FORECASTING DAILY MAXIMUM AND MINIMUM AIR TEMPERATURES IN THE CILACAP DISTRICT USING ARIMA AND EXPONENTIAL SMOOTHING

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ABSTRACT

This research aims to predict daily maximum and minimum air temperatures in Cilacap Regency using ARIMA and Exponential Smoothing. Data was obtained from recordings carried out by BMKG Cilacap using maximum and minimum thermometers taken from January 1, 2016, to December 31, 2021. The results show that the best forecasting model uses the ARIMA (2,1,2) model for maximum temperature and the ARIMA (1,1,1) model for minimum temperature, with the MAPE value of 2.09% for the maximum temperature and 2.44% for the minimum temperature, while the RMSE value obtained is 0.9177 for the maximum temperature and 0.8001 for the minimum temperature. Based on the ARIMA model, Cilacap's daily maximum temperature in 2022 was predicted to be around 30.6°C, with a 95% confidence interval between 28°C - 35°C, while the minimum temperature was predicted to be around 25.1°C, with a 95% confidence interval between 23°C - 28°C

Keywords: Temperature, forecasting, ARIMA, exponential smoothing.

INTRODUCTION

The Meteorological, Climatological, and Geophysical Agency (BMKG) Cilacap is an official institution that provides and distributes information about weather, climate, earthquakes, and others in the Cilacap Regency. Information from BMKG is essential in supporting various daily personal and non-personal activities, such as agencies, institutions, or companies. Among the different information provided by BMKG, the information often presented is related to daily weather. Weather information is vital because it is needed by many agencies or institutions that need weather-related data. Weather data consists of various data sets, including air temperature data. Air temperature is divided into several more data, including daily maximum and minimum air temperatures. Data related to temperature is crucial for several agencies and institutions, especially those related to the aviation, maritime, and agricultural sectors. Even in the aviation sector, air temperature data is necessary so that flights can be carried out and reduce the risk of accidents in aviation. The need for providing and servicing air temperature data is increasing, requiring BMKG to prepare and deliver data quickly, accurately, and precisely. Thus, it is necessary to develop new methods and techniques to provide data related to air temperature.

The average daily air temperature in tropical areas, including Indonesia, is constant throughout the year. Meanwhile, the air temperature will fluctuate significantly during each 24 hours. These fluctuations are closely related to the energy exchange processes in the atmosphere (Vissio, 2020; Purba & Al, 2021; Gillmann et al., 2022). Air temperature information in an area is usually measured in minimum and maximum temperature (Anwar, 2017a; Yi et al., 2019). One factor that influences an area's air temperature is its geographic conditions. The closer you get to the polar regions, the lower the air temperature, and the closer you are to the height of the region, the lower the air temperature (Lakitan & Benyamin, 2002).

Cilacap is one of the cities in Central Java Province that has experienced erratic increases and decreases in air temperature in recent years. The geographical location of Cilacap Regency consists of coastal and mountainous areas, which means that it has unpredictable changes in air temperature, which affect many aspects of the industry. Therefore, accurate forecasting of air temperature is needed. According to BMKG Cilacap records, the lowest air temperature occurred on August 14, 1994, at 17.4^{o}C. In practice, various forecasting methods can predict the value of time series data. In data forecasting, time series often exhibit seasonal behavior. Seasonality is the trend of time series data that repeats every period (Safitri, Dwidayati, & Sugiman, 2017). However, the choice of method depends on various influencing aspects, such as time, data patterns, the type of system model being observed, and the desired level of forecasting accuracy. Besides that, applying a data method must also meet the assumptions used. Time series data analysis has many applications in everyday life and the industrial, agricultural, and other fields (Aswi & Sukarna, 2006; Rosadi D, 2009, 2016b, 2016a).

The type of air temperature forecasting that is usually done is short-term forecasting. Short-term air temperature forecasting is increasingly crucial in line with the increasing demand for information quickly. Data regarding air temperature is generally not stationary. Therefore, one method that can be used for short-term air temperature forecasting is the time series method of ARIMA (Autoregressive Integrated Moving Average) (Anwar, 2017a, 2017b). ARIMA (Autoregressive Integrated Moving Average) is a model intensively developed by George Box and Gwilym Jenkins, which is applied to the analysis and forecasting of time series data, so this model is often known as the Box-Jenkins model. The ARIMA model is formed from a combination of self-regression models (autoregressive) and moving average models with data that has undergone a differencing process as much *d* time. The advantages of the ARIMA method make this method widely used by researchers as a forecasting method (Anwar, 2017b; Fejriani et al., 2020; Hartati, 2017; Hidayah et al., 2015; Hikmah et al., 2023). Besides that, another method, Exponential Smoothing, is a moving average forecasting technique that weighs past data exponentially so that the most recent data has a greater weight in the moving average (Handoko, 2000). Exponential Smoothing is a prediction method capable of resolving seasonal and trend data. Therefore, many researchers use Exponential Smoothing as a forecasting method (Luh et al., 2019; Nur Hamidah et al., 2013; Pujiati et al., 2016; Safitri, Dwidayati, & Kunci, 2017; Santoso et al., 2021; Widjajati et al., 2017). In addition to these methods, other methods can be used to predict minimum and maximum air temperatures, which can be found in the research by Adnyana et al. (2019).

Based on this description, the researchers are interested in predicting the daily maximum and minimum air temperatures in Cilacap Regency using ARIMA and Exponential Smoothing. This research is hoped to provide a general description of daily maximum and minimum air temperatures to be useful for everyone. This research also aims to predict the comfort level of air temperature for people in Cilacap Regency in 2022.

METHOD

Time series research is a quantitative forecasting method based on a series of data tied to the variables of this period. The data used in this method was observational data based on variations of the time series used (Ardiansah et al., 2021; Auliasari et al., 2019). This research was conducted at the Meteorological, Climatological, and Geographical Agency (BMKG) at Gatot Subroto Street No. 20, Tambaksari, Sidanegara, Cilacap Regency, Central Java. The data used was secondary in the form of temperature data taken from synoptic data in the input section. The variables used were daily maximum and minimum temperature data from January 2016 to December 2021.

ARIMA Method

Augmented Dickey-Fuller (ADF) was conducted to determine the stationarity of the data. If data is not stationary in the average (mean) or variance, a differencing process is carried out until the data becomes stationary from the function form of the ACF estimator and (PACF) estimator (Rosadi D, 2009, 2016a). If the data is stationary, the ARMA (Autoregressive Moving Average) model is determined accurately to describe the properties of the data by comparing the ACF/PACF sample plot with the properties of the ACF/PACF function from the ARMA model. To observe from these two functions when the partial autocorrelation function decreases slowly if the autocorrelation function occurs discontinuously at lag-1, the model is MA (1). Likewise, if the autocorrelation function (ACF) decreases slowly when the partial autocorrelation function is interrupted at lag-1, the model is AR (1).

Table 1. ACF and PACF Processes

Process	ACF Sample	PACF Sample
White Noise	Nothing exceeds the interval limit on the lag > 0	Nothing exceeds the interval limit on the lag > 0
AR(p)	Dies down (exponentially decreasing rapidly/sinusoidally	Cut off after lag p (disconnected after lap)
MA(q)	Cut off after lag q (disconnected after lag q)	Dies down (exponentially decreasing rapidly/sinusoidally
ARMA(p,q)	Dies down after lag (q-p) (drops quickly after lag (q-p))	Dies down after lag (p-q) (drops quickly after lag (p-q))

Table 1 explains the ACF and PACF processes for determining the ARIMA model for forecasting. The estimated value is used to determine the final forecasting value. To test whether the estimated coefficient is significant, a statistic t-test is used to distribute student-t with degrees of freedom n-1, with n = number of samples.

A diagnostic check from the estimated model is conducted by verifying the model's suitability to the data's properties. If the model is suitable, then the data calculated by the model (fitted value) will have properties similar to the original data. Two ways can determine whether the residuals are White Noise: first, by seeing whether the sample plot of standardized residual ACF/PACF (residual divided by the estimated standard deviation of the residual) meets the White Noise process properties with a mean of 0 and a variance of 1; second, by carrying out a serial correlation test. If the hypothesis diagnostic check is rejected, the model identified above cannot be used. Then, a model suitable for the data can be identified again. The final method selection in determining the best method is looking at the AIC value (Akaike Information Criterion). AIC is a useful tool in model selection. AIC can only provide a test of relative model quality. The smaller the AIC value, the better the model.

Exponential Smoothing

Data was converted into time series data with Rstudio software. After the data was converted into time series, a data plot was created to determine the data pattern in the form of trend, seasonality, or neither. The model was selected based on parameter values a, b, ϒ obtained. Each model from the two methods was then compared in value error on MAPE and RMSE to determine the best method. After getting the best model, the final step was to predict the maximum and minimum air temperatures and conclude the forecasting results.

RESULT AND DISCUSSION

The data used was 2190 time series, taken from January 1, 2016, to December 31, 2021. The calculation process is assisted using the R software. After the data input process, the data is converted into time series data. The data pattern is obtained as follows:

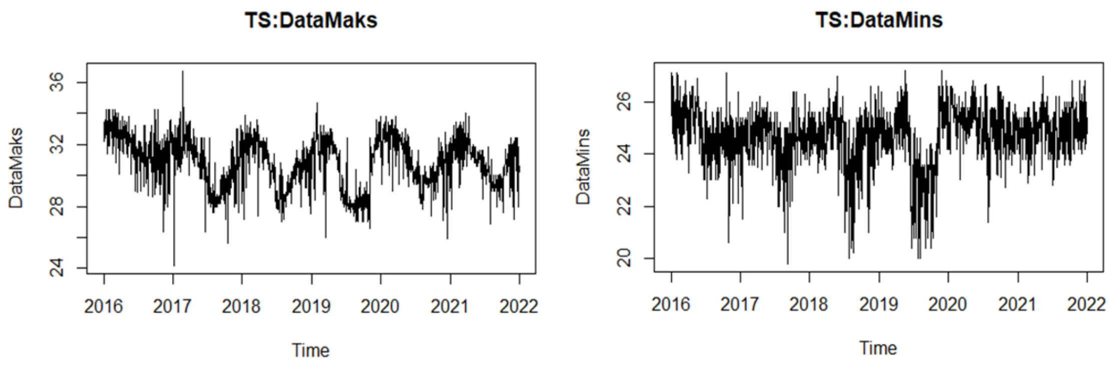

Figure 1. Data pattern of maximum air temperature (left) and minimum air temperature (right)

Based on Figure 1, both data have a seasonal pattern. It has a similar pattern within a specific period.

ARIMA Method

The first thing to do in the ARIMA method is to test the stationarity of the data in terms of variance or mean. Data testing in real-time variance can use the ADF (Augmented Dickey-Fuller Test) test. Based on the ADF test for maximum temperature data, it is obtained p-value=0.02119 < alpha=0.05, so the data is stationary in variance. Following are the ACF and PACF graphs for maximum temperature data:

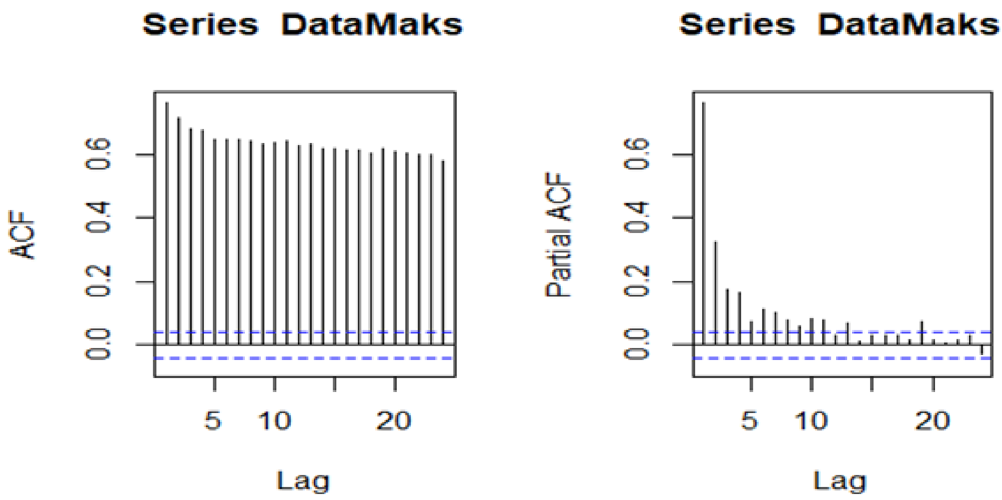

Figure 2. ACF and PACF graphs of maximum air temperature

In Figure 2, the ACF and PACF for maximum air temperature decay slowly towards zero, so the data is not stationary in mean, then it needs a differencing process, so the data becomes stationary. After going through the differencing process with d=1, The ACF and PACF plots for maximum air temperature are presented in Figure 3.

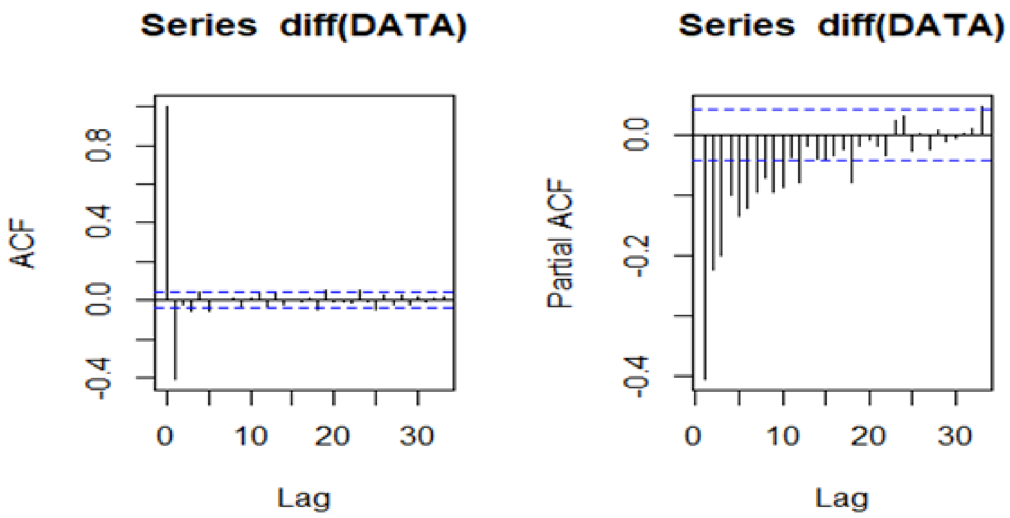

Figure 3. ACF and PACF plot of maximum air temperature after the differencing process

Based on Figure 3, ACF and PACF plots for maximum air temperature decay quickly towards zero, so it can be said that the data is stationary mean. The following is the maximum temperature data pattern after the differencing process.

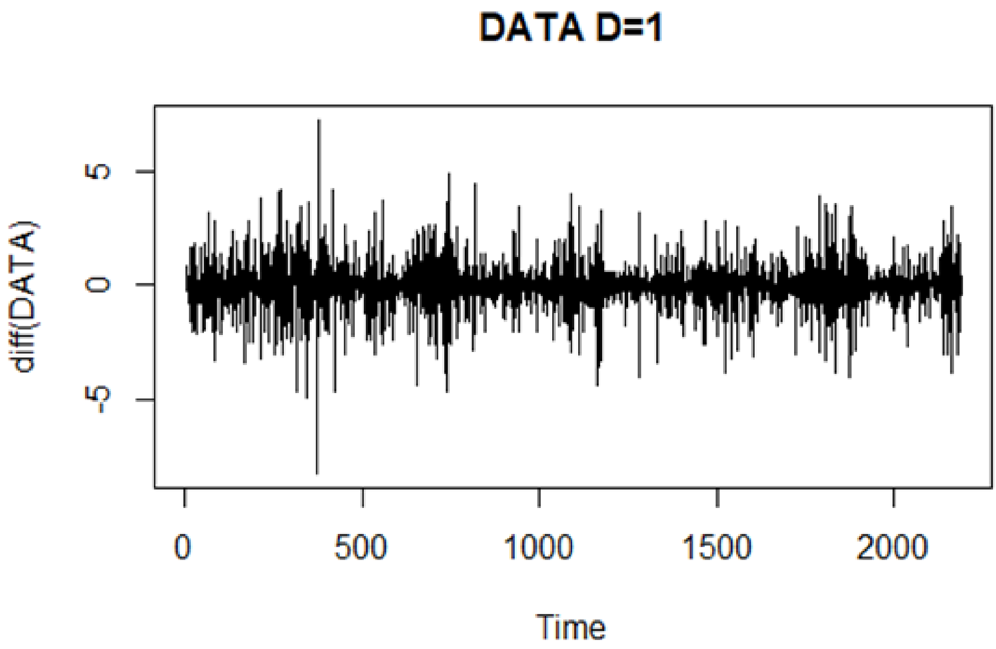

Figure 4. Maximum temperature data pattern after the differencing process

As seen in Figure 4, the maximum temperature data pattern after the differencing process is stationary. Based on the ADF test for minimum temperature data, it is obtained p-value=0.01 < alpha=0.05, so the data is stationary in variance. Following are the ACF and PACF graphs for minimum temperature data.

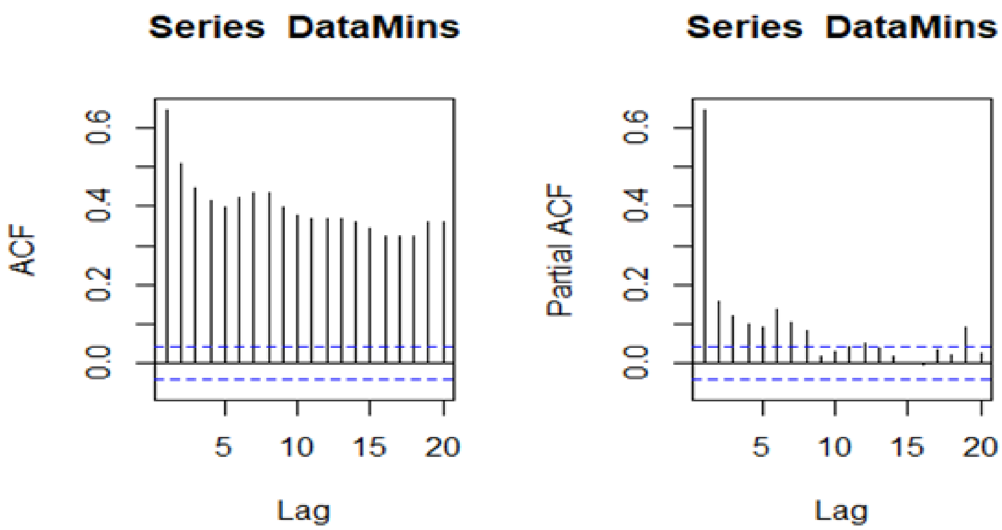

Figure 5. ACF and PACF graph of minimum air temperature

In Figure 5, the minimum temperature ACF and PACF also decay slowly toward zero, and the data is not stationary at the mean. Therefore, it needs a differencing process so that the data becomes stationary. After going through the differencing process with d =1, the ACF and PACF plots of minimum air temperature are obtained as follows.

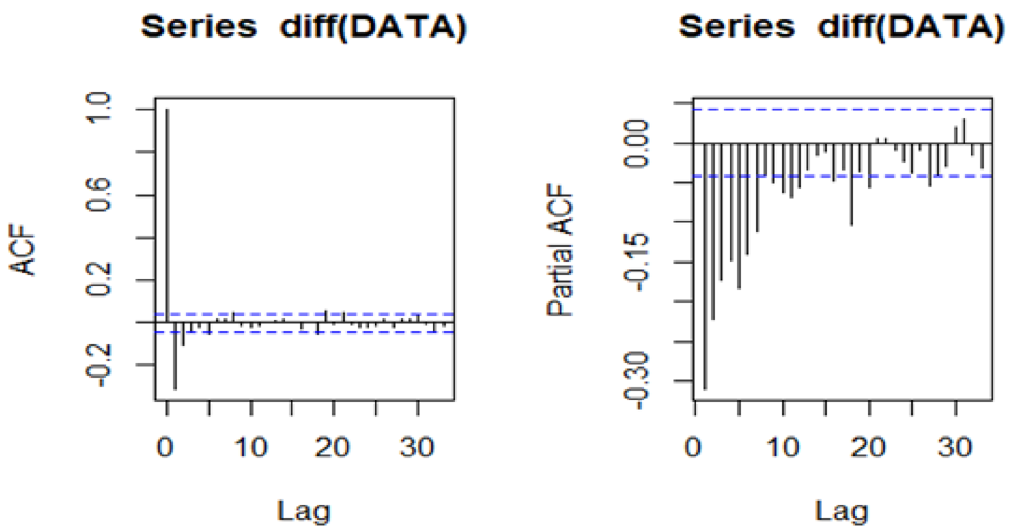

Figure 6. ACF and PACF plot of minimum temperature after the differencing process

As seen in Figure 6, the ACF and PACF plots of minimum temperature also decay slowly toward zero, and the data is not stationary in the mean. Therefore, a differencing process needs to make the data stationary. The following is the minimum temperature data pattern after the differencing process.

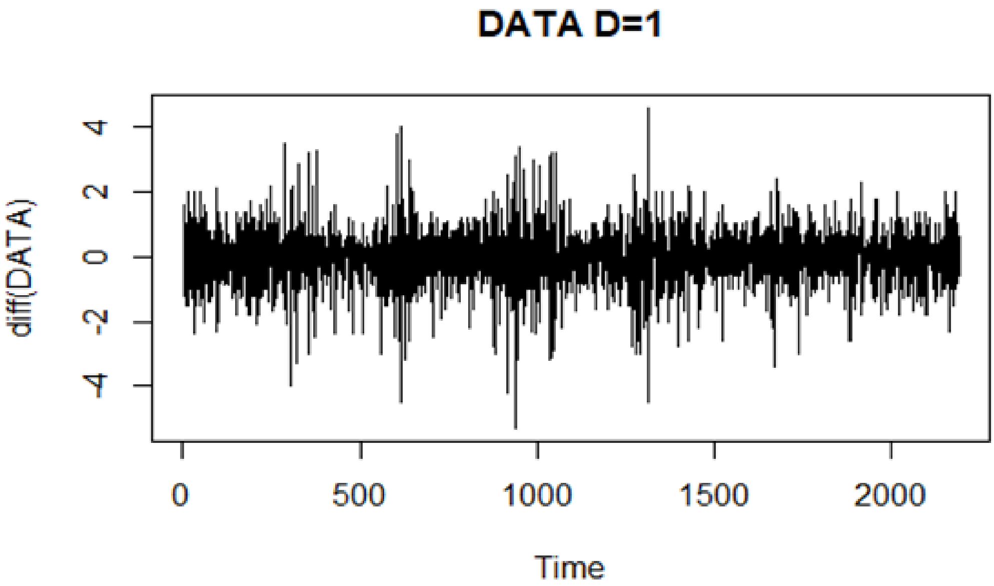

Figure 7. Minimum temperature data pattern after the differencing process

Based on Figure 7, the data is stationary. Therefore, the model needs to be identified. As seen on d=1 for the maximum air temperature in Figure 5, the ACF and PACF graphs are truncated until lag 1 in ACF, then the MA (1) model can be used. For the minimum air temperature in Figure 8 with d =1, the ACF and PACF graphs are truncated until lag 2 in ACF, so the MA (2) model can be used. The following are the ARIMA model estimation results for maximum temperature.

Table 2. ARIMA Model estimation of maximum temperature

Model	P-value	Error	AIC	Result
Arima (0,1,2)	Pr(>|z|) ma1 < 2.2e-16 ma2 < 2.2e-16	MAPE: 2.106893 RMSE: 0.9237616	5,872.95	Significant on alpha
Arima (1,1,1)	Pr(>|z|) ar1 < 2.2e-16 ma1 < 2.2e-16	MAPE: 2.102879 RMSE: 0.9201609	5,855.88	Significant on alpha
Arima (2,1,2)	Pr(>|z|) ar1 0.069226 ar2 8.247e-07 ma1 0.125127 ma2 0.001477	MAPE: 2.098182 RMSE: 0.9177679	5,848.48	Significant on alpha

Based on Table 2, the three models have significant coefficients because the p-value of each is less than 0.05. The ARIMA (2,1,2) model has the smallest error value of the three models with MAPE = 2.098182 and RMSE = 0.9177679. Thus, the ARIMA (2,1,2) is the best model. The following are the ARIMA model estimation results for minimum temperature.

Table 3. ARIMA Model estimation of minimum temperature

Model	P-value	Error	AIC	Result
Arima (1,1,2)	Pr(>|z|) ar1 3.74e-10 ma1 < 2.2e-16 ma2 0.9083	MAPE: 2.443075 RMSE: 0.8001746	5,246.28	Significant on alpha
Arima (1,1,1)	Pr(>|z|) ar1 < 2.2e-16 ma1 < 2.2e-16	MAPE: 2.443044 RMSE: 0.8001771	5,244.30	Significant on alpha
Arima (0,1,2)	Pr(>|z|) ma1 < 2.2e-16 ma2 < 2.2e-16	MAPE: 2.472309 RMSE: 0.8054686	5,273.09	Significant on alpha

Based on Table 3, the three models have significant coefficients because the p-value of each is less than 0.05. Of the three models, the ARIMA (1,1,1) model has the smallest error value, with MAPE = 2.443044 and RMSE = 0.8001771. Thus, ARIMA (1,1,1) is the best model. Here are the results of the diagnostic checking for maximum air temperature.

Table 4. Results of diagnostic checking for maximum air temperature

Model	**Standardized residual**	**ACF residual**	**p-value LjungBox**	**One Sample t-test**	**Result**
Arima (0,1,2)	considered to be in the middle of 0	has autocorrelation	has autocorrelation	p-value = $0.7787 \geq 0.05$	not pass
Arima (1,1,1)	considered to be in the middle of 0	has autocorrelation	has autocorrelation	p-value = $0.7628 \geq 0.05$	not pass
Arima (2,1,2)	considered to be in the middle of 0	has no autocorrelation	has no autocorrelation	p-value = $0.7593 \geq 0.05$	pass

Table 4 shows that the ARIMA (2,1,2) model passes in diagnostic checking, so the ARIMA (2,1,2) model is more suitable for predicting maximum air temperature in Cilacap Regency than the other two models.

Here are the results of the diagnostic checking for minimum temperature. Table 5 shows that the ARIMA (1,1,1) and ARIMA (1,1,2) models pass the diagnostic checking. Therefore, the model with the smallest AIC value is chosen, the ARIMA (1,1,1) model. Thus, the ARIMA (1,1,1) model is more suitable for predicting minimum air temperatures in Cilacap Regency than the other two models.

Table 5. Results of diagnostic checking for minimum air temperature

Model	**Standardized residual**	**ACF residual**	**p-value LjungBox**	**One Sample t-test**	**Result**
Arima (1,1,2)	considered to be in the middle of 0	has no autocorrelation	has no autocorrelation	p-value = $0.8621 \geq 0.05$	pass
Arima (1,1,1)	considered to be in the middle of 0	has no autocorrelation	has no autocorrelation	p-value = $0.8622 \geq 0.05$	pass
Arima (0,1,2)	considered to be in the middle of 0	has autocorrelation	has autocorrelation	p-value = $0.8782 \geq 0.05$	not pass

Exponential Smoothing

The following is the maximum air temperature pattern in the Cilacap Regency using Exponential Smoothing in seasonal multiplication.

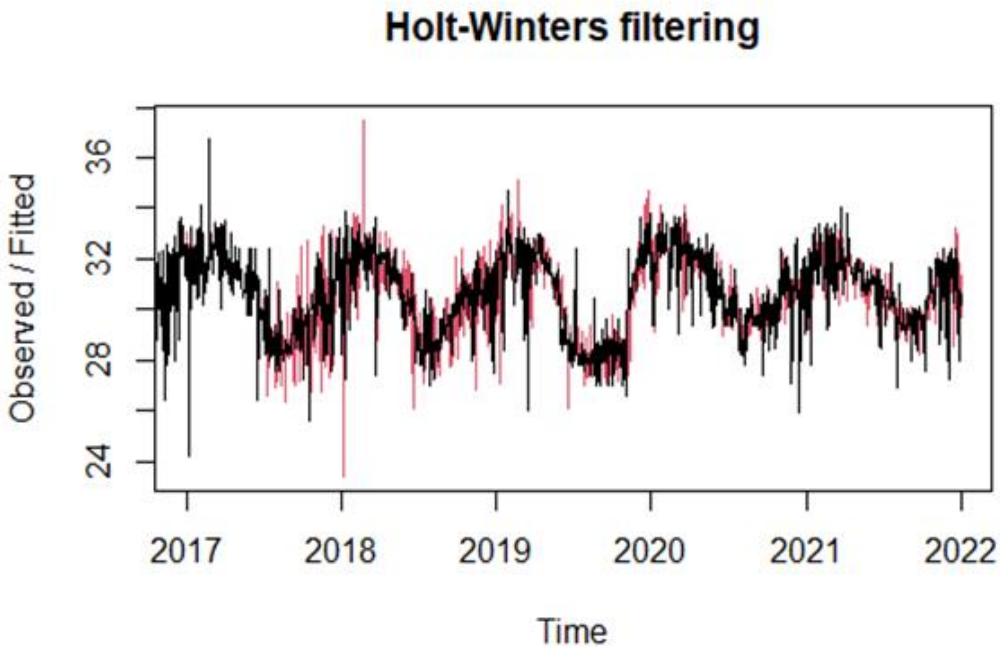

Figure 8. ETS Multi maximum air temperature data pattern

Figure 8 displays the maximum air temperature data pattern using Exponential Smoothing in seasonal multiplication (red color) with parameters α = 0.1654427, β = 0, γ =0.4911464 obtained MSE = 6.343707, RMSE = 2.518672, and MAPE = 2.535541. The following is the minimum air temperature pattern in Cilacap Regency using Exponential Smoothing in seasonal multiplication.

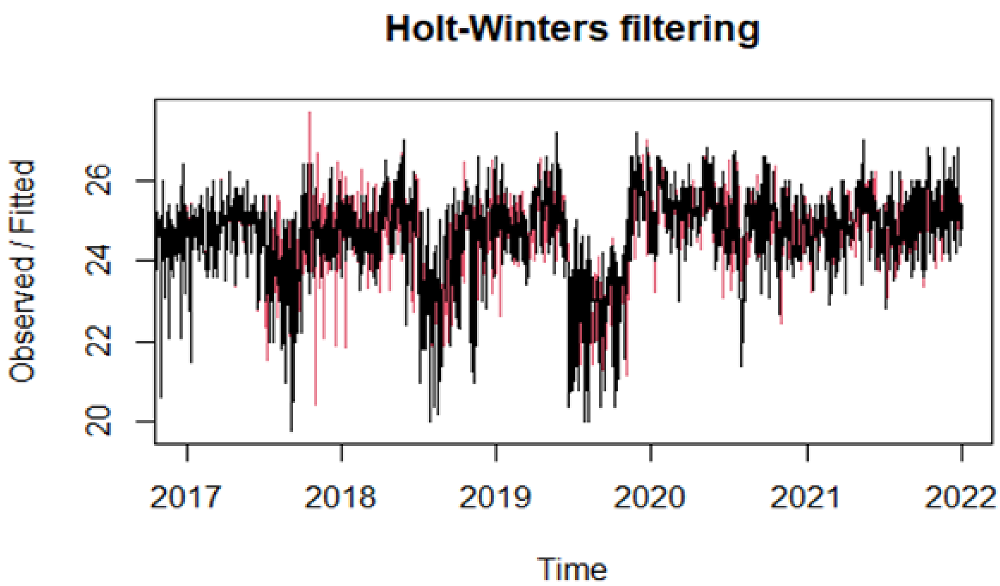

Figure 9. ETS Multi minimum air temperature data pattern

Figure 9 displays the maximum air temperature data pattern using Exponential Smoothing in seasonal multiplication (red color) with parameters α = 0.1561916, β = 0, γ= 0.3416249 obtained MSE = 4.864788, RMSE = 2.205626, and MAPE = 2.971936.

The maximum air temperature pattern by Exponential Smoothing in seasonal additions follows. Figure 10 displays the maximum air temperature data pattern with parameters α= 0.1856616, β = 0, γ = 0.5170383 obtained MSE = 6.38191, RMSE = 2.526244, and MAPE = 2.538972. Figure 11 displays the maximum air temperature data pattern with parameters α = 0.1618416, β = 0, γ= 0.3518946 obtained MSE = 4.85377, RMSE = 2.203127, and MAPE = 2.962606.

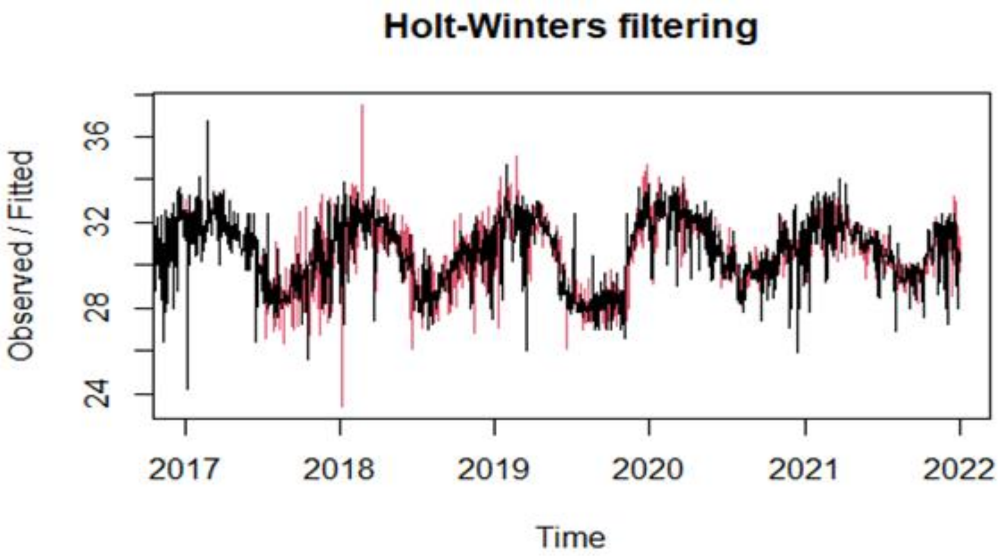

Figure 10. ETS Additive maximum air temperature data pattern

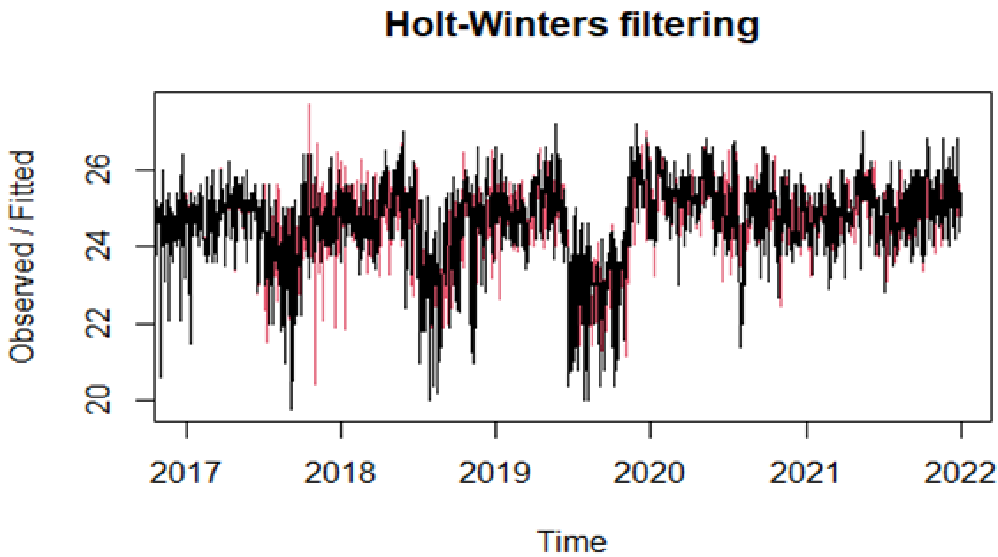

Figure 11. ETS Additive minimum air temperature data pattern

Based on the error values obtained from both Exponential Smoothing methods, it can be concluded that the Exponential Smoothing in seasonal multiplication is more suitable for predicting maximum air temperatures in the Cilacap Regency. This is because the RMSE and MAPE values for Exponential Smoothing in seasonal multiplication on maximum air temperature data are smaller than RMSE and MAPE in seasonal additions. On the other hand, the Exponential Smoothing method in seasonal addition is more suitable for predicting minimum air temperatures in the Cilacap Regency. This is because the RMSE and MAPE values for Exponential Smoothing in seasonal additions on maximum air temperature data are smaller than RMSE and MAPE in seasonal multiplication.

Determination of the Best Model and Forecasting

The following compares error values for the ARIMA model and the Exponential Smoothing selected for each maximum and minimum air temperature in Cilacap Regency.

Table 6. Comparison of error values

Method	RMSE (Max temp.)	MAPE (Max temp.)	RMSE (Min temp.)	MAPE (Min temp.)
ARIMA	0.9177679	2.098182	0.8001771	2.443044
Exponential Smoothing	2.526244	2.538972	2.203127	2.962606

Based on Table 6, it can be concluded that the ARIMA (2,1,2) model is the best method chosen to predict maximum air temperature in the Cilacap Regency. This is because the error values, namely the RMSE and MAPE values for the ARIMA model, are smaller than the Exponential Smoothing. Likewise, for minimum air temperature in the Cilacap Regency, the ARIMA (1,1,1) model is the best method to predict minimum air temperature in the Cilacap Regency. This is also because the ARIMA model's RMSE and MAPE values are smaller than the Exponential Smoothing. The following are the forecasting results for maximum and minimum air temperatures in Cilacap Regency for one year (365 days).

Maximum Temperature

The following are the results of forecasting the maximum air temperature in Cilacap Regency for one year or 365 days using the ARIMA (2,1,2) model.

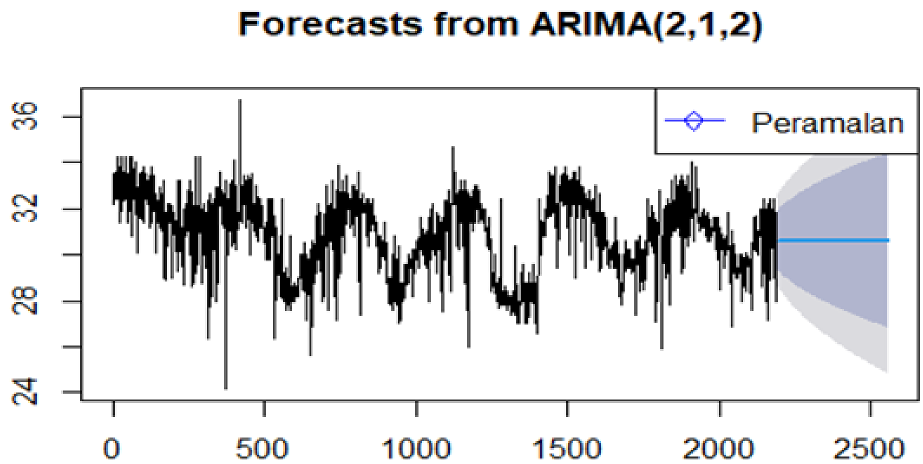

Figure 12. Graph of maximum temperature forecasting results

Based on Figure 12, the results of forecasting using the ARIMA (2,1,2) model show that the maximum air temperature in Cilacap Regency in 2022 was estimated to be around 30.6°C, with a 95% confidence interval between 28°C - 35°C.

Minimum Temperature

The following are the results of forecasting minimum air temperature in Cilacap Regency for one year or 365 days using the ARIMA (1,1,1) model. Based on Figure 13, the results of forecasting using the ARIMA (1,1,1) model show that the minimum temperature in Cilacap Regency in 2022 was estimated to be around 25.1°C, with a 95% confidence interval between 23°C - 28°C.

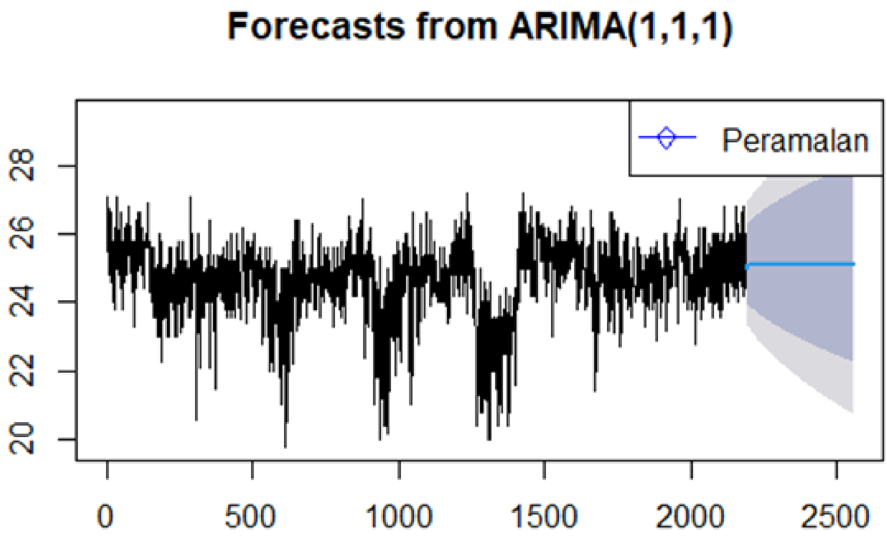

Figure 13. Graph of minimum temperature forecasting results

In this research, maximum and minimum air temperature forecasting in Cilacap Regency was produced using two different methods: ARIMA and Exponential Smoothing. The ARIMA method provides more accurate forecasting of maximum and minimum air temperature than Exponential Smoothing. The ARIMA model's RMSE and MAPE values are smaller than the Exponential Smoothing for maximum and minimum air temperatures. It is predicted that in 2022, the maximum air temperature in Cilacap Regency will be around 30.6°C, with a 95% confidence interval between 28°C - 35°C. Meanwhile, the minimum air temperature in Cilacap Regency is predicted to be around 25.1°C, with a 95% confidence interval between 23°C - 28°C. The ARIMA model has high strength and flexibility in analyzing various time series data, and the forecast value results are more accurate (Montgomery et al., 2008). The advantages of ARIMA are that it is flexible (follows data patterns), has a relatively high level of forecasting accuracy, and is suitable for forecasting several variables quickly, simply, accurately, and cheaply because it only requires historical data to forecast (Meyler et al., 2008).

Earth's temperature influences 51% of differences in thermal sensation assessments and is the only statistically significant meteorological predictor. Regression of subjective thermal sensation on the physiologically equivalent temperature yielded a neutral temperature of 28.6°C. The acceptable comfort range is 19.1°C to 38.1°C with a preferred temperature of 20.8°C (Middel et al., 2016). Therefore, it is predicted that the maximum and minimum air temperatures in Cilacap Regency in 2022 will still be comfortable for the community.

The neutral temperature in urban green spaces for open spaces in equatorial areas when residents do not experience heat or cold stress is 26.2°C. In comparison, the acceptable temperature ranges from 21.6°C to 31.6°C, with the preferred ideal temperature being 24.2°C

(Heng & Chow, 2019). Furthermore, air-conditioned building interiors in hot and humid areas have resulted in thermal discomfort and health risks for people entering and exiting the building. Reports show that instantaneous changes in air temperature can cause a sudden thermoregulatory response. Thermal comfort assessment resulting from movement through spaces with different thermal conditions was conducted in a single-floor office in a hot-humid microclimate, maintained at an air temperature of 24°C (± 0.5). Meanwhile, the office connected to the veranda shows a semi-outdoor air temperature of 35 °C (± 2.1) (Dahlan & Gital, 2016). Based on these two studies, the average maximum and minimum air temperature in Cilacap Regency in 2022 is predicted to remain in the neutral and comfortable temperature category as an industrial or office urban area.

CONCLUSION

Based on these results, the ARIMA (2,1,2) model is the best model selected for predicting maximum air temperature in Cilacap Regency, and the ARIMA (1,1,1) model is the best model selected for predicting minimum air temperature in Cilacap Regency. Based on this model, it is estimated that the average maximum air temperature in 2022 in Cilacap Regency will be around 30.6^{o}C, with a 95% confidence interval between 28^{o}C - 35^{o}C. Meanwhile, the average maximum air temperature in 2022 in Cilacap Regency will be around 25.1^{o}C, with a 95% confidence interval between 23^{o}C - 28^{o}C. Based on the forecasting results, it can be concluded that in 2022, it is predicted that the air temperature in Cilacap Regency will still be quite comfortable for daily activities, industry, and offices.

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