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ANALYZING CLIMATE IMPACTS ON RICE PRODUCTION IN SUMATRA THROUGH SPATIOTEMPORAL MACHINE LEARNING MODELS

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Abstract— *Climate variability poses a major challenge to rice production in Sumatra, a key contributor to Indonesia's food security. This study aims to analyze spatiotemporal climate impacts on rice yields by integrating climatic, geographical, and agricultural datasets. Historical records from 1993–2024, including rainfall, temperature, humidity, and rice production statistics, were collected from BMKG, BPS, and the Ministry of Agriculture. After preprocessing and feature selection, six machine learning algorithms—Linear Regression, Random Forest, Gradient Boosting, Support Vector Regression, Decision Tree, and K-Nearest Neighbors—were evaluated for predictive performance. Results show significant spatial heterogeneity: rainfall strongly affects yields in Aceh and North Sumatra, while temperature stress is critical in southern provinces. Among the tested models, Random Forest achieved the best accuracy (R^2 = 0.985), outperforming other algorithms. These findings highlight the importance of localized adaptation strategies and demonstrate the potential of ensemble machine learning to support climate-resilient rice production.*

Keywords: *climate change, machine learning, spatiotemporal analysis, rice production.*

Intisari— *Variabilitas iklim menjadi tantangan utama bagi produksi padi di Sumatra, yang berperan penting dalam ketahanan pangan Indonesia. Penelitian ini bertujuan menganalisis dampak iklim secara spasial dan temporal terhadap hasil padi dengan mengintegrasikan data iklim, geografis, dan pertanian. Data historis tahun 1993–2024, mencakup curah hujan, suhu, kelembapan, serta produksi padi diperoleh dari BMKG, BPS, dan Kementerian Pertanian. Setelah melalui tahap pra-pemrosesan dan seleksi fitur, enam algoritma machine learning—Linear Regression, Random Forest, Gradient Boosting, Support Vector Regression, Decision Tree, dan K-Nearest Neighbors—dievaluasi kinerjanya. Hasil penelitian menunjukkan adanya heterogenitas spasial yang signifikan: curah hujan berpengaruh besar di Aceh dan Sumatra Utara, sedangkan stres suhu menjadi faktor utama di provinsi bagian selatan. Model Random Forest terbukti paling akurat (R^2 = 0,985), melampaui algoritma lain. Temuan ini menekankan perlunya strategi adaptasi lokal dan potensi pembelajaran mesin ensemble untuk mendukung produksi padi yang tangguh terhadap iklim.*

Kata Kunci: *perubahan iklim, pembelajaran mesin, analisis spasiotemporal, produksi padi.*

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INTRODUCTION

Rice functions not only as as staple food but also as a cornerstone of food security and rural economies sustaining the livelihoods of more than half of the population in Southeast Asia. However, climate change poses an increasingly severe threat to this vital commodity [1]. By mid-century, rice yields in South and Southeast Asia may drop 10-15% due to heat, erratic rain, and drought [2]. The Vast lowland rice ecosystems in Sumatra, Indonesia, make the region highly vulnerable to climate change [3].Traditional agricultural practices are becoming increasingly unreliable due to rising climate variability, placing smallholder farmers at greater risk of both instability and production challenges. A pressing global concern arises from this challenge's, how can food systems effectively adapt to maintain agricultural productivity in the face of changing environmental conditions. The combination of spatiotemporal analysis and machine learning has become a central theme in agricultural research, as it provides data-driven foundations for decision-making while delivering meaningful predictive insights [4]. These developments are strongly connected to the international agenda on climate-smart agriculture and to the Sustainable Development Goals (specifically SDGs 2 and 13), highlighting the essential function of innovative methods in evaluating environmental effects on rice production.

This study applies advanced machine learning techniques to investigate the spatial and temporal patterns of climate variability and their impacts on rice production in Sumatra, Indonesia. Although many studies examined climate impacts on Southeast Asian Agriculture, few explored how regional climate variations rice yield in Sumatra [5], [6]. Although remote sensing and GIS are widely used for land monitoring, their integration with predictive machine learning for estimating crop yields in complex tropical regions like Sumatra remains limited [7], [8]. Temperature extremes, cropping intensity, and rainfall anomalies are widely acknowledged as critical variables. Nevertheless, research investigating the interaction of these factors across provinces remains scarce, particularly when considered over varying spatial and temporal dimensions [9]. This study identifies rice as the main staple and Sumatra as a key agricultural area. Researchs on spatiotemporal variability and rice yield remains fragmented, as most studies use board climate models that overlook, local impacts on productivity [10], [11]. In practical applications, a key limitation is the underutilization of high-resolution remote sensing data and advanced machine learning techniques, despite their significant potential for tracking rice phenology across varied landscapes and dynamic environmental conditions [12], [13]. Worsening El Niño impacts on Sumatra's rainfed rice underscore urgent action [14], [15] Integrating spatiotemporal analysis with AI models enhances yield prediction and climate resilience [16], [17]. Thus, achieving sustainable precision agriculture requires integrating ML with climate-rice models. Considering these factors, further research is needed to refine climate-agriculture interaction analyses in Sumatra. Most studies on climate effects on Indonesia's rice focus on board scales, overlooking regional spatiotemporal variations like in Sumatra. In Sumatra diverse agroecological zones, climate–yield dynamics remain underexplored Temporal lags, spatial autocorrelation, and non-linear effects lack clear understanding.

This study builds a spatiotemporal model using advanced machine learning methods. The goals are: (1) Identify key climatic drivers of rice yield variation, (2) Analyze spatial and temporal climate–yield variability, and (3) Compare advanced AI algorithms with traditional statistical models. This study enhances spatiotemporal and ML methods for climate assessment [18], [19]. This study applies machine learning to model climate impacts on rice yields [20]. It advances climate-agriculture models using spatial-temporal integration [21], [22]. This framework link crop yield, regional diversity, and climate dynamics.

MATERIALS AND METHODS

The sequence of research activities, illustrated in Figure 1, begins with problem identification, followed by a literature review, he selection of the study area, data acquisition, data preprocessing, the determination of appropriate machine learning algorithms, and ultimately, the evaluation of the developed model.

Source: (Research Results, 2025)
Figure 1. Research Flow and Modeling Framework

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Problem Identification

Rice production in Sumatra is vital for national food security but highly vulnerable to climate variability. Rainfall, temperature, and seasons strongly affected crop yields. Conventional models poorly capture complex climate-crop interactions. Limited spatial-temporal detail hinders adaptive agricultural planning.

Study Literature

Rice cultivation in Southeast Asia is highly vulnerable to climate change, driven by shifting rainfall, rising temperatures, and extreme weather. Studies show that changing climates severely impact rice production in Indonesia and other Asian countries, disrupting planting schedules and crop cycles [23], [24]. Recently, machine learning models like Random Forests, SVMs, and Neural Networks effectively captured non-linear climate–yield relationships in agriculture [25], [26]. In the Indonesian context, several studies have examined the vulnerability of rice yields to El Niño events and monsoon variability, indicating that severe climatic fluctuations may decrease production by as much 15 % [27]. Previous studies have employed spatial econometric and statistical models to identify vulnerability hotspots; however, these methods did not incorporate advanced machine learning algorithms for cross-regional comparisons [28], [29]. Recent research has emphasized the importance of combining remote sensing and machine learning to enhance the precision of crop yield forecasting [7]. Unlike previous studies, this research offer's new spatiotemporal analysis of climate effects on Sumatra's rice yields using multiple machine learning model for stronger regional insights.

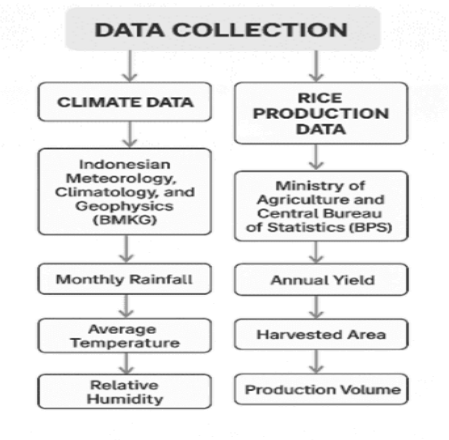
Data Collection

This study analyzes climate variability's impact on rice production in Sumatra (1993–2024) using BMKG and agricultural data, integrating climate and yield records after preprocessing for consistency. The procedure for gathering data is depicted in Figure 2, whereas Table 1 presents a summary of the dataset employed in this study.

Table 1. Research Dataset

Province	Aceh	Aceh	Aceh	Aceh
Year	1993	1994	1995	1996
Production (tons)	13295	12996	13829	14191
Land Area (KM^2)	3235	3290	3392	3482
Rainfall (mm)	1627	1521	1476	1557
Humidity (%)	82.00	82.12	82.72	83.00
Temperature (°C)	26.06	26.92	26.27	26.08

Source: (Research Results, 2025)



Source: (Research Results, 2025)

Figure 2. Data Collection Phase

Pre-processing

The data processing stage aims to convert and refine raw datasets into structured, high-quality inputs, thereby ensuring their appropriateness and effectiveness for implementing machine learning models consistent with the intended objectives of the study [30]. The procedure involves a structured sequence of steps aimed at improving data quality, resolving inconsistencies, and aligning the data architecture with the requirements of the analytical framework [31]. This section outlines the primary objectives of the data preprocessing stage, which is essential for preserving the dataset's integrity, ensuring consistency, and preparing it for analysis [32], the following are the objectives of the data pre-processing stage:

1. Cleaning Data
   Eliminate irrelevant noise, unusual observations, and non-essential records to improve the integrity of the dataset, including the systematic identification and proper handling of missing or abnormal values [33].
2. Normalization
   Standardizing feature scales to comparable ranges helps prevent variables with larger magnitudes from dominating, thereby ensuring a balanced contribution of each attribute to the learning algorithm [34].
3. Data Transformation
   Implement additional data preprocessing techniques, such as transformation or normalization, to adjust the underlying distribution when required by the analytical objectives [35].

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4. Feature Selection
   Important preprocessing stage in machine learning, feature selection improves the efficiency and interpretability of the model by removing redundant or unnecessary variables while keeping the most important features for prediction accuracy [36].
5. Hyperparameter Tuning
   Hyperparameter tuning increases prediction accuracy and generalization by methodically modifying algorithm parameter to balance bias and volatility [37].

Modeling

This study develops models to assess and predict climate impacts on rice yield in Sumatra. The process begins with collecting and preprocessing climate, yield, and spatial datasets. These datasets undergo feature selection and normalization for consistency and performance optimization. Model training and validation follow, applying various machine learning algorithms. The models capture complex, non-linear relationships between climate factors and rice production. Ensemble and kernel methods effectively capture crop yield non-linearity [38].

Linear Regression

Linear regression is a fundamental statistical method used to analyze the relationship between a response variable and one or more explanatory variables [39], as shown in Equation 1.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon \quad (1)$$

Linear Regression provides a transparent, simple baseline model quantifying the marginal linear effects of climatic variables on rice yield, enabling direct interpretability. Linear Regression serves as a benchmark model for agricultural data, evaluating complex machine learning's performance gains in nonlinear, multicollinear environments.

Random Forest

Random Forest is a machine learning method built on the ensemble concept, where multiple decision trees are constructed during training, and the final prediction is produced through majority voting for classification or by averaging the outcomes for regression [40]. Utilizes constructed decision trees and uses random feature subsets at each split to reduce overfitting [41]. Formally, for a set of $\{T_b\}_{b=1}^{B}$, the prediction of a Random Forest for regression can be written in Equation 2. Where, $T_b(x)$ is the prediction of the $b-th$ decision tree.

$$\hat{f}(x) = \sum_{b=1}^{B} T_b(x) \quad (2)$$

Random Forest was chosen for its robustness, ensembles of decision trees, and ability to handle complex, nonlinear agricultural data interactions, reducing overfitting. The accuracy and adaptability of Random Forest's performance were compared because of its restricted interpretability and high computing expenses for huge temporal data.

Gradient Boosting

Gradient Boosting represents an ensemble technique that constructs predictive models through the iterative integration of weak learners, typically decision trees, to minimize a specified loss function [42]. Formally, given a loss function $L(y, F(x))$, the model is updated as Equation 3.

$$F_m(x) = F_{m-1}(x) + \nu \cdot h_m(x) \quad (3)$$

Where, $F_{m-1}(x)$ is the previous model $h_m(x)$ is the weak learner fitted to the gradient of loss, and $\nu \in (0,1]$ is the learning rate controlling the contribution of each learner. Gradient Boosting was prioritized for its strong predictive performance and adaptability to heterogeneous agricultural data. Gradient boosting offers high accuracy but its computationally intensive, risk overfitting (if mistuned), and demands careful interpretation to simpler models.

Support Vector Regression

Support Vector Regression (SVR) functions as an extension of the Support Vector Machine (SVM) framework, commonly employed to address regression problems [43]. SVR finds optimal function linking inputs to targets, minimizing complexity within error ε, tolerance. Equation 4 provides the formulation of the optimization problem.

$$\min_{w,b,\xi_i,\xi_{i^*}} \frac{1}{2}|w|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_{i^*}) \quad (4)$$

SVR, unlike linear models uses kernel function (e.g., RBF) to capture complex climatic variable and rice yield interactions. SVR performance is sensitive to kernel and parameter selection, demanding careful tuning which increases computational complexity. However, its balanced trade-off between predictive accuracy and generalization justifies inclusion.

Decision Tree

Decision Tree is a method that applies a supervised learning technique that is commonly applied in both classification and regression problems, primarily because of its transparent structure and its capability to process categorical as well as numerical variables [44]. The dataset is repeatedly divided into smaller groups according to feature values, with each division designed to either increase information gain or reduce impurity. The most common impurity measure is the Gini Index, defined as Equation 5.

$$Gini(t) = 1 - \sum_{i=1}^{C} p(i|t)^2 \quad (5)$$

Decision tree were chosen for their high interpretability, effectiveness with heterogenous and nonlinear agricultural data, and ability to manage mixed/missing variables. DTs risk overfitting high-dimensional data, limiting generalization. Pruning and cross-validation were used; yet, their explanatory power remains valuable for comparison.

K-Nearest Neighbors

As a supervised learning model, the K-Nearest Neighbors (KNN) approach is widely applied in classification tasks technique of a non-parametric nature, commonly applied in both classification and regression problems [45]. KNN classifies data points by assigning the class most common among its k nearest neighbors, offering robust, simple pattern recognition despite high computational cost on large datasets [46]. The Euclidean distance in Equation 6.

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (6)$$

The K-Nearest Neighbors (KNN) is suitable for heterogeneous agricultural datasets due to its similarity-based prediction. Its strength are simplicity, flexibility, and interpretability for modeling complex patterns without distribution. KNN's sensitivity to irrelevant features, data scaling, and computational inefficiency with large spatiotemporal datasets necessitated careful parameter tuning and data normalization for fair comparison.

Spatiotemporal Analysis for Environmental Studies

Spatial dependence diagnostics and model changes addressed potential spatial autocorrelation, preventing skewed parameter estimates and model overfitting. To achieve objective model evaluation spatial filtering using eigenvector-based spatial filtering (ESF) and spatial cross-validation when significant spatial clustering was found. [47]. To mitigate geographical bias, Random Forest and GBM were trained using spatially blocked k-fold cross validation [48]. This approach robustly estimated climate-yield relationships across Sumatra-Indonesia, mitigating common agricultural spatial autocorrelation [49].

RESULTS AND DISCUSSION

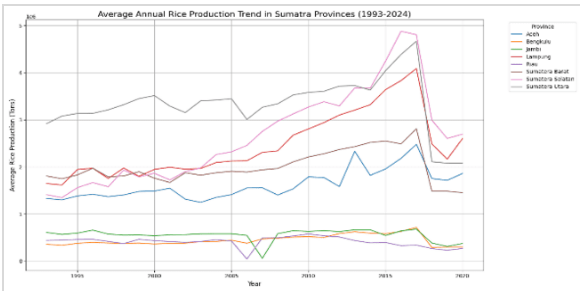
Descriptive Analysis of Climatic and Rice Production Trends

Sumatra's hot, humid climate (26–28°C, >80% humidity) shows stable conditions but distinct wet–dry seasons. Rainfall patterns differ north–south and across years, influenced by ENSO and IOD. Rice yields (1993–2024) vary regionally, peaking in North, South Sumatra, and Lampung, with fluctuations tied to El Niño/La Niña. The data emphasizes these inter-provincial differences and the year-over-year volatility, shown in table 2 below. Rice production in Sumatra peaked mid-2010s, declined after 2017, showing strong provincial disparities and structural vulnerabilities. Figure 3 shows the specific of this interprovincial results trend.

Table 2. Summary of Rice Production and Climatic Data (1993-2024)

Province	Average Production (tons)	Average Rainfall (mm)	Average Humidity (%)	Temp (°C)
Aceh	1,486,900	1,627	82.00	26.06
North Sumatra	1,400,000	2,300	85.00	25.50
West Sumatra	1,300,000	2,140	83.00	26.50
Riau	1,100,000	2,100	83.00	27.00
Jambi	800,000	1,900	81.00	27.50
South Sumatra	3,500,000	1,850	80.00	27.00
Bengkulu	650,000	2,200	84.00	26.00
Lampung	1,900,000	1,950	83.00	26.50

Source: (Research Results, 2025)



Source: (Research Results, 2025)

Figure 3. Average Annual Rice Production Trends

Spatial-Temporal Patterns of Climate Impacts on Rice Yields

Climate impacts on rice yields vary regionally; rainfall and temperature changes differently affect productivity across Sumatra provinces. Table 3 and Figure 4 below provide an overview of the variations in the effects of

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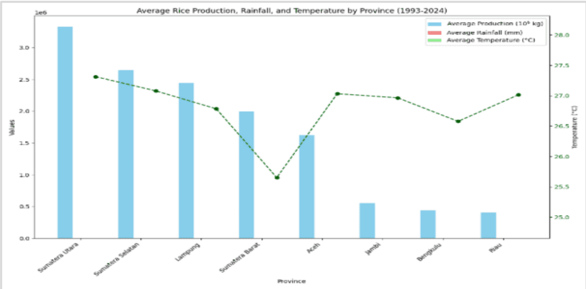
important climatic factors on rice production in the eight Sumatra provinces. Table 3, which presents the average temperature, rainfall, and rice output for eight. Rainfall variation strongly influences rice yields across Sumatra's provinces.



Source: (Research Results, 2025)
Figure 4. Sumatra Rice-Climate Trends

Table 3. Mean Values of Rice Output and Climatic Variables Across Sumatra's Provinces (1993–2024)

Province	Average Production (10^6 kg)	Average Rainfall (mm)	Average Temperature (°C)
Aceh	1,48	1,580	26.29
North Sumatra	2,11	1,850	27.06
West Sumatra	2,44	2,100	26.83
Riau	0.65	1,700	27.52
Jambi	1,18	1,650	27.81
South Sumatra	4,38	1,750	28.11
Bengkulu	0.44	2,200	27.01
Lampung	2,21	1,550	28.02

Source: (Research Results, 2025)

Model Performance Comparison

The forecasting capability of various machine learning algorithms—namely Linear Regression, Random Forest, Gradient Boosting, Support Vector Regression (SVR), and a Neural Network—was evaluated through the statistical indicators R^2, RMSE, and MAE to determine their efficiency in predicting rice production across Sumatra Island, as presented in Table 4. The Random Forest model achieved the best performance with an R^2 of 0.985 and minimal errors (RMSE 114,142.21; MAE 63,135.09). It explained 98.5% of the dependent variable's variance with minimal mean prediction error. Its superior results stem from its ensemble approach that merges multiple trees to reduce overfitting and enhance accuracy. The Gradient Boosting model ranked second with an R^2 of 0.982 and slightly higher errors (RMSE 125,565.34; MAE 74,409.28). The Neural Network achieved an R^2 of 0.978, performing well but with larger errors (RMSE 138,590.23; MAE 82,901.15). The SVR and Linear Regression models performed weaker, with R^2 values of 0.954 and 0.951 respectively, and their higher error rates (SVR RMSE 196,432.11; Linear Regression RMSE 204,501.56) indicate less effective pattern recognition. Overall, simpler models underperformed, revealing non-linear relationships better captured by ensemble and neural network approaches.

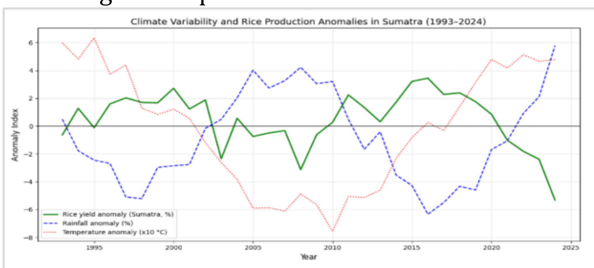
Table 4. Performance Comparison of Machine Learning Models

Model	R^2 Score	RMSE	MAE
Random Forest	0.985	114,142.21	63,135.09
Gradient Boosting	0.982	125,565.34	74,409.28
Neural Network	0.978	138,590.23	82,901.15
SVR	0.954	196,432.11	108,765.43
Linear Regression	0.951	204,501.56	120,321.89

Source: (Research Results, 2025)

Key Climatic Determinants of Rice Production

Feature importance analysis shows land as the main factor for rice prediction in Sumatra (0.928), while temperature (0.025), rainfall (0.024), and humidity (0.022) have smaller yet notable effects (Table 5). Rainfall during planting remains a key factor determining water availability for rice germination and tillering. Although land availability drives most production variability, climatic variables regulate crop resilience to environmental stress. These findings emphasize the vital role of climate indicators in agricultural planning. The quantified effects of rainfall and temperature underscore the importance of seasonal climate forecasts for optimizing irrigation and reducing water deficit risks. Similarly, the moderate yet significant temperature influence highlights the need for developing heat-tolerant rice varieties amid ongoing climate warming. While climatic factors show lower feature importance than land area, their alignment with rice growth physiology—where water and temperature directly affect developmental stages—reinforces their adaptive relevance. Hence, although land expansion may boost short-term yields, sustainable rice production ultimately depends on adopting climate-responsive technologies and policies.



Source: (Research Results, 2025)
Figure 5. Climate Anomalies in Sumatra

Table 5. Feature Importance of Climatic and Land Variables on Rice Production

Rank	Feature	Importance
1	Land Area	0.928
2	Temperature	0.025
3	Rainfall	0.024
4	Humidity	0.022

Source: (Research Results, 2025)

CONCLUSION

This study demonstrates that integrating spatiotemporal analysis with advance machine learning models provides a powerful framework for understanding and predicting the impacts of climate variability on rice production in Sumatra. The Random Forest model achieved the highest predictive accuracy (R^2=0.985), outperforming other algorithms by effectively capturing complex nonlinear interactions between climatic and agricultural variables. Results highlight distinct spatial heterogeneity, where rainfall and temperature exert varying influences across provinces, emphasizing the necessity of localized adaptation measures. While land area remains the dominant factor in yield prediction, climatic parameters significantly affect productivity stability and resilience. Therefore, developing climate-smart agricultural policies, incorporating ensemble machine learning tools, and enhancing early warning systems are essential to support sustainable and climate-resilient rice productions across Sumatra and similar tropical regions

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