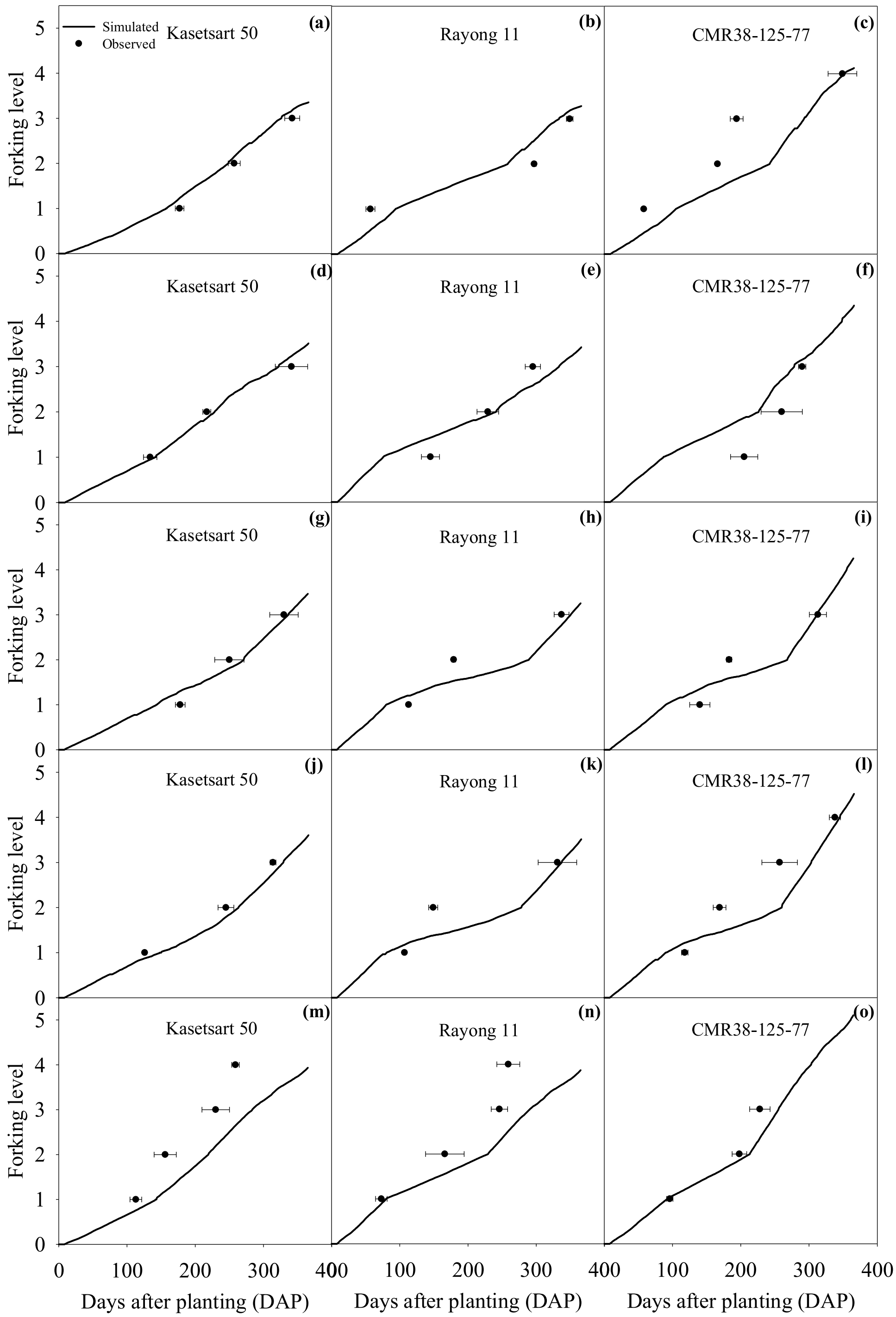

Fig. 6. Simulated (lines) and observed (symbols) forking dates for the genotypes Kasetsart 50, Rayong 11, and CMR38–125–77 planted on 20 April 2015 (a–c), 30 June 2015 (d–f), 5 October 2015 (g–i), and 10 November 2015 (j–l) and 19 May 2016 (m–o).

most genotypes and planting dates (Fig. 7 and Fig. 8). However, the May 2016 planting showed that LAI was not very well simulated for the genotypes Kasetsart 50, Rayong 11, and CMR38–125–77, which had a low d- index (0.44–0.66) and high *n*RMSE (66.7–99.6 %).

The performance results of the CSM–MANIHOT–Cassava model in simulating final total crop and storage root dry weights are presented in Fig. 9 and Table A2. The means for simulated and observed total crop dry weights ranged from 22,720 to 36,915 kg ha^{-1} and from 20,453 to 43,381 kg ha^{-1}, respectively. For simulated and observed storage root dry weights, the means varied from 10,475 to 19,048 kg ha^{-1} and from 9675 to 22,489 kg ha^{-1}, respectively. The differences between the simulated and observed data as expressed by *n*RMSE ranged from 1.6–59.1 % for total crop dry weight and from 0.4–64.4 % for storage root dry weight. The November 2015 planting showed reasonably good simulations for simulated total crop dry weight (*n*RMSE ranged from 6.7–19.1 %) (Fig. 9a and Table A2) and storage root yield (*n*RMSE ranged from 1.0–18.8 %) (Fig. 9b and Table A2). The October 2015 planting showed reasonably good simulations for simulated storage root yield (*n*RMSE ranged from 0.4–20.2 %) (Fig. 9b and Table A2) for all four cassava genotypes. A good agreement for storage root dry weight was found for the genotype Kasetsart 50 for almost all planting dates (*n*RMSE ranged from 2.3–20.2 %), except for the June 2015 planting

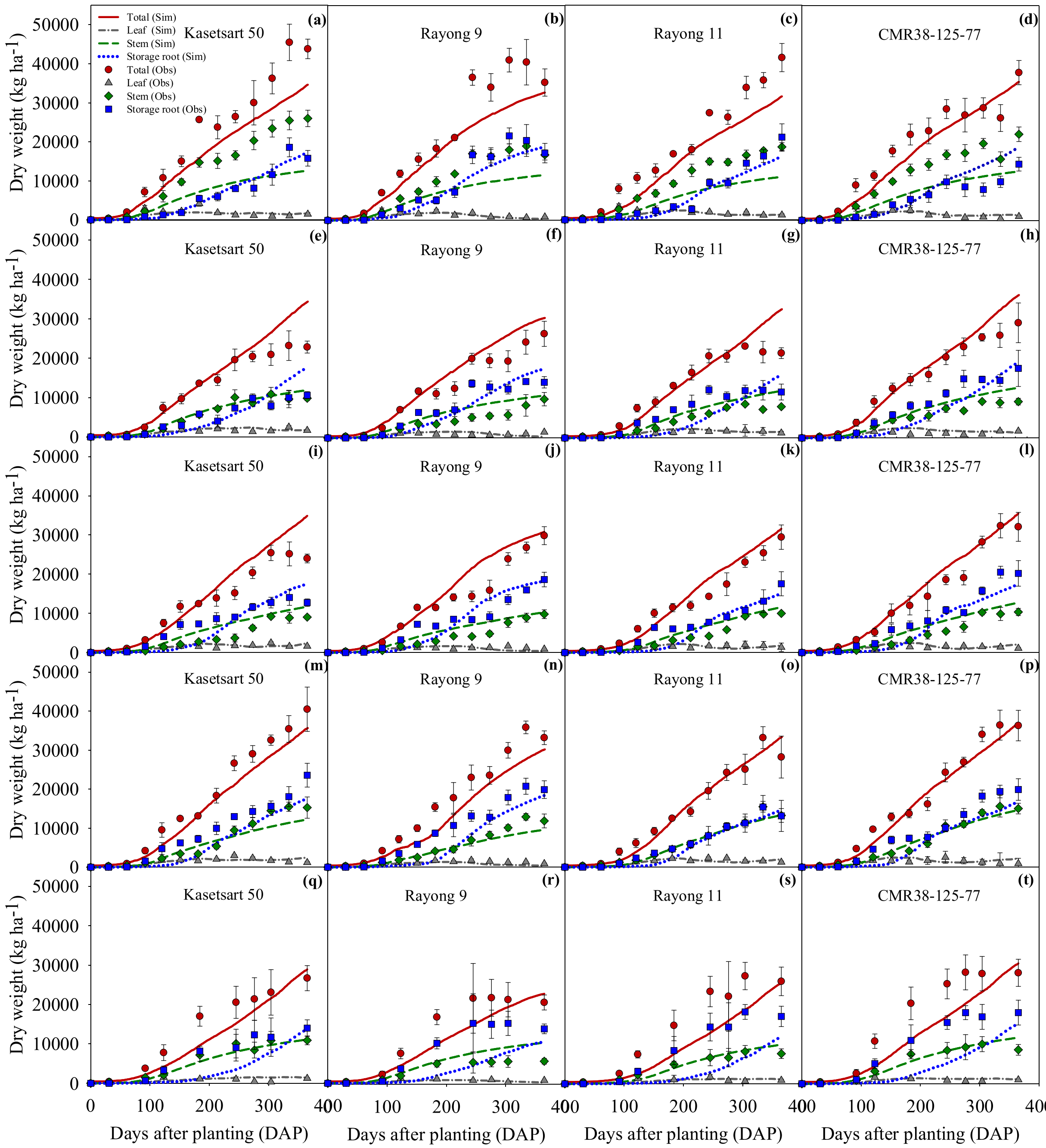

Fig. 7. Simulated (lines) and observed (symbols) total, leaf, stem, and storage root dry weights for the genotype Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77 planted on 20 April 2015 (a–d), 30 June 2015 (e–h), 5 October 2015 (i–l), and 10 November 2015 (m–p) and 19 May 2016 (q–t).

(Fig. 9b and Table A2). The agreement between simulated and observed dry weights at final harvest was moderate to good for almost all comparisons. Overall, the *n*RMSE value was 22.0 % for total crop dry weight and 22.6 % for storage root dry weight. The results from combined analysis of variance indicated that genotype × planting date for simulated and observed total dry weights contributed 3.7 and 5.2 %, respectively, and for simulated and observed storage root dry weights shared 16.1 and 21.9 %, respectively (Table A3).

3.2.2. Model evaluation based on relative performance of cassava genotypes

To identify suitable genotypes for different planting dates, plant breeders commonly use the relative performance with respect to ranking as an alternative approach rather than evaluating the absolute yield level. We, therefore, would like to demonstrate the potential of applying the CSM–MANIHOT–Cassava model for the classification of favorable cassava genotypes for different planting dates. According to the genotype ranking for both final storage root and crop dry weights for each of five planting dates, one superior genotype out of the top two genotypes was classified by both the crop model simulation and the field experiment (Fig. 9a and b). The genotype Kasetsart 50 was one of the top two genotypes based on final total crop dry weight for the April, June, and November 2015 and May 2016 plantings, while the genotype CMR38–125–77 was one of the top two genotypes for the June, October, and November 2015 plantings. For storage root dry weight, the genotype Rayong 9 was identified as one of the top two genotypes for the April and October 2015 plantings, the genotype Kasetsart 50 for the November 2015 planting, and the genotype CMR38–125–77 for the

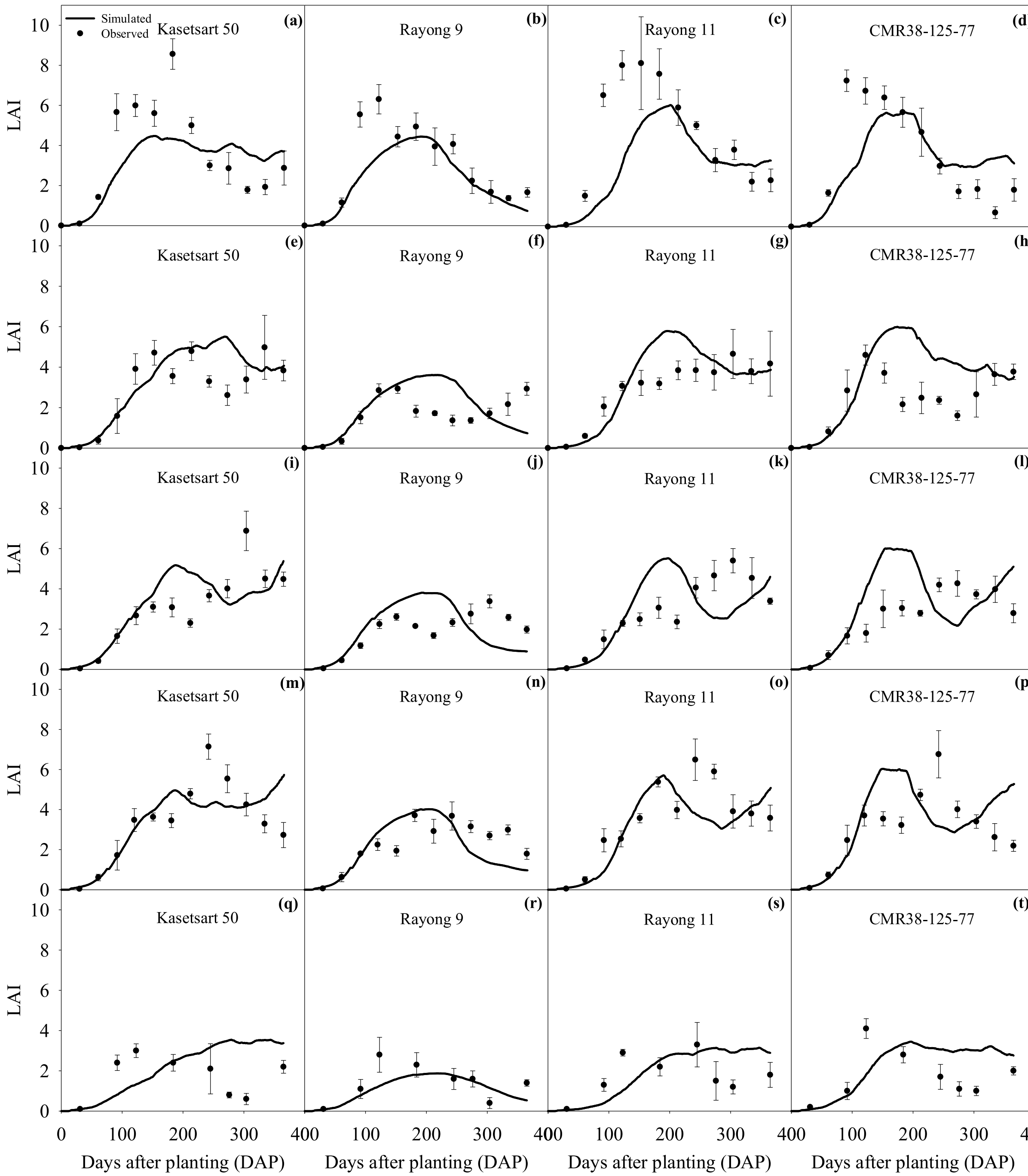

Fig. 8. Simulated (lines) and observed (symbols) leaf area index (LAI) for Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77 planted on 20 April 2015 (a–d), 30 June 2015 (e–h), 5 October 2015 (i–l), and 10 November 2015 (m–p) and 19 May 2016 (q–t).

June and October 2015 and May 2016 plantings.

3.2.3. Model application

Additional simulation for the four cassava genotypes under irrigated condition using 15–years of historical weather data from 2003 until 2018 indicated that simulated total crop biomass ranged from 31,993 to 37,727 kg ha^{-1}, while the storage root dry weight ranged from 13,999 to 21,637 kg ha^{-1} (Table 3). The highest average values for simulated total crop and storage root dry weights were found for the genotype CMR38–125–77 and Rayong 9 for the November planting. For the relative performance, ranking of each genotype with respect to simulated total crop dry weight among the different planting dates was the same, but not for simulated storage root dry weight. The model identified the genotypes CMR38–125–77 and Kasetsart 50 as the top two genotypes in terms of total crop biomass for all planting dates, which was similar to the earlier presented ranking (Fig. 9a). For storage root dry weight (Table 3), the genotype Rayong 9 was classified as one of the top two genotype for all five planting dates, the genotype Kasetsart 50 for the October and November plantings, and the genotype CMR38–125–77 for the April, May, and June plantings.

4. Discussion

4.1. Determination of genetic parameters

The results for genetic parameters determination through the

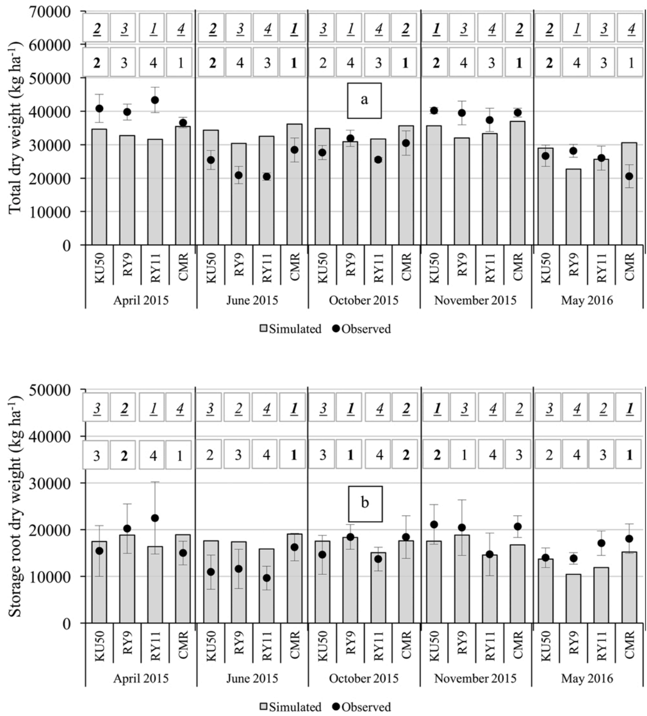

Fig. 9. Simulated (bars) and observed (symbols) dry weights for final crop (a) and storage root (b) for the genotypes Kasetsart 50 (KU50), Rayong 9 (RY9), Rayong 11 (RY11), and CMR38–125–77 (CMR) planted on 20 April 2015, 30 June 2015, 5 October 2015, 10 November 2015, and 19 May 2016. The italicized underlined numbers are the observed ranking, while the normal numbers represent simulated ranking.

calibration process with the experimental data sets from the May 2015, December 2015, and November 2016 plantings indicated the potential for using these derived genetic parameters for the evaluation of the performance of all four cassava genotypes in Thailand under different planting dates. According to the data required for determination of genetic parameters as described by Boote et al. (1996) and Hoogenboom et al. (2019b), this study showed that experimental data from the three selected planting dates with different weather conditions, i.e., May and December 2015 and November 2016 are sufficient for model calibration keeping in mind that there is experimental error for data collected in field experiments. Banterng et al. (2004) showed that the minimum data set from two distinct growing seasons in Thailand was sufficient to calibrate the genetic parameters of the CSM–CROPGRO–Peanut model for different genotypes. This result was confirmed by a study of Suriharn et al. (2007). Banterng et al. (2010) and Vilayvong et al. (2012, 2015) considering also a minimum of two different growing seasons in Thailand as acceptable to derive the genetic parameters for soybean and rice models.

The phenology of cassava is based on the occurrence of forking (Phoncharoen et al., 2019b). The calibration results for the phenological events for the May and December 2015 plantings, which are two extreme dates with respect to temperature and other environmental conditions, showed that the model responded correctly to different environmental inputs. This supports the studies by Irikura et al. (1979); Keating et al. (1982a), and Phoncharoen et al. (2019b) that showed that cassava phenology is affected by temperature and daylength. The model describes the forking event for the genotypes Rayong 11 and CMR38–125–77 through a parameter of PPS1 (photoperiod sensitivity), which is defined in the ecotype file (Hoogenboom et al., 2019b). These two genotypes showed a similar forking pattern that was different from the genotype Kasetsart 50, which is not sensitive to photoperiod. Because the genotype Rayong 9 did not show any forking during the experimental period, and, therefore, this genotype had a high value for the genetic parameter B01ND (1650 growing degree days, GDD).

The CSM–MANIHOT–Cassava model uses the concept of radiation use efficiency for converting solar radiation into biomass accumulation (Hoogenboom et al., 2019b). A large amount of solar radiation during the planting period results in an increase in total crop and storage root dry weights (Fukai et al., 1984; Phuntupan and Banterng, 2017; Phoncharoen et al., 2019a). Simulated leaf dry weight and LAI for the forking genotypes, i.e., Kasetsart 50, Rayong 11, and CMR38–125–77 were higher by increasing the genetic parameter BRnFX. For a non–forking genotype, i.e., Rayong 9, this genetic parameter did not affect leaf growth and LAI. The SLAS parameter explains the ratio of leaf area to leaf weight for each cassava genotype, and it affects simulated LAI (Hoogenboom et al., 2019b).

The model overestimated LAI for the forking genotypes at the end of the growing season for the December 2015 and November 2016 plantings. The current version of model assumes that all the forking points

Table 3
The performances at final harvest of the genotypes Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77 based on long–term simulations with historical weather data from 2003 until 2018 (15 years) for the 20 April, 19 May, 30 June, 5 October, and 10 November planting dates under irrigated conditions.

Planting date	Genotype	Total dry weight (kg ha^{-1}) ±SD[a]	Ranking	Storage root dry weight (kg ha^{-1}) ±SD[a]	Ranking
20 April	Kasetsart 50	34,848 ± 1443	2	18,621 ± 1433	3
	Rayong 9	32,456 ± 1856	4	19,438 ± 1580	2
	Rayong 11	32,753 ± 1415	3	17,747 ± 1378	4
	CMR38–125–77	36,161 ± 1331	1	20,347 ± 1343	1
19 May	Kasetsart 50	35,135 ± 1534	2	19,318 ± 1617	3
	Rayong 9	32,334 ± 1721	4	19,709 ± 1560	2
	Rayong 11	33,366 ± 1557	3	18,411 ± 1508	4
	CMR38–125–77	36,640 ± 1504	1	21,028 ± 1510	1
30 June	Kasetsart 50	35,214 ± 1656	2	19,434 ± 1847	3
	Rayong 9	31,993 ± 1797	4	20,022 ± 1740	2
	Rayong 11	33,664 ± 1613	3	18,324 ± 1749	4
	CMR38–125–77	36,800 ± 1637	1	20,856 ± 1757	1
5 October	Kasetsart 50	35,908 ± 1372	2	18,816 ± 1634	2
	Rayong 9	33,184 ± 1571	4	21,007 ± 1628	1
	Rayong 11	34,117 ± 1499	3	15,404 ± 1696	4
	CMR38–125–77	36,920 ± 1500	1	17,729 ± 1675	3
10 November	Kasetsart 50	36,362 ± 1690	2	18,857 ± 1973	2
	Rayong 9	34,363 ± 1769	4	21,637 ± 1831	1
	Rayong 11	35,311 ± 1641	3	13,999 ± 1789	4
	CMR38–125–77	37,727 ± 1511	1	16,368 ± 1988	3

[a] Standard division.

produce the same number of branches, which does not occur under actual field conditions. As result, the model overpredicted the number of apices. In addition, an occurrence of a none–serious pest, i.e., whitefly (*Bemisia tabaci*) for the November 2016 planting contributed to a decrease in the number of cassava leaves (Macfadyen et al., 2018) and LAI towards the end of the growing season for the genotypes Kasetsart 50, Rayong 11, and CMR38–125–77. The effect of pests on cassava leaves is not included in the model (Hoogenboom et al., 2019b), and, thus, contributed to the overestimation of the LAI. Cassava is recognized as a crop with simultaneous growth of leaf area and storage root (Lebot, 2009), and the balance between growth of leaf (source) and development of storage root (sink) plays an important role for crop productivity. The decreased LAI values for the November 2016 planting were close to the optimum range (3–3.5) as reported by Cock et al. (1979). Hence, the observed values for storage root yield in this planting date were still high. This would be a cause for the gap between observed and simulated storage root yield for the November 2016 planting.

The model also estimated later forking times for the November 2016 planting based on the lower temperatures and shorter daylength, while the observed forking times did not show this trend. Temperatures below 25 °C for a prolonged time at the beginning of the growing season and lower temperatures during the hot season of 2017 (March–June) also contributed to a reduced simulated assimilate production per unit of leaf area for the November 2016 planting in comparison to the December 2015 planting. As a result, the model underestimated LAI and total biomass for this planting from the beginning of the growing season. In addition, the whitefly attack produced thinner stems with less biomass. As we explained previously, the current version of the model does not include the effects of pests and diseases and, thus, overestimated stem biomass for the November 2016 planting. The lower estimated total biomass in addition to the overestimated stem weight reduced the biomass partitioning to the storage roots, resulting in a decrease in their weight. The model underestimated the LAI at the beginning of the growing season (DAP 100–200) for the May planting. This is more evident for the early forking genotypes Rayong 11, and CMR38–125–77, which showed a delay in the simulated forking time for this planting date. However, using the Beer–Lambert law and the extinction coefficient defined for each cultivar in the model (see Table 1), the genotypes Kasetsart 50, Rayong 9, Rayong 11, and CMR38–125–77 intercepted 90 % of the radiation with a LAI of 4.6, 4.1, 5.4, and 4.5, respectively. These LAI values are close to those simulated by the model when the LAI was underestimated, so most of the radiation is being intercepted.

The high values of LAXS for the genotypes Kasetsart 50 and CMR38–125–77 (945 and 710 cm^2), and the large value of LLIFA for the genotype Rayong 9 (2300 GDD) resulted in an increase in simulated leaf and total crop dry weights. The genotype Kasetsart 50 had higher observed values for stem dry weight than the other genotypes for almost all planting dates, and, thus, it had a high value for the genetic parameters NODWT (20.2 g) and NODLT (4.5 cm). The high value for NODWT caused an increase in stem weight and a decrease in storage root dry weight.

4.2. Performance of the CSM–MANIHOT–Cassava model

The model was evaluated with data sets from five different planting dates, including April, June, October, and November 2015 and May 2016. Although some high values of *n*RMSE indicated that there were some differences between the simulated and observed data, overall, the results were satisfactory based on the d-index. The results indicated good agreement between simulated and observed total crop and stem dry weights and storage root yield, with values for the d-index that were generally greater than 0.8, which correspond to the d-index values reported by Gabriel et al. (2014). Some discrepancies between the simulated and observed data can be explained by the potential impact of pests and the quality of soil tillage in the experimental fields, which were not taken into account by the model (Hoogenboom et al., 2019b). Although pest and disease protections were carefully managed for all plating dates, there was some minor pest distribution, such as cassava whitefly and cassava red mite (*Oligonychus biharensis* (Hirst)). These types of pest infestation can disrupt growth of cassava (Graziosi et al., 2017; Macfadyen et al., 2018).

The relative performance for both simulated and observed dry weights at final harvest was analyzed as it is a common approach that is used by breeders to identify the superior genotype for different growing conditions. The response of the model to the different planting dates was less compared to the ranking based on the experimental data. This could partially be due to the effect of other environmental factors that are currently not simulated by the model. Variation in ranking for simulated storage root dry weight of each genotype across different planting dates was higher than the variation in ranking for total crop dry weight, indicating a larger effect of interaction between genotype and planting date for simulated storage root dry weight (Table A3). The model was able to identify at least one preferable genotype from the top two genotypes based on ranking for total crop and storage root dry weights for each planting date. The small differences between these four tested genotypes might be a reason to explain the model's capability in identifying the superior genotype with respect to ranking. All four genotypes that were used in this study are improved cultivars and one is an elite line that is well adapted to the weather conditions in Thailand. Therefore, evaluation of the performance of the model with a wider range of different of genotypes is recommended for further research (Banterng et al., 2006; Phakamas et al., 2008; Suriharn et al., 2008; Putto et al., 2009). A study regarding the potential of a model to classify the superior cassava genotypes for various locations is also of interest to plant breeders as it would be useful to help select the favorable genotypes based on multi–environment yield trials (Banterng et al., 2006; Putto et al., 2008, 2013).

The results from our study demonstrated the capability of the CSM–MANIHOT–Cassava model for model applications using the genetic parameters that were obtained for the four cassava genotypes. The genetic parameters that were obtained in this study can also be useful for future sensitivity analysis to identify the impact of each parameter on growth and final storage root yield of cassava. The information from such a study could then be applied to design ideal plant types for growing cassava in various environments as well as helping with the selection criteria for cassava breeding programs. Further research is also needed for evaluation of the CSM–MANIHOT–Cassava model for other management scenarios such as plant population, irrigation, and nitrogen fertilizer in order to be able to expand the application of the model for decision support.

5. Conclusions

This is the first study on the application of the CSM–MANIHOT–Cassava model for one elite and three commercial cassava genotypes under a tropical savannah climate in Thailand. Model evaluation with the d-index indicated the ability of the model to capture the phenological events and growth for the four cassava genotypes and different planting dates. The results from the modelling approach and an actual experiment indicated that Kasetsart 50 and CMR38–125–77 were the top two genotypes for final total crop biomass. This study showed the potential of using the CSM–MANIHOT–Cassava model as a tool to help with the identification of the suitable genotypes for different planting dates.

Author statement

We are pleased to submit a revised version of our research entitled "Performance of the MANIHOT–Cassava Model for Simulating Planting Date Response of Cassava Genotypes" for possible publication in Field Crops Research.

This is the first study on the application of the

CSM–MANIHOT–Cassava model in DSSAT Version 4.7.5 for the commercial cassava genotypes and an elite line under a tropical savannah climate in Thailand. Our results demonstrate the potential for using the model as tool to help identify the suitable genotype for different planting dates.

We affirm that the content of this manuscript or a major portion has not been published in referred journal, and it is not being submitted for publication elsewhere.

Declaration of Competing Interest

We are pleased to submit an original manuscript of our research entitled "Performance of the CSM–MANIHOT–Cassava model for simulating planting date response of cassava genotypes" for possible publication in Field Crops Research.

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Appendx A

Table A1
Soil profile properties for the 20 April, 25 May, 30 June, 5 October, 10 November, and 15 December 2015 planting dates. The soil profile properties for 19 May 2016 and 3 November 2016 planting dates were similar to 20 Aril 2015 and 25 May 2015 planting dates, respectively.

Planting date	Depth (cm)	pH (1:1 H_2O)	Organic carbon (%)	Total nitrogen (%)	Ammonium (mg kg^{-1})	Nitrate (mg kg^{-1})	Bulk density (g cm^{-3})	Soil particle distribution		
								Sand (%)	Silt (%)	Clay (%)
April 2015	0–15	7.71	0.57	0.03	0.90	10.02	1.51	87.86	10.07	2.07
	15–30	7.69	0.37	0.03	0.39	2.95	1.67	86.86	11.07	2.07
	30–45	7.79	0.33	0.02	0.20	2.51	1.77	85.86	11.07	3.07
	45–60	7.78	0.33	0.02	1.09	5.17	1.77	78.78	13.00	8.22
	60–75	7.21	0.26	0.01	0.87	4.84	1.78	79.78	11.14	9.08
	75–90	6.72	0.18	0.01	1.40	5.22	1.82	77.78	11.07	11.15
	90–105	6.23	0.17	0.01	0.48	4.37	1.87	76.78	12.14	11.08
May 2015	0–15	7.23	0.47	0.03	0.90	10.02	1.51	86.00	8.86	5.14
	15–30	7.01	0.31	0.02	0.39	2.95	1.56	86.00	7.93	6.07
	30–45	6.90	0.30	0.02	0.20	2.51	1.69	82.00	8.93	9.07
	45–60	6.47	0.24	0.01	1.09	5.17	1.59	80.93	8.93	10.14
	60–75	5.90	0.19	0.01	0.87	4.84	1.69	77.93	12.00	10.07
	75–90	5.36	0.17	0.01	1.40	5.22	1.64	76.93	12.00	11.07
	90–105	5.01	0.16	0.01	0.48	4.37	1.74	75.93	12.00	12.07
June 2015	0–15	4.99	0.48	0.02	3.29	66.02	1.50	85.93	7.07	7.00
	15–30	5.15	0.30	0.02	3.62	53.07	1.59	84.00	8.00	8.00
	30–45	5.22	0.26	0.02	2.65	42.89	1.90	79.93	7.07	13.00
	45–60	5.42	0.30	0.02	1.44	15.24	1.88	76.93	5.07	18.00
	60–75	4.98	0.20	0.01	1.10	12.15	1.86	73.93	8.07	18.00
	75–90	4.79	0.17	0.01	1.68	9.86	1.83	74.93	8.07	17.00
	90–105	4.75	0.12	0.01	0.95	4.72	1.88	73.93	7.07	19.00
Planting date	**Depth (cm)**	**pH (1:1 H_2O)**	**Organic carbon (%)**	**Total nitrogen (%)**	**Ammonium (mg kg^{-1})**	**Nitrate (mg kg^{-1})**	**Bulk density (g cm^{-3})**	**Soil particle distribution**		
								Sand (%)	**Silt (%)**	**Clay (%)**
October 2015	0–15	5.56	0.81	0.03	3.04	3.86	1.59	83.93	10.07	6.00
	15–30	5.56	0.48	0.03	3.00	3.46	1.73	79.86	11.14	9.00
	30–45	5.49	0.40	0.02	3.79	6.30	1.84	78.93	11.00	10.07
	45–60	5.37	0.54	0.02	3.27	14.14	1.83	71.86	12.07	16.07
	60–75	5.22	0.29	0.01	2.99	17.66	1.79	69.93	12.07	18.00
	75–90	4.99	0.24	0.01	2.90	15.34	1.85	68.93	11.93	19.14
	90–105	4.83	0.18	0.01	2.61	7.48	1.88	65.86	14.00	20.14
November 2015	0–15	6.39	0.45	0.02	4.90	15.06	1.51	86.86	9.93	3.21
	15–30	6.23	0.31	0.02	5.15	15.39	1.65	88.00	9.86	2.14
	30–45	6.07	0.26	0.01	5.15	8.60	1.76	82.93	10.00	7.07
	45–60	5.71	0.25	0.01	3.56	4.78	1.80	81.86	8.00	10.14
	60–75	5.27	0.19	0.01	4.88	4.17	1.83	77.78	10.08	12.14
	75–90	4.97	0.17	0.01	5.63	6.92	1.87	78.78	9.22	12.00
	90–105	4.86	0.14	0.01	7.27	10.82	1.80	77.00	10.93	12.07
December 2015	0–15	5.57	0.03	0.02	5.71	8.73	1.58	85.86	10.14	4.00
	15–30	5.71	0.02	0.02	4.92	7.45	1.69	85.64	10.14	4.22
	30–45	5.57	0.02	0.02	4.00	5.16	1.75	78.93	11.07	10.00
	45–60	5.47	0.02	0.01	5.86	5.36	1.78	77.57	13.43	9.00
	60–75	5.37	0.01	0.01	4.38	4.19	1.85	77.50	12.50	10.00
	75–90	5.14	0.01	0.01	3.07	6.08	1.94	77.50	11.43	11.07
	90–105	4.93	0.01	0.01	3.79	8.95	1.82	75.35	12.65	12.00

Table A2
Comparison between simulated and observed total crop and storage root dry weights for the 20 April, 30 June, 5 October, and 10 November 2015 and 19 May 2016 planting dates.

Planting date	Genotype	Total dry weight				Storage root dry weight			
		Simulation (kg ha^{-1})	Observation (kg ha^{-1})	RMSE[1] (kg ha^{-1})	*n*RMSE (%)	Simulation (kg ha^{-1})	Observation (kg ha^{-1})	RMSE (kg ha^{-1})	*n*RMSE (%)
April 2015	Kasetsart 50	34,627	40,853	6226	15.2	17,463	15,458	2005	13.0
	Rayong 9	32,737	39,777	7040	17.7	18,866	20,240	1374	6.8
	Rayong 11	31,636	43,381	11,745	27.1	16,371	22,489	6118	27.2
	CMR38–125–77	35,477	36,604	1127	3.1	18,907	15,023	3884	25.9
June 2015	Kasetsart 50	34,370	25,435	8935	35.1	17,612	10,922	6690	61.3
	Rayong 9	30,338	20,893	9445	45.2	17,424	11,601	5823	50.2
	Rayong 11	32,533	20,453	12,080	59.1	15,904	9675	6229	64.4
	CMR38–125–77	36,125	28,412	7713	27.1	19,048	16,267	2781	17.1
October 2015	Kasetsart 50	34,880	27,665	7215	26.1	17,574	14,621	2953	20.2
	Rayong 9	30,927	31,909	982	3.1	18,362	18,437	75	0.4
	Rayong 11	31,719	25,501	6218	24.4	15,099	13,701	1398	10.2
	CMR38–125–77	35,631	30,496	5135	16.8	17,588	18,399	811	4.4
November 2015	Kasetsart 50	35,647	40,173	4526	11.3	17,531	21,120	3589	17.0
	Rayong 9	31,963	39,513	7550	19.1	18,830	20,422	1592	7.8
	Rayong 11	33,329	37,415	4086	10.9	14,563	14,710	147	1.0
	CMR38–125–77	36,915	39,583	2668	6.7	16,767	20,652	3885	18.8
May 2016	Kasetsart 50	28,917	26,687	2230	8.4	13,690	14,013	323	2.3
	Rayong 9	22,720	28,160	5440	19.3	10,475	13,817	3342	24.2
	Rayong 11	25,585	26,004	419	1.6	11,891	17,109	5218	30.5
	CMR38–125–77	30,561	20,515	10,046	49.0	15,225	18,071	2846	15.7

[1] Root mean square error (RMSE), and normalized root mean square error (*n*RMSE).

Table A3
Percentage of sum squares to total sum of squares (%SS) from the combined analysis of the total crop and storage root dry weights for the four cassava genotypes in the 20 April, 30 June, 5 October, and 10 November 2015 and 19 May 2016 planting dates (model evaluation).

Source of variation	Total dry weight (kg ha^{-1})	Storage root dry weight (kg ha^{-1})
Simulation		
Planting date (PD)	60.9	64.3
Genotype (G)	35.4	19.6
PD × G	3.7	16.1
Field observation		
PD	88.7	63.3
Replication/PD (error)	1.6	2.2
G	0.5	2.7
PD × G	5.2	21.9
Pool error	3.0	3.5

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