Model of surface runoff estimation on oil palm plantation with or without biopore infiltration hole using SCS-CN and ANN methods

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Abstract. Surface runoff by rainfall on oil palm-cultivated land can cause erosion. Method conservation of making biopore infiltration hole on sloping oil palm plantations land has been shown to reduce this runoff. It has been experimentally proven in plots with or without biopores. However, the estimation model of the surface runoff event has not been studied comprehensively. The main novelty of this work is using surface runoff and rainfall observation directly database on oil palm land for the predicted runoff. Estimates model of surface runoff on oil palm plantations are essential to know so that farmers can determine which land conservation is more appropriate in the order they can do forecasting and preparedness for extreme events in their land. In the current study, this paper report to compare two methods of estimating surface runoff model on oil palm land that are given biopores and without biopores using (i) conservation service soil - curve number (SCS-CN) and (ii) artificial neural network (ANN) back-propagation. Thirty data of rainfall and runoff events in the three months were used as input data. The results show that the ANN method can provide a more accurate prediction of surface runoff than the SCS-CN method.

1. Introduction
Uncontrolled runoff causes flooding [1] and land degradation [2], especially in high slope areas. It makes nutrients on the surface of the land can be lost and carried away by water. This phenomenon occurs in all field, especially those used as agricultural and plantation land. Several factors that influence the amount of runoff especially in oil palm plantations according to some researchers include the type of soil, type of plant, a slope of land and kind of cover crop. Therefore, many researchers are trying to develop conservation methods to handle the amount of runoff.

One of the conservation methods that continue to be developed is the use of biopore infiltration holes. This method uses a hole in the ground as a medium to be able to continue rainwater directly into the field. Several research reports [3-5] show that biopore infiltration holes can also be filled by compost to increase soil organic matter content. Therefore, this method was adopted to conserve on high slope oil palm plantations. However, a study of the model for determining the amount of rainwater runoff due to the use of biopore infiltration holes in oil palm plantations has not been widely studied.
The model developed by several researchers to review runoff includes conservation service soil-curve numbers (SCS-CN) [6-8], artificial neural networks (ANN) [9, 10]. Literature studies show that these models are generally formed for non-agricultural land. Event-based rainfall-runoff models are to be required for effective tools in operational hydrological forecasting and preparedness for extreme events. Based on this, it is also important to model runoff in oil palm plantations that are given and without being given biopore infiltration holes. Therefore, this paper aims to model runoff in oil palm plantations based on the results of field experiments through the SCS-CN and ANN approaches. Both of these approaches will be compensated for accuracy to be able to estimate the runoff that is most appropriate with the measurement results. This model is expected to be a reference to be able to develop other conservation methods in oil palm plantations further.

2. Material and Method

2.1. Field Experiment Description

The study was performed at oil palm plantations in Aceh province located at 02 ° 27 '30" - 03 ° 00' 00" north latitude and 0 97 ° 45 '00' - 98 ° 10' 00" east longitude. Porosity, soil permeability and organic matter content in the research plots were 51.07%, 2.26 cm/hour, 1.32%, respectively. The biopore infiltration holes made are six holes with a diameter of 10 cm. The distance from the hole to the center of the oil palm plant is 4.5 m from the front and 3.8 m from the side. The soil is drilled 60 cm deep using a ground drill. The hole is filled with compost from 3 kg of empty oil palm bunches.

The experimental plot consisted of fruit namely runoff plots on oil palm land with cover crops of mucuna soil without biopore infiltration holes and runoff plots on oil palm land which had cover crops of mucuna soil with biopori infiltration holes. In the runoff plot, there is a 5-year-old oil palm plant. The slope of the land is 27.78%. The area of each plot is 135.15 m² with a rectangular area of 132 m² and a trapezoidal area of 3.15 m². The distance between runoff plots is 50 cm. The sketch of the experimental plot is presented in Figure 1. Surrounding the experimental plot is limited to an iron plate and in such a way is directed towards the shelter. Every day the water reservoir will be monitoring and measured if there is runoff that is accommodated. Rainfall in the experimental plot was measured using two precipitation meters namely the Ombrometer and Automatic Water Station (AWS). Both types of equipment are placed outside the runoff plot, so that plant canopies do not block them.

2.2. Calculation of Runoff Using the SCS-CN Method

The soil conservation service curve number (SCS-CN) method (USDA, 2004) is one of the methods for computing the direct runoff depth for rainfall event. Equations of prediction of surface runoff
based on the SCS-CN method [11] uses Equation 1-2. The curve number (CN) relates to the influence of the soil hydrology group, land use and the level of treatment given to a land that shows the potential for surface flow for sure rainfall. This analysis uses surface flow curve numbers for various soil hydrological groups and land cover according to Arsyad [12].

\[
Q_{SCC-CN} = \frac{(P - 0.2S)^2}{P + 0.8S}
\]  \hspace{1cm} (1)

\[
S = \frac{25400}{C_N} - 254
\]  \hspace{1cm} (2)

Where \(Q\)-direct runoff (mm); \(P\)-total precipitation (mm); \(S\)-maximum retention capacity obtained as per SCS-CN method (mm); \(C_N\)-curve number that depends on the soil type.

2.3. Prediction of Runoff by ANN Method

Prediction of runoff on oil palm plantations with or without biopore infiltration holes using multilayered ANN feed forward with the back-propagation algorithm. The training uses the type of Levenberg-Marquardt. Network architecture consists of 3 inputs, four hidden layers, and one output or can be written like \([3\ 10\ 10\ 10\ 10\ 1]\). Learning is done with the learning rate parameter; the momentum and gain of each model have the same values, which are 0.1, 0.2, and 0.9. Termination criteria are based on cross-validation between training data and testing data.

ANN input in the form of daily rainfall, average rainfall amount and number of rainfall events in one day. Each hidden layer consists of 10 interconnected fruits. ANN output is a runoff. Following the stages of ANN, 30 pieces of rain event data which caused runoff were divided into three categories, 70% of which were used for training, 15% of data were used for validation, and 15% were used for testing. After the model is conducted training, validation, and testing, the model is ready to be tested on the sample data. Sample data is measured directly from runoff and rainfall in the field. Differences in prediction results from ANN models and direct measurement results will be calculated as errors. Errors are calculated using the coefficient of determination and mean squared error (MSE).

2.4. Measurement of Prediction Model Performance

The performance of the model is measured by looking at the mean squared error (MSE) and coefficient of determination \(R^2\) of the model as was done by several studies [13, 14]. The smaller the MSE value in both the training data and the test data shows that the model is the best model. The classification of error values that have been used by several researchers [15-17] classify models are presented in Table 1. MSE is calculated by Equation 3. The coefficient of determination \(R^2\) is calculated using Equation 4.

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_{i,e} - Y_{i,p})^2
\]  \hspace{1cm} (3)

\[
R^2 = \frac{\sum_{i=1}^{n} (Y_{i,p} - Y_{i,e})^2}{\sum_{i=1}^{n} (Y_{i,p} - Y_{i,e})^2}
\]  \hspace{1cm} (4)

Where \(MSE\)-mean squared error; \(Y_{i,e}\)-experimental data; \(Y_{i,p}\)-prediction data; \(n\)-amount of experimental data; \(Y_e\)-eksperimental average data; \(R^2\)-coefficient of determination.

| MSE (%)       | Evaluation            |
|---------------|-----------------------|
| MSE ≤ 10%     | High accuracy forecasting |
| 11% ≤ MSE ≤ 20% | Good forecasting     |
| 21% ≤ MSE ≤ 50% | Reasonable forecasting |
| MSE ≥ 51%     | Inaccurate forecasting |
3. Result and Discussion

Data on rainfall and runoff occurring in each plot are presented in Figure 2. The graph in Figure 2 explains that in the experimental plots using biopore infiltration holes gave smaller runoff than without using biopore infiltration holes. The correlation between rainfall and runoff on land that is given a biopore infiltration hole is 69.00%. Meanwhile, on land that does not use biopore infiltration holes, the correlation between the rainfall and runoff is 76.31%. It shows that the effect of rainfall on the land not using biopore infiltration holes is 9.58% greater than the land that has biopor infiltration holes in creating runoff. This result is in line with the research report of Bailey et al. [3] which states that on land using biopore infiltration hole conservation methods, that rainfall is not the only strongest/dominant factor to generate runoff on the soil. The researchers [4, 18, 19] stated that there were several other dominant factors in the form of daily average rainfall, number of rainfall events per day, physical and mechanical properties of soil, protective plants and land contours.

![Figure 2. Rainfall and runoff observations during the study](image)

3.1. Prediction Model Using SCS-CN

Runoff predictions using the SCS-CN method on land not using biopore infiltration holes are presented in Figure 3. The limitations of the curve number on the soil type, land cover and land use from the SCS-CN method cause the determination of runoff for certain land conditions such as biopori land use cannot be done. Runoff correlation between prediction and measurement is 63.43%. This value indicates that the SCS-CN method can be used to estimate runoff but with a still low level of accuracy. This is caused by several factors, among others are (i) the SCC-CN method which only depends on the amount of rainfall falling on the ground, (ii) the amount of retention of potential water retention, and (iii) it is not appropriate to classify hydrological groups. On the other hand, the error value of the predicted runoff using MSE from the SCC-CN prediction method is 3.0%. The amount of error value with this MSE according to some researchers [15, 16] as presented in Table 1 has entered into a high-accuracy category in making predictions.

3.2. Prediction Model Using ANN

The prediction of runoff using artificial neural networks (ANN) is shown in Figure 4. The results show that ANN can predict runoff on land that has and without biopore infiltration holes with a very high value of determination. On land using biopore infiltration holes, ANN can determine runoff predictions with a determination value of 88.82%. This value is smaller than 8.18% from the prediction using ANN on land without using biopore infiltration holes whose determination value is 96.73%. Based on the value of its determination, the prediction model for runoff constructed through
this ANN is acceptable. Predicted errors using MSE showed that the fields with and without biopore infiltration holes were 0.55%, 0.42% respectively. This MSE value has shown that the models built with ANN have high accuracy forecasting based on Table 1.

Figure 3. The relationship of runoff results of measurements and predictions using the SCS-CN method

Figure 4. The relationship of runoff results of measurements and predictions using the ANN method

ANN simulation results on land using biopore infiltration holes at the training, validation, and testing stages are presented in Figure 5. In the training phase, there is a relationship between runoff predictions and runoff measurements as in Equation 5. At the stage of validation and testing, there is a relationship between the predicted runoff and runoff measurements, as in Equations 6 and 7. The whole equation is supported by a level of determination of relationships greater than 90%.

\[
Y = 0.9x + 0.002 \quad R^2 = 0.9756 \\
Y = 0.67x + 0.042 \quad R^2 = 0.9131 \\
Y = 1.4x + 0.0021 \quad R^2 = 0.9605 \\
Y = 0.89x + 0.0028 \quad R^2 = 0.9424
\]

ANN simulation results on land without using biopore infiltration holes at the training, validation, and testing stages are presented in Figure 6. In the training phase, there is a relationship between runoff predictions and runoff measurements as in Equation 9. At the stage of validation and testing, there is a relationship between the predicted runoff and runoff measurements, as in Equations 10 and 11. This whole equation is supported by the level of determination of the relationship more significant than 90%. However, the value of determination of ANN simulation results on land without biopore infiltration holes is on average higher than on land using biopore infiltration holes. It is caused by the involvement of factors other than rainfall which cause runoff on land that uses biopore infiltration holes. Therefore, future research, it is important to be able to find these factors to be able to increase the accuracy of the predicted runoff on land using biopore infiltration holes.

\[
Y = 0.99x + 0.00028 \quad R^2 = 0.9978 \\
Y = 0.99x + 0.0032 \quad R^2 = 0.9494 \\
Y = 0.95x + 0.0013 \quad R^2 = 0.9261
\]
4. Conclusions
Predictions of runoff on oil palm plantations that use and without the use of biopore infiltration holes have been carried out by two methods. The SCC-CN method can only predict runoff without biopore infiltration holes. However, the ANN method can predict runoff with or without biopore infiltration holes. ANN method is better than SCS-CN method in terms of coefficient of determination that is equal to 16.88%. Based on the error value, the ANN method has a smaller MSE error of 85.94% compared to the SCC-CN method. Therefore, the model of the ANN method is high accuracy forecasting runoff on oil palm plantations using and without the use of biopore infiltration holes. In addition, these findings may be helpful in solving the problem of serious soil and water loss on the palm oil plantation. Further research is important to find factors other than rainfall that can affect runoff on oil palm land that uses biopore infiltration holes to further improve the accuracy of the model from ANN.

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