**JOURNAL OF SOFT COMPUTING AND DATA MINING**
e-ISSN: 2716-621X

**JSCDM**

Vol. 6 No. 3 (2025) 118-134
https://publisher.uthm.edu.my/ojs/index.php/jscdm

# DLinear Model for Microclimate Prediction of Coffee-Pine Agroforestry

**Heru Nurwarsito[1]*, Mustafa Mat Deris[2], Simon Oakley[3], Didik Suprayogo[4], Cahyo Prayogo[4], Aji Prasetya Wibawa[5]**

[1] *University of Brawijaya, Faculty of Computer Science, Malang, 65145, INDONESIA*
[2] *Universiti Muhammadiyah Malaysia, Faculty of Business and Information Technology, Padang Besar, Perlis 02100, MALAYSIA*
[3] *Lancaster Environment Centre, UK Centre for Ecology & Hydrology, UK*
[4] *University of Brawijaya, Faculty of Agriculture, Malang, 65145, INDONESIA*
[5] *State University of Malang, Faculty of Engineering, Malang, 65145, INDONESIA*

*Corresponding Author: heru@ub.ac.id
DOI: https://doi.org/10.30880/jscdm.2025.06.03.009

**Article Info**

Received: 19 July 2025
Accepted: 6 October 2025
Available online: 30 December 2025

**Keywords**

DLinear model, machine learning models, microclimate prediction, coffee-pine agroforestry, environmental monitoring

**Abstract**

Understanding the Microclimate predictors in coffee-pine agroforestry systems facilitates the prediction of microclimate, enabling the maximization of productivity and viability of the agroforestry systems. Coffee-pine agroforestry systems represent a VIABLE integrated system of agricultural productivity along with environmental sustainability. The models were tested in the dataset across different time frames of daily, weekly, and monthly. In this research, a number of ML approaches and models, including LSTM, DLinear, Transformer, ARIMA, and MLP, were employed in microclimate prediction with focus on variables including Temperature, Humidity, and Intensity. The focus of this study on the deployment of this many models, stems from the aim of harnessing the varied strengths of models on diverse classes of data and predictions. From the analysis, model DLinear always performs excellently over all time frames as compared to other models, where DLinear possesses high accuracy with a mean absolute error (MAE) of 0.43, while LTSM, ARIMA, MLP, and Transformer possess MAE with 1.12, 1.77, 2.27, and 4.74, respectively. These results further enrich the existing research on predicting geographical microclimate in agroforestry systems, providing evidence of the usefulness of various machine learning models in understanding and managing complex ecosystems. Given the range of these types of models, this ensures that a wide spectrum of the problem is addressed, which helps ensure the quality and correctness of the forecasts by using each model of its strengths to tackle a different area of the prediction process.

## 1. Introduction

The exact forecasting of the climatic conditions at a micro level regarding coffee-pine-based agroforestry systems is essential in maximizing the benefits of crop production, ecological viability, and management of agricultural practices and environmental conservation [1]. Microclimates play a significant role in the growth of plants, the soil, and the biodiversity of a landscape, especially in coffee-pine agroforestry, where factors such as shade, moisture, and temperature determine the quality of the coffee and the growth of pine trees [2]. Also, learning microclimate dynamics helps to address sustainable farming [3]. Advances in understanding micrometeorology in agriculture have proven to positively impact agricultural productivity and incremental improvements in ecological resilience [4].

Predictive capabilities in various domains have been bolstered by the latest developments in big data and machine learning. Ecology and climate science have seen improvements in many disciplines, including healthcare and machine learning that have been applied to both disease prediction [5] [6] and species recognition with high accuracy [7]. In climate modules, machine learning is useful for assessing risk in various scenarios and provides guidance for informed decisions based on data [8].

DLinier (Deep Linear) Agroforestry, which incorporates the growing of coffee under pine canopies, has a multitude of agronomic and ecological benefits. the system enhances the quality of coffee beans, nutrient cycling, and reduces the erosion of soil [9] [10]. It also aids in climate change adaptation by promoting biodiversity and increasing carbon sequestration [11]. Coffee-pine Agroforestry systems provide economic and ecological balance [12].

Brawijaya University Forest is established mainly for initiatives related to sustainable agriculture and biodiversity practices. That is why it will assist the studies regarding soil, water, and biodiversity management, which is crucial for resilient agroforestry systems in various climates and environments [12][13] [14]. Predicting microclimate parameters is still plagued by some challenges due to the insurmountable environmental factors, such as canopy cover, soil, and topography [9] [13] [15]. This necessitates data-hungry approaches [15].

The research is integrating various forms of large-scale data and machine learning in microclimate prediction, such as LSTM, DLinear, Transformer, ARIMA, and MLP. LSTM networks are particularly developed for modeling systems where the governing factors are time-dependent and dynamic [16]. On the other hand, DLinear is more appropriate for addressing the nonlinearities in the environmental interactions [17]. On the other hand, Transformer works very well in data measured at discrete time steps [18], and both ARIMA and MLP have been shown to be effective for environmental forecasting applications [19][20]. Unfortunately, machine learning applications for microclimate prediction in coffee-pine agroforestry systems are still scarce at this time [21]. These systems distinctly influence microclimate variables—such as air and soil temperature, humidity, and illumination—which are critical for crop health and environmental sustainability [22][23][24].

This research builds on the earlier works that informed the dissertation entitled Monitoring and Optimization of Microclimate for Coffee Production through Modeling in Coffee-Pine Agroforestry Systems [25]. The initial investigation described an IoT-attached Microclimate recording device. The aim of the study was to evaluate the performance and potential of this system in modifying management practices, increasing productivity growth, and reducing environmental aggressiveness in coffee-pine agroforestry systems. The study will record this data and will allow downloading of the information from the IoT server as and when desired, without being physically present at the Sensor node location [22]. In the following research outcomes, the data circumscribed by the tape was processed and implemented as an input into a computational learning approach for the hypothetical microclimate information of coffee-pine agroforestry changed by a machine learning technique. So, as a result of this process being applied in practice, given the presence of incomplete data series due to various field-related challenges, the process of infilling incomplete microclimate data was addressed for coffee-pine agroforestry landscapes owing to the relevance of machine learning methods [26]. As a follow-up study, research was conducted to build and test a comprehensive and evidence-based model to help predict climate variables at the micro scale in the coffee-pine agroforestry system, using the convergence of big data analysis and machine learning algorithms. Thus, this study hopes to fill the gaps in the existing literature, especially regarding microclimate prediction in areas that use agroforestry systems, which aim to increase agricultural productivity and ecological balance. Upon completion, the hope is that the multifaceted model will be fully validated and able to predict microclimates, then make recommendations to other agroforestry projects across various locations. If this outcome can be achieved, it will transform the way we approach agriculture, environmental conservation, and numerous other sectors that intersect with the environment. The potential benefits for the world are astounding.

That being said, there is limited research that uses advanced deep learning architectures for microclimate predictions in coffee-pine agroforestry systems and even less that analyzes the IoT data in the context of comparing linear and non-linear models. This research attempts to fill the void in the literature by assessing the DLinear model against other benchmarks.

## 2. Related Works

This part considers earlier work related to agroforestry systems microclimate prediction from ecosystemic, technological, and methodological angles. Previous studies showed that temperatures, moisture, and light intensities, microclimates, and other variables are determining agroforestry productivity and sustainability. Recent developments in remote sensing, machine learning, and big data provide a greater ability to model and predict different variables in the environment, thus aiding in more accurate predictions. This study, from

J. of Soft Computing and Data Mining Vol. 6 No. 3 (2025) p. 118-134

published works, focuses on environmental monitoring and machine learning to fill in gaps in prediction for coffee-pine agroforestry systems.

## 2.1 Agroforestry Microclimates

This evidence is important because remote sensing technology is now advancing remote sensing even more through modeling and analyzing microclimates, which is valuable for assisting in understanding microclimatic variability in agroforestry systems. This also illustrates the remote sensing ability to foresee the responses of species to global warming and, hence, it is tied to contemporary studies in this section.

This having been said, [27] has continued with this field by looking at the carbon stocks of various agroforestry systems with a focus on the climatic variables of temperature and humidity, which have an impact on microclimate. Importantly, the paper also makes global comparisons of an agroforestry system in Indonesia.

Imanuddin looks at the intercropping with coffee of Sumatran pine forests and tries to assess the feasibility of agroforestry systems and their possible economic advantages [28]. This covers the explanatory part of the ecological and economic gains accruing from coffee-pine agroforestry systems.

Moreover, Suprayogo studied the litter layer and earthworm populations as indicators of soil health and biodiversity in coffee-pine-based agroforestry systems [29]. Suprayogo also contributed. Sudharta examined soil organic carbon and nitrogen in coffee-pine agroforestry systems under different types of management within the coffee bean production context, which seems particularly relevant to the tremendously important debates about the soil health and agricultural productivity of coffee-pine agroforestry systems [1]. Cahyono focuses on agroforestry innovations, more particularly on pinenut coffee systems, which go hand in hand with the study of the changes and environmental effects of agroforestry systems, especially the UB Forest [30]. Purnomo investigates climate change in relation to soybean agroforestry and discusses canopy and related issues, which squarely relate to the climate change adaptive mechanisms to agroforestry practices in UB Forest [31].

## 2.2 Big Data in Environmental Science

Real-time and the sheer bulk of data created in a day within the scope of Environmental science and engineering (ESE) brings with it a big body of work in terms of improving how data can be analyzed [32]. Incorporation of machine learning processes into the routines of ecologist's workflows can improve the parameters of ecological models and therefore the integrated development of hybrid modeling approaches [33]. This paper seeks to assess the evolution of climate technologies used in the Agriculture Big Data context [12]. To be precise, the inputs include states and trends of different oceanographic and atmospheric parameters such as sea-ice extent, sea-surface temperature, ice motion, ice depth, net shortwave radiation, ice surface skin temperature, and salinity at the sea surface, as well as a land-sea mask in the model input [34].

## 2.3 Machine Learning Applications

Le developed LSTM models for time series forecasting, similar to agricultural time-series predictions like weather and crop cycles [35][36]. Wang used LSTM networks for short- and medium-term load forecasting, demonstrating LSTM’s versatility for agricultural yield predictions [37]. Park show LSTM predicting soil moisture in soybean farming, applicable to climate and soil condition forecasting [38]. However, they face challenges in long-term time series forecasting (LTSF) because the recurrent iterations inherent to LSTM over extended lookback and forecast horizons result in the accumulation of errors. The study to utilize supervised machine learning to predict customer churn in a telecom company based in California [39].

The linear activation functions in DLinear models were specifically discussed by O'Shea and Hoydis for deep learning applications in wireless communication [40]. Christin found such emerging deep learning models horizon unexplored by scientists in the ecological arena; they underscored the ability of deep learning to address complex and heterogeneous data [41]. Apart from bringing the best out of optimizing configurations, transformer architectures have dramatically contributed to transforming the scope of sequence prediction in agriculture by providing the finest-tuned efficient solutions for temporal modelling [9]. Transformers have previously been used for some agricultural problems, which include forecasting in crop yield prediction, land cover classification, and monitoring, etc. [14].

The traditional approaches of machine learning were able to achieve good results from ARIMA and multi-layer perceptrons in environmental and health-related forecasting. Comparatively, the longer the data period of windows is, the better ARIMA performs, and the worse LSTM performs. With regard to this, an example of Alim used ARIMA and XGBoost in modeling human brucellosis outbreaks in China [42]. Tsan later applied LSTM and ARIMA models to forecast influenza-like illness incidence [43]. MLPs were also able to improve dam inflow prediction accuracy, thus showing evidence of the increasing role of A.I in environmental forecasting [44].

## 3. Materials and Methods

A Current Work was conducted within the Coffee-Pine agroforestry System, which is in UB Forest and Mount Arjuno slopes, that is located within Sumbersari Hamlet, Tawang Argo Village, Karangploso, Malang. It could be noted at 7 days49 minutes, and 26 seconds South and 1.

2 degrees 34 minutes, and 41 seconds east. Elevation-1200-1800 m a.s.l., Researchers took UB Forest as a core research area because it comprises diverse environmental conditions with all kinds of agroforestry practices appropriate for machine learning applications. This forest has a huge altitudinal gradient, showing hilly lands, lowlands, diverse microclimates, and therefore a great place for full environmental understanding.

### 3.1 Research Area Description

A Current Work was conducted within the Coffee-Pine agroforestry System, which is in UB Forest and Mount Arjuno slopes, that is located within Sumbersari Hamlet, Tawang Argo Village, Karangploso, Malang. It could be noted at 7 days49 minutes, and 26 seconds South and 112 degrees 34 minutes and 41 seconds east. Elevation-1200-1800 m a.s.l., Researchers took UB Forest as a core research area because it comprises a diverse environmental conditions with all kinds of agroforestry practices appropriate for machine learning application. This forest has a huge altitudinal gradient, showing hilly lands, lowlands, diverse microclimate, and therefore a great place for full environmental understanding.

A total of 4 sensor nodes were deployed across four management intensity plots (BAU, LC, MC, HC), with five sensors (Air temperature, Air humidity, Soil temperature, Soil humidity, and Sunlight Intensity) in each plot. Sensors were placed at representative positions within the coffee-pine zones, approximately 1 m above ground for air temperature and humidity, and 15 cm depth for soil moisture measurements.

### 3.2 Data Collection

Data were collected from April 2024 to December 2024, focusing on environmental variables: moisture, temperature, and sunlight. Modern sensors recorded humidity and soil moisture at various depths and locations within the forest. Instruments included HOBO Solar Radiation Shield with Lascar CAP-2200 (temperature and humidity logger), Odyssey Soil Moisture Sensor Probe, and MX2202 HOBO MX (temperature and light logger). Data were retrieved monthly via USB by field operators. Sensors were placed across plots with different management intensities (BAU, LC, MC, HC) to capture environmental variability critical for coffee-pine agroforestry microclimate modeling. The tools at the UB Forest for gathering the microclimate data are depicted in Fig. 1.

**(a)** **(b)** **(c)**

**Fig. 1** *A HOBO solar radiation shield (a) together with the Lascar electronic temperature and humidity sensors; (b) Offset Soil Moisture Sensor Probe (Odyssey); (c) Hobo MX light intensity & temperature data logger MX2202*

### 3.3 Data Preprocessing

Data cleaning involved identifying as well as correcting the missing or erroneous values using statistical techniques like mean imputation or K-Nearest Neighbors to increase data quality. In addition, some outliers were detected and managed using z-score methods and IQRs. The cleaned data were then normalized using min-max

J. of Soft Computing and Data Mining Vol. 6 No. 3 (2025) p. 118-134

scaling to [0,1] to hasten learning convergence [45] [46]. Z-scores were then applied to the cleaned data as standardization, such that all variables had mean=0 and standard deviation=1-an essential step for algorithms sensitive to variable scale [47][48]. Overall, this process improved data quality while the learning model became more efficient [46][49][50].

## 3.4 Data Analysis Process

The implemented dataset has been prepared for data analysis which includes feature selection and feature engineering prior to training five models: LSTM; DLinear; Transformer; ARIMA; MLP. The performance result of the model will be evaluated by metrics such as MAE, MSE, RMSE, and MAPE, with smaller values indicating that the model is closer to making accurate predictions [51][52]. Such approaches had been exploited for Big Data and machine learning application purposes to improve the prediction of agroforestry complexities concerning microclimates [53].

## 3.5 DLinier (Deep Linear) Model

This DLinear ( Deep Linear model) is accurate in working on time series forecasts by decomposing the given input data into two fundamental components associated with each input: seasonality and trend. The model's view is that the behaviour of any time series can be convincingly captured with those two additive components to achieve a simplified but accurate prediction.

The study employed a linear model specifically created for the advancement of predictions of microclimate under big data applications. The architecture comprises an input layer, a number of linear hidden layers, and an output layer. Raw sensor inputs like temperature and humidity are directed to the input layers. Hidden layers perform linear transformation without nonlinear activation functions; hence, they retain simplicity and interpretability. The output layer has predictions on important microclimate variables [54].

The input time series $x_t$ comprises observations at discrete time steps. This data is processed separately in the model to yield the seasonality ($S_t$) and trend ($T_t$) parts by linear transformations: $S_t = W_s x_t + b_s$ and $T_t = W_t x_t + b_t$, where $W_s$ and $W_t$ are weight matrices and $b_s$ and $b_t$ are biases. The final prediction $\widehat{y_t}$ thus is a summation of both components:

$$\widehat{y_t} = S_t + T_t \tag{1}$$

The DLinear model philosophy involves dealing with it additively, which makes it easy to discern short and long-term trends, which also improves robustness and interpretability of the model. Furthermore, the computational efficiency that comes with the model's use of linear transformations gives great value to the model since it performs optimally on large datasets and on environments with poor computational resources. The simplicity of DLinear makes it learn complicated temporal structures efficiently, resulting in accurate and effective microclimate predictions in agroforestry environments. Predictability and the relative ease of use, not to mention the increased trust by users, are also great advantages [37].

The model, therefore, confines itself to linear transformations of the data and hence makes no use of nonlinear activations. This contributes toward maintaining maximum simplicity and interpretability. Such transparent models will be more useful for researchers to track and communicate predictions in environmental studies and policy contexts [50].

Data on short-term microclimatic phenomena observed over time form the grist of the model here. Initial noise from short periods of time is suppressed using moving averages, which then permit the longer-term trends to emerge. Then the seasonal, trend, and residual components result from the decomposition of these series in two parallel linear processing branches, that is, those that bring together the multiple variables celebrated on season features and those that bring trend features together. The summation of branch outputs follows, then passing to the final layer for forecasting time series data analysis. It perfectly models complex trends, although it is critically suited for imputing seasonal patterns vital for microclimate forecasting in coffee-pine agroforestry systems [55], and can therefore be seen indelibly from Fig. 2.

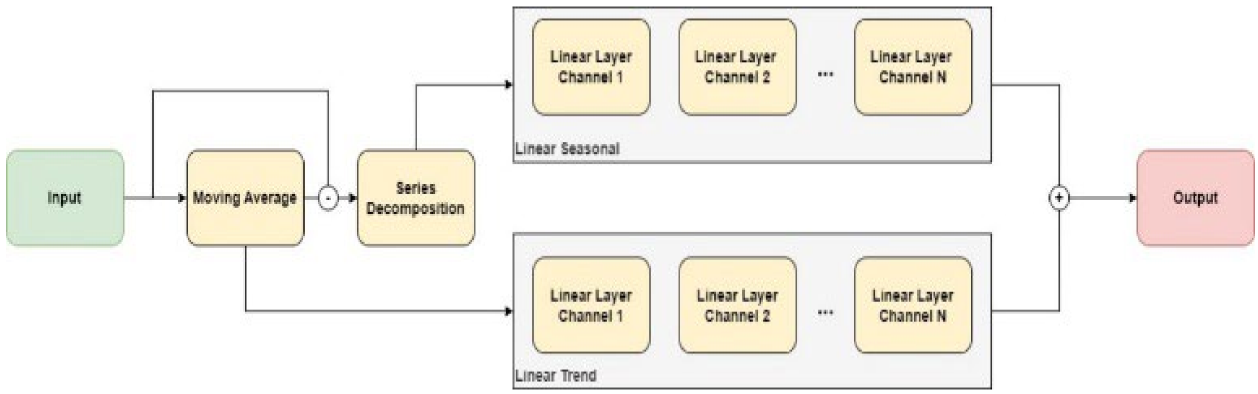


**Fig. 2** *DLinear architecture*

It was discovered that integrating moving average smoothing with decomposing series removed noise while extracting meaningful trends and seasonality from microclimate time series data, therefore improving the quality of the fitting [56]. The linear layers facilitate the processing of the seasonal and trend components in a transparent manner that keeps simplicity and interpretability. Such an interpretation facilitates researchers' ability to understand and trust model outputs [57]. The final output layer integrates seasonal behavior with long-term trends, providing an overall forecast of microclimate at both short- and long-term timescales in the agro-silvopastoral setting [58].

The dataset was split into 70% for training, 15% for validation, and 15% for testing to ensure balanced evaluation across temporal patterns. The DLinear model was trained using the Adam optimizer with a learning rate of 0.001, batch size of 32, and 10 epochs. These parameters were determined empirically after preliminary tuning to minimize validation loss and prevent overfitting.

## 3.6 LSTM (Long Short-Term Memory)

Long Short Term Memory networks have significantly improved over the normal recurrent networks in both design and application. Vanishing gradient problems are gradually solved next by adding memory cells and then putting into the memory an input, forget, and output gate mechanism for controlling information flow. This allows models to learn long-term dependency in sequential data, which is a prerequisite for such applications as microclimate analysis. Anyway, LSTMs have proved their mettle for a number of time series prediction tasks ranging from weather forecasting, speech recognition to financial modeling [59][60][61]. Consequently, more improvements, such as the addition of residual connections and sentiment features, have even enhanced the effectiveness of LSTM in difficult situations [62][63].

## 3.7 ARIMA (Autoregressive Integrated Moving Average)

The ARIMA model is a classical time series analysis approach with three main components: autoregression (AR), differencing (I), and moving average (MA). The ARIMA architecture is particularly effective for non-stationary data because it differentiates to achieve mean stability and then models temporal correlation with autoregressive and moving average terms. Accordingly, we choose (p, d, q) parameters that capture data patterns and noise. Thus, ARIMA is used in the fields of economics, meteorology, and epidemiological studies. In addition, hybrid approaches combining ARIMA with neural network models such as LSTM have been shown to enhance forecasting skills [64][65].

## 3.8 MLP (Multi-Layer Perceptron)

A Multi Layer Perceptron (MLP) is a type of feedforward neural network that includes fully coupled input, hidden, and output layers. Thus, MLPs can model non-linear complicated relationships on data with the help of the activation function ReLU. Training is accomplished using the backpropagation and gradient-based optimization algorithms. MLP is general-purpose and can be applied to classification, regression, or time series predictions; its performance is closely related to appropriate hyperparameter tuning and enough data. The application of regularization techniques is important to avoid overfitting in practice. MLP is found in applications ranging from medical diagnosis, finance modeling, to environmental modeling [65][66][67].

J. of Soft Computing and Data Mining Vol. 6 No. 3 (2025) p. 118-134

### 3.9 Transformer

Transformers are the newest emerging state-of-the-art architecture for sequential data processing, relying on an encoder-decoder structure maintained with the use of multiple heads of self-attention to model complex dependencies without recurrence. Therefore, it allows fast and flexible parallel computation as well as robust performance in natural language processing and can be adapted to temporal series forecasting or image analysis, with positional encoding included to maintain the sequential order of input data. The increased scale and computational efficiency of Transformers enable their extensive use in very sophisticated modeling tasks [68][69][70]. Current focus has been directed in this direction to improve interpretability, particularly for critical applications, where the “black box” nature of the transformed is still a serious concern [71].

## 4. Results and Discussion

This section presents the experimental outcomes and interprets the findings in the context of microclimate prediction. Model performance was assessed using metrics such as MAE, MSE, RMSE, and MAPE across different forecasting horizons (daily, weekly, and monthly). The results show how DLinear model outperforms others with regard to accuracy and efficiency, especially in microclimate data with seasonal and trend components. There were comparisons made with LSTM, Transformer, ARIMA, and MLP to show the balance among complexity, accuracy, and computational. Within agroforestry management, the discussion illustrates the enhanced benefits and machine learning productivity to real ecological sustainability.

### 4.1 Datasets

The study focuses mainly on the two abundant datasets. The first consists of relative light intensity measurements in the coffee-pine agroforestry landscape. This data holds the most importance in understanding the plant growth-related photonic condition and the system's photosynthetic activities. The second dataset involves air temperature and humidity, which are essential for understanding the microclimate surrounding plant growth, hence the system's health. The two very well-curated datasets offer an excellent frame for understanding the UB Forest competing ecosystem.

### 4.2 Experiment Settings

In designing this experiment, achieving perfect accuracy and reliability in the results was of utmost importance. To have a good representation of the different microclimatic zones in the coffee-pine agroforestry system, UB Forest plots were equipped with several sensors measuring the microclimate variables of light, temperature, and humidity. Collecting data over an extended period of time was needed to capture differences in weather events on a macro and micro scale. This ensured that the sensors broadcast real-time data over long periods for full analysis. Data pre-processing, which included cleaning, normalization, and standardization, was performed before the application of machine learning. The said results conduct a thorough characterization of the microclimate at UB Forest and exhibit the high potential of up-to-date machine learning methods for use in the ecological domain. In support of sustainable agroforestry management, these results show the relevance of big data and machine learning in environmental science.

### 4.3 Result Prediction Daily Time Frame

The modeling in this study results in the generation of graphs and assessment metrics (MAE, MSE, RMSE, MAPE) pertaining to every variable (Temperature, Humidity, Intensity) for all models (LSTM, DLinear, Transformer, ARIMA, MLP) over all time frames considered (Daily, Weekly, Monthly). Due to space limitations in this article, it is only displayed in the daily time range. Due to limited space in this article, it is only displayed in the daily time range. The visibility of Fig. 3 shows the results graph for LSTM, DLinear, Transformer, ARIMA, and MLP models in the context of daily temperature prediction.

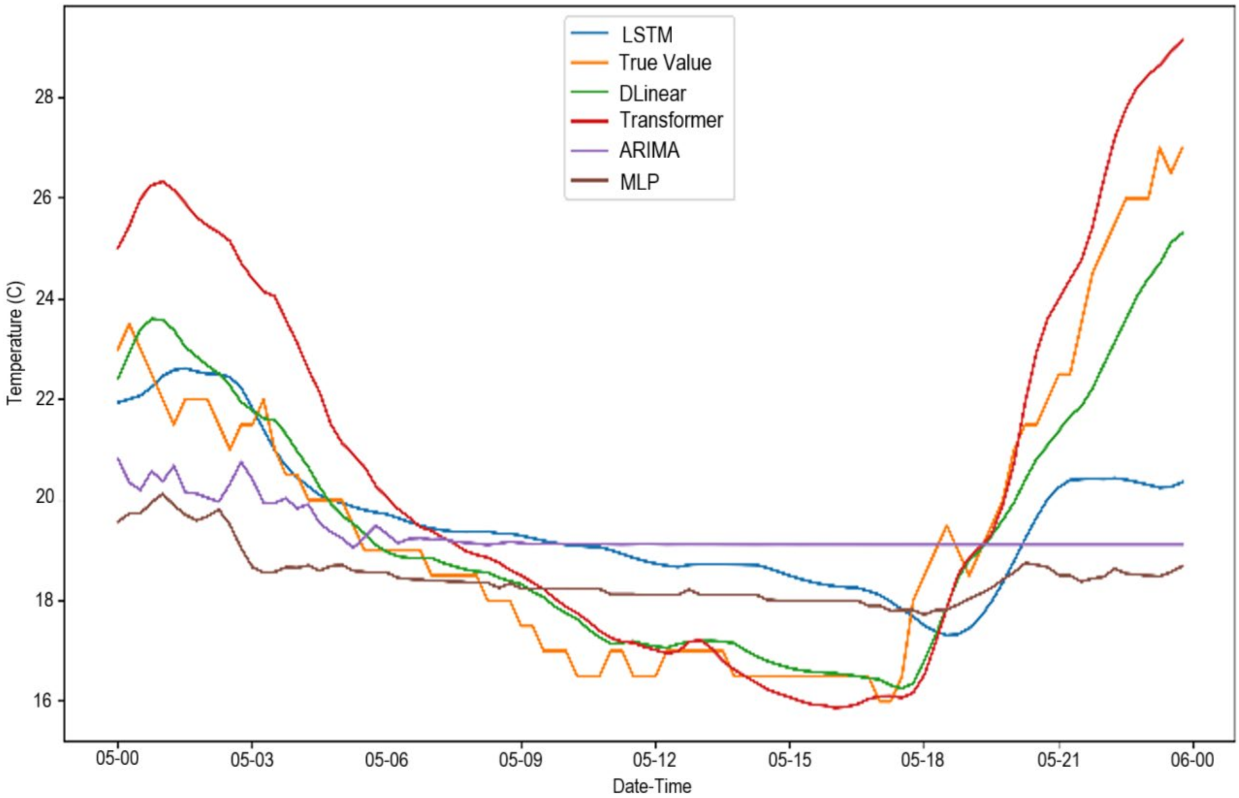


**Fig. 3** *Graph for the LSTM, DLinear, transformer, ARIMA, and MLP models to predict temperature for daily time frame*

The results graph for the LSTM, DLinear, transformer, ARIMA, and MLP models to predict humidity in time daily can be seen in Fig. 4.

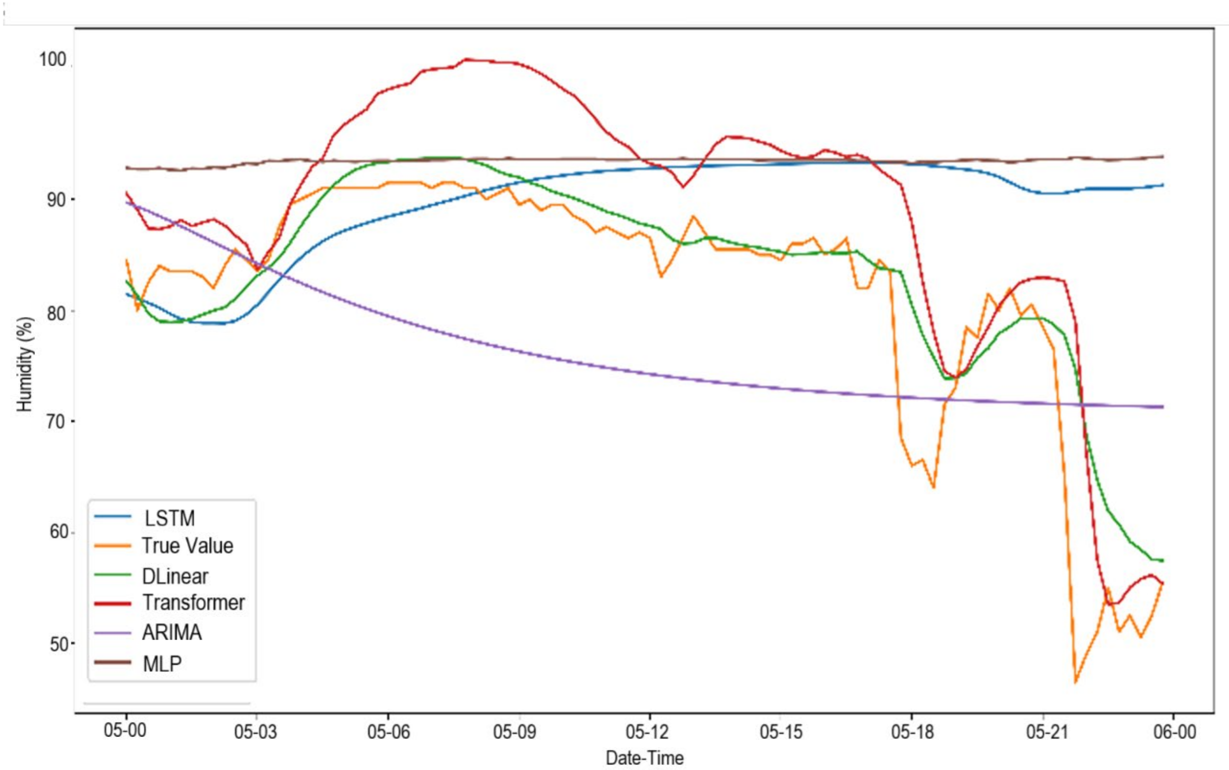


**Fig. 4** *Graph for the LSTM, DLinear, transformer, ARIMA, and MLP models to predict humidity for a daily time frame*

Visibility of Fig. 5 shows the results graph for LSTM, DLinear, Transformer, ARIMA, and MLP models in the context of daily Intensity prediction.

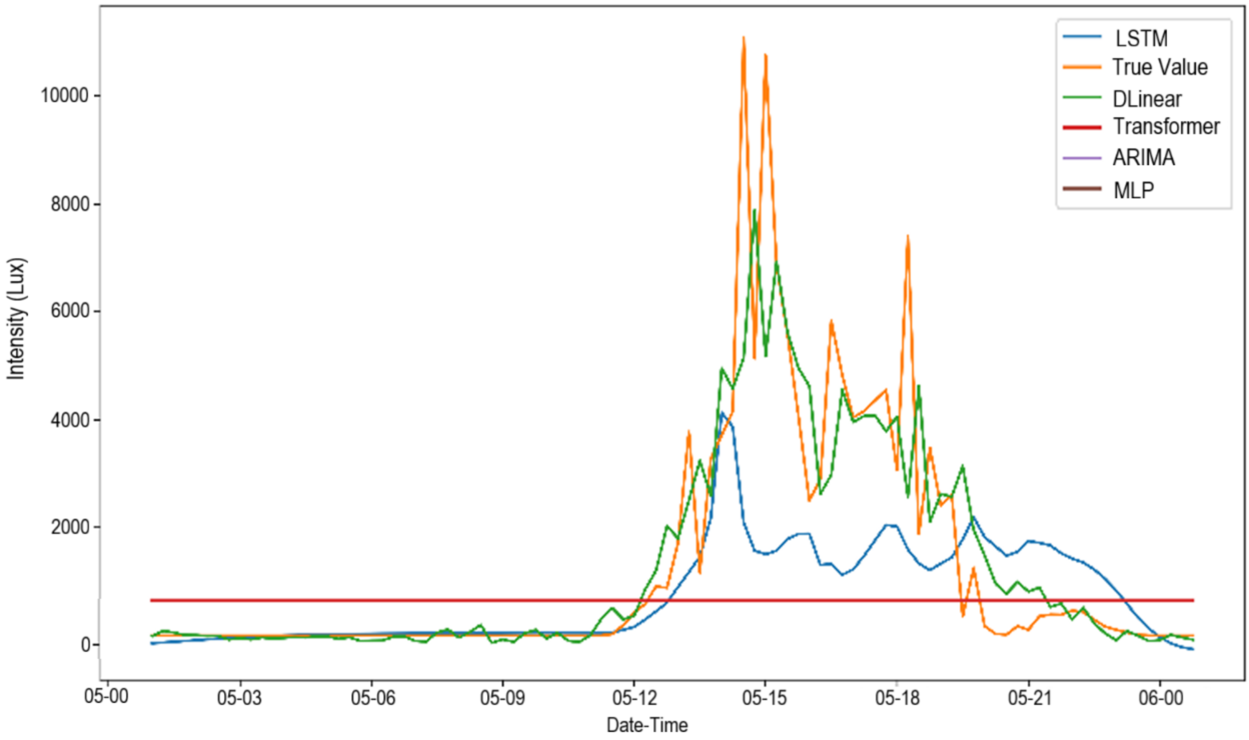


**Fig. 5** *Graph for the LSTM, DLinear, transformer, ARIMA, and MLP models to predict Intensity for daily*

## 4.4 Discussion

This is a comprehensive data analysis, covering all variables (Temperature, Humidity, Intensity), for each model (LSTM, DLinear, Transformer, ARIMA, MLP), across all time frames (Daily, Weekly, Monthly), with a focus on evaluation metrics (MAE, MSE, RMSE, MAPE). Evaluation metrics with LSTM, DLinear, Transformer, ARIMA, and MLP models to predict temperature in all time frames can be seen in Table 1.

Table 1 serves as the foundation for modeling an explanatory variable such as Temperature. In the daily scale, DLinear was the most accurate model, considering that the model's error metrics were the least with metric evaluation MAE 0.68947, MSE 0.87247, RMSE 0.93406, and MAPE 0.03345. During the weekly time frame, DLinear was again the most precise model. DLinear's performance was also outstanding in the monthly time frame. Therefore, in the case of a variable temperature, the model DLinear has more superiority in both daily and weekly time frames in accuracy and related error measures. This measurement possibly could be ascribed to its capacity to measure the linear correlation of prediction in such data sets of temperature. Add in Islamic agents, LSTM performs the best, but naturally, there is declining performance from the Transformer structure, which has proven to be useful in data that is sequential.

The performance of the Linear model in the accuracy and error metrics is better for both daily and weekly time frames when temperature data is considered. This is due to the concentrated nature of this model in predicting extreme values within the temperature data [72]. However, the Transformer model, which is designed to handle sequence data, offers good performance too, although it is not as good as the other architectures such as LSTM, MLP, and ARIMA [73].

**Table 1** *All time frame temperature prediction assessment metrics*

| Time-Frame | Model | MAE | MSE | RMSE | MAPE |
|---|---|---|---|---|---|
| Daily | LSTM | 1.7983 | 5.28985 | 2.29997 | 0.09102 |
| | MLP | 2.0996 | 8.24172 | 2.87084 | 0.10504 |
| | Transformer | 1.3161 | 3.03906 | 1.74329 | 0.0609 |
| | ARIMA | 2.178 | 7.95948 | 2.82125 | 0.1098 |
| | **Dlinear** | **0.68947** | **0.87247** | **0.93406** | **0.03345** |
| Weekly | LSTM | 1.4406 | 3.67688 | 1.91752 | 0.0705 |
| | MLP | 2.1216 | 8.38098 | 2.89499 | 0.10239 |
| | Transformer | 1.3769 | 3.3751 | 1.83714 | 0.06047 |
| | ARIMA | 2.2287 | 9.15619 | 3.02592 | 0.10773 |
| | **Dlinear** | **0.51129** | **0.46679** | **0.68322** | **0.02436** |
| Monthly | LSTM | 1.1215 | 2.0563 | 1.434 | 0.0572 |
| | MLP | 2.2718 | 7.9992 | 2.8283 | 0.1161 |
| | Transformer | 4.7355 | 31.9899 | 5.656 | 0.2232 |
| | ARIMA | 1.7672 | 4.9808 | 2.2318 | 0.0893 |
| | **Dlinear** | **0.4336** | **0.3426** | **0.5853** | **0.0217** |

Table 2 illustrates the Assessment Metrics of LSTM, DLinear, Transformer, ARIMA, and MLP models for predicting Humidity In each time span considered.

**Table 2** *All time frame humidity prediction assessment metrics*

| Time-Frame | Model | MAE | MSE | RMSE | MAPE |
|---|---|---|---|---|---|
| Daily | LSTM | 10.231 | 229.30466 | 15.14281 | 0.12874 |
| | MLP | 11.809 | 270.81748 | 16.45653 | 0.14525 |
| | Transformer | 7.6413 | 86.29015 | 9.28925 | 0.0907 |
| | ARIMA | 10.526 | 135.61186 | 11.64525 | 0.1375 |
| | **Dlinear** | **3.3519** | **30.51998** | **5.52449** | **0.04647** |
| Weekly | LSTM | 9.283 | 147.93053 | 12.16267 | 0.11746 |
| | MLP | 14.163 | 285.1359 | 16.88597 | 0.17127 |
| | Transformer | 5.4042 | 42.02862 | 6.48295 | 0.06846 |
| | ARIMA | 10.105 | 133.7155 | 11.56354 | 0.13314 |
| | **Dlinear** | **2.8859** | **16.26603** | **4.03312** | **0.03881** |
| Monthly | LSTM | 5.7901 | 70.7804 | 8.4131 | 0.0725 |
| | MLP | 10.715 | 181.5174 | 13.4728 | 0.1272 |
| | Transformer | 5.3812 | 39.9948 | 6.3241 | 0.0636 |
| | ARIMA | 12.919 | 201.4062 | 14.1918 | 0.1663 |
| | **Dlinear** | **2.1157** | **9.3793** | **3.0626** | **0.0274** |

As illustrated in Table 2, there is a comparison of the variable Humidity in relation to models and time frames. DLinear outperformed its competitors in terms of statistics by recording the fewest errors; however only applied in the daily time frame, where DLinear recorded an MAE of 3.3519, MSE of 30.51998, RMSE of 5.52449, and MAPE of 0.04647. In the weekly time frame, DLinear again had the best performance. Monthly DLinear also shows the best performance. It has been seen that the DLinear model's predictions of humidity levels were superior to those provided by the other models, no matter the time frame allowed for predictions.

DLinear was invariably better than any other model for predicting humidity over different timescales, i.e., it was a reliable model. It was shown that DLinear did much better than conventional models, such as LSTM, Transformer, ARIMA, and MLP in the case of one-month humidity forecasts [74]. Nevertheless, among the others, LSTM, Transformer, and ARIMA showed moderate to high prediction errors, while ARIMA and MLP were the most ineffective overall [75][76][77]. An overall assessment metric comparison was done for all models-LSTM, DLinear, Transformer, ARIMA, and MLP-over different forecasting horizons as outlined in Table 3.

**Table 3** *All time frame intensity prediction assessment metrics*

| Time-Frame | Model | MAE | MSE | RMSE | MAPE |
|---|---|---|---|---|---|
| Daily | LSTM | 988.86 | 3837594.488 | 1958.97792 | 1.49086 |
| | MLP | 1836.6 | 5540786.365 | 2353.8875 | 1.54831 |
| | Transformer | 1438.8 | 5675527.706 | 2382.33661 | 1.58529 |
| | ARIMA | 1284.1 | 6484794.619 | 2546.52599 | 1.67337 |
| | **Dlinear** | **553.94** | **1517304.359** | **1231.78909** | **1.29886** |
| Weekly | LSTM | 1070.7 | 5368080.715 | 2316.91189 | 1.42925 |
| | MLP | 1924.6 | 7306372.606 | 2703.03026 | 1.46444 |
| | Transformer | 1634.4 | 7682838.844 | 2771.79343 | 1.57237 |
| | ARIMA | 1566 | 8754262.999 | 2958.76038 | 1.76226 |
| | **Dlinear** | **733.18** | **2804285.754** | **1674.60018** | **1.25277** |
| Monthly | LSTM | 984.83 | 5387880.776 | 2321.1809 | 1.4053 |
| | MLP | 1903.1 | 7771004.96 | 2787.6522 | 1.462 |
| | Transformer | 1575.1 | 7989741.438 | 2826.6131 | 1.5555 |
| | ARIMA | 1499.3 | 8996606.455 | 2999.4344 | 1.7464 |
| | **Dlinear** | **761.24** | **3062665.139** | **1750.0472** | **1.2779** |

Specifically, the analysis of the Intensity variable across all models and time scales is found in Table 3. Notably, DLinear provided the best results achieved by the daily forecasting window with an MAE of 553.94, MSE of 1,517,304.359, RMSE of 1,231.78909, and MAPE of 1.29886. In the weekly loss, MDE DLinear has the smallest errors. In the monthly time frame, DLinear is outperforming other models. The DLinear model has shown the best performance in terms of error metrics across all the variables (temperature, humidity, intensity) and time frames (days, weeks, and months). In opposition, ARIMA and MLP models, which could be considered appropriate solutions, have higher errors in almost all metrics and within the variable's scope.

The DLinear model's strong performance indicates that simpler models do best when trends in the data become less complex. DLinear model's performance confirms empirical model selection theory from previous literature which suggests simpler models are often superior [78]. The performance also indicates that modeling the dynamics of the data temporally is an important consideration for microclimate forecasting, as LSTMs and ARIMAs are used for time series predictions in agriculture [79] [80][81]. On the contrary, the performance of the MLP and the Transformer may be due to overfitting, tuning, lack of training data, and the need for complex neural networks to be used more ambitiously and judiciously in relation to the task and data at hand.

The application of the DLinear model is observed to be the most superior when predicting the microclimate of Coffee-Pine Agroforestry. Based on the indicators considered, it would appear that the DLinear is the most informative model to apply. However, this is not the only thing that has to be considered while advertising a conclusion; the characteristics of the data in question, the computational resources available, and the intended users' expertise in relation to building and using the model should be factored in as well.

The superior performance of DLinear can be attributed to its decomposition of temporal patterns into seasonal and trend components, which aligns with the quasi-linear structure of climate variables. Unlike deep nonlinear models such as LSTM or Transformer, DLinear minimizes overfitting in datasets with strong periodicity and low stochastic noise, which is typical of microclimate data.

The statistical analysis based on the ANOVA results, shown in Table 4, the comparison of MAE values across the five predictive models (LSTM, MLP, Transformer, ARIMA, and DLinear) showed a statistically significant difference in performance. With the data available, multiple machine learning techniques were analyzed and constructed to predict the microclimatic conditions in the Coffee-Pine Agroforestry ecosystem. The models analyzed include MLP, LSTM, DLinear, Transformer, and ARIMA, and all were trained on the same dataset consisting of 111,097 records. The uniformity of the dataset volume allows for an equitable comparison of the models. Rather than the previous tables, which evaluated on a daily, weekly, or monthly scale, Table 4 presents an analysis of model performance and training speed comprehensively.

**Table 4** *The statistical analysis ANOVA on MAE across models*

| Component | Value |
|---|---|
| Number of groups (k) | 5 |
| Total observations (N) | 15 |
| Degrees of freedom (Between) | 4 |
| Degrees of freedom (Within) | 10 |
| Sum of Squares (Between) | 2,674,109.13 |
| Sum of Squares (Within) | 97,728.30 |
| Mean Square (Between) | 668,527.28 |
| Mean Square (Within) | 9,772.83 |
| F-value | 68.41 |
| p-value | $3.17 \times 10^{-7}$ |

The current article, utilizing various ML techniques, estimates microclimate conditions of Coffee-Pine Agroforestry using available data. The models include MLP, LSTM, DLinear, Transformer, and ARIMA. All models are built on a single dataset containing 111,097 rows. This dataset facilitates balanced comparison of models. Table 5, unlike previous ones that broke down results by day, week, and month, summarizes overall model results and training efficiency.

Table 5. Results for Model Training Time.

**Table 5** *Results for model training time*

| Parameter | MLP | LSTM | DLinear | Transformer | ARIMA |
|---|---|---|---|---|---|
| Dataset | 111097 | 111097 | 111097 | 111097 | 111097 |
| Epoch | 10 | 10 | 10 | 10 | 10 |
| Training | 903.97 | 5,522.57 | 911.97 | 19,970.21 | 2,176.85 |
| MAE (mean) | 2.27 | 1.12 | 0.43 | 4.74 | 1.77 |

The shortest training duration were recorded for DLinear and MLP (912 s and 904 s, respectively), suggesting high efficiency. On the contrary, the Transformer took significantly longer time for training (about 19,970 s), suggesting high processing time. LSTM and ARIMA were in the middle range for training time of the measured models.

Considering prediction accuracy in terms of MAE, DLinear was most accurate (MAE = 0.43), followed by LSTM (1.12), ARIMA (1.77), MLP (2.27), and Transformer (4.74). Thus, DLinear predicted microclimate variables with higher accuracy as well as higher efficiency than rest models. Predictive accuracy and computational efficiency suggest DLinear is in range of possibilities for real time microclimate prediction in agroforestry.

Nonetheless, certain restrictions are still to be considered. The approach taken is limited to the information available and the calibration of the historical information, as well as the measurements taken from the sensors. If any historical data is of low quality or lack information, any estimates made from that data can be very incorrect and/or misleading. This type of data quality is very vital for any future application. In addition, we understand that after our best effort for this study, implementing DLinear, we may have to accept that DLinear can be at a disadvantage compared to other methods such as LSTM or Transform in the identification of certain complex, non-linear interrelationships. Therefore, in extremely detailed or advanced ecologies, it may become rather unimportant. Finally, the actual conditions under which these results may be generalized and applied to other agroforestry systems or ecosystems need more in-depth examination. Therefore, there is a need for more in-depth examination under different conditions.

As it stands now, the implementation of DLinear forecasting in socketed sensor networks promotes climate-smart agriculture through the seamless understanding and real-time monitoring of microclimate and its changes. Real-time forecasting of microclimate (temperature and humidity) changes can facilitate adaptive changes in irrigation and canopy management, enhancing water use efficiency, and increases resilience to heat stress in coffee–pine systems.

The DLinear model's predictive capacity allows flexibility in how to approach agroforestry management. Knowing how to forecast temperature, humidity, and light intensity accurately can result to adapted forecast irrigation management and other agroforestry practices, such as canopy pruning and coffee plant spatial arrangements, which create a more productive agroforestry system. These anticipatory forecasted conditions can also assist climate adaptive responses to season changes and help coffee-pine farmers schedule management practices more effectively.

## 5. Conclusion and Future Work

The parameters such as Temperature, Humidity and Intensity were adopted in this study. The analysis found that the DLinear model significantly surpassed the performance of other models such as LSTM, Transformer, ARIMA, and MLP for all the time frames and parameters (Temperature, Humidity, Intensity) adopted in this study as it scored the least Error metrics and the highest Accuracy levels. Achieving all this is the linear learning approach of the model which is quite fast with training time lasting for only 912 seconds making it ideal in micro-climate modeling of coffee-pine agroforestry systems. Other models such as MLP for a training time of 904 seconds and ARIMA for a training time of 2177 seconds provided the optimal ranges in terms of the rate of convergence and the accuracy levels of the models trained but fell short of DLinear in terms of performance. LSTM and Transformer enabled handling of sequential data that is complex, however, the associated costs (5523 seconds for training LSTM and 19970 seconds for Transformer) did not translate to significant gains in performance.

This research exemplified how DLinear model offered microclimate forecasting at the intersection of data driven systems and agroforestry system management. This will help in the continual improvement of precision agroforestry, as more AI driven forecasting tools are created and integrated into ecological systems decision making.

Future work may look at trying to adjust more complex models such as LSTM and Transformer or their combination with DLinear in more complicated environments. It would also help to test these models in farming systems found in different locations. In future research, it would be important to add more environmental factors such as soil types or even canopy cover to enhance predictions as well as study the research question on climate change effects over time. These results enhance existing microclimate prediction systems and provide a new perspective on maximizing agricultural output along with respective ecological concerns in different parts of the world that involve agroforestry systems.

## Author Contribution

***Heru Nurwarsito:*** *Writing original draft, Methodology, Conceptualization.* ***Didik Suprayogo:*** *Writing check–originality, Data analysis, Data curation.* ***Simon Oakley:*** *Investigation, Conceptualization.* ***Mustafa Mat Deris****: Proofreading, Artificial Resources.* ***Cahyo Prayogo:*** *Methodology, Data curation.* ***Aji Prasetya Wibawa:*** *Supervision, Methodology.*

## Conflict of Interest

The writers have emphasized that there are no financial or personal conflicts binding them to any interests that could have biased their work in the present paper.

## Data availability

Data will be shared upon request

## Acknowledgement

The authors would like to acknowledge the valuable support received from the UK Centre for Ecology & Hydrology (UKCEH), based at the Lancaster Environment Centre, Lancaster, United Kingdom, through a research scholarship and assistance in providing scientific materials. The authors would like to acknowledge the commitment of the Ecosystem Strengthening Grant Scheme, Institute for Research and Community Service, Universitas Brawijaya (LPPM-UB, Malang, Indonesia), for funding part of this research. Assistance in implementing research activities was also received from forestry management and farmers at Universitas Brawijaya. Finally, we would like to thank the UB AI Research Center. The authors used ChatGPT to assist in grammar checking and language refinement. All content generated was reviewed and verified by the authors, who take full responsibility for the final submission.

## References

[1] Sudharta, K. A., et al. (2022). Soil organic matter and nitrogen in varying management types of coffee-pine agroforestry systems and their effect on coffee bean yield. *Biodiversitas: Journal of Biological Diversity*. https://doi.org/10.13057/biodiv/d231142

[2] Kennedy, A. (1995). Simulated climate change: Are passive greenhouses a valid microcosm for testing the biological effects of environmental perturbations? *Global Change Biology*. https://doi.org/10.1111/j.1365-2486.1995.tb00004.x

[3] Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Frontiers in Sustainable Food Systems*. https://doi.org/10.3389/fsufs.2018.00087

[4] Chen, T.-H., Lee, M.-H., Hsia, I.-W., Hsu, C.-H., Yao, M.-H., & Chang, F.-J. (2022). Develop a smart microclimate control system for greenhouses through system dynamics and machine learning techniques. *Water*. https://doi.org/10.3390/w14233941

[5] Raza, U., Kulkarni, P., & Sooriyabandara, M. (2017). Low power wide area networks: An overview. *IEEE Communications Surveys & Tutorials, 19*(2), 855–873. https://doi.org/10.1109/COMST.2017.2652320

[6] Khanh, Q., Hoang, T. Q., Nguyen, T. T., & Ong, V. K. P. (2022). Predicting and avoiding hazardous occurrences of stuck pipe for the petroleum wells at offshore Vietnam using machine learning techniques. *IOP Conference Series: Earth and Environmental Science*. https://doi.org/10.1088/1755-1315/1091/1/012003

[7] Tabak, M. A., et al. (2018). Machine learning to classify animal species in camera trap images: Applications in ecology. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210x.13120

[8] Mansfield, L. A. (2023). Updates on model hierarchies for understanding and simulating the climate system: A focus on data-informed methods and climate change impacts. *Journal of Advances in Modeling Earth Systems*. https://doi.org/10.1029/2023MS003715

[9] Danabasoglu, G., Lamarque, J., Bacmeister, J., & Bailey, D. A. (2020). The Community Earth System Model version 2 (CESM2). *Journal of Advances in Modeling Earth Systems, 12*(2), e2019MS001916.

[10] Narunsky-Haziza, L., et al. (2022). Pan-cancer analyses reveal cancer-type-specific fungal ecologies and bacteriome interactions. *Cell*. https://doi.org/10.1016/j.cell.2022.09.005

[11] CAHYONO, E. D., PRADESTI, E., PRAYOGO, C., & ISASKAR, R. (2023). EXPLORING THE RELATIVE ADVANTAGES OF LOCAL INNOVATION IN AGROFORESTRY. Frontiers of Agricultural Science & Engineering, 10(1).

[12] Cravero, A., Bustamante, A., Negrier, M., & Galeas, P. (2022). Agricultural big data architectures in the context of climate change: A systematic literature review. *Sustainability*. https://doi.org/10.3390/su14137855

[13] Greiser, C., Meineri, É., Luoto, M., Ehrlén, J., & Hylander, K. (2018). Monthly microclimate models in a managed boreal forest landscape. *Agricultural and Forest Meteorology*. https://doi.org/10.1016/j.agrformet.2017.12.252

[14] Purwins, H.-G., Li, B., Virtanen, T., Schlüter, J., Chang, S.-Y., & Sainath, T. N. (2019). Deep learning for audio signal processing. *IEEE Journal of Selected Topics in Signal Processing*. https://doi.org/10.1109/JSTSP.2019.2908700

[15] Zellweger, F., De Frenne, P., Lenoir, J., Rocchini, D., & Coomes, D. A. (2019). Advances in microclimate ecology arising from remote sensing. *Trends in Ecology & Evolution*. https://doi.org/10.1016/j.tree.2018.12.012

[16] Sherstinsky, A. (2020). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica D: Nonlinear Phenomena*. https://doi.org/10.1016/j.physd.2019.132306

[17] Fischer, T., & Krauß, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2017.11.054

[18] Shi, H., Xu, M., & Li, R. (2018). Deep learning for household load forecasting—A novel pooling deep RNN. *IEEE Transactions on Smart Grid*. https://doi.org/10.1109/TSG.2017.2686012

[19] Ye, Z. (2019). Air pollutants prediction in Shenzhen based on ARIMA and Prophet method. *E3S Web of Conferences*. https://doi.org/10.1051/e3sconf/201913605001

[20] Yan, Z., et al. (2022). A multi-energy load prediction of a building using the multi-layer perceptron neural network method with different optimization algorithms. *Energy Exploration & Exploitation*. https://doi.org/10.1177/01445987221112250

[21] Nurwarsito, H., et al. (2024). Imputation of missing microclimate data of coffee-pine agroforestry with machine learning. *International Journal of Advanced Intelligent Informatics, 10*(1), 27. https://doi.org/10.26555/ijain.v10i1.1439

[22] Nurwarsito, H., et al. (2024). Development of microclimate data recorder on coffee-pine agroforestry using LoRaWAN and IoT technology. *Journal of Robotics and Control, 5*(1), 271–286. https://doi.org/10.18196/jrc.v5i1.20991

[23] Gidey, T., Oliveira, T. S., Crous-Duran, J., & Palma, J. H. N. (2019). Using the Yield-SAFE model to assess the impacts of climate change on yield of coffee (*Coffea arabica* L.) under agroforestry and monoculture systems. *Agroforestry Systems*. https://doi.org/10.1007/s10457-019-00369-5

[24] Sri Budiastuti, M. T., Purnomo, D., & Setyaningrum, D. (2021). Agroforestry system as the best vegetation management to face forest degradation in Indonesia. *Review of Agricultural Science*. https://doi.org/10.7831/ras.10.0_14

[25] Nurwarsito, H. (2024). *Revitalisasi manajemen agroforestri: Uji aplikasi presisi monitoring iklim mikro dan optimalisasi produksi kopi dengan modeling di sistem agroforestri berbasis kopi-pinus*. Universitas Brawijaya.

[26] Nurwarsito, H., Al Azhar, Y. P., Prayogo, C., & Oakley, S. (2021). Management information system for micro climate logging data using REST API with prototype approach in a coffee plantation in UB Forest. In *Proceedings of the 6th International Conference on Sustainable Information Engineering and Technology* (pp. 86–93).

[27] Nandini, R., Krisnawati, N., & Rahayu, A. (2023). Potential development of partnership agroforestry as carbon farming in KHDTK Rarung, Central Lombok. *IOP Conference Series: Earth and Environmental Science*. https://doi.org/10.1088/1755-1315/1180/1/012026

[28] Imanuddin, R., et al. (2020). Reforestation and sustainable management of *Pinus merkusii* forest plantation in Indonesia: A review. *Forests*. https://doi.org/10.3390/f11121235

[29] Suprayogo, D., et al. (2020). Tree and plant interactions in the agroforestry system: Does the management of coffee intensification disrupt the soil hydrological system and pine growth? *IOP Conference Series: Earth and Environmental Science*. https://doi.org/10.1088/1755-1315/449/1/012045

[30] Cahyono, E. D., et al. (2020). Agroforestry innovation through planned farmer behavior: Trimming in pine–coffee systems. *Land, 9*(10), 363.

[31] Purnomo, D., Sri Budiastuti, M. T., & Setyaningrum, D. (2022). The role of soybean agroforestry in mitigating climate change in Indonesia. *IOP Conference Series: Earth and Environmental Science*. https://doi.org/10.1088/1755-1315/1016/1/012024

[32] Zhong, S., et al. (2021). Machine learning: New ideas and tools in environmental science and engineering. *Environmental Science & Technology*. https://doi.org/10.1021/acs.est.1c01339

[33] Tuia, D., et al. (2022). Perspectives in machine learning for wildlife conservation. *Nature Communications*. https://doi.org/10.1038/s41467-022-27980-y

[34] Gregory, W. (2023). Deep learning of systematic sea ice model errors from data assimilation increments. *Journal of Advances in Modeling Earth Systems*. https://doi.org/10.1029/2023MS003757

[35] Li, J., Wu, G., Zhang, Y., & Shi, W. (2024). Optimizing flood predictions by integrating LSTM and physical-based models with mixed historical and simulated data. *Heliyon, 10*(13), e33669. https://doi.org/10.1016/j.heliyon.2024.e33669

[36] Fadhel, A. S., et al. (2024). Enhanced long short-term memory for landfill area estimation based on domestic solid waste prediction. *Journal of Soft Computing and Data Mining, 5*(1). https://doi.org/10.30880/jscdm.2024.05.01.014

[37] Wang, X., et al. (2023). Integrating field images and microclimate data to realize multi-day ahead forecasting of maize crop coverage using CNN-LSTM. *International Journal of Agricultural and Biological Engineering, 16*(2), 199–206. https://doi.org/10.25165/j.ijabe.20231602.7020

[38] Park, S.-H., et al. (2023). Development of a soil moisture prediction model based on recurrent neural network long short-term memory (RNN-LSTM) in soybean cultivation. *Sensors*. https://doi.org/10.3390/s23041976

[39] Chong, A. Y. W., et al. (2023). Customer churn prediction of telecom company using machine learning algorithms. *Journal of Soft Computing and Data Mining, 4*(2). https://doi.org/10.30880/jscdm.2023.04.02.001

[40] Xie, H., et al. (2022). Low-interception waveform: To prevent the recognition of spectrum waveform modulation via adversarial examples. *arXiv*. https://doi.org/10.48550/arxiv.2201.08731

[41] Solís, M., & Calvo-Valverde, L.-A. (2022). Performance of deep learning models with transfer learning for multiple-step-ahead forecasts in monthly time series. *Inteligencia Artificial, 25*(70), 110–125. https://doi.org/10.4114/intartif.vol25iss70pp110-125

[42] Alim, M., et al. (2020). Comparison of ARIMA model and XGBoost model for prediction of human brucellosis in mainland China: A time-series study. *BMJ Open*. https://doi.org/10.1136/bmjopen-2020-039676

[43] Tsan, Y., et al. (2022). The prediction of influenza-like illness and respiratory disease using LSTM and ARIMA. *International Journal of Environmental Research and Public Health*. https://doi.org/10.3390/ijerph19031858

[44] Choi, H. S., et al. (2022). Development of a revised multi-layer perceptron model for dam inflow prediction. *Water*. https://doi.org/10.3390/w14121878

[45] Ampomah, E. K., et al. (2021). Stock market prediction with Gaussian naïve Bayes machine learning algorithm. *Informatica, 45*(2). https://doi.org/10.31449/inf.v45i2.3407

[46] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture, 147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

[47] Reyes, L. J. C., Rangel, H. Á., & Sandoval-Herazo, L. C. (2022). Adjustment of the standardized precipitation index (SPI) for the evaluation of drought in the Arroyo Pechelín Basin, Colombia. *Atmosphere, 13*(2), 236. https://doi.org/10.3390/atmos13020236

[48] Amin, A., et al. (2019). Cross-company customer churn prediction in telecommunication: A comparison of data transformation methods. *International Journal of Information Management, 46*, 304–319. https://doi.org/10.1016/j.ijinfomgt.2018.08.015

[49] De Frenne, P., et al. (2021). Forest microclimates and climate change: Importance, drivers and future research agenda. *Global Change Biology, 27*(11), 2279–2297.

[50] Stark, J., Fridley, J. D., & Gill, J. L. (2022). Microclimate-based species distribution models in complex forested terrain indicate widespread cryptic refugia under climate change. *Global Ecology and Biogeography*. https://doi.org/10.1111/geb.13447

[51] Zaidan, M. A., et al. (2020). Intelligent calibration and virtual sensing for integrated low-cost air quality sensors. *IEEE Sensors Journal, 20*(22), 13638–13652. https://doi.org/10.1109/JSEN.2020.3010316

[52] Liu, S., et al. (2022). A hybrid model for coronavirus disease 2019 forecasting based on ensemble empirical mode decomposition and deep learning. *International Journal of Environmental Research and Public Health*. https://doi.org/10.3390/ijerph20010617

[53] Huang, Y.-C., & Ma, M.-Y. (2022). An improved particle swarm optimization using long short-term memory model for positioning control of a coplanar XXY stage. *Measurement and Control*. https://doi.org/10.1177/00202940221083574

[54] Kearney, M. R., et al. (2014). Microclimate modelling at macro scales: A test of a general microclimate model integrated with gridded continental-scale soil and weather data. *Methods in Ecology and Evolution*. https://doi.org/10.1111/2041-210X.12148

[55] Kraft, P., et al. (2021). Modelling agroforestry's contributions to people—A review of available models. *Agronomy, 11*(11), 2106. https://doi.org/10.3390/agronomy11112106

[56] Dupraz, C., et al. (2019). Hi-sAFe: A 3D agroforestry model for integrating dynamic tree–crop interactions. *Sustainability, 11*(8), 2293. https://doi.org/10.3390/su11082293

[57] Banerjee, S., et al. (2015). Determinants of bacterial communities in Canadian agroforestry systems. *Environmental Microbiology, 18*(6), 1805–1816. https://doi.org/10.1111/1462-2920.12986

[58] de Souza, P. V. D., et al. (2023). Maize yield prediction using artificial neural networks based on a trial network dataset. *Engineering, Technology & Applied Science Research, 13*(2), 10338–10346. https://doi.org/10.48084/etasr.5664

[59] Bareth, R., et al. (2024). Daily average load demand forecasting using LSTM model based on historical load trends. *IET Generation, Transmission & Distribution, 18*(5), 952–962. https://doi.org/10.1049/gtd2.13132

[60] Ta, N., & Gao, B. (2022). Sustainable reuse strategies of enterprise financial management model following deep learning under big data. *Journal of Organizational and End User Computing*. https://doi.org/10.4018/JOEUC.300761

[61] Sahin, S. O., & Kozat, S. S. (2019). Nonuniformly sampled data processing using LSTM networks. *IEEE Transactions on Neural Networks and Learning Systems*. https://doi.org/10.1109/TNNLS.2018.2869822

[62] Yan, Y. (2023). LSTM-based stock price prediction model using news sentiments. *Advances in Economics, Management and Research*. https://doi.org/10.56028/aemr.6.1.57.2023

[63] Ayitey, M., Appiahene, P., & Appiah, O. (2022). Forex market forecasting with two-layer stacked long short-term memory neural network (LSTM) and correlation analysis. *Journal of Electrical Systems and Information Technology*. https://doi.org/10.1186/s43067-022-00054-1

[64] Jain, S., et al. (2024). A novel ensemble ARIMA-LSTM approach for evaluating COVID-19 cases and future outbreak preparedness. *Health Care Science, 3*(6), 409–425. https://doi.org/10.1002/hcs2.123

[65] Tang, C. (2024). Application of ARIMA-LSTM-CQP time rolling window multi-factor stock selection model in quantitative investment. https://doi.org/10.21203/rs.3.rs-3875083/v1

[66] Liu, M., et al. (2023). A multilayer perceptron-based model applied to histopathology image classification of lung adenocarcinoma subtypes. *Frontiers in Oncology, 13*. https://doi.org/10.3389/fonc.2023.1172234

[67] Oyewola, D. O., Dada, E. G., & Misra, S. (2023). Diagnosis of cardiovascular diseases by ensemble optimization deep learning techniques. *International Journal of Healthcare Information Systems and Informatics, 19*(1), 1–21. https://doi.org/10.4018/IJHISI.334021

[68] Vaswani, A., et al. (2017). Attention is all you need. *arXiv*. https://doi.org/10.48550/arxiv.1706.03762

[69] Evstropov, A. M. (2023). Neural network architecture "transformer": Artificial intelligence and its role in natural language processing. *ТРНИО*. https://doi.org/10.18411/trnio-05-2023-633

[70] Liu, C., Wang, B., & Zou, Y. (2023). Combining multi-scale convolutional neural network with long short-term memory neural network for state of charge estimation of lithium-ion batteries. *Journal of Physics: Conference Series*. https://doi.org/10.1088/1742-6596/2456/1/012017

[71] J. B. M., & Ilavarasan, S. (2024). Unlocking market trends: LSTM-based stock price forecasting for intelligent investments (pp. 627–633). https://doi.org/10.56155/978-81-955020-7-3-55

[72] Deng, Y., et al. (2019). A method for hot spot temperature prediction of a 10 kV oil-immersed transformer. *IEEE Access, 7*, 107380–107388. https://doi.org/10.1109/ACCESS.2019.2924709

[73] Li, C., Ren, X., & Zhao, G. (2023). Machine-learning-based imputation method for filling missing values in ground meteorological observation data. *Algorithms, 16*(9), 422.

[74] Ahn, J. Y., et al. (2024). Evaluating time-series prediction of temperature, relative humidity, and $CO_2$ in the greenhouse with transformer-based and RNN-based models. *Agronomy, 14*(3), 417. https://doi.org/10.3390/agronomy14030417

[75] Kaushik, S., et al. (2020). AI in healthcare: Time-series forecasting using statistical, neural, and ensemble architectures. *Frontiers in Big Data, 3*. https://doi.org/10.3389/fdata.2020.00004

[76] Nguyen, V.-H., et al. (2022). Deep learning models for forecasting dengue fever based on climate data in Vietnam. *PLoS Neglected Tropical Diseases, 16*(6), e0010509. https://doi.org/10.1371/journal.pntd.0010509

[77] Yang, L., et al. (2023). Deep-learning model for influenza prediction from multisource heterogeneous data in a megacity: Model development and evaluation. *Journal of Medical Internet Research*. https://doi.org/10.2196/44238

[78] Alexander, D. L. J., Tropsha, A., & Winkler, D. A. (2015). Beware of $R^2$: Simple, unambiguous assessment of the prediction accuracy of QSAR and QSPR models. *Journal of Chemical Information and Modeling, 55*(7), 1316–1322. https://doi.org/10.1021/acs.jcim.5b00206

[79] Elsaraiti, M., & Merabet, A. (2021). A comparative analysis of the ARIMA and LSTM predictive models and their effectiveness for predicting wind speed. *Energies, 14*(20), 6782. https://doi.org/10.3390/en14206782

[80] Zhang, M., et al. (2021). Urban micro-climate prediction through long short-term memory network with long-term monitoring for on-site building energy estimation. *Sustainable Cities and Society, 74*, 103227.

[81] Xu, J. (2024). Forecasting water demand with the long short-term memory deep learning mode. *International Journal of Information Technology & Systems Approach, 17*(1), 1–18. https://doi.org/10.4018/IJITSA.338910