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The Prediction of The Drought Index in The Indragiri Watershed Using SARIMA and SPI Methods

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ABSTRACT

Farmers are concerned about the problem of drought in agriculture because it will disrupt the production system and cause losses. In 2015, the Indragiri Hulu area experienced a drought on 273 hectares of agricultural land. This area is part of the Indragiri River Watershed in Riau Province. To prevent the impact of future droughts, forecasting is required. The level of drought is influenced by rainfall, so the Seasonal Auto Regressive Integrated Moving Average (SARIMA) method is used to model rainfall data. In addition, the Standardized Precipitation Index (SPI) is also used to analyze the drought index. After the analysis, it was found that the best model in forecasting is SARIMA model $(1,0,1)(2,1,1)^{12}$ with an average residual square of 18.0175, and the drought index in the Indragiri watershed is currently included in the "Normal" category. The results of this forecasting are expected to assist the Riau Province National Disaster Management Agency in anticipating and mitigating the impact of future drought disasters.

Keywords: Time Series, Drought Index, SARIMA, SPI

INTRODUCTION

Drought is a natural phenomenon that occurs regularly and reflects recurring climatic conditions in an area. Drought conditions affect the availability of water, both on the surface and underground. When droughts occur on a large scale can be catastrophic with major impacts (Darfia & Rahmalina, 2019). Meteorological drought is a form of drought that occurs when rainfall levels in a season are below normal. Rainfall is considered an important factor in controlling drought (Younes et al., 2011).

Indonesia is an agrarian country with the majority of its population relying on the agricultural sector as the main base of the economy. Therefore, the agricultural sector plays a very important role in the Indonesian economy. However, the occurrence of drought in some areas has a negative impact on the agricultural sector, especially for farmers who suffer losses due to reduce crop yields and even crop failure (Mujtahiddin, 2014).

In 2015, 273 hectares of farmland in Indragiri Hulu, Riau Province, suffered from drought due to the long dry season (P, 2015). Residents had difficulty getting clean water supplies and many farmers experienced crop failure. In addition, the long drought accompanied by 54 hotspots in the region also had an impact on the forest and land fires that occurred in Riau Province (Anonim, 2015).

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Indragiri Hulu Regency is located in the Indragiri River Watershed (DAS), which is one of the largest rivers in Riau Province with a length of 645 km, but only 350 km is navigable. The Indragiri river empties into Di Bawah Lake in West Sumatra Province. The Indragiri catchment area covers a total area of 16,268 km^2 and is divided into two provinces, Riau and West Sumatra, with the Riau catchment area covering 8.811 km^2 and the West Sumatra catchment area covering 7.457 km^2 (Afrizal et al., 2021).

Several studies have been conducted related to drought and forest and land fire mitigation efforts in the Indragiri watershed. These studies include the analysis of the drought index (Afrizal et al., 2021), handling water shortages in watersheds during the dry season (Darwizal, 2019), designing a cropping calendar information system (Sistem Informasi Kalendar Tanam/SI KATAM) to support the improvement of the rice cropping index (Fahri et al., 2020), and detection of forest and land fire hazard levels based on the drought index (Triputra, 2021) (Murdhani, 2021).

Until now, forecasting of future conditions related to drought and forest land fire disaster management in the Indragiri watershed area has not been carried out, except for a small part of the Kelayang irrigation area which has 4 rain stations (Rahmalina, 2020). Therefore, a broader study is needed involving 11 rainfall stations in the Indragiri watershed to predict drought levels as additional and complementary information from previous studies in the context of drought and forest and land fire disaster management.

Rainfall is a factor that affect the level of drought in a region. Rainfall data is classified as time series data. To forecast rainfall in the future, it requires past historical data that is collected periodically and then the patterns of the data are identified. From the results of this identification, estimates can be made for future rainfall conditions. A commonly forecast methods used for times series data, including rainfall data, is *Seasonal Auto Regressive Integrated Moving Average* (SARIMA). this method is used because rainfall data is thought to have a seasonal pattern that needs to be taken into account in forecasting.

The SARIMA method is a time series analysis technique that consist of *Seasonal (*S*),* *Auto Regressive* (AR), *Integrated* (I), and *Moving Average* (MA) components. The SARIMA model is written in the mathematical notation $(p,d,q)(P,D,Q)^S$. p is the Auto Regressive orde which is useful for modelling auto correlation in time series by calculating regression on lag variables of p. d orde indicates the differencing orde applied to the data to produce stationary data. q reresents the orde of the moving average to see q lagged errors. In addition, there is also a seasonal component to the SARIMA method which is represented by p orde in the seasonal Auto Regressive orde, D the differencing orde in the seasonal period and Q the seasonal Moving Average orde and S is the number of periods per session (Supriatna et al., 2017).

The use of the SARIMA model has been widespread in many research cases, including in modeling the number of Covid cases in Padang City (Rahmalina & Puspita, 2021), forecasting the consumer price index (Lubis et al., 2017), forecasting the number of foreign tourists (Hendayanti & Nurhidayati, 2020), forecasting of inflation (Fahrudin & Sumitra, 2020), estimating rainfall (Kafara et al., 2017).

Information on drought potential is essential for prevention and mitigation efforts to reduce negative impacts (Aprilliyanti & Zainuddin, 2017). calculation of drought levels provides an early indication of drought conditions (Utami et al., 2013). one method to calculate the drought index and drought level is the *Standardized Precipitation Index* (SPI). This method is a model used to measure rainfall deficits in various periods by comparing them to normal condition. This method simply uses monthly rainfall data. The SPI method has been widely used by researches to calculate the drought index in the Rejoso watershed of Pasuruan Regency (Khairani et al., 2018), the island of Lombok (Azhar & Gunawan, 2017), Ngrowo DAS (Muliawan, 2015) combined with *Geographic Information System* (GIS) to see the distribution od drought.

Based on the above, a study needs to be conducted to predict rainfall using the SARIMA method, and analyze the drought index based on the prediction results with the SPI method. From the analysis, the level of drought in the Indragiri watershed area of Riau Province will be measured.

MATERIAL AND METHOD

This research used a quantitative approach and relied on secondary data source from the Sumatra III River Basin Center in Riau Province. The data collected was daily rainfall data from 2004 to 2021 which was collected from 11 rainfall stations in the Indragiri watershed area, namely Lubuk Ramo, Lubuk Kebun, Lirik, Talang Jerinjing, Pangkalan Kasai, Pekan Tua, Tembilahan, Sentajo, Air molek, Keritang and Usul.

In this study, the researcher used the research framework listed in Figure 1 as a guide.

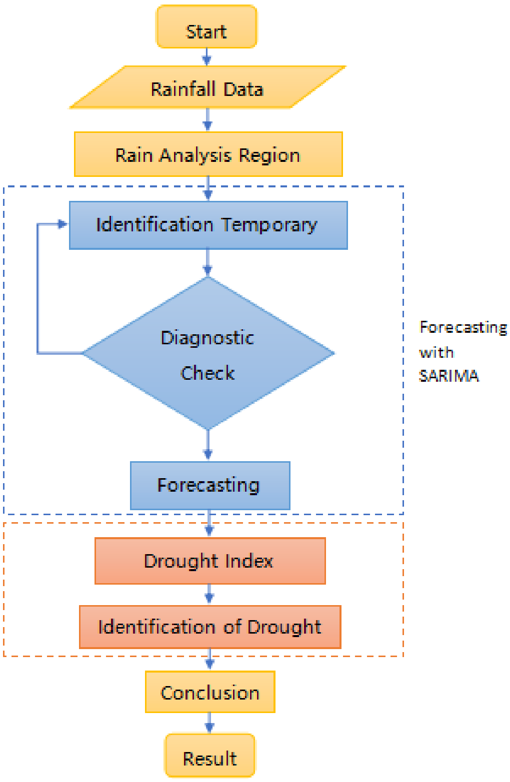

Figure 1. The Research Mechanism

Figure 1 also shows that the data obtained will be analyzed through 3 stages, namely :

1. Regional Rainfall Analysis

The daily rainfall data collected from each rain station was consolidated into monthly rainfall data. Furthermore, using the algebraic method, namely by calculating the average monthly rainfall from eleven rainfall stations, regional rainfall data will be obtained. The average calculation used the following formula :

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n}$$

With :

$\bar{x}$ = average monthly rainfall/regional rainfall

$x_1, x_2, \cdots, x_n$ = monthly rainfall station $1,2,\ldots,n$

n = number of rainfall stations

The regional rainfall data was used as input in the forecasting process.

2. Forecasting Using the SARIMA method

In the initial stage of developing the SARIMA model, the first step was to determine the amount of differencing required to make the average of data stationary, both seasonal and nonseasonal data. This can be seen by looking at the time series data plot and ACF. The second step, to make the variance of the data stationary, requires a transformation method such as the use of the *Box-Cox* method. The *Box-Cox* method is highly recommended to be used in the transformation process (Durrah et al., 2018). the third step is to identify the temporary model by determining the *nonseasonal* orde (p,q) and *seasonal* orde (P,Q) based on the ACF and PACF plot patterns.

The second stage was to conduct a diagnostic test, which consisted of two steps. The first step was to carry out parameter significance testing to determine whether the parameters are significantly different from zero or not. The second step was testing the suitability of the model with the *Ljung-Box* (p−*value* > alpha = 0,05) to ensure that the resifuals meet the white noise requirements and the Kolmogorov Smirnov test (p − *value* > alpha = 0,05) to ensure that the residuals are normally distributed (Yusuf & Yanti, 2021). the third stage is forecasting by selected a model that produced a forecast with the minimum *Mean Squared Error* (MSE) value (Hanum & Murni, 2019).

3. Drought Index Measurement with SPI

The rainfall forecast data obtained in stage 2, then be used to measure the drought index using the SPI method using the following formula (Darfia et al., 2016):

$$Z_{ij} = \frac{x_{ij} - x_{(rt)j}}{\sigma_j}$$

with :

Z_{ij} = SPI value of year i month to j

x_{ij} = monthly rainfall of the year i month to j

$x_{(rt)j}$ = average rainfall of month j

σ_j = standard deviation of month j

Table 1. Classification of SPI value scale

SPI value	Categories
SPI ≥ 2.00	Wet extreme
1.50 ≤ SPI ≤ 1.99	Extremely wet
1.00 ≤ SPI ≤ 1.49	Wet
-0.99 ≤ SPI ≤ 0.99	Normal
-1.00 ≤ SPI ≤ -1.49	Dry
-1.5 ≤ SPI ≤ -1.99	Extremely dry
SPI ≤ -2.00	Dry extreme

RESULTS AND DISCUSSION

Regional Rainfall Analysis

Regional rainfall data in the Indragiri watershed in the 2004-2021 period that has been processed using the algebraic method consist 216 data from 11 rain stations. The data can be seen in the table presented.

Table 2. Rainfall data of Indragiri watershed area (in millimeter)

Year	Jan	Feb	Mar	April	May	June	July	August	Sept	Oct	Nov	Dec
2004	269,51	191,05	261,11	230,65	191,63	105,08	227,18	130,95	175,89	235,84	299,41	277,17
2005	154,38	130,86	197,40	258,77	218,94	104,25	144,42	178,08	220,15	264,22	280,97	240,72
2006	268,55	183,39	232,41	328,68	212,85	151,97	116,62	82,60	103,38	116,32	246,50	314,87
2007	187,68	169,99	173,16	313,94	302,65	109,37	169,11	127,29	212,35	271,10	307,44	245,41
2008	282,92	180,90	423,01	258,02	141,31	163,89	86,34	234,14	277,71	242,22	275,70	193,98
2009	142,53	174,44	307,94	285,22	142,03	75,38	63,96	104,31	169,43	145,73	289,89	338,16
2010	242,36	206,94	280,11	294,22	131,58	226,49	282,73	250,39	171,12	221,36	310,45	154,17
2011	223,06	176,60	157,01	365,09	129,16	196,14	103,52	90,29	134,17	482,53	291,61	195,54
2012	115,32	208,68	173,25	363,14	168,42	59,58	179,02	97,53	185,29	277,15	462,38	230,32
2013	72,96	125,48	104,33	118,55	145,70	75,69	89,54	76,03	105,51	120,14	188,25	142,05
2014	89,02	52,25	75,53	79,10	55,35	28,63	42,32	60,41	78,07	88,55	182,10	202,25
2015	95,46	103,10	142,65	234,51	114,84	48,28	39,37	86,79	41,18	79,34	270,61	174,38
2016	167,76	144,70	189,88	123,13	139,68	73,81	132,95	93,13	100,75	120,49	209,65	65,65
2017	135,67	210,99	202,37	226,91	212,69	138,90	139,20	169,94	223,60	161,64	350,98	258,28
2018	122,35	153,65	197,62	164,48	156,95	120,33	81,26	115,62	87,00	200,70	293,82	180,07
2019	229,65	239,63	201,07	186,44	120,99	95,48	42,18	47,68	64,71	121,33	149,75	195,74
2020	159,39	126,74	174,93	267,18	189,45	118,75	114,00	142,06	237,35	167,59	244,18	174,06
2021	192,24	74,30	192,30	235,44	138,11	99,90	104,58	176,10	183,06	173,79	161,65	150,08

Forecasting Using SARIMA Method

The plot of monthly rainfall data in Indragiri watershed from January 2004 to December 2021 is shown in Figure 2.

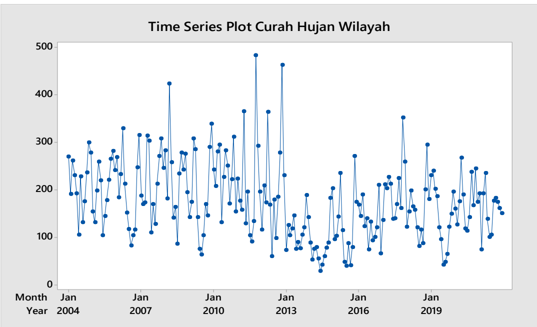

Figure 2. The Plot of Region Rainfall Data

Table 2 and Figure 2 shown that the highest rainfall in the region occurred in October 2011 with 482.53 mm and lowest occurred in June 2014 with 28.63mm. The data plot shows a seasonal pattern, Plot data menunjukkan pola musiman, so it was decided to use the SARIMA (*Seasonal Autoregressive Integrated Moving Average*). The data plot shows fluctuation around the horizontal line, shows that data stationary to mean. However, the data plot shows widening or narrowing pattern, shows that data not stationary to variance. Therefore, it is necessary to test stationarity data to mean and variance.

For the evaluation of data stationary to variance, transformation *Box-Cox* test can be used. If the result of test states that the rounded value is equal to 1, it means the data stationary to variance.

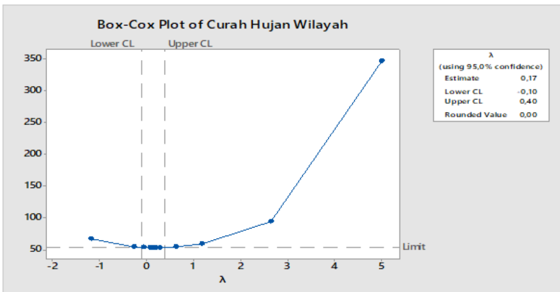

Figure 3. The initial data *Box-Cox* plot

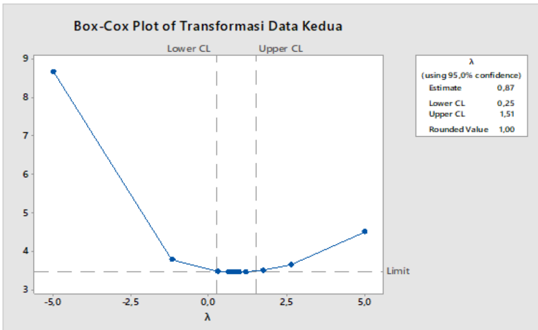

Figure 4. The Plot of *Box-Cox* after transformation

Figure 3 shows the result of transformation *Box-Cox* test, rounded value is 0,00. It is mean that the data not stationary to variance and need 2 times transformation data. After transformation, recheck with *Box-Cox* transformation test as Figure 4, it result shows the rounded value equal to 1, it is mean the data stationary to variance.

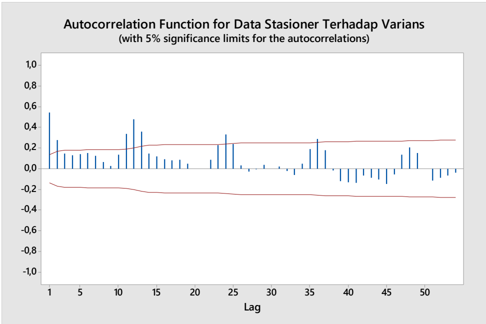

Figure 5. The Plot of ACF Data Stationary to Variance

Figure 5 shows *cut off* at 2nd *lag*, it can be confirmed that the data stationary to mean. Therefore, there is no needed *differencing non-seasonal*, so the orde d = 0. However, the graph is wave-shpaed which indicated a seasonal pattern so needed a *differencing seasonal* with the orde D = 1.

After obtaining the stationary data, next step is identification appropriated model with plot *Autocorrelation Function* (ACF) dan *Partial Autocorrelation Function* (PACF).

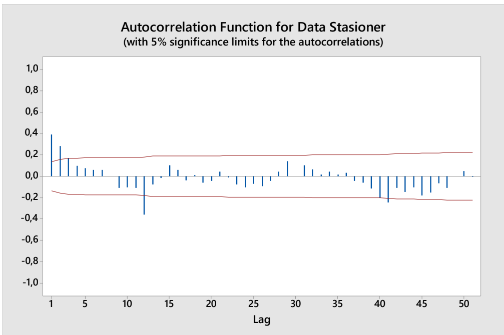

Figure 6. The ACF Plot

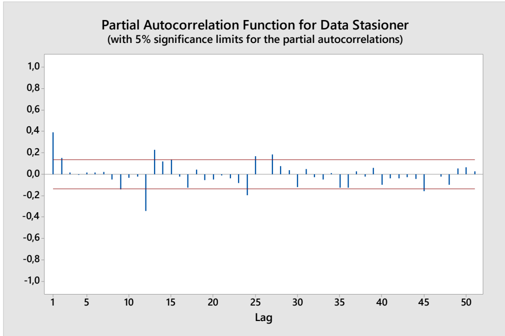

Figure 7. The PACF Plot

Figure 6 shown the ACF plot type *dies down* and *cutt off* at the lag 2 and lag 12 (lag 1 seasonal). The same thing on the PACF plot Figure 7 type *dies down* and *cutt off* on *lag* 2, *lag* 12 (*lag* 1 seasonal), and *lag* 24 (*lag* 2 seasonal) so identification model for temporary are SARIMA$(1,0,1)(2,1,1)^{12}$,SARIMA$(1,0,2)(2,1,1)^{12}$, SARIMA$(2,0,1)(2,1,1)^{12}$, and SARIMA$(2,0,2)(2,1,1)^{12}$.

After identification model temporary, next step is diagnostic testing with parameter signification test and suitably tes of model. The result of parameter signification model can be shown at Table 3. Parameter model SARIMA$(1,0,1)(2,1,1)^{12}$ has a significant value statistically with significant from zero. Every parameters AR 1, MA 1, SAR 1, SAR 2, and SMA 1 have p-*value* < 0,05, And the other model does not significant statistically with p-*value* > 0,05. Therefore, it is mean SARIMA$(1,0,1)(2,1,1)^{12}$ model can be used to the next model suitability test. There was checks the residual follow wh noise process and normally distributed. White noise process means the residual does not auto correlation (random) which can be tested using *L-Jung Box* output (Table. 4).

Table 3. The Result of Significance Test

Model	Parameter	Koef	SE Koef	p-value	Decision
SARIMA $(1,0.1)(2,1,1)^{12}$	AR1	0.8028	0.0804	0.000	Significant
	SAR 12	-0.606	0.0737	0.000	Significant
	SAR 24	-0.377	0.0757	0.000	Significant
	MA 1	0.46	0.121	0.000	Significant
	SMA 12	0.9163	0.055	0.000	Significant
SARIMA $(1,0,2)(2,1,1)^{12}$	AR 1	0.647	0.187	0.001	Significant
	SAR 12	-0.452	0.0785	0.000	Significant
	SAR 24	-0.288	0.0782	0.000	Significant
	MA 1	0.321	0.205	0.120	Not Significant
	MA 2	-0.018	0.111	0.870	Not Significant
	SMA 12	0.9099	0.0655	0.000	Significant
SARIMA $(2,0,1)(2,1,1)^{12}$	AR 1	0.94	0.245	0.000	Significant
	AR 2	-0.081	0.153	0.594	Not Significant
	SAR 12	-0.599	0.0743	0.000	Significant
	SAR 24	-0.379	0.0759	0.000	Significant
	MA 1	0.591	0.23	0.011	Significant
	SMA 12	0.9249	0.0524	0.000	Significant
SARIMA $(2,0,2)(2,1,1)^{12}$	AR 1	0.5	25.6	0.985	Not Significant
	AR 2	0.2	19.3	0.992	Not Significant
	SAR 12	-0.534	0.0766	0.000	Significant
	SAR 24	-0.268	0.0779	0.001	Significant
	MA 1	0.1	25.6	0.996	Not Significant
	MA 2	0.1	10.3	0.992	Not Significant
	SMA 12	0.9246	0.0568	0.000	Significant

Table 4. The Output of L-Jung Box

Lag	*P-Value*
	SARIMA$(1,0,1)(2,1,1)^{12}$
12	0,936
24	0,427
36	0,230
48	0,241

Table 4 shown the SARIMA $(1,0,1)(2,1,1)^{12}$ model, *L-Jung Box* have p-*value* > 0,05 for every lag. It is mean residual from model is random or not auto correlation, so that it can be considered feasible to use in forecasting. To ensure the normal distribution of residual, testing was carried out using Kolmogorov-Smirnov normality test. If the p-*value* > 0,05, it can be concluded that the residual distribution is normal.

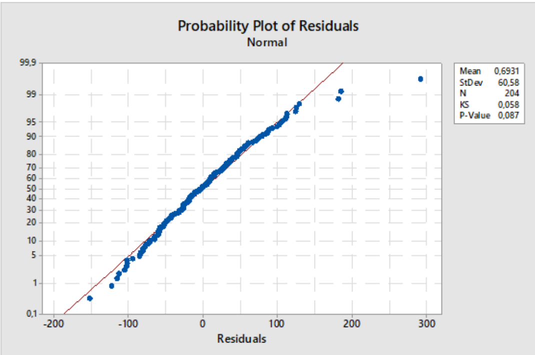

Figure 8. The Plot of Residual SARIMA $(1,0,1)(2,1,1)^{12}$ model

Figure 8 shown the SARIMA $(1,0,1)(2,1,1)^{12}$ model has residual with p-*value* = 0,087 > 0,05 and distributed with the pattern of blue dots follows the normal line. Therefore, it is concluded that the residual of SARIMA $(1,0,1)(2,1,1)^{12}$ model have a normal distribution. Based on the results of the *L-Jung Box* and uji *Kolmogorov-Smirnov* test, it can be concluded SARIMA $(1,0,1)(2,1,1)^{12}$ model meets the model fit test, so it can be used for forecasting. The *Mean Squared* (MS) from this model is 18,0175. The results of forecasting can be seen in Table 5.

Table 5. The result of forecasting for the rainfall in Indragiri watershed

Month	Forecasting Results (in mm)	
	2022	2023
January	130.09	122.33
February	121.00	122.37
March	157.88	151.46
April	181.99	181.82
May	109.60	111.47
June	63.97	61.82
July	66.93	63.57
August	75.08	67.05
September	91.97	94.74
October	140.72	135.21
November	214.75	219.17
December	158.75	156.41

Table 5 shown the result of forecasting model, that indicated the highest rainfall occurred in November 2023 was 219.17 mm and the lowest rainfall occurred in June 2023 was 61.82 mm. figure 9 shown the graph of the forecasting result data.

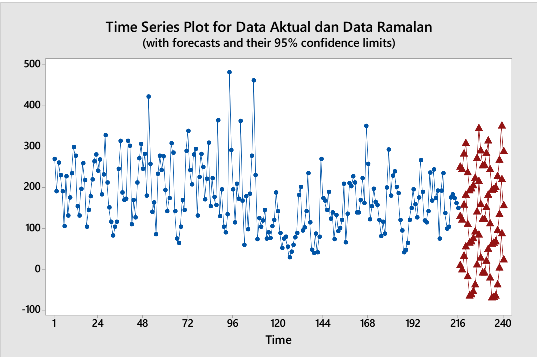

Figure 9. The Plot of Actual and Forecasting Data

Drought Index Measurement with SPI Method

After obtained the rainfall forecasting result of Indragiri watershed in 2022-2023, next step is to calculate the drought index using SPI method based on historical rainfall from 2004-2021 and the forecasting result in 2022-2023.

Table 6. The Drought Index and Drought Properties in Indragiri Watershed

Month	Drought Index	Drought Properties
January 2022	-0.64272	Normal
February 2022	-0.72114	Normal
March 2022	-0.56809	Normal
April 2022	-0.68273	Normal
May 2022	-0.90542	Normal
June 2022	-0.85737	Normal
July 2022	-0.76953	Normal
August 2022	-0.82426	Normal
Sept 2022	-0.8656	Normal
Oct 2022	-0.52788	Normal
Nov 2022	-0.67807	Normal
Dec 2022	-0.70093	Normal
January 2023	-0.76719	Normal
February 2023	-0.69199	Normal
March 2023	-0.65511	Normal
April 2023	-0.68496	Normal
May 2023	-0.86942	Normal
June 2023	-0.90133	Normal
July 2023	-0.82401	Normal
August 2023	-0.97086	Normal
Sept2023	-0.82273	Normal
Oct 2023	-0.58898	Normal
Nov 2023	-0.61528	Normal
Dec 2023	-0.73852	Normal

Table 6 shown the drought index for 2022-2023 in Indragiri watershed, which analyzed using farecasting data from historical rainfall data, has a range between -0,97086 (August 2023) to -0,52788 (October 2022) which can be categorized as “Normal”. Although there are 7 scale of drought properties, the SPI drought index in the Indragiri watershed only covers 1 (one) properties, namely “Normal”.

CONCLUSION

SARIMA $(1,0,1)(2,1,1)^{12}$ Model has been proven to be feasible to use for

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predicting rainfall in the Indragiri watershed area. This is evidenced by the model parameter estimation results there are signifanctly different from zero and have gone through a diagnostic check to ensure that the residual of the model are random, normally distributed, and have a mean square value of 18.0.175. From the results of forecasting using historical rainfall data in the Indragiri watershed, the value of the drought index in 2022-2023 analyzed is normal. This information is expected to help the government, especially the National Disaster Management Agency (BNPB) in an effort to deal with the consequence of drought in the future. In addition, researchers hope that other forecasting methods can also to be used for comparison.

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