



Research article

Modeling nutrient stress in paddy rice: Calibration practicalities, data needs and performance trade-offs for AquaCrop and Decision Support System for Agrotechnology Transfer models

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Abstract

Importance of the work: Often, the application of crop simulation models for nutrient management in paddy rice is constrained by the need for demanding calibration and intensive data requirements.

Objectives: To compare the calibration methods, data requirements and performance of the AquaCrop and Decision Support System for Agrotechnology Transfer (DSSAT) models in simulating the effects of nitrogen on RD43 rice.

Materials and Methods: A pot experiment was conducted using two planting methods (wet direct sowing and transplanting) and three nitrogen levels: recommended (N1), approximately one-half-recommended (N2) and zero-application (N3). Data from this experiment were used to assess model performance in simulating biomass, yield and crop evapotranspiration for RD43 rice.

Results: Nitrogen availability was a key determinant of observed biomass and yield, with yields diminishing as the N application was reduced from N1 to N3. Although both models simulated yield accurately under high fertility (N1), their predictions diverged as fertility declined. Under moderate (N2) and severe (N3) stress, AquaCrop substantially overestimated yield due to calibration limitations. Conversely, DSSAT produced a more graduated response across the N gradient but was more demanding to calibrate. Both models consistently underestimated total crop evapotranspiration.

Main finding: AquaCrop was suitable for general assessment, yet its simplicity constrained precision under severe nutrient deficiency. DSSAT produced a more graduated response at the cost of a more demanding calibration, revealing the necessity to refine paddy-specific biogeochemistry representations in models.

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Introduction

Paddy rice (*Oryza sativa* L.) plays a critical role in global food security, providing sustenance for billions of people and supporting the agricultural economies of many nations, particularly in Asia (Papademetriou et al., 2000). Rice cultivation is central to Thailand's agricultural sector, where it engages 65% of farming households (Rice Department and Department of Internal Trade, 2019). Paddy fields constitute over 40% of the nation's agricultural land, covering approximately 10 million of a total of 23.6 million ha (Office of Agricultural Statistics, 2024). Consequently, efficient water and nutrient management, especially for nitrogen (N), is imperative to optimize yields, enhance resource use efficiency and mitigate the environmental effects of fertilizer application in flooded rice systems (He et al., 2021; Sossa et al., 2025; Kadyampakeni et al., 2025).

Crop simulation models (CSMs) are indispensable tools in modern agricultural science for representing complex interactions within the soil-plant-atmosphere continuum (Di Paola et al., 2016). Such models enable researchers to conduct virtual experiments, which allow for evaluation of scenarios that are otherwise impractical to test via traditional field trials, thereby helping to optimize on-farm strategies and inform policy (Kadiyala et al., 2015).

CSMs vary in complexity, data needs and foundational principles. The Decision Support System for Agrotechnology Transfer (DSSAT) model is a comprehensive, process-based model offering a detailed, mechanistic simulation of the soil-plant-atmosphere system (Hoogenboom et al., 2020). As a carbon-driven model, it calculates biomass based on radiation use efficiency and simulates phenology and biomass partitioning in detail. This mechanistic depth demands intensive data inputs, including comprehensive soil and weather files, specific management records and rigorously calibrated, cultivar-specific genetic coefficients (Jones et al., 2003). Alternatively, the Food and Agriculture Organization's AquaCrop model was developed to balance simplicity with accuracy and robustness, which makes it well-suited for practitioners due to its comparatively low data requirements (Steduto et al., 2009). Its growth engine is water-driven, simulating daily biomass from crop transpiration and prioritizing canopy cover over leaf area index as a key variable (Raes et al., 2009).

While numerous studies have compared the predictive performance of various CSMs (Li et al., 2020; Feleke et al., 2021), they have demonstrated a consistent trade-off between

the complexity and potential accuracy of models, such as DSSAT, and the simplicity and utility of AquaCrop. However, often these comparisons devote less attention to the practical aspects of model application that influence usability, such as the arduous calibration for nutrient stress, the requisite field data for such calibrations and the resulting balance between model complexity, data demands and predictive accuracy under varied fertility conditions (Seidel et al., 2018; Wallach et al., 2024). An appreciation of these practicalities is critical for the effective adoption of crop models in agricultural research. Therefore, the current study involved a detailed comparative case study for rice, which should offer insights for researchers globally who must select and implement models for nutrient management, particularly in environments with limited data availability.

In Thailand, DSSAT has been applied to rice research for over three decades (Pannangpetch et al., 1991; Cheyglinted et al., 2001; Wikarmpapraharn and Kositsakulchai, 2010; Marled and Kositsakulchai, 2021). Although AquaCrop has seen increasing global application for rice under various water and nutrient regimes (Amiri et al., 2014; Amiri, 2016), its application to Thai rice varieties has been less documented (Karakul et al., 2025; Plengwuttikrai et al., 2025). The current study addressed this gap by presenting a comparative analysis of AquaCrop and DSSAT using a detailed dataset from a pot experiment on the RD43 rice variety. RD43 is of growing importance in Thailand due to its short harvest duration, moderate disease resistance and lower glycemic index (Nagprachaya et al., 2017; Vasusans et al., 2017); however, optimal nutrient management strategies for this cultivar, particularly those informed by modeling, remain underexplored.

Therefore, this research investigated several key issues: 1) the differences in the calibration approaches and data requirements between AquaCrop and DSSAT when simulating the response of RD43 rice to varied nitrogen levels; 2) comparison of the performance of AquaCrop versus DSSAT in predicting key variables (biomass, grain yield, evapotranspiration) across a fertility gradient; and 3) the practical trade-offs between calibration simplicity and predictive accuracy when using these models for paddy rice and subsequent guidance that can be offered to researchers.

Materials and Methods

Experimental detail for RD43 paddy rice

A pot experiment was conducted from 13 June 2019 to 4 October 2019 in the experimental field of the Kasetsart University Kamphaeng Saen Campus in Nakhon Pathom, Thailand ($14^{\circ}02'12.40''$ N, $99^{\circ}57'41.90''$ E; Fig. 1). The study utilized the RD43 rice variety, a non-photoperiod-sensitive Thai cultivar recognized for its short maturation period and low glycemic index (Nagprachaya et al., 2017; Vasusans et al., 2017). This cultivar was selected due to its growing importance in Thai rice production and the limited research on its nutrient management using simulation models.

The experiment was arranged as a 2×3 factorial in a completely randomized design. The factors were the two planting methods—wet direct sowing (WS) and transplanting (TP)—and three soil fertility levels. The fertility levels consisted of three nitrogen (N) application rates: a recommended rate (N1; 75.94 kg N/ha), one-half of the recommended rate (N2; 37.97 kg N/ha) and a zero-N control (N3). Following the recommendations of Thailand's Department of Agriculture (Department of Agriculture, 2004), fertilizer for the N1 treatment was applied in two splits: 218.75 kg/ha of 15-15-15 (N-P-K) fertilizer (1.72 g/pot) at 20 days after planting/sowing (DAP) and 93.75 kg/ha of 46-0-0 (urea) fertilizer (0.74 g/pot) at 40 DAP. The N2 treatment received 50% of the N1 rates at the same schedule.

The experiment utilized 36 square plastic pots ($28 \text{ cm} \times 28 \text{ cm}$ and 35 cm deep), each filled with soil to a 20 cm depth. The six treatment combinations were replicated six times. For the WS method, approximately 30 RD43 seeds (0.98 g/pot) were sown directly into each pot on 13 June 2019. For the TP method, seeds were sown in a nursery bed on the same date; subsequently, seedlings aged 20 d were transplanted into the experimental pots on 2 July 2019.

Paddy conditions were prepared by maintaining a continuous standing water level of approximately 5 cm above the soil surface to prevent water stress. The pots were sealed at the bottom to eliminate deep percolation. All plants were harvested on 4 October 2019.

Data collection and measurements

Meteorological data

Daily meteorological data (Fig. 2) were recorded during May–October 2019 using an on-site weather station (Vantage Pro2 Plus; Davis Instruments; USA). The recorded variables were: total rainfall (326.6 mm), maximum and minimum air temperature ($34.4 \pm 2.2^{\circ}\text{C}$ and $25.0 \pm 0.8^{\circ}\text{C}$, respectively), average wind speed ($0.29 \pm 0.18 \text{ m/s}$), solar radiation ($197.1 \pm 57.2 \text{ MJ/m}^2/\text{day}$) and relative humidity ($82.7 \pm 6.1 \%$), where data are presented as mean $\pm$ SD values.

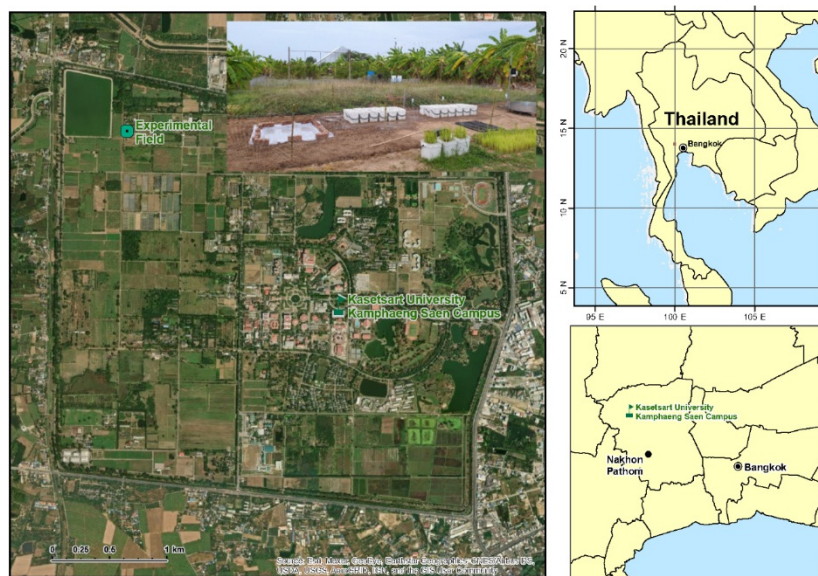


Fig. 1 Experimental field location at Kasetsart University, Kamphaeng Saen Campus, Nakhon Pathom, Thailand

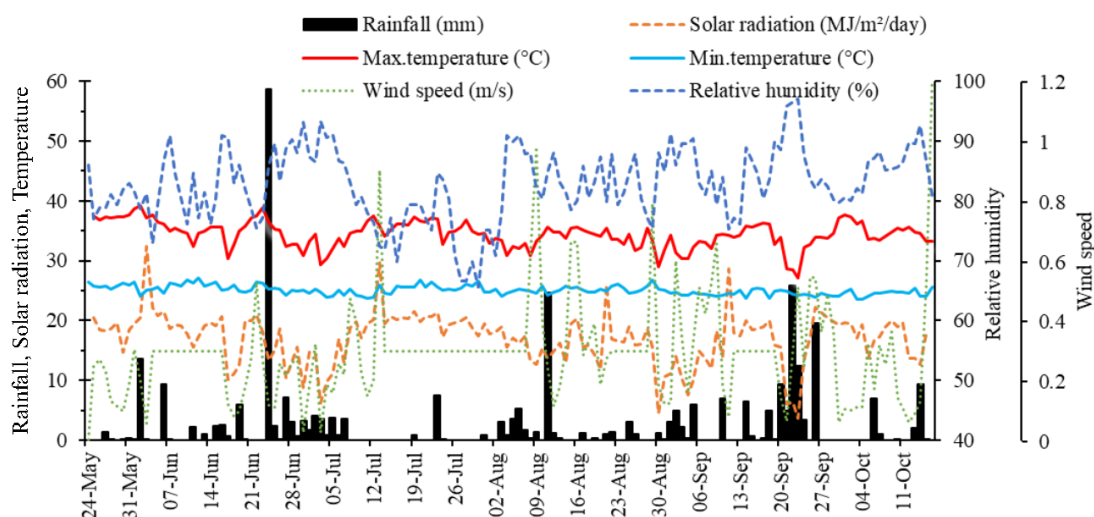


Fig. 2 Daily meteorological data at the experimental field (24 May 2019–15 October 2019). Max. = maximum; Min. = minimum.

Soil properties

Prior to the experiment, samples of the soil used to fill the experimental pots were collected and analyzed for key physical and chemical properties at the Soil Science Laboratory, Faculty of Agriculture at Kamphaeng Saen, Kasetsart University, Thailand. The physical properties were: particle size distribution (84% sand, 14.9% silt, 0.3% clay); bulk density (1.94 g/cm³); and particle density (2.74 g/cm³). The chemical properties were: pH (7.93); organic matter content (0.5%); electrical conductivity (0.64 dS/m); available N (21.32 mg/kg); and cation exchange capacity (5.01 milliequivalents per 100 grams of soil).

Water application and crop water use

The volume of water was recorded that was added daily to each pot to maintain the 5 cm standing water level. Subsequently, daily crop evapotranspiration (ET) was estimated based on the daily decrease in water level.

Rice phenology and development

Key phenological stages—emergence, panicle initiation, anthesis (flowering) and physiological maturity—were observed and their occurrence was recorded in days after planting/sowing (DAP).

Biomass and grain yield

At physiological maturity, all above-ground plant components were harvested, separated and weighed. Then, the samples were oven-dried to a constant weight to determine the total above-ground biomass and dry grain yield.

AquaCrop setup and nutrient response calibration

Simulations of growth, yield and water use for RD43 rice were performed using the FAO AquaCrop model (version 7.0; <https://www.fao.org/aquacrop/software/en>). The model requires four categories of input data: climate, crop, soil and management practices.

Meteorological and climate inputs

Daily meteorological data were formatted into AquaCrop-specific files: rainfall (*.PLU), minimum and maximum air temperature (*.Tnx) and reference evapotranspiration (*.ETo). The ETo values were calculated using the FAO Penman-Monteith equation (Allen et al., 1998). In addition, the model utilized the default atmospheric carbon dioxide file (GlobalAverage.CO2).

Crop cultivar parameterization

Crop parameters were adapted from the default file for lowland paddy rice (PaddyRiceGDD.CRO). For the two establishment methods, the model was set to “sown crop” for WS and “transplanted crop” for TP, with a plant density of 382 plants/m² for both. Based on observations, the initial canopy cover (CCo) was set to 3.82% for WS and 19.10% for TP. Key developmental parameters—phenology, canopy growth coefficient (CGC) and canopy decline coefficient (CDC)—were calibrated using experimental observations for the RD43 cultivar. Default values were retained for conservative parameters such as base and upper temperatures, maximum rooting depth, maximum canopy cover (CCx),

normalized water productivity (WP*) and reference harvest index (HIO). The complete set of default and calibrated parameters for the RD43 cultivar is detailed in Table 1.

Soil profile setup

The soil profile was defined as a loamy sand based on laboratory analysis of the experimental soil. A two-layer profile was created to represent the pot conditions. The 0.20 m upper layer had experimentally determined water content values for the permanent wilting point (PWP) of 20.0%, field capacity (FC) of 37.0% and saturation (SAT) of 48.3%. The saturated hydraulic conductivity (Ksat) for this layer was 1466.4 mm/d. The impermeable pot bottom was simulated by assigning a Ksat of 0 mm/d to the 0.01 m lower layer.

Field management inputs

The management parameters included a bund height of 0.15 m, corresponding to the pot freeboard. Flooded conditions were maintained based on applying an irrigation schedule of 50 mm of water whenever the simulated water level fell to a 10 mm threshold above the soil surface.

Nutrient response calibration

The model response to nutrient availability was calibrated based on a manual, iterative procedure. First, the potential biomass (BMx) was simulated under non-limiting conditions,

yielding 15,131 kg/ha for WS and 16,139 kg/ha for TP. Second, the observed above-ground dry biomass from each fertility treatment (N1, N2, N3) was expressed as a percentage of the corresponding BMx. For WS, these relative biomass values were 49% (N1), 30% (N2) and 12% (N3); for TP, they were 38% (N1), 25% (N2) and 11% (N3). Third, these values were used to adjust AquaCrop's soil fertility stress parameters. The "Minimum soil fertility level for calibration" was adjusted to 88% for WS and 89% for TP. The shape factors (SFs), which govern the stress response curve, were adjusted from a default of 25 to match the observed biomass reductions, using the N3 treatment as the reference for severe stress. A key challenge was a model limitation that prevented simulating fertility stress below a threshold of approximately 17% of potential production, making it difficult to represent the lower observed biomass (11–12%) in the N3 treatment.

DSSAT setup and nutrient response calibration

The second model evaluated was DSSAT (version 4.7.2), utilizing the CERES-Rice crop module (Singh et al., 1993). Similar to the AquaCrop setup, this process required preparing input files for meteorological conditions, soil profile characteristics and crop management. A critical step in the procedure was the calibration of cultivar-specific genetic coefficients to represent the RD43 rice variety accurately.

Table 1 Calibrated AquaCrop crop parameters for RD43 rice under wet direct sowing (WS) and transplanting (TP) methods.

Crop parameter	Unit	Default	Calibrated (WS)	Calibrated (TP)
(A) Growth and development parameters				
Crop establishment method (crop_is_sown)	-	0	1 (sown)	0 (transplanted)
Base temperature for growth	°C	8	8	8
Upper temperature for growth	°C	30	30	30
Canopy growth coefficient	per day	0.12257	0.14571	0.07675
Canopy decline coefficient	per day	0.09330	0.09556	0.09556
Maximum rooting depth	m	0.5	0.5	0.5
Maximum canopy cover	fraction	0.95	0.95	0.95
Normalized water productivity	g/m ²	19	19	19
Reference harvest index	%	43	43	43
Days from sowing to emergence	day	3	3	3 (nursery)
Days from sowing/transplanting to flowering	day	65	59	59
Days from sowing/transplanting to start of senescence	day	73	67	67
Days from sowing/transplanting to physiological maturity	day	104	98	98
Length of the flowering stage	day	19	18	18
Initial canopy cover from canopy size of seedling	%	(varies)	3.82	19.10
Plant density	Plants/ha	1,000,000	3,820,000	3,820,000
(B) Parameters for response to soil fertility stress				
Minimum soil fertility for calibration of stress response	%	50	88	89
Shape factor for response of canopy expansion to soil fertility stress	-	25	5.09	6.45
Shape factor for response of maximum canopy cover to soil fertility stress	-	25	1.57	1.18
Shape factor for response of crop water productivity to soil fertility stress	-	25	2.74	3.23
Shape factor for response of decline of canopy cover to soil fertility stress	-	25	6.84	6.84

Model input preparation

Daily meteorological data (maximum/minimum air temperature, rainfall, solar radiation) were formatted according to DSSAT's YYDOY structure. The soil profile, derived from laboratory analyses, was transformed into the DSSAT soil file format. The pot experiment was replicated based on adjusting the soil profile settings to simulate a closed-bottom system with no deep percolation.

Experimental management practices were specified in the DSSAT Experiment file (X-file). These inputs included the planting method (WS and TP), establishment date and a plant density of 382 plants/m². Irrigation was configured to maintain continuously flooded conditions, with a constant 5 cm flood depth and zero percolation. The three nitrogen treatments (N1, N2, N3) were defined with precise application dates, fertilizer types and amounts according to the experimental protocol. Within the model, simulation options were set to allow both water and nitrogen to be growth-limiting factors.

Calibration of genetic coefficients

A critical component of the DSSAT setup was the calibration of genetic coefficients (GCs) for the RD43 rice variety, as these coefficients govern the simulation of growth, phenology and yield. The Thai rice variety Suphanburi 60 was used as the base for calibration (Jintrawet et al., 2015) because RD43 is not a predefined cultivar in DSSAT. The process was performed using the Generalized Likelihood Uncertainty Estimation (GLUE) tool, which involved 6,000 simulation runs with systematically varied parameter sets. The GLUE tool used

observed data on phenology and final grain yield from all treatments to identify the optimal set of GCs (P1, P2R, P5, P2O, G1, G2, G3, G4) that provided the best fit to the observed performance of RD43. The initial and final calibrated GCs are detailed in Table 2. Using these coefficients, the model simulated the crop's response to soil fertility via its integrated nitrogen balance and uptake sub-models.

Model assessment and data analysis

The practical aspects were compared for calibrating each model and its subsequent performance in simulating key crop variables.

Calibration practicality

The practical aspects were compared qualitatively for calibrating AquaCrop and DSSAT for nutrient response. The comparison focused on the specific procedural steps, the required experimental data and the complexity of adjusting nutrient-related parameters for each model.

Model performance evaluation

Following calibration, model performance was evaluated by comparing simulated outputs (above-ground dry biomass, grain yield, total crop evapotranspiration) against observed data. The agreement between simulated and observed values was quantified using the percentage difference (%Diff), calculated as shown in Equation 1:

$$\%Diff = ((\text{Simulated} - \text{Observed}) / \text{Observed}) \times 100 \quad (1)$$

Table 2 Initial and calibrated genetic coefficients for RD43 Rice in the DSSAT-CERES-Rice model

Parameter	Description	Unit	Initial Value	Calibrated Value
P1	Time period from seedling emergence to start of photoperiod-sensitive phase (basic vegetative phase)	GDD (°C)	540	404.0
P2R	Extent to which phasic development leading to panicle initiation is delayed for each hour increase in photoperiod above P2O (critical photoperiod)	GDD (°C)	154.7	183.2
P5	Time period from beginning of grain filling (3–4 d after flowering) to physiological maturity	GDD (°C)	497	574.9
P2O	Critical photoperiod: longest day length (hours) for which development occurs at maximum rate. Longer daylengths delay development.	hour	11.9	12.3
G1	Potential spikelet number coefficient (spikelets per gram of main culm dry weight at anthesis, less leaf blades/sheaths)	number/g	77.7	79.3
G2	Single grain weight (mass per GDD) under ideal growing conditions (non-limiting light, water, nutrients)	g	0.028	0.029
G3	Tillering coefficient (scalar value) relative to standard cultivar (IR64) under ideal conditions.	-	1	0.99
G4	Temperature tolerance coefficient (scalar influencing high/low temperature stress on spikelet sterility, typically 1.0 for varieties in normal environments)	-	1	1.12

GDD = Growing Degree Days (thermal time required for plant development)

This metric indicates overestimation (positive values) or underestimation (negative values). Further statistical indicators were not calculated due to the limited number of observations; therefore, the comparison relied on mean values.

Statistical analysis

Data from the pot experiment were subjected to a two-way analysis of variance (ANOVA) (Kutner et al., 2005) to evaluate the main effects of the planting methods, nitrogen fertility levels and their interactions on above-ground biomass, grain yield, and crop evapotranspiration. All statistical analyses were performed using the R software environment (R Core Team, 2024). Where significant main effects or interactions were identified, means were compared using Tukey's Honestly Significant Difference (HSD) test. Statistical significance was determined at the $p < 0.05$ and $p < 0.01$ levels.

Results

Experimental rice response to planting methods and nitrogen fertility

Based on the experimental results, the performance of RD43 rice was influenced by both the planting method and the nitrogen fertility level. A two-way analysis of variance confirmed that both factors had significant ($p < 0.05$) main effects on all measured variables (Table 3). Overall, the WS method produced higher values for mean biomass, grain yield

and ET than the TP method. Nitrogen fertility had a marked effect, with the biomass, yield and ET all decreasing as the N application was reduced from N1 to N3. Additionally, significant ($p < 0.05$) interaction effects between the planting method and the nitrogen level were observed for biomass and ET, but not for grain yield.

Comparative model performance in simulating nutrient effects

Table 4 summarizes the performance of the calibrated AquaCrop and DSSAT models in simulating above-ground biomass, grain yield and ET.

Above-ground biomass simulation

Under high fertility (N1), both models produced plausible biomass simulations. The AquaCrop predictions were in closer agreement with the observed values for both WS (+5.7% difference) and TP (+2.9% difference) compared to DSSAT (WS, +9.3%; TP, +37.4%). As fertility decreased to the N2 level, both models overestimated the biomass, though the overestimation was greater for AquaCrop (+36.7% for WS, +46.8% for TP) than for DSSAT (+12.7% for WS, +14.2% for TP). Under severe nutrient stress (N3), AquaCrop substantially overestimated biomass for both WS (+256.3%) and TP (+222.1%), whereas DSSAT overestimated for WS (+12.5%) but underestimated for TP (−35.0%). The substantial overestimations by AquaCrop for the N3 scenarios could be attributed to this model's limitation that prevents setting soil fertility stress below a threshold of approximately 17% of potential production, while the observed relative biomass was lower (11–12%).

Table 3 Observed mean values ($\pm$ SD) for above-ground biomass, dry grain yield and evapotranspiration (ET) of RD43 rice under different planting methods and nitrogen fertility levels, with two-way analysis of variance summary

Nitrogen (N) fertility level	Planting method (PM)	Biomass (g/pot)	Yield (g/pot)	ET (mm)
N1	WS	58.28 $\pm$ 4.27	27.29 $\pm$ 3.24	628.24 $\pm$ 15.71
	TP	48.08 $\pm$ 4.20	21.69 $\pm$ 3.31	605.29 $\pm$ 34.03
N2	WS	36.00 $\pm$ 7.74	17.46 $\pm$ 5.42	557.88 $\pm$ 32.29
	TP	31.58 $\pm$ 4.25	15.33 $\pm$ 2.71	504.33 $\pm$ 17.14
N3	WS	14.81 $\pm$ 2.54	6.53 $\pm$ 1.48	442.84 $\pm$ 14.99
	TP	14.39 $\pm$ 1.83	6.16 $\pm$ 0.89	446.34 $\pm$ 12.35
Source of variation		Significance (p value)		
PM		**	*	**
N		**	**	**
PM $\times$ N interaction		*	ns	*

Values are mean $\pm$ SD of six replications ($n = 6$). WS = wet direct sowing; TP = transplanting; N1 = recommended rate (75.94 kg N/ha); N2 = approximately one-half of recommended rate (37.97 kg N/ha); N3 = zero-N control (0 kg N/ha); ET = daily crop evapotranspiration.

ns = non-significant; * and ** denote significant at $p < 0.05$ and $p < 0.01$, respectively.

Table 4 Comparison of observed experimental data with simulated values from AquaCrop and DSSAT for above-ground biomass, grain yield and evapotranspiration (ET) of RD43 rice

Parameter	N level	Planting method	Observed (experiment)	AquaCrop simulation	AquaCrop (%Diff)	DSSAT simulation	DSSAT (%Diff)
(A)							
Biomass (kg/ha)	N1	WS	7,434	7,856	+5.7	8,127	+9.3
		TP	6,132	6,311	+2.9	8,428	+37.4
	N2	WS	4,591	6,278	+36.7	5,176	+12.7
		TP	4,027	5,911	+46.8	4,600	+14.2
	N3	WS	1,889	6,729	+256.3	2,124	+12.5
		TP	1,835	5,911	+222.1	1,192	−35.0
(B)							
Yield (kg/ha)	N1	WS	3,481	3,378	−3.0	3,141	−9.8
		TP	2,766	2,714	−1.9	3,407	+23.2
	N2	WS	2,228	2,699	+21.2	2,006	−10.0
		TP	1,956	2,542	+30.0	1,665	−14.9
	N3	WS	833	2,893	+247.2	837	+0.5
		TP	786	2,542	+223.4	369	−53.1
(C)							
ET (mm)	N1	WS	628.2	358.0	−43.0	379.9	−39.5
		TP	605.3	416.0	−31.3	378.9	−37.4
	N2	WS	557.9	393.0	−29.6	380.0	−31.9
		TP	504.3	395.0	−21.7	379.0	−24.9
	N3	WS	442.8	389.0	−12.2	380.1	−14.2
		TP	446.3	395.0	−11.5	379.1	−15.1

%Diff = ((Simulated value − Observed value) / Observed value) × 100; WS = wet direct sowing; TP = transplanting; N1 = recommended rate (75.94 kg N/ha); N2 = approximately one-half-recommended rate (37.97 kg N/ha); N3 = zero-N as control (0 kg N/ha).

Positive values for percentage difference (%diff.) indicate model overestimation, while negative values indicate underestimation.

Grain yield simulation

For grain yield under high fertility (N1), AquaCrop's simulations were again in closer agreement with observations (WS, −3.0%; TP, −1.9%) than with DSSAT (WS, −9.8%; TP, +23.2%). At the N2 level, AquaCrop overestimated the yield for both methods (+21.2% for WS, +30.0% for TP), while DSSAT underestimated it (−10.0% for WS, −14.9% for TP). Under severe N stress (N3), AquaCrop once more substantially overestimated grain yield (+247.2% for WS, +223.4% for TP), whereas in contrast, DSSAT provided a much closer estimate for WS (+0.5%) but substantially underestimated the yield for TP (−53.1%).

Evapotranspiration simulation

Both models consistently underestimated ET across all treatments. Under N1 conditions, the magnitude of underestimation was comparable between AquaCrop (−43.0% for WS, −31.3% for TP) and DSSAT (−39.5% for WS, −37.4% for TP). This deviation from observed values diminished as fertility decreased. For AquaCrop, the underestimations fell to −29.6% (WS) and −21.7% (TP) at the N2 level and further to −12.2% (WS) and −11.5% (TP) at the N3 level. A similar trend

was observed for DSSAT, with underestimations of −31.9% (WS, N2), −24.9% (TP, N2), −14.2% (WS, N3) and −15.1% (TP, N3).

Discussion

The comparative analysis of the AquaCrop and DSSAT models revealed critical trade-offs between their calibration practicalities and predictive performance. The experimental results, which established the pronounced effects of planting method and nitrogen availability on rice productivity, provided a robust foundation for this model evaluation. These performance differences were interpreted based on examining the models' contrasting designs, their response to varying nitrogen supply and the broader implications for their application in paddy rice systems.

Contrasting approaches to calibration and data utilization for nutrient response

The divergent calibration approaches of AquaCrop and DSSAT are rooted in their core designs. AquaCrop,

prioritizing simplicity and robustness, applies a direct method for calibrating soil fertility stress (Steduto et al., 2009; Van Gaelen et al., 2014). This approach adjusts parameters based on observed relative biomass under different nitrogen supplies, using aggregated outputs, such as final biomass, to make the calibration process less data-intensive (Van Gaelen et al., 2014). On the other hand, DSSAT is a mechanistic tool that requires a more demanding calibration (Jones et al., 2003; Hoogenboom et al., 2020). Its nutrient response is an emergent property derived from the interaction between calibrated, cultivar-specific genetic coefficients and the internal nitrogen balance sub-models. This mechanistic approach, while powerful, requires comprehensive experimental data covering multiple growth stages across the entire stress gradient. This difference is a critical consideration for model users, particularly given the challenges of collecting such detailed data for the many rice varieties in Thailand (Jintrawet et al., 2015).

Model performance trade-offs under varying nitrogen supply levels in paddy rice

Under high-fertility conditions (N1), both AquaCrop and DSSAT capably simulated biomass and grain yield. This outcome was consistent with other published research, which indicated that well-parameterized models could achieve high accuracy under optimal conditions (Amiri et al., 2014; Li et al., 2020). The comparable performance, despite disparate calibration methods, confirmed that both models adequately captured the potential growth of RD43 rice when nutrients were not limiting.

However, as nitrogen availability decreased, the predictions diverged, with AquaCrop consistently overestimating the biomass and yield under moderate (N2) and especially under severe (N3) stress. This pronounced overestimation under the N3 treatment, as detailed in Table 4, was likely a direct consequence of a structural limitation within the model. AquaCrop's fertility stress mechanism prevents calibration below a certain threshold (approximately 17% of potential production), causing it to underestimate the impact of very low N supply levels (Raes et al., 2009; Van Gaelen et al., 2014). While specific studies detailing this limitation for severe nutrient stress in rice are limited due to AquaCrop's relatively recent application in this context, the current finding aligns with the expected trade-offs of its simplified design compared to more mechanistic models. However, DSSAT produced a more graduated response to decreasing N levels and its more detailed nitrogen balance module enabled a more robust simulation across the fertility gradient.

A shared deficiency was the consistent underestimation of ET by both models, particularly under high fertility. While the percentage of underestimation decreased in the N2 and N3 treatments, this was likely an artifact of the lower absolute ET in smaller, stressed plants rather than an improvement in model accuracy. This systemic underestimation could be attributed to challenges in measuring ET in pots (Karakul et al., 2025), issues in parameterizing canopy development, or algorithmic limitations in calculating evaporation from a flooded surface.

Implications for model selection and application in paddy rice systems

The trade-off between model complexity and practical utility was evident in comparing AquaCrop and DSSAT for simulating nutrient effects in paddy rice. AquaCrop's simpler calibration approach, which relies on final biomass data, is advantageous in data-scarce regions where intensive soil and phenological measurements are unavailable, making it a viable tool for initial assessments (Steduto et al., 2009; Di Paola et al., 2016). However, its utility is constrained in conditions of very low soil fertility. Structural limitations in representing extreme nutrient stress could lead to an overestimation of yield and the model design precludes the mechanistic simulation of dynamic nutrient availability (N, P, K) and its interaction with water management—key drivers of yield gaps in nutrient-poor soils (He et al., 2021; Sossa et al., 2025).

On the other hand, DSSAT's mechanistic approach more effectively captured the crop responses across a broader fertility gradient, provided it was well-calibrated (Hoogenboom et al., 2020). This capability came at the cost of intensive data requirements for robustly calibrating the GCs and characterizing soil N dynamics—a substantial challenge given the genetic diversity of Thai rice varieties (Jintrawet et al., 2015; Seidel et al., 2018). Furthermore, DSSAT's soil nutrient modules were developed primarily for upland systems and do not adequately represent the unique, redox-driven biogeochemical transformations that govern nutrient fate in flooded paddy soils (Li et al., 2020). Therefore, while DSSAT may offer more detailed insights into nitrogen cycling, its outputs must be interpreted with caution due to these paddy-specific biogeochemical limitations.

Study limitations and future research

Several limitations should be considered when interpreting the results of this study. The research was based on a single rice cultivar (RD43) grown in pots under controlled conditions. Although this setup enabled precise control over water and nutrients, it could not replicate fully the complex interactions of a field ecosystem, including lateral water movement, larger soil volumes and field-scale microclimates. Therefore, a crucial next step for future research would be field-scale validation of both models using the calibrated parameters.

Beyond the constraints of a pot study, this analysis has revealed critical research gaps that hinder the reliable application of crop models in Thai rice agriculture. First, the simulation of soil fertility dynamics in paddy systems is inadequate; AquaCrop's simplified module cannot distinguish specific nutrient limitations, while DSSAT's N-module was not designed for the unique biogeochemical processes in flooded soils (Li et al., 2020). Second, a substantial gap exists in the availability of calibrated parameters for key Thai rice varieties, a challenge compounded by the high genetic diversity of local landraces (Jintrawet et al., 2015). Third, an inadequate representation of diverse farmer management practices in typical calibration efforts creates a disconnect with real-world farm variability (Seidel et al., 2018).

These interconnected gaps affirm the compelling need for new, fundamental experimental data. Controlled pot experiments remain one of the most scientifically rigorous and resource-efficient methods for generating the high-quality data required to address these deficiencies (Wallach et al., 2024). This approach permits precise control over environmental factors, which is necessary for isolating the cause-and-effect relationships needed for model improvement. The primary contribution of such an experiment would be a rich dataset for calibrating GCs, parameterizing AquaCrop's fertility response and improving nutrient sub-models for paddy conditions.

Building on foundational pot experiments, future research should prioritize several key areas. Calibration and validation must be expanded to other major Thai rice varieties across different agroecological zones. The AquaCrop soil fertility module warrants further investigation to better capture responses to severe nutrient deficiencies, while the simulation of ET in flooded conditions needs improvement in both models. Another critical research avenue is the evaluation of model performance under combined stresses (such as nutrient and water deficits), particularly for rain-fed systems.

Finally, there is considerable potential in integrating these models with remote sensing and socio-economic analyses to generate tangible impacts for farm management (Kadiyala et al., 2015).

In conclusion, this comparative study has demonstrated the critical trade-offs between calibration simplicity and predictive accuracy in models for simulating nutrient stress in paddy rice. AquaCrop offers a less data-intensive calibration pathway suitable for initial assessments; however, its structural limitations compromise accuracy under severe nitrogen deficiency. Although parameterizing DSSAT is more difficult, it provides a more robust and graduated response across a wider fertility gradient. However, the consistent underestimation of evapotranspiration in both models indicates a shared challenge in simulating paddy-specific conditions. Based on the current results, there is a need for future research focused on field-scale validation, refining model algorithms for flooded systems and developing robust GS sets for diverse Thai rice varieties to enhance the utility of these models in both research and practical nutrient management.

Conflict of Interest

The authors declare that there are no conflicts of interest.

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