J-COSINE (Journal of Computer Science and Informatics Engineering)
Vol. 8, No. 2, December 2024 E-ISSN:2541-0806
Accredited Sinta-4 by RISTEKDIKTI Decree No. 79/E/KPT/2023 P-ISSN:2540-8895

Comparison of ARIMA and Machine Learning Methods for Predicting Urban Land Surface Temperature in Jakarta

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Abstract **Climate change is a global challenge that requires serious attention from various parties, including the government. The existence of surface temperature and various other parameters is certainly closely related to climate change. In this context, this study was conducted to identify the best model in predicting urban land surface temperature in the Jakarta area, as one of the steps to understand and deal with the impacts of climate change. The research used time series data from MERRA-2, NASA, which provides datasets for various climate analyses. A comparison of ARIMA, SVR, LSTM, and ANN methods was conducted to evaluate the performance of each model in forecasting land surface temperature. The results show that the Long-Short Term Memory (LSTM) model provides the best performance with MAPE and R^2 values of 0.8381 and 0.8628. This model has an advantage over other models because it can remember various information that has been stored for a long period of time and can delete irrelevant information. This shows that LSTM is effective in capturing the pattern and variability of the Earth's surface temperature in the Jakarta area. Based on these findings, the government is expected to take concrete steps to address the impacts of climate change, especially issues related to increasing urban land temperature in Jakarta, such as reducing the use of private vehicles and switching to public transportation, expanding green open space, and relocating residents to reduce density.**

Keywords**: ARIMA, Jakarta, Machine Learning, Prediction, Land Surface Temperature.**

I. INTRODUCTION

Weather and climate conditions are important especially in the context of daily activities, for example it can be an important basis in planning development in various sectors, such as transportation, agriculture, economy, health, and other fields [1], [2]. The Meteorology, Climatology and Geophysics Agency (BMKG) is an official government agency responsible for monitoring weather conditions and providing various data on climate parameters in Indonesia to those who need the information. Currently, the demand for weather condition information continues to grow along with the increase in the number of parties that utilize the data [3].

Then talking about temperature, air temperature is one of the important parameters that affect weather and climate conditions [4], [5]. Air temperature also represents terrestrial or earth surface conditions [6]. The existence of air temperature is an important factor in facing social challenges related to protecting human health to ecosystems and environmental sustainability [4]. Air temperature is defined as the degree of heat or cold resulting from the activity of molecular movement in the atmosphere [7]. In the context of temperature, land surface temperature is the temperature sensed when there is an exchange of long radiation and turbulent heat between the Earth's surface and the atmosphere. The use of surface temperature is increasing to monitor climate change in urban areas [8]. Changes in global surface temperature have become a key indicator in understanding climate change [9]. An in-depth understanding of changes in temperature and other climate parameters is crucial in responding to and addressing the impacts caused by global climate change [8]. At present, climate change is closely related to global warming [10], [11].

Global warming is now a global problem due to human activities that continue to pump greenhouse gases, which have the ability to absorb and store heat in the atmosphere [12]–[14]. Global warming can have an impact on climate change, which is a change in the physical conditions of the Earth's atmosphere, including the distribution of human temperature and precipitation [15]. According to some experts, the main target cause of climate change is man-made global warming [16]. Climate change is characterised by several features, such as increased global temperatures, increased CO_2 in the atmosphere, and melting glaciers [15], [17], [18]. This problem was felt by Jakarta residents who felt the hot and stuffy weather on 12 May 2023 with temperatures reaching 35.1°C, because Indonesia is transitioning from the rainy season to the dry season. BMKG's Deputy of Meteorology stated that the lack of clouds made the heat more pronounced, which was also felt especially by office workers [19].

In Indonesia, the problem of global warming due to climate change is increasingly evident, especially in large urban areas such as Jakarta. Jakarta has experienced rapid growth as the largest metropolitan city in Indonesia. The

National Monument area in Jakarta is a centre of community activity that contributes to climate change, including temperature changes, air pollution and adaptation to changing weather conditions. This is due to its status as the national centre of government and economy [20]. As a result, land use change in Jakarta is dynamic, with significant land growth. Indonesia is among the top ten contributors to gas emissions, with 37% from industry, 27% from transport, and 27% from power and heat generation. This is due to heating ventilation systems, rapid population growth, and heavy vehicle activity [21]. Several offences such as air pollution contributed to the decline in air quality and increase in temperature in Jakarta [22]. The international climate organization, the Intergovernmental Panel on Climate Change (IPCC), called on countries around the world including Jakarta to limit the Earth's temperature rise to around 1.5°C. In the IPCC's special report on climate change, it is explained that a 1°C increase will cause very dire effects [23].

Another problem experienced by Jakarta is the higher land surface temperature associated with Urban Heat Island (UHI). UHI is known as the relationship between large urban areas and surface temperatures significantly affecting temperature differences between urban and sub-urban, peri-urban, or rural areas [24]. The rapid growth of built-up land is the main cause of the UHI phenomenon in Jakarta. Built-up land has reached 83% in 2009 and 87% in 2019. This growth has led to an increase in surface temperature, with temperatures reaching 35°C in the east and south. The average temperature increased by 1.4°C over ten years, with the highest temperature reaching 37.1°C [25]. This UHI phenomenon also has an impact on poorer air quality and the environment, as well as increased energy use, which ultimately impacts climate change [20].

The results of processing satellite images of Jakarta's land surface temperature from the MODIS sensor in the previous study showed that in the past 30 years, the average monthly temperature in Jakarta was about 27.2°C with some hot spots reaching 37°C due to industrial and transport factors. From the results of the linear trend test, it is found that the surface air temperature of Jakarta has a constant increase of 0.00126379°C every month [26]. In addition, the wet season of 2016 had lower ground surface temperatures (maximum 29.46°C) than the dry season of 2015 (maximum over 36°C). The difference in surface temperature depends on the season and the rainfall occurring at that time [27].

Prior to 2023, the warmest recorded temperature in a 12-month period was 1.29°C above the baseline temperature and occurred in the period October 2015 to September 2016. In addition, there is a global warming trend caused by excessive greenhouse gases. Research by the Climate Central organization shows that Jakarta is the second hottest city in the world with 17 consecutive days among 700 populated cities, from October 7 to 24, 2023, which is one of the problems faced by the metropolis [28]. Given these facts about the effects of rising air temperatures, air temperature prediction is an area of consistent research due to its broad impact. Weather stations provide predictions, but usually only display daily average temperatures. Predictions with high resolution and more data will help in planning and policy. Temperature prediction is an important feature that increases the prediction horizon for various life applications [29].

The use of forecasting methods greatly affects the prediction results later. Several methods are needed to compare which method produces better predictions. ARIMA is one of the commonly used classical forecasting methods in the case of short-term prediction, but machine learning methods are also gaining popularity. Machine learning can be a comparison method against classical methods and a substitute option for statistical methods in forecasting time series. However, limited information is available on their relative performance in terms of accuracy and computational requirements. Therefore, a comparison between ARIMA and machine learning methods is necessary to find out which method has the best accuracy [30].

This research provides some new contributions to the literature and methods of temperature forecasting in Indonesia. Previous studies predicted the surface temperature of the Jakarta urban area using artificial neural networks [6], spatial analysis [8], and cellular automata modeling [31]. Research conducted by [31] only predicted the climate in Jakarta using classic methods, namely Holt-Winters and SARIMA with meteorological data collected from BMKG, while research by [32], only predict temperature using machine learning such as ANFIS, GRU, and LSTM which are neural network algorithms. Therefore, this research makes a new contribution by comparing classic forecasting models, namely ARIMA with machine learning such as SVR, LSTM, and ANN in identifying the best model to predict urban land surface temperature in Jakarta. These three methods were chosen because of their respective characteristics and advantages. ANN is capable of capturing complex non-linear patterns, which often appear in weather data. LSTM, as part of the recurring nerve network (RNN), is very effective in processing and predicting time series data so it is very accurate to predict temperatures that depend on historical data. Meanwhile, SVRs offer reliability and flexibility in handling small to medium-sized data, as well as being able to find linear and non-linear relationships in data.

In addition, this study uses NASA satellite image data from the MERRA-2 reanalysis project, which allows for the collection of big data. It also allows for regular monitoring without human intervention and can improve the efficiency of time, cost and labor in the data collection process. Research in this area can also provide valuable insights into how climate change can affect the daily lives and activities in downtown Jakarta. In addition, the research is expected to inform government policies for managing the urban environment and addressing rising surface temperatures in Jakarta.

II. Theoretical Backgorund

Prediction of air temperature is an important activity because it is considered as part of climate change analysis. Various studies in the world regarding temperature prediction have also been carried out with several methods, both using classic ARIMA forecasting methods and machine learning such as SVR, LSTM, and ANN. Research by [33] on land surface temperature forecasting with remote sensing technology from 2008 to 2018 in Chennai City, India using the ARIMA model shows that the prediction accuracy of this model is quite good with an RMSE of 1.11 °C. The increase in land surface temperature is due to rapid urbanisation and land use change.

Another related study is a study conducted by [34] on temperature forecasting in Tanjung Priok, North Jakarta using the Conv-BiLSTM and BiLSTM machine learning algorithms. This study used ERA5 temperature data available in Tanjung Priok, North Jakarta for a period of 5 years (4 years for training data and 1 year for test data). The results showed that Conv-BiLSTM performed better than BiL STM when forecasting long-term and short-term temperature data.

Research on temperature prediction was also conducted by [35][35] using the ANFIS LSTM methods. The results showed that the LSTM method gave the highest accuracy in predicting air temperature with an RMSE of 1,360 °C. With high computational speed and the ability to handle complex problems, Artificial Neural Network (ANN) based approaches have also been widely used to predict air temperature. However, no consensus on the best method exists. In addition, it was found that ANN-based techniques can be used for short-term air temperature forecasting [36].

The role of atmospheric air temperature, which is considered as one of the important meteorological parameters, prompted [37] to conduct research to forecast accurate and timely air temperature. Some of the data-based approaches used are ARIMA, Support Vector Regression (SVR), and Quantile Regression Tree (QRT) to calculate short and medium-term air temperatures in North America under continental climate conditions. It was found that SVR performed much better than ARIMA. The SVR model produced more accurate estimates for the daily scale with an RMSE value of 3,592 °C and MAE value of 2,745 °C.

In addition, there are also studies that compare ARIMA, SARIMAX, and LSTM models to produce indoor temperature prediction methods. This research was conducted by [38] which showed the results that the ARIMA model was 16% more efficient than the SARIMAX model, and LSTM was 20% more effective than the ARIMA model. The RMSE values of the LSTM, ARIMA, and SARIMAX models are 1.7598, 1.9717, and 2.4230, respectively. Based on these results, it is clear that the LSTM model has superior performance in terms of accuracy compared to the ARIMA and SARIMAX models. Another study by [39] aims to test SARIMA and ANN with MLP model forecasting accuracy and pattern prediction ability in predicting monthly relative humidity in Delhi, India during 2017-2025. The results showed that the ANN performance with the MLP model achieved better accuracy than the SARIMA model in terms of RMSE and MAE.

III. Data and Methodology

A. Data

This study made use of time series data, namely daily land surface temperature data in Jakarta collected from 11,277 observations between 01 January 1993 to 16 November 2023, via the NASA-organized MERRA-2 project. The MERRA-2 project provides sophisticated retrospective analyses of global climate conditions and atmospheric parameters from the past to the present. The data, accessed via NASA's official website at https://power.larc.nasa.gov/, focuses on the National Monument area in Central Jakarta (latitude 6.1754° N, longitude 106.8272° E).

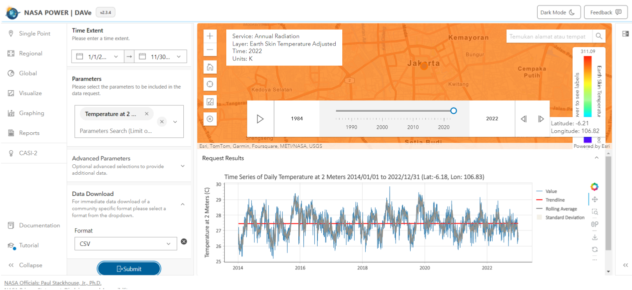


Fig 1. Example of NASA's MERRA-2 website display

Source: https://power.larc.nasa.gov/

B. Methodology

From data entry to model evaluation, methodology is a crucial stage in any research project. An explanation of this research's methodology may be found below.

a) Data Preprocessing and Desciptive Analysis

Data preprocessing is an important stage that aims to obtain final data that can be considered correct and useful for further data mining algorithms. Data used for learning and extracting knowledge is highly influenced by several things such as noise, missing values, and data inconsistencies [40]. The preprocessing stage in this study includes checking for missing values and changing the date data type from date to datetime to produce clean data that is ready for further analysis with various forecasting models.

In addition, descriptive analysis is also important to analyse the characteristics of the data [41]. This research uses descriptive analysis in the form of summary statistics. In addition, data visualisation in the form of line graphs is also used to determine and understand data patterns over time which can provide new insights into the dataset.

b) Autoregressive Integrated Moving Average (ARIMA) Model

Autoregressive Integrated Moving Average (ARIMA) models have been used to analyse and forecast time series in various fields. Autoregressive models are used to adjust for deterministic trends, which include multivariate linear correlations between the series values at time t and the previous p series values. The moving average model is used to adjust for random residuals by calculating the correlation between the series value at time t and q previous values of white noise [42]. Here is the equation for the ARIMA model:

$$X_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_0 - \left(\sum_{j=1}^{q} \theta_j \varepsilon_{t-j}\right) \quad (1)$$

where ε_t is stationary white noise with zero mean and φ_i is its variance, is the AR coefficient, and θ_j is the MA coefficient.

Stationarity is an important requirement for ARIMA models. To see stationarity, testing can be done using the Augmented Dickey-Fuller test [43]. If the data is not stationary, it is necessary to perform differentiation at the d_{th} order to make the data stationary [42]. Least Squares estimation follows to determine model parameters. Significance of parameters is tested using t-test and the model is evaluated with the smallest Akaike Information Criterion (AIC) to find the best fit. Diagnostic testing of the model produced during the estimation stage is crucial. One commonly used test is the Ljung-Box Test, which assesses whether the residuals conform to the assumptions of the error model, such as being white noise. White noise has a mean of 0 and a variance of 1, aligning with standard model evaluation criteria [43].

c) Machine Learning Methods

1) Support Vector Regression (SVR) Model

Support Vector Machine (SVM) is a supervised learning model used for pattern recognition in both regression and classification tasks. SVR, a variant for regression, was developed in 1996. Unlike SVM, SVR focuses only on a small subset of training data, and points outside the margin don't influence model building. The cost function for SVR also disregards training data close to the model prediction. The underlying concept of SVR is to perform a non-linear mapping of the original data x into a higher-dimensional feature space [44]. The goal of SVR is to determine a function $f(x)$ which is a hyperplane in the form of a regression function that can fit all input data with a certain level of error to help predict the target value. The linear SVM function can be expressed in the following equation:

$$f(x) = w \times \varphi(x) + b \quad (2)$$

where $\varphi(x)$ is a non-linear mapping function of the feature of x the high-dimensional input space, w is the weight, and b is the bias coefficient [43]. An illustration of SVR can be presented in Figure 2.

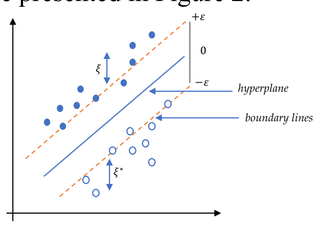


Fig. 2. Illustration of Support Vector Regression (SVR)
Source: [45]

Kernel functions are used to transform the dimensionality of data into a higher dimensional feature space, with the aim of achieving a more organised structure in the form of linear separations. The main advantage of the Radial Basis Function (RBF) kernel lies in its ability to handle data that is not linear and has a complex structure [46].

$$K(x_i, x) = Ae^{-\frac{(x_i - x)^2}{2\sigma^2}} \quad (2)$$

where A is the amplitude of forecasting which is 1, x_i and x are the input vector, and σ is the standard deviation. Figure 3 shows the architecture of SVR.

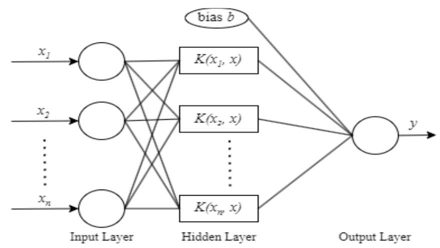


Fig. 3. Architecture of the Support Vector Regression algorithm
Source: [47]

2) Long Short-Term Memory (LSTM) Model

Long Short-Term Memory (LSTM) is one of the ANN methods that apply sequential data [48]. LSTM is usually used for problem solving by classifying, processing, and predicting time-series data due to the scarcity of unknown data duration between important events in time. In LSTM, each output and hidden layer is looped on itself, and so on, until the most accurate result is generated. The LSTM cell structure consists of input cell, output cell, memory cell, and forget cell.

Intuitively, the input gate controls the amount of new information entering the cell, the forget gate controls the amount of information that remains, and the output gate controls the amount of information leaving the cell in the LSTM model [48]. Information is processed through forget gates according to the information to be stored in the memory cell. A sigmoid function is used as activation to calculate the potential value of the input gates in the memory cell and updating data. Forget gates assess the memory cell and cell gates, which then proceed to the output gates to decide the value that will appear. Figure 4 shows the architecture of the LSTM.

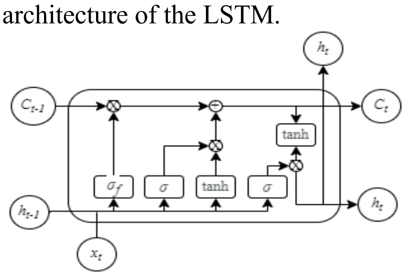


Fig. 4. Architecture of the Long-Short Term Memory algorithm
Source: [49]

3) Artificial Neural Network (ANN) Model

Artificial Neural Network (ANN) is a machine learning algorithm that mimics the human brain's ability to predict patterns through learning and recall. ANNs can identify patterns in historical data to make predictions of future values. The model uses artificial neurons arranged in input layers, output layers, and one or more hidden layers, enabling the relationship between input and output parameters [50].

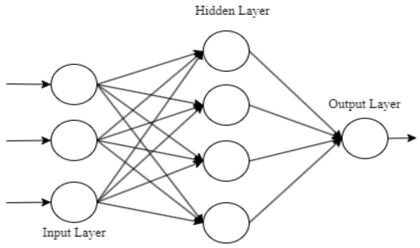


Fig. 5. Multilayer Perceptron (MLP) architecture in Artificial Neural Network algorithm
Source: [51]

The most common ANN architecture is the multilayer perceptron (MLP) structure shown in Figure 5. Using one hidden layer and a number of neurons, this structure provides high accuracy for the function being approximated [52]. The mathematical equation for ANN is:

$$Y = f(w \times x + b) \tag{3}$$

where is the output, is the activation function, is the weight, is the input vector, and is the bias added to the weighted input sum.

d) Model Evaluation Metrics

Model evaluation is very important to assess the performance of a forecast [43]. The following are the evaluation metrics used in this study:

1) Mean Absolute Percentage Error (MAPE)

MAPE is chosen for its intuitive interpretability and its ability to provide a relative measure of error. It expresses the prediction accuracy as a percentage, which makes it easy to understand and compare across different datasets and models. Additionally, MAPE is scale-independent, allowing for comparison between forecasts on different scales [53]. MAPE can be calculated using the following equation:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{y_i}\right| \tag{4}$$

where the x_i value is the predicted i_{th} value, and the y_i element is the true i-th value, and n is the number of data points [54].

2) Coefficient of Determination

The coefficient of determination is selected for its ability to quantify how well the predicted values match the observed data and for being more informative and accurate. It provides a measure of the proportion of variance in the dependent variable that is predictable from the independent variables. An R^2 value close to 1 indicates a high level of explanatory power of the model, making it a crucial metric for understanding the goodness-of-fit of the regression model [54]. R^2 can be calculated using the following equation:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(\bar{y} - y_i)^2} \tag{5}$$

where the y_i value is the predicted i_{th} value, and the y_i element is the true i_{th} value, $\bar{y}$ the average of the true values, and n is the number of data [54].

IV. Result and Discussion

A. Preprocessing Data and Descriptive Analysis

In this study, the data sample used consists of 11,277 rows with a time span of January 1, 1993 to November 16,2023. This data has no missing values. In addition, we changed the date data type from date to datetime. After that, we separated the data as much as 11,077 observations for training and 200 observations to testing. The selection of a representative sample and splitting the data into training and testing sets are critical steps to ensure that the developed forecasting model can be tested and evaluated properly.

TABEL I. Descriptive Analysis Of Land Surface Temperature in Jakarta 1993 – 2023

Size	Value
Mean (°C)	27.9304
Standard Deviation (°C)	0.8247
Minimum (°C)	25.17
Maximum (°C)	31.09

Source: MERRA-2, NASA (processed)

Based on Table I, the land surface temperature in Jakarta reached a maximum of 31.09°C, reflecting the hot conditions caused by population density, vehicles, tall buildings, vehicular and industrial pollution. Jakarta also experiences the urban heat island effect, where the city's temperature is higher than the surrounding area due to development, the use of asphalt and concrete, and the lack of vegetation. Figure 6 shows that the surface temperature data pattern in Jakarta shows volatility, which means that the temperature tends to fluctuate. These fluctuations can be caused by climate change, wind patterns, air pollution, and human activities such as industry and vehicles. The Urban Heat Island effect also contributes to the observed temperature fluctuations, demonstrating the complex interaction between natural factors and human activities in this dense metropolis.

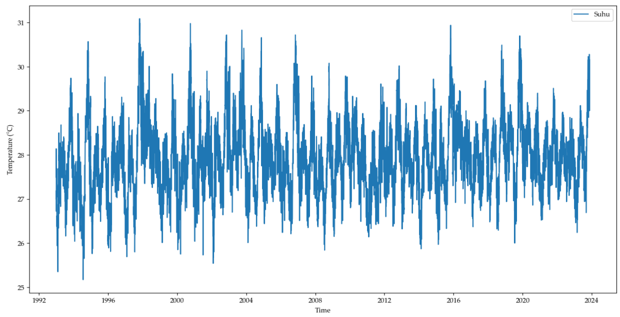


Figure 6. Urban land surface temperature in Jakarta 1993–2023
Source: MERRA-2, NASA (processed)

B. Modelling the Prediction of Land Surface Temperature in Jakarta using ARIMA

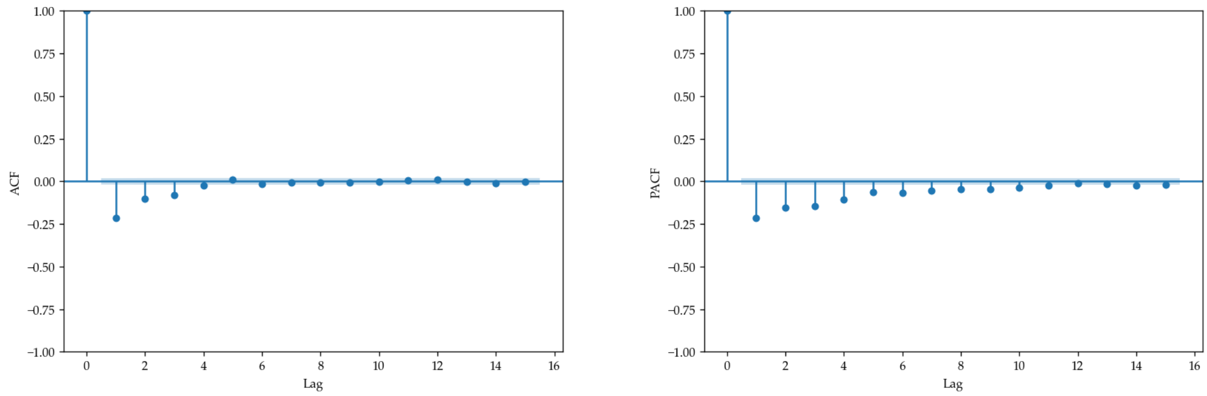
The process of using the ARIMA method begins with checking stationarity in the initial data. Usually, the stationarity test is conducted using the Augmented Dicky-Fuller (ADF) test. Data is said to be stationary if the p-value is less than 5%. If the data is not stationary, differencing is required.

TABEL II. TEST STIONARITYI USING AUGMENTED DICKEY-FULLER

Augmented Dicky-Fuller (ADF) Test					
Level			1st *Difference*		
Lag	ADF	*p-value*	Lag	ADF	*p-value*
1	-0.6221	0.4570	1	-132.1	0.01
2	-0.4711	0.5090	2	-96.6	0.01
3	-0.3774	0.5360	3	-82.8	0.01
4	-0.3148	0.5540	4	-72.7	0.01
5	-0.2486	0.5730	5	-63.8	0.01
6	-0.2106	0.5840	6	-58.5	0.01
7	-0.1658	0.5960	7	-54.1	0.01
8	-0.1473	0.6020	8	-50.5	0.01
9	-0.1233	0.6090	9	-47.6	0.01
10	-0.0984	0.6160	10	-45.2	0.01
11	-0.0883	0.6190	11	-42.6	0.01
12	-0.0729	0.6230	12	-39.9	0.01

Table II is the result of the stationarity test up. The results show that the data is not stationary at the level because the p-value at each lag is more than 5%. Therefore, the data needs to be first differenced, thus showing that the data is stationary because the p-value on each lag is smaller than 5%. Thus, the first differencing results can be used to identify the best model in predicting urban land surface temperature in Jakarta using the ARIMA method.

After first differencing, the ACF plot no longer forms the tails off slowly pattern shown in Figure 7(a). However, there is a cut off at the first lag which indicates the presence of an MA(1) component. In addition, the PACF pattern at the first differencing in Figure 7(b) shows that there are significant PACF values at lags 1, 2, 3, 4, and 5. This also indicates the presence of AR(1), AR(2), AR(3), AR(4), or AR(5) components in the ARIMA model to be formed. The next step is to estimate the model parameters. First, the best model is selected based on the smallest AIC value. Several candidate models are obtained from the previous ACF and PACF analysis and the automatic ARIMA model. Table 3 presents a comparison of five candidate ARIMA models based on their respective AIC values.



(a) (b)

Fig. 7. (a) ACF pattern on first differencing, (b) PACF patterns on first diferencing
Source: MERRA-2, NASA (processed)

Based on Table III, it can be seen that the ARIMA(1,1,1) model has the lowest Akaike Information Criterion (AIC) value, which is 7642.60. This indicates that the ARIMA(1,1,1) model is the best model among the other four candidates. Parameter estimation of this model is done using the Least Square (LS) method. Therefore, Table IV below presents the parameter estimation results for the ARIMA(1,1,1) model using the Least Square method.

TABEL III. COMPARISON OF ARIMA CANDIDATE MODELS

Model	AIC
ARIMA(1,0,0)	8469.38
ARIMA(0,0,1)	18861.35
ARIMA(1,0,1)	7969.31
ARIMA(1,1,1)	7642.60
ARIMA(4,1,1)	7643.12

Source: MERRA-2, NASA (processed)

Based on Table 4, the AR(1) and MA(1) coefficients are significant at the 5% significance level, indicating the real contribution of each parameter to the model. Thus, the ARIMA(1,1,1) model is statistically relevant and fits the observed data and is suitable for use in predicting land surface temperature in Jakarta.

TABEL IV. PARAMETER ESTIMATION RESULTS OF ARIMA(1,1,1) MODEL

	Estimation	Std. Error	z-value	Pr(>|z|)
ar1	0.5156	0.0147	35.171	< 2e-16
ma1	-0.8242	0.0096	-85.901	< 2e-16

Source: MERRA-2, NASA (processed)

The next step will be to conduct a diagnostic test on the model. The diagnostic test results with the Box-Ljung test yielded a p-value of 0.9481, greater than the 5% significance level, so the null hypothesis (H_0), which states that the residuals meets the white noise assumption, is not rejected. This indicates that the residuals of the model are white noise and the residuals can be considered as random noise. These results indicate that the ARIMA(1,1,1) model is able to capture the data pattern well and the residuals are random, increasing confidence in the reliability of the model in explaining variations in land surface temperature in Jakarta.

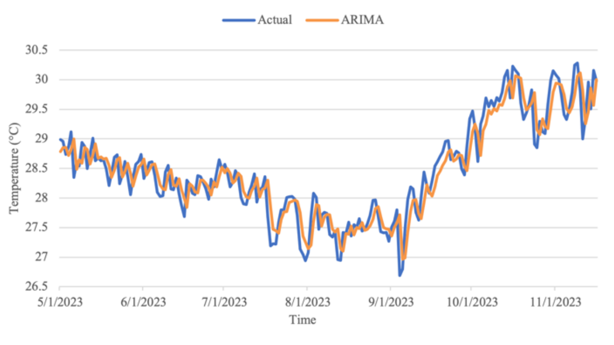


Fig. 8. Prediction results of fitted data of land surface temperature in Jakarta with ARIMA(1,1,1)
Source: MERRA-2, NASA (processed)

Figure 8 shows the predicted land surface temperature in Jakarta using fitted data from May 1, 2023 to November 16, 2023. The temperature prediction for November 17, 2023 was calculated using AR coefficient of 0.5156 and MA of -0.8242, resulting in an estimated temperature of 29.74°C. This result is based on the characteristics of the historical data and the patterns identified by the ARIMA(1,1,1) model. Although this forecasting provides an initial view of future temperature conditions, external factors and unexpected changes may affect the actual results. To improve forecasting accuracy, it is important to consider other models, such as machine learning methods. These approaches include Support Vector Regression (SVR), Long-Short Term Memory (LSTM), and Artificial Neural Network (ANN). Understanding and comparing classical ARIMA methods with machine learning models can provide better insight into temperature variations in Jakarta and improve forecasting accuracy.

C. Modelling the Prediction of Land Surface Temperature in Jakarta using Support Vector Regression (SVR)

Modeling the prediction of land surface temperature in Jakarta using the ARIMA model shows less accurate results and tends to be flat. As an alternative, machine learning method with Support Vector Regression (SVR) model using Radial Basis Function (RBF) kernel. The main parameters in the SVR model are Gamma, C, and Epsilon. Gamma controls the extent to which the influence of one data sample can reach other data samples in building the model. The C parameter sets the level of error tolerance in the model, with higher values of C making the model more stringent against errors in the training data. The Epsilon parameter sets the tolerance limit for treating predictions that are close to correct but still considered errors. With this parameter configuration, the SVR model is expected to provide accurate temperature predictions and adapt well to complex patterns in the data.

Based on Table V, the experimental results show that the Support Vector Regression (SVR) model with Radial Basis Function (RBF) kernel and Gamma, C, and Epsilon parameters of 0.5, 10, and 0.05, respectively, produces the smallest RMSE value. These results indicate that the parameter configuration provides the most accurate SVR model. The optimal parameter selection process is essential for good model performance. Thus, these parameters can be considered as the optimal configuration to model the relationship between input and output variables in the data. The predicted results compared to the actual data can be seen in Figure 9, which shows that the RBF kernel performs very well in model testing and training.

TABEL V. COMPARISON OF RBF KERNEL PERFORMANCE AND MAIN PARAMETERS IN SUPPORT VECTOR REGRESSION

Kernel	Gamma	Cost (C)	Epsilon	RMSE
RBF	0.1	10	0.01	0.2949
RBF	0.1	10	0.05	0.2949
RBF	0.1	100	0.01	0.2949
RBF	0.1	100	0.05	0.2948
RBF	0.5	10	0.01	0.2946
RBF	0.5	10	0.05	0.2945
RBF	0.5	100	0.01	0.2951
RBF	0.5	100	0.05	0.2951

Source: *Output* Python

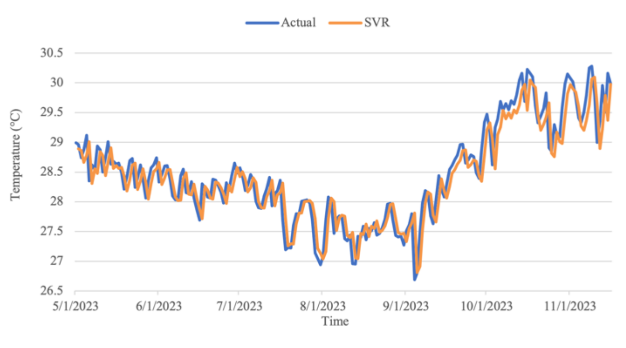


Figure 9. Prediction results of testing data Land surface temperature in Jakarta with SVR
Source: MERRA-2, NASA (processed)

The SVR model using RBF kernel with Gamma, C, and Epsilon parameters of 0.5, 10, and 0.05 respectively resulted in a MAPE value of 0.9727. The low MAPE indicates that the SVR-RBF model is able to adjust complex data patterns with high precision. In addition to MAPE, another accuracy is shown using the coefficient of determination (R^2) value of 0.8177, which means that about 81.77% of the target data variability can be explained by the model. These results show that SVR-RBF successfully captures complex data structures and provides accurate predictions.

D. Modelling the Prediction of Land Surface Temperature in Jakarta using Long-Short Term Memory (LSTM)

In addition to using SVR, prediction of land surface temperature in Jakarta is also done with the Long-Short Term Memory (LSTM) algorithm, which is often used for forecasting time series data. Data is normalized using min-max to accelerate convergence and maintain model stability. The LSTM model is built sequentially, with each layer having one input and output sensor. Layer dense is used to add fully connected layers, usually followed by a non-linear function. The loss function used is MSE with Adam's optimizer, which is efficient in stochastic optimization because it only requires the first slope with a small memory [55].

The model training process is performed for 100 epochs with a batch size of 32. The selection of the number of epochs involves adjustments to avoid overfitting and underfitting. A larger batch size can speed up training, but requires more memory, and vice versa. The EarlyStopping technique is used to stop training early if the model's performance does not improve over several consecutive epochs, preventing overfitting and stopping training when the model achieves optimal performance on the validation data. Table 6 shows that the LSTM model training process only lasted for 7 iterations because the loss and val loss values did not change significantly for 2 consecutive epochs by displaying a verbose message.

Based on Table VI, the model stopped training faster than the initial epoch value specified, which is 100, at the 7th epoch because the condition monitored by the 'EarlyStopping' callback was met, which is an insignificant change in the loss function. After the model search, the next step is to predict the land surface temperature in Jakarta using the LSTM method. The prediction of the testing data in Figure 9 aims to show the comparison between the prediction results produced by the LSTM model and the actual data measured in this study. This step is important to validate the performance of the model and gain an understanding of how well the model can generalize information from new data.

TABEL VI. NUMBER OF ITERATIONS IN THE LSTM MODEL TRAINING PROCESS

Epoch	***Loss***	***Val Loss***
1	0.0256	0.0104
2	0.0063	0.0052
3	0.0042	0.0029
4	0.0037	0.0026
5	0.0036	0.0026
6	0.0036	0.0026
7	0.0036	0.0026

Source: *Output* Python

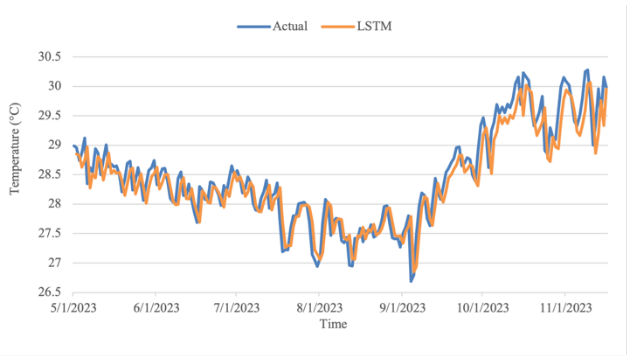


Figure 10. *Prediction results of testing data Land surface temperature in Jakarta with LSTM*
Source: MERRA-2, NASA (processed)

In Figure 10, the gap between the blue line (actual data) and the orange line (LSTM prediction results) is especially visible between the middle of 01/09/2023 and 01/10/2023 to the end, indicating a mismatch between the actual data and the prediction results. However, the periods mid 01/06/2023 and 01/07/2023 to 01/08/2023 have no significant gap. After normalizing the data, a denormalization process is performed to return the data to its true scale so that it can be properly evaluated and interpreted. The significant gap may be due to the high MAPE value of 0.8381, indicating that the LSTM model is not good enough to describe the actual data. However, the high R^2 value of 0.8628 indicates that the model can explain most of the variation in the data, so the model is good enough to describe the actual data.

E. Modelling the Prediction of Land Surface Temperature in Jakarta using Artificial Neural Network (ANN)

To build the best model in predicting urban land surface temperature in Jakarta using Artificial Neural Network (ANN) method, the initialization of model object and input layer is done with Sequential function. The hidden layer and output layer are added using the Dense (fully connected) layer. The process of adding hidden layers considers the number of neurons, the number of input features, and the activation function. In this case, 12 neuron units with one input feature and a Rectified Linear Unit (ReLU) activation function were used, which was chosen because it is computationally simple and can help the model learn quickly and stably as there is no restriction on the growth of positive values so as to reduce overfitting.

Then, the model was compiled with the loss function mean square error (MSE) and the optimizer Adaptive Moment Estimation (Adam) algorithm due to the efficiency of adapting the learning rate based on uncentered mean and variance estimation. The training process was conducted with 32 samples per parameter update and 100 iterations. An object monitors the change in loss value, allowing the model to stop training early if there is no significant change in loss after a few iterations. The training process lasted for 11 iterations according to Table VII, as there was no significant change in loss from the seventh to the eleventh iteration.

TABEL VII. NUMBER OF ITERATIONS IN THE ANN MODEL TRAINING PROCESS

Iteration	**Loss Value**
1	0.0231
2	0.0161
3	0.0152
4	0.0147
5	0.0145
6	0.0144
7	0.0143
8	0.0143
9	0.0143
10	0.0143
11	0.0143

Source: *Output Python*

After the model training process, then the prediction of urban land surface temperature in Jakarta using testing data is carried out. The prediction results in Figure 11 show that the model generated during the model training shows good accuracy. This can be seen from the small gap between the testing data and the predicted data from mid-June to September 2023. This indicates that the ANN model is generally successful in reproducing the patterns in the testing data. In addition, the model is also able to capture significant changes in the data, which is reflected in the resulting fluctuation pattern that is in accordance with the testing data. However, from mid-September to November 2023, there is a gap that is slightly larger than the prediction results of the previous few months. This indicates the potential for overfitting where the ANN model is too close to or memorises the training data and is less able to generalise to new data.

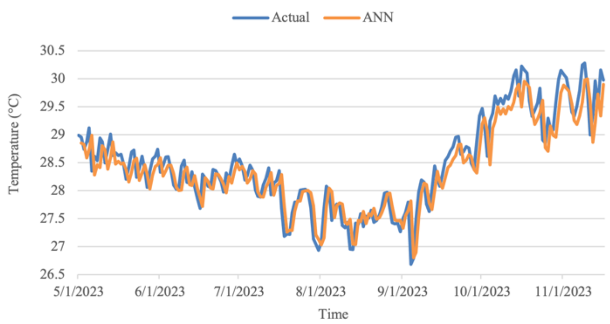


Fig. 11. Prediction results of testing data of land surface temperature in Jakarta with ANN
Source: MERRA-2, NASA (processed)

The MAPE value of the Artificial Neural Network model formed is 0.8934. This value indicates the relative error rate of the model in accurately predicting temperature. In addition, the gap between the testing data and the data predicted by the model can be explained by the MAPE value obtained. In predicting air temperature, high accuracy is very crucial, especially in determining policies by the government. Therefore, the MAPE value of 0.8934 is considered still high enough to allow for poor results in predicting urban land surface temperature in Jakarta. In addition to the MAPE value, the R-squared (R^2) value can also explain the goodness of the model in making predictions. The R^2 value of the ANN model is 0.8570, which means that about 85.70% of the variation in urban land surface temperature in Jakarta can be explained by the ANN model obtained. This result shows that the ANN model is quite effective in capturing the general pattern in the data. In addition, the model also performed well in explaining the variation of urban land surface temperature in Jakarta.

F. Evaluation of Prediction Model

Figure 12 shows the visualization of the prediction results of urban land surface temperature testing data in Jakarta using ARIMA, SVR, LSTM, and ANN methods. The LSTM model provides visualizations that are close to the actual data, demonstrating its ability to capture and model the complex patterns of land surface temperature well. This success demonstrates the potential of the LSTM model to provide accurate predictions in the context of Jakarta's urban environment. As such, the LSTM model can be considered an effective and reliable option in predicting land surface temperature in the region.

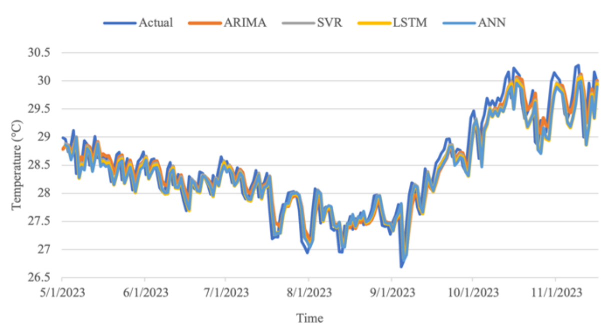


Fig. 12. Comparison of testing data predictions with four forecasting methods
Source: MERRA-2, NASA (processed)

Table VIII shows the prediction of land surface temperature in Jakarta for December 2023 using five methods. The ARIMA model gives flat predictions, which is not suitable for long-term predictions. Other methods such as SVR, LSTM, and ANN show decreasing patterns that are more adaptive to the dynamics of the data, addressing gradual changes such as land surface temperature. These models are able to handle complex and non-linear patterns in the data, providing an adaptive response to dynamic land surface temperature fluctuations. Evaluation of the models using metrics such as MAPE and coefficient of determination (R^2) provides a comprehensive picture of the performance and predictive accuracy of the models.

Table IX summarizes the evaluation of land surface temperature prediction models in Jakarta using ARIMA, SVR, LSTM, and ANN. The evaluation results show that the LSTM model provides the lowest MAPE value and the highest coefficient of determination. These results are in line with research [38] that the LSTM model has superior performance in terms of accuracy compared to the ARIMA and SARIMAX models. The LSTM model has advantages due to its ability to remember information over a long period of time and delete irrelevant ones, as well as the existence of a forget gate that is not owned by the other two machine learning methods, making it more efficient in forecasting and processing data based on a specific time series. However, the SVR model provides poor results because it tends to be suitable for high-dimensional data, while this study only uses one input variable, namely land surface temperature in Jakarta, so the results are less good than the ARIMA model.

TABEL VIII. PREDICTED LAND SURFACE TEMPERATURE IN JAKARTA IN DECEMBER 2023 WITH ARIMA, SVR, LSTM, AND ANN

Time	ARIMA	SVR	LSTM	ANN	Time	ARIMA	SVR	LSTM	ANN
01/12/2023	29.8379	28.4465	28.0903	28.0057	17/12/2023	29.8379	28.0151	27.7470	27.9154
02/12/2023	29.8379	28.3946	28.0413	27.9819	18/12/2023	29.8379	28.0050	27.7417	27.9152
03/12/2023	29.8379	28.3477	27.9983	27.9643	19/12/2023	29.8379	27.9959	27.7371	27.9151
04/12/2023	29.8379	28.3052	27.9605	27.9513	20/12/2023	29.8379	27.9877	27.7331	27.9150
05/12/2023	29.8379	28.2668	27.9275	27.9417	21/12/2023	29.8379	27.9803	27.7296	27.9149
06/12/2023	29.8379	28.2322	27.8986	27.9346	22/12/2023	29.8379	27.9737	27.7266	27.9149
07/12/2023	29.8379	28.2009	27.8734	27.9294	23/12/2023	29.8379	27.9677	27.7241	27.9148
08/12/2023	29.8379	28.1726	27.8515	27.9256	24/12/2023	29.8379	27.9623	27.7218	27.9148
09/12/2023	29.8379	28.1471	27.8323	27.9227	25/12/2023	29.8379	27.9574	27.7199	27.9148
10/12/2023	29.8379	28.1241	27.8157	27.9206	26/12/2023	29.8379	27.9530	27.7182	27.9148
11/12/2023	29.8379	28.1033	27.8013	27.9191	27/12/2023	29.8379	27.9490	27.7168	27.9148
12/12/2023	29.8379	28.0845	27.7887	27.9179	28/12/2023	29.8379	27.9455	27.7155	27.9147
13/12/2023	29.8379	28.0676	27.7778	27.9171	29/12/2023	29.8379	27.9422	27.7145	27.9147
14/12/2023	29.8379	28.0524	27.7684	27.9165	30/12/2023	29.8379	27.9393	27.7135	27.9147
15/12/2023	29.8379	28.0386	27.7602	27.9160	31/12/2023	29.8379	27.9367	27.7127	27.9147
16/12/2023	29.8379	28.0263	27.7531	27.9157					

Source: MERRA-2, NASA (processed)

TABEL IX. EVALUATION RESULTS OF LAND SURFACE TEMPERATURE PREDICTION MODELS IN JAKARTA

Model	MAPE	R^2
ARIMA(1,1,1)	0.9425	0.8306
Support Vector Regression	0.9727	0.8177
Long Short-Term Memory	0.8381	0.8628
Artificial Neural Network	0.8931	0.8596

Source: MERRA-2, NASA (processed)

V. CONCLUTION

Identification of the data pattern shows that the data tends to have an upward long-term trend. The data also shows a fairly volatile pattern and the presence of seasonal components that show recurring trends in time, direction, and amplitude. The results using machine learning models namely SVR, LSTM, and ANN show that the prediction of urban land surface temperature in Jakarta using the ARIMA model will tend to stabilise at 29°C-30°C until December 2023.

Based on the calculation of several measures of mode accuracy, it is found that the LSTM model provides superior performance and accuracy compared to the other three models. The LSTM model shows the smallest accuracy measure with a Mean Absolute Percentage Error (MAPE) of 0.8381 and a coefficient of determination (R^2) of 0.8628. Meanwhile, the other three models, namely ARIMA, SVR, and ANN, show accuracy results that are not significantly different.

In addition, suggestions for the government to urge people to reduce the use of private vehicles and switch to public transport to prevent global warming. There is a need for policies to expand green open spaces and relocate residents to reduce density so as to minimise the Urban Heat Island phenomenon which will have an impact on rising air temperatures in Jakarta.

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