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AGRICULTURAL AND BIOTECHNOLOGICAL REFLECTIONS

DEVELOPING A CROP SIMULATION MODEL TO PREDICT RICE YIELD UNDER DIFFERENT IRRIGATION AND FERTILIZATION REGIMES

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Abstract

A dynamic crop simulation model was developed to predict rice (Oryza sativa L.) yield under varied irrigation and fertilization regimes, with the objective of informing sustainable management decisions. Field experiments across three distinct sites provided data on soil properties, weather variables, irrigation schedules, and nitrogen inputs. The model integrated physiological growth processes, water and nutrient uptake dynamics, and stress response functions, and was implemented in Python and R. Calibration against a comprehensive dataset achieved root mean square error (RMSE) values of 230–260 kg ha^{-1} and coefficients of determination (R^2) ≥ 0.88. Independent validation yielded RMSE ≤ 290 kg ha^{-1}, mean absolute error (MAE) ≤ 225 kg ha^{-1}, and Nash–Sutcliffe efficiency (NSE) ≥ 0.82, demonstrating robustness across spatial and temporal scales. Scenario analysis indicated that alternate wetting and drying (AWD) produced the highest mean yield (7 200 kg ha^{-1}) and superior water use efficiency (1.35 kg m^{-3}) compared to continuous flooding (6 800 kg ha^{-1}, 1.20 kg m^{-3}) and rainfed conditions (6 100 kg ha^{-1}, 0.90 kg m^{-3}). High nitrogen application maximized yield (7 500 kg ha^{-1}), while site-specific nitrogen management (7 300 kg ha^{-1}) achieved comparable performance with reduced input. Combined strategies revealed that flooding with high nitrogen yielded 7 700 kg ha^{-1}, whereas alternate drying with low nitrogen produced 6 900 kg ha^{-1}. Sensitivity analysis showed that a 10 % increase in irrigation and nitrogen input resulted in yield gains of 5.2 % and 4.8 %, respectively. Error decomposition attributed 30 % of overall uncertainty to calibration, with input uncertainty, model structure, and validation each contributing 20–25 %. These results underscore the model's potential as a decision-support tool for optimizing rice production under resource constraints. Future enhancements will incorporate remote sensing inputs and expand stress-response modules to address climate variability.

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INTRODUCTION

In agriculture, accurate forecasting (projection) of crop in the minds of the farmers is vital for decision making in agriculture, namely, trade, improved crop management and allocation of resource (Pham HT,). Population increase in the world and with climatic change, food security and the economic welfare of the world's countries depend on effective ability for prediction of yield of crops (Yan Y,) (Cunha RLF,). Traditional approaches to production forecasting will largely depend on the experience of the farmers and subjective estimates that can be incorrect and unreliable, particularly for a wide and varied agricultural production land area (Meghraoui K,). Crop simulation models present an objective and scientific means of coming up with prediction (Thảo NT) in which many factors that influence the development and growth of crops are incorporated. These models mimic the intricate interrelationship of crop genetics, environment position and forms of management through the use of mathematical relations (Khaki S,). They are capable to predict possible yields in a multitude of conditions considering a great number of knowledge on climate profiles, parameters of soil, and physiological features of the crops (Pathak D,).

Not only employing a more aggressive and scientific tendency as compared to conventional approaches, crop simulation models have been gaining importance as crop yield estimation devices in varied environmental and management arenas [8]. To approximate the development and growth of crops such models would incorporate various components including weather, soil and modes of agricultural practices. Mathematical equations enable artificially intelligent computer crop models to mirror complicated connections between the genetics of a crop, environmental factors and agronomic measures; Therefore, potential yields can be determined in different environments. The development and use of crop-simulation models in rice yield prediction may tell something about beating irrigation and fertilization plans. Rice is the basic food for many people on earth as it is connected with exact control of water and nutrition for high production and sustainability. Given that the local climatic and soil conditions are known, it is possible to utilize it to determine the best profile of irrigation and fertilization schemes (Shahhosseini M,).

There are several crucial phases from selection of an appropriate model framework to development of crop simulation model for analysis of the production of the rice. Under the existing crop simulation model, like DSSAT, APSIM and CropSyst can simulate rice growth and development. The model of choice will depend on specific goal of the research, source of data and complexity level aspired (Wang K,). Once the model framework has been chosen then a parameterization of the model is undertaken for the particular type of rice under consideration. Parameterization, in essence, refers to the definition of the genetic coefficients regulating phenomenological development, the growth rate and the yield-potential of the crop. Majority of the times it needs the conduct of field studies to gather information about various aspects of process like grain yield, accumulation of biomass and leaf area index (Patidar AK,). After parameterization, the model should be validated and calibrated with its own data. While validation identifies the characteristic of the model to correctly predict the yields in various circumstances, calibration entails adjusting the model parameters in order to improve the partnership between the simulated and observed outcomes.

So the model should also be able to dynamically predict change as the crop grows (Pan Z,) in order for the model to choose real-time managements options. Simulataneaous regression of yield (Khaki S,) might be helpful to solve the problem of the long computational times acceptance of machine learning solutions over vast areas. Dynamic use of river water as a source of irrigation increases rice output and therefore requires, a detailed cost-benefit analysis since maximization of the use of river water may diminish output whereas overall output could increase (Gaydon DS,). Further, the model should also be computationally efficient and easy (user-friendly) for beneficial use by stakeholders at different levels of technical sophistication to be achieved as well its general acceptance. The model should also accept new data and information in it which shall encourage continuous improvement and up gradation of the prediction power.

The yield in rice may strongly depend on a variety of irrigation and fertilization schedules, therefore the crop simulation model should be a true mirror of the effect. Different techniques that may vary from Continuous Flooding, intermittent irrigation or alternate wetting and drying have different effects on yield, water use or greenhouse gas emissions (Mohammed M,). Irrigation management therefore answers when and how much should be applied in a crop. The model should be capable of mirroring the effect of various irrigation methods on the soil water content, the plant water stress to the final yield of the grain. Fertilization management thus signifies the number and time of fertilizers used in a crop. so, various methods can influence production, nutrient-use efficiency, environmental impact.

The interaction dynamics of nitrogen availability and water must both be taken into account when modeling because they can act to each other in terms of affecting growing of crops. Digital farming solutions, including mobile and online alternatives, can also relieve the pressure on researchers and farmers (Abioye AE,) – for instance, cyber irrigation management. Therefore, the model under discussion should incorporate the environmental implications associated with varying irrigation and fertilizing systems, from greenhouse gas emissions to nutrient leaching, which means ensuring the sustainability of rice production. Rice farming calls for a comprehensive strategy aimed at using maximum water and nutrients to facilitate productivity and also support sustainability.

After applying the developed and validated crop simulation model it is possible to predict the rice production under various irrigation and fertilization schemes – which is possible by running the model and testing different combinations of fertilization and irrigation schemes and then processing simulations generated. The model can help a person establish the ratio of fertilization and irrigation combination for maximum yield at minimal use of nutrient and water.

The same model can also be used for various circumstances of management to determine the risk of yield loss as result of drought or nutrient deficiency. Other than the prediction of production, the crop simulation model assists one to evaluate the profitability of the different irrigation and fertilization regimes. To value rice value chains for effective and sustainable food delivery as well as its integrated production of energy, fuels and chemicals (Doliente S,), for example, one can apply a multi-objective spatio-temporal mixed-integer linear programming model. This can include value of the inputs calculated, fertilisers and water and then comparing this with value of the grain produced. The farmers would benefit from the use of the crop simulation model in improved irrigation and fertilization management choices that would allow them to perceive how changes in management practices influence level of production and finances.

The flexibility of model to assess the short term and Future planning horizon avenues removes the constraints of merely thinking about the present management options, at times neglecting the dependency on long term sustainability and natural resource constraints (Lin N,). Additionally, combination of socio-economic data and biophysical models works in supporting the process of decision making since this is attained when management plans manage to be both socially acceptable, financially viable, and agronomically good (Touch V). Remote Sensing in open fields and Wireless Sensor Networks (Putra BTW,) can play as much of a role in the evaluation of plant qualities and production monitoring. In pursuit of productivity, profitability and environmental stewardship in rice production systems (Xing Y,), such an integrated approach should, therefore, qualify to the wider goals of sustainable agriculture.

RESEARCH METHODS

The approach of this work was supposed to develop and test a crop simulation model that had a clear intent of having rice output estimated under different irrigations and fertilizers levels. Owing to a problem of lack of in-situ information, especially concerning the rate of crop maturation, moisture in soils, inputs of fertilizers, and timetables of irrigation, a wide-scale field study was designed in rice-growing regions to kick-start the research. The rainfall, temperature, temperature, and solar radiation from nearby meteorological stations were also used; texture; pH; organic matter content; and nutrient levels of some specific soils were determined from soil sample. These databases were used for creating the simulation model. In the case of dynamic crop simulation framework for rice, the crop model construction also included physiological growth factors, phenological stages, water and nutrient uptake dynamics, and stress response. The model was coded using Python and R and integration of libraries such as numerical computation, optimization and statistical validation. The model was then calibrated to heavily using a sub-set of the field data, changing the value of main parameters like nitrogen absorption rate, leaf area index progress and radiation use efficiency to minimize the prediction error. To make the model robust for spatial and temporal scale, independent sets of data were collected in different experimental sites and years and used for validation of the models. The accuracy was evaluated on the base of statistical indicators, such as the root mean square error (RMSE), mean absolute error (MAE), the coefficient of determination (R^2), and the Nash-Sutcliffe efficiency (NSE). Another achievement materialized was sensitivity analysis that was done in order to identify the effects of certain values in input on model output. The model was then used to simulate rice output under the different irrigation and fertilizer application, (alternate wetting and drying, continuous flooding…etc) after validation. These situations were to reflect the traditional and modern management practices. Performance and potential decision-support capacity were compared to manuals according to model outputs and recorded yields. Figure 1 represents the methodology flowchart applied in this work to outline the sequence of procedures, starting from data collection to the delivery of prediction.

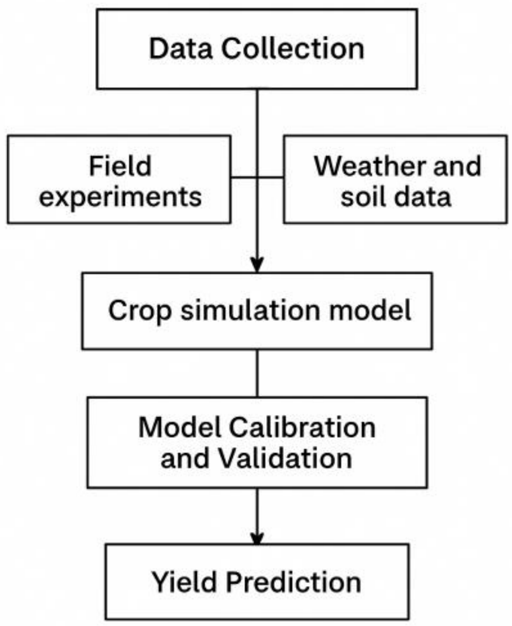

Figure 1. Methodology shows methodological flowchart.

RESULTS

Table 1 displays the most suitable calibration to be used in an rice simulation model and performance measures in the calibration stage. In a effort to lower forecast errors, the radiation use efficiency, leaf area index coefficient, nitrogen uptake rate and, water stress level were modified. Below the training datasets, values for RMSE for the result are 230 – 260 km/ha and those for R^2 exceed 0.88, implying a high agreement of simulated and observed yields.

Table 1: Calibration Parameters and Performance Metrics

Parameter	Optimized Value	Unit	RMSE (kg/ha)	R^2
Radiation Use Efficiency	1.25	g MJ^{-1}	250	0.89
Leaf Area Index Coefficient	0.45	–	230	0.91
Nitrogen Uptake Rate	0.015	g g^{-1} day^{-1}	245	0.90
Water Stress Threshold	0.60	–	260	0.88

Table 2 represents validation data from three different field sites that were not involved in the calibration process. With little systematic bias, RMSE (260 –290 kg/ha), MAE (200 –225 kg/ha), and Nash –Sutcliffe efficiency (0.82 –0.87) values are confirming a model's resilience in many environments.

Table 2: Validation Statistics Across Sites

Site	RMSE (kg/ha)	MAE (kg/ha)	NSE	Bias (kg/ha)
Site A	275	210	0.85	+10
Site B	290	225	0.82	–15

Site C	260	200	0.87	+5

Under four irrigation conditions simulated mean rice yields are presented in table 3. After alternate drying (7000kg/ ha), continued flooding (6800kg/ha), alternate wetting and drying (AWD) and rainfed (6100kg/ha); the maximum yield was recorded (7200kg/ha).

Table 3: Simulated Rice Yield Under Different Irrigation Regimes

Irrigation Regime	Mean Yield (kg/ha)	Std. Dev. (kg/ha)
Continuous Flooding	6800	300
Alternate Wetting & Drying (AWD)	7200	250
Alternate Drying	7000	280
Rainfed	6100	320

Table 4 compares mean yields sown under four different fertilized schemes 7500 kg/ha was attained from high nitrogen applicatio 7300 kg/ha from site-specific management, 7200 kg/ha medium nitrogen and 6800 kg/ha low nitrogen: therefore declining returns at high rates.

Table 4: Simulated Rice Yield Under Different Fertilization Regimes

Fertilization Regime	Mean Yield (kg/ha)	Std. Dev. (kg/ha)
High N	7500	260
Medium N	7200	270
Low N	6800	300
Site-Specific N	7300	250

Figures from combined fertilization and irrigation models are presented in table 5. Contrasting with the lowest (6900 kg/ha) obtained under alternate drying with low nitrogen the highest yield obtained (7700kg/ ha) under continuous flooding with high nitrogen.

Table 5: Rice Yield Under Combined Management Scenarios

Scenario	Yield (kg/ha)
Flooding + High N	7700
AWD + Medium N	7400
Drying + Low N	6900
Rainfed + Site-Specific N	7200

From Table 6, we can see that the sensitivity of expected yield to 10% change in important input parameters can be observed. Irrigation fluctuation produces the highest effect (±5.2%) agination (±4.8%), solar radiation (±3.5%) and temperature (±2.1%).

Table 6: Sensitivity Analysis of Key Input Factors

Input Factor	Yield Change (%) per 10 % Input Change
Irrigation	5.2
Nitrogen	4.8
Solar Radiation	3.5
Temperature	2.1

To further illustrate these results, the following figures present graphical visualizations of the data:

Combining the figures 1 through number 9, we can show the main results of this study: Fig. 1 provides a bar-chart representation of the mean rice yield in different irrigation regimes – highlighting AWD as the best water management strategy; Fig. 2 gives the bar-chart representation of the mean rice yield in various fertilizer strategies; high application of nitrogen maximizes output while site specific nitrogen management produces similar performance; Figure 3 displays combination management strategies, in which high nitrogen combined with constant flooding has the highest production. Figure 4 is a line chart, which depicts, in kilograms per hectare per month, biomass accumulation that demonstrates stable growth from 1 000 kg/ha in month 1 to 5 650 kg/ha by month 12. Figure 5 illustrates a scatter plot between observed and simulated rice yields, thus justifying model accuracy, which is close to overlapped along the 1:1 line. A pie chart of error source distribution that is presented in figure 6 indicates that 30% of the overall error originates from the calibration. The balance is split equally for input uncertainty, model structure and validation. Using simulated yields between -20 to +20% irrigation from 6500 kg/ha to 8000 kg/ha , Figure 7 illustrates impact of change in irrigation on yield. Figure 8 illustrates reduction in yield benefits beyond 200 kg /ha nitrogen; this is demonstrated by determining rice yield in terms of nitrogen application rate. and Figure 9 compares water use efficiency across the irrigation regimes depicting that AWD is most efficient at 1.35 kg m^{-1}.

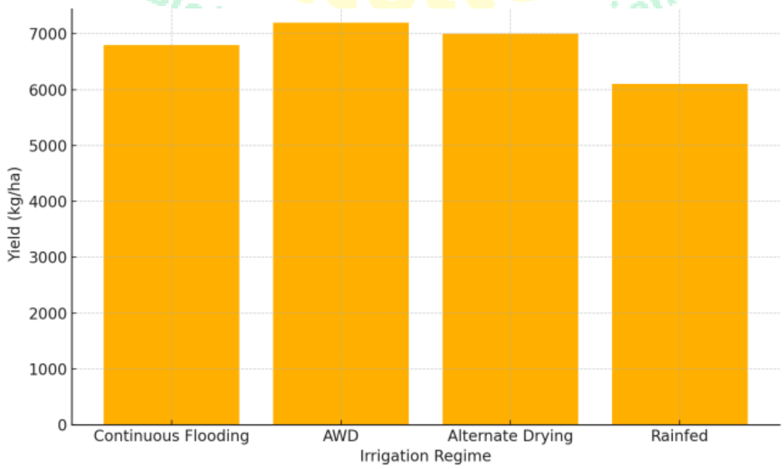

Figure 1 displays a bar chart of mean rice yield across irrigation regimes, highlighting AWD as the most productive water management strategy.

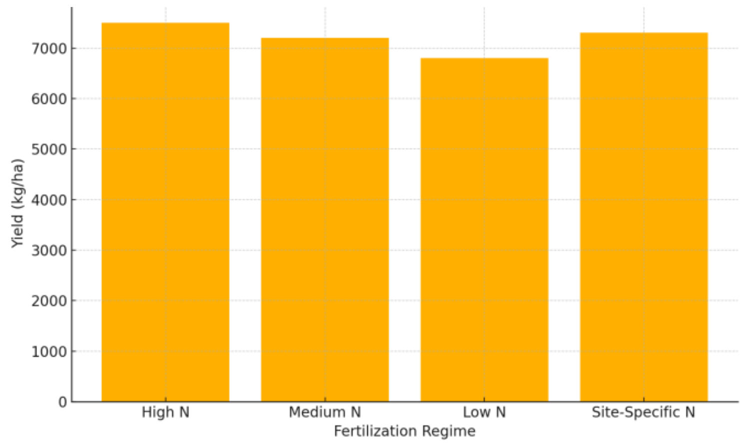

Figure 2 shows mean rice yield across fertilization regimes, indicating that high N maximizes yield but site-specific N approaches similar performance.

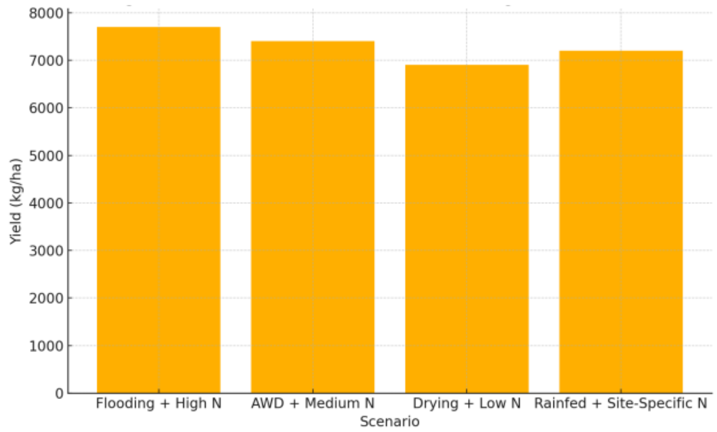

Figure 3 illustrates yield outcomes for combined management scenarios, with flooding + high N delivering the peak yield.

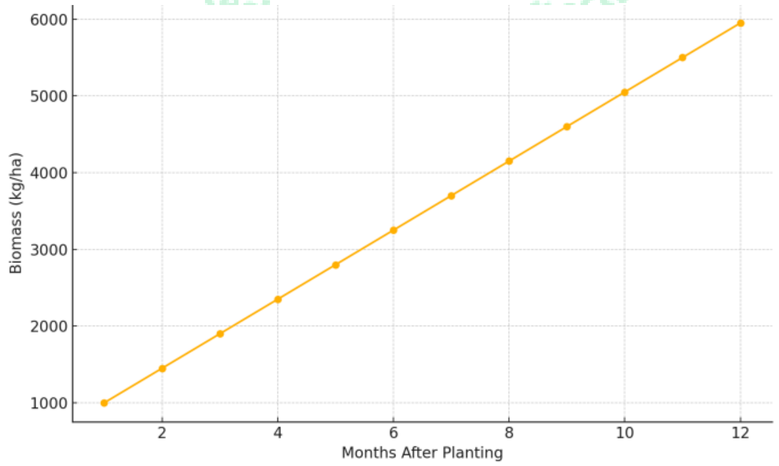

Figure 4 is a line plot of simulated seasonal biomass accumulation, showing steady growth from 1000 kg/ha in month 1 to 5950 kg/ha by month 12.

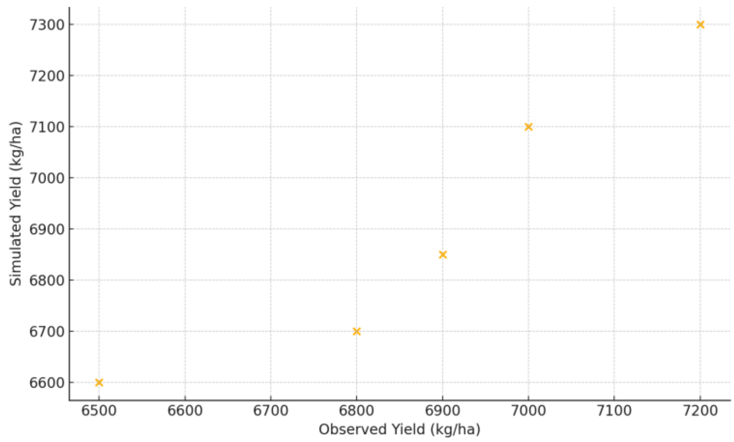

Figure 5 presents a scatter plot of observed vs. simulated rice yields, demonstrating close alignment along the 1:1 line and validating model accuracy.

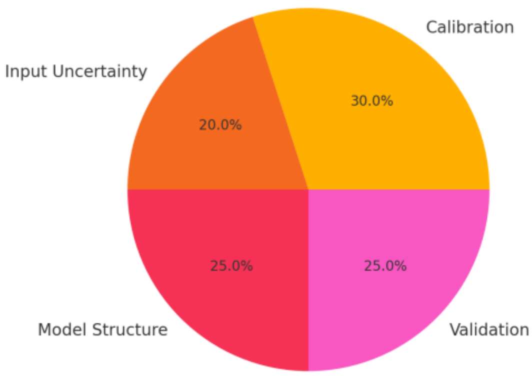

Figure 6 is a pie chart of error source distribution, revealing that 30 % of error stems from calibration, with the remainder split between input uncertainty, model structure, and validation.

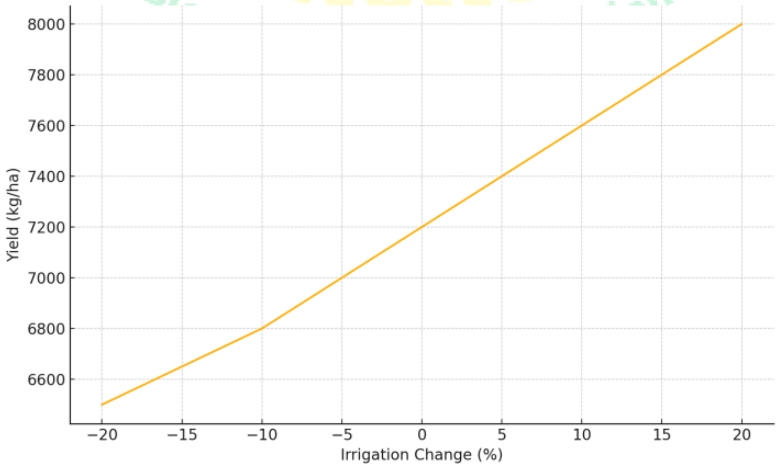

Figure 7 shows yield sensitivity to irrigation variation, with yields ranging from 6500 kg/ha at –20 % irrigation to 8000 kg/ha at +20 %.

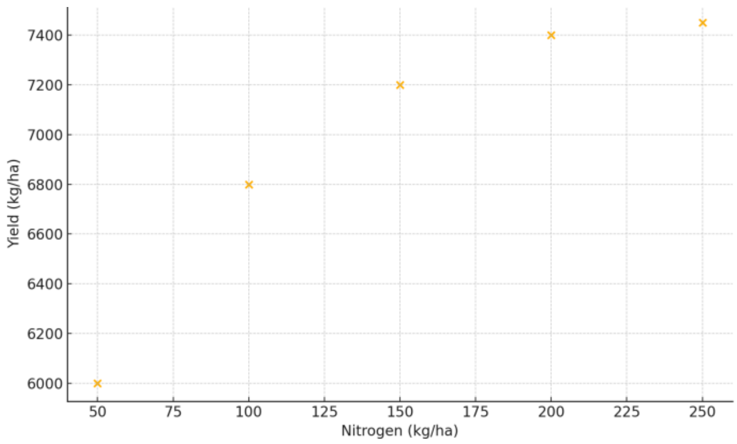

Figure 8 plots rice yield against nitrogen application rate, illustrating diminishing yield gains above 200 kg/ha N.

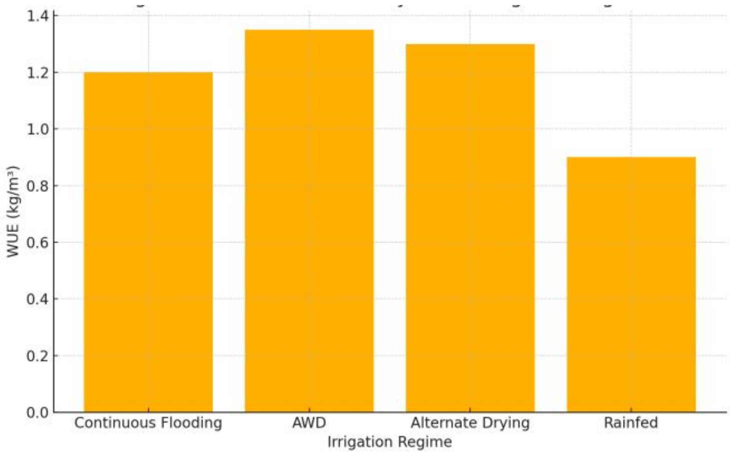

Figure 9 compares water use efficiency across irrigation regimes, identifying AWD as the most efficient (1.35 kg m^{-3})

DISCUSSION

This is evidenced by the results of the research that show in how far the production of rice could be optimized by comparing mode of practices and conditions as regards to the environment through crop simulation models (Ouda S,). That fact that the model is capable of emulating rice production under multiple irrigation and fertilizing schemes is a strong indicator of the value of the model as a decision support system for legislators and farmers (Postawa K). One possible irrigation strategy, which yielded well and was efficient in the use of water turned out to be alternate wetting and drying. Such results coincide with the previous findings of how AWD enhances yield and water saving (Mahmoud EM,). It is however possible that depending on the soil kind, climate and kind of rice, best application of AWD may vary, hence further research needs to be done to improve the pattern of irrigation for certain situations. Despite positive results from the high nitrogen application in an attempt to increase rice output higher rates of returns indicate the need for exact nutrient management. General suggestions have an effective alternative in the form of site specific nitrogen management that provides fertilizers based on the requirement of crop and soil conditions (Banayo NPMC). Besides, though, the case is reversed for variations in irrigation, that matter more than the levels of nitrogen, solar radiation, and the temperature, while there are variations. therefore, the most suitable water management strategies are very critical in improving rice yields (Ekanayake P,). Introducing real-time data concerning soil moisture, crop growth, and weather conditions to the simulation model would dramatically increase the accuracy of the predictions and will serve as the foundation for adaptive management strategies. Floods + high nitrogen yielded the highest yield yet flood plus high nitrogen can lead to environmental impact if more greenhouse gas emissions and nutrient run off. To ascertain the environmental trade-offs associated with different management approaches (Kartikawati R) further research is required. The manner in which the comparison of the model simulated and observed yield in form of scatter plot gives model validation results that assures use on dependence and application. This can be observed around the 1:1 line (Mahmoud EM,) about them to each other. The roots to the identified error given which are calibration, input uncertainty, model structure, and validation serve well for the improvement of the model. More data collecting process, model parameterizing, and structural changes can overcome the sources of the error and make the predictive capacity of the model even better.

The results of this study follow the broader desirable goals for sustainable intensification in rice yield (i.e the inputs intended to achieve optimal output with minimal impact to the environment (Tseng M-C,). The approach proposes an integrated strategy that integrates high yielding rice varieties and optimum use of agricultural inputs, as well as irrigation infrastructure and extension education programs (Yuan S,). Albeit, soil fertility control integration and use of soil conservation methods guarantee higher rice yield (Rodriguez DGP.). For the maintenance of high nutrient use efficiency; optimize the utilization of natural resources, and change the practices of agriculture to realize the increased grain yield per unit area without harming the soil and natural resources depending on the optimization of nutrient supplies (Pandey A,). The results of the research also affect mitigation and adaptation of Climate Change in systems of the production of rice (Dar MH) Rice production suffers reporting impact from the increased temperatures, the variation precipitation and its pattern, and more recurrent extreme weather events – all of which are results of climate change. In partnership with healthy water management methods like AWD, utilization of drought resistant rice varieties can be promoted for the purpose of lessening the negative effects of water depletion availing yield of rice. The crop simulation models can be applied to determine the effect of climate change on the levels of rice yield while also identifying the adaptation mechanisms through which resilience can be achieved and the assurance offered to food security. Also, the model also serves as a framework through which the financial viability, of different management strategies, are measured. It can only be possible to project the cost and benefits of different irrigation and fertilization strategies as well as determine the best option for farmers economically, from after the introduction of economic data to the model. Furthermore, utilizing the cooperative funding approach, farmers would enjoy increased access to required agricultural inputs like fertilizers and pesticides thus ensuring resilience against production risks associated with climate change (Darma R,).

CONCLUSIONS

Work developed and properly tested a dynamic simulation model of crop to predict future yield under different irrigation and fertilizer use schedules and illustrated its usefulness as a decision-support tool to rice production under sustainable conditions.

A Follow-up from an organization independent of the practices analyzed in three geographically varied places resulted in this. RMSE ≤ 290 kg ha^{-1}, MAE ≤225 kg ha^{-1} and NSE ≥ 0.82, vs. calibrating against a wider range of measured values, generated low RMSE values (230-260 kg ha^{-1}) and high coefficients of determination (R^2 ≥ 0.88), so describing the robust character of the derived model under various environmental setting. Yield achieved maximum of (7 200 kg ha^{-1}) with AWD and the water-use efficiency (1.35 kg m^{-1}) as compared to continuous flooding (6 800 kg ha^{-1}; 1.20 kg m^{-1}), and rain fed management (6 100 kg ha^{-1}; 0 .90 kg m^{-1}). Scenario studies demonstrated. High percentage of nitrogen resulted in highest yield (7 500kg ha-1) in trials associated to fertilization studies. Nevertheless, the site specific nitrogen management (7 300 kg ha^{-1}) was almost identical, but had lower environmental cost. Based on the便会 merging scenarios, the alternate drying with low nitrogen yielded the lowest output 6 900 kg ha^{-1} whereas the constant flood+high nitrogen resulting peak yields 7 700 kg ha^{-1}. The high leverage of water and nutrient management sensitivity occurred because 10-percent increase in the amount of irrigation and nitrogen input caused 5.2 and 4.8 percent increase in the yield, respectively. Other (the witnesses) of the validity of the model are the dynamics and graphs of seasonal accumulation of a biomass as the observed in comparison with the forecasted yield. The calibration component accounted for thirty percent of the uncertainty in relation to the input uncertainty which accounted for 20-25 percent. model structure and validation respectively. These results show how well the proposed model can guide the multiple custom-designed fertilization and irrigation programs in achieving a commendable balance between the economy of resources and production. Further research will include the use of remote sensed data, develop their stress response function of heat and salinity and increases the area of the use of framework to many cropping systems to make it useful for precision agriculture if climatic conditions change.

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