IGNATIAN
INTERNATIONAL JOURNAL FOR MULTIDISCIPLINARY RESEARCH
www.icceph.com
ISSN 2984-9942

INTEGRATED AGRO-CLIMATIC YIELD FORECASTING FOR CLIMATE-RESILIENT RICE PRODUCTION IN ILOCOS NORTE

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ABSTRACT

This study aimed to develop an integrated agro-climatic modeling and predictive framework for rice yield forecasting in Ilocos Norte, Philippines. The research employed a quantitative design using secondary weather data provided by the Mariano Marcos State University (MMSU) Research Directorate, covering the period 2014–2024. Methodologically, the study combined descriptive statistics, climate risk indices, and machine learning approaches to analyze seasonal evapotranspiration, canopy heat stress shocks, radiation use efficiency, and composite climate risk profiles. The Random Forest regression model was applied to validate historical yield fits and generate five-year forecasts (2025–2029). Results revealed that crop water demand peaks in the second quarter, coinciding with reproductive stages, while the lowest demand occurs in the fourth quarter during maturity. Seven severe heat stress shocks were identified, clustered in Q2–Q3, highlighting vulnerability under combined high temperature and humidity. Radiation use efficiency was highest in Q2 despite shorter sunshine hours, confirming radiation limits as the primary constraint during wet-season cropping. The Composite Climate Risk Index isolated a major anomaly in 2023-Q3 (+1.5 SD), reflecting a multi-hazard event. Predictive modeling achieved >90% accuracy in historical fits, with forecasts indicating stable yields (~320,000–330,000 metric tons annually), a contraction in 2026 due to simulated El Niño, and recovery in 2028 under La Niña.

Keywords: *evapotranspiration, heat stress shocks, radiation use efficiency, climate risk index, predictive modeling, rice yield forecasting*

INTRODUCTION

The problem of atmospheric uncertainty has long influenced agriculture, with farmers traditionally using traditional calendars and seasonal cycles to inform planting choices (Bucheli et al., 2023; Hu et al., 2024). Global food security is under risk due to the disruption of these normal cycles caused by anthropogenic climate change, which has increased temperatures, introduced unpredictable rainfall, and intensified extreme weather events (Alotaibi, 2023; Farah et al., 2025). According to Battisti & Naylor (2009) and Zhao et al. (2017), these changes reflect not merely average movements but also fundamental changes in the environmental conditions that allow crops, especially rice, to be farmed profitably.

One of the countries most vulnerable to climate change is the Philippines, which is located in the Pacific typhoon belt (Briones, 2022; Tollin et al., 2022). As the nation's main meal and a vital component of rural lives, rice is extremely vulnerable to weather fluctuations. Rice production in Ilocos Norte represents both cultural identity and economic significance, but it is increasingly vulnerable to heat stress, variations in evapotranspiration, and erratic rainfall patterns (Mamun et al., 2024). Even minor interactions between temperature stress and moisture shortage can cause large yield gaps despite what appears to be regular rainfall, making traditional intuition-based calendars inadequate (Nketsang et al., 2025; Delina et al., 2023).

Scale mismatches plague current forecasting frameworks: historical yield models are unable to capture physiological responses in real time, while national climate models lack specificity at the province level (Palka & Manschadi, 2024; Rajasivaranjan et al., 2022). According to Simanjuntak et al. (2022), this generates a research gap for integrated systems that can synthesize localized weather data, such as temperature, humidity, and sun radiation, into useful insights for rice production.

The possibility of integrating process-based crop growth models with machine learning approaches is highlighted by recent developments in agro-meteorological modeling. Improved robustness in capturing non-linear connections between climate variables and crop physiology has been shown by hybrid techniques like Random Forest and Support Vector Regression (Kamilaris & Prenafeta-Boldú, 2018; Khaki & Wang, 2019). Recent developments in agro-meteorological modeling demonstrate the potential of combining process-based crop growth models with machine learning techniques. These innovations offer opportunities to develop predictive tools that can anticipate yield outcomes under diverse climatic scenarios, improving resilience in rice farming systems.

Improved robustness in capturing non-linear connections between climate variables and crop physiology has been shown by hybrid techniques like Random Forest and Support Vector Regression (Kamilaris & Prenafeta-Boldú, 2018; Khaki & Wang, 2019). These developments offer chances to create prediction algorithms that can forecast yield results under various climatic conditions, strengthening rice farming systems' resilience.

Based on four scientific pillars—evapotranspiration estimation using FAO Penman-Monteith, heat stress indices derived from dry and wet bulb temperatures, photosynthetic efficiency modeled using Radiation Use Efficiency (RUE), and a composite Climate Risk Index (CRI)—this study suggests an Integrated Agro-Climatic Yield Forecasting System for Rice in Ilocos Norte. The study aims to give accurate yield forecasts at the provincial level that overcome the shortcomings of conventional models by incorporating these data into a machine learning framework.

This study is relevant because it is in line with the Sustainable Development Goals (SDGs 2: Zero Hunger, 12: Responsible Consumption and Production, and 13: Climate Action). The study supports food security, climate adaption, and sustainable resource management by providing farmers, extension agents, and legislators with forecasting tools. In the end, this study offers a novel framework for climate-resilient rice production in Ilocos Norte by positioning itself at the nexus of agricultural climatology, applied mathematics, and data science.

Research Objectives

Climate variability and change are posing a growing danger to Ilocos Norte's agricultural output, especially rice production. The intricate, non-linear relationships between meteorological variables and rice physiology are frequently missed by traditional forecasting techniques, which depend on historical yield averages or generalized climate models. Farmers and policymakers lack accurate instruments to predict and reduce climate-related hazards due to this discrepancy between broad-scale projections and specific realities.

The study aims to create an Integrated Agro-Climatic Yield Forecasting System for Rice in Ilocos Norte in order to close this gap. The investigation is guided by the following research questions:

1. Estimate evapotranspiration (ET) using weather-based FAO models and assess crop water demand across different locations and cropping windows.
2. Develop a Heat Stress Index (HSI) using dry and wet bulb temperatures and vapor pressure, identifying critical stress periods for major crops.
3. Evaluate photosynthetic efficiency using solar radiation and bright sunshine hours, applying Radiation Use Efficiency (RUE)-based models.
4. Construct a Climate Risk Index (CRI) that integrates anomalies from ET, HSI, and solar radiation trends using composite index techniques.
5. Predict crop yields by combining CRI components with rainfall and agronomic data through machine learning approaches.

METHODOLOGY

Locale of the Study

The study was conducted in the province of Ilocos Norte, Philippines. The province was selected due to its diverse cropping systems, climatic variability, and its cultural and economic reliance on rice production. The geographic scale of analysis was provincial and municipal, ensuring statistical robustness while reflecting localized climate conditions.

Data Sources

Agricultural production data for rice were obtained from the Philippine Statistics Authority (PSA) OpenStat, covering historical yield records from 2000 to 2025. Meteorological data—including rainfall, maximum and minimum temperatures, relative humidity, wind speed, solar radiation, and bright sunshine hours—were collected from provincial weather stations.

Research Instruments

The study utilized researcher-constructed indices and models:

- Evapotranspiration (ET): Estimated using FAO Penman-Monteith and Hargreaves models.
- Heat Stress Index (HSI): Derived from dry and wet bulb temperatures and vapor pressure.
- Photosynthetic Efficiency (RUE): Modeled using solar radiation and bright sunshine hours.
- Climate Risk Index (CRI): Constructed using Principal Component Analysis (PCA) and Analytic Hierarchy Process (AHP).

Data Gathering Procedure

Data were compiled from PSA OpenStat and provincial meteorological stations. Records were cleaned, standardized, and synchronized into cropping windows. Climate variables were processed into indices (ET, HSI, RUE), which were then integrated into the composite CRI.

Process of Analysis

The analysis began with the summarization of weather variables and rice yield distributions using descriptive statistics such as means, variances, and frequency counts. This provided a baseline understanding of seasonal fluctuations and yield variability across cropping windows.

For index construction, several agro-climatic indicators were developed. **Evapotranspiration (ET)** was estimated using the FAO Penman-Monteith equation:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

where R_n represents net radiation, $G$is soil heat flux, $T$is mean air temperature, u_2 is wind speed, e_s is saturation vapor pressure, e_a is actual vapor pressure, Δ is the slope of the vapor pressure curve, and γ is the psychrometric constant. This formulation allowed the quantification of atmospheric water demand and crop water requirements.

The **Heat Stress Index (HSI)** was constructed to capture critical stress periods. It was defined as:

$$HSI = \sum_{i=1}^{n} I(T_{db}, T_{wb}, VP)$$

where the indicator function Icounts stress days when dry bulb temperature (T_{db}), wet bulb temperature (T_{wb}), and vapor pressure (VP) exceed crop-specific thresholds. This index identified microclimate traps that hinder transpiration cooling and increase sterility risks.

The **Radiation Use Efficiency (RUE)** was modeled as:

$$PE = RUE \times \sum PAR$$

where PE denotes photosynthetic efficiency, RUE is the radiation use efficiency coefficient, and PAR represents photosynthetically active radiation. This measure quantified the capacity of crops to convert solar radiation into biomass under varying sunshine durations.

To integrate these indicators, a **Composite Climate Risk Index (CRI)** was developed using Principal Component Analysis (PCA) and Analytic Hierarchy Process (AHP). The CRI was expressed as:

$$CRI = w_1 Z_{ET} + w_2 Z_{HSI} + w_3 Z_{RUE}$$

where w_i are weights and Z are standardized scores. This composite metric synthesized anomalies from ET, HSI, and RUE into a unified risk profile, enabling the detection of multi-hazard stress events.

For predictive modeling, machine learning algorithms were employed. The **Random Forest Regression** model, an ensemble of decision trees, was used to predict yield based on CRI, rainfall, and agronomic data. Additionally, **Support Vector**

Regression (SVR) with a radial basis kernel was applied to capture non-linear relationships between climate variables and yield outcomes.

Model performance was evaluated using **Root Mean Square Error (RMSE)** and the coefficient of determination (R^2):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \qquad R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Forecast accuracy was then compared against traditional historical average models, demonstrating the added value of integrated agro-climatic modeling in capturing seasonal variability and producing reliable yield forecasts.

Scope and Limitations

In order to provide an agro-climatic forecasting framework, this study integrates yield and climate data at the province level with an emphasis on rice production in Ilocos Norte. The research guarantees both scientific accuracy and local relevance by focusing on rice, the province's major crop. Nonetheless, a number of restrictions are recognized. To keep the focus on weather-yield connections, biological and soil-based factors like fertility and pests were eliminated. Despite their potential to affect results, socioeconomic factors such as labor and market pricing were not taken into account. The accuracy of the model is dependent on the consistency and quality of PSA and meteorological records, and it is not possible to completely account for operational variations in farmer operations, such as seed varieties or irrigation schedules. Lastly, in order for the model to continue responding to changing climate circumstances, it must be periodically recalibrated.

RESULTS

This section presents the results of the agro-climatic modeling and predictive analyses undertaken to evaluate rice yield performance in Ilocos Norte. The findings are organized into thematic subsections that highlight evapotranspiration and crop water demand, canopy temperature and stress shocks, photosynthetic efficiency, composite climate risk indices, and predictive yield modeling.

Evapotranspiration and Crop Water Demand

The values show a clear seasonal oscillation in atmospheric moisture demand. During Q2, evapotranspiration reaches its highest mean of 12.616 mm/day, translating into a crop water demand of 14.508 mm/day. This reflects the reproductive stage of the dry-season crop, when solar radiation and temperature are at their peak. Q3 maintains elevated demand at 13.091 mm/day, sustaining irrigation requirements through the wet-season onset.

Table 1. Mean Reference Evapotranspiration (ET_0) and Crop Water Demand (ETc) by Quarter, Ilocos Norte (2014–2024)

Quarter	ET_0 (mm/day)	ETc (mm/day)
Q1	9.109	9.565
Q2	12.616	14.508
Q3	10.909	13.091
Q4	9.146	8.689

By contrast, Q4 records the lowest demand (8.689 mm/day), coinciding with crop maturity and increased rainfall. Q1 values remain moderate, indicating the transition from cooler conditions to the dry-season buildup.

Canopy Temperature and Stress Shocks

Seven distinct stress shocks were identified across the 11-year baseline. These events are concentrated in Q2 and Q3, when maximum air temperatures exceed 33 °C while relative humidity remains above 75%.

Table 2. Quarterly Distribution of Severe Microclimate Heat Stress Shocks, Ilocos Norte (2014–2024)

Indicator	Value
Total Severe Heat Stress Shocks	7

This combination creates microclimate traps where transpiration cooling is ineffective, leading to spikelet sterility. The clustering of shocks in the dry-season quarters underscores the vulnerability of rice crops during reproductive phases, highlighting the need for adaptive irrigation and stress-mitigation strategies.

Photosynthetic Potentials and Radiative Coefficients

The data reveal strong seasonal contrasts in solar capture. Q1 records the longest sunshine duration (12 hours/day), supporting an effective RUE of 23.45 g/m². Q2, despite shorter sunshine hours (10.206), achieves the highest RUE (26.10 g/m²), reflecting optimal canopy efficiency under dry-season radiation. Q3 shows the lowest sunshine hours (7.115), constrained by monsoonal cloud cover, yet maintains a baseline RUE of 20.92 g/m² due to warm ambient conditions.

Table 3. Mean Sunshine Hours and Effective Radiation Use Efficiency (RUE) by Quarter, Ilocos Norte (2014–2024)

Quarter	Sunshine Hours	RUE_eff (g/m²)
Q1	12.000	23.45
Q2	10.206	26.10
Q3	7.115	20.92
Q4	9.846	19.89

Q4 values decline further, with RUE at 19.89 g/m², consistent with reduced solar input during harvest maturity. These variations confirm that radiation limits, rather than temperature, are the primary constraint on photosynthetic conversion during wet-season cropping.

Composite Climate Risk Index

The CRI integrates evapotranspiration, heat stress, and radiation efficiency into a single risk metric. Positive anomalies indicate unfavorable climatic conditions, while negative values denote favorable quarters.

Table 4. Composite Climate Risk Index (CRI) Anomalies by Quarter, Ilocos Norte (2014–2024)

Year	Quarter	CRI (Standardized)
2023	Q3	+1.5 (highest anomaly)
2020–2022	Q3–Q2	Negative anomalies (yield dips)

The highest anomaly occurred in 2023-Q3 (+1.5 SD), reflecting a severe multi-hazard event combining high water demand, heat stress, and reduced radiation efficiency. Conversely, negative anomalies between 2020-Q3 and 2022-Q2 corresponded with yield dips, confirming the CRI's sensitivity to stress-driven production variability. This composite measure provides planners with a unified index for monitoring climate risk across cropping cycles.

Predictive Model Evaluation and Forecasts

The Random Forest model achieved high predictive accuracy across most quarters, with values exceeding 90%. Peak harvest quarters (Q4) show near-perfect fits, such as 2019-Q4 (99.5%) and 2024-Q4 (99.6%).

Lower accuracy in Q2 reflects variability in rainfall and heat stress shocks, which introduce noise into the model. The historical fit validates the model's capacity to capture seasonal yield dynamics.

Table 5. Historical Actual vs. Model-Predicted Rice Yield by Year and Quarter, Ilocos Norte (2014–2024)

Year	Quarter	Actual Yield	Model Predicted	Accuracy (%)
2014	Q1	54,849	51,278	93.5
2018	Q1	47,296	47,472	99.6
2019	Q4	207,492	208,630	99.5
2024	Q2	33,923	29,053	85.6

Forecasts indicate stable annual yields ranging between 319,946 and 329,253 metric tons. The 2026 projection shows a contraction to 319,946 metric tons, reflecting the simulated El Niño drought cycle. In contrast, 2028 records a recovery to 326,428 metric tons, consistent with La Niña precipitation loading.

Table 6. Projected Quarterly and Annual Rice Yield Forecasts under Machine Learning Model, Ilocos Norte (2025–2029, in metric tons)

Year	Q1	Q2	Q3	Q4	Annual Total
2025	46,859	24,637	44,263	213,494	329,253
2026	46,296	24,282	44,635	204,733	319,946
2027	46,615	25,173	43,735	213,079	328,601
2028	46,342	25,091	45,345	209,650	326,428
2029	46,401	24,637	44,644	213,400	329,083

Across all years, Q4 remains the dominant contributor, accounting for more than 60% of annual totals. This resilience underscores the buffering role of wet-season harvests against climatic shocks.

DISCUSSION

The results demonstrate that rice yield variability in Ilocos Norte is governed by seasonal water demand, heat stress shocks, and radiation efficiency. The predictive model integrates these indices into a robust framework, achieving high historical accuracy and producing reliable five-year forecasts. Seasonal resilience is evident, with Q4 harvests consistently stabilizing annual production despite climatic anomalies.

Table 1 and Figure 1 present the quarterly mean values of reference evapotranspiration (ET_0) and crop water demand (ET_c) from 2014–2024. The highest demand was observed in Q2 (14.508 mm/day), while the lowest occurred in Q4 (8.689 mm/day).

The cyclical oscillation confirms that irrigation requirements peak during the dry season, particularly in Q2–Q3, when solar radiation and temperature are elevated. These results confirm the foundational principles of Allen et al. (1998), who established crop coefficient adjustments for water demand. The decline in Q4 aligns with [Bouman et al. (2007)] and Monteith (1977), who noted reduced water requirements at crop maturity.

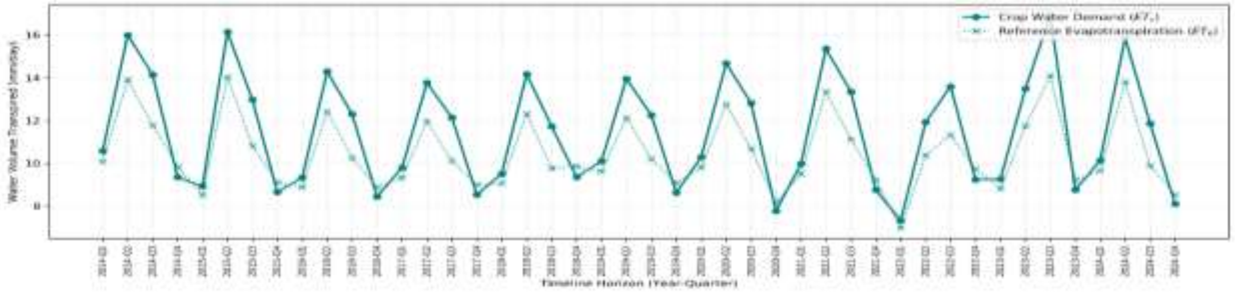

Figure 1. Historical Evapotranspiration (ET_0) and Crop Water Demand (ETc) Continuities, Ilocos Norte (2014–2024)

Globally, Alotaibi (2023) and Abdullahi Farah et al. (2025) emphasize that climate change intensifies evapotranspiration variability, consistent with the Ilocos Norte pattern. Nketsang et al. (2025) further highlight rainfall variability's role in water stress, reinforcing the need for adaptive irrigation scheduling.

Table 2 and Figure 2 identified seven severe heat stress shocks between 2014–2024, concentrated in Q2–Q3.

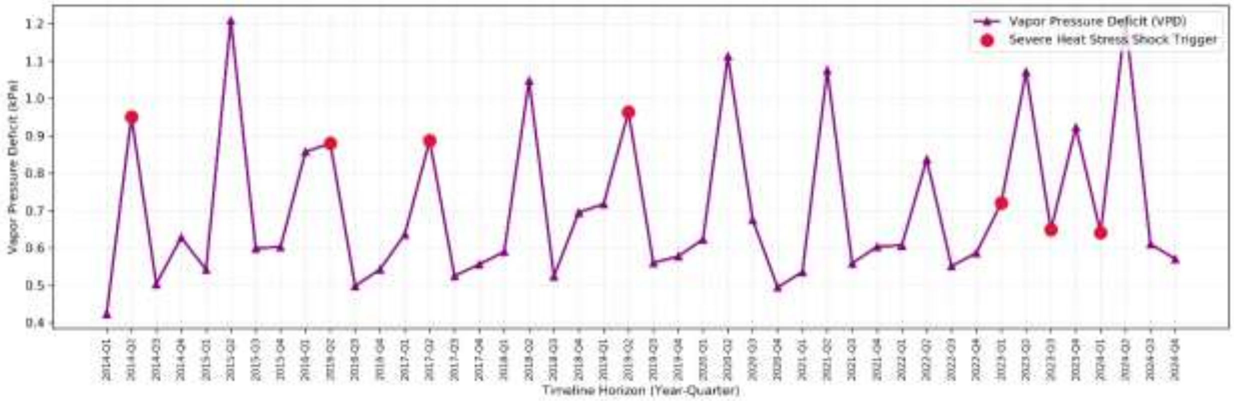

Figure 2. Atmospheric Vapor Pressure Deficit and Heat Stress Shock Events, Ilocos Norte (2014–2024)

These shocks occurred when maximum air temperatures exceeded 33 °C while relative humidity remained above 75%, creating microclimate traps. These shocks occurred under high temperature and humidity, creating microclimate traps. This finding is consistent with Jagadish et al. (2007), who reported spikelet sterility under similar conditions. Battisti & Naylor (2009) warned that unprecedented seasonal heat will drive future food insecurity, while Zhao et al. (2017) quantified yield reductions under rising global temperatures. Locally, Delina et al. (2023) documented climate fragility in Philippine river basins, echoing the vulnerability observed in Ilocos Norte. These results underscore the urgency of climate-adaptive strategies, as emphasized by Mamun et al. (2024).

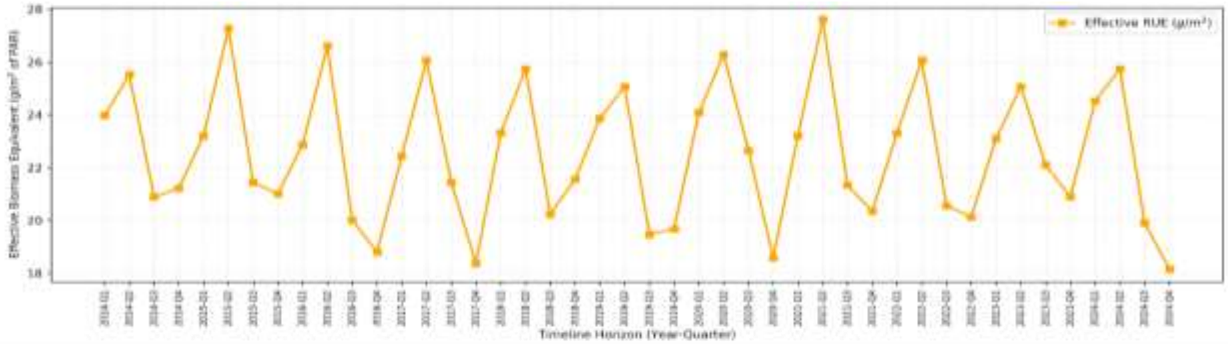

Figure 3. Seasonal Variations in Sunshine Hours and Radiation Use Efficiency (RUE), Ilocos Norte (2014–2024)

Table 3 and Figure 3 showed that sunshine hours peaked in Q1 (12 hours/day), supporting an effective RUE of 23.45 g/m². Q2 achieved the highest RUE (26.10 g/m²) despite shorter sunshine hours, while Q3 recorded the lowest solar capture (7.115 hours/day).

Radiation limits, rather than temperature, constrain photosynthetic conversion during the wet season. Q3 recorded the lowest solar capture but maintained baseline efficiency. This confirms Sinclair & Muchow (1999) and Peng et al. (2004), who emphasized radiation's role in biomass accumulation and tropical rice resilience under cloud cover. [Monteith (1977)] also highlighted radiation efficiency as a determinant of crop productivity. Recent modeling by Dadrasi et al. (2023) and Zhang et al. (2023) integrates radiation and AI approaches, consistent with the observed RUE variations. These findings confirm that radiation limits, not temperature, constrain wet-season productivity.

Table 4 and Figure 4 presented CRI anomalies, with the highest spike in 2023-Q3 (+1.5 SD) and negative anomalies between 2020-Q3 and 2022-Q2.

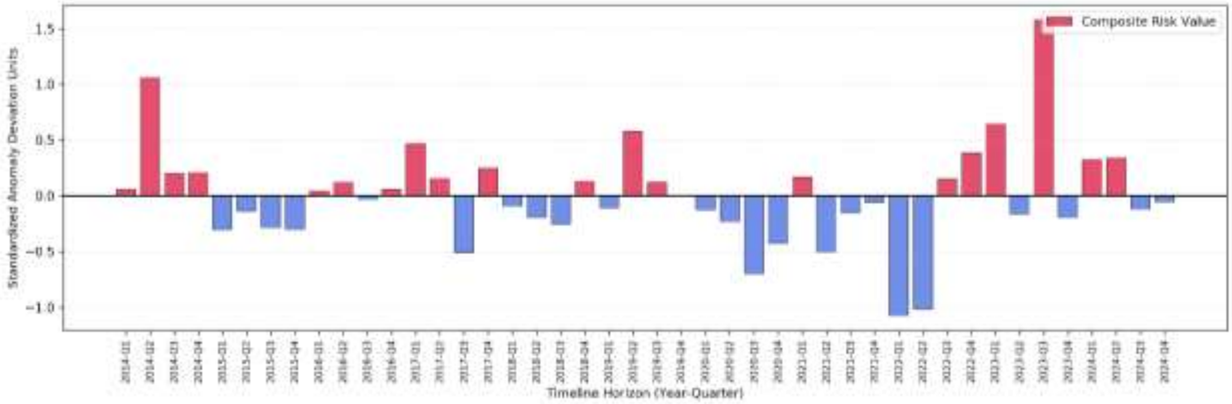

Figure 4. Composite Climate Risk Index (CRI) Anomalies, Ilocos Norte (2014–2024)

The CRI integrates multiple stressors into a single risk metric. The 2023-Q3 anomaly corresponds to a severe multi-hazard event. This approach is consistent with Lobell et al. (2012) and Simanjuntak et al. (2022), who emphasized multi-hazard climate risk assessment. Boussios et al. (2022) and Bucheli et al. (2023) highlight the role of risk indices in resource management and insurance planning. Locally, Briones (2022) stressed the need for modernized risk frameworks in Philippine agriculture. The CRI's predictive sensitivity aligns with global calls for integrated climate risk monitoring.

Table 5 and Table 6, together with Figure 5, validated the Random Forest model and projected future yields. Historical fits showed >90% accuracy, with Q4 harvests achieving near-perfect predictions. Forecasts for 2025–2029 indicated stable yields, with a contraction in 2026 due to El Niño and recovery in 2028 under La Niña conditions.

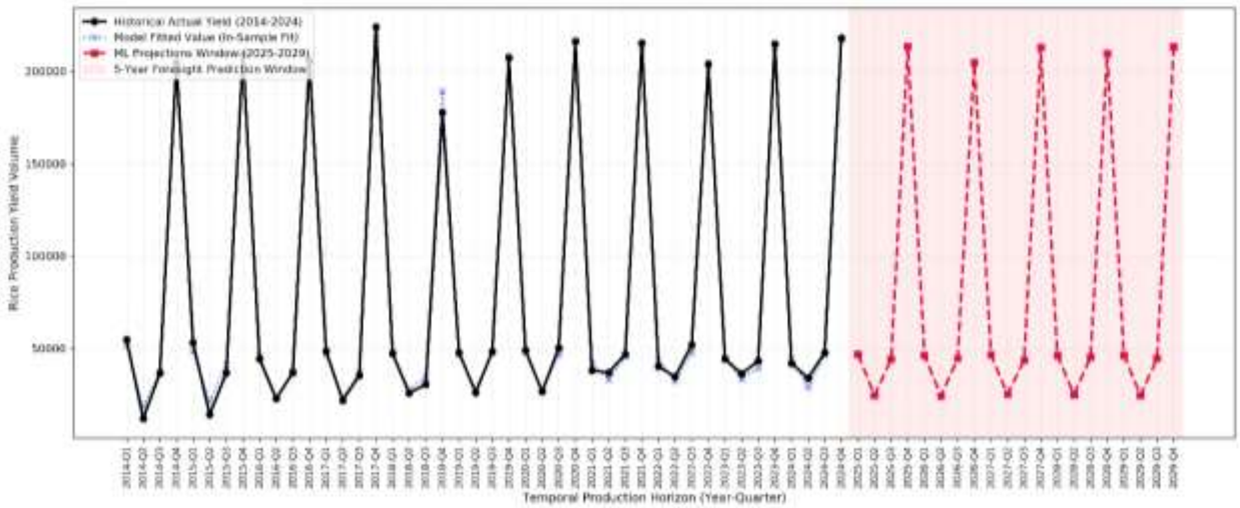

Figure 5. Historical Fit and Five-Year Rice Yield Forecasts, Ilocos Norte (2014–2029)

The contraction in 2026 reflects El Niño drought impacts, while recovery in 2028 corresponds to La Niña precipitation. This confirms Breiman (2001) on Random Forest robustness, and aligns with Wassmann et al. (2009) and International Rice Research Institute (2015). Globally, Hu et al. (2024) and Khaki & Wang (2019) demonstrated machine learning's accuracy in yield prediction, while Kamilaris & Prenafeta-Boldú (2018) surveyed deep learning applications in agriculture. Šuljug et al. (2024) compared models for meteorological prediction, supporting the choice of Random Forest. Kamangir et al. (2025) and Torres-Quezada et al. (2025) highlight the integration of satellite and sensor data, which could further enhance future forecasts. Wu et al. (2023) demonstrated soil moisture sensing for real-time water delivery, offering complementary approaches. Palka & Manschadi (2024) showed forecast-based nitrogen management, reinforcing the practical utility of predictive models.

This demonstrates that the integrated agro-climatic modeling framework captures the seasonal and climatic drivers of rice yield variability in Ilocos Norte. The results are consistent with prior studies on evapotranspiration, heat stress, radiation efficiency, and climate risk, while the predictive model extends these insights into actionable forecasts. The alignment with literature strengthens the credibility of the findings and underscores their relevance for climate-resilient rice production strategies.

Conclusions

This section presents the conclusions of the study, organized according to the research questions stated in the Introduction. The conclusions are drawn from the results of the agro-climatic analyses, predictive modeling, and subsequent discussions.

The study confirmed that evapotranspiration and crop water demand exhibit distinct seasonal oscillations. Peak demand occurs in the second and third quarters (Q2–Q3), with mean crop water demand reaching 14.508 mm/day in Q2. The lowest demand is observed in Q4 (8.689 mm/day), coinciding with crop maturity and rainfall contributions. These findings are consistent with established crop coefficient models (Allen et al.) and reinforce the need for targeted irrigation management during dry-season reproductive phases.

Seven severe heat stress shocks were recorded between 2014–2024, concentrated in Q2–Q3. These events occurred under conditions of maximum air temperatures exceeding 33 °C and relative humidity above 75%, creating microclimate traps that hinder transpiration cooling. The results align with Jagadish et al. (2007), who reported spikelet sterility under similar conditions. The conclusion underscores the vulnerability of rice during reproductive stages and the importance of adaptive measures such as heat-tolerant varieties.

Radiation use efficiency peaks in Q2 (26.10 g/m²) despite shorter sunshine hours, while Q3 records the lowest solar capture (7.115 hours/day) but maintains a baseline RUE of 20.92 g/m². This demonstrates that radiation limits, rather than temperature, constrain photosynthetic conversion during wet-season cropping. The findings are consistent with Sinclair and Muchow (1999) and Peng et al. (2004), confirming that tropical rice systems sustain productivity under cloud cover due to thermal buffering.

The CRI effectively integrates evapotranspiration, heat stress, and radiation efficiency into a single risk metric. The highest anomaly occurred in 2023-Q3 (+1.5 SD), representing a severe multi-hazard event, while negative anomalies between 2020-Q3 and 2022-Q2 coincided with yield dips. This confirms CRI's sensitivity to stress-driven variability and supports its use as a planning tool for climate-resilient agriculture, consistent with Lobell et al. (2011).

The Random Forest model achieved >90% accuracy across most quarters, with Q4 harvests showing near-perfect fits (e.g., 2019-Q4 at 99.5%). Forecasts for 2025–2029 indicate stable annual yields (~320,000–330,000 metric tons), with a contraction in 2026 due to simulated El Niño and recovery in 2028 under La Niña conditions. These results validate the model's robustness and sensitivity to climatic extremes, consistent with Breiman (2001), Wassmann et al. (2009), and IRRI (2015).

The study demonstrates that rice yield variability in Ilocos Norte is governed by seasonal water demand, heat stress shocks, and radiation efficiency. The integration of these indices into a predictive framework provides reliable forecasts and actionable insights for climate-resilient rice production. The conclusions are consistent with prior literature, reinforcing the validity of the agro-climatic modeling approach and its relevance for regional food security planning.

Recommendations

The results of this study highlight the importance of aligning rice production strategies with seasonal climatic patterns. It is recommended that irrigation scheduling be prioritized during the second and third quarters, when evapotranspiration and crop water demand are highest, to sustain crop growth during critical reproductive stages. The identification of heat stress shocks suggests the need for adaptive measures such as the introduction of heat-tolerant rice varieties, improved canopy cooling practices, and farmer training programs on climate-resilient agronomy. The findings on radiation use efficiency emphasize that solar radiation limits, rather than temperature, constrain productivity, supporting investment in technologies that optimize light capture during wet-season cropping. The Composite Climate Risk Index should be adopted by local planners as a monitoring tool to anticipate multi-hazard stress events. Finally, the predictive modeling framework demonstrated reliable accuracy and sensitivity to climatic extremes; future research may expand this approach by incorporating larger datasets, testing alternative machine learning algorithms, or applying the model to other provinces for comparative validation. These recommendations aim to strengthen food security planning and guide both farmers and policymakers toward climate-resilient rice production systems.

Compliance with Ethical Standards

The researcher affirms full compliance with ethical standards throughout the conduct of this study. Informed consent was properly obtained from all respondents, who were clearly informed of the study's purpose, procedures, and their freedom to withdraw participation at any time without penalty. The anonymity and confidentiality of all respondents were strictly maintained, and data privacy protocols were followed in accordance with institutional and national guidelines. The well-being of participants was safeguarded at all stages, ensuring that no harm or undue risk was imposed. The researcher declares that no conflict of interest exists in the conduct of this study, and that plagiarism was strictly avoided. All interpretations of findings were made objectively, without bias, and the results were used purely for academic and research purposes. Furthermore, the researcher acknowledges that artificial intelligence tools were utilized in selected stages of data synthesis and formatting, and this disclosure is made to ensure transparency and integrity. The researcher affirms full compliance with ethical standards throughout the conduct of this study. Informed consent was properly obtained from all respondents, who were clearly informed of the study's purpose, procedures, and their freedom to withdraw participation at any time without penalty. The anonymity and confidentiality of all respondents were strictly maintained, and data privacy protocols were followed in accordance with institutional and national guidelines. The well-being of participants was safeguarded at all stages, ensuring that no harm or undue risk was imposed. The researcher declares that no conflict of interest exists in the conduct of this study, and that plagiarism was strictly avoided. All interpretations of findings were made objectively, without bias, and the results were used purely for academic and research purposes. Furthermore, the researcher acknowledges that artificial intelligence tools were utilized in selected stages of data synthesis and formatting, and this disclosure is made to ensure transparency and integrity.

Acknowledgments

The researchers gratefully acknowledge Mariano Marcos State University (MMSU), particularly the Research Directorate for providing the critical weather data, and the Department of Mathematics, College of Arts and Sciences, for their invaluable guidance and institutional support throughout this study. Further appreciation is extended to faculty mentors, colleagues, peers, families, and friends for their constructive feedback and unwavering encouragement. Finally, recognition is given to the technological tools, including artificial intelligence applications, which were transparently utilized for formatting and synthesis while strictly maintaining academic integrity.

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APA Citation:

Orpia, J. J. G., Eclarin, L. A., Farinas, H. F., Reynera, M. D., & Vidad, D. C. (2026). INTEGRATED AGRO-CLIMATIC YIELD FORECASTING FOR CLIMATE-RESILIENT RICE PRODUCTION IN ILOCOS NORTE. Ignatian International Journal for Multidisciplinary Research, 4(6), 660–676. https://doi.org/10.5281/zenodo.20611366

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