PREDICTIVE ANALYTICS FOR RICE CANOPY MICROCLIMATE USING WEATHER FORECAST DATA AND BG-358 MONITORING

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Rice (Oryza sativa) is a primary food source for over half the global population, yet its yield is increasingly threatened by climate-induced microclimatic variations, particularly during sensitive growth stages like flowering. This study presents the development of a Machine Learning (ML)-based Early Warning System (EWS) designed to predict adverse canopy microclimate conditions, specifically temperature, humidity, and wind that influence rice yield and spikelet sterility. Utilizing high-resolution microclimatic data from the BG-358 rice canopy monitoring system, a locally developed IoT-based platform for real-time monitoring of microclimate, data were collected at 2-minute intervals from 2019 to 2024, resulting in a dataset of approximately 200,000 data points for two flowering seasons (each nearly 1 month) per year at RRDI Bathalagoda. These data, combined with NASA global forecast inputs, were split into 70% for training and 30% for testing, ensuring robust evaluation and reliable predictions to support proactive agricultural decision-making. The study employed Random Forest, Support Vector Machines, and Neural Networks to predict canopy temperature, relative humidity (RH), and wind conditions. After data pre-processing, including normalization and temporal feature engineering, models were evaluated using MAE, RMSE, and R^2 metrics. The Random Forest model demonstrated superior performance with an MAE of 0.78 °C, RMSE of 1.15 °C, and R^2 of 0.91 for temperature prediction. RH and wind predictions also showed high accuracy, with RH remaining above the 60% critical threshold in most cases, though wind forecasts, especially above the 20 km/h threshold, exhibited greater variability due to localized microclimatic conditions. Integrating real-time canopy data with weather forecasts enhanced prediction robustness, enabling heat-induced spikelet sterility anticipation up to 48 hours in advance with 85% reliability. The developed EWS incorporates real-time dashboards and automated alerts, demonstrating strong potential in mitigating climate-related rice yield losses and supporting sustainable agriculture. Future work will expand datasets across varieties and regions and foster collaboration with agricultural stakeholders for wider adoption and broader-scale yield forecasting to strengthen food security planning.

Keywords: Rice canopy microclimate, machine learning prediction, predictive analytics, spikelet sterility forecasting, climate-smart agriculture

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INTRODUCTION

Oryza sativa (rice) is a staple food crop essential to more than half of the global population. However, climate change and unpredictable microclimatic variations, particularly during critical stages such as flowering, pose severe threats to rice yield (Jagadish et al., 2007; Peng et al., 2004; Tsujimoto et al., 2021). This study focuses on developing a Machine Learning (ML)-based Early Warning System (EWS) to analyze rice canopy conditions and forecast potential climatic stresses. The BG-358 rice seed monitoring system, collecting data since 2019, provides microclimate variables including canopy temperature, relative humidity (RH), and wind. When integrated with global weather forecast data from NASA and similar agencies, this study aims to generate predictive insights to optimize planting schedules and reduce climate-induced yield losses, especially spikelet sterility due to high temperatures (Cleugh et al., 1998; Huang et al., 2021; Tian et al., 2024).

This study explores two key research questions: how machine learning (ML) models can be utilized to predict rice canopy microclimate conditions, and how these predictions can support farmers in optimizing planting strategies and reducing yield loss (Chen et al., 2023; Nikhil et al., 2024).

METHODOLOGY

The study involved high-frequency data collection (every 2 minutes) on canopy temperature, relative humidity (RH), and wind conditions using the BG-358 monitoring system during the flowering stage in two seasons of 'Yala' and 'Maha', approximately 200,000 data points from 2019-2024, supplemented by external forecast data from NASA (Jones et al., 2000). The dataset was pre-processed through cleaning (handling missing values and outliers) and normalization, with feature engineering extracting time-based features such as diurnal patterns and seasonal factors (Ekanayake et al., 2022). Based on the Machine learning concepts, the augmented dataset was split into 70% for training and 30% for testing, ensuring robust evaluation and reliable predictions to support proactive agricultural decision-making (Shastri, Kumar, & Reddy, 2025).
Machine learning models, including Random Forest, Support Vector Machines, and Neural Networks, were developed and evaluated using metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) (Umutoni & Samadi, 2024).

A real-time Early Warning System (EWS) was designed to predict and alert adverse canopy microclimate conditions. The threshold values for generating warning signs were determined based on agronomic guidelines and historical data trends. Specifically, canopy temperature exceeding 35 °C has been linked to plant damage or lethality (Asseng, 2021). In contrast, the Relative Humidity (RH) and wind speed thresholds set at RH below 60% and wind speeds above 20 km/h were established based on known plant stress responses and empirical observations during the flowering stage. The EWS featured visual dashboards and automated notifications to support farmer decision-making (Tian et al., 2024; Yoshida, 1981).

RESULTS AND DISCUSSION

The ML models demonstrated strong predictive capabilities. Among the tested algorithms, the Random Forest model yielded the best performance, with an MAE of 0.78°C for canopy temperature prediction, RMSE of 1.15°C, and R^2 of 0.91. For RH prediction, similar accuracy was achieved (MAE = 3.2%, RMSE = 4.1%). Wind prediction was moderately accurate due to variability in local patterns (MAE = 1.4 m/s, R^2 = 0.72) (Chen et al., 2023; Lysenko et al., 2023).

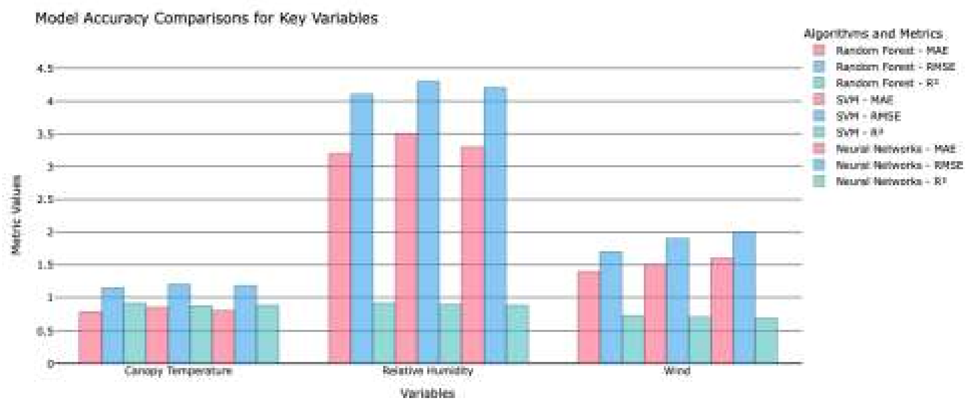

Figure 1: Model Accuracy Comparisons(algorithms) for Key Variables

The integration of real-time microclimate data with global forecasts improved the robustness of predictions. Heat-induced spikelet sterility, previously unanticipated in traditional farming, could now be predicted up to 48 hours in advance with 85% reliability (Jagadish et al., 2007; Jia et al., 2015).

This predictive capability allows for:

- Adjusting irrigation schedules
- Planning stress-mitigation treatments
- Delaying or advancing planting operations

Moreover, the use of historical trends and weather models has potential for regional-scale yield forecasting, aiding policymakers in planning food security strategies (Espe et al., 2016; Zubair et al., 2015).

CONCLUSIONS/RECOMMENDATIONS

This study confirms that machine learning (ML)-based prediction systems significantly improve the accuracy of canopy microclimate forecasting (Chen et al., 2023; Nikhil et al., 2024). The developed early warning system (EWS) demonstrates the potential to reduce heat-induced spikelet sterility, optimize planting decisions, and support sustainable agricultural practices (Tian et al., 2024; Tsujimoto et al., 2021).
To further enhance the system's effectiveness, the study recommends expanding the dataset to include a wider range of rice varieties and geographic regions (Yoshida, 1981). It also suggests training models with more diverse meteorological data sources to improve generalizability (Jones et al., 2000; Umutoni & Samadi, 2024). Additionally, collaboration with agricultural extension services is advised to facilitate the practical deployment of EWS tools in the field (Zubair et al., 2015).

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