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RESEARCH ARTICLE

Evaluating rice yield and resource efficiency: DSSAT analysis of conventional vs. AWD techniques in Coimbatore

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Abstract

Rice cultivation is a key activity of Indian agriculture, contributing significantly to global rice production and exports. Optimal yield is crucial and influenced by various agronomical and environmental factors. For the experiment, the decision support system for agro technology transfer (DSSAT) of the rice crop model is utilized to validate the grain and straw yield in addition to resource productivity metrics and leaf area index. The study was conducted during the Zaid season from January to May in both 2022 and 2023 at the Thensangampalayam village, Coimbatore district, Tamil Nadu. The CO-55 rice variety was used for 2 cultivation methods i.e., conventional and alternate wetting and drying (AWD), along with drone spray of nano urea. The model was calibrated and validated with the input of comprehensive datasets of soil profile, meteorological parameters, crop-specific cultivation methods, agronomic practices and genetic coefficients. AWD consistently outperformed the conventional method in both grain and straw yields. DSSAT simulations achieved a high accuracy of 99.78 % in grain yield and 91.67 % in straw yield between the 2 cultivation methods. The AWD also outperformed in water use efficiency with 2.3 kg/m^3 compared to conventional at 1.8 kg/m^3. Leaf Area Index was recorded high in the conventional method at heading stage with 6.96 and AWD at 6.46. The study provides valuable information on adaptive farming practices and climate-resilient crop management strategies.

Keywords

Rice; DSSAT model; grain yield; straw yield; genetic coefficient; alternate wetting and drying

Introduction

Rice (*Oryza sativa* L.) is a staple crop of critical importance in India and is essential for global food security. In 2024, global rice exports are projected to reach approximately 22.9 million tons. (India Rice stat, 2024). With India positioned as the second largest producer of rice, achieving optimal yield remains a crucial objective amidst increasing population and to cater its needs along with changing climatic conditions. Recent research accentuates the use of model-based simulation models to analyze soil and meteorological parameters for predicting rice yield responses to changing climate and population growth. understanding how yield changes are linked with environmental variability and management interventions. Therefore, achieving sustainable production and food system resilience requires predicting rice yield under diverse conditions using highly developed computer-based tools that simulate crop growth and development.

Rice is cultivated under different ecosystems namely irrigated, rainfed lowland, deep water and upland (1). Based on the topography and ecosystem of the experimental location, the selection of specific cultivars or varieties (2) and cultivation methods of rice also play a key role in bringing variations in rice yield. Traditionally, rice cultivation relies on conventional methods that demand significant water usage. Ineffective water management can result in decreased yields, highlighting the critical need for adopting efficient cultivation practices to achieve optimal rice production

Proper irrigation management and timely application of nitrogen are crucial factors in the cultivation of rice (3). In addition to the foliar application of nitrogen at recommended doses, nano urea is also employed. This dual approach aims to enhance nutrient efficiency and improve overall crop performance. Drone spraying of nano urea in rice crops at crucial stages of crop growth like active tillering and panicle initiation is a new frontier in precision agriculture. Due to its nanoscale formulation, nano urea presents major advantages over traditional urea with regards to enhancement in the efficiency of nutrient uptake and less harm to the environment. Drone application ensures precision targeting and uniform coverage of any nutrient for optimal delivery at the right place of the plants. It has been observed that nano urea can increase crop yield significantly by decreasing nitrogen losses caused by leaching and volatilization. According to the studies (4,5), this technology has the potential to enhance fertilizer use efficiency, reduce huge amount of fertilizer and GHG emissions (6), therefore making it a promising addition to enhance rice productivity.

Environmental factors, such as temperature, solar radiation, rainfall, humidity, evapotranspiration and CO_2 emissions significantly impact crop production by disrupting irrigation schedules, photosynthetic activity and physiological metabolism, which directly affect the grain and straw yield of plant (7). Minimal variations in temperature can affect the performance of the cultivar and also the genetic coefficient of rice crop. Solar radiation is a crucial factor closely related to the leaf area index (LAI). Leaf growth significantly impacts the photosynthetic activity of rice, which in turn influences the accumulation of photosynthetic products in the grain during the filling stage and affects overall yield (8).

The DSSAT is a crucial tool for agronomic research and decision-making, providing detailed simulations of crop growth and yield. Developed and maintained by the University of Florida, DSSAT integrates multiple crop models, including CERES-Rice and Oryza2000, to offer comprehensive forecasts of plant development and productivity. The system allows users to evaluate the impacts of various environmental, meteorological and management conditions on crop performance. By accounting for factors such as soil characteristics, weather patterns and agricultural practices, DSSAT facilitates the optimization of crop management strategies and improves understanding of crop responses to different conditions. (9).

Recent study, simulations and validation tests carried out emphasize the reliability and usefulness of DSSAT in rice production studies. For yield prediction, calibration and validation of rice cultivars, cultivation methods, soil parameters, environmental factors and nitrogen levels using DSSAT are required in simulating yield under varying conditions (10).

A study on optimizing transplanting windows for rice cultivars in Punjab, India (11), by validating their prediction power on field data using DSSAT (11) compared DSSAT with other models projecting rice phenology and yield under projected climatic scenarios, which clearly offered better accuracy and applicability (12), employed the DSSAT in simulating upland rice yield responses to variable plant densities and nitrogen management strategies in order to guide optimization in rice-growing practices (13) explored the ability of DSSAT to compute the impact of climate change on rice production, with a view toward production processes and challenges that may be encountered in the near future, in Anambra state, Nigeria, using a set of historical climatic data (14).

This study emphasizes the need for DSSAT crop model simulations to predict rice yield under vastly different agroclimatic conditions and management practices. This study builds on these validations in order to employ DSSAT's capabilities for sustainable rice production. By incorporating detailed weather data and site-specific management practices, DSSAT is capable of providing accurate predictions that are extremely important for enhancing productivity and ensuring food security and as well as formulating appropriate agricultural policies in the times of a changing climate.

Materials and Methods

Study Area and Experimental Design

The study was conducted in Thensangampalayam village, situated at approximately 10.7650° N latitude and 77.7362° E longitude in Aliyar, Coimbatore, Tamil Nadu (Fig. 1). The climate remains mostly hot and humid throughout much of the year, with distinct wet and dry seasons. Monsoonal rains typically occur from July to September with an average rainfall of 700-800 mm, contributing significantly to the local agricultural cycles. The soil types in the area include sandy and clay loam predominantly, which support the cultivation of a variety of crops, such as rice, pulses and cotton. The study was conducted over 2 Zaid seasons, from January to May in both 2022 and 2023.

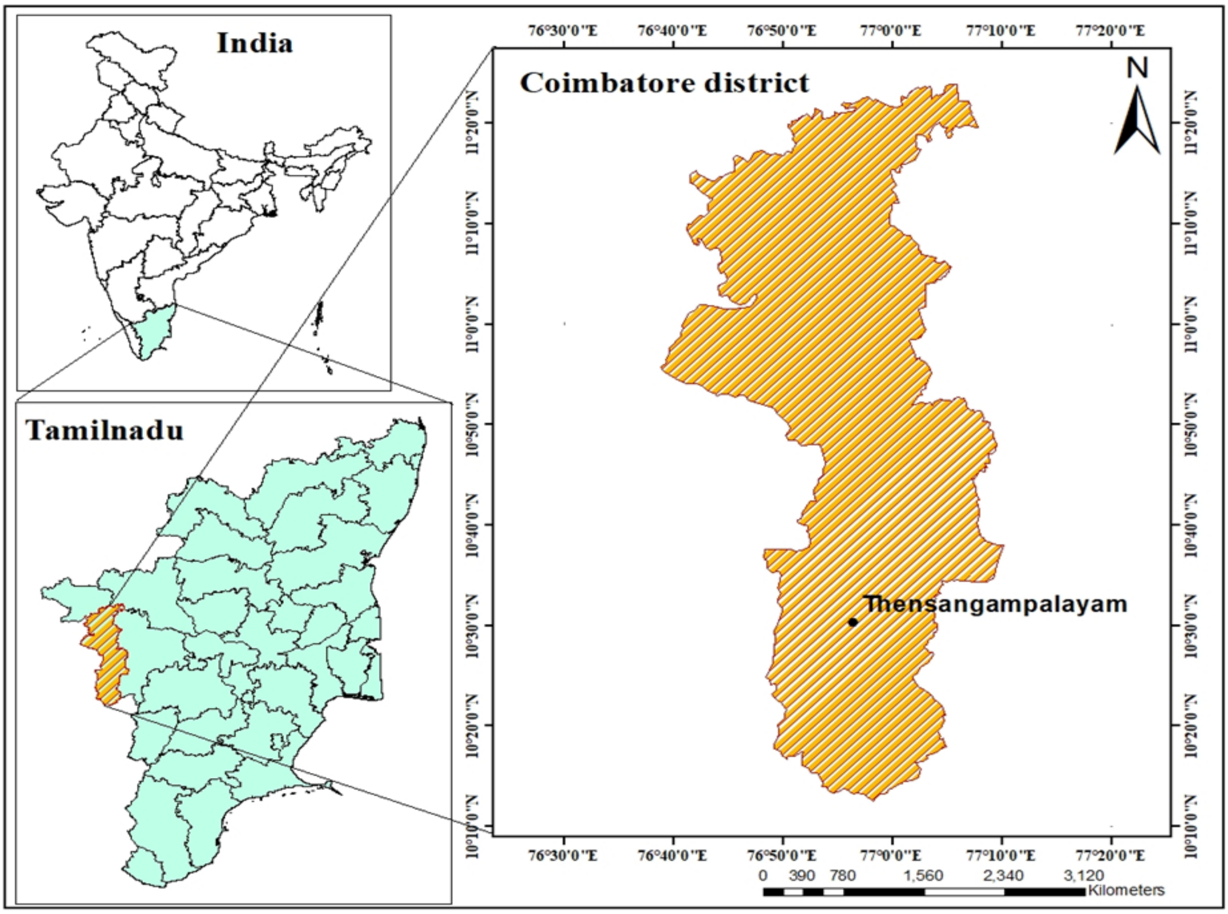

Fig. 1. Digital latitude and longitude map of Thensangampalayam village.

Plant Material and Sowing Date

The CO 55 rice variety was sourced from Tamil Nadu Agricultural University, known for its short duration of 110-115 days, was chosen for this study as this variety is well-suited to the *Zaid* season (December-January). The conventional method of crop was sown on 08-01-2022, 10-01-2023 and Alternate Wetting and Drying method was sown on 11-01-2022 and 14-01-2023 in an area of 150 ha. The cultivar was line sown in the field at a distance of 20 cm between rows for the conventional method and 25 cm for the AWD method.

Cultivation Methods

Two cultivation methods were compared: the conventional method and the AWD. The conventional method involves continuous submergence of rice fields with water maintained at 5 cm above the soil surface. Whereas, the AWD method uses intermittent wetting and drying of rice fields which helps in the aeration of soil and water use efficiency.

Fertilization and Nutrient Management

Nitrogen was applied using (IFFCO) neem-coated urea at recommended rates of 150-50-50 kg/ha NPK in split doses, while 0.4 % (IFFCO) nano urea sprayed via drone at 2 critical growth stages: active tillering and panicle initiation. This combined approach is designed to enhance nutrient uptake efficiency and minimize environmental impact (Fig. 2).

Fig. 2. Drone spray of nano urea in the experimental field.

Soil Data and Meteorological Parameters

The soil samples of the experimental field were collected and analysed for texture, pH, organic matter, nitrogen, phosphorus and potassium content. The soil data is presented in Table 1. Daily weather data, including temperature, rainfall, solar radiation and humidity were obtained from the nearest meteorological station to provide accurate input for the DSSAT model. The meteorological data for 2022 and 2023 are presented in a visual graph representing various meteorological parameters (Fig. 3).

The Table 1 dataset provides soil properties for different depths in a soil profile. Each row represents a specific soil depth range and the columns provide various measurements for those depths. The soil file for the study region is created using the soil information of the selected district. It involves soil texture, soil classification, the soil family CSC scheme, soil depth (cm), albedo (Fraction), evaporation limit (cm), flow rate (fractions per day), run-off curve number, mineralization factor (0 to 1), photosynthesis factor (0 to 1), buffer determination process pH, nitrogen, phosphorus and potassium determination process. The model also requires horizon-specific data, including the amount of horizon andits thickness (cm), field potential, crop point, air-dry level, reduced drained limit (cm^3 cm^{-3}), organic carbon content (%), its root development factor (kg^{-1}), water and buffer pH and cation exchange capacity (0.0 to 1.0) (15).

DSSAT v4.7.5 CERES-Rice Model Validation and Calibration

DSSAT v4.7.5 CERES-Rice modelling system is an advanced physiologically based rice growth simulation model used to predict rice growth, development and response to various climatic conditions (16). The model was calibrated using the 2022 experimental data adjusting genetic coefficients to match observed growth stages and yield. Validation was performed using the 2023 experimental data to ensure the model's accuracy in predicting grain and straw yields. Calibration techniques for DSSAT models have been thoroughly discussed in many research studies (17,18).

The detailed flowchart of the process of model calibration and validation is represented in Fig. 4 below.

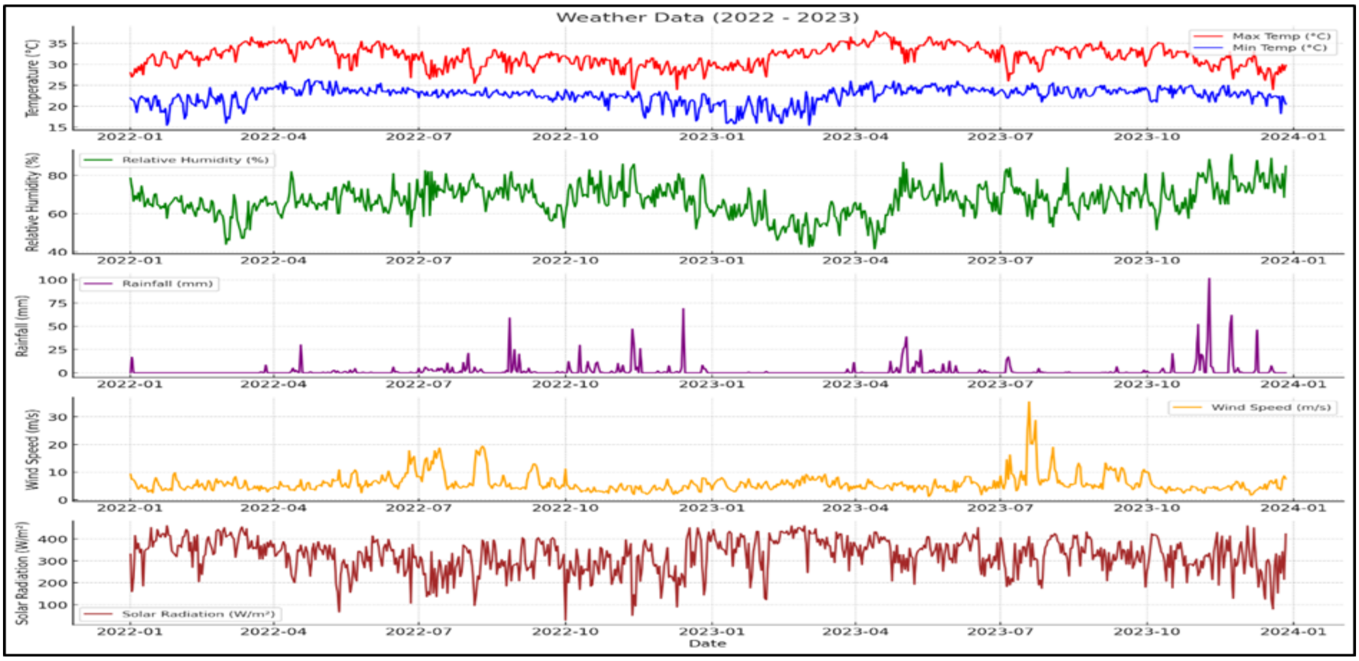

Fig. 3. Meteorological data of the cropping season of years 2022 and 2023.

Table 1. Physical and chemical properties of experimental soil used for DSSAT validation.

DEPTH (cm)	LOWER LIMIT (cm^3/ cm^3)	UPPER LIMIT (cm^3/cm^3)	Saturation Point of Soil water content (cm^3/cm^3)	ExtractableSoil water content (cm^3/cm^3)	Initial Soil water content (cm^3/cm^3)	Root Distribution Factor	BULK DENSITY (g/cm^3)	Soil pH	Organic Carbon (%)
0-5	0.098	0.147	0.198	0.049	0.147	1	1.45	8.5	0.96
5-15	0.098	0.147	0.198	0.049	0.147	1	1.45	8.5	0.96
15-22	0.098	0.147	0.198	0.049	0.147	1	1.45	8.5	0.96
22-34	0.105	0.158	0.21	0.053	0.158	0.45	1.45	8.5	0.93
34-45	0.105	0.158	0.21	0.053	0.158	0.45	1.45	8.5	0.93
45-57	0.105	0.158	0.21	0.053	0.158	0.45	1.45	8.5	0.93
57-67	0.116	0.171	0.221	0.055	0.171	0.26	1.48	8.4	0.57
67-77	0.116	0.171	0.221	0.055	0.171	0.26	1.48	8.4	0.57
77-94	0.125	0.178	0.222	0.053	0.178	0.15	1.48	8.4	0.6
94-111	0.125	0.178	0.222	0.053	0.178	0.15	1.48	8.4	0.6

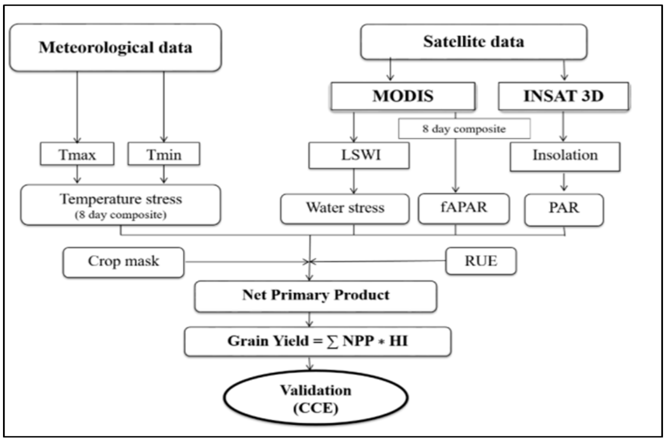

Fig. 4. Flow chart depicting the methodology of the semi-physical approach-based rice yield estimation.

Crop Coefficient Measurement

The model calibration was done to estimate the genotype coefficients to confirm the accuracy between model predictions and observed values based on the model approach (19). The CERES-Rice model was calibrated with the data obtained from the 2022 and 2023 field experiments with the treatment receiving 360 kg N ha^{-1}. The Detailed description of 8 coefficients has been provided in Table 2. The genetic coefficient of the cultivar CO-55 was calibrated by considering the varietal coefficients which are determined by thermal time from emergence to the end of the juvenile stage (P1), critical photoperiod (P20), rate of photo induction (P2R), optimum photoperiod (P2), thermal time for grain filling (P5), conversion efficiency from sunlight to assimilates (G1), grain size (G2), tillering coefficient (G3) and temperature tolerance coefficient (G4) (20). The genetic coefficients of the cultivar used in the experiment are provided in in Table 3.

Statistical Analysis

Calibration is a fundamental aspect of model verification (21). It ensures the simulated values closely match observed data. After inputting weather, soil, genotype and crop management data, the CERES-Rice model was run and simulated results were compared to observed data. Coefficients were adjusted to align the model's predictions of phenological events with actual data. Genetic coefficients affecting developmental stages were derived by calibrating phenology, growth and grain development parameters. Validation involved comparing observed and simulated data to ensure consistent predictions of growth and yield. The model is considered valid if the simulated data falls within the expected confidence intervals, as determined by statistical analysis.

Table 3. Genotypic Coefficients of Cultivar used in the experiment.

Genetic Coefficients	Cultivar (CO55)
P1 (Thermal Time)	850
P2R (Photoperiod Sensitivity)	200
P5 (Thermal Time to Flowering)	640
P2O (Critical Photoperiod)	11.4
G1 (Spikelet Number Coefficient)	65.8
G2 (Single Grain Weight)	0.028
G3 (Tillering Coefficient or Maximum Tillers)	1
THOT (Base Temperature for Growth)	83
TCLDP (Critical Temperature for Leaf Development)	1
TCLDF (Critical Temperature for Flowering)	0

Model performance evaluation was statistically presented by the absolute Root Mean Square Error (RMSE), normalized root mean square error (RMSEn), coefficient of residual mass (CRM) and Modelling efficiency (ME). The RMSE and RMSEn elucidate the magnitude of the average error but do not provide information about the relative size of the average difference between the observed and predicted. But, CRM indicates the direction of the error magnitude. The root mean square error (RMSE) was calculated using the following equation (22).

$$\text{Root Mean Square Error (RMSE)} \quad \sqrt{\sum_{i=1} \frac{(Pi-Oi)_2}{n}}$$

(Eqn.01)

The simulation is considered excellent with a RMSEn less than 10 %, good if it is greater than 10 % and less than 20 %, fair if it is greater than 20 % and less than 30 % and poor if it is greater than 30 %. The following equation was used to calculate RMSEn (23).

Table 2. Detailed description of 8 coefficients.

Name	Description
Juvenile phase coefficient (P1)	The period in Growing Degree Days (GDD) °C over a base temperature of 9 °C from seedling emergence, during which the rice plant is not responsive to changes in photoperiod. This phase is also known as the basic vegetative phase of the plant.
Critical photoperiod (P2O)	The longest day length (in hours) at which development occurs at a maximum rate. Development slows down for day lengths longer than P2O.
Photoperiodism coefficient (P2R)	The extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in °C) for each hour increase in photoperiod above P2O.
Grain filling duration coefficient (P5)	The period in GDD (°C) from the start of grain filling to physiological maturity with a base temperature of 9 °C.
Spikelet number coefficient (G1)	Determined by the number of spikelets per gram of main culm dry weight (excluding leaf blades and sheaths) at anthesis.
Single grain weight (G2)	The weight of a single grain (in grams) under ideal growing conditions.
Tillering coefficient (G3)	Tillering coefficient relative to a reference variety (e.g., IR 64), indicating the tillering capacity of the rice variety.
Temperature tolerance coefficient (G4)	Typically, a coefficient representing temperature tolerance under normal growing conditions for the variety.

Normalized Root Mean Square Error (RMSEn) =

$$\left[\frac{\text{RSME}}{\text{Mean of observed values}}\right] \text{X } 100 \quad \text{(Eqn.02)}$$

The Coefficient of Residual Mass (CRM) was also used to measure the tendency of the model to overestimate or underestimate the measured values. A negative CRM indicates overestimation and positive CRM indicates underestimation (24). The CRM was calculated using the following equation:

$$\text{Coefficient of Residual Mass (CRM)} = \frac{\sum_{i-1}^{n} Oi - \sum_{i-1}^{n} Pi}{\sum_{i-1}^{n} Oi} \quad \text{(Eqn.03)}$$

Modelling efficiency varies between negative infinity to 1.0. A negative modelling efficiency (ME) shows that the mean value of the experimental data is a higher predictor than the model value whereas a ME of 1.0 signifies a perfect model agreement with observations (25).

$$\text{Modelling efficiency (ME)} = \frac{\sum_{i-1}^{n}(Oi - O) - (Pi - Oi)^2}{\sum_{i-1}^{n}(Oi - O)^2} \quad \text{(Eqn.04)}$$

Where *Pi* and *Oi* are the predicted and observed values, *n* is the number of observations and *O* is the mean of the observed values.

Results

1. Environmental Factors

Environmental factors play a crucial role in determining crop growth and grain yield. In this study, several key factors were analysed to understand their influence on rice yield productivity under conventional and AWD methods. The environmental factors and WUE along with growth stages are presented in a graphical representation of environmental factors with yield in Fig. 5.

2. Analysis of Environmental Factors

Temperature:

Maximum Temperature (^{0}C): in both years, shown only a slight variation in maximum temperature with average of 33.6˚C for conventional and 34.2˚C for AWD in *Zaid* 2022 and averaging 33.3˚Cfor conventional and 34˚C for AWD in *Zaid* 2023 respectively.

In general, higher temperatures indicate crop stress and an increase in the rate of evapotranspiration.

Minimum Temperature (˚C): Minimum temperature ranged from 20.5˚C to 24.6˚C across both methods in 2 years, this shows the optimal influence on crop development and metabolic processes differently between conventional and AWD methods.

Average Temperature (˚C): Average temperature remained overall at a stable ground at 27.1˚C to 29.5˚C, further this indicates a consistent thermal environment for rice growth with a minor effect on crop physiological activities.

Solar Radiation (MJ/m^2):

Solar radiation levels ranged from 13 MJ/m^2 to 17 MJ/m^2 across the research study period. Consistent levels of solar radiation ensure optimal photosynthetic activity and also help in better grain yield with AWD consistently receives more solar energy than the conventional method because of the alternate wetting and drying which aerates the soil and helps for better growth of biomass of plants.

Rainfall (mm):

Rainfall patterns, however, showed strong variation: from 288.33 mm to 286.11 mm under conventional methods and from 219.04 mm to 228.17 mm under the AWD method. The irrigation cycles were controlled in the AWD method and hence, applied less water at the early growth stages and used the water more efficiently at peak demand periods.

Evapotranspiration (mm):

Evapotranspiration rates for grain yield ranged from 26.0 to 143.1 mm, whereas for straw yield, they ranged from 26.3 to 30.5 mm. The AWD method consistently exhibited lower evapotranspiration rates, which led to reduced water loss and improved WUE compared to conventional irrigation practices.

Water Use Efficiency, WUE (kg/m^3):

On the WUE measures, AWD recorded relatively increased values of 2.3 kg/m^3 against the conventional with 1.8 kg/m^3. This difference underpinned AWD's ability to enhance water resources and bring about better crop productivity under varying environmental conditions.

3. Impact of Environmental Factors on Yield

Yield was notably influenced by environmental and management factors, with AWD showing clear advantages over conventional methods. Although temperature fluctuations and solar radiation had minimal variation, they were positively correlated with grain and straw yields, with AWD performing better. Higher rainfall improved yields for both methods, but AWD demonstrated superior water use efficiency and crop response. AWD also achieved higher yields with less evapotranspiration, indicating more efficient water use. Overall, AWD had significantly higher WUE compared to conventional methods, leading to enhanced yield and straw production.

4. Yield Comparison:

Table 4 provides the grain yield for both conventional and AWD methods for 2 *Zaid* seasons with observed and simulated yield. The observed yield of rice for the conventional method was 5836 kg/ha and 5790 kg/ha respectively, in 2022 and 2023. For the AWD method, the yield was 6012 kg/ha in 2022 and 6005 kg/ha in 2023. The yield remained relatively consistent across both years and methods, with a slight increase observed in AWD-2023. The prediction accuracy for the conventional treatment is high, especially in 2023 (98.96 %). For the AWD treatment, the prediction accuracy is also very high, with both years above 99.78 %.

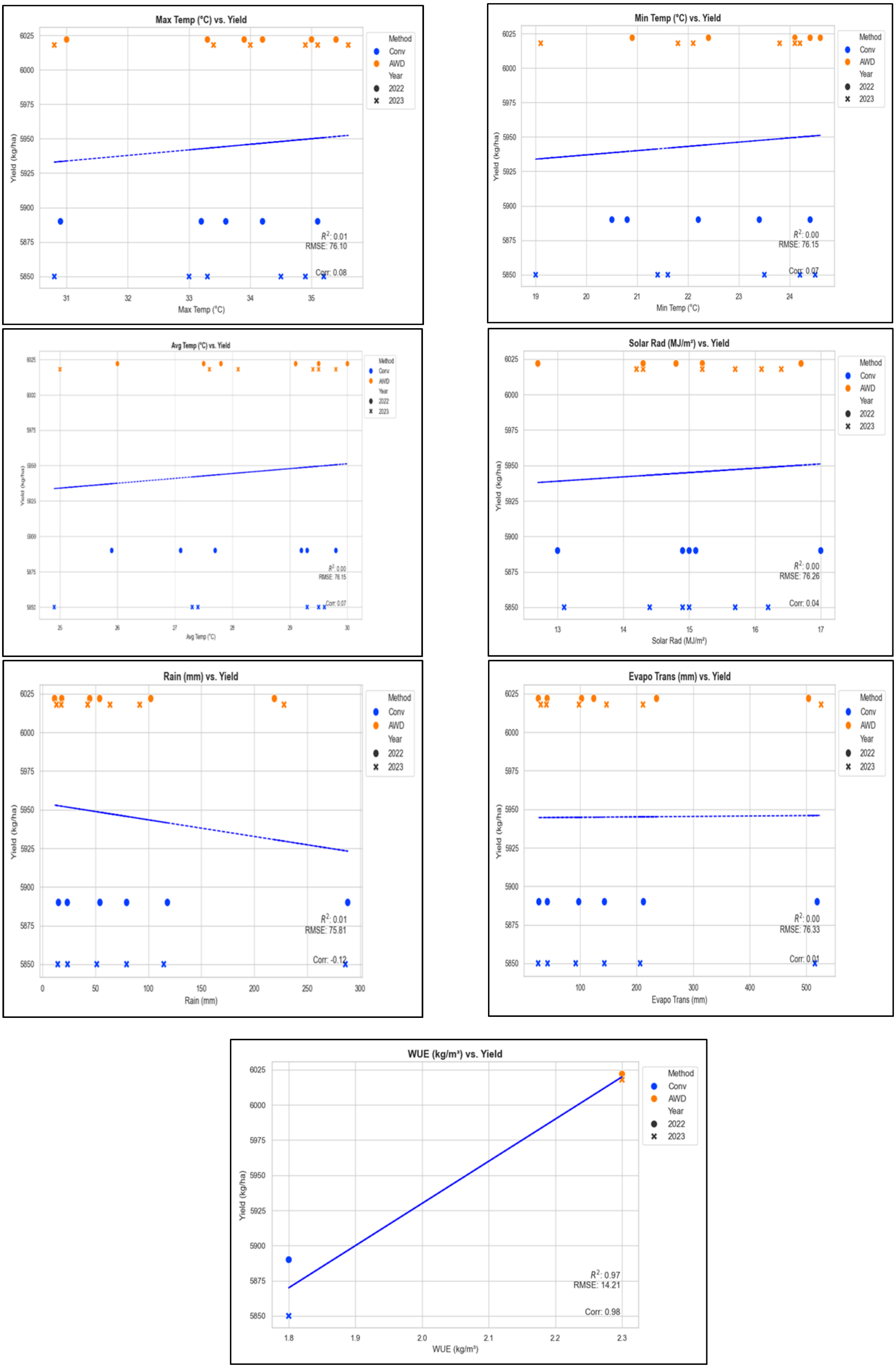

Fig. 5. Graphical representation of correlation and regression of environmental factors vs yield with RSME values.

Table 4. Grain yield (kg/ha) for conventional and AWD methods in 2022 and 2023.

Year	Treatment	Simulated Yield	Measured Yield	Difference (Simulated - Measured)	Accuracy (%)
Zaid 2022	Conventional	5890	5836	54	99.07 %
Zaid 2023	Conventional	5850	5790	60	98.96 %
Zaid 2022	AWD	6022	6012	10	99.83 %
Zaid 2023	AWD	6018	6005	13	99.78 %

5. Straw Yield

Table 5 provides the straw yield for both conventional and AWD for 2 *Zaid* seasons with observed and simulated straw yield. The observed total dry biomass was highest for the conventional method in 2022 (12623 kg/ha) and lowest for the AWD method in 2022 (13638 kg/ha). The harvest index varied between 0.895 and 0.919, indicating a stable proportion of biomass being converted into grain yield. The prediction accuracy for the conventional treatment is lower than AWD, with 89.52 % in 2022 and 89.84 % in 2023 with the simulated ones. For the AWD treatment, the accuracy is better than Conventional with 91.89 % in 2022 and 91.60 % in 2023. This suggests that the usage of DSSAT model is best for crop yield validation.

6. Nitrogen Uptake:

Nitrogen uptake ranged from 161 kg/ha to 189 kg/ha, showing consistent nutrient uptake across different treatments

Discussion

1.Environmental Factors on Grain Yield

Temperature (Maximum, Minimum, Average)

Temperature is one of the important factors which affect crop development and yield. In this research, the results on average temperature and grain yield established a moderate relationship in both the conventional and AWD methods. This in accordance with past studies that changes in temperature significantly affect rice growth and yield. In particular, high temperatures at the time of grain filling cause reduced yield due to heat stress (26).

Solar Radiation

Solar radiation plays a key role in photosynthesis, crop growth and yield. Accordingly, the regression analysis revealed a positive correlation between solar radiation and grain yield, indicating that with an increased amount of radiation, there would be a corresponding increase in yield. This agrees with the idea put across by (27) concerning the role of solar radiation in maximizing rice yield potential.

Rainfall and Evapotranspiration

Rainfall and ET both have a great influence on the water availability for the crops. The variable correctness of the relationship between rainfall and grain yield indicated the influence of excess and inadequate rainfall might be negative on yield. Proper water management, like that with AWD, could ensure that WUE is maximized while maintaining yield, which had been supported by another study (28).

2. Alternate Wetting and Drying Irrigation

AWD is an irrigation technique extensively used in many rice producing nations that has yielded optimal results because it floods and subsequently dries the rice field which may conserve water without yield loss but improve WUE and also improve aeration of soil and also helps in stopping the conversion of nitrogen into ammonia unlike from the conventional method. Several studies have shown that AWD could significantly save water without reducing rice yield or even improving rice productivity (29,30). Results of this study were in agreement with published reports as AWD had a better WUE and similar grain yield compared to conventional methods. Recent research also confirms the benefits of AWD irrigation. For example, demonstrated better soil water balance and crop performance with AWD in Italy (32). It was found that improved nitrogen use efficiency is one of the underlying mechanisms by which AWD works when it is combined with controlled release fertilizers (33). A more moderate AWD, when combined with rice straw incorporation as suggested by will further optimize water use and yield while reducing GHG emissions (31).

3. Water Use Efficiency, WUE

This study clearly showed that, in all sets of experiments, AWD methods had higher WUE of 2.3 compared with conventional irrigation. This is in accordance with studies of which proved that AWD can reduce water use by up to 30 %, without losing yield. Optimal use of water in the irrigation can significantly enhance the yield performance of the crop (32).

Table 5. Straw yield at maturity (kg/ha).

Crop Year	Treatment	Simulated Straw Yield	Measured Straw Yield	Difference (Simulated - Measured)	Accuracy (%)
Zaid 2022	Conventional	14097	12623	1474	89.52 %
Zaid 2023	Conventional	13504	12136	1368	89.84 %
Zaid 2022	AWD	14840	13638	1202	91.89 %
Zaid 2023	AWD	14442	13232	1210	91.60 %

4. Nitrogen Uptake:

The consistency of nitrogen uptake under various treatments signifies that the fertilization management was efficient and also use of drone spray of nano urea at critical growth stages also observed a positive correlation with grain yield. This shows efficient nutrient utilization; this is indeed crucial for maintaining the soil health level and crop fertility. The application of nano urea enhanced the nutrient uptake which showed the increase in grain and straw yield because nano urea has larger surface area and this gives the higher rate of penetration into the soil (33). These studies are in accordance with the results of (34).

5. Grain Yield and Straw Yield

In the experiment, grain yield and straw yield for conventional and alternate wetting and drying methods was simulated using DSSAT CERS Rice crop model and are compared with observed results.

From the above study, grain yield and straw yield were significantly higher in the alternative wetting and drying when compared to conventional method and also matched with simulated results with a high accuracy of 98 % over both years. AWD outperformed the conventional method in water use efficiency and in grain yield and Straw yield. This accentuates the importance of AWD method and its use in present research studies (35). There were several trends noted across different phases from emergence to harvest. First, AWD always deviates in terms of radiation and rainfall as compared with conventional, these are key variables that may affect crop growth and water management options. At the same time, both methods also show very different responses to minimum and maximum temperatures, whereby AWD normally has lower temperatures during the most critical phases of growth, hence influencing crop development and stress responses. While there is generally higher WUE observed in AWD during specific phases, AWD demonstrates asymptotic variability in its optimization of water use under changing environmental conditions. Several recent studies-for instance, a study have therefore underlined the need for such comparative analyses toward the understanding of how water management strategies drive crop productivity and resource use efficiency, advocating individually tailored approaches toward resilience and sustainability in agriculture (39).

6. Environmental and Practical Implications

Water use efficiency: Higher yield of grains and Straw yield in AWD are associated with increased water use efficiency; hence, it is a more resourceful and resource-efficient technique compared to conventional irrigation methods (36). The experimental results align with another study (37).

Environmental Benefits: With the reduction in methane emissions by about 40 % and saving water, AWD contributes more towards sustainable methods of rice production (38).

Challenges in Adoption

Despite the apparent benefits, proper management and monitoring of the adoption by AWD will be required to maintain optimum water levels in order to avoid losses because of inappropriate irrigation scheduling.

From the above Table 6, LAI trends show distinctive results in the conventional method than in the AWD method, this indicates the optimal development of the canopy in the conventional method than the AWD method. The maximum LAI was observed at the ending stage in conventional method (6.99 (2023) compared to 6.46 (2023) in AWD.

This difference shows that the continuous availability of water in traditional method is one of the reasons for consistent vegetative growth, but AWD cannot be accounted back it has 6.46 in heading stage which does not vary much difference but AWD is efficient in water consumption management in rice (39).

LAI and solar radiation play a correlated role in the grain yield and biomass yield of rice that should be taken into account with paramount importance. The more the LAI, the more the photosynthetic mechanism and more yield (40).

Table 7 depicts the resource productivity metrics for conventional and AWD methods of rice cultivation from 2022 to 2023. The serious observation can be that the length of the growing seasons has slight variations; hence, would likely create primary impacts on crop development and resource efficiency. In general, conventional methods preferably have higher water-use efficiency due to precipitation and AWD methods show comparable ET efficiency regarding the use of dry matter for yield productivity. In this study, the nitrogen application rates

Table 6. Leaf Area Index (LAI) comparison across crop growth stages for conventional and AWD methods.

Crop Growth Stage	Conventional-2022	Conventional-2023	AWD 2022	AWD 2023
Start Sim	0	0	0	0
Transplant	0.11	0.11	0.05	0.05
End Juvenile	1.73	2.52	1.35	1.86
Panicle Initiation	5.66	6.27	5.13	5.59
Heading	6.45	6.99	5.98	6.46
Beginning Grain Fill	5.71	6.18	5.35	5.77
End Main Fill	2.2	2.19	2.09	2.12
End Tillering Fill	2.01	2.09	1.88	1.86
Maturity	2.01	2.09	1.88	1.86
Harvest	2.01	2.09	1.88	1.86

Table 7. Resource productivity metrics of rice for conventional and AWD in 2022 and 2023.

Resource Productivity Metrics	Conventional 2022	Conventional 2023	AWD 2022	AWD 2023
Growing season length (days)	131	128	126	122
Precipitation (mm)	211.4	60.4	204.3	55.9
Dry Matter Productivity				
Precipitation (kg [DM]/ha per mm [rain])	6.83	22.36	7.26	25.22
Evapotranspiration (kg [DM]/ha per mm	2.89	2.96	2.68	2.75
Transpiration (kg [DM]/ha per mm	4.32	4.53	4.23	4.45
Irrigation (kg [DM]/ha per mm	0.4	0.37	0.76	0.72
Yield Productivity				
Precipitation (kg [yield]/ha per mm [rain])	28.6	9.94	2.93	10.78
Evapotranspiration (kg [yield]/ha per mm [ET])	1.24	1.19	1.19	1.15
Transpiration (kg [yield]/ha per mm	1.81	2.01	1.7	1.9
Irrigation (kg [yield]/ha per mm	1.7	0.17	0.31	0.31
Nitrogen Application (kg [N applied]/ha)	360	360	360	360
N Uptake (kg [N uptake]/ha)	172	161	176	172
Nitrogen Use Efficiency				
N applied efficiency (kg [DM]/kg [N applied])	40.1	37.5	41.2	39.2
N uptake efficiency (kg [DM]/kg [N uptake])	84	83.9	80.1	84

were similar across methodologies and years, but the uptakes under AWD were variable, which may signify the differences in available nitrogen and variances in management practice.

Calibration Process

Calibration is the tuning of model parameters so that it simulates the measured field data. The input parameters with regard to crop growth stages, temperature response, water uptake and formation of yield are taken into consideration.

Grain Yield Calibration: Correct calibration for grain yield will ensure the model simulates yield properly under varying conditions. As such, one is normally expected to adjust factors like harvest index, duration of grain filling and temperature sensitivity etc. On the other hand, DSSAT uses rice varieties, dates of planting and management practice data to further fine-tune these parameters to predict grain yields more accurately.

Straw Yield Calibration: Straw yield calibration is achieved by modifying parameters that regulate biomass accumulation and partitioning. The factors include the leaf area index, photosynthesis rates and biomass partitioning coefficients. Accurate top yield calibration is important to understand the growth and health of rice plants in general, which affects grain yield.

Yield Validation

Validation is the process of comparing model predictions with independent datasets to assess the accuracy of the model.

Grain Yield Validation:

Validation means to have reliable predictions of grain yield concerning different environments and various management practices. Substantively, validation of DSSAT involves the evaluation of model accuracy based on independent field data. If validation is done successfully, then the model can be used in predictions of the impact of various irrigation practices like AWD, yields. This thus gives way to water-use optimization and yield predictions (41). Validation of straw yield involves a comparison of simulated biomass with measured data. This step is very important to ensure that the model truly replicates the crop's growth dynamics. To accurate predictions of straw yield are of value to understand plant health and stress responses that are significant in rice crop management under a wide range of environmental conditions.

Importance of DSSAT in Rice Yield Studies

1. Predictive Accuracy:

The DSSAT calibration and validation for both grain and straw yield yields display detailed dynamics, hence ensuring a basis of high predictive accuracy. This reliability is very essential to be used in planning and decision-making processes in rice production (42). Simulation of various irrigation techniques, such as AWD, enables researchers and farmers to optimize different practices targeted at developing yield with sustainability (43).

2. Scenario Analysis:

DSSAT enables scenario studies on the potential impact of climate change, alternative management practices and genetic improvements. Clearly, one of the critical tools in the development of resilient rice production systems is DSSAT. Comparative simulations run for conventional and AWD practices in DSSAT will identify those most productive and resource efficient to bring about high yield.

Optimization of Resources

In particular, DSSAT optimizes water, nutrients and other inputs by providing accurate yield predictions under diversified management scenarios. This assumes great significance in water-scarce regions of the world. The ability of this model to predict yield outcomes under AWD practices supports a sustainable water management strategy that has higher WUE with lesser environmental concern.

Limitations of DSSAT model

a. DSSAT requires a vast amount of input data on soil properties, weather conditions and crop management practices, etc. obtaining the accurate and upto date data can be challenging.

b. It operates only on field or plot scales, which may not be feasible for large scale research assessments.

c. Like every other crop model, DSSAT requires calibration and validation of data against different conditions, which is a labour- intensive process and often cannot yield accurate results.

d. Adaptability of DSSAT to present day climatic change scenarios is crucial to make it as a widely adaptable solution for research.

e. DSSAT requires a lot of training and expertise to make its effective use which may further limit its reach and accessibility in certain research contexts (44).

Overcoming these deficiencies will require further research and development in order to advance model accuracy, ease of use and applicability across diverse agricultural landscapes and for a range of future climate scenarios.

Conclusion

The DSSAT crop model accurately simulates rice yields under diverse conditions, showing promise for regional use. Refining it could improve agricultural decision-making. Drone-sprayed nano urea and AWD irrigation enhance fertilizer precision, reduce pollution and improve water management, boosting crop resilience and yields. Ongoing refinement supports sustainable agriculture.

Future Research Directions and Suggestions Refinement of Model Parameters: Further research studies should consider inclusion of more precision parameters like remote sensing data can further enhance the accuracy in the prediction of yield using various climatic conditions (45,46). From the analysis of DSSAT model data for rice find out the agricultural practice that gives maximum yield with a minimum input of resources.

1. Environmental Impact: Consider the environmental implications of such recommended practices on water use efficiency and nutrient management in rice production.

2. Risk Management: Through proactive management strategies, we can minimize the potential risks identified by the model, for example, from pest outbreaks or nutrient deficiencies or weather-related incidents.

3. Future Research Directions: This could include further research in refining the model to improve the accuracy of yield responses to different climate conditions or incorporating other relevant pest and disease dynamics.

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Authors' contributions

AS carried out the experiment, observations and drafted the manuscript. NS guided the research by formulating the concept of research and approved the final manuscript. PS guided with research concept and formulating research parameters. KR involved in design and conceived the study. PJ, VR, NSS participated in analysis of the data. All authors reviewed the results and endorsed the manuscript's final version.

Compliance with ethical standards

Conflict of interest: Authors declare no conflict of interest

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