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Prediction index drought use neural network based rainfall

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ABSTRACT

Prolonged dry seasons compared to rainy seasons often lead to drought, making drought index observations essential. In Indonesia, drought monitoring commonly uses the standardized precipitation index (SPI), yet there is no common standard for drought index measurement. Therefore, this research applies the Z-score index (ZSI) and China-Z index (CZI), which, like SPI, are rainfall-based drought indices but have rarely been explored in previous research. To predict ZSI and CZI, this research compares the weighted moving average (WMA) and multilayer perceptron (MLP) methods. Two input scenarios are tested: the previous two periods (t-2, t-1) and the previous three periods (t-3, t-2, t-1). The results show that MLP outperforms WMA, with the best performance achieved by the MLP model at a mean absolute percentage error (MAPE) of 4.177% using the three-variable input scenario and MLP architecture 3-6-10-1.

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1. INTRODUCTION

Climate change is a research topic that continues to be researched by academics and practitioners because almost the entire world is experiencing problems, namely rising sea levels, temperature, excessive rainfall, and drought. Climate change increases the frequency of extreme hydrology, such as floods and droughts. The problem of lack of rainfall causes climate problems and has an impact on the ecosystem. Extreme weather, such as drought, is influenced by rainfall [1], [2]. In recent years, extreme weather has often occurred. Drought is an environmental problem in several countries, including Indonesia. Severe drought can damage various fields such as agriculture (dry land resulting in crop failure), the environment, industry, and human life (lack of water or dehydration) [3], [4]. The drought in recent years has continued to increase, causing a shortage of water sources due to the lack of rainfall [5]. In addition to reduced rainfall, human activities can also affect drought.

Several countries are struggling with the impacts of drought. The impacts of drought include water shortages or water availability, decreased agricultural productivity, food security, environmental degradation, and other losses [4], [6]. Drought is less than average rainfall in a place over a long period of time [7], [8]. Types of drought include: meteorological drought, which is less than average rainfall in a certain area, hydrological drought is a lack of surface and groundwater for water supply, and agricultural drought is when crops do not find the water supply they need [9], [10]. One of the impacts of climate change is drought; therefore, it is very necessary to identify, observe and analyze temporal, and spatial drought predictions [11], [12]. Significant management of water and land resources can reduce environmental damage, one of which is monitoring and predicting droughts [13], [14]. Methods that are often used to predict with good results are random forest [15], multi-layer perceptron artificial neural network (MLP-ANN) [16], [17].

Mitigation strategies that can be used to reduce the impact of drought include drought monitoring and assessment [18]. Drought monitoring tools that can be used are drought indices including the standardized precipitation index (SPI), Z-score index (ZSI), China-Z index (CZI), rainfall anomaly index (RAI), rainfall departure (RD), precipitation deciles (PD), deciles index (DI), and percent of normal index (PNI) which are drought indices based on rainfall [2], [19]–[21]. The standardized precipitation evapotranspiration index (SPEI) is a drought index based on temperature [22]. The index for assessing drought situations is the Palmer drought severity index (PDSI), and a statistical downscaling model (SDSM) is very good for predicting drought in arid and semi-arid areas [23]. The drought index can provide information regarding the area, severity, duration, and frequency of drought [24]. The drought index that is frequently observed, analyzed, and predicted is the SPI [25]–[27]. Several methods used to predict the drought index include neural networks, fuzzy logic, and long short-term memory (LSTM) [28]–[30]. Comparing the empirical mode decomposition (EMD), detrended fluctuation analysis (DFA) and deep belief network (DBN), and multilayer perceptron (MLP) models in predicting SPI, with the EMD-DFA results providing accurate drought index prediction results [31]. The climate hazards group infrared precipitation with station data (CHIRPS) rainfall dataset shows that the drought indices CZI, SPI, and ZSI can effectively detect drought, and the results of spatiotemporal drought condition analysis can be used for policy and sustainable development [32]. Analyzing drought vulnerability using the analytic hierarchy process (AHP) based on groundwater resources index, waterway density index, climate index, land use index, and topography index indicators, research results [33] that land use affects drought vulnerability and risk. Hybrid models for analyzing the reconnaissance drought index (RDI), namely support vector regression (SVR) and wavelet analysis (W) can be used to predict good drought with root mean square error (RMSE)=0.301, mean absolute error (MAE)=0.166, Willmott index (WI)=0.910, Nash–Sutcliffe efficiency (NSE)=0.936 [34]. The decision tree (DT) method has good results in predicting the SPI drought index and assessing drought mitigation [35]. The nonlinear autoregressive neural network (NARNN) model is the best algorithm for predicting the SPI drought index with RMSE=0.997 [36].

Indonesia is a tropical country with two seasons, namely the rainy and dry seasons. In recent years, climate change has disrupted the usual seasonal patterns, leading to prolonged dry or rainy seasons. A longer dry season can cause drought, highlighting the importance of drought index observations. In Indonesia, drought monitoring often uses the SPI, but there is no general standard for drought index measurement. Thus, this research adopts the ZSI and CZI, which, like SPI, are rainfall-based drought indices but have rarely been investigated in predictive research [19]. Previous research has mainly focused on SPI prediction using methods such as wavelet-decomposed hybrid models (WBRF), bi-directional long short-term memory (Bi-LSTM) [27]; complementary ensemble empirical mode decomposition (CEEMD) with LSTM [25]; and EMD-extreme learning machine (ELM) hybrid models [20]. These approaches show that neural networks and time series models achieve good results. However, research that predicts ZSI and CZI indices remains limited, especially using relatively simple models for comparison. To address this gap, this research proposes the weighted moving average (WMA) and MLP methods for predicting ZSI and CZI indices. Two prediction scenarios are applied, based on the previous two periods $(t-2,\ t-1)$ and the previous three periods $(t-3,\ t-2,\ t-1)$. This research aims to identify the most appropriate model and input scenario for accurately predicting ZSI and CZI drought indices.

2. METHOD

2.1. Dataset

Data was downloaded from the website *https://hidrologi.dpuair.jatimprov.go.id/pelayanan/*, the area researched was Pandanlaras station, Krucil sub-district, Probolinggo district, East Java province. Data in the form of rainfall (mm) each month from 2003 to 2023. Data from this research are as in Figure 1, with an average value of 287.19 mm; standard deviation 197.15 mm; minimum 3 mm; maximum 860 mm; and median 281 mm. Rainfall data is then processed to calculate the drought index ZSI and CZI, with the formulas ZSI as in (1) and CZI (2) from the research [2].

$$Z = \frac{(x-\mu)}{\sigma} \tag{1}$$

$$Z = \left(\frac{6}{C_{si}}\left(\frac{C_{si}}{2}\varphi + 1\right)^{1/3}\right) - \left(\frac{6}{C_{si}} + \frac{C_{si}}{6}\right) \tag{2}$$

Description of (1), μ is the average, with (3), σ is the standard deviation, and with (4). In (2), C_{si} is the skewness coefficient with (5), φ is the standard variate with (6).

$$\mu = \frac{\sum_{i=1}^{n} rainfall_i}{n} \tag{3}$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(rainfall_i-\mu)^2}{n}} \tag{4}$$

$$C_{si} = \frac{\sum_{i=1}^{n}(rainfall_i-\mu)^3}{n\sigma^3} \tag{5}$$

$$\varphi = \frac{rainfall-\mu}{\sigma} \tag{6}$$

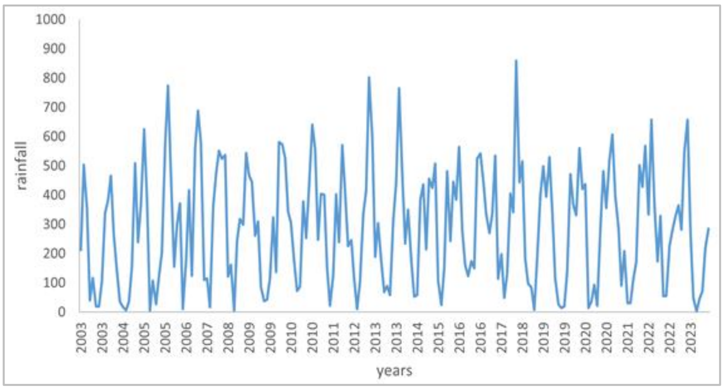


Figure 1. Rainfall data

The results of the calculation of the ZSI drought index, as shown in Figure 2. CZI as shown in Figure 3, with the mean, standard deviation, minimum, maximum, and median values in Table 1. Based on Table 1, the standard deviation value is 1, meaning a small dispersion value with a distance value of 1 from the average.

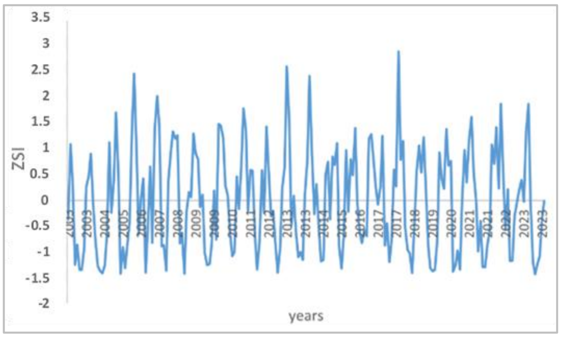


Figure 2. ZSI drought index

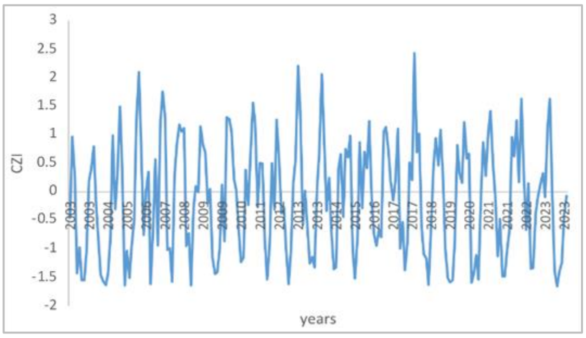


Figure 3. CZI drought index

Table 1. Drought index statistical values

Value	ZSI	CZI
Mean	1.19×10^{-16}	-0.124
Standard deviation	1	0.992
Minimum	-1.442	-1.656
Maximum	2.905	2.435
Median	-0.031	-0.094

2.2. Proposed method

This research predicts the ZSI and CZI drought indices using the WMA and MLP methods. Unlike previous research [20], which focused on SPI prediction, this research applies different drought indices (ZSI and CZI) and compares a statistical approach, WMA, with a neural network approach, MLP. The input data are ZSI and CZI indices derived from rainfall records. Two input scenarios are tested: scenario 1 (two inputs): drought indices at (x_1) t-1, (x_2) t-2. Scenario 2 (three inputs): drought indices at (x_1) $t-3, (x_2)\ t-2$, and $(x_3)\ t-1$. For the WMA method, the prediction uses a WMA, where the drought indices at $(x_1)\ t-3, (x_2)\ t-2$, and $(x_3)\ t-1$ are multiplied by weights w=[1, 2, 3] as in (7) [37]. For the MLP method, the input variables are the drought indices $(x_1)\ t-3, (x_2)\ t-2, (x_3)\ t-1$, depending on the scenario. The MLP architecture is optimized to minimize prediction error, with the output being the predicted ZSI or CZI value at time t. The workflow of the proposed method is shown in Figure 4, where ZSI and CZI index data are processed as inputs into both WMA and MLP models under the defined scenarios. Table 2 is an example of predicting WMA with two input and three input scenarios. The weights in this research are the results of experiments that have the best prediction accuracy.

$$F_t = \frac{wY_{t-1}+wY_{t-2}+wY_{t-3}}{\sum w} \tag{7}$$

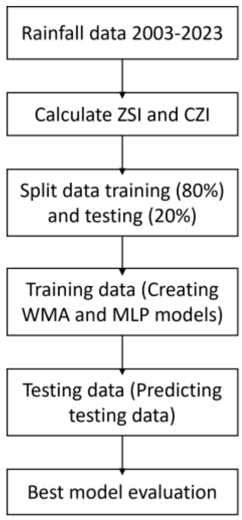
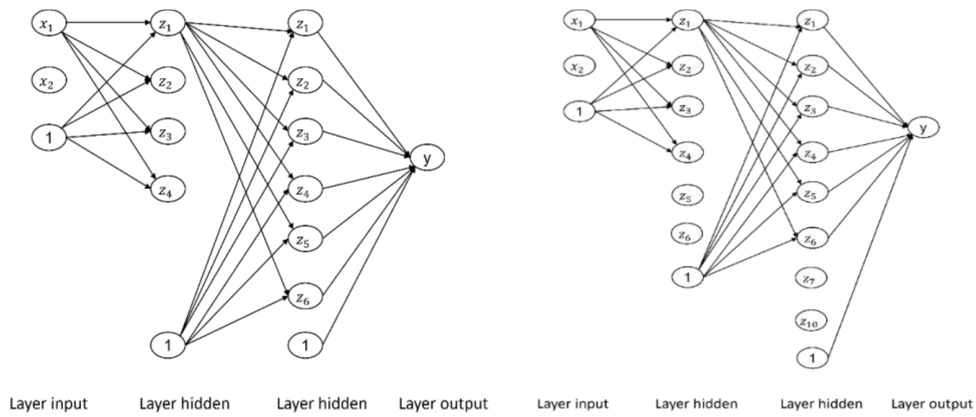


Figure 4. Research proposed

Table 2. WMA predictions

Actual data	Prediction data ($F_t = \frac{1.Y_{t-1}+2Y_{t-2}}{3}$)	Prediction data ($F_t = \frac{1.Y_{t-1}+2Y_{t-2}+3Y_{t-3}}{6}$)
-0.448		
0.965		
0.265	$=\frac{(1*0.965)+(2*-0.448)}{3}$=0.667	
-1.429	$=\frac{(1*0.265)+(2*0.965)}{3}$=0.909	$=\frac{(1*0.265)+(2*0.965)+(3*-0.448)}{6}$=1.972
-0.976	$=\frac{(1*-1.429)+(2*0.265)}{3}$=-1.252	$=\frac{(1*-1.429)+(2*0.265)+(3*0.965)}{6}$=-0.899
-1.551	$=\frac{(1*-0.976)+(2*-1.429)}{3}$=-1.929	$=\frac{(1*-0.976)+(2*-1.429)+(3*0.265)}{6}$=-3.834
-1.551	$=\frac{(1*-1.551)+(2*-0.976)}{3}$=-2.202	$=\frac{(1*-1.551)+(2*-0.976)+(3*-1.429)}{6}$=-3.504
-1.057	$=\frac{(1*-1.551)+(2*-1.551)}{3}$=-2.585	$=\frac{(1*-1.551)+(2*-0.976)+(3*-1.429)}{6}$=-4.653

The MLP method in this research uses the best architectural scenario based on experiments, as shown in Figure 5. The MLP method uses two inputs with the architecture [2-4-6-1] (Figure 5(a)), namely two neurons in the input layer, four neurons in the hidden layer, six neurons in the hidden layer, and one neuron in the output layer, and three inputs with the architecture [3-6-10-1] (Figure 5(b)), namely three neurons in the input layer, six neurons in the hidden layer, ten neurons in the hidden layer, and one neuron in the output layer. The MLP method in this research uses 2 hidden layers, and the output layer has 1 neuron. Each hidden layer and output layer has two processes, namely the direction of the incoming arrow called z_{in}, y_{in} and the direction of the arrow is called out z_{out}, y_{out}. All login processes (z_{in}, y_{in}) calculate the input with weights as in (8), description w is the weight and b is the bias. To optimize learning, the MLP model applies the mean absolute percentage error (MAPE) as the loss function, with the RMSprop optimizer to accelerate convergence, learning rate=0.01. The model is trained using 100 epochs and a batch size of 2, which were found to provide stable convergence and reliable prediction performance across different input scenarios.



(a) (b)

Figure 5. MLP architecture of (a) 2-inputs and (b) 3-inputs

$$y_{in} = b + \sum_{i=1} w_i * z_i \tag{8}$$

This research predicts the ZSI and CZI drought indices using several methods. The most appropriate method for predicting the ZSI and CZI drought indices is evaluated using the MAPE (9) [27].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|index\ drought\ actual_i - index\ drought\ prediction_i|}{|index\ drought\ actual_i|} * 100 \tag{9}$$

3. RESULTS AND DISCUSSION

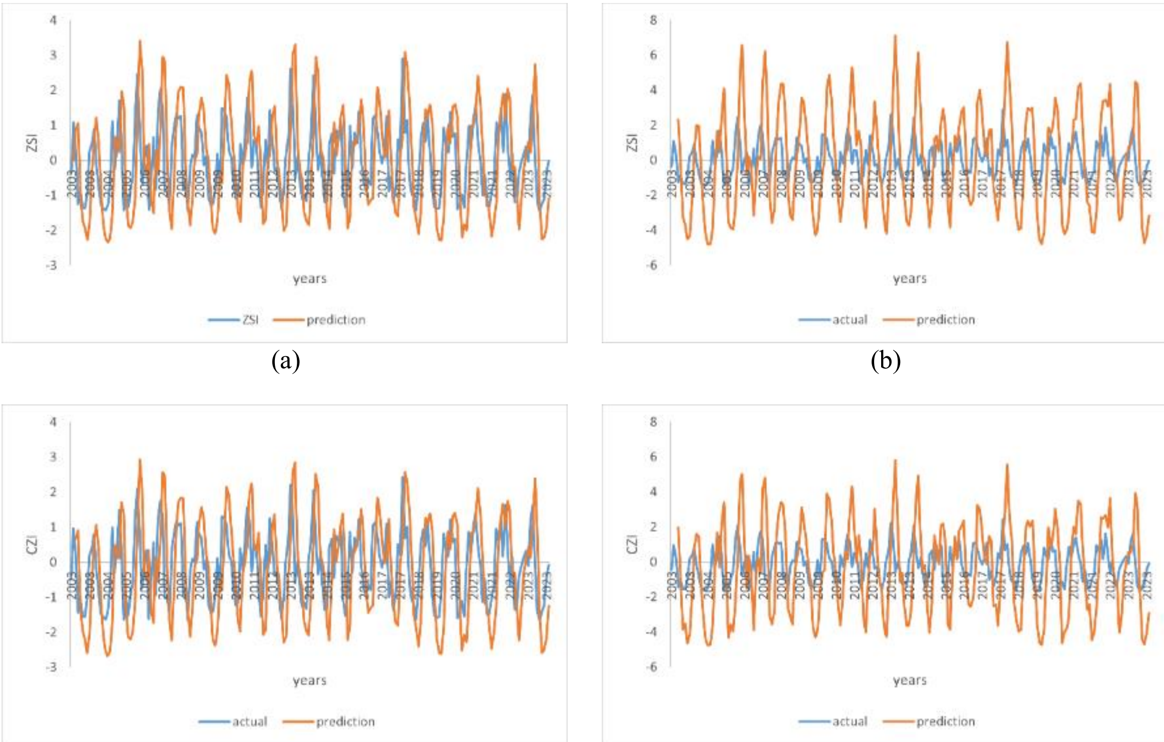
This research predicts the ZSI and CZI drought indices using the WMA and MLP methods. The inputs of this research are the ZSI and CZI drought indices in the period $(t-1, t-2, t-3)$. Drought index value from rainfall data calculation. Figure 6 is the result of WMA prediction based on 2-month and 3-month periods on the ZSI and CZI drought index; the orange color graph is the prediction result, and blue is the actual data. Figure 6(a) shows the ZSI WMA 2 times, Figure 6(b) shows the ZSI WMA 3 times, Figure 6(c) shows the CZI WMA 2 times, and Figure 6(d) shows the CZI WMA 3 times. Table 3 is the statistical value of the ZSI and CZI index prediction result with WMA. Table 4 is the MAPE value from the ZSI and CZI index prediction result with WMA. Based on Table 4, the WMA method has the lowest percentage error with 2 times 2-period $(t-1, t-2)$, and in Figure 6, the orange graph is almost close to the blue graph.

Table 5 is the MAPE value of the MLP method in predicting the drought index. The MLP method conducted training and evaluation experiments five times, by setting the optimizer to RMSprop, with a learning rate of 0.01, epochs of 100, and batch size 2. Based on Table 5, the MLP method has the lowest MAPE with three input variables $x_1 = t-3, x_2 = t-2, x_3 = t-1$. Based on Tables 4 and 5, the smallest MAPE value of the WMA and MLP methods is the MLP method, which is 4.177%, meaning the error value is 4% against the actual data. Figure 7 shows the result of the MLP prediction with two variables $x_1 = t-2, x_2 = t-1$, and three variables $x_1 = t-3, x_2 = t-2, x_3 = t-1$; Figure 7(a) shows the ZSI 2 variables, Figure 7(b) shows the ZSI 3 variables, Figure 7(c) shows the CZI 2 variables, and Figure 7(d) shows the CZI 3 variables. Based on Table 5, the MLP method has the lowest percentage error with three variables $x_1 = t-3, x_2 = t-2, x_3 = t-1$, and in Figure 7, the orange and blue graphs show that the prediction results are almost accurate.

This research predicts the ZSI and CZI drought indices using the WMA and MLP methods. Based on the results of the MAPE evaluation, the method that is closest to the accuracy in predicting the ZSI and CZI indices is MLP with a scenario of three input variables, and the MLP architecture is 3-6-10-1. The WMA and MLP methods have the same input, namely the ZSI and CZI indices from the previous period data $t-3,\ t-2,\ t-1$, the difference is that the WMA method only calculates the average of the accumulation of the multiplication of the drought index and weight. The MLP method accumulates the multiplication of each variable and weight, then there is a weight improvement process to get a more precise value in the prediction. The process is carried out repeatedly. So, the MLP method has a smaller prediction error.

Research [2] predicted SPEI, CZI, SPI, ZSI, DI, PNI, and RAI using artificial neural network (ANN), LSTM, SVM, random forest, and k-nearest neighbors (k-NN) methods; the best model in predicting was linear kernel SVM. Prediction SPI, ZSI with genetic programming (GP) models show that the model is able to predict drought well [7]. The linear regression method is able to predict SPI, ZSI, RAI, SPEI, and RDI well [12]. Traditional statistical models such as ARIMA have also been widely applied for drought forecasting, particularly for SPI, due to their ability to capture temporal dependencies. However, ARIMA is limited in handling nonlinear patterns commonly present in climate and rainfall data. Similarly, DT models provide interpretable results and can capture simple nonlinear relationships, but their prediction accuracy is often lower than ensemble methods such as random forest or gradient boosting. Compared to these traditional approaches, the MLP model in this research achieved lower error values (MAPE=4.177%), indicating that neural network–based methods are more effective in capturing the nonlinear characteristics of drought indices such as ZSI and CZI.

Despite the promising results, this research has several limitations. First, the rainfall dataset used in this research is relatively limited in terms of temporal coverage and spatial resolution, which may affect the robustness of the model. Second, the use of neural networks such as MLP carries an inherent risk of overfitting, especially when training with sparse data. Although measures such as input scenario testing were applied, the potential risk cannot be fully eliminated. Third, the developed models were trained and validated only for a specific region and for two rainfall-based indices (ZSI and CZI). Therefore, the generalization of the results to other regions, climate conditions, or drought indices may require retraining or further adaptation.



(a) (b)

(c) (d)

Figure 6. Prediction WMA of (a) ZSI WMA 2 times, (b) ZSI WMA 3 times, (c) CZI WMA 2 times, and (d) CZI WMA 3 times

Table 3. WMA prediction statistics

Value	ZSI		CZI	
	2 times	3 times	2 times	3 times
Minimum	-2.332	-4.794	-2.674	-4.758
Maximum	3.415	7.116	2.934	5.797
Standard deviation	1.458	2.928	1.460	2.663
Median	0.077	0.207	-0.058	-0.334
Mean	0.003	0.007	-0.204	-0.370

Table 4. MAPE WMA prediction (%)

Index	2 times	3 times
ZSI	609.37	1475.39
CZI	347.48	348.43

Table 5. MAPE statistics of MLP (%)

Value	ZSI		CZI	
	two variables	three variables	two variables	three variables
Minimum	176.375	4.177	128.984	10.030
Maximum	326.313	17.381	644.352	56.035
Standard deviation	283.499	8.643	213.315	17.722
Median	263.734	10.553	243.341	21.350
Mean	78.682	6.733	132.256	12.412

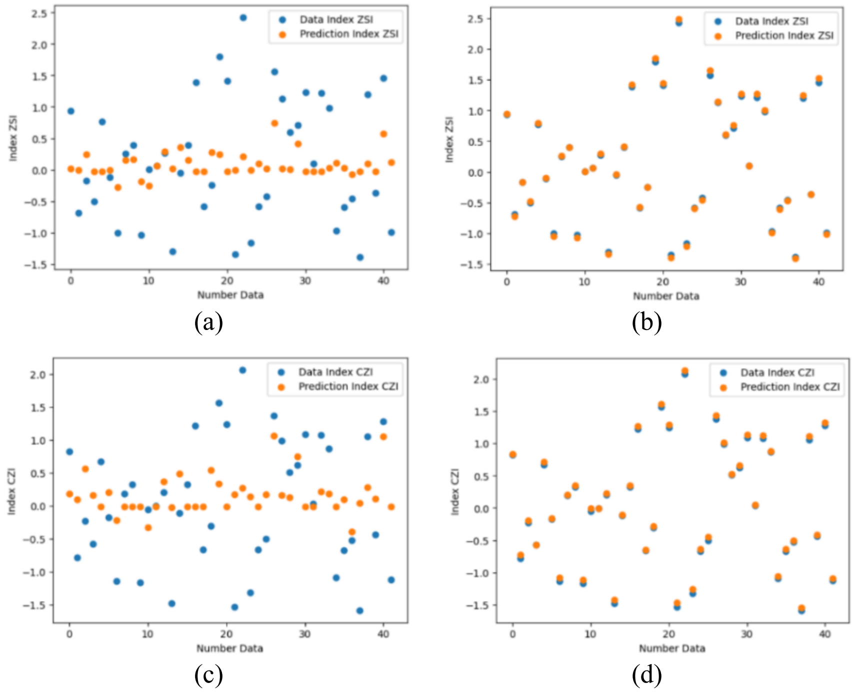


Figure 7. MLP prediction of (a) ZSI 2 variables, (b) ZSI 3 variables, (c) CZI 2 variables, and (d) CZI 3 variables

4. CONCLUSION

This research investigated the prediction of ZSI and CZI drought indices using the WMA and MLP methods under two input scenarios: two previous periods $(t-2,\ t-1)$ and three previous periods $(t-3,\ t-2,\ t-1)$. The results show that MLP consistently outperforms WMA in prediction accuracy. The best performance was achieved by the MLP model with a MAPE of 4.177% using the three-variable input scenario. The optimal MLP architecture obtained is 3-6-10-1. These findings demonstrate that MLP can serve as a reliable model for predicting rainfall-based drought indices beyond SPI, particularly ZSI and CZI, which have been rarely examined in previous research. For future research, several potential extensions can be considered to enhance the applicability of drought prediction models. First, multimodal inputs such as combining rainfall with temperature, humidity, or soil moisture data could improve prediction robustness. Second, real-time or near-real-time drought prediction systems could be developed to support early warning and rapid response.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Nur Nafiiyah	✓	✓	✓	✓			✓		✓	✓	✓			
Ali Mokhtar	✓	✓			✓	✓				✓		✓		

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

All researchers do not have a conflict.

DATA AVAILABILITY

Data was downloaded from the website Hidrologi SDA Jawa Timur at https://hidrologi.dpuair.jatimprov.go.id/pelayanan/.

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