JURNAL TEKNOINFO
Volume 16, Nomor 2, Juli 2022, Page 252-257
ISSN: 1693-0010(Print), ISSN: 2615-224X(Online)
Available online at https://ejurnal.teknokrat.ac.id/index.php/teknoinfo/index

A MULTICRITERIA INDEX USING NEURAL NETWORK TO EVALUATE THE POTENTIAL LANDS OF MAIZE

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Abstract

The criteria for planting maize should be consistent with sensible and ecological criteria to determine the potential lands. However, there is still a lack of proven methodology for this evaluation. The purpose of this analysis was to determine the parameters that affect the multi-criteria decision of maize, with the aim of a new method on the land suitability analysis. The land suitability analysis proposed was based on GIS-analysis and management parameters such as distance from roads, rivers, slope, LULC, elevation, soil type, NDVI, SAVI, rainfall, and temperature. We have found a sample of 4590 maize in Tuban, East Java, Indonesia. Based on the above criteria, maize has been classified into four groups according to FAO. Moreover, we analyzed was done using Neural Network. Results showed that the integrated AHP with Neural Network to evaluate the lands inferred that 66.7 percent of the study area was classified as highly suitable, 30.2 percent were moderately suitable, and 3 percent were marginally suitable for Maize Cultivation in Tuban Regency. The approach presented in this analysis can be extended in this analysis can be extended to other maize areas also other crops as a decision-making system.

Keyword: Maize, Suitable Lands, Decision-Making System, Multi-Criteria, GIS, Neural Network.

1. INTRODUCING

The world's population is increasing and is expected to rise every year. Crop production would need to increase twice to feed this rising population [1]. However, as the population increases, so does the consumption of maize and other crops, farmland is divided. Some of the most fertile farmland has been converted into industrial, commercial, or other lands. In face of the climate change and adverse weather conditions, Indonesia wants to find a way of growing crop production [2]. Changes in land use are an anthropogenic phenomenon that can take place actively and indirectly at local, regional, and global levels [3]. The anthropogenic were knows as changes in land use while the results of risk, such as a typhoon or an earthquake. The use of ANN to solve a complex relationship and a non-linearity between crop production and the differences between predictor parameters. The best method for extracting information from imprecise and non-linear data is considered to be ANN [4],[5]. ANN techniques have proven as an important tool for various applications in many fields like the prediction of crop production. Maize is still known as an important feed, nutritional food, and industrial crop [6]. As a result of global warming reported that have been a reduction in crop yields [7]. These improvements are also supported by the model, which forecasts that possible food and feed demand, such as maize, will be further reduced in the future [5, 6]. The supported model uses Geographic Information Systems (GIS) are a

key role in the process of agricultural management. Using remote spatial analysis, GIS able to enhance land suitability assessment [9]. Distance from roads, rivers, slope, LULC, elevation, soil type, NDVI, SAVI, rainfall, and temperature was used to discover the suitable locations for maize planting. The most popular techniques for urban monitoring applications involve the utilization of multispectral sensor imaging data. Pixel-and object-based classification.

Previous research studies in Indonesia [10][11] suggested some implications of new research subjects [12], especially classification of micro-level countries [13], and alternative technologies utilizing remote sensing [14]. There are several types of machine learning that we are familiar with, including Forward propagation (FP), Backpropagation (BP), Extreme Learning Machine (ELM), and Support Vector Machine (SVM). The fundamental purpose of a Forward Propagation (FP) is to learn and map the connections between inputs and outputs. The FP

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learning rule is used to optimize a system's weight and threshold settings to obtain the lowest possible error [15]. It may also be defined as a complicated relationship between a network set's input and output values. The value of each node or neuron is decided by the input received from other network system components. Each input signal is multiplied by the value of the associated input line weight. Backpropagation is a gradient descent method using connection parameters for each step or iteration[16].

In this study, an index was developed to evaluate the maize soils based on management parameters that limit the accessibility and can be assessed using a GIS. The objectives of this research have been extended for maize growing areas by weighted the parameters to evaluate the possible method to predict the yield maize of each village and suitable lands for maize production using an artificial neural network.

2. RESEARCH METHODS

Some 4590-maize located in twenty subdistricts and twenty-two villages in Tuban Regencywere analyzed in this study (Figure 1).

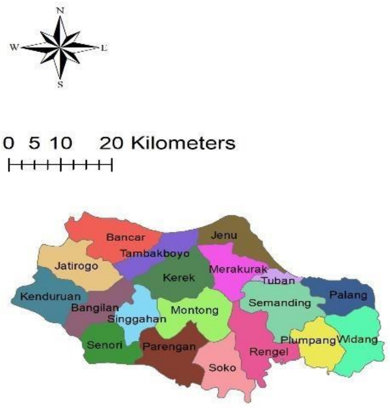

Figure 1. Tuban Regency

This regency is most on the agricultural sector and fishery sector and it has the topography of this regency for the water availability through the river in southern area will help throughout the dry season.
Maize was selected on each subdistrict during the field in 2018 for the ground truth data. The number of maizes selected in each subdistrict was proportional to the total planted area.

2.1. Datasets for potential maize

The datasets for maize production were performed on the parameters for the variousclassification of the categories by FAO. (Table 1). These classifications were to evaluate each parameter of land for a particular use. The assessment of land was reclassified into 4 levels. Lastly, the levels were weighted by the expert decision support.

Table 1. Dataset and Source

Parameters	Suitable lands			
	High	Moderate	Marginal	Not Suitable
Distance from Roads	<394	394 – 882	882 – 1426	>1426
Distance from Rivers	<406	406 – 1179	1179 - 2378	>2378
Slope (%)	0 – 8	8 – 15	15 – 25	>25
LULC	Vegetat ion	Forest	Urban	Waterbody
Elevation	0 – 25	25 – 125	125 – 250	>250
Soil Type	Litosol	Grumusol	Alluvial	Regosol

NDVI	0.259 – 0.26	0.2589-0.259	0.2589-0.2586	0.257 –0.286
SAVI	0.389 – 0.391	0.889 – 0.389	0.3888 – 0.3889	0.385-0.3883
Rainfall	> 2102	1802 – 2102	1484 – 1802	< 1484
Temperature (^{o}C)	20 – 22	18 – 20	15 – 18	9 - 15

The parameters were categorized into 4 classes from FAO class. The weight techniqueswere used to evaluate the suitable land (SL) in the study area using the following expression:

$$SL = \sum^{n}_{j=1} W_j * P_j \qquad (1)$$

where Wj is the weight of the parameters and Pj is the reclass of the parameters value andn is the number of parameters.

2.2. Artificial Neural Network (ANN)

In this study, the input variables of the parameters for the maize cultivation. This study developed comparing the use of forward propagation neural network and backpropagationneural network.

1. Forward Propagation Neural Network (FP-NN)
   Preactivation and activation were taken during the forward propagation at each node of thehidden and to the output layer (**Figure 2**).

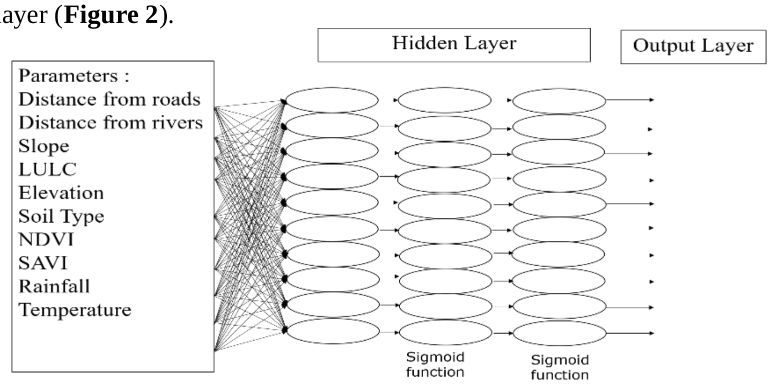

Figure 2. Forward Propagation Neural Network

Preactivation is a weighted number of inputs with a linear transformation. Preactivationdefined in the following expression:

$$Z = \theta \ \sum^{n}_{j=1} P_j * W_j + b \qquad (2)$$

where z1 is output, p1, p2...., Pn is the input parameters, w1, w2. , wn represents the combination of weights that generates the output. θ is the unit step function, Wj is weightsconnected to the input of the nth, b is the bias.

Activation is the determination weight sum of inputs through the activation function. Thereare four common activation functions, sigmoid, tangent (tanh), ReLU, and softmax. In this study, the activation function utilized sigmoid using the following expression:

$$s(z) = \frac{1}{1+ e^{-z}} \ or \ \frac{1}{1+Exp(-z)} \qquad (3)$$

2. Backpropagation Neural Network (BPN)
   BPN is a forward propagation neural network that uses a backpropagation algorithm. In forward transmission, data were processed from the parameters as the input layer to the other layer with the weights using the preactivation and activation function, then the error has measured the difference between actual output and calculated output to minimize error values. (**Figure 3**). To minimize the error values could define the loss function using the following expression:

$$LF = 0.5 \sum_{i=0}^{n} (Predicted\ Output - Actual\ Output)^2 \tag{4}$$

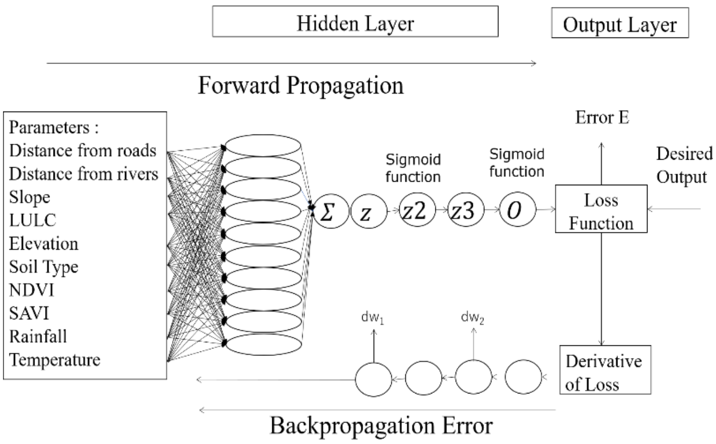

Figure 3. Backpropagation Neural Network

3. RESULT AND DISCUSSIONS

Accordingly, we trained the parameters using two types of ANN models. From this differentapproach distinguish the sustainability for the environment. The input parameters were scaled to nullify the value that impacts the variable to its size. The min-max normalization was then used to translate the data into a common variable of range.

3.1. FP-NN

There is no standard for the selection of parameters in the neural network, the input dataset of the parameters was normalized so at the best combination for the model. Accordingto Table 2, forward Propagation Neural Network weights using random numbers and able toproportion of each village yield for the output layer.

Table 2. Perfor,amce Yield Prediction of FP-ANN Models

Village	Input	Predicted Output
Kapu	280, 290,1,1,0,4,0.25949,0.39034,21.03175,1 980.5	7.3
Tegalrejo	0, 820,1,255,25,7,0.2589,0.38907,21.73275 ,1632.8333	6.19
Tahulu	280, 290,1,255,25,7,0.25887,0.38891,20.8475 4,2252.5	6.59
Mandirejo	280, 0,1,255,0,4,0.25913,0.38953,20.56209,1	7.28

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	980.5		
Bogorejo	0, 290,1,255,0,4,0.25889,0.38907,20.44498 ,2252.5		6.41
Sumberejo	0, 0,1,255,0,4,0.25908,0.38946,20.81601,1 980.5	7.12	
Sendanghaji	0, 0,1,255,0,4,0.25889,0.38894,19.96484,1 980.5	6.36	

3.2. BPN

BPN utilized the weight from on the multicriteria index from the expert opinions about 67 percent of highly suitable lands with loss 0.0098, 30.2 percent of moderately lands with loss0.05, 3 percent of marginally lands with loss 0.10, 0.01 percent not suitable areas were discovered with loss 0.01 (**Table 3**).

Table 3. Performance Suitable Lands Using BPN Models

Suitable lands	Precentage Area (%)	Loss
Highly Suitable	66.7	0.0098
Moderately Suitable	30.2	0.05
Marginally Suitable	3	0.10
Not Suitable	0.01	0.01

4. CONCLUSION

This study demonstrates and comparing the model using an artificial neural network in predicting maize yield and suitable lands in Tuban Regency. The datasets of weight show the prioritized was the rainfall, followed by soil type, temperature, distance from roads, distance rivers and other parameters has the lower weights. This research study is important in Tuban Regency because food security is threatened by drought due to climate and variability. The historical and current data of agro-climatic unified in a model as a decision- making method for combating and managing climate change. The model is designed to integrate various farming scenarios to forecast maize yield, such as the integration of agro- climatic parameters with various farming practices. This method will also help farmers make better decisions, including prevention and adaptation measures, to increase crop production profits. The model is available to specific stakeholders and decision-makers, such as the Department of Agriculture and small-scale farmers. This study can be improved to ensure by adding fertilizer application and improve the model with the hidden layer and comparing the activation function. The status of this model can however be validated by comparing maize production with the actual production in the 2018 season.

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