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RAINFALL PREDICTION USING SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE AND GEOGRAPHIC INFORMATION SYSTEM APPROACH

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Abstract—*Rainfall is one indicator to determine the estimated adequacy of groundwater on agricultural land. The groundwater availability produced by rain can determine cropping patterns in an area. The availability of rainfall data depends on the accuracy of information on current climate conditions. This case causes the related parties to find difficulty determining the classification of cropping patterns in the future. Accurate rainfall prediction models are needed to overcome the problem of shifting rain patterns. Rainfall prediction models in determining cropping patterns are recommended by FAO, such as linear regression, which is still widely used today. This study aims to develop a new model of rainfall prediction by using the method SARIMA to determine cropping patterns to increase crop yields. Rainfall data was used from 2010 to 2020 from seven rainfall collection stations in Sleman Regency, and they are used as training data to predict future rainfall. The output of the data analysis is a prediction of rainfall in the range of January-April, which is predicted to be high, May-August, which is predicted to be low; and September-December, which is predicted to be moderate. In addition, based on the identified cropping patterns, recommendations can be given to farmers to set cropping schedules and strategies to increase the productivity of the farmland. The testing of accuracy forecasting used relative mean absolute error (RMAE) for 12 months. The results of the forecasting accuracy test for 12 months in Sleman Regency showed RMAE average of 1.46 was considered low, for it was still below 10%.*

Keywords: *Prediction, Seasonal Autoregressive Integrated Moving Average, Cropping Pattern*.

Intisari—*Curah hujan merupakan salah satu indikator untuk menentukan estimasi kecukupan air tanah pada lahan pertanian. Ketersediaan air tanah yang dihasilkan oleh hujan dapat menentukan pola tanam di suatu daerah. Namun ketersediaan data curah hujan biasanya bergantung pada data yang akurat tentang kondisi iklim saat ini. Kasus ini menyebabkan pihak terkait kesulitan menentukan klasifikasi pola tanam di masa mendatang. Model prediksi curah hujan yang akurat sangat dibutuhkan untuk mengatasi masalah pergeseran pola hujan. Model prediksi curah hujan dalam menentukan pola tanam direkomendasikan oleh FAO, seperti regresi linier yang masih banyak digunakan hingga saat ini. Penelitian ini bertujuan untuk mengembangkan model baru prediksi curah hujan dengan menggunakan metode SARIMA untuk menentukan pola tanam guna meningkatkan hasil panen. Data curah hujan yang digunakan dari tahun 2010 hingga 2020 dari tujuh stasiun pengumpul curah hujan di Kabupaten Sleman, digunakan sebagai data latih untuk memprediksi curah hujan yang akan datang. Output dari analisis data tersebut berupa prediksi curah hujan pada kisaran bulan Januari-April yang diperkirakan tinggi, Mei-Agustus yang diperkirakan rendah, dan September-Desember yang diperkirakan sedang. Selain itu, berdasarkan pola tanam yang teridentifikasi, rekomendasi dapat diberikan kepada petani untuk mengatur jadwal dan strategi penanaman guna meningkatkan produktivitas lahan pertanian. Pengujian akurasi peramalan menggunakan relative mean absolute error (RMAE) selama periode 12 bulan. Hasil uji akurasi peramalan periode 12 bulan di Kabupaten Sleman menunjukkan rata-rata RMAE sebesar 1,46 tergolong rendah karena masih di bawah 10%.*

Kata Kunci: *Prediksi, Seasonal Autoregressive Integrated Moving Average, Pola Tanam.*

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INTRODUCTION

Changes in rain patterns have occurred in the last few decades in several parts of Indonesia, such as the shift in the beginning of the rainy season and changes in rainfall patterns. In addition, there is a trend of monthly rainfall with increasing diversity and deviation as well as an increase in the frequency of extreme climate events, especially rainfall, wind, and tidal flooding, in northern Sumatra and Kalimantan in particular, where rainfall tends to be lower, but with a longer period [1].

On the other hand, in the southern regions of Java and Bali, rainfall tends to increase but with a shorter period [2]. The previous study on time series data forecasting indicates that the accuracy of the predictions for rainfall and weather is still inadequate, as the forecasting errors remain substantial and the predictions are still unreliable.

One of the reasons is because the weather data have a non-linear structure [3]. The literature review of the rainfall prediction model with acceptable accuracy used to make cropping patterns have not produced accurate long-term rainfall results [4], [5].

It is still using methods with a high level of complexity. The literature also shows that no rainfall prediction model is integrated with the planting period model. The solution proposed in this study is related to rainfall data patterns in Indonesia, which generally have three main characteristics: moderate rainfall (January–April), low rainfall (May-August), and rainfall. September–December). There has been a change in the timing of rain in the last 15 years [6], but the rice cropping pattern in Indonesia follows the three rainfalls. The proposed rainfall model, by taking into account the life cycle of food plants, is the leading study in the preparation of the model. This contributes novelty to the existing forecasting models for pattern plants.

Rainfall has an essential role in the development of activities on agricultural land. Rainfall is used as a variable in determining between wet and dry months. Wet and dry months are used to classify climate and weather forecasts in an area. To increase agricultural yields, predictions of the amount of rainfall are recommended by World Food Organization (*Food and Agriculture Organization*). Indonesia is a country with a tropical climate because it has relatively high humidity, high rainfall, and an annual temperature above 18 degrees Celsius. Some areas on Java, Sumatra, and Kalimantan islands have tropical areas, so there are tropical forests in their part of the region. Sleman Regency is one of the regions on Java Island. Topography can be distinguished based on altitude and land slope. Physically, Sleman Regency area is relatively flat in the southern area, except for the hilly areas in the south eastern part of Prambanan District and partly in Gamping District. The north area is relatively sloping, and on the north side, the slopes of Merapi are relatively steep, and there are about 100 springs. Most of the area of Sleman Regency is fertile agricultural land with technical irrigation support in the west and south.

In addition, Sleman Regency has a wet tropical climate with a rainy season between November - and April and a dry season between May - and October. In 2000, the total number of rainy days of 25 days occurred in March; however, the average amount of Rainfall in February was 16.2 mm with 20 days of rainy days. The lowest relative humidity in 2000 was in August at 74% and the highest in March and November at 87%, respectively, while the lowest air temperature was 26.1 degrees Celsius in January and November, and the highest air temperature was 27.4 degrees Celsius in September.

Sleman Regency area has good potential for agricultural land yields. Therefore, it affects the welfare of the local population. People's activities in agriculture or plantations require information [7] that is related to the quantity and quality of water and areas of water availability because these things will affect what types of crops will be planted in a specific area [8], the cropping pattern (whether a particular type of plant will be planted throughout the year or only in certain months), the pattern of irrigation, the level of agricultural production, and so on [9]. In connection with several things in the previous paragraph, from the point of view of computer science, prediction methods can be used to in various fields such as health [10], agriculture [8] and so on and also in various cases determine specific areas (classification of areas) in the research area that can become places with sufficient water intake based on variables [11]. They are rainfall [12], humidity [13], slope conditions [14], soil type (porosity and permeability), distribution of springs in rivers [15], and irrigation networks [16], which are very important for agricultural activities [17].

The impact of shifting rainfall patterns affects agricultural resources and infrastructure[18], which causes shifts in planting time [19], seasons [20], and cropping patterns. The potency of shortening the rainy season and increasing rainfall in the southern part of Java and Bali resulted in changes in the beginning and duration of the growing season. This case is affecting the productivity of agricultural products. Seeing the sufficient potential in Sleman Regency area in the agricultural sector, it is very suitable for the development of research that is being carried out. Planning for research data needs in the form of rainfall data, air humidity, air temperature, and wind speed in the Sleman Regency area.

The data is available at the Meteorology, Climatology, and Geophysics Agency within the government of Sleman Regency. Based on the literature review carried out in previous studies for the prediction of agricultural cultivation, linear prediction methods are still used, which have weaknesses in short-term prediction inconsistencies to affect the accuracy of prediction results. This research aimed to explore alternative approaches and develop new methods and processing steps to achieve an optimal level of accuracy in predicting rainfall. The ultimate goal was establishing a local cropping pattern planning model based on reliable rainfall predictions. The output is a prediction model for rainfall and cropping pattern recommendations.

MATERIALS AND METHODS

The activity of collecting forecast rainfall data aims to get the suitability of cropping patterns in the Sleman Regency area. The first step is data pre-processing which is carried out to obtain high data quality and validity. The novelties in this research are:

1. Develop alternative methods for predicting location-specific rainfall which has an optimum with an error value below 10%.
2. A novel method for grouping data based on mass patterns of plants was generated.

Data

The type of data in this study is secondary data from rainfall data, air temperature, air humidity, and wind speed obtained from the Meteorology, Climatology, and Geophysics Agency of Sleman Regency.

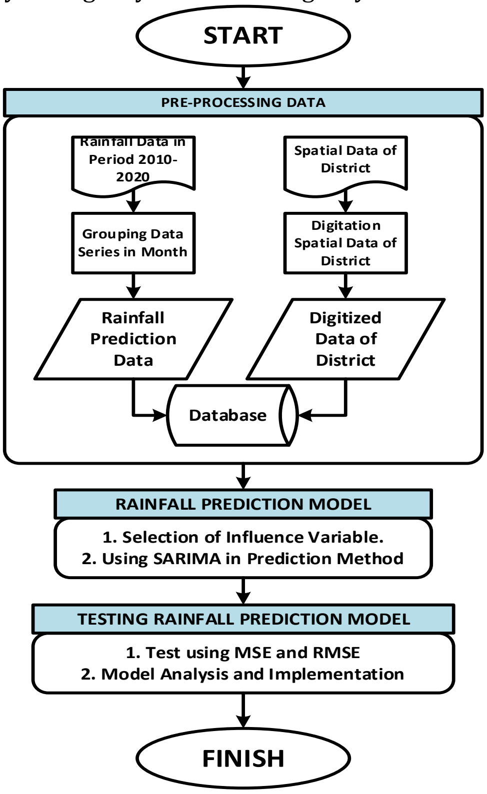

Figure 1 Propose Method

1. The initial stage is to collect references for enriching the material according to the reference in the research. The references consist of all literature studies on rainfall prediction methods and their relation to cropping patterns on agricultural land. Data needs include rainfall data with monthly series starting from 2010 to 2020, while for sub-district spatial data in the form of administrative data for 17 sub-districts in Sleman district.
2. Phase II is carried out by modelling rainfall predictions involving several variables, namely rainfall, humidity, temperature, and regional spatiality. The investigation of influential variables used statistical methods, namely the test of determination (R2), to see how much influence each variable used in the study had. Then the prediction process is carried out using the Seasonal Autoregressive Integrated Moving Average (SARIMA) method. Furthermore, at this stage, algorithms are also arranged and implemented in a rainfall prediction model using the Seasonal Autoregressive Integrated Moving Average method.
3. Phase – III, namely, testing the rainfall prediction model using the Seasonal Autoregressive Integrated Moving method Average with test size RMSE (Root Mean Squared Error) and MSE (Mean Squared Error). Tests are carried out to see the error value prediction, and a suitable error value is close to 0.

The procedure to find planting period and cropping pattern is described in Algorithm 1.

Algorithm 1: Procedure to Planting Period and Cropping Pattern.

Input: $data[N]$=*monthly rainfall during planting period.*
$dasarian[N]$=*basic form in period of planting.*

For i=1 **to** N−1 **do**
If $dasarian[i]$<>$dasarian[i+1]$ **then**
$hasil$=0
Else then
$hasil$=1
End If
End For
If $hasil$==1 **then**
$hasil$="*paddy*"
Else then
If ($SUM(data)4$) ≥ 200 **then**
$hasil$="*padi*"

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Else If $(SUM(data)4) \geq 100\ AND\ (SUM(data)4) < 200$
then
hasil palawija" ="
Else then
hasil="bera"
End If
End If

Algorithm 1 (Procedure to Planting Period and Cropping Pattern) is used in determining the planting period and cropping pattern based on the primary value of rainfall. It is known that in one planting period, there are four months of planting time (the process from planting to harvesting), so a successive baseline value is needed in a period of 3 months.

Experimental Research

3. Experimental Research

The implementation of the data forecasting process by using the method of seasonal autoregressive integrated moving average (SARIMA) is carried out in several stages, including:

1) Pre-processing Data;
2) Identification of Plot Data;
3) Parameter Estimation;
4) Diagnostic Checking;
5) Forecasting Data.

1. Pre-Processing Data

In this step, the first thing to do is *pre-process* research data which consists of monthly rainfall data, for the period from 2015 to 2020. Pre-processing of rainfall data is carried out by adding daily rainfall data into monthly periods for locations in the Sleman Regency. Pre-processing of rainfall data begins with checking monthly data series from January 2015 to December 2020. Rainfall data consists of 60 DHF case *records* from 2015 to 2020 with four weather data collection stations in all sub-districts in Sleman Regency, so the total *records* are 240 data from monthly rainfall.

The step of pre-processing data is essential to improve accuracy in forecasting. A data table consists of rows and columns; rows in a data table represent units, also called observations. In this case, the monthly Rainfall amount is shown, while columns in a table represent variables measured in a unit. A data table consists of rows and columns of *n* units of observation with *m* variables that can be measured. Unfortunately, it is not always possible to obtain a complete data matrix in practice. Experiments of pre-processing data were carried out for all missing values from the total data on the amount of rainfall. The proposed method requires input in the form of monthly rainfall data with monthly data series, but the application of the method requires sufficient data with a *seasonal* trend. The main difficulty that occurs is that when there is no rain in an area, the report is not recorded correctly, so the data characteristics cannot be identified as patterns. Therefore, it is necessary to re-record areas where there are no cases in a specific month by inputting zero **(0)**; this is done to know the performance of forecasting and the level of achievement of adequate accuracy for the application of the proposed method. An example of the process results on the initial five records monthly rainfall data series for several areas in Sleman Regency is shown in Table 1.

Table 1. Incomplete Rainfall Data

No	Year	Month											
		1	2	3	4	5	6	7	8	9	10	11	12
1	2015	347.3	417.7	457.7	432.4	178.1	56.8	-	-	-	-	96.8	416.1
2	2016	7.9	16.0	13.7	2.6	1.9	6.4	3.2	6.4	4.8	6.4	17.7	10.9
3	2017	414.5	336.9	135.3	283.3	18.7	46.4	36.7	1.5	-	TTU	316.4	319.3
4	2018	412.4	517.6	195.5	244.4	245.8	226.4	78.1	0.6	0.9	43.3	407.8	329.5
5	2019	377.3	279.5	298	155.6	69.4	5.2	TTU	-	-	87.6	430.5	453.7

(Source: Badan Pusat Statistik, 2020)

In Table 1, there are several columns with the input in the form of TTU, and TTU means that the data on the amount of rainfall is not measured. The following process is to input data on the part of the month which is not filled with data with a value of zero (0) in Table 1 to complete the needs of preprocessing data. The results are shown in Table 2.

Table 2. Data of The Amount of Rainfall after Normalization

No	Year	Month											
		1	2	3	4	5	6	7	8	9	10	11	12
1	2015	347.3	417.7	457.7	432.4	178.1	56.8	**0**	**0**	**0**	**0**	96.8	416.1
2	2016	7.9	16.0	13.7	2.6	1.9	6.4	3.2	6.4	4.8	6.4	17.7	10.9
3	2017	414.5	336.9	135.3	283.3	18.7	46.4	36.7	1.5	**0**	**0**	316.4	319.3
4	2018	412.4	517.6	195.5	244.4	245.8	226.4	78.1	0.6	0.9	43.3	407.8	329.5
5	2019	377.3	279.5	298	155.6	69.4	5.2	**0**	**0**	**0**	87.6	430.5	453.7

(Source: Badan Pusat Statistik, 2020)

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All the processes mentioned above are carried out from January 2015 to December 2020. The data is sufficient enough to proceed with the following process.

2. Identification of Plot Data Series.

After data is clean and has a monthly period, the next step is to identify the data series plots and test the stationarity of the data as a condition used in forecasting rainfall by using the SARIMA method. These steps are intended to get an initial estimate of the model's shape that fits the data. Data series plots are identified to determine whether the data has a trending nature (has an upward trend or can also decrease in a certain period), is seasonal, or random. The data is displayed in the form of a time series plot.

Through the time series plot, it will be seen that the data has a stationary tendency or has not been seen with the naked eye, for example, given an example of data on the amount of rainfall from 2015 to 2020 as shown in Table 3.

Table 3. Data Sample of Total Rainfall during 2015 - 2020

No	The Year 2015		The Year 2016		The Year 2017		The Year 2018		The Year 2019		The Year 2020	
1	Jan	254.3	Jan	400.7	Jan	377.3	Jan	412.4	Jan	414.5	Jan	347.3
2	Feb	311.6	Feb	322.7	Feb	279.5	Feb	517.6	Feb	336.9	Feb	417.7
3	March	413.6	March	334.7	March	298	March	195.5	March	135.3	March	457.7
4	April	131.2	April	264.6	April	155.6	April	244.4	April	283.3	April	432.4
5	May	319.3	May	334.7	May	69.4	May	245.8	May	18.7	May	178.1
6	June	113.1	June	0	June	5.2	June	226.4	June	46.4	June	56.8
7	July	34.5	July	0	July	0	July	78.1	July	36.7	July	0
8	August	155.2	August	0	August	0	August	0.6	August	1.5	August	0
9	Sept	400.5	Sept	0.5	Sept	0	Sept	0.9	Sept	0	Sept	0
10	Oct	157.2	Oct	19	Oct	87.6	Oct	43.3	Oct	0	Oct	0
11	Nov	240	Nov	371.3	Nov	430.5	Nov	407.8	Nov	316.4	Nov	96.8
12	Dec	512.3	Dec	388.5	Dec	453.7	Dec	329.5	Dec	319.3	Dec	416.1

The initial assumption is that the data has a stationary tendency, so it is necessary to represent the data as a whole by plotting the research data. Further checking is the stationarity test. If the results show that the data is not stationary, then the step of differencing must be done. In order to get an overview of the implementation, we shown in *Figure 1*.

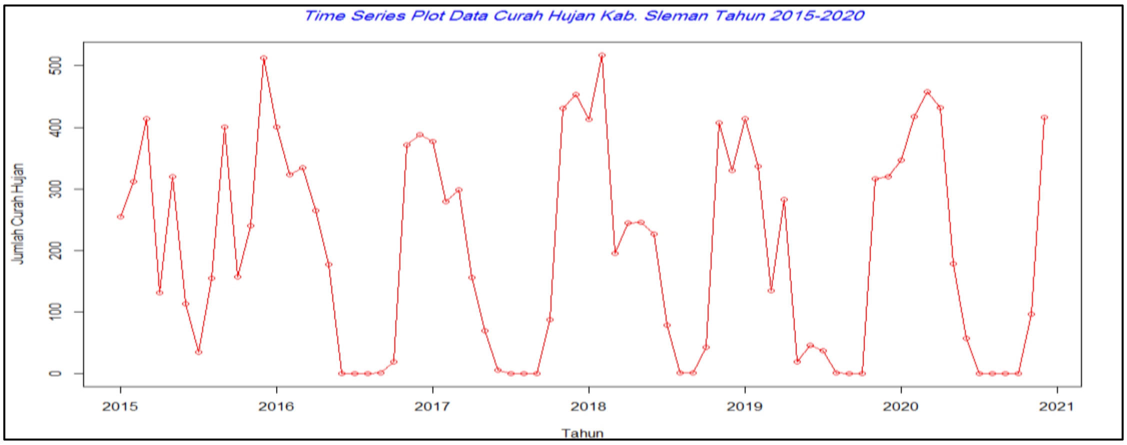

Figure 2. Data Plot of total Rainfall in 2015-2020

Based on the observations of the plot series from *Figure 2*, it can be seen that there is a repeating seasonal pattern (*seasonal*) in months 2, 3, 4, 5, 7, 8, 9, 13, 14, 22, 23 so on. However, there is also a trend pattern in the plot of the data series in months 18, 19, 20, 21, etc. To sharpen the analysis, it is necessary to prove through the stationarity test of the data. The stationarity test in this study was carried out using *the Augmented Dickey-Fuller* test.

```
> #uji stasioneritas data menggunakan adf.test Dicky Fuller untuk melihat data stasioner
> adf.test(data)

	Augmented Dickey-Fuller Test

data:  data
Dickey-Fuller = -6.4547, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

Figure 3. Results of ADF Rainfall Test

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In the ADF test results shown in Figure 3, the ADF value obtained is -6.4547, and the *p-value* is 0.01, so it can be concluded that the data does not contain an element of trend or the data has met the seasonal nature.

Furthermore, identification is carried out based on the ACF plot and PACF *differencing* to determine the optimum *lag* on ACF and PACF plots because it will be an alternative temporary model. Furthermore, identification is carried out based on ACF and PACF differencing plots to determine the optimum lag in ACF and PACF plots because they will be alternative temporary models. Meanwhile, ACF plots and the second order PACF differencing plots are shown sequentially in Figure 4 and Figure 5.

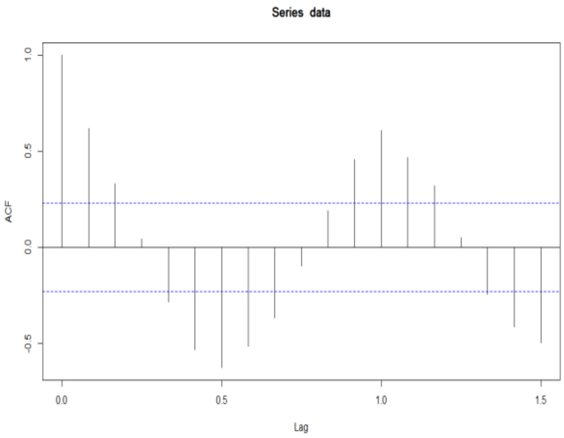

Figure 4. Data Plot of ACF Rainfall in Sleman Regency

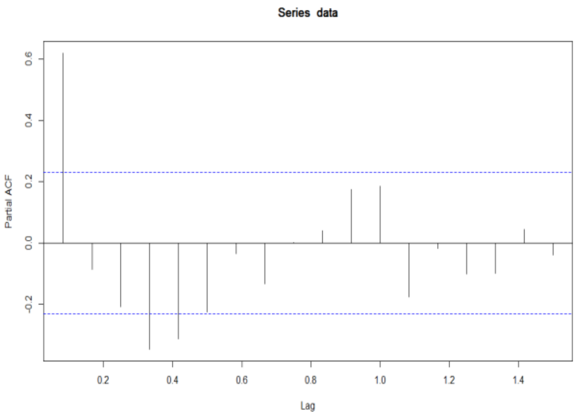

Figure 5. Plot PACF Data of Rainfall in Sleman Regency

From Figure 4 and Figure 5, it is identified that the data shows stationary in the seasonal average at lag-6 because it dries down (lag drops slowly).

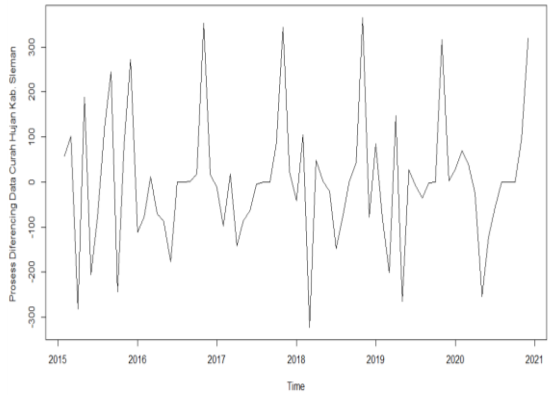

Figure 6. Plot Differencing

3. Parameter Estimation

Estimation parameter is used to obtain a temporary model for further parameter testing on the temporary model. The method used to estimate the parameters of the interim model is to look at the MSE value in each model. Based on the plots in Figure 4 and Figure 5, it can be seen that PACF function is significant at lag-2 (MA=2) and the function of PACF is significant at lag-1 (AR=1), so it can be concluded that some possible model estimates are as follows:

a) Model 1 : SARIMA (1,1,1(1,1,0)6
b) Model 2 : SARIMA (1,1,1)(2,1,0
c) Model 3 : SARIMA (2,1,2)(1,1,0)6
d) Model 4 : SARIMA (2,1,2)(2,1,0)6

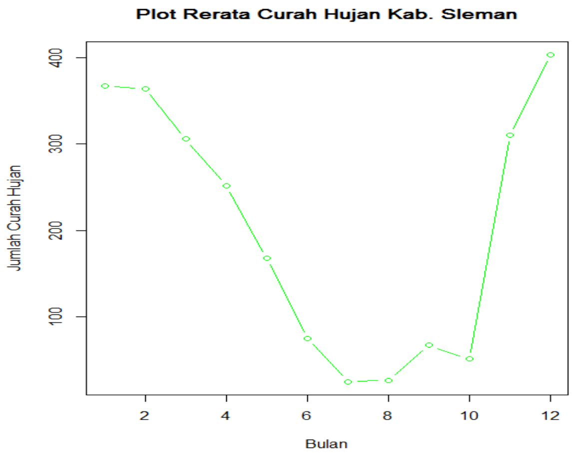

Figure 7. The value of Rainfall Prediction Results for 12 Months Period

RESULTS AND DISCUSSION

The results of rainfall forecasting are obtained by using the SARIMA method for Sleman Regency area as shown in the form of a distribution table in Table 4.

Table 4. Prediction Results from 12 Months of Rainfall

No	The Year 2021	
1	Jan	390.8
2	Feb	380.1
3	March	352.8
4	April	353.4
5	May	138.4
6	June	50.7
7	July	8.84
8	August	15.6
9	Sept	9.71
10	Oct	10.64
11	Nov	171.2
12	Dec	369.3

The results of the rainfall forecasting are collected, and then they are analysed with the results of the estimated rainfall in each month. The categories can be seen in table 5.

Table 5. Rainfall Category

No	Rainfall	Characteristic
1	100	Dry
2	100-200	Moist
3	>200 (more than)	Wet

Determining the characteristic of rain is based on rainfall data used the Oldeman method to determine the natural characteristic of rain by month. The grouping of rainfall prediction results is divided into three: Rainfall less than 100 mm is dry, average rainfall between 100-200 mm in the valley, and rain has an average of over 200 mm is wet. Furthermore, the determination of the cropping pattern based on the suitability of the cropping pattern can be seen in table 6.

Table 6. Determination of Crops Pattern

Description	Month											
	Jan	Feb	March	April	May	June	July	August	Sept	Oct	Nov	Dec
Rainfall Data Prediction	390,8	380,1	352,8	353,4	138,4	50,7	8,84	15,6	9,71	10,64	171,2	369,3
Planting Time	1				2				3			
Cropping Pattern	Rice Plant					Palawija					Rice Plant	

The cropping pattern was based on conditions of adequate rainfall that occurred during the planting to harvest period, ranging from 1 mm/day to 72.7 mm/day. Rainfall patterns in Indonesia generally have three main characteristics, namely high rainfall (around January – to April), low Rainfall (around May-August), and moderate Rainfall (around September – to December). Even though there has been a change in peak rainfall in the last 12 years, the cropping pattern in Indonesia follows the three types of rainfall characteristics. The rice cropping pattern is carried out if, on three consecutive bases, the rainfall value is more than 50 mm or the average monthly rainfall is at least 200 mm in one planting period. The cropping pattern of Malawi is carried out if the average monthly rainfall is between 100 mm to 200 mm, and tillage or fallow is carried out if the average monthly rainfall is less than 100 mm.

Based on Table 6, the results of rainfall forecasts obtained in January, February, March, April, and May have relatively high rainfall, with relatively high rainfall conditions which greatly determine the suitability and optimization of cultivation of crops, such as rice. Furthermore, June, July, August, September, and October have a tendency for dry months or very little rainfall so that it can be optimized for the cultivation of tobacco, soybeans, corn, peanuts, green beans, cassava, and sweet potatoes.

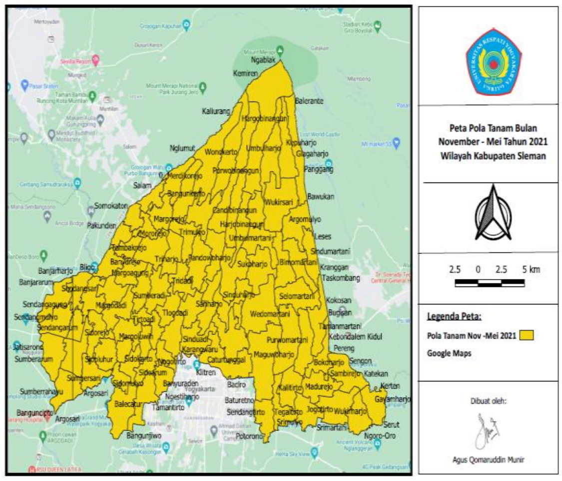

Figure 8. Predicted Map of Cropping Pattern from November – May 2021

In Figure 8, the spatial distribution analysis for the planting period from November to May 2021 by taking into account the prediction of the amount of rainfall for the period from January to December 2021. It can be concluded that it is recommended that the appropriate plant is rice.

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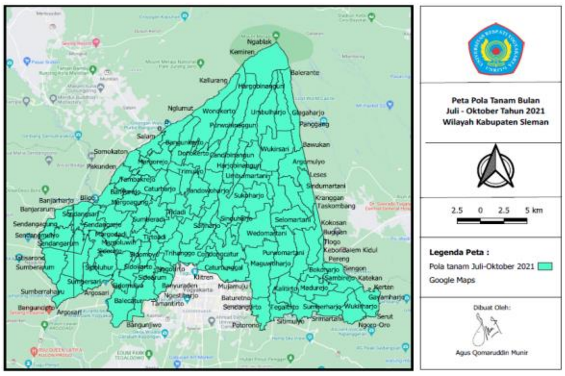

Figure 9. Map of Prediction on Cropping Patterns during July – October 2021

In Figure 9, the spatial distribution analysis for the planting period from July to October 2021 by taking into account the prediction of the amount of rainfall for the period from January to December 2021, it is recommended that the appropriate crops are secondary crops.

1. Forecasting Accuracy Testing

The forecast used to predict this rainfall data is a quantitative forecast based on the analysis of the relationship pattern between the variables to be estimated and the time variable, which is a time series. Quantitative forecasting can only be used in the following three conditions exist; they are such as:

a. There is information about other circumstances.
b. The information can be quantified in the form of data.
c. It can be assumed that the past pattern will continue in the future.

Several steps guide research on forecasting rainfall data: literature review, identification of problems and methods, data collection at BMKG of Sleman regency, working on forecasting analysis, checking the accuracy and error rate, and making research reports and documentation. In this sub-discussion, the accuracy of the forecasting results is tested by comparing the actual rainfall data in 2021 and the data from the 2021 forecasting results. The predicted and actual data can be seen in table 7.

Table 7. The Comparison of Actual Data and Predicted Rainfall Data in 2021

No	Month	The Year 2021 (Actual)	The Year 2021 (Prediction)	*Error*
1	Jan	457	390,8	66,2
2	Feb	337	380,1	-43,1
3	March	560	352,8	207,2
4	April	413	353,4	59,6
5	May	22	138,4	116,4
6	June	20	50,7	-30,7
7	July	5	8,84	-3,84
8	August	16	15,6	0,4
9	Sept	8,11	9,71	-1,6
10	Oct	5,3	10,64	-5,34
11	Nov	164	171,2	-7,2
12	Dec	390	369,3	20,7

If it is presented in graphical form, it is shown in Figure 10.

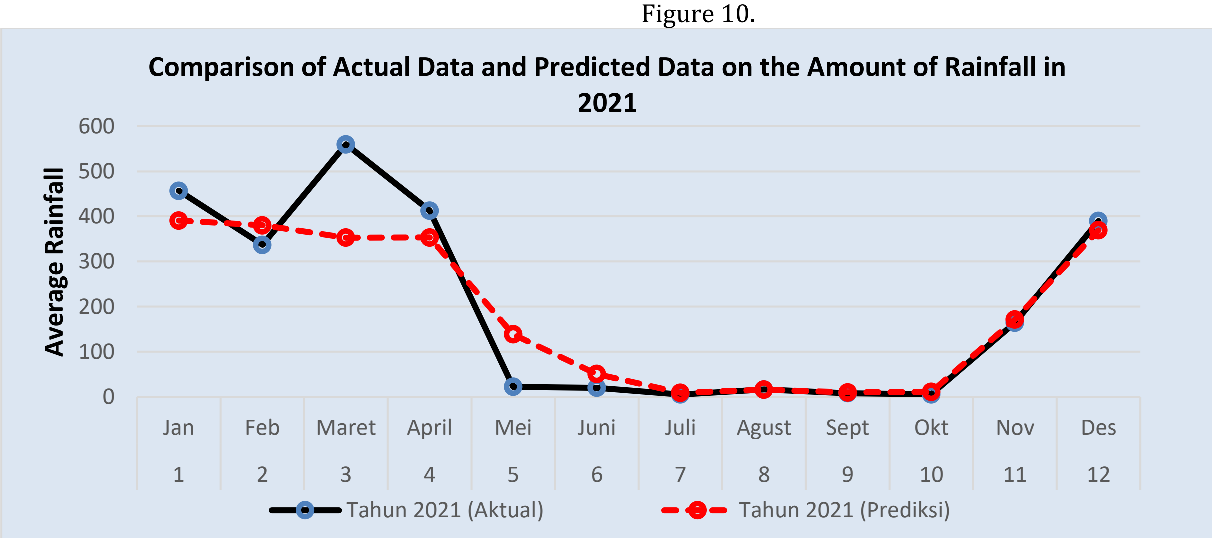

Figure 10. Actual Graph and Predicted Rainfall Data During 12 Months Period

Figure 10 shows that the actual data plot and the predicted average rainfall data from January to December 2021 have similar plots to the actual data for the same period. From January to March 2021, the prediction data has the same pattern in January, February, April, and May, while the prediction pattern is slightly different for March and June. Meanwhile, the prediction data has a similar pattern for July to December. Thus the accuracy of the prediction data is quite adequate.

Based on the rainfall forecasts obtained in January, February, March, April, and May, relatively high rainfall occurred, with relatively high rainfall conditions significantly determining the suitability and optimization of agricultural crop cultivation, such as rice. Furthermore, June, July, August, September, and October have a tendency for dry months or very little rainfall to be optimized for the cultivation of tobacco, soybeans, corn, peanuts, green beans, cassava, and sweet potatoes.

CONCLUSION

The results of the research and discussion that were carried out temporarily obtained the following conclusions, pre-processing of rainfall data for the 2015-2020 period can improve forecasting accuracy compared to rainfall data that is not pre-processed. The rainfall prediction model using the SARIMA method is proven to predict 12 months with an accuracy rate of 98.54% of the predicted rainfall data. Precipitation forecasts can be classified a year into two categories: dry months and wet months. In the wet months (high rainfall), rice is suitable for planting from January to May. For the dry months between June and October, tobacco, soybeans, corn, peanuts, green beans, cassava and sweet potatoes. In addition, there are similarities in the determination of planting period-I (January-April), planting season II (May-August), and planting season III (September-December) between the research model and the cropping pattern guidelines issued by Sleman Regency.

REFERENCE

[1] L. Q. Avia, “Change in rainfall per-decades over Java Island, Indonesia,” *IOP Conf Ser Earth Environ Sci*, vol. 374, no. 1, pp. 1–11, 2019, doi: 10.1088/1755-1315/374/1/012037.

[2] M. Zele *et al.*, “Spatial and Temporal Variability of Rainfall Trends in Response to Climate Change — A Case Study : Syria,” 2022.

[3] G. Shrivastava *et al.*, “Application of Artificial Neural Networks in Weather Forecasting: A Comprehensive Literature Review,” *Int J Comput Appl*, vol. 51, no. 18, pp. 17–29, 2012, doi: 10.5120/8142-1867.

[4] K. Alotaibi, A. R. *et al.*, “Future predictions of rainfall and temperature using GCM and ANN for arid regions: A case study for the Qassim region, Saudi Arabia,” *Water (Switzerland)*, vol. 10, no. 9, 2018, doi: 10.3390/w10091260.

[5] A. Q. Munir, S. Hartati, and A. Musdholifah, “Early identification model for dengue haemorrhagic fever (DHF) outbreak areas using rule-based stratification approach,” *International Journal of Intelligent Engineering and Systems*, vol. 12, no. 2, pp. 246–260, 2019, doi: 10.22266/IJIES2019.0430.24.

[6] A. Motamedi, A. Gohari, and A. T. Haghighi, “Three-decade assessment of dry and wet spells change across Iran, a fingerprint of climate change,” *Sci Rep*, vol. 13, no. 1, pp. 1–12, 2023, doi: 10.1038/s41598-023-30040-0.

[7] Munir AQ *et al.*, “GEOGRAPHIC INFORMATION SYSTEMS FOR AGRICULTURAL SUITABLE LAND,” vol. 4, no. 1, pp. 97–105, 2023.

[8] M. Dhanaraju, et al“Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture,” *Agriculture (Switzerland)*, vol. 12, no. 10, pp. 1–26, 2022, doi: 10.3390/agriculture12101745.

[9] M. Mokarram and F. Aminzadeh, “Gis-Based Multicriteria Land Suitability Evaluation Using Ordered Weight Averaging With Fuzzy Quantifier : a Case Study in Shavur Plain , Iran,” *Archives*, vol. 38, pp. 508–512, 1996.

[10] I. Buyung, A. Q. Munir, and P. Wanda, “Effective Breast Cancer Detection using Novel Deep Learning Algorithm,” *JITK (Jurnal Ilmu Pengetahuan dan Teknologi Komputer)*, vol. 8, no. 2, pp. 98–104, 2023, doi: 10.33480/jitk.v8i2.4077.

[11] M. Zhu *et al.*, “A review of the application of machine learning in water quality evaluation,” *Eco-Environment & Health*, vol. 1, no. 2, pp. 107–116, 2022, doi: 10.1016/j.eehl.2022.06.001.

[12] A. Y. Barrera-Animas *et al.*, “Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting,” *Machine Learning with Applications*, vol. 7, no. November 2021, p. 100204, 2022, doi: 10.1016/j.mlwa.2021.100204.

[13] F. Hafeez *et al.*, “Distant temperature and humidity monitoring: Prediction and measurement,” *Indonesian Journal of Electrical Engineering and Computer*

VOL. 9. NO. 1 AUGUST 2023
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Science, vol. 24, no. 3, pp. 1405–1413, 2021, doi: 10.11591/ijeecs.v24.i3.pp1405-1413.

[14] S. Y. Siswanto and M. I. S. Sule, "The Impact of slope steepness and land use type on soil properties in Cirandu Sub-Sub Catchment, Citarum Watershed," *IOP Conf Ser Earth Environ Sci*, vol. 393, no. 1, 2019, doi: 10.1088/1755-1315/393/1/012059.

[15] J. Gu *et al.*, "A Stacking Ensemble Learning Model for Monthly Rainfall Prediction in the Taihu Basin, China," *Water (Switzerland)*, vol. 14, no. 3, pp. 1–20, 2022, doi: 10.3390/w14030492.

[16] M. Champness, L. Vial, and C. Ballester, "Evaluating the Performance and Opportunity Cost of a Smart-Sensed Automated Irrigation System for Water-Saving Rice Cultivation in Temperate Australia," 2023.

[17] I. L. Selley *et al.*, *Encyclopedia of Geology - 1-5 Volume - Elsevier Academy*. 2005.

[18] A. Syed, T. Raza, T. T. Bhatti, and N. S. Eash, "Climate Impacts on the agricultural sector of Pakistan: Risks and solutions," *Environmental Challenges*, vol. 6, no. July 2021, p. 100433, 2022, doi: 10.1016/j.envc.2021.100433.

[19] J. L. Hatfield and J. H. Prueger, "Temperature extremes: Effect on plant growth and development," *Weather Clim Extrem*, vol. 10, pp. 4–10, 2015, doi: 10.1016/j.wace.2015.08.001.

[20] C. M. Godde *et al.*,, "Impacts of climate change on the livestock food supply chain; a review of the evidence," *Glob Food Sec*, vo. 28, no. January, p. 100488, 2021, doi: 10.1016/j.gfs.2020.100488.

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