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# Determination of Upland Rice Cultivar Coefficient Specific Parameters for DSSAT (Version 4.7)-CERES-Rice Crop Simulation Model and Evaluation of the Crop Model under Different Temperature Treatments conditions

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## Abstract

To develop basis for strategic or arranged decision making towards crop yield improvement in Thailand, a new method in which crop models could be used is essential. Therefore, the objective of this study was to measure cultivar specific parameters by using DSSAT (v4.7) Cropping Simulation Model (CSM) with five upland rice genotypes namely Dawk Pa-yawm, Mai Tahk, Bow Leb Nahng, Dawk Kha 50 and Dawk Kahm. Experiment was laid out in a Completely Randomized Design (CRD) with split plot design. Results showed that five upland rice genotypes had significantly affected each other by different temperature treatments (28˚C, 30˚C, 32˚C) with grain yield, tops weight, harvest index, flowering, and maturity date. At the same time, all the phenological traits had highly significant variation with the genotypes. The cultivar specific parameters obtained by using a temperature tolerant cultivar (Basmati 385) with five upland genotypes involved in the DSSAT4.7-CSM. Model evaluation results indicated that utilizing the estimated cultivar coefficient parameters, model simulated well with varying temperature treatments as indicated by the agreement index (d-statistic) closer to unity. Hence, it was estimated that model calibration and evaluation was realistic in the limits of test cropping seasons and that CSM fitted with cultivar specific parameters can be used in simulation studies for investigation, farm managing or decision making. This electronic document is a "live" template. The various components of your paper [title, text, heads, etc.] are already defined on the style sheet, as illustrated by the portions given in this document.

**Keywords**

DSSAT-CERES-Rice Crop Simulation Model, Temperature, Phenology, Upland Rice, Genotypic Cultivar Coefficient

## 1. Introduction

Crop simulation models have been utilized globally as an effective or planned research for decision support tools in crop productivity or resources management. Several crop models used from long time to assist crop management practices with exploring physiological processes under different environments [1]. The Decision Support Systems for Agrotechnology Transfer (DSSAT) is a popular package software comprises crop simulation models (CSM) for over 42 different crops including rice. The DSSAT software consists of: 1) data base management system for soil, weather, genetic coefficients, and management inputs; 2) crop simulation models (CSM); 3) series of utility programs; 4) series of weather generation programs; 5) strategy evaluation program to evaluate options including choice of variety, planting date, plant population density, row spacing, soil type, irrigation, fertilizer application, initial conditions on yields, water stress in the vegetative or reproductive stages of development, and net returns. DSSAT-CSM models simulate growth, development, and yield of crops as a function of the soil-plant-atmosphere-management dynamics [2].

Crop modelling can also be useful to understand the scientist, researchers define research priorities. Using a model to estimate the importance and the effect of certain parameters, a researcher can observe which factors should be more studied in future research, thus increasing the understanding of the system. Crop Simulation Models (CSM) are tools of systems that define procedures of crop growth and development as an act of weather, soil conditions, crop management and help in solving problems related to crop production [3]. CSM was used to simulate grain yield, biomass, and water balance in rice crop [4]. For dynamic crop simulation model accurate estimation of crop cultivar coefficients is the main point into use (for research as well as decision making) for improvement, identification and consequently narrowing gaps in our knowledge over crops and biophysical aspects for improved agricultural productivity.

Rice (*Oryza sativa* L.) rice is one of the most important crops and it represents a staple food for over half of the world's population, with a global production of more than 700 million tons per year and a harvested area reaching 165 million ha [5]. In 2050 world's population growth will be 10 billion and the demand for rice will grow faster than other crops [6]. There are already many challenges to attaining higher productivity of rice. Climate change e.g., high temperature and its consequences are the major challenges which affect the production of rice crop.

Upland rice suffers severely from irregular environmental factors, e.g., air temperature, drought, and precipitation [7]. Temperature is attributed by its impact on crop yield, due to expansion under excess heat stress conditions that greatly influences the growth duration and yield of the rice plant [8]. The temperature rise is one of issues of climate change that has the effect of rice production in Thailand, especially to the development and growing of upland rice plants reported by [9]. In the growing season the mean temperature, temperature sum, ranges, distribution pattern and diurnal changes or a combination of these, highly correlated with grain yields had a significant issue [10]. Due to global warming and climatic risk, the current rice productions in Thailand are in danger. To fulfil the increase rice demand of ever-growing population pressures, an estimation of likely impact is vital for planning strategies.

For estimating cultivar coefficients, numerous methods have been recognized. However, these methods need key knowledge regarding a specific crop cultivar such as planting dates, flowering dates, physiological maturity dates and final grain yield, which in most cases are not available. Genetic coefficient calculator (GENECALC) which is a sub module in the Decision Support System for Agrotechnology Transfer (DSSAT v4.7) was used to determine cultivar coefficients for new peanut lines in Thailand from standard varietal trials reported by [11]. Some researchers used generalized possibility uncertainty estimation (GLUE) method to estimate maize cultivar coefficients [12]. Hence, DSSAT v4.7 has GLUE module for estimating crop cultivar coefficients [13]. All the above-mentioned approaches to estimate crop cultivar coefficients for use in dynamic crop models need some degree of information on a particular cultivar. Therefore, in situations where there is scarcity of data from typical variety trials or other devoted experiments, repeated field experimentations would be the only option. For dynamic crop simulation model accurate estimation of crop cultivar coefficients is the main point into use (for research as well as decision making) for improvement, identification and consequently narrowing gaps in our knowledge over crops and biophysical aspects for improved agricultural productivity. Therefore, objectives of current study are: 1) to determine upland rice crop growth and development indices under optimum temperature conditions; 2) to estimate upland rice cultivar parameters and calibrate DSSAT-CERES-Rice model using the same management; 3) to evaluate DSSAT-CERES-Rice model for simulating growth and yield under the rainfed upland conditions.

## 2. Material and Methods

### 2.1. Field Experiment for Model Calibration

For model calibration, five popular upland rice genotypes namely, Dawk Pa-yawm, Mai Tahk, Bow Leb Nahng, Dawk Kha 50 and Dawk Kahm were grown on 8$^{th}$ July 2018 to calibrate the CSM-CERES-Rice model by using a temperature tolerant cultivar (Basmati 385). The experiment was conducted as a split plot using

Complete Block Design (CRD) as main plots with three replications. The main plots had five upland rice genotypes and sub plots had three different temperature treatments (28˚C, 30˚C and 32˚C). Temperature treatments were set up by using the data logger (UA-003-09 HOBO Pendant, for Temp/Light) from starting of the experiment. Each plot had 5 rows, with 10 plants each. Standard agronomic practices were followed for treatment of fertilizers, weed and insect control. The crop management data (*i.e.*, phenological data) required for the simulation of the crop model include planting date, (50% and 100%) germination date, flowering and maturity, tillers number, panicles number, leaf area index, grain yield, biomass and 1000 grain weight were recorded harvest.

## 2.2. Description of the DSSAT-CERES-Rice Model

CERES-Rice present in DSSAT v4.7which is an advanced physiologically based model, was used to calibrate and evaluate the crop simulation model. Genetic co-efficients for the five upland rice genotypes were used to calibrate CERES-Rice model. Soil analysis was carried out before started of the experiments to analyze soil fertility and to carryout proper fertilizer management. Weather parameters including maximum and minimum temperatures, rainfall with air intensity were recorded from Kho Hong Agro meteorological station. Daily solar radiation ($MJm^{-2}$ $day^{-1}$) was calculated by using weatherman tools in DSSAT v4.7. Dawk Kahm genotype was used as border crop to avoid the varietal errors. To run the model the following five input files were created:

### 2.2.1. Daily Weather Model

Maximum and minimum air temperatures, precipitation, rainfall, and solar radiation (derived from sunshine hour data) were collected from the weather station of Kho Hong Agro meteorological office, Hat Yai, Thailand.

### 2.2.2. Soil Data

Soil data were collected at the depth of soil characteristics at 0 - 20, 20 - 40, 40 - 60, and 60 - 80 cm before planting. Soil classes, organic carbon (%), sand, silt, clay (%), soil texture, soil pH in water, field capacity (%), organic carbon (%), cation exchange capacity, total nitrogen, potassium and phosphorus, potential root distribution and depth were taken (**Table 1**).

### 2.2.3. Management Practices

Plant density, planting date, irrigation, weeding, plant row spacing, sowing depth, amount and types of fertilizers, insecticide application was done whenever necessary.

### 2.2.4. Plant Profile Data

Sowing date, emergence date, flowering date, physiological maturity date, panicle initiation (when 50% and 100% of the crop had reached those stages), planting density, plant height, tops weight (grain weight), harvest index and grain yield per genotype, *i.e.*, grain yield per area of production.

**Table 1.** Soil Physical, chemical and morphological analysis for model calibration.

| Measured Parameters / Soil textural classes | units | Layers (cm) 0 - 20 Sandy clay loam | 20 - 40 Sandy clay loam | 40 - 60 Sandy clay loam | 60 - 80 Sandy clay loam | Average Sandy clay loam |
|---|---|---|---|---|---|---|
| Sand | % | 47.00 | 60.98 | 61.92 | 67.50 | 61.52 |
| Silt | % | 9.00 | 11.47 | 11.68 | 9.00 | 12.46 |
| clay | % | 24.10 | 25.50 | 26.60 | 26.00 | 27.08 |
| Total N | % | 0.06 | 0.06 | 0.06 | 0.06 | 0.05 |
| Organic matter | % | 1.40 | 1.30 | 1.33 | 1.23 | 1.34 |
| Organic carbon | % | 1.45 | 0.90 | 0.83 | 0.73 | 0.81 |
| Available P | $mgkg^{-1}$ | 147.49 | 131.35 | 141.32 | 120.23 | 140.05 |
| Field capacity | % | 15.90 | 15.70 | 15.50 | 13.40 | 15.70 |
| Available K | $mgkg^{-1}$ | 140.00 | 115.50 | 70.00 | 87.00 | 108.50 |
| Available Ca | $mgkg^{-1}$ | 131.95 | 121.82 | 130.50 | 109.00 | 154.89 |
| Available Fe | $mgkg^{-1}$ | 119.34 | 127.92 | 104.34 | 99.80 | 137.20 |
| CEC | Meq100g | 11.14 | 13.12 | 12.27 | 12.00 | 3.08 |
| Ec | $mgkg^{-1}$ | 100.00 | 95.10 | 95.30 | 87.00 | 100.13 |
| pH | $mgkg^{-1}$ | 5.05 | 5.24 | 5.02 | 5.00 | 5.20 |

### 2.2.5. Genetic Coefficients File

Table 2 showed the genetic coefficients that were determined in the CERES-Rice model with the parameters namely P1 (Time period or basic vegetative phase), P2O (Critical photoperiod), P2R (Photoperiodism coefficients), P5 (Grain filling duration coefficient), G1 (Spikelet number coefficient), G2 (Single grain weight), G3 (Tillering coefficients) and G4 (Temperature tolerance coefficient). The genetic coefficients or cultivar coefficient values as obtained through GLUE runs were replaced by calculated values against tested genotypes and saved it in RICER047.CUL file in DSSAT model. Model calibration was done several times for P2O, P2R, G3 and G4 and subsequently suitable values for the coefficients were selected.

## 2.3. Experiments for Model Evaluation

For model evaluation, selected five upland rice genotypes namely Dawk Pa-yawm, Mai Tahk, Bow Leb Nahng, Dawk Kha 50 and Dawk Kahm and three temperature treatments were laid out in a Completely Randomized Design (CRD) under split plot design structure with three replications in the 2017/2018 and 2018/2019 growing seasons at the research area of Plant Science Department, faculty of Natural Resources, Prince of Songkla University Hat Yai campus, Thailand. Soil samples were collected fifteen days before sowing for important chemical and physical characterization (Table 3). We must do two seasons research experimental work for model evaluation. Here planting was done on $24^{th}$

**Table 2.** Genetic cultivar coefficients for the DSSAT-CERES-Rice model.

| Stage | Description |
|---|---|
| P1 (Juvenile Phase) | Time period or basic vegetative phase of the plant (expressed as growing degree days [GDD] in ˚C from seedling emergence during which the rice plant is not responsive to changes in photoperiod. |
| P2O (Critical Photoperiod) | Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate. |
| P2R (Photoperiodism Coefficients) | Extent to which phasic development leading to panicle initiation is delayed (expressed as GDD) for each hour increase in photoperiod above P2O. |
| P5 (Grain filling duration coefficient) | Time period in GDD) from beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9˚C. |
| G1 (Spikelet number coefficient) | Potential spikelet number coefficient as estimated from the number of spikelets per gm of main culm dry weight (less lead blades and sheaths plus spikes) at anthesis. |
| G2 (Single grain weight) | Under ideal growing conditions, *i.e.*, non limiting light, water, nutrients, and absence of pests and diseases. |
| G3 (Tillering coefficient) | A higher tillering cultivar would have coefficient greater than 1.0 G4 (Temperature tolerance coefficient) = Usually 1.0 for genotypes grown in normal environments. |
| G4 (Temperature tolerance coefficient) | Usually, 1.0 for genotypes grown in normal environments. G4 for japonica type rice growing in a warmer environment would be 1.0 or greater. Likewise, the G4 value for Indica type rice in very cool environments or season would be less than 1.0. |

**Table 3.** Chemical properties for model evaluation experiments.

| Depth | Organic carbon % | Total N % | pH ($H_2O$) | P (Bray1) (mg/kg) | Exchangeable P (cmol) |
|---|---|---|---|---|---|
| 0 - 10 | 1.7 | 1.3 | 5.00 | 98.00 | 0.09 |
| 10 - 25 | 1.5 | 0.9 | 5.02 | 87.50 | 0.07 |
| 25 - 35 | 0.9 | 0.8 | 5.01 | 95.50 | 0.06 |

July for the 2017/2018 and 2018/2019 seasons. Different fertilizers whenever necessary. Other management practices were carried out accordingly. The number of days to anthesis and physiological maturity, and grain filling data were collected. Moreover, grain yield and total plant biomass was measured at physiological maturity.

## 2.4. Statistical Analysis

The analysis of variance (ANOVA) to evaluate cultivars growth and development and the effect of different temperatures was done. Mean separation was done by Least Square Difference (LSD) for split plot design to see the varietal differences. Test of significance between the 2017/2018 and 2018/2019 experiments and simulated and measured quantities was performed by R/agricolae program [14]. This research focused to simulate the effect of different temperatures on yield performed for phenology, grain yield, tops weight, leaf area index, harvest index, and tillers number.

### 2.5. Model Calibration

Calibration is the process of adjusting some model parameters to local environmental conditions and obtains genetic coefficients for new cultivar used in modeling study [15]. According to [16] model calibration was done by the Root Mean Square Error (RMSE).

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

### 2.6. Model Evaluation

Model performance was evaluated by comparing the simulated versus observed values from upland rice experiment under rainfed conditions where an agreement index or d stat index [16] was used. The RMSEn gives the level of error associated with each evaluation between the observed and simulated values.

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i'| + |O_i'|)^2} \tag{2}$$

$$\text{RMSEn} = (\text{RMSE} \times 100)/\bar{O} \tag{3}$$

where $S_i$ = simulated value, $O_i$ = observed value, n = number of observations, $\bar{O}$ = overall mean of observed values, $S_i' = S_i - \bar{O}$ and $O_i' = O_i - \bar{O}$.

## 3. Results and Discussion

### 3.1. Weather Conditions

From Figure 1 and Figure 2 it was showed that in both 2017 and 2018 years, weather conditions had no visible variations. The maximum and minimum

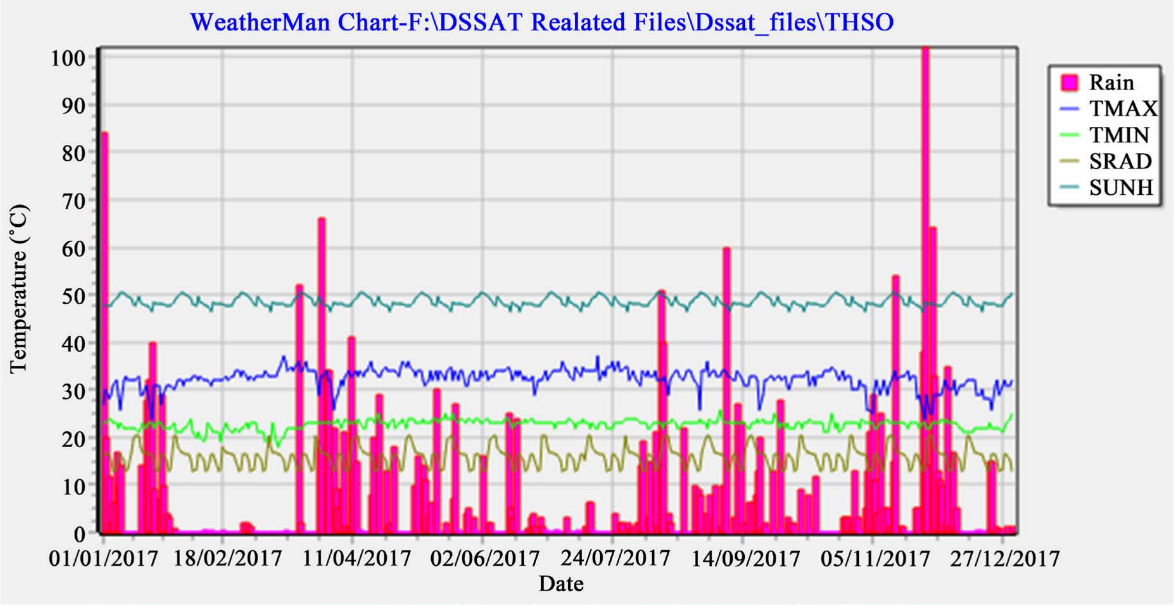


Figure 1. Mean daily maximum, minimum temperature, rainfall, solar radiation, sunshine determined in 2017/2018 year.

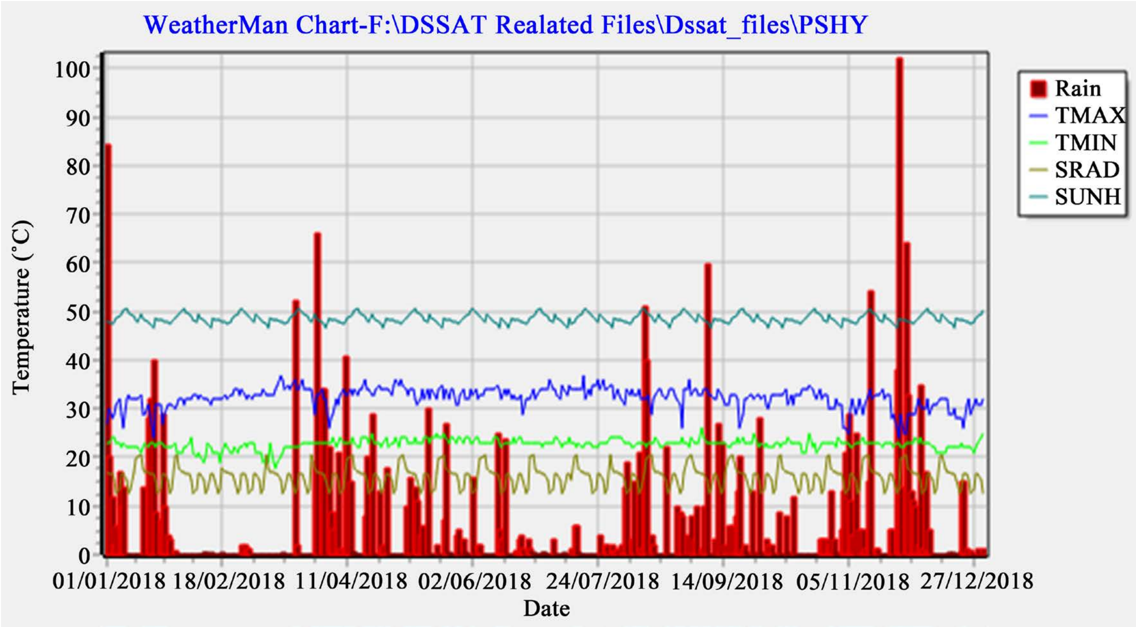


**Figure 2.** Mean daily maximum, minimum temperature, rainfall, solar radiation, sunshine determined in 2018/2019 year.

temperatures ranged between 25˚C to 38˚C and 18˚C to 22˚C. Highest maximum temperature (35˚C) and highest minimum temperature (26˚C) shown at ambient temperature 28˚C and 32˚C for 2018 Solar radiation ranged from 10.2 to 20 $MJ \cdot m^{-2} \cdot d^{-1}$, rainfall was reported between 20 - 980 mm and the highest rainfall was shown in the month of November to mid-December. After that January month was second most rainfall month near about 850 mm rainfall, respectively. Extreme high temperature beyond the average temperature hampered during experiment might have negative influence on upland rice yield, crop growth and development.

### 3.2. Soil Condition

Different soil layers of the study site with surroundings contain sandy clay loam texture and were highly acidic. Special management e.g., irrigation due to higher clay contents and drainage system should be adopted for heavy rainfall. As the soil was acidic, phosphorus fixation was required to improve soil pH, phosphorus fertilizers were added.

### 3.3. Analysis of Variance Result of Yield and Yield Attributes

Although ANOVA results (Table 4) for yield contributing traits using least significant differences (LSD) test ($P < 0.05$ and $P < 0.01$) revealed that some traits showed highly significant differences with temperatures and genotypes. Grain yield, tops weight, harvest index, flowering date, and maturity date was significantly affected by temperatures. Non-significant difference for tillers number, and leaf area index occurred possibly due to the optimum input of temperatures at the early stage. Whereas all the phenological traits had shown highly significant

**Table 4.** Mean squares from analysis of variance for 5 upland rice genotypes.

| Source | df | Mean Squares | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | TN | TW | LAI | HI | GY | FD | MD |
| Replication | 2 | 3.82 | 6,897,576 | 0.00054 | 0.00037 | 1,123,827 | 287.20 | 37.70 |
| Temperature (T) | 2 | 8.96 | 7,714,899** | 0.0017 | 0.00050** | 21,101,974** | 1488.40** | 4.29** |
| Error (a) | 4 | 3.46 | 1,909,466** | 0.0003 | 0.00034 | 895,471** | 248.000** | 19.00** |
| Genotypes (G) | 4 | 26360** | 1,412,628** | 0.0310** | 0.17674** | 8,577,099** | 2.00** | 9.48** |
| T× G | 8 | 2.20 | 275,655** | 0.0017 | 0.00008 | 210,410** | 5.01** | 1.844** |
| Error (b) | 24 | 5.99 | 123,482 | 0.0019 | 0.00012 | 61,252 | 0.82 | 1.94 |
| CV% (a) | | 3.41 | 16.67 | 1.04 | 3.06 | 16.51 | 17.28 | 3.87 |
| CV% (b) | | 4.49 | 4.06 | 1.71 | 1.80 | 4.32 | 0.99 | 1.27 |

**Table 5.** F values for selected variables between upland rice cultivars for 2017/2018 and 2018/2019 seasons.

| Variables | 2018 | 2019 |
|---|---|---|
| Harvest index at 50% flowering | $0.97^{ns}$ | $1.22^{ns}$ |
| Grain yield at harvest | $2.568^{**}$ | $1.67^{**}$ |
| Tops weight at physiological maturity | $4.67^{**}$ | $2.22^{**}$ |

variation among different genotypes. Grain yield, flowering date and maturity date had interaction effects between temperature and genotype.

### 3.4. Harvest Index, Grain Yield and Tops Weight

Table 5 showed that both grain yield at harvesting period and tops weight at physiological maturity varied significantly ($P < 0.05$) during 2017/2018 and 2018/2019 seasons, except harvest index at 50% flowering did not fluctuate. So, there was significant variation among genotypes in the 2018 and 2019 seasons. Also, there was inter seasonal variation in the tested variables for tops weight and grain yield. The similarity in the parameters for the 2018 and 2019 growing seasons suggested that at the growing condition period rainfed condition, nutrients, fertilizers, and other managements were affected the yield contributing traits. Though, sowing date for both seasons was the same 24$^{th}$ July, and weather elements were comparatively similar in both years, finally the similarity could not be expected.

### 3.5. CERES-Rice Model Calibration

Experiment for estimation cultivar coefficient was used for model calibration. Data of observed and simulated days to anthesis, physiological maturity, grain yield, by product and tops weight were collected for all the genotypes (Table 6(a) and Table 6(b)) indicating that cultivar specific parameters within the model were reasonably adjusted. Similarly, there was a good relationship among observed and simulated variables (d state values were respectively 0.97, 0.98, 1.0,

**Table 6.** (a) Simulated and observed values of days to anthesis, days to maturity and grain yield for upland rice genotypes. (b) Simulated and observed values of by product yield and tops weight for upland rice genotypes.

(a)

| Cultivar | By product (kg·ha$^{-1}$) | | | Tops weight (kg·ha$^{-1}$) | | |
|---|---|---|---|---|---|---|
| | Obs. | Sim. | RMSE | Obs. | Sim. | RMSE |
| Dawk Pa-yawm | 7208 | 7440 | 190 | 6890 | 6980 | 102 |
| Mai Tahk | 8050 | 8080 | 98 | 8879 | 8996 | 165 |
| Bow Leb Nahng | 8515 | 8720 | 87 | 7760 | 7890 | 89 |
| Dawk Kha 50 | 7350 | 7860 | 97 | 8850 | 8960 | 104 |
| Dawk Kahm | 7660 | 7860 | 95 | 7590 | 7780 | 93 |

(b)

| Genotype | Days to anthesis | | | Days to maturity | | | Grain yield | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Sim. | RMSE | Obs. | Sim. | RMSE | Obs. | Sim. | RMSE |
| Dawk Pa-yawm | 65 | 66 | 7.5 | 110 | 112 | 8.5 | 6476 | 6525 | 89 |
| Mai Tahk | 63 | 64 | 5.7 | 108 | 109 | 6.5 | 7230 | 7340 | 218 |
| Bow Leb Nahng | 60 | 60 | 3.5 | 113 | 114 | 3.4 | 5990 | 6020 | 78 |
| Dawk Kha 50 | 68 | 69 | 4.8 | 100 | 100 | 7.2 | 6200 | 6340 | 135 |
| Dawk Kahm | 59 | 59 | 7.0 | 104 | 104 | 6.8 | 6860 | 6998 | 115 |

1.0 and 0.99 for all the yield attributes. Dawk Pa-yawm showed high RMSE with respect to both number of anthesis days and physiological maturity than other genotypes. Mai Tahk had higher RMSE with respect to grain yield and tops weight also indicated that was high yielding genotypes and the yield is associated with the growth duration since it took longer than others to attain anthesis and physiological maturity. Besides, Bow Leb Nahng had lower RMSE with anthesis days, maturity days, grain yield, by product and tops weight indicated lower yielding genotype.

## 3.6. Cultivar Specific Parameters

Table 7 showed that Dawk Kahm genotype required few thermal units to complete juvenile stage (P1) compared to Mai Tahk genotype. This allowed Mai Tahk required extra time to accumulate photosynthesis before flowering and hence higher yielding genotype compared to other cultivars. Dawk Kahm was formerly bred for temperature tolerance condition indicated that few temperature units of short duration were just required to attain end of juvenile stage. Dawk Kha 50 required few temperature units from anthesis to physiological maturity (P5), contrasting Mai Tahk with highest thermal time requirement (G4). Spikelet number coefficient (G1) and single grain weight (G2) also high in Mai Tahk cultivar and lower in Dawk kahm cultivar. This resembled to differences in grain size between the two cultivars. The rate of grain development was high in Mai Tahk compared to others since this could be a temperature tolerant cultivar for rainfed environment with upland condition. Temperature tolerant coefficient (G5) was for the cultivars varied from 0.78˚C-1.09˚C for Dawk kahm to Mai Tahk genotypes.

### 3.7. Model Evaluation

The cultivar specific parameters found from experiments were used to evaluate CSM-CERES-Rice for simulating different temperature treatments under rainfed upland condition. The model simulated well the average number of anthesis to maturity days with high degree of agreement as indicated by the agreement index (d-statistics) (Table 8). This is an indication that the model calibration and resulting cultivar specific parameters were reasonably estimated. Generally, there were significant different ($p < 0.05$) between observed and simulated data at all temperature treatments and in all variables. Especially simulated yield decreased as temperature increased in both model simulation and experimental observations. This suggests that the CERES-Rice model is sensitive to climatic variables such as temperature. Furthermore t-test showed significant difference ($P < 0.05$) between simulated and observed yields at all temperature treatments (Table 9).

For model evaluation, a comparison was made for the five upland rice genotypes between simulated and observed grain yield at 28˚C, 30˚C and 32˚C temperature treatments (Table 7). In this study all the genotypes had shown a close agreement between observed and simulated values of grain yield data. Results showed that Mai Tahk and Bow Leb Nahng were the best cultivars due to

**Table 7.** Cultivar coefficients for the five upland rice genotypes.

| Genotypes | Genetic coefficient values | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | P1 | P2O | P2R | P5 | G1 | G2 | G3 | G4 |
| Dawk Pa-yawm | 120.0 | 10.8 | 250.0 | 672.0 | 82.1 | 0.018 | 0.68 | 0.98 |
| Mai Tahk | 130.0 | 10.8 | 250.0 | 735.0 | 82.9 | 0.027 | 0.89 | 1.09 |
| Bow Leb Nahng | 119.0 | 10.8 | 250.0 | 560.0 | 78.8 | 0.024 | 0.78 | 0.90 |
| Dawk Kha-50 | 118.0 | 10.8 | 250.0 | 500.0 | 80.8 | 0.020 | 0.82 | 0.95 |
| Dawk Kahm | 115.0 | 10.8 | 250.0 | 450.0 | 68.3 | 0.019 | 0.65 | 0.78 |

**Table 8.** Observed and simulated values of yield attributes as affected by three temperature treatments under rainfed conditions.

| Variable Name | Mean obs. | Mean Sim. | r-Square | RMSE | d-Stat. |
|---|---|---|---|---|---|
| Anthesis day | 58 | 58 | 0.98 | 0.92 | 0.98 |
| By product(kg/ha) | 6850 | 7000 | 0.97 | 297 | 0.07 |
| Tops weight (kg/ha) | 5960 | 6150 | 0.99 | 300 | 0.99 |
| Grain yield (Kg/ha) | 5470 | 5680 | 0.99 | 310 | 0.99 |
| Maturity day | 97 | 99 | 0.87 | 1 | 0.98 |

**Table 9.** Observed vs. simulated grain yields at different temperature treatments.

| Genotypes | 28˚C | | 30˚C | | 32˚C | |
|---|---|---|---|---|---|---|
| | Observed | Simulated | Observed | Simulated | Observed | Simulated |
| Dawk Pa-yawm | 3583 | 3734 | 3920 | 4350 | 3239 | 3497 |
| Mai Tahk | 4480 | 4860 | 5200 | 5500 | 3300 | 3880 |
| Bow Leb Nahng | 4200 | 4367 | 4920 | 5000 | 3600 | 3694 |
| Dawk Kha-50 | 3308 | 3650 | 3829 | 4220 | 2835 | 3055 |
| Dawk Kahm | 3947 | 4230 | 4100 | 4331 | 3021 | 3230 |

increasing simulated grain yield and best performed with the moderate temperature at 30˚C (Mai Tahk 5500 kg·ha$^{-1}$ and Bow Leb Nahng 5000 kg·ha$^{-1}$). Whereas at 32˚C temperature treatment, a large variation for all the genotypes decreased in yield with the maximum temperature increased. Highest reduction in simulated yield was recorded for Dawk Kha 50 cultivar (3650 kg·ha$^{-1}$ at 28˚C, 4220 kg·ha$^{-1}$ at 30˚C and 3055 kg·ha$^{-1}$ at 32˚C) compared to others while minimum temperature increased at high temperature (30˚C) stage.

## 4. Conclusion

Unavailability of experimental data related upland rice genotypes have hampered DSSAT-CSM use in many areas and research such as biophysical resource application, economical, cost effective tactical or strategic decision-making processes. Here, simulation experiments done using these cultivar parameters predicted reasonably well the crop growth and yield under varying temperature treatments. It showed that highest simulated grain yield bearing genotype was Mai Tahk 5500 kg/ha with 30˚C and the simulated yield of upland rice ranges (3055 - 5500) kg/ha with temperature ranging 28˚C - 32˚C. The CSM-CERES-Rice model was well validated and showed reliability of simulations with different temperatures for phenology and yield attributes of upland rice genotypes. Our study assessed the DSSAT–CERES–Rice model in a CRD experiment including two factors; one of genotype (5 Thai upland rice genotypes) and another one of different temperature treatments (3 levels) to identify the variations of grain yield in southern Thailand under changing climatic (weather, soil) conditions. Study results revealed that increase in temperature, solely lead to decrease in grain yield of upland rice. Thus, CERES-Rice model could be safely used as a tool to assess different agronomic and climatic change parameters.

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## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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