Simulation-based forecasting of temperature dynamics in Indonesia's new capital city region using seasonal ARIMA

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Abstract: *Accurate temperature forecasting is essential for supporting climate responsive urban planning and infrastructure development in emerging smart cities. This study investigates the temperature dynamics of Sepaku District, East Kalimantan, Indonesia, the core area of the country's new capital city (Nusantara), using a Seasonal Autoregressive Integrated Moving Average (SARIMA) model. Daily temperature data collected from January 1, 2022, to March 31, 2024, were analyzed to simulate temporal temperature variations and forecast future trends. The forecasting framework involved time series preprocessing, parameter optimization, and model validation using Root Mean Square Error (RMSE) and Mean Squared Error (MSE). The optimized SARIMA model demonstrated strong predictive capability, achieving an RMSE of 0.93 and an MSE of 1.23, indicating high agreement between observed and predicted temperatures. The results reveal the effectiveness of SARIMA in capturing seasonal temperature fluctuations and providing reliable short term forecasts for the study area. This simulation framework offers a practical tool for climate informed decision making, environmental risk assessment, and sustainable urban development planning in Indonesia's new capital region.*

Keywords: *Temperature forecasting; SARIMA; Time series simulation; Climate modeling; Nusantara Capital City; Urban climate*

Introduction

The Indonesia Government, under president Joko Widodo's administration, has made the significant decision to relocate the capital of the archipelago from Jakarta to the proposed Nusantara Capital City (IKN) in Kalimantan, specifically North Penajam Passer in district Sepaku. This strategic move is driven by the objectives of fostering economic growth, reducing inter-regional disparities, and improving overall welfare [1].

The relocation to IKN presents both opportunities and challenges. On one hand, it offers strategic benefits such as the potential for new economic development zones and opportunities to address regional disparities. However, it also raises concerns regarding defense policy and the necessity for robust infrastructure to safeguard the city against various threats, both military, and non-military [2]. The choice of IKN as new capital is strategically advantageous for energy security, particularly with a focus on renewable energy source like the Kayan river hydroelectric power plant.

The development of such infrastructure is expected to drive economic growth, foster environmental sustainability, and promote social progress in the region [3]. The relocation process is seen as crucial for regional planning, institutional development, and achieving balanced growth and economic quality across Indonesia, particularly in the eastern part of the archipelago [4]. It represents a significant step towards reshaping the country's landscape and addressing longstanding challenges associated with urban congestion and regional disparities.
Timeseries forecasting is an essential analytical tool that enables the prediction of future values by examining historical data [5] [27].

This field has seen the development of numerous methodologies designed to enhance the accuracy of the predictions and minimize randomness. Among the innovative approaches employed are neuro-fuzzy-PSO (particle swarm optimization) hybrid models [7], which combine neural networks, fuzzy logic, and PSO to refine forecasting precision. Another notable technique includes weighted self-constructing clustering, which dynamically adjust the clustering of data to improve forecast outcomes [8]. Traditional approaches like exponential smoothing, ARIMA, and SARIMA continue to be widely utilized due to their effectiveness in handling different types of seasonal data. These conventional models remain foundational in the field, providing robust solutions for various forecasting scenarios. The continual evolution of forecasting methods not only tackles the inherent challenges of prediction-such as dealing with noisy data and accounting for sudden changes in trends-but also significantly contributes to decision-making processes across various industries. By delivering insights into future trends and patterns, time series forecasting plays a pivotal role in strategic planning, resource allocation, and risk management. As such, the ongoing refinement and integration of both old and new forecasting techniques are critical for improving the accuracy and applicability of predictive outcomes.

A novel time series forecasting model that offers improved predictions where traditional models fall short. This advancement is crucial because not all time series problems can be effectively addressed using conventional methodologies. Traditional models often struggle with complex patterns and non-linear relationships inherent in some dataset. The proposed model integrates advanced statistical technique and machine learning algorithms to enhance its predictive capabilities. It also overcomes the limitation of traditional model like ARIMA, and SARIMA, which typically assume linearity and stationarity in the time series data [9].

Weather time series forecasting involves predicting future weather attributes like temperature, humidity, and wind speed using various techniques such as deep leaning models like convolutional neural network (CNN), XGBoost , ARIMA [10], or SARIMA [11], LSTM [12], and hybrid neural networks. It is crucial for various sectors like marine, agriculture, and disaster prediction [11]. Deep learning methods, particularly Long Short-term Memory (LSTM) and Gated Recurrent Unit (GRU), have shown superior performance in weather forecasting compared to classical methods [13]. Additionally, the fusion or recurrent neural network with fuzzy time series (FTS) has been proposed to enhance prediction accuracy in uncertain time series data [10]. Furthermore, the application of extreme gradient boosting (XGBoost) and unsupervised model like ARIMA and LSTM has been explored for weather visibility prediction, yielding promising results [13]. A novel seasonal forecasting method based on F1-transform has been developed to predict weather parameters using daily datasets, outperforming traditional methods like ARIMA and artificial neural networks [14].

Weather time series forecasting using seasonal autoregressive integrated moving average (SARIMA) model has shown promising results in various studies. The SARIMA model has been utilized to predict atmospheric water vapor (AWV) changes in the east Asian region, demonstrating superior performance with low error metrics and high accuracy [15]. Additionally, SARIMA has been employed to forecast rainfall and temperature trends in Chattogram, Bangladesh, showcasing its effectiveness in capturing seasonal variations and long-term trends in climate data [16]. Furthermore, SARIMA has been compared with other forecasting techniques like HK-SARIMA and YJNSTF for rainfall prediction in Kerala, India, with SARIMA proving to be more reliable across different geographic regions [17]. These findings collectively highlight the efficacy of SARIMA in time series weather forecasting, making it valuable tool for studying and predicting weather variability.

Method

The dataset employed in this research comprises daily weather records collected in Sepaku, East Borneo, Indonesia, where the Indonesian Nusantara New Capital is located. The span of the data collection covers a period beginning on January 1, 2022 and extending until March 31, 2024. The extensive dataset allows for a detailed examination of weather patterns over more than two years, providing a comprehensive insight into climatic variations in this spesfic region. The temporal coverage is critical for analyzing seasonal changes and other long-term meteorological trends. An example of the dataset used in our study is presented in Figure 1 below. This visual representation offers a clear overview of the data structure and format, facilitating an understanding of the variables and their temporal distribution within the scope of the research.

Figure 1 presents the sample dataset employed for our research endeavors. The dataset encompasses 821 rows and 33 columns, encapsulating a wealth of comprehensive and complete weather data. Each row represents a distinct observation, while each column corresponds to a specific weather parameter or attribute. These attributes collectively from the basis for our analysis and modeling efforts. The list of columns present in this dataset can be seen in Figure 2.

tempmax	tempmin	temp	feelslikemax	feelslikemin	feelslike	dew	humidity	...	solarenergy	uvindex	severerisk	sunrise	sunset	moonphase	conditions	description	icon
32.0	25.7	27.9	37.9	25.7	31.0	24.4	82.0	...	13.0	6	NaN	2022-01-01T06:11:15	2022-01-01T18:21:46	0.94	Rain, Partially cloudy	Partly cloudy throughout the day with late aft...	rain
32.0	25.0	27.4	37.9	25.0	29.5	23.7	81.2	...	14.7	6	NaN	2022-01-02T06:11:44	2022-01-02T18:22:14	0.98	Partially cloudy	Partly cloudy throughout the day.	partly-cloudy-day
29.3	24.0	26.6	34.0	24.0	28.4	24.1	86.5	...	16.2	7	NaN	2022-01-03T06:12:12	2022-01-03T18:22:41	0.00	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain
29.0	24.0	26.1	34.5	24.0	27.9	24.3	90.1	...	13.5	6	NaN	2022-01-04T06:12:40	2022-01-04T18:23:08	0.05	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain
31.0	24.0	26.8	40.6	24.0	29.7	24.5	87.9	...	21.0	9	NaN	2022-01-05T06:13:08	2022-01-05T18:23:34	0.08	Rain, Partially cloudy	Partly cloudy throughout the day with rain.	rain

Figure 1. Raw data sample

```
df.columns

Index(['name', 'datetime', 'tempmax', 'tempmin', 'temp', 'feelslikemax',
       'feelslikemin', 'feelslike', 'dew', 'humidity', 'precip', 'precipprob',
       'precipcover', 'preciptype', 'snow', 'snowdepth', 'windgust',
       'windspeed', 'winddir', 'sealevelpressure', 'cloudcover', 'visibility',
       'solarradiation', 'solarenergy', 'uvindex', 'severerisk', 'sunrise',
       'sunset', 'moonphase', 'conditions', 'description', 'icon', 'stations'],
      dtype='object')
```

Figure 2. List of columns

The columns depicted in figure 2 above provide a comprehensive representation of the dataset utilized in this research. The 'name' column identifies the location under observation, 'Sepaku', while the 'datetime' column records the date and time of each weather observation. Essential meteorological parameters such as the maximum and minimum temperatures, recorded in the 'tempmax' and 'tempmin' columns, offer insights into the temperature fluctuations experienced over time. The 'temp' column contains the recorded temperature data for each observation, providing a detailed account of the prevailing weather conditions. There are still many columns that not used in this research and the last columns is 'station' column, which documents the weather recording station's details including their geographical coordinates.

To facilitate temperature time series forecasting we focus on the 'datetime' and 'temp' columns, as illustrated in figure 3 below. These columns are crucial for analyzing the temporal patterns of temperature variations over the recorded period. By leveraging this time-stamped temperature data, we can use predictive model such as ARIMA to forecast future temperature trends in Sepaku district. The utilization of ARIMA model enables us to anticipate potential fluctuation in temperature, aiding in proactive decision-making and resource allocation in various sectors sensitive to weather variations.

```
df = df[['datetime', 'temp']]
df.head(5)
```

	datetime	temp
0	1/1/2022	27.9
1	1/2/2022	27.4
2	1/3/2022	26.6
3	1/4/2022	26.1
4	1/5/2022	26.8

Figure 3. Data sample

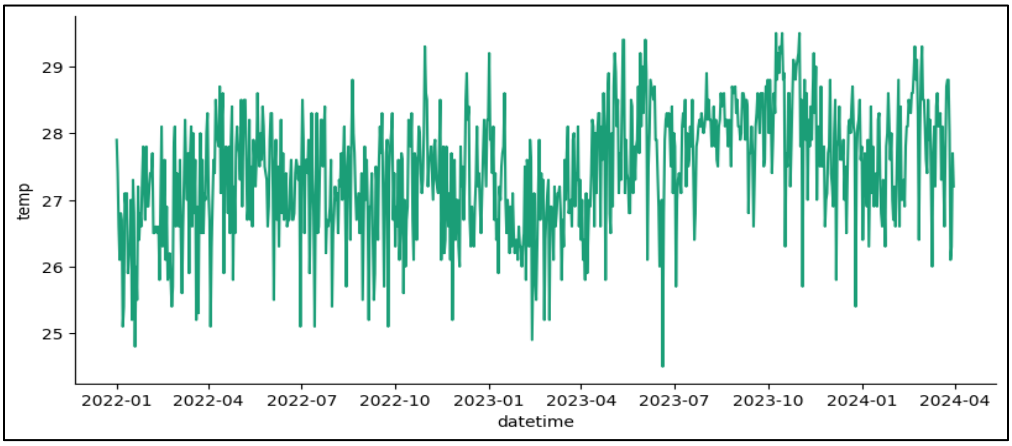

Figure 4. Daily temperature

From the figure 3 above, it is evident that the datetime format currently employed does not adhere to the standard format typically used in time series data processing. Therefore, we conducted a conversion of the datetime format to align it with the standardized format. The resulting converted datetime format is depicted in figure 4 below, showcasing the successful adjustment to the standardized format. With the datetime format now standardized, we can proceed with confidence in conducting robust time series forecasting analyses.

```
[ ] df['datetime'] = pd.to_datetime(df['datetime'])

df.head(5)
```

	datetime	temp
0	2022-01-01	27.9
1	2022-01-02	27.4
2	2022-01-03	26.6
3	2022-01-04	26.1
4	2022-01-05	26.8

Figure 5. Datetime format conversion

In the subsequent stage, we conducted observations to determine the highest and lowest temperatures. On both October 9th and 15th, 2023, Sepaku experienced its hottest conditions in the past two years, with the temperature reaching 29.5 degrees Celsius. A similar occurrence transpired approximately fifteen days later, on November 1st, 2023. Conversely, on June 20th, 2023, Sepaku recorded its lowest temperature at 24.5 degrees Celsius. We generated a plot illustrating the daily temperature, which is depicted in figure 5 below.

Perex-Chacon et.al [18] introduce MV-bigPSF, a novel algorithm specifically designed for forecasting multivariate big data time series. The algorithm uses pattern recognition across multiple time series to identify interdependencies and patterns, which enhances prediction accuracy by comparing these patterns to predict the target time series. MV-bigPSF is particularly noted for its efficiency and simplicity, requiring only two parameters for adjustment and capable of multistep forecasting. To validate its performance, MV-bigPSF then tested against traditional univariate and multivariate methods using real-world power consumption data and it shows significant improvements, outperforming the best univariate method by 12.8% and the best multivariate method by 44.8% in terms of mean absolute percentage error (MAPE), it was also 1.83 times faster than the quickest multivariate method tested.

Research conducted forecasting on cereal production in Ethiopia using data from

2000 to 2021 to estimate production until 2030 [19]. The analysis employed the non-parametric Mann-Kendall trend test, facilitated by the PAST software, to assess the trends in cereal production. Then utilize the ARIMA to forecast the future production levels. The results indicate a significant increasing trend in grain production over the years, with all the major cereal crops showing upward trajectories. Both ARIMA method and Mann-Kendall trend test demonstrated strong predictive performance.

The crucial factor in management of agricultural water resources and irrigation scheduling. The research compares the complexity, computational cost, data efficiency, and accuracy of conventional statistical models like SARIMA to deep learning model like temporal fusion transformer (TFT). The research finds that the deep learning models surpass the most commonly used statistical model, SARIMA [20].

Mauro et.al [21] utilized multivariate time series forecasting to tackles the challenge of predicting key metrics that determine the behaviour of cellular traffic, aiming to equip network operators with tools for better managing mobile network traffic and optimizing resources. The research gathered data from a real urban cellular network and employed hybrid models like vector autoregressive (VAR) combined with CNN, LSTM, and GRU. The results show that hybrid models demonstrate superior performance compared to solely statistical or deep learning model, significantly reducing forecasting error. ARIMA was employed to precisely forecast time series from road accident data in the UK. This research also employed a fusion of machine learning algorithms, and econometric technique to analyze longitudinal historical data [22].

Behmiri et.al [23] pioneering in systematically comparing these varied approaches. By integrating air temperature into both short- and mid-term load forecasting models, and utilizing time-series methods alongside feed-forward neural networks. The models which include feature temperature consistently outperform those that omit it across all time horizons. The ARIMA model was also employed to anticipate occurrence of dengue fever in Magalang, Philipines, by analyzing historical data encompassing dengue fever incidences and climatic variable spanning from 2016 to 2019 [24]. The result shows that the effectiveness of ARIMA model in forecasting is proven. Through meticulous examination of past trends and correlations between dengue fever occurrence and climatic factors, research was able to develop a reliable framework for predicting the likelihood of dengue fever incident in the future.

Shen et.al [6] proposed FDNet model, a Focal Decomposed Network, for time series forecasting, emphasizing efficiency, robustness, and practically. FDNet prioritizes fine-grained local features from input sequences. Three main keys are: deep time series forecasting, mitigates distribution shift by eschewing global coarse-grained feature, and independent from specific time series biases [25]. The work presents an analytical approach to forecasting earthquake time-series. The findings contribute to earthquake prediction by demonstrating the utility and effectiveness of SARIMAX model in capturing implications of the results offer valuable insights for decision-makers and stakeholders involved in disaster preparedness and mitigation strategies.

ARIMA is a flexible model capable of handling various types of time series data, including trends, and seasonality. When ARIMA is specifically employed to forecast data with seasonality, it is referred to as Seasonal-ARIMA or SARIMA. Ther precise selection of ARIMA parameters (p, d, q) is crucial for achieving accurate predictions. Based on the various methods discussed above, we have adopted for the SARIMA approach, which is statistically applicable for forecasting time series data.

In the SARIMA model, the components that can be broken down are Seasonal, Autoregression, Integrated, and Moving Average. The 'Seasonal' component indicates that this model can handle seasonal data patterns. 'Autoregression' refers to a linear regression model that predicts future values based on past data within the time series. 'Integrated' is the integration process used to make the time series data stationary, and 'Moving average' is the process of calculating the average of previous prediction errors within the time series.

One of the key considerations guiding our decision to utilize the SARIMA model is its robust predictive performance, effectiveness, and high efficacy [15], [19], [16], [17]. By leveraging SARIMA model, we have consistently achieved reliable and precise predictions, demonstrating its capability to capture and model complex temporal patterns with remarkable accuracy. Moreover, the SARIMA model has been lauded for its versatility and applicability across diverse domains. This flexibility allows SARIMA to accommodate different types of data and adapt to evolving conditions, making it a valuable tool for forecasting in dynamic and complex environments.

Result and Discussion

As previously explained, we utilized the SARIMA method for time series analysis of weather data in the new capital city of Indonesia located in Sepaku district, East Borneo. Initially, we observed significant noise in the daily temperature graph, and upon closer examination in figure 5, at each data point, it can be observed that there is only minimal change in temperature for each date. By employing the rolling function in the pandas dataframe library, we were able to visualize a cleaner temperature graph, as depicted in figure 6, as the data has been aggregated.

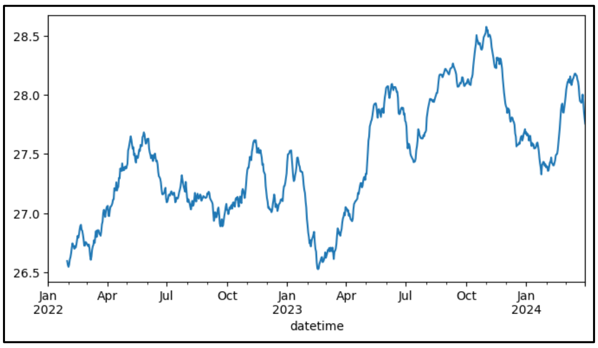

Figure 6. Clearer temperature

At this stage, we have presented a cleaner and more easily interpretable daily temperature graph. The graph clearly displays the beginning and end of the data, along with the measured temperature in Celsius units. To perform forecasting, we divided the data into actual and predicted data. Both of these data sets are represented in the 'temp_act' and 'temp_pred' columns, an example of which is shown in figure 7.

Figure 7shows an example of the top 10 data points from the dataset that we divided into actual and prediction data. Subsequently we validated the SARIMA model we used by calculating the root mean squared error (RMSE) between the actual and prediction data, the results of which can be seen in figure 8.

The RMSE value we obtained is 0.9300, which is relatively small. This value allows us to forecast the temperature in Sepaku district for the upcoming days with an average error of only 0.9300 degrees Celsius. This level of error is acceptable for temperature forecasting, considering the various influencing factors.

To ensure the appropriate use of SARIMA parameters, we iterated through different SARIMA parameters and employed grid search to explore various parameter combinations repeatedly to obtain the appropriate Akaike Criterion Value [26]. The AIC value is used to select a good statistical model, as seen in figure 9.

datetime	temp_act	temp_pred
2022-01-02	27.4	27.9
2022-01-03	26.6	27.4
2022-01-04	26.1	26.6
2022-01-05	26.8	26.1
2022-01-06	26.7	26.8
2022-01-07	25.1	26.7
2022-01-08	25.4	25.1
2022-01-09	27.1	25.4
2022-01-10	26.9	27.1
2022-01-11	27.1	26.9

Figure 1. Actual and prediction data

```
[ ] from sklearn.metrics import mean_squared_error as mse
    from math import sqrt

    #Calculate rmse
    temp_pred_err = sqrt(mse(one_step_df.temp_act, one_step_df.temp_pred))
    print('The rmse is: ', temp_pred_err)

    The rmse is:  0.9300340932644062
```

Figure 8. RMSE value

```
sarimax(1, 0, 1)x(0, 0, 1, 12)12 - AIC:1923.3615675523388
sarimax(1, 0, 1)x(0, 1, 0, 12)12 - AIC:2375.8003416221436
sarimax(1, 0, 1)x(0, 1, 1, 12)12 - AIC:1926.3542624894671
sarimax(1, 0, 1)x(1, 0, 0, 12)12 - AIC:2634.806492260508
sarimax(1, 0, 1)x(1, 0, 1, 12)12 - AIC:1925.7336868292145
sarimax(1, 0, 1)x(1, 1, 0, 12)12 - AIC:2163.356356066627
sarimax(1, 0, 1)x(1, 1, 1, 12)12 - AIC:1928.3270817289374
sarimax(1, 1, 0)x(0, 0, 0, 12)12 - AIC:2075.8297539684886
sarimax(1, 1, 0)x(0, 0, 1, 12)12 - AIC:2077.6483965096236
sarimax(1, 1, 0)x(0, 1, 0, 12)12 - AIC:2613.756972202879
sarimax(1, 1, 0)x(0, 1, 1, 12)12 - AIC:2103.023790730603
sarimax(1, 1, 0)x(1, 0, 0, 12)12 - AIC:2077.6594300097913
sarimax(1, 1, 0)x(1, 0, 1, 12)12 - AIC:2079.5357115057536
sarimax(1, 1, 0)x(1, 1, 0, 12)12 - AIC:2390.5083773948963
sarimax(1, 1, 0)x(1, 1, 1, 12)12 - AIC:2104.945883840124
sarimax(1, 1, 1)x(0, 0, 0, 12)12 - AIC:1872.9140582742461
sarimax(1, 1, 1)x(0, 0, 1, 12)12 - AIC:1874.8945596482752
sarimax(1, 1, 1)x(0, 1, 0, 12)12 - AIC:2380.305209098123
sarimax(1, 1, 1)x(0, 1, 1, 12)12 - AIC:1905.4687893113987
sarimax(1, 1, 1)x(1, 0, 0, 12)12 - AIC:1874.8953711043885
sarimax(1, 1, 1)x(1, 0, 1, 12)12 - AIC:1876.872379445148
sarimax(1, 1, 1)x(1, 1, 0, 12)12 - AIC:2169.8654061504603
sarimax(1, 1, 1)x(1, 1, 1, 12)12 - AIC:1907.4633085559663
```

Figure 9. AIC values

From figure 9, we obtained the lowest AIC value of 1872.914 for the parameter combination sarimax(1, 1, 1)x(0, 0, 0, 12)12. This AIC value is the lowest, indicating that this parameter combination is the most optimal for the SARIMA model. We present the forecast data alongside the existing data, as shown in figure 10 below.

Figure 10 illustrates the comparison between the actual temperature data and the predicted for the IKN. The blue line represents the actual temperature, while the orange line represents the forecasted temperature. The graph shows noticeable fluctuations in the observed temperature data, characterized by peaks and valley over time. The x-axis denotes the range of months, and the y-axis indicates the temperature range in degrees Celsius.

The forecasting process was conducted by calculating the mean squared error (MSE) to quantify the accuracy of the temperature prediction for upcoming days. MSE is a commonly used metric to evaluate the performance of predictive models, providing insight into the average squared difference between the actual and predicted values. The lower MSE value, the closer the predicted values are to the actual observations, indicating higher accuracy in the forecasting model. Figure 11 presents the MSE formula, showcasing how the MSE value changes over time as the forecasting model predicts the temperature for each subsequent day.

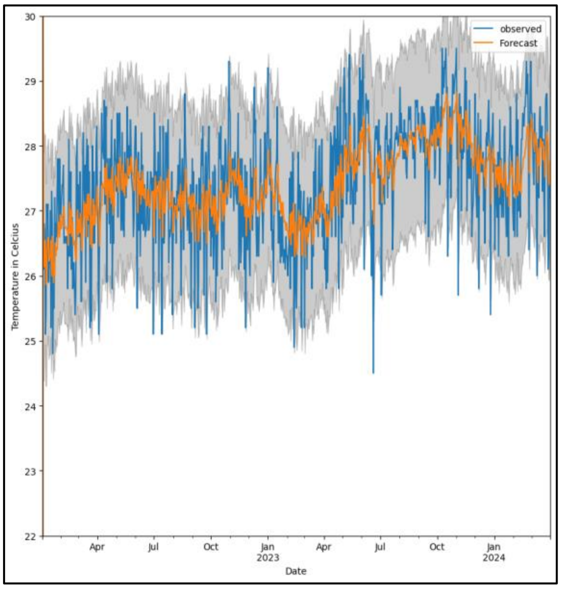

Figure 10. Temperature forecast

```
y_forecasted = pred.predicted_mean
y_truth = one_step_df.temp_act['2022-01-01':]
print(y_forecasted.shape)
print(y_truth.shape)

MSE = sqrt(mse(y_truth, y_forecasted).mean())
print('Mean squared error of the forecast is {}'.format(round(MSE, 2)))

(820,)
(820,)
Mean squared error of the forecast is 1.23
```

Figure 11. MSE value

The MSE value of 1.23 for temperature prediction in Sepaku district as depicted in figure 11, indicates a favorable performance of the SARIMA model. A lower MSE value suggests that the model's predictions are closer to the actual observed values, indicating greater accuracy in forecasting. This result indicates that the SARIMA model effectively captures the underlying patterns and dynamics in the temperature time series data, enabling it to make reliable predictions. The relatively small prediction errors further validate the suitability of the SARIMA model for forecasting temperature in Sepaku district, demonstrating its effectiveness in handling the complexities of the data and providing valuable insights for further temperature trends.

Conclusion

We have implemented the SARIMA model to forecast the temperature from weather data in Sepaku district, East Borneo. Before we conduct the exploration, we divided the dataset into actual and prediction data. Then we tested the model by calculating the RMSE value, resulting in an RMSE value of 0.93 for the SARIMA model, which is relatively small and indicates that the model is suitable for use. Indeed, during the experiment, the model performed well, providing highly accurate prediction results, as evidenced by MSE value of only 1.23.

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Author Contributions

Conceptualization, Author 1. and Author 2.; methodology, Author 2.; software, Author 1.; validation, Author 2.; formal analysis, Author 1.; investigation, Author 2; resources, Author 1 and Author 2.; data curation, Author 2 ; writing—original draft preparation, Author 1 and Author 2.; writing—review and editing, Author 2.; visualization, Author 1 and Author 2.; supervision, Author 2.; project administration, Author 1.; funding acquisition, Author 2. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Praditya, E., Suprapto, F. A., Ali, Y., Surjaatmadja, S., & Duarte, R. (2023). Nusantara Capital City (IKN): Threats and Defense Strategies for Indonesia's New Capital. The Journal of Indonesia Sustainable Development Planning, 4(1), 21–34. https://doi.org/10.46456/jisdep.v4i1.420

[2] Alviani, A., Gusmiarti, A. D., Putri, D. A., & Hashmi, H. R. (2022). Indonesia'S New Capital Nusantara: Contemplating Ikn Strategic Defence and Indonesia – Malaysia Border Diplomacy. Jurnal Diplomasi Pertahanan, 8(3), 104. https://doi.org/10.33172/jdp.v8i3.1376

[3] Al Vayed, D., & Purnomo, E. P. (2023). Challenges and opportunities: application of clean and affordable energy in the development of the national capital of the archipelago. Jurnal Pengelolaan Sumberdaya Alam Dan Lingkungan, 13(1), 102–113. https://doi.org/10.29244/jpsl.13.1.102-113

[4] Farida, F. (2021). Indonesia's capital city relocation: A perspective of regional planning. Jurnal Perspektif Pembiayaan Dan Pembangunan Daerah, 9(3), 221–234. https://doi.org/10.22437/ppd.v9i3.12013

[5] Al-Mekhlafy, M. A. S. H., Ahmed, M. A. F., & Yosuef, M. G. (2020). Time Series Forecasting: A Hybrid Neuro-Fuzzy-Particle Swarm Optimization Model. International Journal of Computer Applications, 176(40), 1–8. https://doi.org/10.5120/ijca2020920457

[6] Shen, L., Wei, Y., Wang, Y., & Qiu, H. (2023). FDNet: Focal Decomposed Network for efficient, robust and practical time series forecasting. Knowledge-Based Systems, 275, 110666. https://doi.org/10.1016/j.knosys.2023.110666

[7] Jimeng Shi, Mahek Jain, G. N. (2022). Time Series Forecasting (TSF) using various DL models.

[8] Arratia, A. (2014). Time Series Models in Finance (pp. 109–143). https://doi.org/10.2991/978-94-6239-070-6_4

[9] Vijayakumar, V. (2022). FeRM Model for Time Series Forecasting. Research Square, 1–11.

[10] Asoke Nath, Swapnil Saha, Himashri Basu, & Shalini Torcato. (2023). Visibility Analysis and Time Series Forecasting. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 3307, 103–116. https://doi.org/10.32628/cseit2390321

[11] Chen, P., Niu, A., Liu, D., Jiang, W., & Ma, B. (2018). Time Series Forecasting of Temperatures using SARIMA: An Example from Nanjing. IOP Conference Series: Materials Science and Engineering, 394(5). https://doi.org/10.1088/1757-899X/394/5/052024

[12] Nugraha, Y. E. N., Ariawan, I., & Arifin, W. A. (2023). Weather Forecast From Time Series Data Using Lstm Algorithm. Jurnal Teknologi Informasi Dan Komunikasi, 14(1), 144–152. https://doi.org/10.51903/jtikp.v14i1.531

[13] Di Martino, F., & Sessa, S. (2019). Seasonal time series forecasting by F1-fuzzy transform. Sensors (Switzerland), 19(16), 1–14. https://doi.org/10.3390/s19163611

[14] Shende, M. K., Salih, S. Q., Bokde, N. D., Scholz, M., Oudah, A. Y., & Yaseen, Z. M. (2022). Natural Time Series Parameters Forecasting: Validation of the Pattern-Sequence-Based Forecasting (PSF) Algorithm; A New Python Package. Applied Sciences (Switzerland), 12(12). https://doi.org/10.3390/app12126194

[15] Tang, C., Tong, Z., Wei, Y., Wu, X., Tian, X., & Yang, J. (2023). Time–Frequency Characteristics and SARIMA Forecasting of Atmospheric Water Vapor in East Asia. Atmosphere, 14(5), 1–24. https://doi.org/10.3390/atmos14050899

[16] Masum, M. H., Islam, R., Hossen, M. A., & Akhie, A. A. (2022). Time Series Prediction of Rainfall and Temperature Trend using ARIMA Model. Journal of Scientific Research, 14(1), 215–227. https://doi.org/10.3329/jsr.v14i1.54973

[17] Kabbilawsh, P., Sathish Kumar, D., & Chithra, N. R. (2022). Performance evaluation of univariate time-series techniques for forecasting monthly rainfall data. Journal of Water and Climate Change, 13(12), 4151–4176. https://doi.org/10.2166/wcc.2022.107

[18] Pérez-Chacón, R., Asencio-Cortés, G., Troncoso, A., & Martínez-Álvarez, F. (2024). Pattern sequence-based algorithm for multivariate big data time series forecasting: Application to electricity consumption. Future Generation Computer Systems, 154(October 2023), 397–412. https://doi.org/10.1016/j.future.2023.12.021

[19] Bezabih, G., Wale, M., Satheesh, N., Workneh Fanta, S., & Atlabachew, M. (2023). Forecasting cereal crops production using time series analysis in Ethiopia. Journal of the Saudi Society of Agricultural Sciences, 22(8), 546–559. https://doi.org/10.1016/j.jssas.2023.07.001

[20] Ahmadi, A., Daccache, A., Sadegh, M., & Snyder, R. L. (2023). Statistical and deep learning models for reference evapotranspiration time series forecasting: A comparison of accuracy, complexity, and data efficiency. Computers and Electronics in Agriculture, 215(July), 108424. https://doi.org/10.1016/j.compag.2023.108424

[21] Di Mauro, M., Galatro, G., Postiglione, F., Song, W., & Liotta, A. (2024). Hybrid learning strategies for multivariate time series forecasting of network quality metrics. Computer Networks, 243(March), 110286. https://doi.org/10.1016/j.comnet.2024.110286

[22] Sufian, M. A., Varadarajan, J., & Niu, M. (2024). Enhancing prediction and analysis of UK road traffic accident severity using AI: Integration of machine learning, econometric techniques, and time series forecasting in public health research. Heliyon, 10(7), e28547. https://doi.org/10.1016/j.heliyon.2024.e28547

[23] Bashiri Behmiri, N., Fezzi, C., & Ravazzolo, F. (2023). Incorporating air temperature into mid-term electricity load forecasting models using time-series

regressions and neural networks. Energy, 278(April), 127831. https://doi.org/10.1016/j.energy.2023.127831

[24] Mendoza, A. P. (2024). Dengue incidence forecasting model in Magalang, Pampanga using time series analysis. Informatics in Medicine Unlocked, 44(October 2023), 101439. https://doi.org/10.1016/j.imu.2023.101439

[25] Nurtas, M., Zhantaev, Z., & Altaibek, A. (2024). Earthquake time-series forecast in Kazakhstan territory: Forecasting accuracy with SARIMAX. Procedia Computer Science, 231(2023), 353–358. https://doi.org/10.1016/j.procs.2023.12.216

[26] Zhao, Y., Zhang, W., & Liu, X. (2024). Grid search with a weighted error function: Hyper-parameter optimization for financial time series forecasting. Applied Soft Computing, 154(January), 111362. https://doi.org/10.1016/j.asoc.2024.111362

[27] Wang, Z.-Y., Lin, Y.-C., Lee, S.-J., & Lai, C.-C. (2017). A Time Series Forecasting Method. ITM Web of Conferences, 12, 03008. https://doi.org/10.1051/itmconf/20171203008