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RAINFALL FORECASTING OF SALT PRODUCING AREAS IN PANGKEP REGENCY USING STATISTICAL DOWNSCALING MODEL WITH LINEARIZED RIDGE REGRESSION DUMMY

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ABSTRACT

Pangkep Regency is one of the regions in South Sulawesi that is the center of national salt production. Salt production in the area is still dependent on sea water evaporation, which means rainfall is one of the determining factors of success for salt production. Statistical downscaling is an accurate method for rainfall forecasting by linking the local scale rainfall in Pangkep Regency (response variable) with the global scale of the global circulation model/GCM output (predictor variable). However, the GCM output rainfall has a large dimension, which is an 8×8 grid (64 predictor variables), causing multicollinearity. The linearized ridge regression (LRR) method is used to overcome this problem. This method combines the performance of generalized ridge regression and Liu-type methods to reduce multicollinearity. In addition, dummy variables based on the K-means clustering technique were added to the model to overcome heteroscedasticity. The purpose of this study is to obtain the results of rainfall forecasting in Pangkep Regency using the LRR method in the statistical downscaling model. The model generated from the LRR method with dummy variables is better at explaining the variability of rainfall in Pangkep Regency. The R^2 value is higher (72%) than without dummy variables (57%). The addition of dummy variables in the LLR model has better accuracy in forecasting rainfall. The actual rainfall correlation of Pangkep Regency with has the largest correlation (0.76) with the smallest mean absolute percentage error value (0.49). The results obtained are that the months of May - November tend to have relatively low rainfall, so that salt farmers can produce salt with good quantity and quality.

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1. INTRODUCTION

Indonesia as a region with a tropical climate in certain months causes climate instability [1]. Salt production in coastal areas of Indonesia utilizes the high intensity of sunlight, usually using the solar evaporation method or evaporation of seawater on open land. Climate and weather conditions play an important role in salt production that depends on sunlight [2]. Rainfall is one of the factors that determine the success of salt production in Indonesia. Increased rainfall and cloudy skies lead to a lack of sunlight intensity needed to evaporate seawater. Conversely, high sunlight intensity favors successful and increased salt production.

South Sulawesi, including Pangkep Regency, has the potential to become a national salt production center [3]. Pangkep Regency is one of the Regencies involved in salt production, which is the main livelihood for most of its residents during the dry season [4]. Accurate rainfall prediction is important as it affects salt production and human activities in general [5]. Data from the Ministry of Maritime Affairs and Fisheries shows a significant decrease in salt production in the Pangkep Regency from 2019 to 2021, signaling the need for a more accurate method to forecast rainfall to increase salt production [6][7].

The Meteorology Climatology and Geophysics Agency (BMKG) uses various general methods such as Autoregressive Integrated Moving Average (ARIMA), Adaptive Neuro Fuzzy Inference System (ANFIS), and Wavelet to forecast the weather [8]. However, these methods only forecast rainfall data based on local climate variables observed on the earth's surface. This results in the method still having a low level of accuracy (60%-70%) because they do not involve the global-scale climate circulation of the atmosphere [9]. Therefore, to improve the rainfall forecast method, utilized atmospheric rainfall data from the Global Circulation Model (GCM) is needed [10].

According to Wigena in [11], the Global Circulation Model (GCM) is a numerical representation of the climate system and the interactions between its components, including the atmosphere, ocean, cryosphere, biosphere, and chemosphere [12]. GCMs produce simulations of global climate variables on specific grids and can be used to predict climate patterns on various time scales. However, the information from GCMs is global, so statistical downscaling is needed to produce climate information on a local scale with high resolution [13].

Statistical Downscaling is a statistical approach that links global climate variables to local climate variables (rainfall) [14]. This approach is based on the relationship between the global grid (predictor) and the local grid (response) by using statistical models to translate global anomalies into anomalies in local climate variables. GCMs produce large data with high correlation between grids, which raises the problem of multicollinearity [15].

To overcome the multicollinearity problem, one method that can be used is Ridge Regression (RR). Ridge Regression requires determining the optimal ridge constant value, while Generalized Ridge Regression (GRR) requires a constant for each regression variable. However, since determining the optimal constant in both methods is difficult, these methods are rarely used. Therefore, Liu and Gao developed Linearized Ridge Regression (LRR) which combines the concept of GRR with the Liu-type method [16].

The use of statistical methods through Statistical Downscaling models in rainfall forecasting continues to grow. [11] utilized the cross-correlation function to determine the highest correlation between global climate variables based on local climate in rainfall forecasting in Indramayu Regency. [12] used Liu-type regression in statistical downscaling modeling to forecast rainfall in Pangkep Regency. Furthermore, to improve the accuracy of rainfall forecast results [12] compare the dummy results in the statistical downscaling model between hierarchical and non-hierarchical methods [3]. In addition, [17] applied projection pursuit regression (PPR) on statistical downscaling modeling for daily rainfall forecasting. [18] used principal component regression and latent root regression methods to forecast rainfall in Pangkep Regency.

The LRR method is proposed to be used in forecasting rainfall in Pangkep Regency by utilizing statistical downscaling. the purpose of this study is to intensify salt production through more accurate rainfall forecasting in Pangkep Regency using LRR in Statistical Downscaling modeling. In addition, dummy variables from the clustering results of Pangkep Regency rainfall data are used in this study to reduce the effects of heteroscedasticity. The clustering is obtained from the results of K-means.

2. RESEARCH METHODS

2.1 Data

The data source used in this research is local rainfall data of Pangkep Regency (in millimeters per month) obtained from the Meteorological, Climatological and Geophysical Agency (BMKG) station IV Makassar and global-scale rainfall data from the Global Circulation Model Climate Model Intercomparison Project (GCM CMIP5). The global-scale rainfall data from GCM using 8×8 grids which each grids contain rainfall data with the size of $(2.5° \times 2.5°)$ above Pangkep Regency area at $119.57°$E to $129.37°$E and $-17.83°$S to $5.17°$S. Global-scale rainfall data are used as predictor variables totaling 64 variables (X) and local rainfall data response variables (y). In addition, in this research use K-means non-hierarchical cluster of local rainfall data to build rainfall categories as dummy variables (D) to improve the forecasting model.

2.2 Analysis Methods

The analytical methods used are Linearized Ridge Regression (LRR) with Statistical Downscaling. The analysis starts with K-means non-hierarchical cluster of local rainfall data to build dummy variables as addition for predictor variables in LRR model.

The following steps were taken in this research:

1. Explore data using create a box diagram of the data line and use descriptive statistical methods to understand the pattern and characteristics of the local rainfall data dan global-scale rainfall data.
2. Determine multicollinearity of predictor variables in global-scale rainfall data using Variance Inflation Factor (VIF) value. If the VIF > 10, then there is multicollinearity between variables [19].
$$VIF = \frac{1}{1 - R_j^2}; j = 1, 2, \dots, 64 \tag{1}$$
3. Split the data into two groups: training data and testing data. Training data is from January 1999 to December 2021 for train the model and testing data is from January 2022 to July 2023 for validating the goodness of the model for forecasting.
4. Apply statistical downscaling techniques on the global-scale rainfall data to match the local rainfall data at the research location Pangkep Regency. Statistical downscaling is done by identifying the highest cross-correlation function (CCF) value at the lag of each predictor variable against the response variable. Predictors that have been statistically downscaled will be used with the response variable and dummy variables to form a model [18].
5. Form a model using linearized ridge regression (LRR) which is a combination and extension of GRR and Liu-type [16]. The analysis steps using LRR are as follows:
    a. Standardize predictor variable and response variables
    $$y_i^* = \frac{y_i - \bar{y}}{s_y};\ x_i^* = \frac{x_i - \bar{x}}{s_x} \tag{2}$$
    b. Estimate parameters of multiple regression using LRR from Equation (2) with dummy variables and without dummy variables
    $$\widehat{\boldsymbol{\beta}}^*_{LRR} = \left(\boldsymbol{X}^{*\prime}\boldsymbol{X}^* + \boldsymbol{I}\right)^{-1}\left[\left(\boldsymbol{X}^{*\prime}\boldsymbol{X}^*\right) + \boldsymbol{QDQ}'\right] \tag{3}$$
    with $\boldsymbol{X}^*$ is a matrix of predictor variables (GCM and dummy) standardized on GCM climate variables, $\boldsymbol{I}$ is the corresponding identity matrix, $\boldsymbol{Q}$ is a matrix containing the eigenvectors of the matrix $\boldsymbol{X}^{*\prime}\boldsymbol{X}^*$. While $\boldsymbol{D}$ is a diagonal matrix containing the constants of the LRR method, namely
    $$\boldsymbol{d} = [(\boldsymbol{H} \circ \boldsymbol{G})'(\boldsymbol{H} \circ \boldsymbol{G})]^{-1}(\boldsymbol{H} \circ \boldsymbol{G})'\left[\boldsymbol{y}^* - (\boldsymbol{Z} \circ \boldsymbol{U})\boldsymbol{1}_{p+1}\right] \tag{4}$$
    with $\boldsymbol{H} = (\boldsymbol{h}_1, \dots, \boldsymbol{h}_n)'$; $\boldsymbol{h}_i = \boldsymbol{Q}'_{-i}\, \boldsymbol{z}_i$; $\boldsymbol{Q}_{-\mathbf{i}} = (\boldsymbol{q}_{1;-i}, \dots, \boldsymbol{q}_{p;-i})$ is an orthogonal matrix such that $\boldsymbol{Q}'_{-i}\left(\boldsymbol{X}^{*\prime}\boldsymbol{X}^* - \boldsymbol{x_i}^*\boldsymbol{x_i}^{*\prime}\right)\boldsymbol{Q}_i = \boldsymbol{\Lambda}_{-i} \triangleq diag(\lambda_{i;-i}, \dots, \lambda_{p;-i})$ where $\lambda_{i;-i} \geq \dots \geq \lambda_{p;-i} > 0$ is the eigenvalue of $\boldsymbol{X}^{*\prime}\boldsymbol{X}^* - \boldsymbol{x_i}^*\boldsymbol{x_i}^{*\prime}$, $\boldsymbol{q}_{1;-i}, \dots, \boldsymbol{q}_{p;-i}$ is the eigenvector corresponding to the eigenvalue. $\boldsymbol{Z} = (\boldsymbol{z}_1, \dots, \boldsymbol{z}_n)'$; $z_i = \left(\boldsymbol{X}^{*\prime}\boldsymbol{X}^* + \boldsymbol{I} - \boldsymbol{x_i}^*\boldsymbol{x_i}^{*\prime}\right)^{-1}\boldsymbol{x_i}^*$; $\boldsymbol{G} = (\boldsymbol{g_1}, \dots, \boldsymbol{g_n})'$; $\boldsymbol{g}_i = \boldsymbol{Q}'_{-i}\big(\boldsymbol{X}^{*\prime}\boldsymbol{X}^* -$

$\boldsymbol{x_i}^*\boldsymbol{x_i}^{*\prime})^{-1}(\boldsymbol{X}^{*\prime}\boldsymbol{y}^* - \boldsymbol{x_i}^* y_i^*)$; $\boldsymbol{U} = (\boldsymbol{u}_1, \dots, \boldsymbol{u}_n)'$; $\boldsymbol{u}_i = (\boldsymbol{X}^{*\prime}\boldsymbol{X}^* + \boldsymbol{I} - \boldsymbol{x_i}^*\boldsymbol{x_i}^{*\prime})^{-1}(\boldsymbol{X}'\boldsymbol{y} - \boldsymbol{X}^{*\prime}\boldsymbol{y}^* - \boldsymbol{x_i}^* y_i^*)$; and $\mathbf{1}_{p+1} = (1, \dots, 1)'$.

c. Build LRR model based on parameter estimation with dummy variables and without dummy variables

d. Measure the goodness of the model between with dummy variables and without dummy variables using R-Square value (R^2).

6. Validate the model that has been made using the MAPE (Mean Absolute Percentage Error) value. MAPE value is the value used for the average absolute percentage error [20].

$$MAPE = \sum \frac{\left(\frac{|Actual - Forecast|}{Actual}\right) * 100}{n} \tag{5}$$

7. Forecast the rainfall using the LRR model for January 2023 – Juli 2024 period, to identify the best month for extending salt production in Pangkep Regency.

3. RESULTS AND DISCUSSION

3.1 Exploration Data and Statistics Descriptive

a) Local Rainfall Data

The following are the results of data exploration using boxplot diagrams on local rainfall data from BMKG, to determine the characteristics of rainfall data that will be used in model.

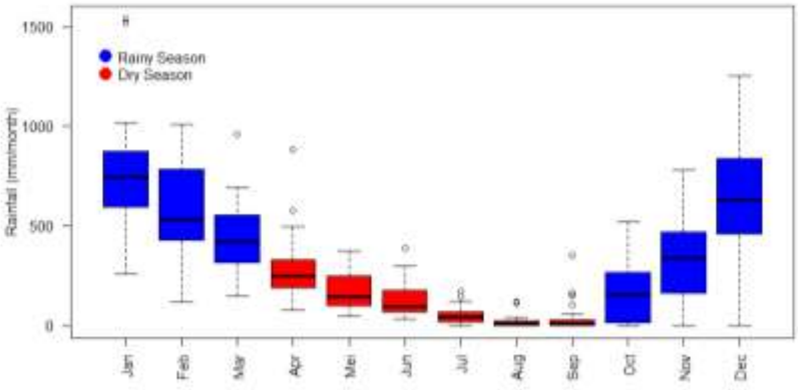

Figure 1. Exploration of Rainfall Data from BMKG

Based on the results of data exploration on rainfall data on a global scale derived from BMKG in Figure 1, monthly rainfall data from 1999-2023 in the Pangkep Regency area has the lowest rainfall in August with an average of 19.96 mm/month and the highest rainfall in January with an average of 773.5 mm/month. The dry season with low rainfall occurs from April to September as indicated by the red color in the boxplot (intensity 0-279 mm/month) while the rainy season with intensity between 524-1541 mm/month occurs from October - March.

b) Rainfall Data in the Atmosphere

The following are the results of data exploration using box-plot diagrams on atmospheric rainfall data using GCMs to determine the characteristics of rainfall data that will be used in model building.

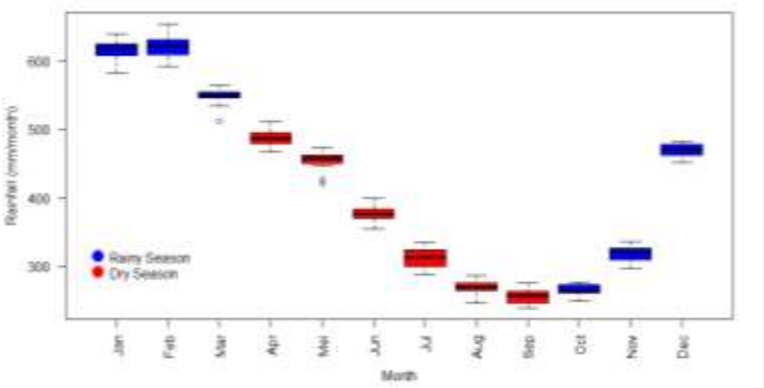

Figure 2. Exploration of Atmospheric Rainfall Data taken using GCMs

Figure 2 explains that atmospheric rainfall data from the GCM has a similar pattern to local rainfall data in Pangkep Regency with a monsoon rainfall pattern that has a clear difference between the rainy season period and the dry season period. Therefore, monthly rainfall data from 1999-2023 in the atmosphere of the Pangkep Regency area has the lowest rainfall in September with an average of 255.55 mm/month and the highest rainfall in February with an average of 610.28. The dry season with low rainfall occurs from April to September as indicated by the red color in the boxplot (intensity 0-279 mm/month) while the rainy season with intensity between 524-1541 mm/month occurs from October - March. In general, January rainfall in Pangkep Regency occurs in February in atmospheric data, therefore it is necessary to cross-correlate using CCF to determine the highest correlation between rainfall in Pangkep regency and atmospheric rainfall.

3.2 Cross-correlation Function (CCF)

The usage of statistical downscaling requires a high correlation between global-scale variables and local-scale variables (rainfall measured at the earth's surface) which can be seen through the Cross-Correlation Function (CCF) value. Alignment of the use of global scale data and local scale data is done by statistical downscaling on the data by identifying the highest cross correlation function (CCF) value of each predictor variable against the response variable. **Figure 3** presents an example of the highest cross-correlation results between local rainfall (y) and global-scale rainfall from GCM outputs on the first grid (X_1).

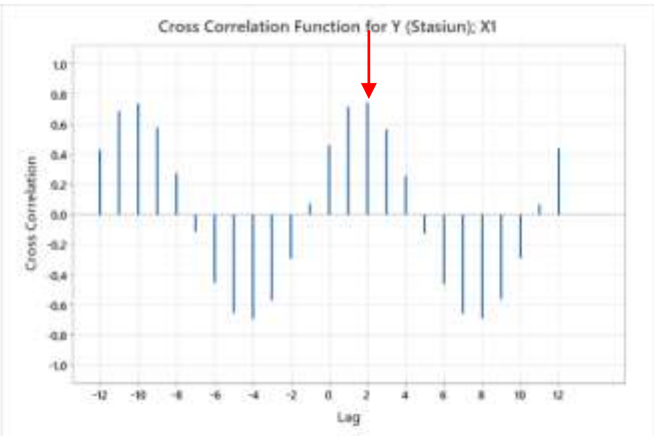

Figure 3. The CCF results on variable X_1

Based on **Figure 3**, the CCF value of the X_1 variable obtained, it is known that the highest correlation value is at lag +2, this means that the local rainfall value has a strong correlation with the GCM rainfall value in the following 2 periods. Data that has been statistically downscaled will be used in model building with local rainfall data in Pangkep Regency.

3.3 Identification of Multicollinearity

It is important to detect and resolve multicollinearity in order to make the regression analysis results more reliable and their interpretation more trustworthy. Multicollinearity identification is performed on the CCF result predictor variables (64 variables). The statistical value used to identify multicollinearity is the VIF value. If the VIF value is greater than 10, it indicates a strong correlation between the grids of the output data. The following multicollinearity identification results show that there is multicollinearity in rainfall data based on GCMs.

Table 1. VIF Values of GCM

Predictor	VIF	Predictor	VIF	Predictor	VIF	Predictor	VIF
X_1	42.81	X_{17}	1178.66	X_{33}	1989.52	X_{49}	2039.77
X_2	471.32	X_{18}	1433.74	X_{34}	2398.40	X_{50}	3186.92
X_3	526.31	X_{19}	874.68	X_{35}	1277.36	X_{51}	1440.56
X_4	480.6	X_{20}	947.52	X_{36}	593.84	X_{52}	949.07
X_5	121.83	X_{21}	116.35	X_{37}	113.75	X_{53}	147.73
X_6	24.05	X_{22}	7.99	X_{38}	32.29	X_{54}	49.56
X_7	43.17	X_{23}	8.27	X_{39}	50.82	X_{55}	37.37
X_8	30.29	X_{24}	8.32	X_{40}	116.71	X_{56}	120.28
X_9	462.64	X_{25}	1715.71	X_{41}	1628.44	X_{57}	958.25
X_{10}	1126.81	X_{26}	2191.42	X_{42}	2705.36	X_{58}	1560.32
X_{11}	998.69	X_{27}	1429.59	X_{43}	1355.66	X_{59}	696.88
X_{12}	1133.26	X_{28}	868.38	X_{44}	401.87	X_{60}	428.19
X_{13}	243.74	X_{29}	154.60	X_{45}	159.73	X_{61}	71.59
X_{14}	35.10	X_{30}	42.76	X_{46}	54.82	X_{62}	30.32
X_{15}	25.31	X_{31}	4.26	X_{47}	51.84	X_{63}	53.05
X_{16}	11.72	X_{32}	29.55	X_{48}	94.50	X_{64}	82.90

Table 1 presents the VIP values of the global-scale climate change GCM outputs. The VIF values of the 64 GCM variables range from 4.26 to 3186.92. There are only 4 variables with VIF values less than 10 ($X_{22}, X_{23}, X_{24}, X_{31}$), while the majority, namely 60 variables, have VIF values more than 10. This indicates that there is a high correlation between GCM data grids. Therefore, the LRR method is used in the statistical downscaling model to overcome this problem.

3.4 Statistical Downscaling model with Linearized Ridge Regression

LRR is a regression method that combines the principles of GRR with Liu-type. This method overcomes the multicollinearity problem based on the regulation value. The first step in the LRR method is to estimate the constant *d*. In the formation of the model, the use of dummy variables will be considered, which are variables that represent low, medium, and high rainfall categories. The following is a comparison between a model without dummy variables and a model using dummy variables which are variables that represent the effect of using a value of R^2.

Table 2. Best Model Comparison Table

Variable	R^2	RMSE
LRR without Dummy	0.57	330.21
LRR with Dummy	0.72	169.12

Based on the results in **Table 2**, the model with dummy variables has a higher R^2 value than the model without dummy variables. This means that 72% of atmospheric rainfall data can explain the variance of local rainfall data in Pangkep Regency. In addition, the addition of dummy variables to the statistical model can reduce the RMSE value to 169.12.

The following model is generated based on the results of parameter estimation for the LRR model on data that has been statistically downscaled with dummy variables.

$$\hat{y} = -628{,}35 + 14{,}71X_1 + 434{,}80X_2 - 425{,}77X_3 + 483{,}02X_4 - 142{,}24X_5 + 4{,}93X_6 - 0{,}79X_7 + 76{,}39X_8 - 661{,}52X_9 - 392{,}13X_{10} + 722{,}2X_{11} - 839{,}85X_{12} + 161{,}68X_{13} - 27{,}93X_{14} + 60{,}29X_{15} - 20{,}41X_{16} + \cdots - 16{,}75X_{64} + 847{,}22D_1 - 287{,}01D_2 - 591{,}73D_3$$

where $\hat{y}$ represents the forecast of local rainfall, X_1-X_{64} are the global-scale rainfall outputs of GCM on grids 1 through 64, and D_1-D_3 are dummy variables determined based on K-means results.

Based on the model obtained, the model formed can be known that all GCM rainfall data which is global-scale rainfall data in the atmosphere as a predictor variable has a significant effect on rainfall data that falls to earth sourced from BMKG. This means that in forecasting rainfall, the influence of global-scale data optimizes the results of rainfall forecasting on a local scale.

3.5 Validation of Model

The model validation stage is an important step in testing the reliability of the model to produce rainfall data forecasts. The statistical values used to see the goodness of the model are the correlation value and MAPE. The correlation value between the actual data and the predicted data from the LRR dummy model, measures how well the predicted rainfall can follow the actual rainfall pattern. While MAPE is used to see how far the distance between the estimated value and the actual value. Table 3 presents the results of rainfall forecasting using the LRR model with actual rainfall data from BMKG for Pangkep Regency for the period January 2022 - July 2023.

Table 3. Validation Value Table

Validation	Value of LRR Model
MAPE	0.49
Correlations	0.76

The LRR model is capable of accurately predicting rainfall data in Pangkep Regency. The correlation value between actual rainfall data and forecasted data is 0.75 (Table 3). This indicates that the rainfall predictions from the LRR model can closely follow the actual rainfall patterns. Furthermore, the LRR model demonstrates accurate rainfall predictions with a relatively small error, as evidenced by the Mean Absolute Percentage Error (MAPE) value of 0.49%.

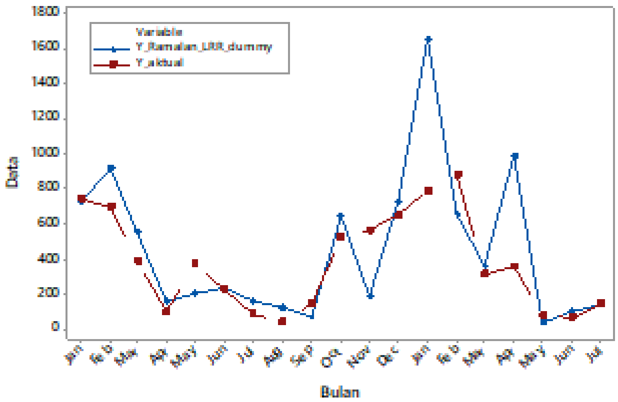

Figure 4. Comparison Plot of Rainfall Forecast Results using LRR and Rainfall Actual Data from January 2022 – July 2023.

Figure 4 presents a plot of the actual rainfall in Pangkep Regency against the predictions from the LRR model. The model is capable of making rainfall predictions that closely align with the actual rainfall, particularly in the months of January, April, June, and October of 2022, as well as in March, May, June, and July of 2023. The LRR model fails to accurately forecast rainfall, especially in November 2022, and January and April 2023. However, the model successfully predicts rainfall well for the period from January 2022 to July 2023 in general. This indicates that the rainfall forecast results using the LRR model fall within the acceptable category and can effectively predict rainfall in Pangkep Regency.

3.6 Rainfall Forecasting

The following are the results of rainfall forecasting using the linearized ridge regression model for Pangkep Regency for the period January - December 2023.

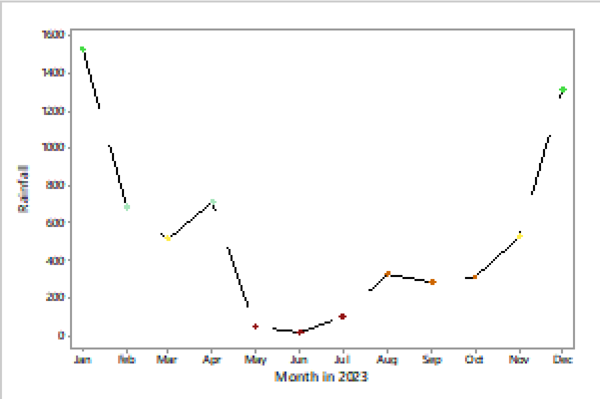

Figure 5. Plot of Forecast Results Using LRR of Jan – Dec 2023

The following values of rainfall forecasting results using LRR for the period to December 2023 are presented in **Figure 5**. Based on the results presented in **Figure 5**, The green-colored plot indicates high rainfall which is a sign not to carry out salt production. The orange-colored plot indicates moderate rainfall which is a warning sign and to be vigilant when carrying out salt production. The red-colored plot indicates low rainfall, which is a sign that it is the right month to carry out salt production. The forecasting results for January to December 2023 show that rainfall in Pangkep Regency in January-April and December tends to have high rainfall which will result in the failure of the salt production harvest, so salt farmers need to be careful when deciding to carry out salt production in that month. While May to November tends to have relatively low rainfall. Therefore, in May until July salt farmers can consider doing salt production so that salt production can increase and the salt produced will have good quality.

4. CONCLUSIONS

Statistical downscaling model with Linearized Ridge Regression (LRR) is a suitable model for forecasting rainfall that can extend salt production in the Pangkep Regency. The LRR Model forecasting results show that from January to April and October to December the rainfall tends to be high, which will extend the salt production. In contrast, from May to September rainfall tends to be relatively low, so salt production can increase and the salt produced will be of good quality.

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