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Evaluating Genetic Coefficients of KUML4 Mung Bean Variety for a Crop Simulation Model

Tawatchai Inboonchuay[1)], Audthasit Wongmaneeroj[1)], Napaporn Phankamolsil[1*)], Sirinapa Chungopast[1)], Sahaschai Kongthon[2)] and Prakit Somta[3)]

[1)] Department of Soil Science, Faculty of Agriculture at Kamphaeng Saen, Kasetsart University, Kamphaeng Saen campus, Nakhon Pathom 73140, Thailand
[2)] Ministry of Agriculture and Cooperatives, Bangkok 10200, Thailand
[3)] Department of Agronomy, Faculty of Agriculture at Kamphaeng Saen, Kasetsart University, Kamphaeng Saen Campus, Nakhon Pathom 73140, Thailand

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*) Corresponding author:
E-mail: agrnpp@ku.ac.th

ABSTRACT

The Decision Support System for Agrotechnology Transfer (DSSAT) cropping system model is a part of the management module that processes user inputs describing crop management. The precision and accuracy of cropping models require recent research to calibrate and validate models according to climate changes and new cultivars. This study aims to determine the genetic coefficient (GC) of the mung bean variety KUML4 for the CSM-CROPGRO Model and compare predicted data from the model with observed data in the phenology, growth, yield and yield component used in DSSAT. Mung bean is planted in two seasons (dry and rainy seasons) at two locations. Plant growth is monitored at V4, R3, R6 and R7. DSSAT CROPGRO-cowpea model is used to calibrate the GC with the generalized likelihood uncertainty estimation (GLUE). Results show that the GC evaluation of mung bean by using the second planting date in the highest growth and yield plot, then the genetic coefficient of KUML4 was calibrated by GLUE until predicted values of plant growth and development were close to observed values. The GC of KUML4 mung bean could estimate growth, such as shoot weight, leaf area index, and plant height. The prediction of mung bean yield is acceptable.

INTRODUCTION

Mung bean (*Vigna radiata* (L.) R. Wilczek var. radiata) is an essential food legume crop in Southeast Asia (Sequeros et al., 2021; Phankamolsil et al., 2023). Its low productivity is usually grown under water-limited environments (Biswas et al., 2018). Mung bean has been considered a portion of healthy food that is a rich source of nutrition, especially protein and iron (Dahiya et al., 2015). The demand for mung bean in Thailand is ca. 113,000 t, and approximately 90% of the total yield of mung bean production is used for local consumption and the food industry (Thongthip et al., 2023). Cropping systems are extremely complex, as there are normally multiple objectives that must be considered for long-term sustainability (Geng et al., 1990). Several dynamic crop simulation models have been developed to support strategic decision-making in agronomic research, crop production, and land-use planning (Hoogenboom et al., 2004; Tsuji et al.,1998). Crop simulation models are progressively adopted in agricultural research and development (Casanova et al., 2000). The plant simulation model could be applicable in many aspects such as plant breeding in case of varieties and physiological trials including management such as fertilization, irrigation, weeding, and plant population (Casanova et al., 2000; Guerra et al., 2008; Tsuji et al., 1998).

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Crop simulation models generate plant growth and development from input datasets such as soil weather, crop management and genetic-specific parameters (Boote et al., 1998). Recent studies have shown that the CSM-CROPGRO- Peanut model, which is also included in the DSSAT, can be applied as a breeding tool in Thailand to assist in understanding the Genotype × Environment interaction and related issues associated with efficient breeding programs (Banterng et al. 2003, Anothai et al., 2008, Phakamas et al., 2008). Soil, weather, and management information using specific data or existing datasets from other studies. To operate properly, DSSAT needs a database related to the climate and soil of the designated area, crop management, and information about the genotypes concerning seven genetic coefficients that simulate the phenotypic expression of the genes under varying environments (Boote et al., 2003), which can vary depending on the duration of each growth stage within the crop's life cycle (Boote et al., 2003), and related crop physiology. Recently, the genetic coefficient of mung bean in Thailand or tropical conditions has been inaccessible.

Cultivar coefficients are typically established using data collected in experiments conducted under optimum conditions and free from water, nutrient, and pest infection. Hoogenboom et al. (1999) recommended that the experiment be conducted over different planting dates at the same location or for the same planting date across multiple locations to achieve a more precise estimation of cultivar coefficients. This recommendation is difficult to implement for breeding applications that involve a wide range of genotypes (Banterng et al., 2004). It is almost impossible to conduct experiments and collect informative data on plant growth and development for various cultivars that change regularly due to new releases by plant breeding programs. Consequently, there is now a lack of cultivar coefficients describing new and recently released varieties for using crop simulation models that belong to DSSAT.

The generalized likelihood uncertainty estimation (GLUE) method is a Bayesian Monte Carlo parameter estimation technique that utilizes a likelihood function to measure the closeness of fit of modelled and observed data. GLUE was adopted to estimate plant genetic coefficients by He et al. (2010a, 2010b). The enhanced genetic algorithms for accurately estimating parameters of the rice growth models Rice-Grow and ORYZA2000 (Zhuang et al., 2013). However, using an optimization algorithm to obtain the model parameters in a specific crop model is complicated since hands-on programming is always needed. That is why the trial-and-error method is still commonly used. The calibration of genetic coefficients involves estimating the parameter set necessary for the DSSAT model to accurately predict values that align with real system data from experimental fields. In each iteration step, the criterion for optimization is to minimize the root mean square error (RMSE). Estimating genetic coefficients begins with phenological events and is followed by determining growth yield and yield component coefficients.

This study aimed to determine the genetic coefficient of KUML4 for the CSM-CROPGRO model and subsequently compare the predicted data generated by the model with observed data for the development period, yield, and yield components as utilized in DSSAT.

MATERIALS AND METHODS

Field Trial

Mung bean variety KUML4 was planted in dry season conditions on February 3, 2021, and rainy season on June 1, 2021, at the Chainat field crop research centre. Kamphaeng Saen site was started on March 2, 2021, for the dry season and June 17, 2021, in the rainy season (Fig. 1). Mung bean was grown with 50 x 20 cm spacing and incorporated with Rhizobium before planting. Mung bean seed was planted 4-5 seeds per hole and then thinned to 3 plants. The experimental plot size is 8 m wide and 14 m. long with 3 replication plots in each treatment. Basal application of 12-24-12 fertilizer was applied as 25 kg/rai at 20 DAP (day after planting). Plant growth was monitored at V4 (Fourth node), R3 (beginning seed), R6 (1st harvest) and R7 (2nd harvest). By recording 3 consecutive plants within 1 row for leaf area, dry weight of stem leaf pod and seed. Daily weather conditions such as rainfall, solar radiation, and minimum and maximum temperatures were recorded. Soil profile description and soil analysis in the experimental plot were determined. Plant information about emergence date, harvesting date, and duration in each growing stage, as well as irrigation, yield, and yield component, were investigated.

Genetic Coefficient Calibration

CSM-CROPGRO-Cowpea in DSSAT version 4.7 required 18 parameters to describe phenology and plant growth, as shown in Table 1 (Hoogenboom et al., 2017). To determine the genetic information used in the model, environmental information was monitored, which consisted of rainfall (mm), solar energy (MJ), temperature minimum and maximum (°C). Soil physical and chemical properties such as texture, color, drainage, reaction (pH), bulk density, fertility, and water holding capacity combined with management information such as planting date, variety, plant spacing, emergence date, irrigation, fertilizer application (type and rate) were monitored. All parameters mentioned above were used to determine and calibrate the genetic coefficient along the growth period and adjusted among 3 sites to comply with the life cycle observed (Boote et al., 2003).

A module of cowpea (*Vigna unguiculata*) classified in the same genus of mung bean (*Vigna radiata*) was used in the DSSAT crop simulation model currently unavailable in mung bean. This study started an experiment using cowpea module information in the Sapphaya soil series to calibrate the genetic coefficient with GLUE.

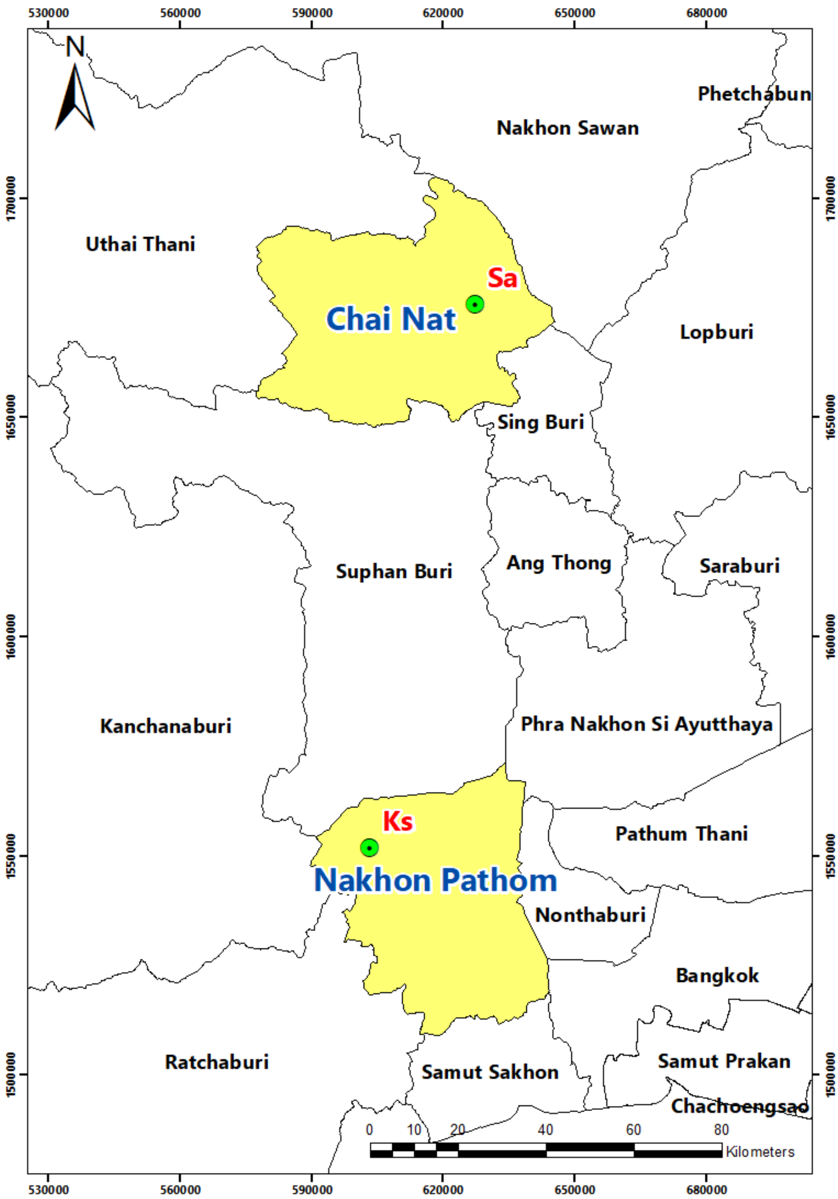


Fig. 1. Experimental plot location at Chainat field crop research center and Kamphaeng Saen site, Nakhon Pathom province

The genetic coefficient of cowpea (*Vigna unguiculata*) was used as the default generic coefficient in the DSSAT model. To adjust the genetic coefficient of the mung bean variety, the KUML4 simulation model generated 10,000 random for phenological events and 10,000 random for growth and development. A generic coefficient from the first random implement will be input to the crop simulation model for the prediction growth and development of mung beans compared with the observed value from the experimental field. The procedure was repeated until the predicted value was close to the observed value. Low root mean square error (RMSE) (Wallach & Goffinet, 1987) and index of agreement (d) close to 1 (Willmott, 1982) was used as an indicator.

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

Where: Pi = Predicted yield, Oi = Actual yield, n = number of observations

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|P_i'| + |O_i'|)^2}\right], 0 \le d \le 1 \quad \text{..........2)}$$

Where: n is the total number of observations, Pi is the predicted value, Oi is the observed value, and Ō is the overall mean of the observed values, P/i = Pi - Ō and O/i = Oi - Ō.

RESULTS AND DISCUSSION

The Weather during the Growing Period on Each Planting Date

The presents data (Fig. 2) on maximum and minimum temperatures, rainfall, and solar radiation throughout the experimental period for both plots, tracking their respective growth stages across multiple planting dates. Between January, March, and December, temperature and solar radiation levels are relatively low compared to other periods of the year.

Table 1. Cultivar coefficients used in the CSM-CROPGRO-Cowpea model in DSSAT4.7

No.	Cultivar trait	Acronym	Unit
1	Critical short-day length below which reproductive development progresses with no day length effect	CSDL	h
2	Slope of the relative response of development to photoperiod with time	PPSEN	per hour
3	Time between plant emergence and flower appearance (R1)	EMFL	photothermal days
4	Time between first flower and first pod (R3)	FLSH	photothermal days
5	Time between first flower and first seed (R5)	FLSD	photothermal days
6	Time between first seed (R5) and physiological maturity (R7)	SDPM	photothermal days
7	Time between first flower (R1) and end of leaf expansion	FLLF	photothermal days
8	Maximum leaf photosynthesis rate at 30°C, 350 vpm CO_2, and high light	LFMAX	mg $CO_2/m^2/s$
9	Specific leaf area of cultivar under standard growth conditions	SLAVR	cm^2/g
10	Maximum size of full leaf (three leaflets)	SIZLF	cm^2
11	Maximum fraction of daily growth that is partitioned to seed+shell	XFRT	
12	Maximum weight per seed	WTPSD	g
13	Seed filling duration for pod cohort at standard growth conditions	SFDUR	photothermal days
14	Average seed per pod under standard growing conditions	SDPDV	number per pod
15	Time required for cultivar to reach final pod load under optimal conditions	PODUR	photothermal days
16	The maximum ratio of [seed/(seed+shell)] at maturity.	THRESH	
17	Fraction protein in seeds	SDPRO	g (protein) per g (seed)
18	Fraction oil in seeds	SDLIP	g (oil) per g (seed)

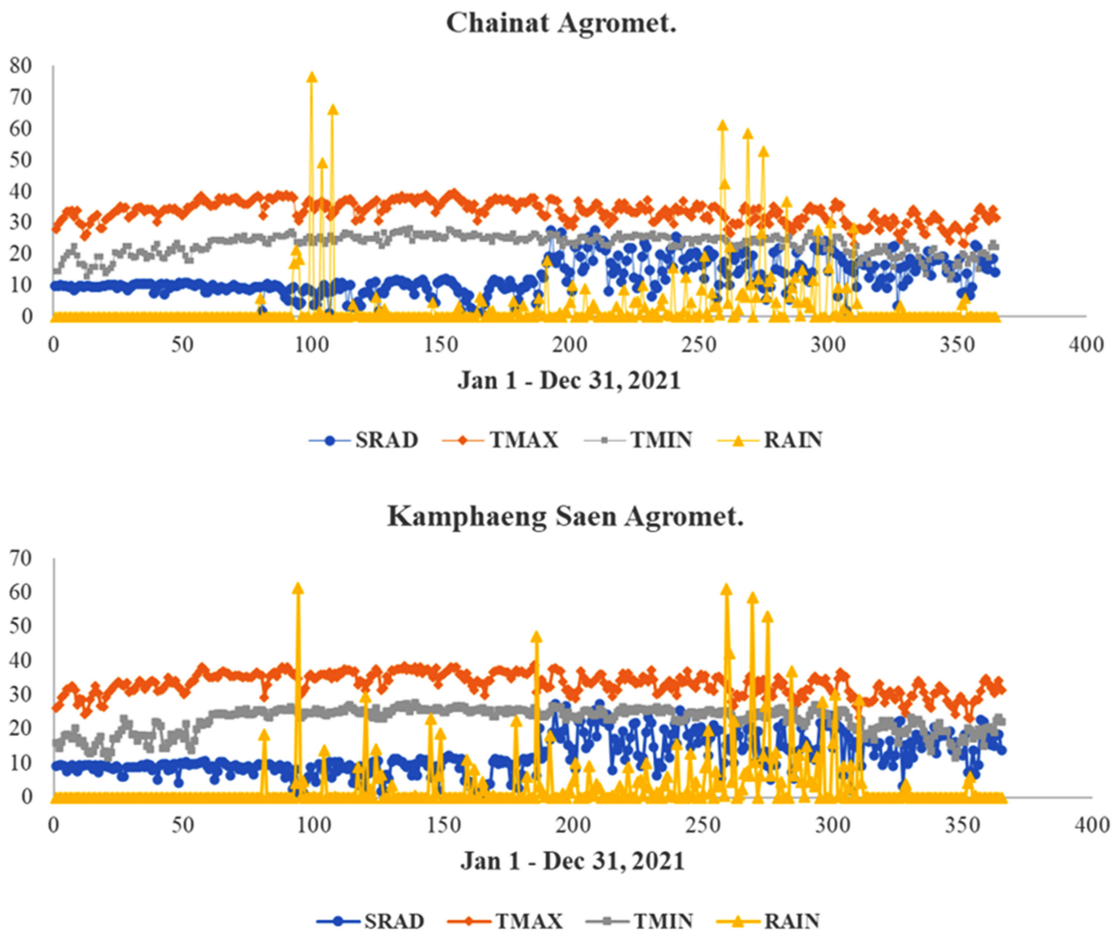
Remarks: Source: Boote et al. (1998); Hartkamp et al. (2002); Hoogenboom et al. (2010)

The diminished solar radiation is attributed to the clear skies prevalent during winter. Consequently, the growth and development of plants during this period are significantly influenced by these lower temperatures and reduced solar radiation levels, as previously noted. Subsequently, during the rainy season beginning in June, there is a notable increase in the variation of solar radiation compared to other times of the year. From June to the end of October, the average temperature ranges from 25 to 30 degrees Celsius, while there is an increase in the variation of solar radiation, primarily attributed to cloudy skies during the rainy season.

In Nakhon Pathom, rainfall starts in March and steadily increases until peaking in September and October, which is crucial for farming by ensuring a reliable water supply for crops. Conversely, Chainat has lower rainfall. During dry spells, irrigation is used for mung beans. Climate change has affected rainfall patterns, impacting non-irrigated production areas.

Physical and Chemical Soil Properties

The research employs two distinct experimental plots, each covering an area of approximately 0.5 rai, equivalent to 0.08 hectares. These test plots are strategically placed in two contrasting geographical regions with distinct soil types and climatic conditions. The first plot is situated at Chainat Field Crop Research Center, which had soil classified as fine-textured soil. This affects the crop's growth and productivity based on the properties of these fine-textured soils.



Remarks: SRAD: Solar radiation (MJ/m^2); TMAX: Maximum temperature (°C); TMIN: Minimum temperature (°C), RAIN: Rainfall (mm)

Fig. 2. Daily climatological information from weather station at Chainat field crop research center and Kasetsart University on 2021

This site offers an excellent chance to study how mung beans respond to the soil characteristics in this province. The second plot is located at Kasetsart University's Kamphaeng Saen campus, Nakhon Pathom province, where the soil has a different profile, and its texture was characterized as medium-textured. Differentiation in soil texture between these two sites brings another dimension to this research, increasing it to cover all aspects related to mung bean farming across diverse soil conditions.

The experimental design includes a seasonal approach, both the dry and rainy seasons. In the dry season, the planting period is from February to April, when precipitation levels are typically lower, and water management becomes an important factor. On the other hand, the rainy season experiments are conducted with planting dates ranging from May to July, occurring at the same time as increased rainfall and potentially different pest and disease stress.

Two seasons also assisted the researchers in gathering many more results on how the mung bean crop performs under different environmental conditions and different planting periods for farmers and other stakeholders in mung bean production to get a better base and appropriate conclusion. Thus, it helped in presenting more useful information to farmers and members in the value chain for mung beans production. It can do well in fine and medium textured soil conditions throughout the year varying seasons. At the experimental sites, soil samples were collected at 0-30 cm and 30-45 cm layers before commencing the experiments.

In Kamphaeng Saen of Nakhon Pathom province, the Kamphaeng Saen soil series is loamy sand with a pH of 7 for moderately alkaline 7.96 to 8.19, and low amounts of organic matter range from 0.32 to 0.61 percent. The variation by depth of soil organic matter content is associated with the decomposition of organic matter from the soil and the residues of plants left by previous crops. The conversion of an organic compound to soil organic matter was also described by Fernandes et al. (1997). The subsoil contains less organic matter due to topsoil's active decomposition cycles that do not allow for organic matter build up in the subsoil (Bohn et al., 2001; Brady & Weil, 2008). The total nitrogen content in both the topsoil and subsoil was quite low, measuring at 0.06%. Particularly, the topsoil had a higher total nitrogen content than the subsoil, which tended to decrease with increasing soil depth, correlating with soil organic matter levels (Brady & Weil, 2008). The very low total nitrogen levels could result from factors such as plant and soil microbe consumption and nitrogen loss through leaching and volatilization into the atmosphere as gaseous compounds (Robertson & Groffman, 2007). The soil's available phosphorus levels are very high and high, with the topsoil and subsoil registering values of 54.65 mg/kg and 34.10 mg/kg, respectively (Soil Survey Division Staff, 1993). The higher phosphorus content in the topsoil than the subsoil might be connected to the organic phosphorus in organic matter (Weil & Brady, 2017; Sanchez, 2019). The exchangeable potassium data for both topsoil and subsoil are quite high, with values of 147.9 mg/kg and 116.3 mg/kg, respectively, classified as "very high." The level of exchangeable potassium is associated with the clay content in each soil layer, the parent material and the type of clay mineral present. The soil profile description in Fig. 3 reveals a deep soil profile with a development type classified as Ap1-Ap2-Bt1-Bt2-Btk1-Btk2. The soil's parent material is alluvium, and the topsoil exhibits a dark yellowish-brown color. Soil texture is loamy sand in both top and subsoil. The field soil's pH level is moderately alkaline, measuring at 8.0. The soil profile reveals the presence of an argillic horizon (Bt) and a Bk horizon in the subsoil. Furthermore, the subsoil horizon exhibits clay accumulation and secondary calcium carbonate accumulation (Btk), indicating that the soil is moderately developed (Buol et al., 2011) (Table 2).

The analysis of the Sapphaya soil series before the experiment at Chainat province, conducted at depths of 0-28 cm and 28-42 cm, revealed a sandy clay loam texture with a moderately alkaline pH of 7.78 and 7.70, respectively. The soil organic matter levels were measured as medium at 1.67% and low at 0.99%, while the total nitrogen content was classified as very low at 0.07% and 0.05%, respectively. Available phosphorus for top and subsoil was moderately high at 21.63 and 24.27 mg/kg. Exchangeable potassium levels were 120.3 mg/kg for the topsoil and 68.8 mg/kg for the subsoil, indicating a very high concentration in the topsoil and a medium concentration in the subsoil. The moderate organic matter content in the topsoil results in elevated cation absorption and the release of a portion of available potassium for plant uptake (Brady & Weil, 2008). In the studies of deep soil profiles from the Sapphaya soil series (Fig. 3), diagnostic horizons Apg1-Apg2-Bg1-Bg2-Bg3-Bg4 are evident in the soil profile. The parent material consists of alluvial deposits, and the topsoil appears as a very dark greyish-brown layer extending to a depth of 28 cm. The soil fertility is rated as medium, and both the topsoil and subsoil exhibit a sandy clay loam texture. Strong brown mottling and a moderately acidic field soil reaction are observed in the subsoil. Additionally, pH levels increase with depth. The parent material and topsoil management practice influence the medium soil fertility in both experimental plots (Eswaran et al., 1997).

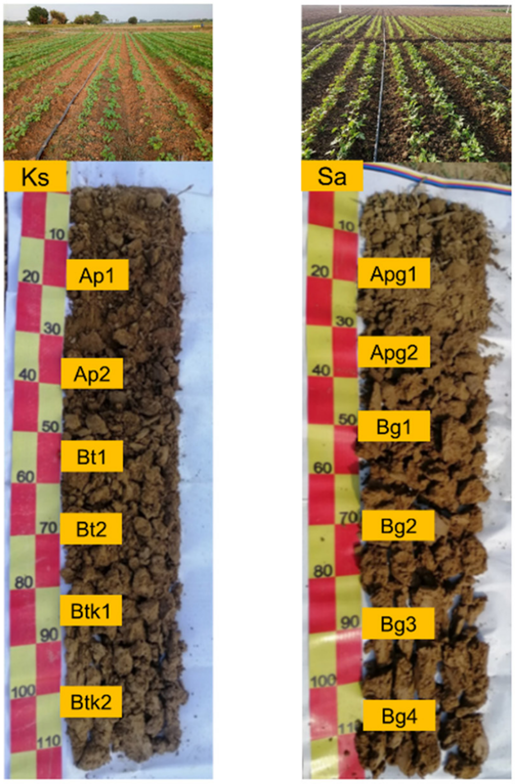


Fig. 3. Topography and soil profile of Kamphaeng Saen soil series at Kasetsart University, Kamphaeng Saen campus (Ks), Sapphaya at Chainat field crop research center (Sa)

Table 2. Soil physical and chemical properties at Chainat field crop research center and Kamphaeng Saen site

Soil series	Depth (cm)	pH	OM	Total N	Avai.P	Exch. K	Sand	Silt	Clay	Soil Texture*
			(........%.......)		(........mg/kg........)		(...............%...............)			
Sa	0-28	7.78	1.67	0.07	21.63	120.36	12.75	43.65	43.60	SiC
	28-42	7.70	0.99	0.05	24.27	68.86	15.28	40.92	43.80	SiC
	42-60	7.58	0.41	0.03	2.40	45.05	23.36	34.35	42.29	C
	60-80	7.47	0.25	0.02	1.28	36.43	29.78	33.08	37.14	CL
	80-100	7.55	0.20	0.01	1.53	32.25	20.63	44.09	35.28	CL
	100-115	7.67	0.22	0.02	1.49	32.50	10.54	50.31	39.15	SiCL
Ks	0-30	7.96	0.61	0.06	54.65	147.90	63.63	25.61	10.76	SL
	30-45	8.19	0.32	0.06	34.10	116.37	59.90	28.44	11.66	SL
	45-60	8.19	0.22	0.04	0.45	126.38	52.01	32.86	15.13	SL
	60-76	8.23	0.15	0.04	0.49	123.84	55.45	25.85	18.70	SL
	76-92	8.15	0.07	0.02	0.49	123.83	51.88	29.53	18.59	L
	92-115	8.18	0.20	0.03	0.42	137.02	45.64	38.40	15.96	L

Remarks: *SiC = Silty clay, C = Clay, CL =Clay loam, SiCL =Silty clay loam, SL = Sandy Loam, L = Loam

Calibration of Genetic Coefficient

This study design is to determine the genetic coefficients of the mung bean variety KUML4. The coefficients were established across several variables for two different geographical locations and were evaluated in both the dry and rainy seasons. This study aimed to provide better calibration and validation data for a crop simulation model and, thus, improve the ability to forecast and estimate the variety's performance under different environmental conditions. To determine the genetic coefficient of KUML4, the focus was on the second planting date, June 1, 2021, in the plot showing the highest growth and yield. Using this selection, we detailed the variety's genetic evaluation under the favorable conditions of the rainy season. GLUE (Generalized Likelihood Uncertainty Estimation) was used to interpret the parameters of the KUML4 genetic model. This process was continued until the simulated output matched the observed field data, as shown in Table 3. This approach confirmed that the crop simulation system properly predicted the mung bean variety's growth and phenological development parameters, making it more reliable for future use. As shown in Fig. 4, a comparison of monitored predicted and actual plant growth data proved the system's precision across various factors. The correlation coefficients (r^2) for stem weight (r^2 = 0.98), maximum leaf area index (r^2 = 0.974), and plant height (r^2 = 0.958) showed remarkably strong agreements. These findings suggest the model can accurately replicate these important parameters, providing useful information regarding mung bean growth and development. However, the prediction for leaf weight, though still reliable (r^2 = 0.885), displayed a slightly lower correlation than the mentioned variables. This suggests that additional refinements may be needed to improve the ability of the system to predict leaf weight more accurately. Considering the mung bean yield predictions, the estimation for pod weight (r^2 = 0.963) and grain weight (r^2 = 0.953) were rather accurate, showing that the system is good at predicting these important yield factors. Nevertheless, their respective correlation coefficients indicated that the estimation of shoot weight and the number of leaves per plant exhibited room for improvement. The current version of the DSSAT model does not include a module specifically for mung beans. Therefore, the phenotypic characteristics of KUML4 were utilized as a starting point for this project. The experimental field for this study was located in the Kamphaeng Saen soil series at the Soil Science Department's field on the Kamphaeng Saen campus. Weather data from the Nakhon Pathom Meteorological Station, located approximately 4 km from the experimental field, was adopted for this site. However, the document did not report certain essential information, such as cultivation practices and development information. It is important to improve the initial data regarding soil nitrogen fixation. In any case, ensuring the quality of input data should be a top priority in future studies involving the genetic coefficient of KUML4.

The calibration of the genetic coefficient using the secondary planting date on June 1, 2021, in the Sapphaya soil series, located in Chainat province, revealed coefficients applicable for simulating growth variables such as plant height, maximum leaf area index, grain weight, and pod weight. However, the predicted data for leaf weight, shoot weight, and the number of leaves per plant were lower than the observed data from the experimental field. This finding aligns with the observations of Tongyai (1994), who found that predicted biomass was approximately 10-12% lower than the observed data. The genetic coefficient evaluation closely predicted mung bean growth development for the four planting dates.

Table 3. Cultivar coefficients of KUML 4 used in the CSM-CROPGRO-Cowpea model in DSSAT4.7

Cultivar trait	Cultivar coefficient	Cultivar trait	Cultivar coefficient
CSDL	13.09	SIZLF	260
PPSEN	0.111	XFRT	0.683
EM-FL	18.4	WTPSD	0.081
FL-SH	1.059	SFDUR	19.8
FL-SD	2.32	SDPDV	15
SD-PM	14.85	PODUR	5
FL-LF	27.8	THRSH	79
LFMAX	1.941	SDPRO	0.25
SLAVR	259.5	SDLIP	0.065

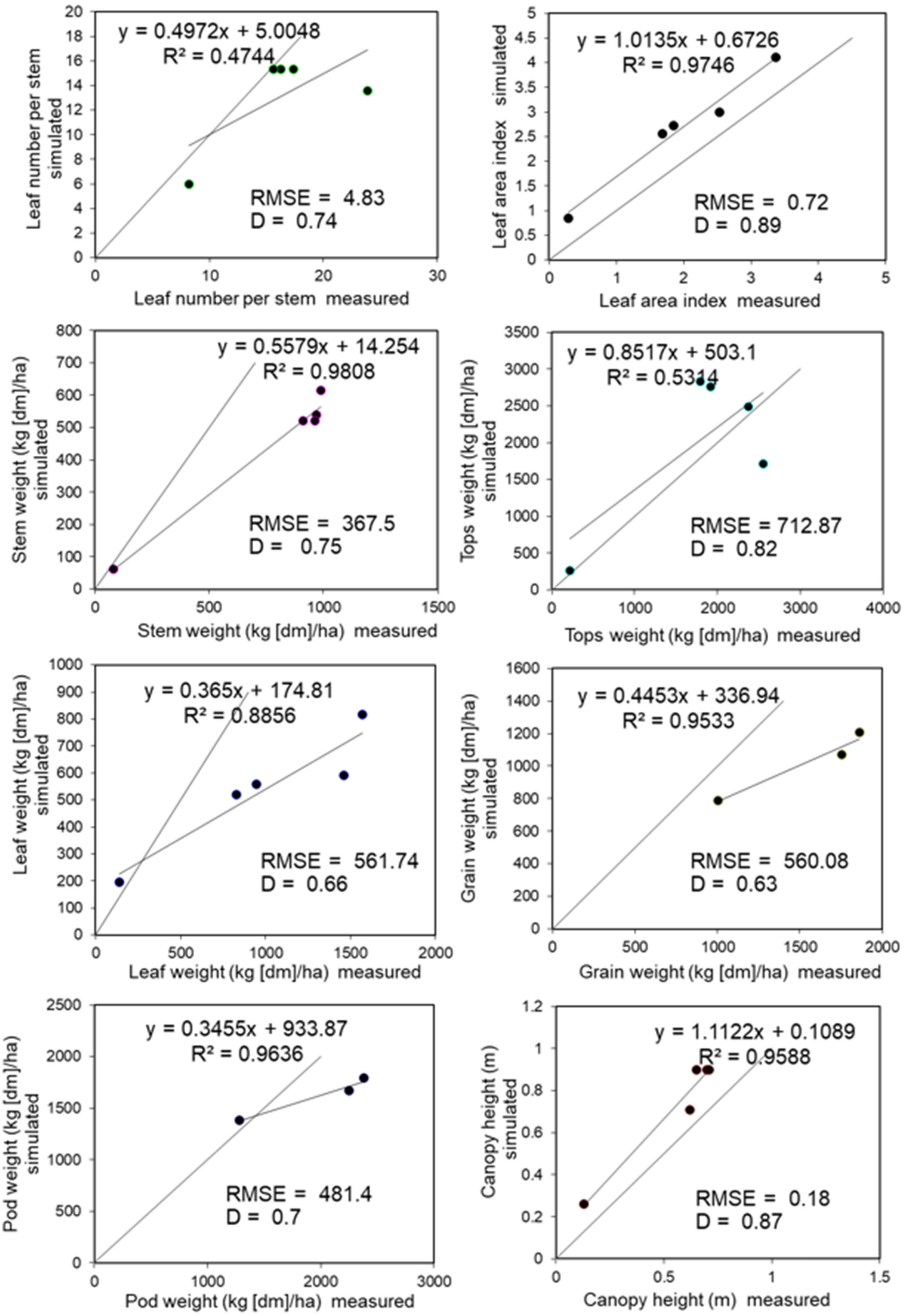


Fig. 4. Simulation versus observed values for growth and yield of mung bean

Model Validation

Comparing the field-observed data with the model's simulated output, as shown in Table 4, provides us with useful information about the accuracy and performance of the model in predicting mung bean growth. These assessments are essential for understanding the model's strengths and weaknesses, helping to refine and improve its usefulness. Among the predicted output variables, the estimate of mung bean growth, especially the leaf area index, is particularly impressive. On February 3, 2021, a remarkable cohort of mung beans emerged from the Sapphaya soil series to insist on a Root Mean Square Error (RMSE) value of just 0.71 and a high level of the model's accuracy. Moreover, the index of agreement (d) approached 0.89, suggesting the ability of the model to match the field observations closely. Other growth measurements that included shoot weight, stem weight, number of leaves per plant, and pod weight were also included to enhance the accuracy. These variables strongly agreed with the observed data, with d values of 0.82, 0.75, 0.74, and 0.70, respectively. This finding indicates that the model performs well in replicating mung bean growth, enhancing its ability to predict key growth parameters. The model did have some trouble estimating grain weight and leaf weight. The RMSE values of such parameters were relatively high, indicating significant deviations from the observed values. The index of agreement for both grain weight and leaf weight prediction was in the medium range, suggesting further requirements for improvement. The results from experiments conducted during the rainy season in the same area showed that the model's performance remained reliable for the same set of growth parameters. The accuracy of grain weight estimations was remarkable, with an RMSE of 94.03 and an almost perfect index of agreement (d = 0.99). Meanwhile, pod weight strongly correlated with the estimates (d = 0.97). For example, if the model stated that 10 pods (with estimated weight) existed, that was (on average) nearly true. The shoot and stem weights had a less satisfactory association with the estimates (d = 0.88 and d = 0.73). Nonetheless, some limitations remained in estimating variables such as leaf number, maximum leaf area index, and leaf weight, which yielded comparatively less favorable results. Model validation using data from four different planting dates demonstrated that the simulation model could accurately predict mung bean growth.

With regard to the first planting date in the Kamphaeng Saen soil series, the best growth prediction of mung bean was observed in pod weight with RMSE = 55.74 and d = 0.99. The underestimation of seed weight, shoot weight, and maximum leaf area index revealed an index of agreement equal to 0.78, 0.76, and 0.72, respectively. In the case of the second planting date on June 17 in the same area, a good estimation of mung bean growth was observed for the maximum leaf area index, with an RMSE of 0.54 and a d index of 0.85. Shoot and leaf weights showed underestimation with the same d value of 0.75. Our findings highlight the difficulty of accurately modelling mung bean growth, particularly with changes in seasons and environmental factors.

Using data from four different planting dates, we validated the growth model for mung beans. The model predicted the growth accurately, especially for the maximum leaf area index. It is concluded that the growth predictions for mung bean pods, grains, and shoots were quite reliable for three of the four planting dates. However, they did not correspond well for the 2nd planting date at a location in Kamphaeng Saen. In the three reliable cases, the model overestimated yield and shoot weight, as did a previous version of the model. The model appears to produce results lower than those actually obtained, and this may relate to our lack of accounting for pests and leaf decomposition. The simulation model was not biased in that it underestimated fresh weight, pod weight, and shoot weight for a second planting date in one soil series (Kamphaeng Saen). This study also considers pests and plant decomposition when accounting for observed variations between model outputs and actual data (Buddhaboon et al., 2018). The simulation model also underestimated the fresh, pod, and shoot weights for the second planting date in the Kamphaeng Saen soil series on June 17, 2021. The pests that affect mung beans may also contribute to the observed data variations in the simulation model.

Table 4. Statistical agreement (Root mean square error; RMSE and agreement index; d) between simulated and observed values for crop characters of KUML4

Planting date 1 Chainat (3 Feb 2021)	Mean (Obs)	Mean (Sim)	R^2	RMSE	*d*
Leaf number per stem	16.3	13.1	0.47	4.82	0.74
LAI, maximum	1.94	2.64	0.97	0.71	0.89
Leaf wt.	989	536	0.88	561.7	0.66
Stem wt.	783	451	0.98	367.4	0.75
Grain wt.	1539	1022	0.95	560.1	0.63
Top wt. at maturity	1772	2012	0.53	712.8	0.82
Pod wt.	1973	1616	0.96	481.4	0.70
Planting date 2 Chainat (1 Jun 2021)					
Leaf number per stem	16.2	13.1	0.3	4.54	0.65
LAI, maximum	2.21	1.26	0.55	1.14	0.67
Leaf wt.	922	316	0.25	676.7	0.49
Stem wt.	946	502	0.92	483.8	0.73
Grain wt.	1070	1097	0.98	94.03	0.99
Top wt. at maturity	1868	1886	0.76	637.89	0.88
Pod wt.	1372	1603	0.97	277.06	0.97
Planting date 1 Nakhon Pathom (2 Mar 2021)					
Leaf number per stem	18.1	13.6	0.47	5.36	0.68
LAI, maximum	2.87	2.07	0.43	1.18	0.72
Leaf wt.	1041	372	0.94	739.8	0.53
Stem wt.	843	386	0.91	497.3	0.64
Grain wt.	1090	842	0.99	249.2	0.78
Top wt. at maturity	1884	1584	0.34	822.3	0.76
Pod wt.	1397	1376	0.97	55.74	0.99
Planting date 2 Nakhon Pathom (17 Jun 2021)					
Leaf number per stem	15.2	12.8	0.106	5.51	0.49
LAI, maximum	1.48	1.21	0.62	0.54	0.85
Leaf wt.	829	523	0.51	424.8	0.75
Stem wt.	1020	568	0.74	540.3	0.75
Grain wt.	1135	2494	1	1374.5	0.11
Top wt. at maturity	1848	3004	0.72	1566.4	0.68
Pod wt.	1456	3432	1	1989.1	0.11

Remarks: Leaf wt., Stem wt., Grain wt., Top wt. at maturity, Pod wt. reported in kg [dm]//ha

Although crop models with genetic parameters observed in this research could predict the yield and growth of mung bean, further studies are required to investigate the influence of plant diseases. Further studies are also needed to investigate the influence of insect factors. Crop models are advantageous because they can simulate changes across different growing seasons and locations. Therefore, further evaluating mung beans' genetic coefficients under various environmental conditions is important. The assessment of CSM-CROPGRO-Cowpea has demonstrated its ability to stimulate the growth of the mung bean variety KUML4. Consequently, this model presents itself as an additional option to assist in making informed decisions regarding suitable technology for mung bean production in Thailand. It shows the many benefits of using crop simulation models for different crops. The assessment of CSM-CROPGRO-Cowpea exhibited that it could effectively simulate the growth of the mung bean variety KUML4. As a result, this model offers an additional tool for making informed decisions regarding suitable technology for mung bean production in Thailand, highlighting crop simulation models' adaptability across various crop applications (Banterng et al., 2010; Ahmad et al., 2013).

CONCLUSION

The CSM-CROPGRO-Cowpea Model was used to evaluate the genetic coefficient of KUML4 mung beans in both the dry and rainy seasons. Plant growth index, namely, stem, leaf, and grain biomass, were monitored in this study. Overall, the results suggest that the genetic coefficient of KUML4 could effectively predict mung bean growth, including shoot weight, leaf area index, and plant height. It also was accurate for the predicted weights of pods and seeds. Nevertheless, additional research is required to improve the shoot weight estimation and the number of leaves per plant.

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