A Comparative Study of the Forest Fire Danger Index Calculation Methods Using Backpropagation

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Abstract. Forest fires are one of the threats of disasters in Indonesia. Rising earth temperatures add to the higher potential contribution of forest fires. Many forest fire hazard index calculation methods have been developed to analyze the impact categories arising from changes in meteorological parameters. Each calculation method has advantages in calculating the magnitude of the potential. One method of calculating the forest fire hazard index is needed from many choices of methods that have the highest level of accuracy to predict the potential for a fire. A comparative study of the methods will be validated and guide the best calculating procedure to be implemented for the prediction. Predictions that have excellent accuracy and precision can be used as an early warning system. This study will predict forest fires for each calculation method using the Backpropagation algorithm, then analyze the accuracy of the prediction results using Relative Operating Characteristics (ROC). The methods compared include the methods that have been used in Indonesia as a country that has tropical rainforests, namely Keetch-Byram Drought Index (KBDI), Standard Precipitation Index (SPI), McArthur Forest Fire Danger Index (MFFDI), and Fire Weather Index (FWI). Through a comparative study of this calculation model, it is concluded that MFFDI is the best method of calculating the fire hazard index with an accuracy value of 0.917 and a precision value of 0.667.

Keywords: Backpropagation, Forest fire, Forest Fire Danger Index, ROC.

1. Introduction

Forest fires are a disaster in the dry season that continues to be a threat in tropical rainforest regions such as Indonesia [1]. Areas of Indonesia that have the potential for forest fires every dry season are Sumatra Island and Kalimantan Island. The losses incurred are not only ecological disasters in the form of carbon dioxide emissions but also economic losses [2]. Based on information from the official website of the National Disaster Management Agency (www.bnpb.go.id) shows that forest fires are the third-largest disaster after floods and earthquakes. 2016 was the year where the majority of forest fires were 178 times. The magnitude of the opportunity for forest fires and the impact caused by this is of particular concern for finding prevention solutions.

Forest fire prevention must be carried out based on the hazard index standards measured using calculation methods and parameters [3]. The current forest fire hazard index used by Indonesia is the Standard Precipitation Index (SPI), as published on the official website of the Meteorology, Climatology, and Geophysics Agency (www.bmkg.go.id). Several studies have been conducted using SPI as a method of adaptation and mitigation to deal with climate change, but there are not many studies that correctly calculate the index of the potential for a forest fire hazard.
Forest fire hazard index calculation methods are currently being developed in Europe and America, which combine the calculation of the number and water content of the fuel, the rate of spread, and the intensity of the fire [4]. Indonesia uses calculation methods that have been developed by other countries despite having a high number of forest fires, even though Indonesia is a country that has tropical rain forests. The character of tropical rain forests is having a high rainfall of more than 60 inches per year [5]. An abnormal condition because it has high rainfall, but forest fires often occur.

In this study, several methods of calculating the index of forest fire hazard will be compared in calculating the performance of the index and predicted using the Backpropagation algorithm. Prediction results will be compared with the actual situation to be analyzed using ROC. The results of this comparison will be concluded which method is most suitable to be applied. The appropriate measure, in this case, is one that has a similarity value to the actual conditions. Then the time series data from each method is trained into artificial neural networks using backpropagation algorithms and tested for accuracy and precision of predictions.

2. Material and Methods

2.1. Study Area

Based on data recorded from the history of rainfall, Indonesia has often experienced drought in recent years [6]. Almost every five years, there are severe droughts such as 1972, 1977, 1982, 1987, 1991, 1997, and until now continues to be a threat that is one of the factors causing forest fires. Drought and forest fires correlate because meteorological factors are instrumental in contributing to the number of fires and the extent of the smoking area [7]. Meteorological factors in question include rainfall, maximum temperature, humidity, wind speed, and the length of sun exposure. This was confirmed by Field (2004), which states that fire and drought are strictly related relations in Indonesian territory [8].

![Figure 1. Potential for an Ease of Fire](image)

This research was carried out in East Kalimantan Province by sampling meteorological data in the tropical rain forest area of the Bukit Soeharto Forest Park. The determination of this location is based on the Meteorology, Climatology, and Geophysics Agency (www.bmkg.go.id), which shows that southern and eastern Kalimantan are areas that have flammable potential. Figure 1 shows that the eastern and southern parts of Kalimantan Island, the southern part of Sulawesi Island, the central and eastern parts of Java Island, Bali Island, Nusa Tenggara Islands are the areas with the highest fire potential. The meteorological data used are monthly data with a period of 8 years (2009-2016).
2.2. Method

Compared forest fire danger index calculation methods are Keetch-Byram Drought Index (KBDI), Standard Precipitation Index (SPI), McArthur Forest Fire Danger Index (MFFDI), and Fire Weather Index (FWI). The method used to compare is the Backpropagation algorithm and Relative Operating Characteristic (ROC).

2.2.1. Backpropagation. Backpropagation is a popular algorithm in artificial neural networks that can solve complex problems through a supervised learning system. The application of artificial neural networks to predict the risk of forest fires have also been carried out in the City of Cape Town, which results in a low, medium, high, and extreme prediction category with an accuracy of 97% [9]. The risk of forest fire hazards needs to be predicted to reduce the number of possible losses. The classification of results arranged in four categories is sufficient to represent the level of danger of forest fires. In general, backpropagation has three layers for computing: the input layer, hidden layer, and output layer. Each layer has input data (neurons), and each neuron is connected to the neurons in the next layer, which are weighted. The calculation process is carried out through two stages, namely the advanced calculation stage, namely the input parameters are moved to the output layer, and the backward calculation to calculate the error threshold from the output layer to the input layer. These two steps are repeated until they reach the expected error threshold value [10]. Research using backpropagation as a method choice has been highly developed since it was first introduced in the 1970s. One recent update is the use of Gradient Descent, which functions for machine learning, is changed using another algorithm, namely Moore-Penrose Pseudo Inverse, which produces promising conclusions for learning variations [11]. Another innovation using this method is to predict local rainfall using meteorological data on the internet using data from the Japan Meteorological Agency, which produces rainfall volumes that can be predicted accurately [12]. Both of these studies show that backpropagation undergoes a process of improving performance that adjusts to the current situation.

2.2.2. Relative Operating Characteristic (ROC). ROC analysis was chosen because it has advantages in choosing the optimal index that does not depend on the class of data distribution [3]. The accuracy of each index is classified into four values: TP as true positive, FP as false positive, TN as true negative, and FN as false-negative [13]. TP is defined as a condition that predicted forest fires and actual forest fires, FP is defined as predicted to burn but does not occur fire, TN is defined as predicted not to burn, but fire occurs, and FN is defined by predicted not to burn and correct to no fire. Based on these four conditions, it can be concluded in two values, namely TPR as True Positive Rate and FPR as False Positive Rate, which is shown in Equations 1 and 2. TPR is defined as the correct value of predicted forest fires and actual forest fires, and FPR is defined as the value of prediction errors and no fires. In addition to the two assessments, the ROC also makes it possible to look for values of accuracy and precision as written in Equations 3 and 4. Accuracy (ACC) is defined as the value of two conditions that indicate the occurrence of fire compared to all existing conditions, and precision is the ideal condition the predicted value and reality is proportional to the correct predictive value.

\[
TPR = \frac{TP}{TP + FN} \quad (1)
\]
\[
FPR = \frac{FP}{FP + TN} \quad (2)
\]
\[
ACC = \frac{(TP + FN)}{(TP + FP + TN + FN)} \quad (3)
\]
\[
Precision = \frac{TP}{(TP + FP)} \quad (4)
\]

2.3. Forest Fire Danger Index Calculation Methods

2.3.1. Keetch-Byram Drought Index (KBDI). KBDI is commonly used to determine the danger of forest fires in Indonesia, which has tropical rain forests [14]. KBDI is used to calculate the potential
danger of forest fires because drought and forest fires have a close relationship [7], then Rudy (2018) researched to analyze the drought index in the Siak River Basin using the KBDI method producing an accuracy of 0.859 in 2009 [15]. Although it was developed by the Forest Service of the United States Department of Agriculture [16], KBDI is widely used in Indonesia as a tropical country because it can measure the rate of humidity that is affected by vegetation cover and transpiration capacity [17]. Crane (1982) revised the equation to calculate the Drought Factor (dQ) in units of the International System from the original version written by Keetch and Byram (1968) where $Q =$ moisture deficiency (mm), $T =$ daily maximum temperature (°C), $R =$ mean annual precipitation (mm), and $d\tau =$ time increment (=1 day) [18]. The calculation method is presented in equation 5. Furthermore, today's drought index obtained from yesterday's drought index is added by today's drought factor, or tomorrow's drought index is obtained from today's drought index added by tomorrow's drought factor.

$$dQ = \frac{[203.2 - Q][0.968 \exp(0.0875T + 1.5552) - 8.30]d\tau}{1 + 10.88 \exp(-0.001736R)} x10^{-3}$$ (5)

Drought index classification results calculated ranged from 0 to 800, which were initially divided into eight stages, ranging from 0 to 99 are stage 0 and 700 to 800 are stage 7 [19]. In its application made simpler divided into four levels, namely low for the index value 0-200, moderate for the index value of 200-400, high for the index value of 400-600, and extreme for the index value of 600-800 [20]. In this study, the input layer in backpropagation is four units (consisting of moisture deficiency, maximum temperature, mean annual precipitation, and drought factor), and the output layer is 1 unit (prediction of forest fires). The prediction of forest fire is determined based on the index of forest fire hazard that is produced from the KBDI manual calculation for the value of 1 is predicted to burn sourced from high and extreme indexes, while the value of 0 is a prediction of not burning with low and moderate indexes.

### 2.3.2 Standard Precipitation Index (SPI)

The SPI calculation method is most widely used by researchers in Indonesia to measure the level of drought. SPI has advantages because it can be used to measure the unusual state of precipitation over a long period [21]. Unusual circumstances related to climate change become vigilance for all people. With the variable precipitation, the SPI can be used to predict periods of severe drought in months that will occur in Indonesia in 2045 [22]. A beneficial finding to be used as a mitigation and early warning system.

The SPI calculation is a scaled two-parameter gamma distribution and depends on the probability function shown in equation 6 [23].

$$G(x) = \frac{1}{\beta \tau(\alpha)} \int_0^x x^{\alpha-1}e^{-x/\beta}dx \text{ for } x > 0,$$ (6)

where $\alpha =$ the shape parameter, $\beta =$ the scale parameter, $x =$ the precipitation value, and $\tau(\alpha) =$ the gamma function.

If $x$ is 0, then the gamma distribution is undefined. Precipitation may be zero, so the cumulative probability distribution is written in equation 7.

$$H(x) = q + (1 - q)G(x),$$ (7)

where $q =$ the probability of the zero precipitation value.

The SPI value is calculated by equations 8 and 9.
If the value of $H(x)$ is between 0 - 0.5

$$SPI = -\left( t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 + d_2 t^2 + d_3 t^3}\right), \text{ where } t = \sqrt{\frac{1}{(H(x))^2}}$$

If the value of $H(x)$ is between 0.51 – 1

$$SPI = +\left( t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 + d_2 t^2 + d_3 t^3}\right), \text{ where } t = \sqrt{\frac{1}{(1.0 - H(x))^2}}$$

where the coefficient is determined $c_0=2.51517$, $c_1=0.802856$, $c_2=0.010328$, $d_1=1.432788$, $d_2=0.189269$, $d_3=0.001308$ [23].

World Meteorological Organization (2012) released the Standard Precipitation Index User Guide to provide an overview of the standard of using SPI throughout the world. In the user guide, it is explained that SPI is very flexible to be used to measure the drought index in a span of 1, 3, 6, 9, 12, to 12 months. Classification to determine the intensity of SPI dryness is extremely wet for SPI values ranging from 2.0 and above, very wet for 1.5 to 1.9, moderately wet for 1.0 to 1.49, near normal for -0.99 to 0.99, moderately dry for -1.0 to -1.49, severely dry for -1.5 to -1.99, and extremely dry for SPI values of -2 and below [24].

The input layer consists of 2 cells, namely precipitation and temperature, while the output layer has one cell, which is fire prediction. Fire prediction in this method consists of 2 categories, namely a value of 1 for prediction of burning for severely dry and extremely dry indexes, value of 0 for prediction of not burning with extremely wet, very wet, moderately wet, near normal, and moderately dry index.

2.3.3. McArthur Forest Fire Danger Index (MFFDI). The McArthur method has been successfully implemented in New South Wales fire-prone areas using additional parameters such as the presence of fuel, oxygen, and the cause of the fire [25]. Forest fuel consisting of dry leaves, fallen tree branches, and dry wood on the forest floor significantly contributes during the dry season. With a small spark, the forest can burn if the forest fuel has low humidity.

McArthur requires much data to calculate the potential value of a fire hazard [26]. Several data were collected from the meteorological station to obtain the supporting parameter patterns for forest fires. Khastagir (2018) stated that previous studies have proven that there is a close relationship between the index of a forest fire hazard with climate parameters such as temperature, humidity, wind speed, and drought factors. In this study, using the equation derived by Noble et al. states that previous studies have proven that there is a close relationship between the index of a forest fire hazard with climate parameters such as temperature, humidity, wind speed, and drought factors. In this study, the equation derived by Noble (1980), as shown in equation 10.

$$FFDI = 2 \exp(-0.45 + 0.987 \ln DF + 0.0338T + 0.0345RH + 0.0234U),$$

where $T$ = the temperature (°C), $RH$ = the relatifs humidity (%), $U$ = the wind speed (km/h), and $DF$ = the drought factor.

The drought factor is essential in calculating the forest fire hazard index. McArthur has developed its drought factor calculation, but in its application as in Australia using the drought factor Keetch-Byram Drought Index (KBDI) or Mount's Soil Dryness Index (MSDI) depending on the state of the region [27] and in this study, using the DF value of KBDI or a maximum of 10.
The fire hazard rating system according to the National Fire Warning System (2009) divides the forest fire hazard index into six categories namely catastrophic (code red) for values over 100, extreme for 75-99, severe for 50-74, very high for 25-49, high for 12-24, and low to moderate 0-11 [29]. In this study, the input layer has four cells, namely, temperature, relative humidity, wind speed, and drought factor. The output layer has one cell, which is a value of 1 for prediction of fire (extreme, and severe), the value of 0 for prediction of no fire (low, moderate, and very high).

2.3.4. Fire Weather Index (FWI). FWI is one of the most effective methods for calculating forest fire hazard index, in the long run, using meteorological data parameters [30]. The main parameters used in the FWI method are the water content in the fuel and its consistency [31]. In its home country, FWI was successfully applied to detect potential fires with weather variables, including relative humidity, temperature, and wind speed [32]. The use of weather data as a basis for the calculation of fire hazard indices confirms that there is a close relationship between forest fires and drought.

Wagner (1974), as shown in Figure 2 illustrates the calculation of FWI sourced from three components, namely the Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), and Drought Code (DC). Furthermore, the three components become the basis for the calculation of the Initial Spread Index (ISI) and Adjusted Duff Moisture Code (ADMC). The final results of the FWI calculation will be obtained from the ISI, and ADMC calculations with the classification of forest fire risk being extreme for FWI limits more than 25, high for 13-24, moderate for 6-12, low for 2-5, and very low for 0-1.

![Figure 2. Block Diagram of Fire Weather Index](image)

The input layer in backpropagation is four cells, namely rainfall, relative humidity, wind speed, and temperature. The output layer has one cell with a value of 1 for prediction of a fire and a value of 0 for a prediction for no fire. Fire prediction occurs for extreme and high indices, while prediction does not occur with fire with very low, low, and moderate indexes.

3. Result

3.1. Training and Testing using Backpropagation

Artificial neural network architecture is built with three layers, namely the input layer, the hidden layer, and the output layer. Each layer has neuron cells. In this study, the cells in the input layer are the parameters used in the index calculation. The number of cells in the hidden layer is determined together with the learning rate and Mean Squared Error at the beginning of the initialization before the learning process begins. The output layer in this study is one cell containing a prediction of a fire or no fire that refers to the index value of each calculation method. Each value is presented in Table 1.
Table 1. Backpropagation Element

|                  | KBDI | SPI | MFFDI | FWI |
|------------------|------|-----|-------|-----|
| Input layer cell | 3    | 2   | 4     | 4   |
| Output layer cell| 1    | 1   | 1     | 1   |
| Hidden cell layer| 20   | 20  | 20    | 20  |
| Learning Rate    | 0.1  | 0.1 | 0.1   | 0.1 |
| Mean Squared Error| 0.001| 0.001| 0.001| 0.001 |
| Activation Function| Llogsig, Pureline | Logsig, Pureline | Logsig, Pureline | Logsig, Pureline |
| A convergence of iteration to | 15871 | Not convergence | 12451 | 19252 |

Training and testing of data in this study using the Matlab R2016b tool with functions provided in the Neural Network Toolbox. In the first stage, 60 data are trained (60 months data) with the input data layer being the parameter of each index calculation method, and the output layer is the real data of the fire incident that occurred. Figure 3 until Figure 6 shows the training results of each calculation method where KBDI converges at the 15871 iterations, SPI does not converge using two cells at the input layer and the same network architecture as the other methods show that MFFDI converges at the 12451 iterations, and FWI converges on the 19252 iterations.
Figure 5. Data Training Results for MFFDI Method

Figure 6. Data Training Results for FWI Method

Data testing was performed using 36 data (36-month data) that were not previously trained in backpropagation. Figure 7, until Figure 10, shows the results of each method by comparison between targets and outputs produced by backpropagation. Figure 7 shows the KBDI method, and the network predicts that there will not be a fire within three years (36 data), but in fact, there are fires five times so that it can be concluded that the KBDI 31 data is predicted to be accurate and five is predicted to be wrong (86.11%). Figure 5 shows the SPI method of 36 data tested showed 32 data following the target (88.89%). The MFFDI method produces test results that 34 are correct from 36 data (94.44%), and the FWI method shows 26 results that are true (72.22%).

Figure 7. Forest Fire Prediction Results of the KBDI Methods

Figure 8. Forest Fire Prediction Results of the SPI Methods

Figure 9. Forest Fire Prediction Results of the MFFDI Methods

Figure 10. Forest Fire Prediction Results of the FWI Methods

3.2. Analysis using ROC

Referring to Karouni, Daya, & Bahlak (2013), dividing four classification categories to test the truth of the test results with actual conditions, namely TP (predicted forest fires and real forest fires), FP (predicted to burn but did not occur), TN (predicted not to burn but there was a fire), and FN (predicted not to burn and did not fire). Based on the test results using backpropagation and compared to the actual data yielded the data presented in Table 2.
Table 2. ROC Values, TPR, FPR, Accuracy, and Precision

|     | TP | FP | TN | FN | TPR | FPR | Accuracy | Precision |
|-----|----|----|----|----|-----|-----|----------|-----------|
| KBDI| 0  | 0  | 5  | 31 | 0.000| 0.000| 0.861    | 0.000     |
| SPI | 1  | 1  | 4  | 30 | 0.032| 0.200| 0.861    | 0.500     |
| MFFDI| 4  | 2  | 1  | 29 | 0.121| 0.667| 0.917    | 0.667     |
| FWI | 5  | 10 | 0  | 21 | 0.192| 1.000| 0.722    | 0.333     |

Based on the summary in Table 2, the FWI method has the highest TPR and FPR. A high TPR indicates that Backpropagation has succeeded in predicting forest fires in certain months and, in fact, accurate forest fires. However, it becomes inconsistent if FWI also has a high FPR because FPR indicates that Backpropagation predicts forest fires will occur in certain months, and in fact, there is no fire. However, these two conclusions show that the FWI method predicts most fires, while KBDI does not predict fires as long as 36 data are tested. The MFFDI method is considered to have the highest accuracy value because it succeeded in predicting four times forest fires, and it was proven that there were indeed forest fires. While the FWI method has the lowest accuracy because it predicts 15 times that a forest fire will occur, but in fact, it only occurs five times. Whereas KBDI and SPI are methods that have low accuracy and precision values to predict forest fires.

4. Discussion

Based on training and testing data using backpropagation to analysis using RoC, it can be concluded as in Table 3 that MFFDI is the best method for predicting forest fires, which can ultimately be used as the most appropriate method of calculating fire hazard index because it has the best accuracy and precision. While the FWI method is also worth considering because it has a sensitive calculation of the potential for a forest fire. The KBDI and SPI methods do not appear to be suitable for use as a model for calculating the fire hazard index because they have low accuracy and precision.

Table 3. TPR, FPR, Accuracy, and Precision

|     | TPR | FPR | Accuracy | Precision |
|-----|-----|-----|----------|-----------|
| Best Index | FWI | FWI | MFFDI | MFFDI |
| Worst Index | KBDI | KBDI | FWI | KBDI |

In terms of preventive action, FWI is the best method because it can predict forest fires for one month before forest fires three times, MFFDI predicts two times and SPI 1 time. The large number of FWI predicts that fires show that FWI is more sensitive to the potential for forest fires. However, the number of errors in predicting becomes a problem in itself to be used as a reference for early warning systems.

The accuracy of MFFDI in predicting the occurrence of forest fires and the potential of FWI preventive actions that are sensitive to potential forest fires is an exciting combination of methods to be used as a reference in calculating the index of forest fire hazard. Each has advantages and disadvantages that can be combined to complement each other. Further research is needed to explore the relationship between forest fires, meteorological data, methods of calculating the hazard index of forest fires, and tropical rain forests.

As a conclusion, the four index calculation methods compared show that McArthur FFDI is the best calculation method with the highest level of accuracy and precision. While the FWI Method should be considered as a choice because it can predict more forest fires than the MFFDI Method.
KBDI and SPI are highly recommended methods to predict forest fires but can be used to measure drought levels.

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