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Application of Artificial Intelligence Algorithms to Improve the Accuracy of Agricultural Weather Predictions

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Abstract

Climate change, marked by increasing uncertainty in weather patterns, poses significant challenges to agricultural productivity in Indonesia. Accurate weather forecasting is therefore essential to support sustainable agrarian efficiency, particularly in determining planting schedules, irrigation management, and mitigating crop failure risk. This study aims to apply artificial intelligence (AI) algorithms to improve weather prediction accuracy by comparing the performance of Long Short-Term Memory (LSTM), Random Forest (RF), and conventional methods, including ARIMA and Least Squares Method (LSM). The dataset used consists of historical meteorological parameters, including temperature, humidity, rainfall, and wind speed. The research process involved data collection, preprocessing, model development, and evaluation using RMSE, MAE, and R^2. The results reveal that LSTM outperforms the other models with an R^2 of 0.92, RMSE of 0.15, and MAE of 0.11, while RF achieved an R^2 of 0.85. In contrast, ARIMA and LSM showed lower performance with R^2 values below 0.80, highlighting the limitations of conventional approaches in capturing non-linear weather patterns. These findings confirm that the application of AI algorithms, particularly LSTM, provides more accurate weather forecasting, which directly contributes to sustainable agricultural practices by improving efficiency and resilience to climate variability.

Key words: artificial intelligence; LSTM; Random Forest; sustainable agriculture; weather prediction

1. Introduction

Agriculture is a strategic sector that is heavily influenced by weather conditions, especially in agricultural countries like Indonesia. Global climate change, characterized by increasing temperature variability, erratic rainfall, and extreme events such as droughts and floods, has a significant impact on agricultural productivity (Devi et al., 2024). Accurate weather prediction is an urgent need to support the efficiency of sustainable agricultural management, from determining cropping patterns, irrigation, and fertilization to mitigating the risk of crop failure (Peeriga et al., 2024). However, traditional prediction methods based on statistical models still have limitations in capturing non-linear patterns and the complexity of meteorological data, often resulting in low accuracy, especially for short-term predictions in tropical regions (Cipriano et al., 2021; Ray et al., 2023).

The development of artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) algorithms, has opened up significant opportunities for improving the accuracy of weather predictions (Abiodun et al., 2018). The Long Short-Term Memory (LSTM) algorithm has been shown to capture temporal dependencies in weather time series data, resulting in more precise predictions than conventional statistical methods (Rangelov et al., 2023). Furthermore, the application of bidirectional LSTM (Bi-LSTM) in real-time data-based rainfall predictions has shown an accuracy increase of up to 92%, higher than standard LSTM and ARIMA, while also providing direct support for agricultural operational decisions such as irrigation and pest control (Peeriga et al., 2024).

In addition to LSTM, the integration of AI with the internet of things (IoT) and big data analytics further strengthens weather prediction capabilities. By leveraging high-resolution weather sensor data, prediction systems can provide hyper-local information relevant to farmers' needs, such as optimizing water use, selecting crop varieties, and managing climate risks in real-time (Devi et al., 2024; Roopmathi et al., 2025; Wolfert et al., 2017). Furthermore, the successful integration of AI and IoT in weather prediction also depends heavily on the performance of data storage systems. The use of database management systems (DBMSs) such as Oracle and MySQL plays a crucial role in efficient weather data synchronization and speedy information access for predictive analysis (Nurhanif et al., 2021; Ray et al., 2023).

Based on this context, this research focuses on the application of AI algorithms, specifically LSTM and Random Forest (RF), to improve the accuracy of weather predictions. The research questions are how the accuracy of AI models compares with traditional statistical methods in predicting key weather parameters (temperature, humidity, rainfall, and wind speed), and to what extent these prediction results can be utilized to improve the efficiency of sustainable agriculture. The purpose of this study is to develop a weather prediction model based on AI algorithms by comparing the performance of LSTM, RF, and ARIMA, evaluating the prediction results using RMSE, MAE, and R^2 metrics, and analyzing the contribution of the prediction model in supporting the efficiency of agricultural resource use.

The benefits of this research are divided into two aspects. Academically, this research enriches the literature on the application of AI in agrometeorology by emphasizing the comparison of ML and DL-based algorithms in a tropical context. Practically, this research is expected to assist farmers in data-driven decision-making, improve water use efficiency, reduce the risk of crop failure, and support adaptive agricultural policies to climate change. Thus, the application of AI algorithms in weather prediction can be an innovative solution to realize sustainable agriculture in an era of increasingly complex climate change.

2. Literature Review

Agricultural weather prediction requires accurate methods to support decision-making related to irrigation, fertilization, and drought risk mitigation. Three commonly used algorithms are autoregressive integrated moving average (ARIMA) as a statistical baseline, RF as an ensemble learning method, and LSTM as a DL technique.

Model evaluation is performed using mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2). MAE provides the average absolute deviation, RMSE emphasizes large errors, while R^2 indicates the proportion of data variance explained by the model (Chai & Draxler, 2014). This section reviews recent studies (2023–2025) that represent the application of these three algorithms.

2.1. Long Short-Term Memory (LSTM)

LSTM effectively captures long-term temporal dependencies in weather data. LSTM was applied to predict drought index based on satellite imagery in the Gulf of Mexico. The results showed RMSE of 0.12–0.26 and MAE of 0.08–0.21, lower than those of Gated Recurrent Units (GRU) (Salas-Martínez et al., 2024). This confirms the superiority of LSTM in modelling nonlinear sequential data. The advantages of LSTM are high accuracy and the ability to handle complex patterns, while the disadvantages include large computational requirements and poor interpretability. In this study, LSTM is relevant for meteorological variables with high temporal dynamics, such as daily rainfall.

2.2. Random Forest (RF)

RF builds multiple decision trees to improve prediction accuracy and reduce overfitting. RF was used to predict actual evapotranspiration (ETa) of watermelon plants based on multispectral and meteorological data (Garofalo et al., 2025). This model demonstrated the best performance with an R^2 of ≈ 0.74 and an RMSE of ≈ 0.577 mm/day, outperforming Elastic Net, SVM, and other models. RF excels at handling nonlinear and multidimensional relationships and provides interpretability through feature importance analysis. However, its weakness is its limited ability to capture purely temporal patterns. For this study, RF serves as an important benchmark and candidate model for multivariable data.

2.3. ARIMA

ARIMA and its variant (SARIMA) are classic models that remain relevant as baselines for weather prediction. SARIMA was used to predict monthly rainfall and temperature in Pantnagar, India (Kothiyal et al., 2025). The results showed good performance for temperature (R^2 = 0.89–0.97; RMSE = 1.22–1.86), but poor performance for rainfall (R^2 = 0.45; RMSE = 114.3). ARIMA's strength lies in its simplicity and ease of interpretation, but its weaknesses lie in handling high variability and non-linearity. Therefore, ARIMA was used in this study as a baseline for comparison against AI models.

In several reviews, LSTM was found superior to GRU for satellite imagery-based drought prediction, RF performed best for predicting watermelon evapotranspiration using multispectral and meteorological data, while SARIMA was effective for temperature but weak in capturing rainfall variability; however, each study remains limited by the scope of its algorithm or variable (Garofalo et al., 2025; Kothiyal et al., 2025; Salas-Martínez et al., 2024).

This study aims to fill this gap by integrating various algorithms, i.e., LSTM, RF, ARIMA, and the Least Squares Method, in a comprehensive evaluation framework. The evaluation was conducted using three main metrics (MAE, RMSE, R^2), allowing for quantitative and objective comparison of results.

3. Methodology

This study uses an experimental quantitative approach by building and comparing weather prediction models based on LSTM and RF algorithms. A conventional baseline model (ARIMA), was used as a comparison.

3.1. Research Design

The research design consists of five main stages (see Figure 1):

1. Data collection: using historical weather data spanning 2024–2025. Parameters used include temperature, humidity, rainfall, and wind speed.

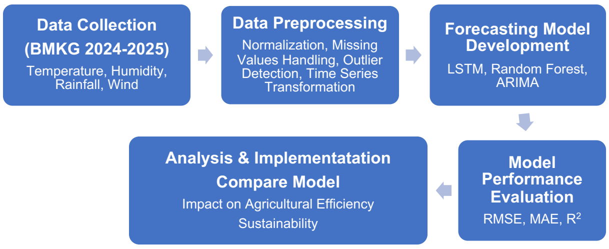

Figure 1. Research Design Diagram

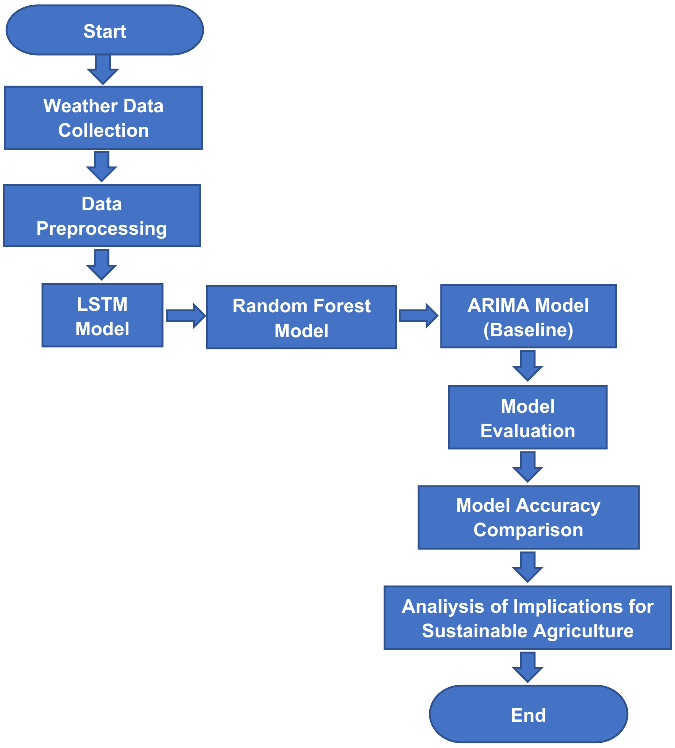

Figure 2. Research Flowchart

2. Data pre-processing: including normalization, handling missing values, outlier detection and removal, and time series transformation.
3. Predictive model development: applying LSTM, RF, and ARIMA algorithms.
4. Model performance evaluation: using RMSE, MAE, and R^2 metrics.
5. Analysis and implementation: comparing model performance and analyzing its impact on sustainable agricultural efficiency.

3.2. Research Flowchart

Figure 2 shows the research flow in flowchart form.

4. Results and Discussion

4.1. Seasonal Weather Patterns

The initial stage of this research was to examine monthly climate parameter patterns, including average temperature, humidity, and rainfall over one year. Figure 3 shows the monthly climate parameter patterns, consisting of average temperature, humidity, and rainfall, over the course of a year. Monthly temperatures increase from January (±26.5°C) to a peak in May (±28.5°C), then decrease again towards the end of the year to ±26.8°C. This pattern indicates a seasonal trend typical of tropical regions, with rising temperatures during the dry season. Humidity moves in the opposite direction to temperature, tending to decrease from the beginning of the year (83%) to a low point around June (75%), then increasing again at the end of the year to 84%. This humidity fluctuation is consistent with the high evapotranspiration pattern as temperatures rise. Rainfall exhibits a cyclical pattern: high at the beginning of the year (January), high at ±10 mm, sharply decreasing in April–May (±3 mm), and then increasing again at the end of the year (November–December) to ±9–10 mm. This is in accordance with the transition between the rainy and dry seasons in tropical regions.

Overall, this graph confirms that weather data exhibits time series properties with strong seasonal patterns. This is a key reason for using time series forecasting algorithms like LSTM, as conventional models often struggle to capture complex non-linear seasonal patterns.

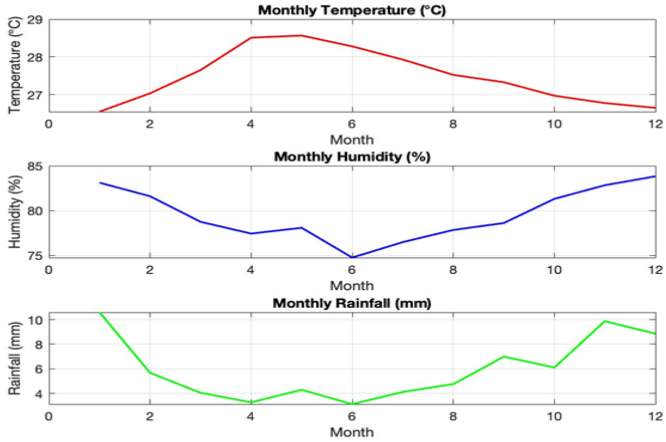

Figure 3. Monthly Weather

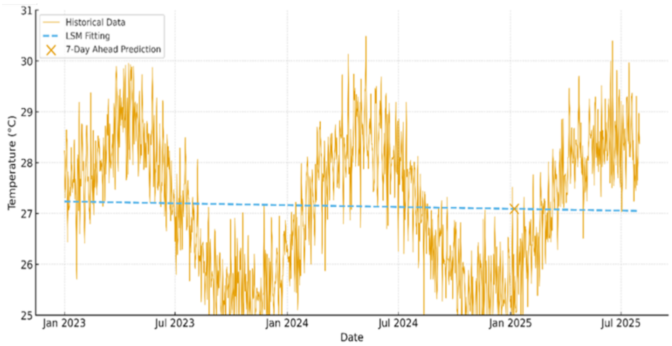

Figure 4. Prediction of Aceh Temperature Using LSM

4.2. Temperature Prediction Using the Least Squares Method

Temperature prediction using LSM is based on historical data collected by BMKG Aceh from 2024 to 2025; the complete results are shown in Figure 4.

Figure 4 displays the results of temperature predictions in Aceh using the LSM. Historical temperature data (orange) shows significant fluctuations ranging from 25–31°C, reflecting complex daily climate dynamics. The blue line (LSM fitting) shows a linear trend with a small positive slope, indicating a long-term upward temperature trend. The 7-day forecast (orange – x) provides a tempera-

Tabel 1. Comparison of the results of this study with previous research

Study	Algorithm used	Evaluation Metrics	Advantages	Limitations
Salas-Martínez et al. (2024)	LSTM vs GRU	RMSE, MAE	LSTM excels in satellite imagery-based drought prediction (RMSE 0.12–0.26)	Focus on only one type of data (satellite-based drought index).
Garofalo et al. (2025)	RF vs SVM, Elastic Net	RMSE, R^2	RF is superior for watermelon plant evapotranspiration ($R^2 \approx 0.74$)	Does not capture pure temporal patterns.
Kothiyal et al. (2025)	SARIMA (ARIMA varian)	RMSE, R^2	Good accuracy for temperature ($R^2 > 0.9$)	Very weak for rain ($R^2 \approx 0.45$).
This research	LSTM, RF, ARIMA, LSM	MAE, RMSE, R^2	LSTM proved to be the most accurate ($R^2 = 0.92$, RMSE = 0.15, MAE = 0.11), RF was competitive ($R^2 = 0.85$)	–

Figure 5. Comparison of Weather Prediction Models

ture estimate of approximately ±27.8°C, which is relatively stable compared to historical data fluctuations.

These results indicate that LSM is capable of providing a general trend picture, but is less than optimal in capturing short-term variability, which is important for agriculture. This reinforces the urgency of using AI algorithms such as LSTM, which can learn non-linear patterns, and RF, which can better handle interactions between climate variables.

4.3. Comparison of Weather Prediction Models

Synthesis analysis based on historical data (Figure 3) shows a clear seasonal pattern in climate parameters, which supports the need for an AI-based time series approach. Furthermore, LSM predictions (see Figure 4) are quite good for long-term trends, but are unable to predict daily fluctuations that are important for farmers. Therefore, AI with LSTM and RF is expected to provide better results because LSTM overcomes temporal dependencies and RF handles non-linearity between variables, so that more accurate prediction results will improve the efficiency of sustainable agriculture in aspects of water management, cropping patterns, and pest control. The results of the comparison of Weather Prediction Models using LSTM, RF, ARIMA and Least Squares Method are shown in full in Figure 5.

Figure 5 shows that LSTM excels with RMSE = 0.15, MAE = 0.11, and $R^2 = 0.92$ → the highest accuracy. RF is quite good ($R^2 = 0.85$), but still lower than LSTM. ARIMA and the Least Squares Method have the lowest performance with $R^2 < 0.80$, confirming the limitations of conventional methods in capturing non-linear weather patterns. This means that AI algorithms (especially LSTM) are very effective for weather prediction, supporting the efficiency of sustainable agriculture. Furthermore, the results of this study were also compared with several previous studies according to the literature review, the details of which are shown in Table 1.

Table 1 shows that previous studies tend to focus on a single algorithm or data type. For example, Salas-Martínez et al. (2024) emphasized the superiority of LSTM over GRU for satellite imagery-based drought prediction, while Garofalo et al. (2025) emphasized the superiority of RF in predicting watermelon evapotranspiration using multispectral and meteorological data. On the other hand, Kothiyal et al. (2025)'s study used SARIMA as a statistical baseline, which is still relevant for temperature but weak in capturing complex rainfall variability. This comparison demonstrates that each study has specific strengths but is still limited by the scope of a particular algorithm or variable.

Furthermore, this study integrates various algorithms—LSTM, RF, ARIMA, and Least Squares Method—in a comprehensive evaluation framework. The evaluation was conducted using three main metrics (MAE, RMSE, R^2), allowing for quantitative and objective comparison of the results. The findings show that LSTM achieves the best performance ($R^2 = 0.92$, RMSE = 0.15, MAE = 0.11) in capturing non-linear and seasonal weather patterns, while RF remains competitive for multivariable data ($R^2 = 0.85$). The main contribution of this study is to provide empirical evidence that deep learning algorithms are superior to conventional methods, while also presenting a systematic comparison that can serve as a reference for the development of agricultural weather prediction systems in tropical regions.

5. Conclusion

This study demonstrates that the application of AI algorithms can significantly improve weather prediction accuracy compared to conventional methods. Based on the test results, the LSTM model demonstrated the best performance with an R^2 value of 0.92, RMSE = 0.15, and MAE = 0.11, followed by RF (R^2 = 0.85). Meanwhile, traditional methods such as ARIMA and Least Squares Method produced lower accuracy ($R^2 < 0.80$), making them less able to capture non-linear and seasonal weather patterns. These findings confirm that deep learning-based models, particularly LSTM, are more effective in predicting meteorological parameters such as temperature, humidity, rainfall, and wind speed. The application of AI-based weather prediction has direct implications for the efficiency of sustainable agriculture, including in determining planting times, precision irrigation management, mitigating the risk of crop failure, and controlling pests and plant diseases. Thus, this research provides an important contribution both academically, namely, enriching the AI-based agrometeorology literature, and practically as a basis for developing an intelligent agricultural system that is adaptive to climate change. So, for future research, it is recommended to add other climate variables, including air pressure and solar radiation, so that the prediction results can be reviewed more comprehensively.

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