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Performance of a model in simulating growth and stability for cassava grown after rice

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Abstract

Selecting the appropriate genotype for growing cassava (*Manihot esculenta* Crantz) after rice (*Oryza sativa* L.) can help increase the supply of cassava and improve land use efficiency. However, conducting the selection requires data from many years of multi-environment yield trials. A systems analysis approach using crop models can support this process. This study aimed to evaluate a potential application of the Cropping System Model (CSM)-MANIHOT-Cassava in determining genotype stability across different upper paddy field conditions when planted following rice. Four cassava genotypes, that is, Kasetsart 50, Rayong 9, Rayong 11, and CMR38-125-77, were evaluated for the six different environments in Thailand from the 2015 through 2018 growing seasons. The data required for the model were recorded, including biomass and yield. The cultivar coefficients of the CSM-MANIHOT-Cassava model for the four genotypes were calibrated and evaluated with the experimental data. The model was then run for historical weather data from 1988 to 2018 for the six environments for production under rain-fed conditions in upper paddy fields following rice. The overall results showed that the model was able to simulate biomass and yield of the four cassava genotypes quite well when compared to the experimental data. The model identified the same stable genotypes as presented in the actual trials. The genotype CMR38-125-77 was found to be a stable genotype and had the highest mean performance for both the actual yield trials and the simulation study. Therefore, the CSM-MANIHOT-Cassava model could be used to help identify the favorable genotype for planting in various paddy field conditions after rice harvest.

1 | INTRODUCTION

Cassava (*Manihot esculenta* Crantz) is recognized as one of the most important food, feed, and energy crops across the globe (El-Sharkawy, 2012; Jansson et al., 2009). It can be grown in tropical and subtropical regions between a latitude of 30 °N and 30 °S, in poor soils, and under conditions with a low and unpredictable rainfall (El-Sharkawy, 1993). In 2018, there were approximately 24.59 million hectares of harvested cassava worldwide with a fresh storage root of 278 Tg (Food and Agriculture Organization of the United Nations (FAO), 2020). As the world's population will continue to increase, the demand for cassava will increase as well as a source for food, feed, and energy.

Abbreviations: ASEAN, Association of the Southeast Asian Nations; CSM, Cropping System Model; DAP, days after planting; DSSAT, Decision Support System for Agrotechnology Transfer; MSD, mean square deviation; NODWT, node weight of the first stem of the shoot before forking; RCBD, randomized complete block design.

Many countries in Southeast Asia, including Thailand are members of the Association of the Southeast Asian Nations (ASEAN), are now producing cassava for the world market. In Thailand, cassava is commonly planted under upland conditions with a normal growing season ranging from 6 to 18 mo, depending on the genotype and growing conditions (Howeler, 2007). In 2018, the total harvested area of cassava in Thailand was around 1.39 million hectares, producing 32 Tg of storage root fresh weight (FAO, 2020). Finding alternative production areas can increase global cassava production, which is one way to fulfill the high worldwide cassava demand. Planting cassava after rice (*Oryza sativa* L.) in Thailand is one of the potential options for increasing the total production, as well as improving land use efficiency. Most of Thai farmers in the rainfed areas normally grow only a single crop of rice during the rainy season that ranges from June to December. During the dry season, some farmers leave their paddy fields fallow for about 10 mo because of limited water availability. In some places, however, there is sufficient residual soil moisture, as well as a suitable soil texture to complete both the growth and storage root formation of cassava.

The performances of the commonly released cassava genotypes in Thailand are normally evaluated for upland conditions (Curran & Cooke, 2008). Therefore, it is important to select a suitable cassava genotype that adapts well to upper paddy fields, while also providing a high yield when planted following rice. Studies have evaluated the performance of different cassava genotypes that were grown following paddy rice (Polthanee et al., 2014; Sawatraksa et al., 2018, 2019). To achieve the best cassava genotype for a wide range of environments, further studies under various conditions of upper paddy fields during the off-season of rice are needed. This evaluation process requires many years of multi-environment yield trials, which are laborious, time consuming, and expensive. In addition, it is very difficult to conduct experiments that cover all growing environments.

The Cropping System Model (CSM)-MANIHOT-Cassava (Moreno-Cadena et al., 2020) is a part of the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2010, 2019a). This model was improved from the CSM-CROPSIM-Cassava model, which was calibrated for application in Thailand (Keawmuangmoon & Jintrawet, 2014; Kumsueb & Jintrawet, 2020). The cassava module simulates growth and yield for various cassava genotypes under different management practices and for many environmental conditions, including upland conditions (Kaweewong et al., 2013; Phoncharoen et al., 2021). However, until now there has not been an evaluation of the CSM-MANIHOT-Cassava model for its ability to simulate growth and yield under upper paddy fields after rice. If the cassava model provides reasonable output in terms of growth and yield, then it could also be used as a supporting tool to select the suitable cassava genotypes by generating the response of crop for the other upper paddy field conditions. The objective of this study was to evaluate the potential of the CSM-MANIHOT-Cassava model in determining yield stability of different cassava genotypes grown in upper paddy fields after rice.

Core Ideas

- Planting cassava after rice can increase cassava supply and land use efficiency.
- The CSM-MANIHOT-Cassava provides an oppotunity to simulate crop response to environmental conditions.
- The CSM-MANIHOT-Cassava model was able to identify a stable genotype for different paddy field conditions after growing rice.

2 | MATERIALS AND METHODS

2.1 | Multi-environment trials

This study evaluated four cassava genotypes that have different maturity durations and branching types, that is, Kasetsart 50 (medium maturity and branching), Rayong 9 (late maturity and non-branching), Rayong11 (late maturity and branching), and CMR38-125-77 (early maturity and branching). These genotypes were grown in upper paddy fields in Thailand from December 2015 to June 2018 (Figure 1) for a total of six environments (four locations for a year testing and one location for 2 yr testing) (Table 1). A randomized complete block design (RCBD) with four replications was used for each environment. The plot size was 15 by 8 m, with a spacing of 1 m between rows and 1 m between plants within the row. Crop management practices were conducted as described by Sawatraksa et al. (2018, 2019). Prior to planting, the experimental field was first plowed in order to incorporate rice straw into the soil. The second plowing and the preparation of soil ridges were conducted about 2 wk after the first plowing. For plant material, at 12 mo after planting, the healthy stems of cassava were cut as stakes to 20 cm in length. The stakes were soaked for 5–10 min in Thiamethoxam (3-(2-chloro-thiazol-5-ylmethyl)−5-methyl-(1, 3, 5)-oxadiazinan-4-ylidene-N-nitroamine 25% WG) at a rate of 4 g per 20 L to prevent mealybugs. The stakes were then inserted vertically into the soil ridges so that two-thirds of the length was buried. Supplementary irrigation was applied immediately after planting in order to facilitate germination. For the experiment in Kham Pom, irrigation was also applied again at 60 days after planting (DAP). At 30 and 60 DAP, manual weed control was conducted and chemical

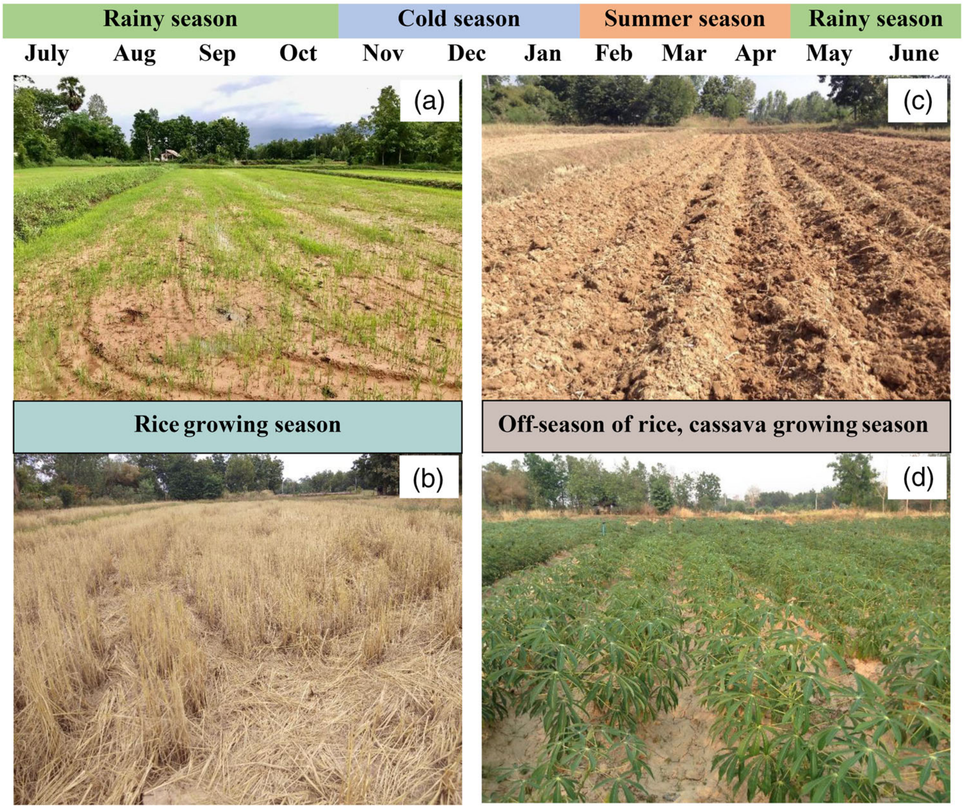

FIGURE 1 Crop calendar for rice–cassava cropping system for (a) planting rice, (b) harvested rice, (c) preparing soil for planting cassava, and (d) cassava in paddy field in Ban Kho, Thailand

TABLE 1 Locations and planting dates for all experiments

Year	Location	Geographical coordinate	Elevation (m a.s.l.)	Planting date
2015	Ban Kho	16.5˚N, 102.7˚E	173	10 Dec.
2015	Non Daeng	15.5˚N, 103.1˚E	188	13 Dec.
2016	Ban Kho	16.5˚N, 102.7˚E	173	12 Dec.
2016	Kham Pom	16.2˚N, 102.6˚E	171	22 Dec.
2016	Kham Thao	17.2˚N, 104.7˚E	147	17 Dec.
2017	Khok Kung	16.1˚N, 102.1˚E	202	13 Dec.

fertilizer 15–7–18 ($N–P_2O_5–K_2O$) was applied at a rate of 312.5 kg ha^{-1}.

Data on cassava management, such as planting date, planting method, row spacing, plant population, fertilizer application, irrigation, and harvesting time were recorded. Soil samples were taken prior to planting for each experimental site at depths of 0–15, 15–30, 30–45, 45–60, 60–75, 75–90, and 90–105 cm. The soil samples were then used for analysis of the physical and chemical properties, which included bulk density, cation exchange capacity, electrical conductivity, pH, organic matter, total N, available P, and exchangeable K. The weather data, including daily maximum and minimum temperature, daily total rainfall, and total solar radiation, were obtained from the meteorological station at each experimental site.

Aboveground, storage root, and total dry weights were collected from six sampled plants in the middle rows of each plot at 30, 60, 90, 120, 150, and 180 DAP. In addition, 18 sampled plants in the middle rows of each plot were also harvested at 180 DAP to determine final biomass. The sampled plants were separated into leaves, stems, roots, and storage roots, and then about 10% of total fresh weight of each organ was subsampled. The subsamples were oven dried at 80 ^{o}C to a constant weight to determine dry weight values, and these values were then used to calculate dry weight for the entire fresh weight samples.

TABLE 2 Soil physical and chemical properties prior to planting cassava for the five locations

Location	Depth	Bulk density	pH	Cation exchange capacity	Electrical conductivity	Organic matter	Total N	Available P	Exchangeable K
	cm	g cm^{-3}		cmol kg^{-1}	dS m^{-1}	g kg^{-1}		mg kg^{-1}	
Ban Kho[a]	0–15	1.53	5.90	8.39	0.06	8.20	0.37	4.11	64.25
	15–30	1.62	6.25	8.50	0.04	6.81	0.31	4.11	52.17
	30–45	1.65	6.31	16.57	0.04	2.61	0.12	1.94	79.23
	45–60	1.71	6.31	19.31	0.04	2.23	0.10	1.92	98.55
	60–75	1.71	5.97	15.62	0.03	1.34	0.05	2.29	77.30
	75–90	1.75	5.70	13.57	0.03	1.32	0.06	2.67	65.22
	90–105	1.77	5.84	12.58	0.02	0.90	0.03	1.94	65.22
Non Daeng	0–15	1.56	5.01	2.03	0.03	5.00	0.31	8.05	59.13
	15–30	1.62	5.34	1.69	0.02	4.17	0.21	6.23	49.82
	30–45	1.64	5.47	5.14	0.02	2.89	0.21	3.07	49.82
	45–60	1.76	5.31	18.31	0.01	3.04	0.24	1.40	75.42
	60–75	1.77	5.42	15.76	0.01	2.55	0.20	1.09	67.97
	75–90	1.78	5.41	15.02	0.01	2.05	0.19	1.01	67.97
	90–105	1.79	5.42	18.07	0.01	1.95	0.17	1.17	74.96
Kham Pom	0–15	1.50	5.87	3.56	0.03	3.07	0.20	3.78	23.29
	15–30	1.64	6.07	4.24	0.05	1.90	0.19	2.59	15.69
	30–45	1.69	6.16	4.93	0.07	1.66	0.18	2.44	15.21
	45–60	1.73	5.36	3.84	0.13	1.32	0.17	2.34	12.84
	60–75	1.75	4.80	6.48	0.15	1.24	0.17	2.29	13.79
	75–90	1.75	4.83	3.77	0.16	1.02	0.17	2.27	11.89
	90–105	1.77	4.68	3.59	0.14	0.78	0.16	2.42	11.41

(Continues)

TABLE 2 (Continued)

Location	Depth	Bulk density	pH	Cation exchange capacity	Electrical conductivity	Organic matter	Total N	Available P	Exchangeable K
Kham Thao	0–15	1.50	4.85	7.20	0.04	12.61	0.76	6.52	63.69
	15–30	1.67	5.55	7.95	0.03	8.69	0.58	4.36	38.98
	30–45	1.68	5.99	8.55	0.02	4.81	0.47	4.96	31.37
	45–60	1.69	6.00	8.88	0.02	3.14	0.37	4.73	38.97
	60–75	1.69	6.11	12.38	0.02	2.02	0.40	4.16	50.86
	75–90	1.74	6.20	10.36	0.02	1.60	0.35	4.51	53.71
	90–105	1.75	6.22	10.65	0.02	1.15	0.36	3.67	48.96
Khok Kung	0–15	1.36	5.82	11.38	0.08	13.01	0.64	13.44	94.17
	15–30	1.50	6.10	12.01	0.07	9.89	0.56	8.73	75.59
	30–45	1.58	5.55	13.77	0.07	8.47	0.46	5.91	61.24
	45–60	1.63	5.56	14.73	0.05	6.25	0.40	3.42	56.17
	60–75	1.63	5.47	14.52	0.04	5.44	0.30	3.06	54.90
	75–90	1.83	5.48	17.79	0.04	4.82	0.32	2.42	52.37
	90–105	1.87	5.34	11.95	0.04	4.42	0.35	2.27	51.95

[a]The four cassava genotypes were planted in Ban Kho for 2 yr (Dec. 2015 and Dec. 2016).

2.2 | Model calibration, evaluation, and application

The inputs required for the CSM-MANIHOT-Cassava model in the DSSAT v4.7.5 include crop management, soil properties, daily weather conditions, and genetic coefficients (Hoogenboom et al., 2012; Moreno-Cadena et al., 2020; Tsuji et al., 1994). The genetic coefficients for the four cassava genotypes were obtained from Phoncharoen et al. (2021). These coefficients were derived from the experiment designed specifically at Khon Kaen University with different planting dates. These experiments were also conducted under upland field conditions with good management practices to obtain optimum conditions for plant growth, avoiding drought, lack of nutrients, and other stresses. For this present study, however, the genetic coefficients were recalibrated with our data in order to achieve improved values for the genetic coefficients for cassava grown under upper paddy field conditions with water as a limiting factor. The data sets from three different environmental sites, that is, Ban Kho and Non Daeng in 2015 and Kham Thao in 2016, were used for this recalibration process. The only modification was adjustment of the value for node weight of the first stem of the shoot before forking (NODWT). The accuracy of the genetic coefficients was determined by comparing the simulated aboveground, storage root, and total dry weights with the corresponding observed values from the actual experiments. In order to evaluate the model, the derived genetic coefficients of the four cassava genotypes were used as input for the model to simulate growth and yield with independent data sets of the experiments conducted at Ban Kho and Kham Pom in 2016 and Khok Kung in 2017. The agreement index (d) (Willmott et al., 1985) was used to test the agreement between simulated and observed data. As recommended by Li et al. (2015) and Liu et al. (2013), the d values >.9 indicate the excellent agreement; values >.8 and <.9 indicate good agreement; values >.7 and <.8 indicate moderate agreement; and values <.7 indicate poor agreement between simulated and observed values.

For model application, the aboveground, storage root, and total crop dry weights for the four cassava genotypes for six different environments using historical weather data from 1988 to 2018 were simulated with the CSM-MANIHOT-Cassava model based on the final calibrated genetic coefficients. The crop management scenarios were very similar to the actual management practices of the experiments.

2.3 | Stability analyses for observed and simulated data

Stability analyses were conducted for observed and simulated aboveground, storage root, and total dry weights using the procedure outlined by Eberhart and Russell (1966). A regression coefficient and a deviation from regression were obtained by regressing between dry weight and environmental index. An environmental index was calculated for each testing environment by subtracting the grand mean of all experiments from the mean of all genotypes in each environment. The mean square deviation (MSD) was used to measure the deviation from regression, because it can be tested directly with an F test against the pooled error (Patanothai & Atkins, 1974). The t test was used to determine the significant difference between the regression coefficients derived based on observed data from actual experiment and simulated data. A stable genotype was defined as one with a regression coefficient near 1.0 and a small deviation from regression (Eberhart & Russell, 1966). A high mean yield was also a desirable attribute, although not necessarily an indicator of yield stability.

3 | RESULTS AND DISCUSSION

3.1 | Soil and weather conditions

Soil samples were obtained prior to planting at 15-cm increments until a depth of 105 cm and analyzed for physical and chemical properties. Bulk density for all test environments ranged from 1.36 to 1.87 g cm^{-3}, and soil pH varied from 4.68 to 6.48 (Table 2). Total N ranged from 0.03 to 0.76 g kg^{-1}, organic matter varied from 0.78 to 13.01 g kg^{-1}, available P ranged from 1.01 to 13.44 mg kg^{-1}, and exchangeable K ranged from 11.41 to 98.55 mg kg^{-1}. Howeler (2002) reported the optimum soil properties for cassava. Only the Kham Pom location that had available P and exchangeable K lower than the optimal levels. For total N and organic matter, all environments showed lower values than the optimum values. According to the results from Table 2, Khok Kung had the highest organic matter, available P, and exchangeable K when compared to the other environments. Kham Pom had a higher electrical conductivity in the subsoil than the other environments.

There was limited rainfall from November to April for all environments (Figure 2). The average annual total rainfall for 1988–2018 was 1,229 mm for Ban Kho, 1,320 mm for Non Daeng, 1,188 mm for Kham Pom, 2,364 mm for Kham Thao, and 1,156 mm for Khok Kung. Daily solar radiation was normally distributed throughout the year, peaking between March and April. Average solar radiation by month during 1988–2018 were 16.33–20.38 MJ m^{-2} for Ban Kho, 16.78–21.04 MJ m^{-2} for Non Daeng, 16.48–21.05 MJ m^{-2} for Kham Pom, 14.16–19.75 MJ m^{-2} for Kham Thao, and 15.48–20.69 MJ m^{-2} for Khok Kung. Average air temperature by month during 1988–2018 for Ban Kho ranged from 17.05 to 36.17 ˚C, for Non Daeng varied from 17.37 to 36.80 ˚C, for Kham Pom ranged from 16.83 to 36.44 ˚C,

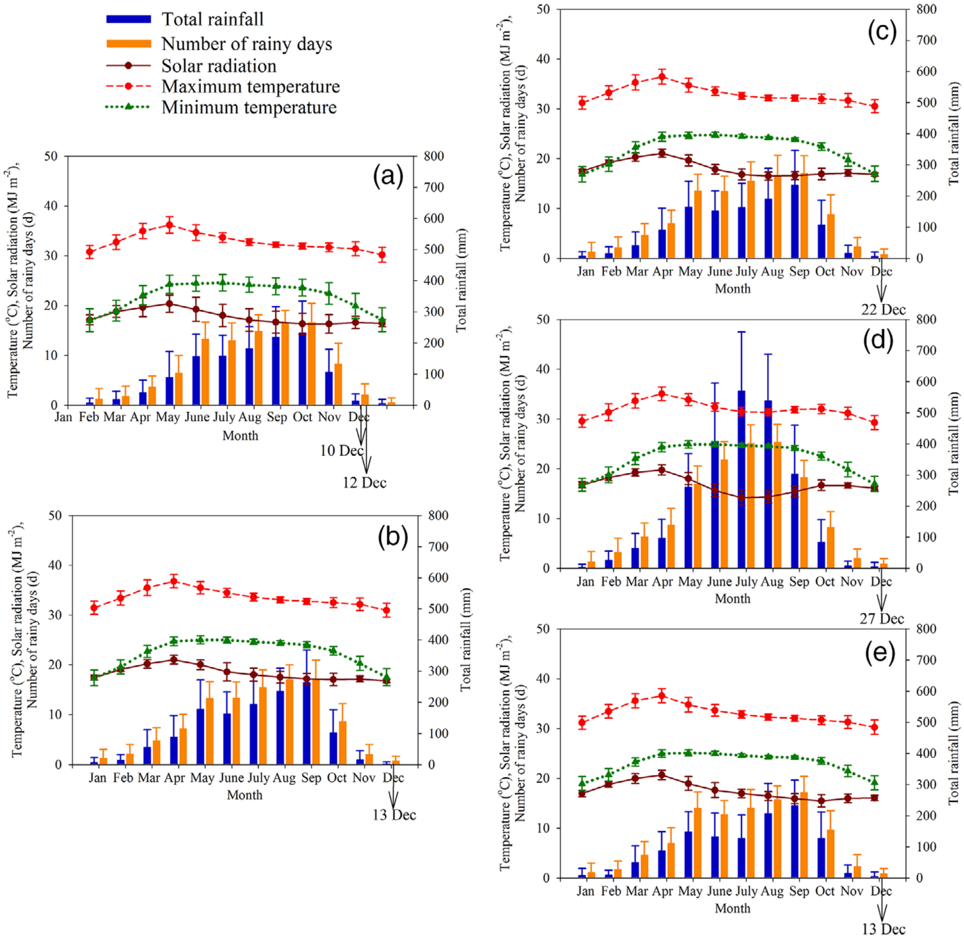

FIGURE 2 Monthly average maximum temperature, minimum temperature, solar radiation, and rainfall, and the number of rainy days for (a) Ban Kho, (b) Non Daeng, (c) Kham Pom, (d) Kham Thao, and (e) Khok Kung (values are averaged for 1988–2018)

for Kham Thao ranged from 16.76 to 35.06 ˚C, and for Khok Kung varied from 18.94 to 36.57 ˚C. The highest daily air temperature was found in April, and the lowest daily air temperature was recorded during December and January. For weather conditions during the period of growing cassava after rice (from December to June), Kham Thao had higher average total rainfall for 1988–2018 than the other environments, while average solar radiation in Kham Thao was lower when compared with the other environments. There was a small difference for average air temperature across environments.

3.2 | Model performance

3.2.1 | Model calibration and evaluation

For model calibration, the simulated values for total, aboveground, and storage root dry weights for the four cassava genotypes for Ban Kho and Non Daeng for 2015 and Kham Thao for 2016 were compared with the observed values (Figure 3). The values of NODWT were adjusted for all four genotypes in order to get better calibration results for upper paddy field conditions with water limitation (Table 3). The growth of four cassava genotypes was first simulated for the three environments with genetic coefficients from Phoncharoen et al. (2021). The values of NODWT for all four genotypes were adjusted manually until reciving a good agreement between observed and simulated values for total, aboveground, and storage root dry weights. The new values for NODWT were 15.0 for Kasetsart 50, 14.0 for Rayong 9, and 8.0 for both Rayong 11 and CMR38-125-77. These values were lower than the values of genetic coefficients from Phoncharoen et al. (2021). The results from the model calibration showed good to excellent agreement for simulating total and storage root dry weights for all three environments with the *d* values ranging from .80 to .99, except for storage root dry weight for the genotype Kasetsart 50 (*d* = .77) for Non Daeng and for the genotype CMR38-125-77 (*d* = .72) for Kham Thao. The simulated and observed aboveground dry weights for all three environments had a moderate to excellent level of agreement (*d* = .70–.99), except for the genotype Rayong 11 (*d* = .68)

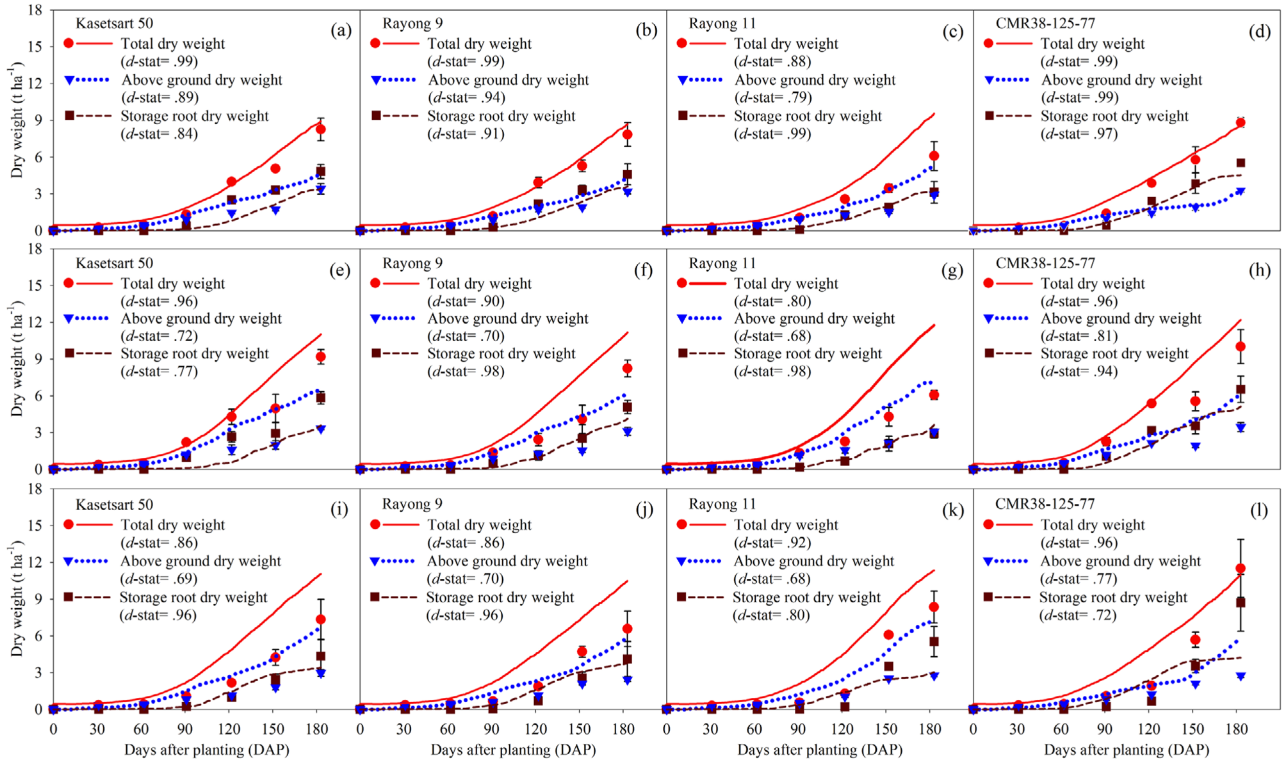

FIGURE 3 Simulated (lines) and observed (symbols) values for model calibration based on total, aboveground, and storage root dry weights of Kasetsart 50, Rayong 9, Rayong 11, and CMR38-125-77 at (a–d) Ban Kho in 2015, (e–h) Non Daeng in 2015, and (i–l) Kham Thao in 2016

for Non Daeng and the genotype Kasetsart 50 (d = .69) and the genotype Rayong 11 (d = .68) for Kham Thao.

To evaluate the model, three independent data sets were obtained from three environments, that is, Ban Kho and Kham Pom for 2016 and Khok Kung for 2017. Good to excellent agreements for total and storage root dry weights were achieved for almost all genotypes and environments (d = .80–.96), except for total dry weight for the genotype Rayong 9 (d = .73) for Ban Kho and the genotype Rayong 11 (d = .70) for Kham Pom and storage root dry weight for the genotype Kasetsart 50 (d = .70) and the genotype Rayong 11 (d = .79) for Kham Pom (Figure 4). Simulated and observed aboveground dry weights for the four genotypes were in poor to excellent agreement with the d values ranging from .38 to .96. Differences between simulated and observed values could be due to the fact that the model did not account for some of the field conditions, such as quality of tillage, and biotic stresses such as pests, diseases, and weeds (Hoogenboom et al., 2019b). In addition, the poor performance of the model for aboveground dry weight for Kham Pom might be due to high soil salinity in the subsoil that was not represented by the model. The soil salinity in the subsoil increases crop stress and reduces cassava growth and final storage root yield (Cruz et al., 2017; Gleadow et al., 2016; Sawatraksa et al., 2019). In general, however, the CSM-MANIHOT-Cassava model was able to simulate the growth and development response of the four cassava genotypes for the different environmental conditions quite well.

3.3 | Stability analysis

To determine the performance of cassava genotypes for suitability for paddy field conditions after rice, a stability analysis (Eberhart & Russell, 1966) was conducted for both observed and simulated for total, aboveground, and storage root dry weights (Table 4). The mean values for simulated total dry weight for the six environments were higher than observed values for all cassava genotypes, indicating an overestimation (Table 4). The differences between simulated and observed values might be caused by other stress factors such as those discussed previously, which were not considered by the model, as indicated by lower values of MSD found in the analysis of simulated yield when compared to the actual yield (Banterng et al., 2006; Hoogenboom et al., 2019a, 2019b).

There were significant differences among the four cassava genotypes in simulated and observed total dry weights (Table 4). The genotype CMR38-125-77 had the highest values for both simulated and observed total dry weights with weather data representing the experimental conditions and with the long-term (1988–2018) historical weather data. There were also no significant differences between the regres-

TABLE 3 Genetic coefficients for the four cassava genotypes as defined in the CSM-MANIHOT-Cassava model

Crop file	Abbreviation	Definition	Genotype			
			Kasetsart 50	Rayong 9	Rayong 11	CMR38-125-77
Genotype	B01ND	Duration from planting to first forking (thermal units)	510	1,650	250	300
	B12ND	Duration from first forking to second forking (thermal units)	330	1	615	505
	B23ND	Duration from second forking to third forking (thermal units)	260	1	240	175
	BR1FX	Branch number per fork at fork 1 (no.)	3.0	1.0	3.5	3.5
	BR2FX	Branch number per fork at fork 2 (no.)	2.0	1.0	2.7	2.5
	BR3FX	Branch number per fork at fork 3 (no.)	2.5	1.0	2.0	1.5
	BR4FX	Branch number per fork at fork 4 (no.)	2.0	1.0	1.5	1.5
	LAXS	Area/leaf at maximum area/leaf, cm^2	945	655	690	710
	SLAS	Specific leaf lamina area when crop growing without stress, $cm^2\ g^{-1}$	230	230	252	245
	LLIFA	Leaf life, from full expansion to start senescence (thermal units)	1,460	2,300	1,400	1,250
	LPEFR	Leaf-petiole weight fraction (no.)	0.33	0.33	0.33	0.33
	LNSLP	Slope for leaf production (no.)	1.49	1.38	1.52	1.40
	NODWT[a]	Individual node weight, g	15.0	14.0	8.0	8.0
	NODLT	Internode length, cm	4.5	4.0	2.5	4.0
Ecotype	PARUE	Radiation use efficiency, g dry matter MJ^{-1}	1.60	1.67	1.65	1.65
	KCAN	Photosynthetically active radiation (PAR) extinction parameter (no.)	0.50	0.56	0.43	0.51
	PPS1	Photoperiod sensitivity for phase 1 (% drop for 10h pp. change)	0.00	0.00	0.02	0.01

[a]The values for NODWT were adjusted for this study, and the other genetic coefficients values for the four cassava genotypes were reported by Phoncharoen et al. (2021).

sion coefficients derived from the simulated and observed data. These results indicate that the model performed well in capturing the response of cassava genotypes to these environments. The values of MSD for both simulated and observed total dry weights was also rather small (MSD = 0.005–0.391).

Aboveground dry weight was overestimated for all four genotypes (Table 4). This discrepancy can be explained by other factors that are not simulated by the model, as discussed previously. There were no significant differences between the four cassava genotypes for observed aboveground dry weight, which ranged from 2.73 to 2.95 t ha^{-1}. However, there were significant differences among the four cassava genotypes for the simulated values based on the weather data during the experiment and on the long-term (1988–2018) historical weather data. Genotype Rayong 11 had the highest average simulated aboveground dry weight. The difference between the regression coefficients derived from the simulated and observed data was not significant. The magnitude of the MSD for both the simulated and observed data was rather small (MSD = 0.005–0.079).

For storage root dry weight, the mean value for simulated storage root dry weight for the six environments (2.73–5.21 t ha^{-1}) was lower than the observed value (3.44–5.76 t ha^{-1}) for all cassava genotypes, indicating an underestimation (Table 4). This underestimation is probably due to the other environmental factors that were not considered by the model, but in field conditions affected the partitioning capacity to the storage root. Among the four cassava genotypes, the genotype CMR38-125-77 had the highest storage root dry weight for both the simulated and observed data using either the weather data during the experiment or the long-term (1988–2018) historical weather data. Only one, that is, geno-

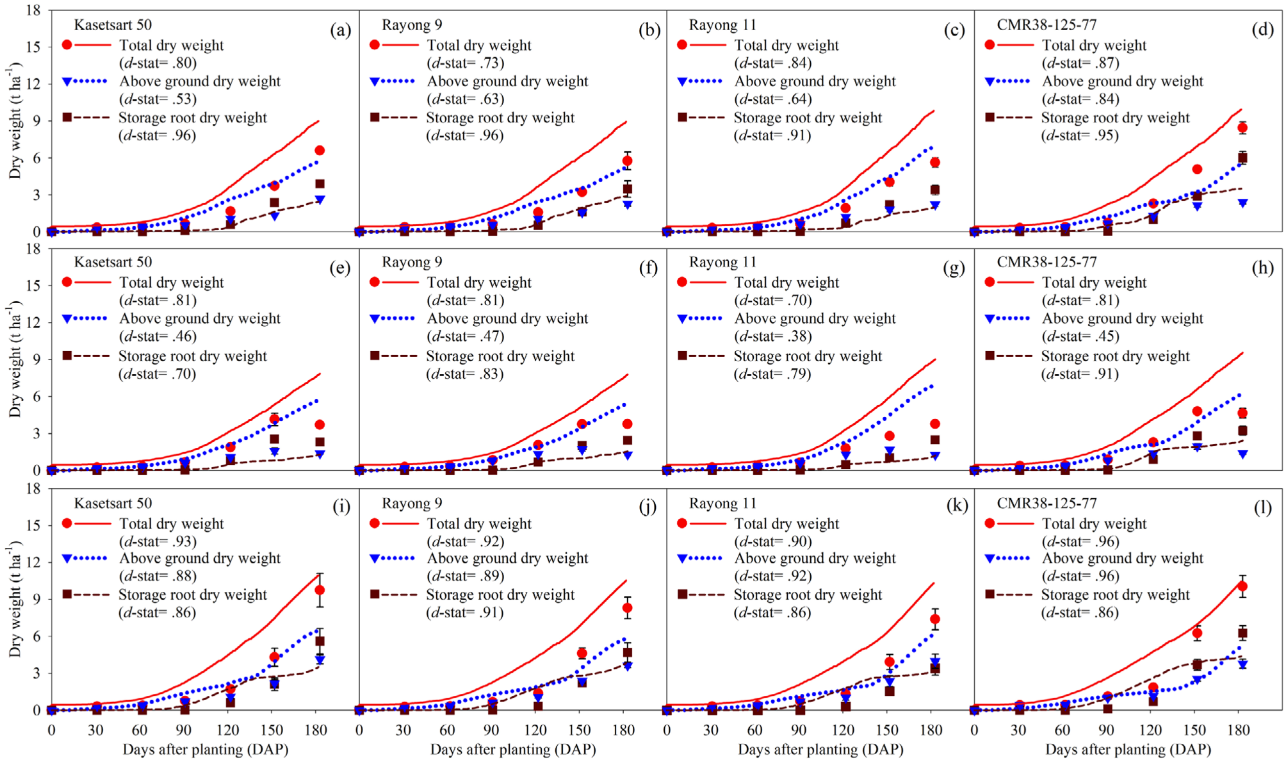

FIGURE 4 Simulated (lines) and observed (symbols) values for model evaluation based on total, aboveground, and storage root dry weights of Kasetsart 50, Rayong 9, Rayong 11, and CMR38-125-77 at (a–d) Ban Kho in 2016, (e–h) Kham Pom in 2016, and (i–l) Khok Kung in 2017

type CMR38-125-77, out of four genotypes showed a significant difference between the regression coefficients derived from the actual experiment and the simulation with the historical weather data (from 1988 to 2018). The MSD for the observed values (MSD = 0.091–0.366) was higher than for the simulated data (MSD = 0.002–0.017).

A study (Wongnoi et al., 2020) for the genotypes Kasetsart 50, Rayong 9, Rayong 11, and CMR38-125-77 grown under upland field in Thailand indicated that the values for storage root dry weights for the first 6 mo (during rainy season) varied from 5.50 to 13.30 t ha^{-1}, which are higher than our simulated and observed storage root values. Lower storage root yields obtained from our growing conditions might be due to less amount of rainfall during the dry season. With the supplementary irrigation, therefore, it can help improve the storage root yield of cassava for growing on upper paddy field during the off-season of rice.

There was no significant difference of the regression coefficients between the simulation with weather data representing the experimental conditions and with the weather data from 1988 to 2018 (Table 4), indicating a similar crop response. However, the differences in crop dry weight between the simulations that were conducted with the weather data from the experimental period (2015–2018) and with the long-term historical weather data from 1988 to 2018 indicate the variability in the annual weather conditions. This finding suggests the importance of using at least 30 yr of historical weather data for the simulation analyses to support decision making.

To select the desirable genotype across environments, the relative performance of the individual genotype rather than the absolute yield is of primary concern. Although the ranks for observed and simulated means for total, aboveground, and storage root dry weights for all tested environments were different (Table 4), the CMR38-125-77 was identified as the best genotype based on ranking for simulated and observed dry weights with weather data representing the experimental conditions and with the long-term (1988–2018) historical weather data. This indicates a capability of the model to identify an outstanding genetype for different environmental conditions.

The results in Table 4 indicate that the genotype CMR38-125-77 was not only outstanding in terms of both simulated and observed values for total and storage root dry weights, but it also had a regression coefficient close to 1.0 and a small deviation from regression. Therefore, based on the explanation for stability analysis provided by Eberhart and Russell (1966), it is the most preferable genotype on the basis of total biomass and yield for production in paddy field conditions. The desirable performance of the genotype CMR38-125-77 grown under experimental field conditions after rice has also been reported in terms of chlorophyll fluorescence (Fv/Fm and F'v/F'm) and growth rate for leave, stem, storage root, and crop (Sawatraksa et al., 2018; 2019). For the experiments under upland conditions, the genotype CMR38-125-77 also

TABLE 4 Mean dry weight, regression coefficients between dry weight and environmental index, and mean square deviation (MSD) from regression for observed and simulated data for the six environments

	Dry weight, t ha^{-1}[a]			Regression coefficient[b]			MSD		
Genotype	Observed	Simulated[c]	Simulated[d]	Observed	Simulated[c]	Simulated[d]	Observed	Simulated[c]	Simulated[d]
	Total dry weight								
Kasetsart 50	7.37b	9.85ab	9.77b	1.07A	1.11A	1.10A	0.391	0.128	0.005
Rayong 9	7.01bc	9.66b	10.02b	0.92A	1.08A	1.13A[†]	0.106	0.044	0.005
Rayong 11	6.24c	10.35a	11.17a	0.82A	0.87A	1.05A	0.343	0.049	0.010
CMR38-125-77	8.74a	10.36a	10.89a	1.19A	0.95A	0.72A	0.302	0.211	0.047
F test	**	*	**						
	Aboveground dry weight								
Kasetsart 50	2.87	5.98b	5.10b	1.12A	0.93A	1.07A	0.008	0.079	0.006
Rayong 9	2.73	5.51c	5.01b	0.88A[†]	0.83A	0.90A	0.005	0.036	0.014
Rayong 11	2.75	6.62a	5.89a	1.05A	0.88A	1.07A	0.016	0.061	0.010
CMR38-125-77	2.95	5.38c	4.73c	0.96A	1.35A	0.96A	0.011	0.072	0.027
F test	ns	**	**						
	Storage root dry weight								
Kasetsart 50	4.47b	2.96c	3.78c	0.93A	0.99A	1.02A	0.366	0.012	0.002
Rayong 9	4.25bc	3.30b	4.19b	0.90A	1.02A	1.00A	0.091	0.012	0.005
Rayong 11	3.44c	2.73d	4.28b	0.70A	0.99A	1.14A	0.280	0.011	0.008
CMR38-125-77	5.76a	4.04a	5.21a	1.48A	1.01AB	0.85B[†]	0.221	0.017	0.006
F test	**	**	**						

[a]Values in the same column followed by the same small letter are not significantly different at the .01 and .05 by the least significant difference (LSD) test.
[b]Regression coefficients in the same row followed by the same capital letter are not significantly different at the .05 by *t* test.
[c]Simulation of the dry weight for the four cassava genotypes with weather data during the experimentation of crop.
[d]Simulation of the dry weight for the four cassava genotypes with historical weather data (from 1988–2018).
*Significant at the .05 probability level.
**Significant at the .01 probability level.
[†]Significantly different from 1 at the .05 probability level.

showed an outstanding performance with respect to physiology (Fv/Fm, F'v/F'm, net photosynthesis, stomatal conductance, water use efficiency, relative water content for leaf, leaf area index, and specific leaf area), biomass, and yield (Janket et al., 2018; Phoncharoen et al., 2019a, 2019b ; Phosaengsri et al., 2019; Wongnoi et al., 2020). Therefore, the genotype CMR38-125-77 is not only a suitable genetic resource for production under upland condition, but our study also demonstrates that it is an appropriate genotype for production under paddy field conditions in Thailand.

The application of the CSM-MANIHOT-Cassava model as a supporting tool provides an advanced strategy to determine yield performance and stability for cassava genotypes under different abiotic factors, such as soil chemical and physical properties and climatic conditions, which are of major concern by plant breeders. The information from actual field experiments is normally the result of a combination of both abiotic and biotic factors, such as pests and diseases, resulting in an unclear picture to determine whether a genotype is stable because of adaptation to local soil and weather conditions or if it possesses resistances to biotic stresses (Banterng et al., 2006). Our study showed the capability of the CSM-MANIHOT-Cassava model to assist with the identification of suitable cassava genotypes for production during the off-season of rice on paddy fields, which would be difficult to obtain with actual field experiments.

Studies have shown the potential for crop simulation models to predict yield for different crops in multi-environment trials. Banterng et al. (2006) used the CROPGRO-Peanut model to predict pod yield for test peanut lines under various environmental conditions in Thailand and found that the model performed well in evaluating the stability for peanut breeding lines. Suriharn et al. (2008) confirmed the capability of the CSM-CROPGRO-Peanut model in simulating yield of peanut breeding lines. Anothai et al. (2009) showed that the CSM-CROPGRO-Peanut model simulated GGE biplot patterns that were similar to the field trials and that it can be used to help identify stable peanut lines. The CSM-CROPGRO-Peanut model was also used by Phakamas et al. (2010) to determine pattern of genotype × location interactions (G × L). Salmerŕn et al. (2017) estimated the genotype × environment interactions (G × E) for soybean [*Glycine max* (L.) Merr.] yield using the CSM-CROPGRO-Soybean model of DSSAT, while Adnan et al. (2020) applied the CSM-CERES-Maize model of DSSAT in simulating G × E interactions for maize (*Zea mays* L.).

This is the first study to show the performance of the CSM-MANIHOT-Cassava model in determining yield stability for different cassava genotypes grown under upper paddy field conditions during the off-season of rice. The application of this model can assist plant breeders since it decreases time and resources for evaluating genotype stability under a wide range of environments. Although planting the suitable cassava genotype following rice is an alternative cropping system to help increase product supply and land use efficiency, it could also disrupt the nutrient balance in the field, and soil fertility generally plays an important role for crop productivity. The crop models are mathematical abstractions of the real-world interactions between crop environments, and they also provide the option to simulate the response of crops to different nutrient and water conditions (Hoogenboom, 2000; Hoogenboom et al., 2019b). Applications of both the rice and cassava simulation models together with actual field experiments to explore the appropriate management strategies for supporting both cassava and rice are also interesting for future research. In addition, there are many different fields with respect to local soil and weather conditions. Study to select representative experimental sites for testing is a significant issue for future research as well, that can also be addressed with crop simulation models (Putto et al., 2009).

4 | CONCLUSION

Crop simulation models are becoming increasingly important tools for assessing yield stability for different crops. The results of this study showed that the CSM-MANIHOT-Cassava model can be a useful tool to help identify stable cassava genotypes across multiple environments. Nonsignificant difference between simulation and observation for the regression coefficients that were obtained from stability analysis indicated that the CSM-MANIHOT-Cassava model performed well in capturing the responses of genotypes to environments. Based on both actual experimental data and simulation results, the cassava genotype CMR38-125-77 was considered to be the most favorable one among the genotypes tested for cassava production on upper paddy fields during the off-season of rice.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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REFERENCES

Adnan, A. A., Diels, J., Jibrin, J. M., Kamara, A. Y., Shaibu, A. S., Craufurd, P., & Menkir, A. (2020). CERES-Maize model for simulating genotype-by-environment interaction of maize and its stability in the dry and wet savannas of Nigeria. *Field Crops Research*, *253*, 107826. https://doi.org/10.1016/j.fcr.2020.107826

Anothai, J., Patanothai, A., Pannangpetch, K., Jogloy, S., Boote, K. J., & Hoogenboom, G. (2009). Multi-environment evaluation of peanut lines by model simulation with the cultivar coefficients derived from a reduced set of observed field data. *Field Crops Research*, *110*, 111–122. https://doi.org/10.1016/j.fcr.2008.07.009

Banterng, P., Patanothai, A., Pannangpetch, K., Jogloy, S., & Hoogenboom, G. (2006). Yield stability evaluation of peanut lines: A comparison of an experimental versus a simulation approach. *Field Crops Research*, *96*, 168–175. https://doi.org/10.1016/j.fcr.2005.06.008

Cruz, J. L., Coelho Filho, M. A., Coelho, E. F., & Santos, A. A. D. (2017). Salinity reduces carbon assimilation and the harvest index of cassava plants (*Manihot esculenta* Crantz). *Acta Scientiarum*, *39*, 545–555. https://doi.org/10.4025/actasciagron.v39i4.32952

Curran, S. R., & Cooke, A. M. (2008). Unexpected outcomes of Thai cassava trade: A case of global complexity and local unsustainability. *Globalizations*, *5*, 111–127. https://doi.org/10.1080/14747730802057449

Eberhart, S. A., & Russell, W. A. (1966). Stability parameters for comparing varieties. *Crop Science*, *6*, 36–40. https://doi.org/10.2135/cropsci1966.0011183x000600010011x

El-Sharkawy, M. A. (1993). Drought-tolerant cassava for Africa, Asia, and Latin America: Breeding projects work to stabilize productivity without increasing pressures on limited natural resources. *Bioscience*, *43*, 441–451. https://doi.org/10.2307/1311903

El-Sharkawy, M. A. (2012). Stress-tolerant cassava: The role of integrative ecophysiology-breeding research in crop improvement. *Open Journal of Soil Science*, *2*, 162–186. https://doi.org/10.4236/ojss.2012.22022

Food and Agriculture Organization of the United Nations (FAO). (2020). Statistics databases. Rome: FAO. Retrieved from http://www.fao.org/faostat/en/#data/QC (accessed 14 Aug. 2020).

Gleadow, R., Pegg, A., & Blomstedt, C. K. (2016). Resilience of cassava (*Manihot esculenta* Crantz) to salinity: Implications for food security in low-lying regions. *Journal of Experimental Botany*, *67*, 5403–5413. https://doi.org/10.1093/jxb/erw302

Hoogenboom, G. (2000). Contribution of agrometeorology to the simulation of crop production and its applications. *Agricultural and Forest Meteorology*, *103*, 137–157. https://doi.org/10.1016/S0168-1923(00)00108-8

Hoogenboom, G., Jones, J. W., Traore, P. C. S., & Boote, K. J. (2012). Experiments and data for model evaluation and application. In J. Kihara, D. Fatondji, J. W. Jones, G. Hoogenboom, R. Tabo, & A. Bationo (Eds.), *Improving soil fertility recommendations in Africa using the Decision Support Systems for Agrotechnology Transfers (DSSAT)* (pp. 9–18). Dordrecht, the Netherlands: Springer.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lisazo, J. I., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., & Tsuji, G. Y. (2010). *Decision support system for agrotechnology transfer version (DSSAT) 4.5* [CD]. Honolulu, HI: University of Hawaii.

Hoogenboom, G., Porter, C. H., Boote, K. J., Shelia, V., Wilkens, P. W., Singh, U., White, J. W., Asseng, S., Lizaso, J. I., Moreno, L. P., Pavan, W., Ogoshi, R., Hunt, L. A., Tsuji, G. Y., & Jones, J. W. (2019a). The DSSAT crop modeling ecosystem. In K. J. Boote (Ed.), *Advances in crop modeling for a sustainable agriculture* (pp. 173–216). Cambridge, UK: Burleigh Dodds Science Publishing. https://doi.org/10.19103/AS.2019.0061.10

Hoogenboom, G., Porter, C. H., Shelia, V., Boote, K. J., Singh, U., White, J. W., Hunt, L. A., Ogoshi, R., Lizaso, J. I., Koo, J., Asseng, S., Singels, A., Moreno, L. P., & Jones, J. W. (2019b). *Decision Support System for Agrotechnology Transfer (DSSAT) version 4.7* (www.DSSAT.net). Gainesville, FL: DSSAT Foundation.

Howeler, R. H. (2002). Cassava mineral nutrition and fertilization. In R. J. Hillocks, J. M. Thresh, & A. C. Bellotti (Eds.), *Cassava: Biology, production and utilization* (pp. 115–147). Wallingford, UK: CABI Publishing.

Howeler, R. H. (Ed.). (2007). *Cassava research and development in Asia: Exploring new opportunities for an ancient crop*. Bangkok, Thailand: Centro International de Agriculture Tropical (CIAT) & the Department of Agriculture (DOA) of Thailand.

Janket, A., Vorasoot, N., Toomsan, B., Kaewpradit, W., Banterng, P., Kesmala, T., Theerakulpisut, P., & Jogloy, S. (2018). Seasonal variation in starch accumulation and starch granule size in cassava genotypes in a tropical savanna climate. *Agronomy*, *8*, 297. https://doi.org/10.3390/agronomy8120297

Jansson, C., Westerbergh, A., Zhang, J., Hu, X., & Sun, C. (2009). Cassava, a potential biofuel crop in (the) People's Republic of China. *Applied Energy*, *86*, S95–S99. https://doi.org/10.1016/j.apenergy.2009.05.011

Kaweewong, J., Tawornpruek, S., Yampracha, S., Yost, R., Kongton, S., & Kongkeaw, T. (2013). Cassava nitrogen requirements in Thailand and crop simulation model predictions. *Soil Science*, *178*, 248–255. https://doi.org/10.1097/SS.0b013e31829a283f

Keawmuangmoon, T., & Jintrawet, A. (2014). iCassFert-NPK: The design and web-based implementation of an interactive web-based approach for cassava production NPK fertilizer recommendations in Thailand. *Khon Kaen Agriculture Journal*, *42*, 66–72.

Kumsueb, B., & Jintrawet, A. (2020). Recent evaluations and applications of a cassava model in Thailand: A review. *Current Applied Science and Technology*, *20*, 156–162.

Li, Z. T., Yang, J. Y., Drury, C. F., & Hoogenboom, G. (2015). Evaluation of the DSSAT-CSM for simulating yield and soil organic C and N of a long-term maize and wheat rotation experiment in the Loess Plateau of Northwestern China. *Agricultural Systems*, *135*, 90–104. https://doi.org/10.1016/j.agsy.2014.12.006

Liu, S., Yang, J. Y., Zhang, X. Y., Drury, C. F., Reynolds, W. D., & Hoogenboom, G. (2013). Modelling crop yield, soil water content and soil temperature for a soybean-maize rotation under conventional and conservation tillage systems in Northeast China. *Agricultural Water Management*, *123*, 32–44. https://doi.org/10.1016/j.agwat.2013.03.001

Moreno-Cadena, L. P., Hoogenboom, G., Fisher, M. J., Ramirez-Villegas, J., Prager, S. D., Becerra Lopez-Lavalle, L. A., Pypers, P., Mejia De Tafur, M. S., Wallach, D., Muñoz-Carpena, R., & Asseng, S. (2020). Importance of genetic parameters and uncertainty of MANIHOT, a new mechanistic cassava simulation model. *European Journal of Agronomy*, *115*, 126031. https://doi.org/10.1016/j.eja.2020.126031

Patanothai, A., & Atkins, R. E. (1974). Yield stability of single crosses and three-way hybrids of grain sorghum. *Crop Science*, *14*, 287–290. https://doi.org/10.2135/cropsci1974.0011183x001400020035x

Phakamas, N., Patanothai, A., Pannangpetch, K., Jogloy, S., & Hoogenboom, G. (2010). Determination of adaptive responses of peanut genotypes and patterns of genotype × location interaction using the CSM-CROPGRO-Peanut model. *International Journal of Plant Production*, *4*, 223–234.

Phoncharoen, P., Banterng, P., Cadena, L. P. M., Vorasoot, N., Jogloy, S., Theerakulpisut, P., & Hoogenboom, G. (2021). Capability of the MANIHOT-Cassava Model to identify the suitable cassava genotypes and growing environments. *Field Crops Research*, *264*, 108073. https://doi.org/10.1016/j.fcr.2021.108073

Phoncharoen, P., Banterng, P., Vorasoot, N., Jogloy, S., Theerakulpisut, P., & Hoogenboom, G. (2019a). The impact of seasonal environments in a tropical savanna climate on forking, leaf area index, and biomass of cassava genotypes. *Agronomy*, *9*, 19. https://doi.org/10.3390/agronomy9010019

Phoncharoen, P., Banterng, P., Vorasoot, N., Jogloy, S., Theerakulpisut, P., & Hoogenboom, G. (2019b). Growth rates and yields of cassava at different planting dates in a tropical savanna climate. *Scientia Agricola*, *76*, 376–388. https://doi.org/10.1590/1678-992x-2017-0413

Phosaengsri, W., Banterng, P., Vorasoot, N., Jogloy, S., & Theerakulpisut, P. (2019). Leaf performances of cassava genotypes in different seasons and its relationship with biomass. *Turkish Journal of Field Crops*, *24*, 54–64. https://doi.org/10.17557/TJFC.564116

Polthanee, A., Janthajam, C., & Promkhambu, A. (2014). Growth, yield and starch of cassava following rainfed lowland rice in northeast Thailand. *International Journal of Agricultural Research*, *9*, 319–324. https://doi.org/10.3923/ijar.2014.319.324

Putto, C., Patanothai, A., Jogloy, S., Pannangpetch, K., Boote, K. J., & Hoogenboom, G. (2009). Determination of efficient test sites for evaluation of peanut breeding lines using the CSM-CROPGRO-peanut model. *Field Crops Research*, *110*, 272–281. https://doi.org/10.1016/j.fcr.2008.09.007

Salmerón, M., Purcell, L. C., Vories, E. D., & Shannon, G. (2017). Simulation of genotype-by-environment interactions on irrigated soybean yields in the U.S. Midsouth. *Agricultural Systems*, *150*, 120–129. https://doi.org/10.1016/j.agsy.2016.10.008

Sawatraksa, N., Banterng, P., Jogloy, S., Vorasoot, N., & Hoogenboom, G. (2018). Chlorophyll fluorescence and biomass of four cassava genotypes grown under rain-fed upper paddy field conditions in the tropics. *Journal of Agronomy and Crop Science*, *204*, 554–565. https://doi.org/10.1111/jac.12285

Sawatraksa, N., Banterng, P., Jogloy, S., Vorasoot, N., & Hoogenboom, G. (2019). Cassava growth analysis of production during the off-season of paddy rice. *Crop Science*, *59*, 760–771. https://doi.org/10.2135/cropsci2018.07.0435

Suriharn, B., Patanothai, A., Pannangpetch, K., Jogloy, S., & Hoogenboom, G. (2008). Yield performance and stability evaluation of peanut breeding lines with the CSM-CROPGRO-Peanut model. *Crop Science*, *48*, 1365–1372. https://doi.org/10.2135/cropsci2007.09.0523

Tsuji, G. Y., & Uehara, G., & S. Balas. (Eds.). (1994). *DSSAT Version 3* (Vols. *1–3)*. Honolulu, HI: University of Hawaii.

Willmott, C. J., Ackleson, S. G., Davis, R. E., Feddema, J. J., Klink, K. M., Legates, D. R., O'donnell, J., & Rowe, C. M. (1985). Statistics for the evaluation and comparison of models. *Journal of Geophysical Research*, *90*, 8995–9005. https://doi.org/10.1029/JC090iC05p08995

Wongnoi, S., Banterng, P., Vorasoot, N., Jogloy, S., & Theerakulpisut, P. (2020). Physiology, growth and yield of different cassava genotypes planted in upland with dry environment during high storage root accumulation stage. *Agronomy*, *10*, 576. https://doi.org/10.3390/agronomy10040576

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