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Exploring Rice Yield Variability Under Climate Change Through NDVI Analysis

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Abstract

This study presents a novel approach to predicting paddy yields in Brunei's Wasan Rice Scheme using projected normalized difference vegetation index (NDVI) values derived from climate projections under three time periods: near future (2020–2046), mid-future (2047–2073), and far future (2074–2100). Employing CMIP6 socioeconomic pathways (SSP245, SSP370, SSP585), random forest (RF) and multiple linear regression (MLR) models were utilised to link historical NDVI with meteorological factors such as rainfall and temperature. Results indicate that main-season yields are expected to decline or stabilize across scenarios, while off-season NDVI consistently increases, reflecting robust vegetation recovery. These findings emphasize the differential impacts of climate change across growing seasons, providing critical insights for agricultural planning and adaptation strategies. By integrating scenario-based NDVI projections and predictive modeling, this study offers a comprehensive framework for understanding future crop dynamics under changing climatic conditions.

Keywords

Crop yield forecasting, NDVI, remote sensing, random forest, polynomial regression

Introduction

Predicting rice output has become increasingly important in the context of climate change, as it directly affects both economic stability and food security (Budathoki et al., 2022). Moreover, half of the world's population is fed by rice, a staple grain. In the Asian region, studies have shown that rainfall patterns significantly influence rice yields. For instance, research indicates that both deficit and excessive rainfall can adversely affect monsoon-season rice yields, with optimal rainfall thresholds being crucial for maximizing production (Maiti et al., 2024). Additionally, a case study in Indonesia demonstrated that projected changes in rainfall patterns due to climate change could lead to yield reductions of up to 11.77% by the 2050s, emphasizing the need for adaptive strategies to manage these impacts (Ansari et al., 2021). Accurate rice yield prediction allows farmers, policymakers, and researchers to anticipate and mitigate the impacts of climate change on rice production.

By utilising advanced technologies such as the Normalised Difference Vegetation Index (NDVI) from remote sensing, stakeholders can monitor crop health, growth stages, and potential

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stress factors in real time (Alfiance Kaligis & Xaverius Manggau, 2023; Pandit et al., 2023; Shoaib, 2023). NDVI helps in assessing vegetative cover and biomass, which are critical indicators of crop yield potential. Several studies have demonstrated that NDVI reflecting peak greenness is the most effective parameter in forecasting crop yield (Zhang & Zhang, 2016; Johnson et al., 2021; Singha & Swain, 2022; Yu et al., 2022). The crop peak NDVI occurs during the period between flowering and milky ripeness (Shuai et al., 2013), which is the grain filling phase of the crop growth stage (Funk & Budde, 2009). Therefore, peak NDVI values were used to indicate the response of crop health to climate change at the field level.

Peak NDVI greenness can be used as a predictor of rice yield (S. Rodimtsev et al., 2023; S. A. Rodimtsev et al., 2023). Rice has also been related to a normalised difference index to monitor crop health and estimate crop yield using an empirical relationship because vegetation indices derived from spectral reflectance exhibit traits that are specific to crop development and health (Ryu et al., 2020). Mosleh et. al. used NDVI to forecast rice yield during the initial and peak greenness stages of the crop (Mosleh et al., 2016). The key to ensuring food security is accurately predicting the rice harvest before the growing season ends (Huang et al., 2013; Nuarsa et al., 2011).

The goal is to forecast paddy yield for the main and off seasons by constructing a future NDVI prediction model in Brunei. Consequently, our objectives are for the following purposes: (i) to identify the peak-NDVI for the main and off seasons during 2010-2019 in the paddy field of Brunei Muara District; (ii) to investigate the relationships between meteorological variables and NDVI and forecast the peak-NDVI trend from 2020 to 2100, which are further categorised into three separate future periods (i.e., near, mid, and far future periods); and (iii) to examine the performance of several regression models (linear, quadratic, and cubic) in forecasting future paddy output based on the expected peak-NDVI values for three future periods. This study can reveal the changes in NDVI values of paddy fields in Brunei Muara and determine the underlying causes of their dynamic shifts. Additionally, this research will offer a theoretical framework for addressing future climate change, and early estimation of crop yield can assist in formulating cultivation management and policies in Brunei to address potential challenges related to climate change.

Methodology

The research focuses on Wasan Rice Scheme (Figure 1), the largest wet rice agricultural farm in Brunei Muara, with a humid continental climate. The Wasan Rice Scheme involves two cooperatives, Mukim Pengkalan Batu Consulative Council and KOSEKA, with KOSEKA having the largest rice acreage. The scheme is supported by nearby water resources, including Imang Dam.

To forecast rice yield based on climate-driven NDVI, this study utilises a comprehensive dataset that includes both historical and future climate data and mean peak NDVI data. The peak NDVI time series is derived from the MODIS NDVI products, specifically the MOD13Q1, which provides vegetation indices at a spatial resolution of 250 meters and a temporal resolution of 16 days. MODIS (Moderate Resolution Imaging Spectroradiometer) is a key instrument aboard NASA's Terra and Aqua satellites. The peak NDVI time series (2010–2019) was extracted using QGIS, an open-source geographic information system, to analyse the maximum NDVI values during the rice heading stage in the study region. The mean peak NDVI values are found during these stages, resulting in at least two peak NDVI values per year. Peak NDVI values are predicted for future seasons based on January and June, as they are the peak NDVI months for the main season and off season, respectively.

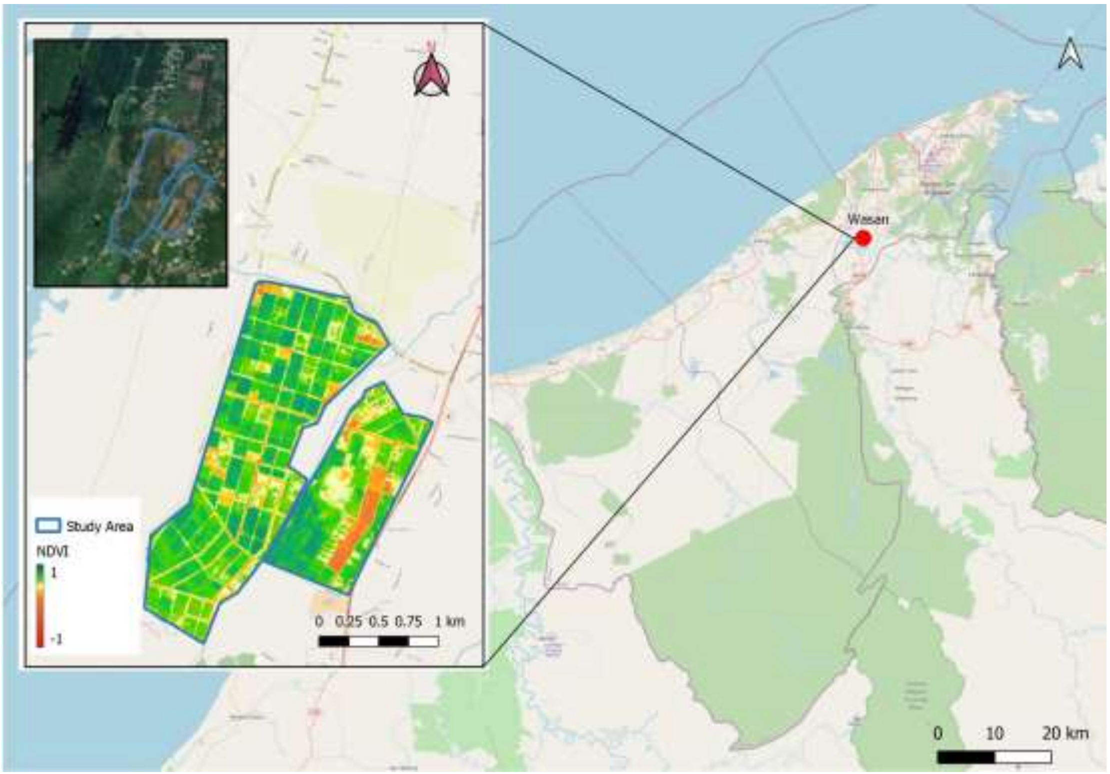

Figure 1. Wasan rice field in the Brunei Muara district.

The study used climatic parameters such as rainfall (Pr), minimum temperature (Tmin), and maximum temperature (Tmax) from 1979 to 2019 to downscale CMIP6 climate projections for three socioeconomic pathways (SSP245, SSP270, and SSP585). Seven General Circulation Models (GCMs) were selected based on the published work by Rhymee et al. (2022): AWI-CM-1-MR (developed by the Alfred Wegener Institute) (Semmler et al., 2020), ACCESS-CM2 (Australian Bureau of Meteorology and CSIRO) (Bi et al., 2013), MIROC6 (Japan's University of Tokyo and JAMSTEC) (Tatebe et al., 2019), MRI-ESM2-0 (Meteorological Research Institute, Japan) (Yukimoto et al., 2019), MPI-ESM1-2-LR (Max Planck Institute for Meteorology, Germany) (Mauritsen et al., 2019), NorESM2-LM (Norwegian Climate Centre) (Seland et al., 2020), and INM-CM5-0 (Institute of Numerical Mathematics, Russia) (Volodin et al., 2018). The selected GCMs were bias-corrected using quantile delta mapping (QDM) based on the R-package MBC (version 0.10-7) in R software (version 4.4.1). QDM retains statistical traits like mean, variance, and correlation qualities in data at all quantiles, ensuring accurate climate model simulations (Chen et al., 2013). The research aims to forecast future peak NDVI values for the growing season by establishing a link between delayed climatic factors and NDVI. The study considers nine predictors from three average groups of projected climate data sets, using lagged climate predictors two weeks, one month, and two months prior to the peak NDVI date. Specifically, the averages are calculated for two weeks (Pr_2W, Tmin_2W, Tmax_2W), one month (Pr_1M, Tmin_1M, Tmax_1M), and two months (Pr_2M, Tmin_2M, Tmax_2M) before the peak NDVI. The Department of Agriculture and Agrifood, Brunei (DAA) provided crop data from 2010-2019 showing the average paddy yield in the Wasan area.

Figure 2 illustrates the flowchart of methodology. The study used QGIS to calculate NDVI values from MODIS NDVI images of the Wasan paddy field. Simple linear regression and random forest regression were used to determine the effect of climatic parameters on NDVI from 2010 to 2019 for calibration purposes. The flowchart presents a detailed process for paddy yield prediction using NDVI values obtained from MODIS satellite images and meteorological data. First, the MODIS satellite images spanning from 2010-2019 are used to extract the peak NDVI greenness during the main and off seasons. Then, using zonal statistics in QGIS, mean NDVI values are calculated. The peak NDVI values are then predicted using two prediction models, random forest and linear regression.

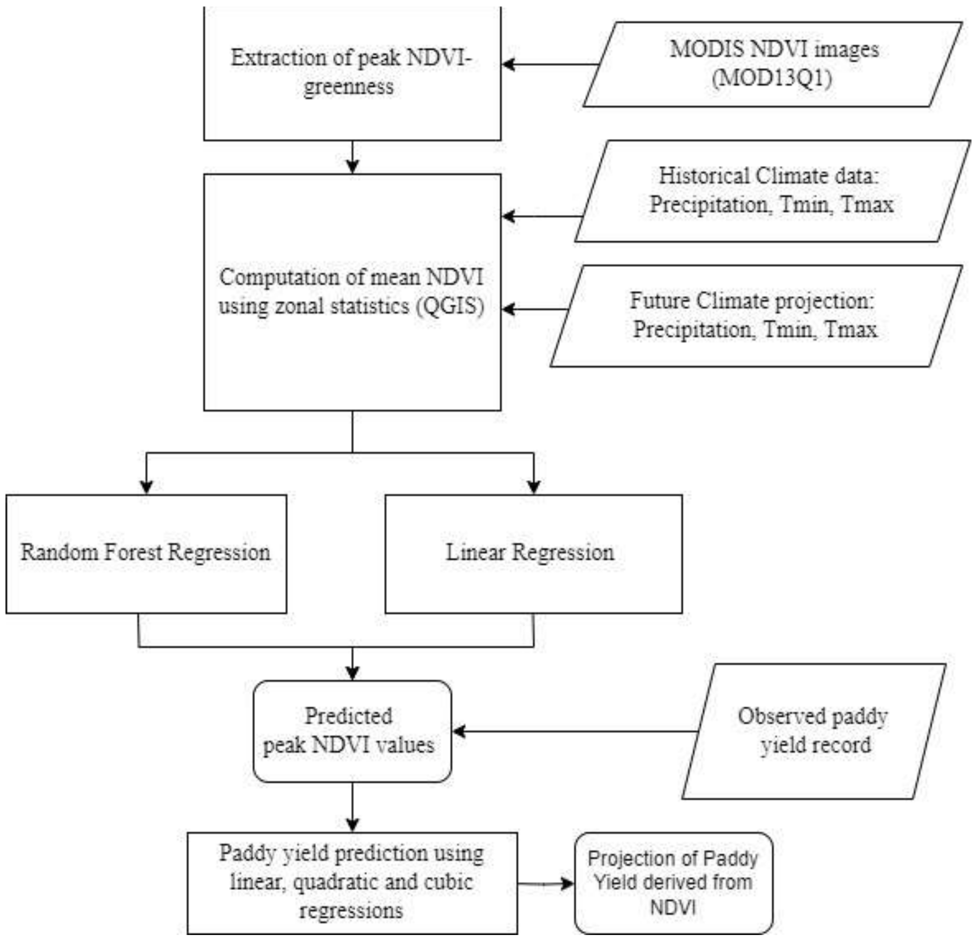

Figure 2. The flowchart of prediction of paddy yield based on the predicted NDVI values for paddy.

The three polynomial regression models employed to forecast paddy yield trends across two growing seasons are shown in Equations 1-3. The yield per season, expressed in metric tonnes per hectare (Mt/ha), is represented by Y, which functions as a dependent variable correlated with x, the predicted peak NDVI. The constants a, b, c, and d serve as the polynomial regression coefficients for each respective model.

$$\text{Linear: } Y = ax + b \qquad \text{(Equation 1)}$$

$$\text{Quadratic: } Y = ax^2 + bx + c \qquad \text{(Equation 2)}$$

$$\text{Cubic: } Y = ax^3 + bx^2 + \text{cx} + \text{d} \qquad \text{(Equation 3)}$$

The performance of both the NDVI prediction models and the paddy yield models is assessed and compared using statistical metrics, including RMSE (root mean square error) and R^2 (coefficient of determination). The best-performing models for both NDVI and paddy yield predictions are then selected based on these evaluations.

Results and Discussion

The future NDVI models are based on annual mean peak NDVI values from the main and off seasons. Peak NDVI values are selected during calibration, representing the crop's maximum vegetation growth observed in pixel data before harvesting. Linear regression predictors are chosen based on climatic variables with the highest adjusted R^2, that includes Tmax_2W and Pr_1M as the predictors of the linear regression model for the NDVI prediction:

$$NDVI = 0.413 + 0.00856 * Tmax\_2W + 0.00294 * Pr\_1M \qquad \text{(Equation 4)}$$

The random forest model's importance is based on node impurity increase, with Pr_1M and Pr_2M being the most significant variables, indicating a correlation between NDVI values. The dataset from 2010-2019 used for RF-based NDVI prediction was split into 75% and 25% for the calibration and validation periods, respectively. The validation period for annual LR-based NDVI prediction is 2017-2019. The RF model outperformed the LR model in predicting NDVI values during calibration and validation periods. RF achieved an R^2 of 0.94 and an RMSE of 0.015, while LR had an R^2 of 0.109 and an RMSE of 0.570 during the calibration period. The validation findings provided further supporting evidence for the robustness of the RF model, which attained a R^2 value of 0.817 and an RMSE value of 0.016, in contrast to the LR model's R^2 value of 0.401 and RMSE value of 0.200.

The seasonal RF model for paddy shows a projected mean peak NDVI for both main and off seasons is illustrated in Figure 3. The main season peak NDVI shows a similar trend under all SSPs. The near future trend of SSP245 is decreasing. In the next future period, NDVI exhibits an increasing trend, possibly due to significant changes in both Pr_1M and Pr_2M, as these two variables are the most important predictors in the RF model. In the far future, the NDVI trend displays a decline. Under SSP370, the NDVI displays a consistent trend during both near and mid future periods, mirroring the pattern seen under SSP245. On the other hand, NDVI exhibits a steady or slightly increasing pattern, indicating stable vegetation conditions during the off season under SSP245. In contrast, both SSP370 and SSP585 scenarios demonstrate more pronounced increases in NDVI, suggesting enhanced vegetation growth and recovery during this period.

Previous studies have examined the relationship between NDVI and crop yields for staple crops like rice, wheat, and maize (Huang et al., 2013; Islam et al., 2023; Liu et al., 2024; Singha & Swain, 2022). However, these studies focused on historical NDVI trends for rice yield prediction, without considering future projections or socioeconomic pathways. This study fills this gap by using a random forest model with predicted NDVI values based on CMIP6 climate projections, providing insights into how crop health and productivity may change under different climatic conditions. Understanding both immediate and long-term impacts of climate variability on crop production is essential for effective adaptation strategies (Minoli et al., 2022), and long-term NDVI prediction facilitates this by providing insights into how climate impacts evolve over time across near, mid and far future periods.

The performance of the three regression models for the rice yield prediction during the validation periods is in Table1. The rice yield model based on cubic regression yields the best coefficient of determination (R2 = 0.752) with an RMSE of 0.450, according to the results. Thus, in order to forecast paddy yield in Brunei for both the main and off seasons, this study used cubic regression. Figures 4 illustrate how the yield of rice varies under all SSPs for the main and off seasons.

Table 1. The validation of polynomial regression models for predicting rice yield.

Regression Models	R^2	RMSE
Linear: Y= $4.80x - 0.65$	0.029	0.430
Quadratic: $Y = -15.54x^2 + 26.64x - 8.29$	0.051	0.490
Cubic: Y=$-1624.00x^3 + 3404.20x^2 - 2368.20x + 549.4$	0.752	0.450

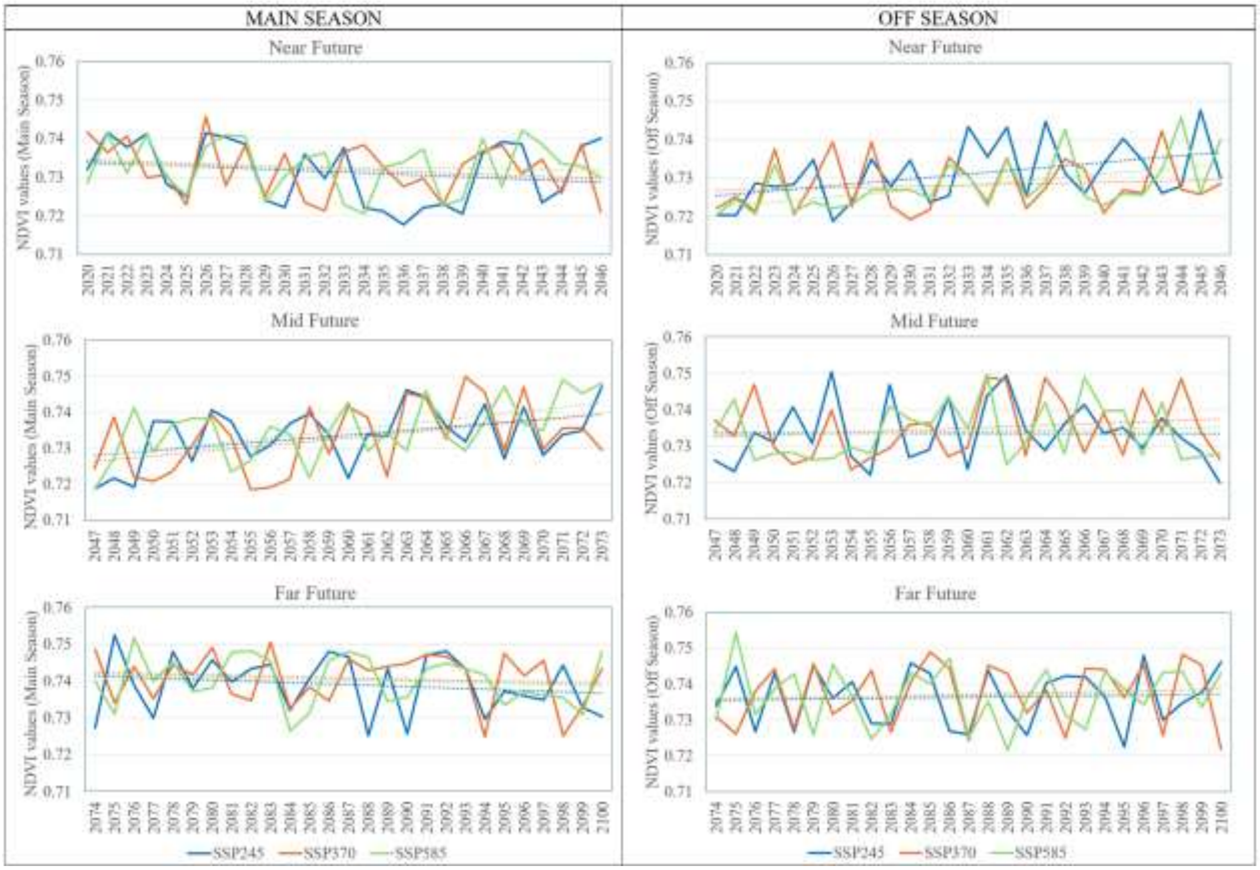

Figure 3. RF model projections of mean NDVI in Wasan's paddy fields under different climate scenarios (SSP245, SSP370, SSP585) over the future periods for the main and off seasons.

The analysis of paddy yield trends across future periods and SSPs highlights distinct seasonal patterns, with varying impacts on the main and off seasons is depicted in Figure 4. In the main season, SSP245 and SSP370 exhibit declining trends in the near future, followed by recovery in the mid future and stabilization in the far future. Under SSP585, the main season shows a slight decline in the near future but a notable increase in the mid future before stabilising in the far future. In contrast, the off season consistently demonstrates positive trends across all SSPs in the near future, with SSP585 showing the steepest growth. While trends stabilise for SSP245 and SSP585 in the mid future, SSP370 shows a minor increase. In the far future, SSP245 and SSP370 remain stable, while SSP585 continues to show slight growth, underscoring more consistent improvements during the off season.

Zheng's study, focused on the Songnen Plain of China, identified slight increases in rice yields under SSP245 in the near and mid future but significant declines under SSP585 in the far future due to extreme weather events (Zheng et al., 2022). Arunrat's research in Thailand observed similar gradual yield increases under SSP245 across all periods, contrasted with substantial reductions under SSP585 in specific decades such as the 2030s, 2055, and 2080s (Arunrat et al., 2022). Zhao's study, analysing South America, found minimal changes under SSP126 but significant challenges for rice production under SSP245 and SSP585 due to increasing extreme weather events in the far future (Zhao et al., 2022).

The current study, centered on Brunei's Wasan Rice Scheme, reflects these broader trends, with declining main season yields under SSP585 in the near and far future, alongside recovery under SSP245 in the mid future. However, it offers a unique perspective by emphasizing seasonal differences. Unlike other studies, this research reveals consistent positive off-season yield trends across all SSPs, particularly SSP585, providing novel insights into seasonal resilience and opportunities for adaptive strategies in response to climate change.

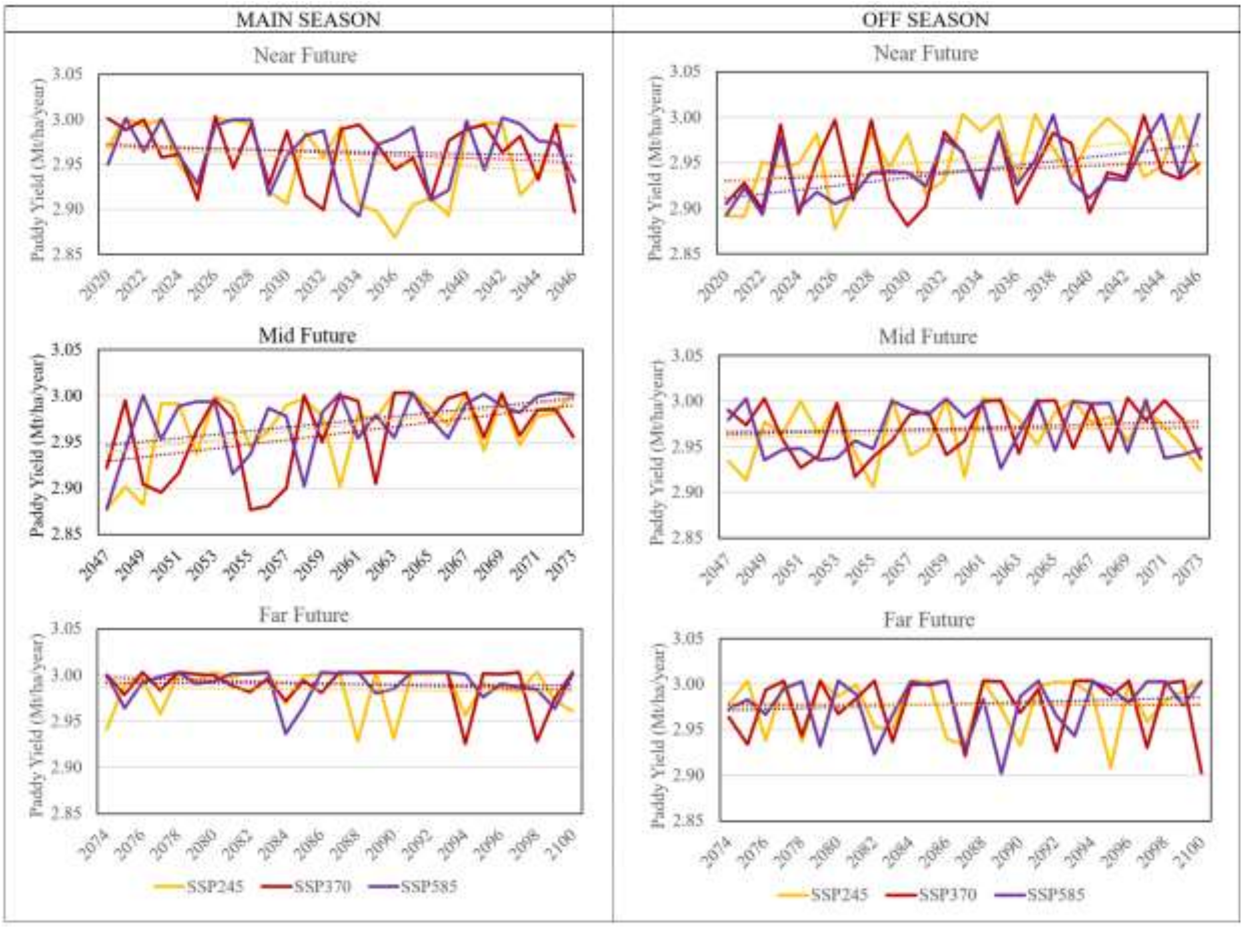

Figure 4. Rice yield under different climate scenarios (ZSSP245, SSP370, SSP585) over the future periods for the main and off seasons.

Conclusion

The study uses multiple linear regression and random forest regression to predict the annual NDVI model for paddy yield. The developed peak-NDVI models show consistent trends across different Shared Socioeconomic Pathways (SSPs), with varying patterns in the near, mid, and far future periods. The main season yield shows consistent trends across different SSPs, while the off-season yield shows a gradual increase, possibly influenced by rising precipitation trends. The main paddy yield of SSP245 is expected to decrease slightly in the near future, then increase in the mid future, but show a significant downward trend in the far future. This study offers a preliminary framework for predicting rice yield based on NDVI data and climate projections, serving as a valuable tool to identify potential vulnerabilities and guide adaptation strategies. While further refinement and validation are recommended to enhance predictive accuracy, the findings provide critical insights into rice production dynamics under changing climatic conditions.

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