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Forecasting the Monthly Temperature and Rainfall in Chuping Perlis

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Abstract

This study focuses on the forecasting of monthly temperature and rainfall patterns in Chuping, Perlis, with the aim of providing valuable insights into the region's climate. Various forecasting methods were employed, including Simple Seasonal Exponential Smoothing (SSES), Holt Winter Additive, Holt Winter Multiplicative, and Seasonal ARIMA. The accuracy of these models was assessed using key error metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results of the analysis revealed that the Simple Seasonal Exponential Smoothing (SSES) model consistently outperformed the other methods, exhibiting the lowest error metrics for both temperature and rainfall forecasts. Specifically, for monthly temperature, the lowest error metrics values were found to be 0.401 for MAE, 0.465 for RMSE, and 1.434 for MAPE. For monthly rainfall, the SSES model demonstrated that the MAE of 1.528, RMSE of 1.952, and MAPE of 157.477, indicating its superior accuracy in capturing the seasonal patterns in Chuping's climate. The study's conclusions indicate a predictable climate in Chuping, with stable temperature and rainfall patterns expected over the next 31 months, until the end of 2025. This reliability in forecasting provides valuable information for various sectors, including agriculture and environmental management, which rely on accurate climate predictions for planning and resource allocation.

Keywords: Forecasting, Simple Seasonal Exponential Smoothing (SSES), Holt-Winter Additive, Holt-Winter Multiplicative, Seasonal ARIMA.

INTRODUCTION

Chuping, Perlis, Malaysia, is well known for its broad agricultural industry, which includes several different agricultural products such as rice and rubber. Additionally, it holds the distinction of being the largest sugarcane production area in the country (Perlis State Government, n.d.). The success and productivity of these agricultural activities significantly impact the local economy, generating employment opportunities, stimulating rural development and supporting the livelihoods of many individuals in the region as well as the agricultural sector in Chuping contributes to the overall economic growth of Perlis. The prosperity and productivity of these agricultural activities in Chuping are closely linked to weather conditions, mainly factors such as rainfall and temperature. [1].

Temperature plays a pivotal role in determining crop growth, flowering, and fruit development, directly influencing the overall quality and quantity of agricultural produce [2]. Notably, Chuping experiences consistently high temperatures, recording the highest temperatures in the country in recent years [3]. Such extreme heat can have adverse effects on agriculture, leading to reduced crop yields and potential financial losses for farmers. In the context of Chuping's agricultural practices, understanding the impact of temperature fluctuations is of paramount importance. Prolonged exposure to high temperatures can result in heat stress for crops, affecting their physiological processes and hindering their growth and development.

Certain crops, such as rice and sugarcane, are particularly sensitive to extreme heat, leading to reduced photosynthetic activity, decreased grain and sugar yields, and even crop failure [2].

Research conducted by [4] in the Klang Valley, Malaysia, highlights a warming trend with increasing minimum temperatures surpassing maximum temperatures, particularly in urban areas. Such temperature changes have implications for local climate and environment, necessitating adaptation strategies to address the increasing occurrence of extreme temperature events. In Chuping, where agricultural activities heavily rely on weather patterns, it is crucial to comprehend the relationship between temperature variations and crop productivity.

Adequate and well-distributed rainfall is vital for crop growth and water supply in Chuping [2]. Accurate rainfall predictions are crucial for effective water resource management, agricultural planning, and disaster preparedness. Chuping's agricultural activities depend heavily on seasonal rainfall patterns, and proper timing of rainfall is essential for seed germination and crop growth. [5] discovered that heavy rainfall can significantly reduce maize output in cooler places, and this effect increases in regions with inadequate drainage. Excessive rainfall can reduce crop production in a variety of ways, including direct physical damage, delayed planting and harvesting, reduced root growth, oxygen deficit, and nutrient loss. Conversely, insufficient watering and a lack of rainfall can also result in crop failure and plant death.

By conducting comprehensive research on weather forecasting and meteorological analysis in Chuping, Perlis, the community can benefit from improved weather predictions that contribute to the overall prosperity and well-being of the local agricultural industry and the wider community [1]. Accurate weather forecast is of immense significance for various sectors, particularly in agricultural regions like Chuping, Perlis, Malaysia. The local agricultural sector heavily relies on timely and precise weather forecasts to optimize crop management, irrigation schedules, and pest control strategies. However, Chuping faces a significant challenge due to limited studies and research in weather prediction specifically tailored to its agricultural needs. This lack of comprehensive localized research hampers the ability of farmers and agricultural stakeholders to make informed decisions, resulting in potential crop losses, inefficient resource utilization, and reduced productivity, it might lead to inconveniences, economic losses, and safety concerns for the local community.

In the context of Chuping's agricultural sector, accurate rainfall forecasts are essential for determining optimal irrigation timing and quantities. Insufficient or excessive irrigation can lead to water wastage or inadequate water supply for crops, impacting their growth and productivity. Similarly, accurate forecasts of temperature are crucial for implementing appropriate crop management strategies and pest control measures. Inaccurate predictions in these areas can adversely affect crop growth, yield, and overall quality [2].

To address these pressing challenges and the lack of comprehensive research, therefore, the primary objective of this research is to design and implement a specialized time series forecasting model that can capture the unique weather patterns of Chuping, Perlis, and significantly enhance the accuracy and reliability of weather forecasts, especially concerning rainfall and temperature. By conducting this study, we aim to fill the research gap and offer tangible benefits to the local people by providing region-specific and precise weather forecasts. These insights will empower the community, particularly farmers and agricultural stakeholders, to make well-informed decisions, improve resource management practices, and ultimately bolster the agricultural sector's productivity and sustainability in Chuping, Perlis. The objectives of the study are as follows: (i) to find the best forecast model for forecasting the temperature and rainfall in Chuping, Perlis and (ii) to forecast the future temperature and rainfall condition in Chuping, Perlis.

LITERATURE REVIEW

Based on the research of [6], weather forecast is a critical aspect of understanding and anticipating meteorological conditions, enabling effective planning and decision-making across various sectors at given location. In the context of Chuping, Perlis, Malaysia, accurate and timely weather forecasting holds particular significance due to the region's unique geographical location and its impact on local communities and key sectors. Weather forecasting is essential for numerous applications across various sectors. It helps individuals and organizations make informed decisions related to agriculture, transportation, energy production, disaster preparedness, and public safety [7]. This literature review aims to explore the existing research and approaches related to weather forecast in Chuping, Perlis, shedding light on the climate and weather patterns specific to the region.

2.1 Weather Forecast

Weather forecasting is the practice of applying scientific and technological approaches to estimate the state of the atmosphere and forecast weather conditions for a given area and time in the future. It entails analysing meteorological data such as temperature, humidity, air pressure, wind speed, and precipitation patterns in order to make accurate forecasts about future weather events [6]. Weather forecasting is critical because of its importance in a variety of industries and its impact on the community. The agricultural sector relies heavily on accurate weather forecasts to plan planting and harvesting schedules, optimise irrigation operations, and manage crop diseases and pests [7]. In Chuping, where agriculture is a major economic activity, precise weather prediction can help farmers make informed decisions regarding crop selection, fertilizer application, and water management, leading to improved yields and reduced losses.

Weather forecasts are also crucial for the transportation sector, aiding in the planning of safe routes and scheduling of maritime, air, and land transportation activities [8]. Additionally, timely and accurate weather forecasts are essential for disaster management and preparedness in the region. Severe weather events, such as tropical storms, heavy rainfall, or droughts, can have detrimental impacts on infrastructure, properties, livelihoods, and public safety. By providing advance warnings and enabling effective response strategies, weather prediction empowers the local community and relevant authorities to mitigate risks, minimize damages, and ensure the safety and well-being of residents [9]. Thus, accurate weather forecasting in Chuping, Perlis, has far-reaching implications for sectors like agriculture, transportation, and disaster management, ultimately contributing to the region's socioeconomic development and resilience. This review aims to contribute to the development of improved weather prediction models for Chuping, Perlis, supporting the region's socioeconomic development and enhancing its resilience to weather-related challenges.

Several research studies have made significant contributions to the field of weather forecasting. [10] developed an ARIMA-based weather forecasting tool for Varanasi, utilizing 65 years of daily meteorological data, particularly focusing on rainfall and temperature. Their study demonstrated that the ARIMA model accurately estimated future values for a remarkable fifteen-year timeframe. [11] compared the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Holt-Winters methods, providing valuable insights into climate prediction. Their work is especially relevant for cities vulnerable to climate change impacts, such as Jakarta. Additionally, [12] emphasized the importance of statistical modeling, specifically exponential smoothing, in agrometeorological time series analysis. They applied this approach to generate forecasts based on air temperature, wind speed, and precipitation data from diverse locations. Lastly, [13]) explored the applicability of both additive and multiplicative forms of the Holt-Winters model for predicting environmental variables, highlighting the multiplicative model's superior efficiency in predicting climate parameters, especially those displaying stable cyclic and seasonal behavior. These studies collectively contribute to the advancement of weather forecasting models and offer insights into their potential applications in various regions and sectors.

2.2 Temperature

The Oxford Dictionary defines temperature as the degree or intensity of heat present in a substance or object, and in the context of weather, it refers to the measurement of the average kinetic energy of air molecules or the atmospheric condition of warmth or coldness. Temperature is a fundamental physical quantity that is commonly measured in degrees Celsius, Fahrenheit, or Kelvin. Forecasting temperature is crucial due to its significance in various domains and its impact on daily activities and well-being.

A significant portion of the research in temperature forecasting employs statistical models, particularly SARIMA and ARIMA, due to their effectiveness in handling seasonality and trends. For instance, [14] conducted a comparative study on the monthly temperature forecast of Cameron Highlands, finding the SARIMA (1,1,2) (1,1,1) model to surpass the ARAR method in predictive accuracy, indicating an anticipated temperature rise of 1.6°C in 2021. Similarly, [15] applied SARIMA models to predict temperature and assess outdoor thermal comfort for tourists in Bangladesh, showcasing the model's reliability in forecasting. Further demonstrating the utility of SARIMA, [16] validated its accuracy in weather forecasting using data from an Albanian meteorological station, enhancing the model's credibility in predicting weather patterns. In contrast, [17] focused on ARIMA models to analyze temperature variability and trends in Karachi, Pakistan, identifying the ARIMA (2,1,4) model as optimal and noting an increasing temperature trend with significant implications.

Exploring the frontier of machine learning for temperature forecasting, Marwah (2021) delved into the development of machine learning algorithms, including the MLP-NN model, for predicting meteorological parameters in Terengganu, Malaysia. This study highlighted the potential of machine learning approaches, particularly the effectiveness of the MLP-NN model in forecasting daily and monthly temperatures, illustrating the expanding capabilities of machine learning in meteorological applications.

Beyond traditional statistical and machine learning models, some studies explore alternative forecasting methods. [18] emphasized the relevance of the simple exponential smoothing method for predicting daily temperatures in Faisalabad and Lahore, Punjab, Pakistan. This method's suitability for modeling and forecasting in the context of climate change showcases the diverse array of techniques available for temperature forecasting.

2.3 Rainfall

The definition of rainfall, according to the [19], refers to the precipitation in the form of rain that falls from the atmosphere to the Earth's surface. It plays a crucial role in the water cycle and has significant implications for various aspects of human life and the environment [20]. A notable body of research on rainfall forecasting relies on statistical models, especially SARIMA and ARIMA, for their predictive capabilities in addressing seasonality and non-linear trends in rainfall data.

[21] emphasize the importance of accurate rainfall prediction for various societal and environmental applications. Ray *et al*. (2021) demonstrated the effectiveness of the SARIMA model in forecasting monthly average rainfall and temperature in South Asian countries, highlighting its utility in regional climate data analysis. Similarly, Ali (2013) applied the SARIMA (2,1,3)(0,1,1) model to monthly rainfall data from the Baghdad meteorological station, identifying it as the best-fit model for accurate predictions. Further, a study by [22] on the application of an ARIMA model for predicting monthly rainfall in Khordha district, Odisha, underscores the model's potential for enhancing local planning and management practices related to rainfall.

The Exponential Smoothing Holt-Winter method is another forecasting approach highlighted in the literature for its precision in forecasting rainfall patterns. [23] explored its application in Mataram City, demonstrating the method's accuracy through low MAPE, MAD, and MSE values, which underscore its effectiveness as a decision-support tool in regions with unpredictable climate variations. On the other hand, [24] applied the Holt-Winters Exponential Smoothing method to rainfall data in Abiansemal District, focusing on agricultural planning. The study compared additive and multiplicative models, finding the multiplicative model to exhibit lower MAE and MAPE values, thus indicating its superiority for rainfall forecasting in agricultural contexts.

METHODOLOGY

This section outlines the methodology employed to analyze the historical weather data and forecast future weather patterns in Chuping, Perlis. The study utilizes secondary data obtained from MyMetData Malaysia, encompassing two key weather parameters: temperature and rainfall. The data collection period spans from 2018 to 2023, providing a comprehensive and recent dataset for analysis.

3.1 Data Collection

The data collection procedure involves accessing the historical weather data from the MyMetData Malaysia database for the specified time range. This dataset covers a significant duration, allowing for a detailed examination of temperature variations and rainfall patterns in Chuping, Perlis over the past five years. The historical data is considered reliable and accurate, having been collected and validated by meteorological experts.

3.3 Simple Exponential Smoothing (SES)

Simple Exponential Smoothing (SES) is a forecasting technique predicated on the assumption that time series data fluctuate around a stable mean. This method aims to smooth out the series akin to a moving average, favoring it for future projections. Significantly, SES prioritizes recent observations over past data, offering a more pragmatic approach for forecasting compared to other methods due to this weighting mechanism [25] [12] [26].

3.3.1 Simple Seasonal Exponential Smoothing (SSES)

The Simple Seasonal Exponential Smoothing (SSES) method is intended for time series that demonstrate a constant seasonal pattern but no identifiable trend. It uses smoothing parameters to account for both the series' level and seasonal changes, effectively capturing seasonal impacts in the data. The Level is estimated as

$$L_t = \alpha(y_t - s_{t-m}) + (1-\alpha)\,(L_{t-1})$$
$$L_t = L_{t-1} + \alpha[y_t - (s_{t-m} - L_{t-1})]$$
$$L_t = L_{t-1} + \alpha e_t$$

where:
L_t = Time series level a time t
y_t = Time series data at time t
e_t = Error term at time t
s_{t-m} = Seasonal effect for season t-m
L_{t-1} = Level forecast for time t made at time t-1

The smoothing form of the equation for seasonal indexes is expressed as

$$S_t = \delta(y_t - L_t) + (1-\delta)\,(s_{t-m})$$

and the smoothed forecast value is given as

$$F_t = L_t + L_{t-p+m}$$

where:
δ = Seasonal smoothing parameter
α = Smoothing coefficient for trend
F_t = Smoothed forecast valueo

3.3.1 Holt-Winter

The Holt-Winter exponential smoothing approach is intended to handle time series data with both trends and seasonal patterns. This method uses three main components: original data, trend, and seasonality to apply three sequential weights for prediction, designated as α, β, and γ. The Holt-Winter exponential smoothing strategy consists of two separate models: additive and multiplicative. As explained by [26], the additive model is used when the original data plot shows generally stable (constant) seasonal fluctuations, and the multiplicative model when the original data plot shows varied seasonal fluctuations. The Holt-Winters Exponential Smoothing method's computation steps are as follows:

in Level Smoothing
Additive Model:

$$L_t = \alpha(y_t - s_{t-s}) + (1-\alpha)\,(L_{t-1} + b_{t-1})$$

Multiplicative Model:

$$L_t = \alpha(y_t/L_t) + (1-\gamma)(L_{t-1} + b_{t-1})$$

in Trend Smoothing
Additive Model:

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)\, b_{t-1}$$

Multiplicative Model:

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)\, b_{t-1}$$

in Seasonal Smoothing
Additive Model:

$$s_t - \gamma(y_t - L_t) + (1-\gamma)\, s_{t-s}$$

Multiplicative Model:

$$s_t = \gamma(y_t/L_t) + (1-\gamma)\, s_{t-s}$$

in Forecasting Period t
Additive Model:

$$F_{t+m} = L_t + b_t m + s_{t-s+m}$$

Multiplicative Model:

$$F_{t+m} = (L_t + b_t m)\, s_{t-s+m}$$

where:
L_t = Level in the 2nd period t
L_{t-a}= Level in the 2nd period t -1
b_t= Trend in the 2nd period t
b_{t-1}= Trend in the 2nd period t -1
s_t = Seasonality in the 2nd year t
s_{t-s} = Smoothing of seasonal factors
y_t = Data in the 2nd period t
s = seasonal length
t = Seasonal period
m = Forecasted time period
α = Level weighting parameter (0< α <1)
β = Trend weighting parameter (0< β <1)
γ = Seasonal smoothing weighting parameter

3.4 ARIMA

The ARIMA model, first introduced by [27] and later improved by [28], stands for Auto-Regressive Integrated Moving Average. It is a well-known technique in the field of time series forecasting, acting as an effective tool for analyzing and forecasting future values within a time series dataset. This model is defined by three critical parameters: p, d, and q, each of which corresponds to a different component of the data:

p: Seasonality and determines the number or order of auto-regression terms (AR terms).
d: Trend and indicates the number or order of differences applied to the time series data.
q: Noise and denotes the number or order of moving average terms (MA terms).

The ARIMA model has proven to be an effective approach in time series forecasting, making it widely adopted in various fields with its ability to account for seasonality, trend, and noise. [29].

The equation of the ARIMA model with the parameters p, d, q can be expressed as: $y_t=\varphi_1 y_{t-1}+\varphi_2 y_{t-2}+\ldots+\varphi_p y_{t-p}+\theta_1 et-1+\theta 2e_{t-2}+\cdots+\theta_q e_{t-q}+e_t$

where:

$\varphi_1, \varphi_2, \ldots, \varphi_p$ = Auto-regression coefficients
$\theta_1, \theta_2, \ldots, \theta_q$ = Moving average coefficients

3.4.1 SARIMA

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model enhances the ARIMA framework by integrating seasonality into the forecasting of time series data. This enhanced model introduces additional parameters such as the seasonal cycle parameter S and seasonal coefficients P, D and Q, which are like the non-seasonal parameters p, d and q but are specifically designed to capture seasonal patterns [30]. To determine the parameter set for optimal model fit, the Akaik Information Criterion (AIC) was employed. The Akaike information criterion helps to strike a balance between model simplicity and the model's ability to fit the data well, thereby facilitating the selection of the most appropriate parameters [31]. Unlike traditional ARIMA models, which may not handle seasonal changes effectively, SARIMA models are good at identifying and adjusting for underlying trends and seasonal fluctuations in time series data.

The equation of the SARIMA model with the parameters p, d, q, P, D, Q, S can be expressed as:

$$(1-\varphi_1 B-\varphi_2 B^2-\ldots-\varphi_p B^p)(1-B)^d(1-B^s)^D y_t$$
$$= c+(1+\theta_1 B+\theta_2 B^2+\ldots+\theta_q B^q)(1-\Theta_1 B^s-\Theta_2 B^2-\ldots-\Theta_q B^q)e^t$$

where:

B = Backshift operator (representing the differencing operation),
s = Seasonal period,
c = Constant term (intercept),
P, D, Q = Seasonal auto-regression, seasonal differencing, and seasonal moving average coefficients, respectively,
$\Theta_1, \Theta_2, \ldots, \Theta_q$ = Seasonal moving average coefficients,

By incorporating SARIMA models, it can effectively capture and forecast the seasonal variations in temperature and rainfall in Chuping, Perlis.

3.5 Measuring Forecast Error

In forecasting, accuracy is the criterion that determines the best forecast method and therefore, it is the most important concern in evaluating the quality of a forecast. The goal of the forecast is minimizing errors. [18] highlights the following accuracy measures are commonly employed in the literature to assess forecast precision. Those are Mean absolute error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

$$\text{MAE} = \frac{1}{n}\sum_{t-1}^{n}|e_t|$$
$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t-1}^{n} {e_t}^2}$$

$$\text{MAPE} = \frac{1}{n}\sum_{t-1}^{n} \frac{|e_t|}{y_t} \cdot 100\%$$

3.6 Data Analysis and Evaluation

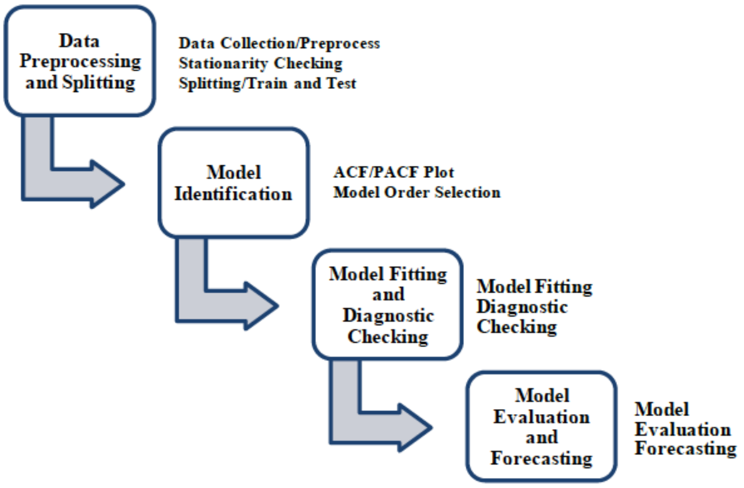

Figure 1 Flow Diagram for the work process

Weather forecasting in Chuping faces challenges due to a lack of comprehensive weather monitoring infrastructure, making it difficult to obtain precise and localized forecasts. To overcome this, we follow a four-phase process to build the forecasting models using seasonal ARIMA techniques.

In the first phase, we collect historical weather data from 2018 to 2023, including relevant variables. We then preprocess the data by cleaning it, handling missing values, smoothing outliers, and applying necessary transformations. A crucial step is checking for stationarity in the time series. If the data is not stationary (constant mean and variance), we apply transformations like differencing or logarithmic transformations to achieve stationarity. After preprocessing, we split the data into a training set (70-80%) for model estimation and a testing set (20-30%) for model evaluation. In the second phase, we conduct an Autocorrelation and Partial Autocorrelation (ACF and PACF) analysis on the transformed series. This helps us identify potential autoregressive (AR) and moving average (MA) orders for the model. The third phase involves model fitting and diagnostic checking. We estimate the parameters of the chosen model using maximum likelihood estimation or other suitable methods. The model is then fitted to the training data. We perform a thorough analysis of the residuals (differences between observed values and model predictions) to ensure that no significant autocorrelation or patterns remain, indicating that the model captures all relevant information. In the final phase, we evaluate the model's performance by applying it to the testing set and comparing predicted values against actual weather observations. Using evaluation metrics such as MAE, RMSE, and MAPE, we measure the accuracy of the forecasts. Once the model has been evaluated and deemed satisfactory, we utilize it to generate forecasts of future weather conditions for the next future 2 years. Through this iterative process, we can continuously forecast the weather condition in Chuping.

RESULT AND DISCUSSION

4.1 Data Exploration

Descriptive statistics and exploratory plots serve as valuable tools for gaining insights into the key characteristics of the data [32]. In this study, we utilized a dataset containing monthly average temperature and monthly average rainfall data for Chuping, Perlis, spanning from January 2018 to May 2023. Table 1 summarizes the descriptive statistics of this five-year time series dataset, consisting of 65 data points for each parameter. The temperature in Chuping ranged from 26.4°C to 29.3°C, with an average temperature of 27.6°C. Notably, the range between the minimum and maximum temperatures is relatively narrow, suggesting a lack of extreme hot or cold days during this period. On the other hand, the average monthly rainfall was 5.2mm, with values varying between 0.0mm and 11.1mm. While the monthly average rainfall appears relatively low on average, the presence of a maximum value of 11.1mm indicates occasional short periods of heavy rainfall within the year.

To gain further insight into the patterns of these datasets, we conducted graphical analyses, as depicted in Figure 2 and Figure 3. Figure 2 illustrates the temperature data series, showing a recurring seasonal pattern characterized by annual fluctuations. This indicates that the average monthly temperature in Chuping was influenced by seasonal factors throughout the study period. Similarly, Figure 3 displays the monthly average rainfall data series, also exhibiting a seasonal pattern with periodic fluctuations, confirming the presence of seasonality in this dataset. Additionally, when examining the trend component of the monthly average temperature data series, a declining trend is observed from 2018 to 2023. This downward trend remains consistent, particularly during the years 2018 to 2020.

Table 1 Descriptive Statistics of Monthly Average Temperature and Rainfall data

Meteorological elements	Mean	Median	Min	Max	Std
Temperature (°C)	27.6	27.7	26.4	29.3	0.750
Rainfall (mm)	5.2	5.4	0	11.1	3.242

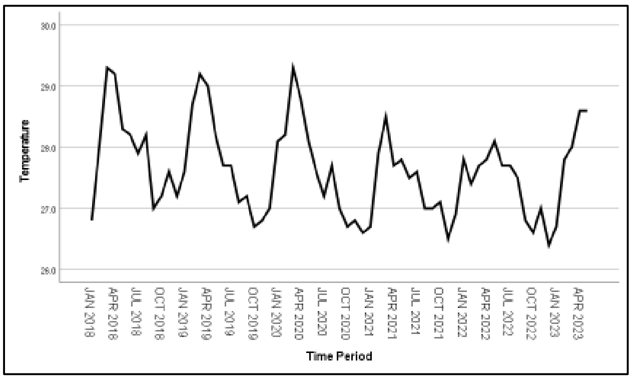

Figure 2: Time series plot of monthly average temperature in Chuping district from Jan 2018 - May 2023

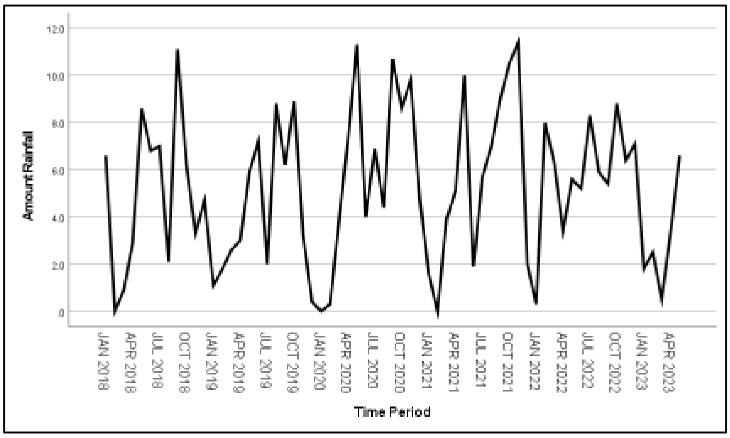

Figure 3: Time series plot of monthly average rainfall in Chuping district from Jan 2018 - May 2023

4.2 Model Evaluation

To evaluate and compare the performance of two models Exponential Smoothing and seasonal ARIMA from January 2018 to May 2023 we employed three standard error metrics; Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These metrics serve as indicators of how the models predict values.

For both temperature and rainfall datasets we calculated MAE, RMSE, and MAPE for each Exponential Smoothing and seasonal ARIMA model. The results are presented in Table 2 and Table 3. Notably Table 2 shows that the Simple Seasonal Exponential Smoothing method achieved the values for RMSE (0.465), MAPE (1.434) and MAE (0.401) in the temperature series. Similarly, Table 3 demonstrates that for the rainfall dataset the Simple Seasonal Exponential Smoothing method performed best across all three accuracy measures which are RMSE (1.952), MAPE (157.477) and MAE (1.528).

These findings emphasize that when it comes to accuracy in predicting temperature and average rainfall data series the Simple Seasonal Exponential Smoothing method outperforms models. Therefore, it is deemed as the time series model, for these datasets.

Table 2 Accuracy measures for Average Temperature

Models	**RMSE**	**MAPE**	**MAE**
Simple Seasonal Exponential Smoothing	0.465	1.434	0.401
Holt's Winter Additive	0.502	1.545	0.436
Holt's Winter Multiplicative	0.493	1.471	0.416
ARIMA (1,0,0) (1,0,0)	0.654	2.246	0.630

Table 3 Accuracy measures for Average Rainfall

Models	RMSE	MAPE	MAE
Simple Seasonal Exponential Smoothing	1.952	157.477	1.528
Holt's Winter Additive	2.380	191.607	2.048
ARIMA (0,0,0) (1,0,0)	3.114	263.974	2.587

4.3 Future Forecasting

After developing the best fitted time series model, forecasting is carried out for both monthly average temperature and rainfall of Chuping, Perlis. Figure 4 and Figure 5, where the blue line shows the forecast for June 2023 to December 2025 of both monthly average temperature and rainfall series. The data in Table 4 shows the forecasting data for June 2023 to December 2025 more clearly. Table 4 shows that in 2023, the forecasted values for temperature in June until December is below the median of 27.7°C, where the temperature is 27.6°C in June, 27.5°C in July, 27.4°C in August, 26.9°C in September, 26.7°C in October, 26.8°C in November, and 26.7°C in December. The forecasted temperature is similar for both year 2024 and 2025, where the temperature in January is 27.2°C, 27.9°C in February, 28.5°C in March, 28.4°C in April, 28.1°C in May, 27.6°C in June, 27.5°C in July, 27.4°C in August, 26.9°C in September, 26.7 °C in October, 26.8°C in November, and 26.7°C in December. There are four months in 2024 and 2025—February, March, April, and May—where the temperature is higher than the median. According to the research, temperatures would be higher early in the year and lower after May. This is because, as the Northeast Monsoon gives way to the Southwest Monsoon, Chuping, Perlis has warmer temperatures in the early months of the year because of less cloud cover and more sunlight.

On the other hand, the forecasted values for Rainfall in 2023, the rainfall is 4.9mm in June, 5.9mm in July, 5.6mm in August, 8.4mm in September, 8.5mm in October, 6.7mm in November, and 3.7mm in December. The forecasted rainfall is similar for both year 2024 and 2025, where the rainfall in January is 1.8mm, 2.0mm in February 2.9mm in March, 4.1mm in April, 7.9mm in May, 4.9mm in June, 5.9mm in July, 5.6mm in August, 8.4mm in September, 8.5mm in October, 6.7mm in November, and 3.7mm in December. For both the years 2024 and 2025, there are 6 months that have rainfall exceeds larger than median of 5.4mm, which is May, July, August, September, October, and November. This is because rainfall variance is influenced by the intensity of the Southwest Monsoon, which causes heavier rainfall during its peak seasons.

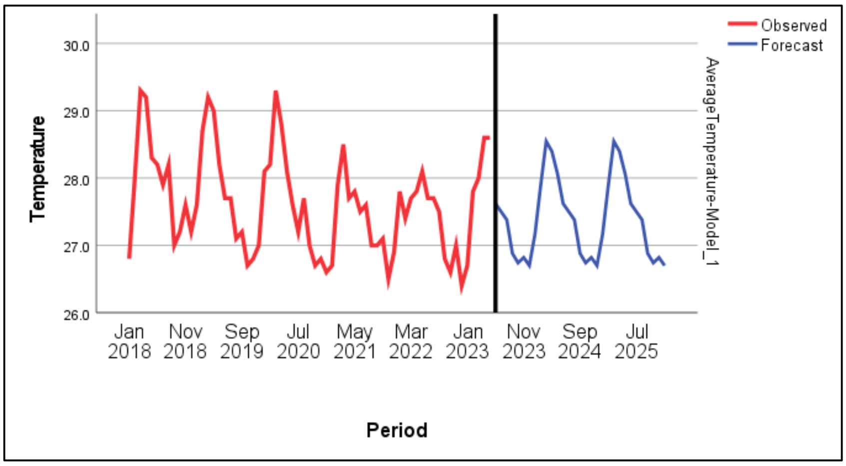

Figure 4: Forecast from best fitted model for temperature data series

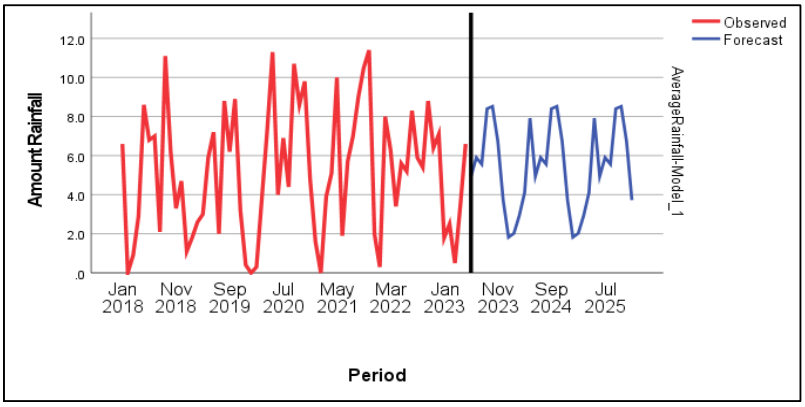

Figure 5: Forecast from best fitted model for rainfall data series

Table 4 Forecasting Data for June 2023 to December 2025

Year	Month	Average Temperature (°C)	Average Rainfall (mm)
2023	6	27.6	4.9
	7	27.5	5.9
	8	27.4	5.6
	9	26.9	8.4
	10	26.7	8.5
	11	26.8	6.7
	12	26.7	3.7
2024	1	27.2	1.8
	2	27.9	2.0
	3	28.5	2.9
	4	28.4	4.1
	5	28.1	7.9

continued

	6	27.6	4.9
	7	27.5	5.9
	8	27.4	5.6
	9	26.9	8.4
	10	26.7	8.5
	11	26.8	6.7
	12	26.7	3.7
2025	1	27.2	1.8
	2	27.9	2.0
	3	28.5	2.9
	4	28.4	4.1
	5	28.1	7.9
	6	27.6	4.9
	7	27.5	5.9
	8	27.4	5.6
	9	26.9	8.4
	10	26.7	8.5
	11	26.8	6.7
	12	26.7	3.7

The forecasting results clearly show that the Simple Seasonal Exponential Smoothing model outperforms other models like Holt's Winter methods and seasonal ARIMA in forecasting temperature and rainfall in Chuping, Perlis. These estimates show a clear seasonal pattern in both temperature and rainfall from 2023 to 2025. Temperature tends to be higher in the early months of each year, peaking around March, and then gradually decreases towards the end of the year. This indicates a clear seasonal trend, with warmer temperatures in the first half of the year and cooler temperatures in the latter half. Such patterns could be crucial for sectors like agriculture and tourism, aiding in planning and resource allocation.

Similarly, rainfall shows a seasonal variation with higher amounts expected in the latter half of the year, particularly from May to November. This suggests a wetter second half of the year, which could have significant implications for water resource management, agriculture, and flood risk planning. The accuracy of the Simple Seasonal Exponential Smoothing model in capturing these patterns highlights its utility in environmental and planning sectors for future forecasting.

CONCLUSION

Overall, Chuping's climate seems to be characterized by warm temperatures with occasional bursts of rain. This type of climate is suitable for a variety of crops, such as rice, maize, and sugarcane.

This study embarked on a comprehensive analysis of various time-series forecasting methods to identify the most suitable model for forecasting temperature and rainfall in Chuping. Three primary forecasting techniques were employed: Simple Seasonal Exponential Smoothing (SSES), Holt Winter Additive, Holt Winter Multiplicative, and Seasonal ARIMA (Seasonal Autoregressive Integrated Moving Average).

In the nutshell, by analyzing the measurer error with 3 types of metrics errors: MAE, RMSE, and MAPE, the research successfully identified the Simple Seasonal Exponential Smoothing (SSES) model as the most accurate for forecasting temperature and rainfall in Chuping, Perlis. This model demonstrated superior accuracy over others like Holt's Winter methods and ARIMA, exhibiting the lowest error metrics. Based on the effectiveness of the Simple Seasonal Exponential Smoothing model in capturing seasonal patterns in Chuping, and the observed consistency in the forecasted data, it can be concluded that the climatic conditions in Chuping are expected to remain relatively stable for the next 31 months, until the end of 2025.

The SSES method's reliability in forecasting these patterns suggests that significant deviations in monthly temperature and rainfall are unlikely during this period. This conclusion offers a degree of predictability and stability for planning and management in various sectors like agriculture and environmental management, affected by these climatic factors in Chuping.

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REFERENCES

[1] Wen, Y. W. J., Ponnusamy, R. R., & Kang, H. M. (2019). Application of weather index-based insurance for paddy yield: The case of Malaysia. *Int. J. Adv. Appl. Sci*, *6*, 51-59.

[2] Md Nor, S. M., Wan Hussin, W. M. R., & Ab Latif, Z. (2019). Impacts of rainfall patterns on paddy productivity in Perlis, Malaysia. *Environmental Science and Pollution Research*, 26(12), 12429-12440.

[3] Laman Web Rasmi Jabatan Meteorologi Malaysia. (2020). Met.gov.my. https://www.met.gov.my/en/penerbitan/laporan-tahunan/

[4] Yatim, A. N. M., Latif, M. T., Ahamad, F., Khan, M. F., Nadzir, M. S. M., & Juneng, L. (2019). Observed trends in extreme temperature over the Klang Valley, Malaysia. Advances in Atmospheric Sciences, 36, 1355-1370.

[5] Li, Y., Guan, K., Schnitkey, G. D., DeLucia, E., & Peng, B. (2019). Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States. Global Change Biology.

[6] Iseh, A. J., & Woma, T. Y. (2013). Weather forecasting models, methods and applications. *Int. J. Eng. Res. Technol*, 2, 1945-1956.

[7] Ongoma, V. (2022, February). The science of weather forecasting: what it takes and why it's so hard to get right. The Conversation. https://theconversation.com/the-science-of-weather-forecasting-what-it-takes-and-why-its-so-hard-to-get-right-175740#:~:text=Weather%20forecasting%20is%20an%20important,vital%20in%20the%20coming%20years.

[8] Hoey, B. (2020, October 29). The Benefits of Forecasting in Transportation Planning. Flexis.com; flexis Information Systems Inc.

[9] Merz, B., Kuhlicke, C., Kunz, M., Pittore, M., Babeyko, A., Bresch, D. N., … Wurpts, A. (2020). Impact Forecasting to Support Emergency Management of Natural Hazards. *Reviews of Geophysics.*

[10] Shivhare, N., Rahul, A. K., Dwivedi, S. B., & Dikshit, P. K. S. (2019). ARIMA based daily weather forecasting tool: A case study for Varanasi. Mausam, 70(1), 133-140.

[11] Natayu, A., Clarke, Q. J. H., & Fikri, M. (2022). Benchmark of Holt-Winters and SARIMA Methods in Predicting Jakarta Climate.

[12] Murat M, Malinowska I, Hoffmann H and Baranowski P. (2016). Statistical modelling of agrometeorological time series by exponential smoothing. International Agrophysics 30: 57–65.

[13] Heydari, M., Ghadim, H. B., Rashidi, M., & Noori, M. (2020). Application of holt-winters time series models for predicting climatic parameters (case study: Robat Garah-Bil Station, Iran). *Pol J Environ Stud*, 29(1), 617-627.

[14] Nurzawanah Raihah Zamri, & Azmi, N. (2021). Global Warming in Cameron Highlands: Forecasting its Temperature Level via ARIMA vs ARAR. 2084(1), 012009–012009.

[15] Hossen, S. M., Ismail, M. T., & tabash, m. I. (2021). The impact of seasonality in temperature forecast on tourist arrivals in bangladesh: an empirical evidence. *GeoJournal of Tourism and Geosites*, 34(1), 20–27.

[16] Xhabafti, M., & Sinaj, v. (2022). Weather forecasting based on the application of SARIMA models. *Circular Economy*, 549.

[17] Amjad, M., Khan, A., Fatima, K., Ajaz, O., Ali, S., & Main, K. (2022). Analysis of Temperature Variability, Trends and Prediction in the Karachi Region of Pakistan Using ARIMA Models. *Atmosphere*, 14(1), 88.

[18] Saba Zafar, M. K., Khan, M. I., & Nida, H. (2020). Application of simple exponential smoothing method for temperature forecasting in two major cities of the Punjab, Pakistan.

[19] Oxford Learner's Dictionaries | Find definitions, translations, and grammar explanations at Oxford Learner's Dictionaries. (2023). Oxfordlearnersdictionaries.com. https://www.oxfordlearnersdictionaries.com/

[20] Precipitation and the Water Cycle | U.S. Geological Survey. (2019). Usgs.gov. https://www.usgs.gov/special-topics/water-science-school/science/precipitation-and-water-cycle#:~:text=Rain%20and%20snow%20are%20key,drinks%20to%20plants%20and%20animals.

[21] Mohammed, M., Kolapalli, R., Golla, N., & Maturi, S. (2020). Prediction of Rainfall Using Machine Learning Techniques. http://www.ijstr.org/final-print/jan2020/Prediction-Of-Rainfall-Using-Machine-Learning-Techniques.pdf

[22] Swain, S., Nandi, S., & Patel, P. (2018). Development of an ARIMA Model for Monthly Rainfall Forecasting over Khordha District, Odisha, India. *Recent Findings in Intelligent Computing Techniques: Proceedings of the 5th ICACNI 2017, Volume 2*, *708*, 325.

[23] Pertiwi, D. D. (2020). Applied Exponential SMoothing Holt-Winter Method for Rainfall Forecast in Mataram City. J Int Comp & He Inf, 1(2).

[24] Wiguna, I. K. A. G., Utami, N. L. P. A. C., Parwita, W. G. S., Udayana, I. P. A. E. D., & Sudipa, I. G. I. (2023). Rainfall Forecasting Using the Holt-Winters Exponential Smoothing Method. Jurnal Info Sains: Informatika dan Sains, 13(01), 15-23.

[25] Olaofe, ZO, 2015. Wind energy predictions of small-scale turbine output using exponential smoothing and feed-forward neural network. International Journal of Energy Engineering 5: 28-42.

[26] Siregar B, Butar-Butar IA., Rahmat RF, Andayani U and Fahmi F, 2017. Comparison of exponential smoothing methods in forecasting palm oil real production. Journal of Physics: Conference Series 801: Article # 0120041.

[27] Box G.E.P. and Jenkins G., 1970. Time Series Analysis: forecasting and control. San Francisco, Holden-Day.

[28] Box G.E.P. and Tiao G.C., 1975. Intervention Analysis with Applications to Economic and Environmental Problems. *JASA*, 70, 70-79

[29] Siami-Namini, S., Tavakoli, N., Siami Namin, A., (2018). A Comparison of ARIMA and LSTM in Forecasting Time Series, in: 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA). Presented at the 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), IEEE, Orlando, FL, pp. 1394–1401.

[30] Farida, M., Zeghdoudi, H., (2020). On Modelling seasonal ARIMA series: Comparison, Application and Forecast (Number of Injured in Road Accidents in Northeast Algeria). *WSEAS Trans. Syst. Control*. 15, 235–246.

[31] Mantalos, P., Mattheou, K., Karagrigoriou, A., (2010). Forecasting ARMA models: a comparative study of information criteria focusing on MDIC. J. Stat. Comput. Simul. 80, 61–73.

[32] Marera DHSV, 2016. An application of exponential smoothing methods to weather related data. MS Thesis, School of Statistics and Actuarial Science, Faculty of Science.