Drought Disaster Forecasting Based On Rainfall Runoff Transformation Modelling (Case Studies In Tukad Petanu Watershed)

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(Case Studies In Tukad Petanu Watershed)

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ABSTRACT

Drought is one of the major weather related disasters. Persisting over months or years, it can affect large areas and may have serious environmental, social and economic impacts. drought is a normal, recurrent feature of climate, although many erroneously consider it a rare and random event. It occurs in virtually all areas, whatever their normal climate may be, and the characteristics of a drought may be very different from one region to another. Drought is difficult to define precisely, but operational definitions often help define the onset, severity, and end of droughts. An operational definition of drought helps people to identify the beginning, end, and degree of severity of a drought.

Early detection of droughts helps to implement drought mitigation strategies and measures, before they occur. Therefore, drought forecasting plays an important role in the planning and management of water resources systems, especially during dry climatic periods. However, drought analysis and forecasting are not always easy. This study developed an objective drought analysis through a rainfaal runoff model which developed from simulated Feed Forward Backpropagation Neural Network to generate flow (discharge/runoff) rate. The drought analysis built on the drought threshold with probability of 0,5 called Q_{normal} (Q_{50}). From the resulted flow rate, the deficit and drought duration will be estimated and this way mean can be used to droughts analysisi effectively and forecast future drought conditions. In addition, based on the forecast discharge data, can also be used to predict the incidence of drought in the next years.

From the results of the analysis to get the level of performance models, feed forward back propagation neural network method, type 3-10-5-1 architecture (model 5) provide the most optimum results to describe the rainfall-runoff relationships that occur in the watershed Tukad Petanu. The value of MSE network is 0,05584, “r” for training process is 0,8688 (86,88%) and 0,7536 (75,36%) for testing and AAE value is 0,1322 for training process and 0,1971 for testing process. That is mean the pattern of the target data with the prediction data shows a pattern close to each other, which means it has a balance between the process of memorization and generalization of network. So, the rainfall runoff transformation can be used to calculate the drought deficit, duration and drought forecasting. From analysis of drought can be seen that the results between the $Q_{simulasi}$ and $Q_{observasi}$ compared to Q_{normal} showed a significant difference. This can be seen in the duration of the drought that occurred on average for a year. Based $Q_{observasi}$, average drought duration obtained for 5.8 months while based $Q_{simulasi}$, average drought duration obtained during 7.3 months. As for the dry months, based on the two analyzes ($Q_{observasi}$ and $Q_{simulasi}$), the month began to dry starting with the average in July and ends in December. In the last in forecasting, from the analysis result obtained, in 2004 $Q_{maximum}$ will occur in May as big as 4,343 m3/dt and in August the discharge in the amount of 2,245 m^3/dt. Dry (drought) season will start in July and will end in December. The value of the deficit amounted to 1,011 m^3/dt. in 2005 $Q_{maximum}$ will occur in January as big as 2,783 m3/dt and in August the discharge in the amount of 1,592 m^3/dt. Dry (drought) season will start in July and will end in December. The value of the deficit amounted to 0,332 m^3/dt.

Keywords : drought, rainfall runoff transformation, feed forward backpropagation neural network, forcasting

1. Introduction

Drought is one of the major weather related disasters. Persisting over months or years, it can affect large areas and may have serious environmental, social and economic impacts. According to The Disaster Handbook Institute of Food and Agricultural Sciences University of Florida (1998), drought is a normal, recurrent feature of climate, although many erroneously consider it a rare and random event. It occurs in virtually all areas, whatever their normal climate may be, and the characteristics of a drought may be very different from one region to another.

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Technically, drought is a “temporary” condition, even though it may last for long periods of time. Drought is an insidious hazard of nature. Unlike many disasters which are sudden, droughts result when there is less than normal precipitation over an extended period of time, usually a season or more. The decreased water input results in a water shortage for some activity, group, or environmental sector. Drought can also occur when the temperature is higher than normal for a sustained period of time; this causes more water to be drawn off by evaporation. Other possible causes are delays in the start of the rainy season or timing of rains in relation to principal crop growth stages (rain at the “wrong” time). High winds and low relative humidity can make matters much worse. Drought is not a disaster for nature itself, the disaster occurs when we consider the demand people place on their water supply. Human beings often increase the impact of drought because of high use of water which cannot be supported when the natural supply decreases. Droughts occur in both developing and developed countries and can result in economic and environmental impacts and personal hardships. All societies are vulnerable to this "natural" hazard.

Drought is difficult to define precisely, but operational definitions often help define the onset, severity, and end of droughts. An operational definition of drought helps people to identify the beginning, end, and degree of severity of a drought. This definition is usually made by comparing the current situation to the historical average, often based on a 30-year period of record (according to World Meteorological Organization recommendations, 2005). The following categories of drought are usually considered:

- Meteorological
  Meteorological drought is usually defined on the basis of the degree of dryness (in comparison to some “normal” or average amount) and the duration of the dry period. Definitions of meteorological drought must be consideredas specific to a region since the atmospheric conditions that result in deficiencies of precipitation are highly variable from region to region.
- Agricultural
  Agricultural drought links various characteristics of meteorological (or hydrological) drought to agricultural impacts, focusing on precipitation shortages, differences between actual and potential evapotranspiration, soil water deficits, reduced groundwater or reservoir levels, and so forth.
- Hydrological
  Hydrological drought is associated with the effects of periods of precipitation (including snowfall) shortfalls on surface or subsurface water supply (i.e., streamflow, reservoir and lake levels, groundwater). The frequency and severity of hydrological drought is often defined on a watershed or river basin scale.
- Hydrological with respect of the land use
  Although climate is a primary contributor to hydrological drought, other factors such as changes in land use (e.g., deforestation), land degradation, and the construction of dams all affect the hydrological characteristics of the basin.
- Socio economic
  This occurs when physical water shortage starts to affect people, individuallyand collectively or, in more abstract terms, most socio-economic definitions of drought are associated with the supply and demand of an economic good. These operational definitionscan also be used to analyse drought frequency, severity, and duration for a given historical period.

Early detection of droughts helps to implement drought mitigation strategies and measures, before they occur. Therefore, drought forecasting plays an important role in the planning and management of water resources systems, especially during dry climatic periods. However, drought assessment and forecasting which will used to drought planning are not always easy. This study developed a drought forecasting where happened in Tukad Petanu watershed. This location was selected because Tukad Petanu watershed where located in Badung and Gianyar regency is one of the areas of national strategic river is used as water source for irrigation dan drinking water in SARBAGITA region. Tukad Petanu watershed has a drainage area of 59,30 km^2. This year, 2014, Bali and most regions in Indonesia was hit by drought. Long drought this year is to be a natural disaster. Drought occurs everywhere. Reduced supply of clean water. Many of the plants to wither and die. Nothing can be done by the government and citizens. Can only wait until this drought ends soon. Now, the dry season is very different to previous years. The heat of the sun was very high. Especially in Bali, Balinese people are not used to the extreme heat. As a result of a drought that occurred this year, 119 hectares of rice crops in of Bali experienced a crop failure, because a lot of rice fields affected by drought due to no water. Since most of the water from the river to the rice fields. Many rivers are experiencing drought. Long drought this year are not predictable beforehand. So that farmers can not determine the exact type of plants to be planted when the drought and the society to be difficult to find clean water too.

Knowledge of droughts has been an important aspect in the planning and management of water resource systems. According to Samiee, M., 2003 in Hadiani, 2009, besides using rainfall data, analysis of drought in the watershed are also advised to use the discharge (runoff) data where the drought analysis based on drought treshold was calculated by statistically method. Drought index is the ratio of the deficit to the vast arid watershed in question. In this study, dry (driught) conditions when the discharge is under normal discharge or median of the data flow for each year in which the deficit is the difference between the volume of water shortages and the threshold.

In this study, a drought forecasting was developed according from rainfall-runoff data. Rainfall-runoff transformation of a watershed is one of the most complex hydrologic phenomena, non linier process, with fickle time and spatial distribution. Rainfall-runoff transformation have been developed using analysis of hydrologic system with model representing moderation of nature fact which in fact. The model formed by a set of mathematical equation which reflect behavior from parameter in hydrology, where in this research the modelization for rainfall-runoff relationship. In this study, application of Feed Forward Backpropagation Neural Networks model for analysis of rainfall-runoff relationship which can be used to discharge estimate on a watershed. Feed Forward Backpropagation Neural Networks is one of artificial intellegence which learning ability from data and do not consume time for model executing. This model was used to learn rainfall-runoff relationship at Tukad Petanu Watershed. Model verification using statistical method was based on mean square error (MSE), root mean square error (RMSE), absolute average error (AAE) and the correlation coefisient (r). Analysis of the problem is formulated as follows how to model Feed Forward Backpropagation Neural Networks in estimated discharge based on rainfall data and estimated the drought disaster forecast in Tukad Petanu watershed?

2. Study Area and Data

In this study, object for investigation is The Petanu River (Tukad Petanu) watershed in Gianyar and Badung Regency, has a drainage area of 59,30 km^2. The basin is equipped with three rain gauges (R1 = Tegallalang station; R2 = Tampaksiring station; R3 = Ubud station), one runoff recording station (Q1 = Bedahulu station) and one climatology recording station (C1 = Tampaksiring station) (Fig. 1.c). The rainfall and runoff monthly data at the average of (R1, R2 and R3) stations were used for model investigation. The data contains information for a period of ten years (1994 to 2003). The entire database is represented by 120 monthly values of rainfall-runoff pairs and evapotranspiration from Tukad Petanu watershed. The database was collected by the BMKG Region III and Departement of Public Work in Bali Province.

3. Methodology

3.1 Data Analysis

3.1.1 Data Rainfall Analysis

In this study, hydrological data are obtained from several rainfall stations, and the data in the form of monthly rainfall data at several stations rain. Monthly rainfall data used as input data (input) in the modeling. Analysis of rainfall data includes test the consistency of the data and the average rainfall areas (areas of rainfall.

1. Consistency Test Data

In a series of rainfall data, and the data can occur nonhomogenitas inequality (inconsistency) data. Data is not homogeneous and inconsistent cause analysis results are not rigorous. Therefore, before the data is used for analysis, must be subjected to the test of consistency. Consistency test carried out by the method of RAPS (Rescaled Adjusted Partial Sums) using data from the station it self is test the cumulative deviation from the average value divided by the cumulative root mean deviation of the mean value. The equation is as follows:

$$S_o^* = 0, S_k^* = \sum_{i=1}^{k=1} (Y_i - Y') \quad \text{with k = 1, 2, 3,......., n} \qquad (1)$$

$$S_k^{**} = \frac{S_k^*}{D_y} \qquad (2)$$

$$D_y^2 = \frac{\sum_{i=1}^{n} (Y_i - Y')^2}{n} \qquad (3)$$

$$Q = maks\left|S_k^{**}\right| \qquad 0 \le k \le n \qquad (4)$$

$$R = maks\, S_k^{**} - \min S_k^{**} \qquad 0 \le k \le n \qquad (5)$$

2. Rain territory

Rainfall is needed to rain runoff transformation is the average rainfall throughout the region. Observer stations scattered rain in a rain catchment area as a point (point rainfall). To change the point rainfall (rainfall point) to be rainy regions (regional rainfall) used the approach to the aritmatic average method. Equation rain areas with aritmatic averagre method is as follows:

$$\overline{R} = \sum_{i=1}^{n} \frac{R_1 + R2 + ... + R_n}{n}$$ with r = rainfall in a station and n = amount of station

(6)

3.1.2 Evavotranspiration

Evapotranspiration is the process of evaporation and transpiration related to what happens to the land covered by vegetation. The analysis includes the calculation of evapotranspiration potential and actual evapotranspiration. The calculation of the estimated potential evapotranspiration (Et_0) in the Indonesian region were analyzed using a simplified Penman formula (Anonymous, 2006):

$$Et_0 = c.[W(0,75.Rs - Rn1] + (1 - w).f(U).(e_a - e_d) \quad (7)$$

And actual evapotranspiration as follows:

$$E_{aktual} = EP - \Delta E \quad (8)$$

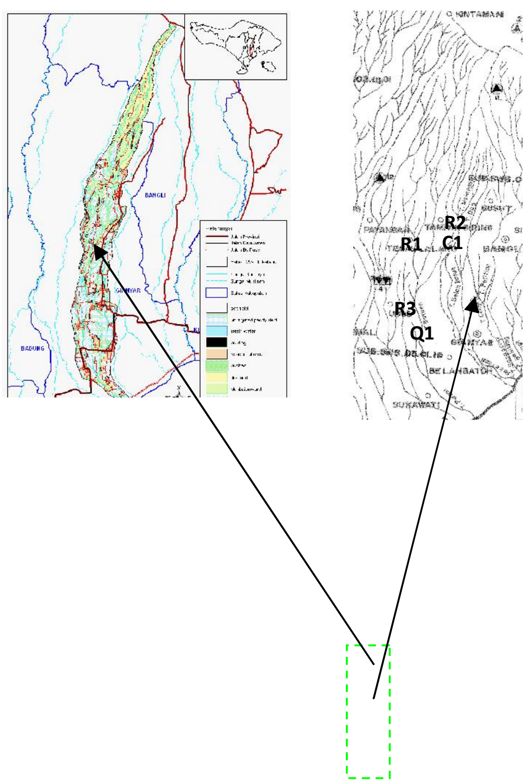


Figure 1. Tukad Petanu Watershed

3.2 Artificial Neural Networks

Artificial neural networks employ mathematical simulation of biological nervous systems in order to process acquired information and derive predictive outputs after the network has been properly trained for pattern recognition (Tombul and Ogul, 2006). The feed-forward backpropagation neural networks (FFBNN) is the most commonly used ANNs in hydrological applications. FFBNN is consisted of a number of computational elements described as neurons. The neurons are organized in three layer: the input layer contains the input unit that receive information from outside world and will be introduced to the network, one or more hidden layer of computation neurons where the data are processed and output layer of computation neurons where the results for given inputs are produced. Each neuron is fully connected to neurons in the next layer (Figure 2). All input to a neuron in a particular layer is from the proceeding layer and these undirectional strengths are known as weights and biases.

Backpropagation is usually employed for training the MLP network. Thus MLP network is known as a back-propagation network (BPN). The back-propagation consists of two passes: a forward propagation and backward propagation. In the forward propagation, an input pattern is applied to the input layer and its effect is propagated layer by layer through network. The activity at a neuron is computed as the weighted sum of the outputs of the neurons of the previous layer. The output of the neuron is computed from a nonlinier activation function. From the input layer to hidden layer, activation function will be used is the logistic sigmoid (logsig). This activation function is continuously differentiable, symetric and bounded between 0 and 1. The mathematical expression of the logistic sigmoid function is given by

$$y = f(x) = \frac{1}{1 + e^{-\alpha x}} \tag{9}$$

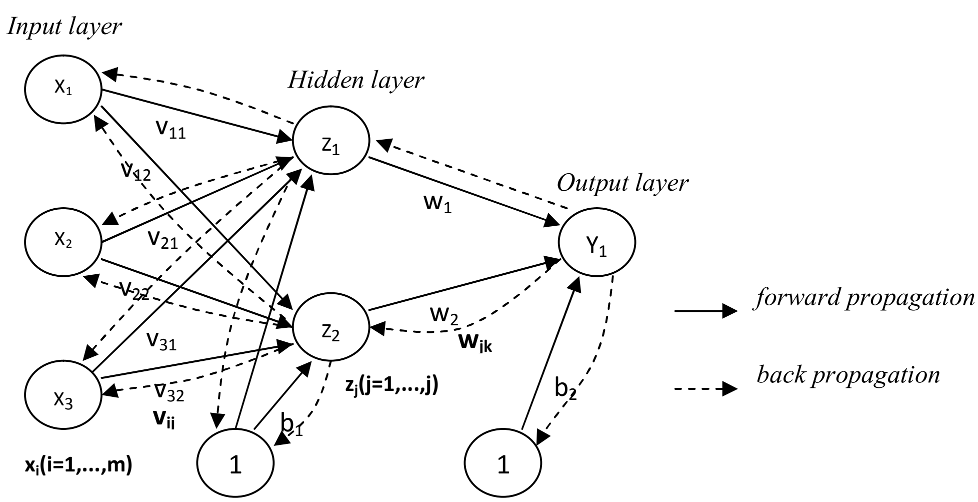


Figure 2. Architecture of the feed-forward multilayer perceptron (MLP)

While between hidden layer to output layer, activation function will be used is the identity (purelin). The mathematical expression of the logistic sigmoid function is given by

$$f(x) = x \tag{10}$$

In the backpropagation pass, the sum of squared deviaton of the output from the target value at neurons of output layer defines the error signal propagated back to the previous layers. The paramaters are adjusted to minimize errors in the computations. So in this study, for modeling rainfall-runoff relationship will be used feed forward backpropagation neural network for training method.

3.3 Model Applicaton

The training and testing data set collected during years 1994 to 2003 were selected to evaluate the performance of the neural network model for Tukad Petanu watershed. Since the original recorded data contain area rainfall, evapotranspiration, runoff data and additional data from previous runoff data (t-n). In this study, the data used consist of two sets: the six years of data (1994-1999) are used for model calibration (training) in the case of ANNs, and the remaing four years of data (2000-2004) are used for model validation (testing).The input and target values of each feature (rainfall, evapotranspiration, runoff and runoff (t-1)) are normalized or preprocessing into appropriate scale by using the maximum and minimum values such that both are contained in the unit interval [-1,1]. Following Santosa (2007), the general scale down procedure is given by

$$X' = \frac{X - X_{\min}}{X_{maks} - X_{\min}}(BA - BB) + (BB) \tag{11}$$

In this study, we used multilayer perceptron with six networks architecture scenario. Architecture 1 (2-5-1) have two input neurons were given from areal rainfall and evapotranspiration, one hidden layer with five neurons and one output layer. Architecture 2 (3-5-1) have three input neurons were given from areal rainfall, evapotranspiration and runoff t-1, one hidden layer with five neurons and one output layer. Architecture 3 (4-5-1) have four input neurons were given from areal rainfall, evapotranspiration, runoff t-1 and runoff t-2, one hidden layer with five neurons and one output layer. Architecture 4 (2-5-10-1) have two input neurons were given from areal rainfall and evapotranspiration, one hidden layer with five neurons, second hidden layer with ten neurons and one output layer. Architecture 5 (3-5-10-1) have three input neurons were given from areal rainfall, evapotranspiration and runoff t-1, one hidden layer with five neurons, second hidden layer with ten neurons and one output layer. And the last, Architecture 6 (4-5-10-1) have four input neurons were given from areal rainfall, evapotranspiration, runoff t-1 and runoff t-2, one hidden layer with five neurons, second hidden layer with ten neurons and one output layer.

3.4 Model Performance Criteria

Traditional statistical criteria is adopted here to help select the desired optimal network model. The selection procedure is based on the following statistics: coeffisient of corelation (*r*), mean square error (MSE), root mean square error (RMSE) and absolute average error (AAE). These are defined by

$$r = \frac{n\sum_{j=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2}\sqrt{n\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2}} \tag{12}$$

$$MSE_{(t)} = \frac{1}{n}\sum_{j=1}^{n}(y_j(t) - d_j(t))^2 \tag{13}$$

$$RMSE(t) = \sqrt{\frac{\sum_{j=1}^{n}(y_j(t) - d_j(t))^2}{n}} \tag{14}$$

$$AAE = \frac{1}{n}\sum \frac{Abs(Q_{comp} - Q_{obs})}{Q_{obs}} \tag{15}$$

3.5 Statistical Analysis Data

Statistical analysis data aim to determine:

1. Threshold (X_0), is limit value which is determined based on the purpose of the analysis (Fleigh, A.K., et.al, 2006 in Hadiani, 2009), appropriate of selected distribution.
2. X_0 is the Q_{50}, where Q_{50} is Q_{normal} with probability 0,5 or a median of data

3.6 Drought Analysis

In mitigation of drought planning, drought analysis is needed. Parameters of drought in river discharge are as an input into the planning and management of irrigation das to be more accurate (Hadiani, 2009 in Frandy, E.Y, 2014). Each method of analysis of drought have different indicators, the indicators used are usually turned away indices that are the result of analysis parameters that depend from watershed needs (eg. used for agricultural use in the form of data flow river variables (discharge), soil moisture, etc.)

3.7 Analysis Framework

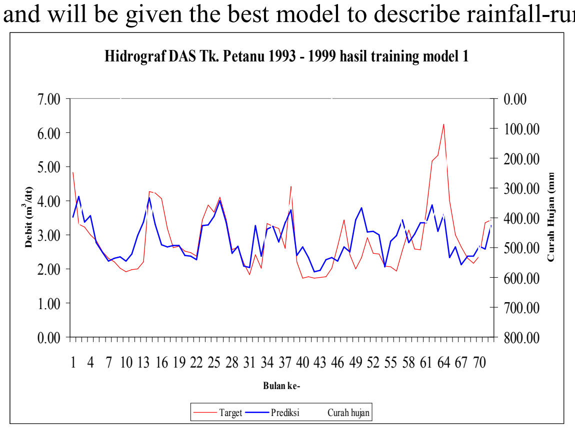
This research is a quantitative descriptive study using secondary data. This study uses Microsoft Excel as a data processor for the analysis of statistical and Matlab software for feed forward backpropagation neural network (FFBNN) analysis. The framework starts with the model preparation are collect of rainfall data, river discharge data and climatic data to calculate evavoptranspiration. Dry (drought) criteria determined by the deficit, the duration and intensity of rainfall. There are several methods that use the median as a threshold, where the selection of the threshold is based on certain characteristics depending on needs, where the value of the deficit difference volume of water shortage to the value of threshold.

In data processing, first step is preparing the rainfall and discharge (runoff) data years 1993-2003, and then test the consistency of the rainfall data with Rescaled Adjustes Partial Sum (RAPS) method. Next, calculate rainfall regions using arithmetic averages. Based on climatological data, performed the analysis process to find evavoptranspiration value. Further, the discharge analysis of 1994-2003 by using Feed Forward Backpropagation Neural Network, the data 1994-1999 to use in the training process and the testing process used data from 2000-2003. Furthermore, drought deficit and duration were calculated which deficit of the year 1994-2003 based on observational data compared with a deficit in 1994-2003 based on the simulation data. For drought prediction, discharge data prediction (year 2004-2005) will be used and in the last we will get in the drought prediction (2004-2005).

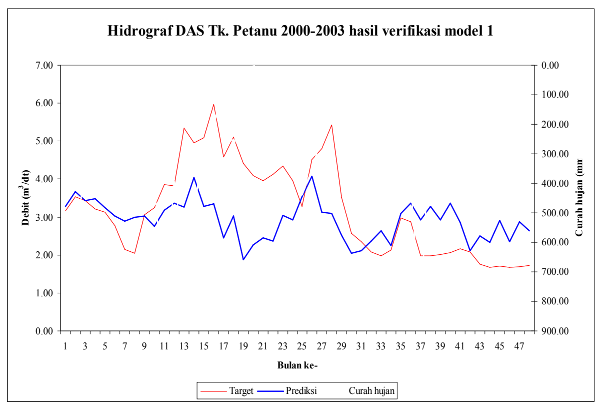
4. Results and Discussion

4.1 Rainfall-Runoff Modelling

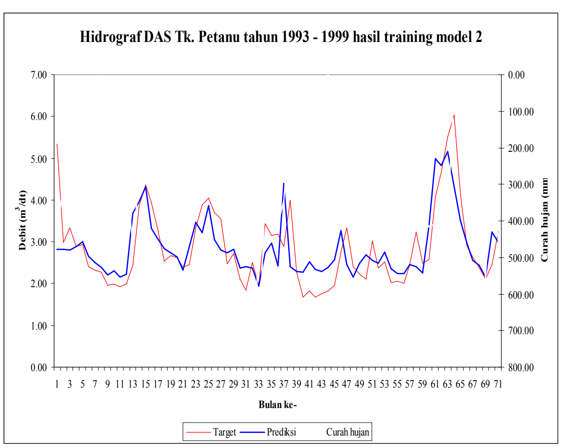
The ANNs programming was developed using MATLAB 7.0.1 release 14 for all training and testing phases. From this program, we used the *newff*, *train*, and *sim* MATLAB command lines to create, to train and to obtain output from the networks. The training and testing period consisted of 72 samples (6 years) and 48 samples (4 years), respectively. Figure 3a until 3f presents the better model and table 1 until table 2 presents the efficiency and the errors (r, MSE, RMSE and AAE), while table 1 and 2 presents the general efficiency and the errors for all model and will be given the best model to describe rainfall-runoff at Tukad Petanu watershed.



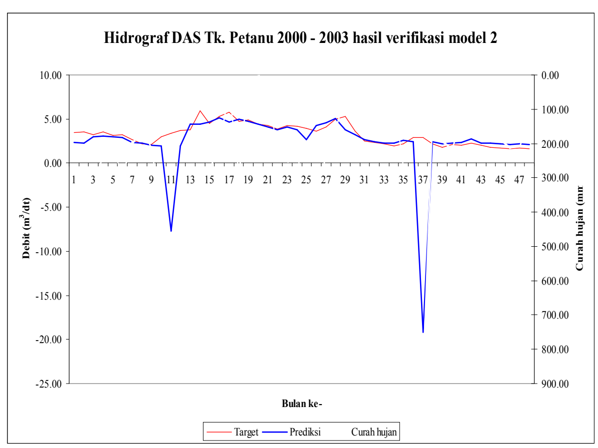
Training (architecture 1)



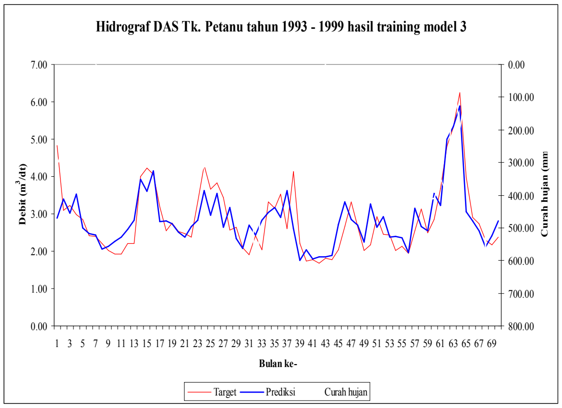
Testing (architecture 1)



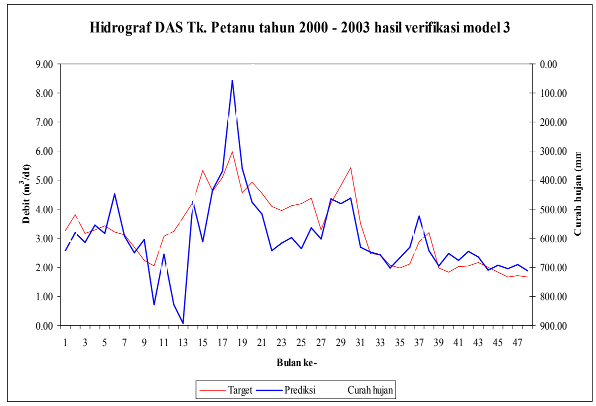
Training (architecture 2)



Testing (architecture 2)

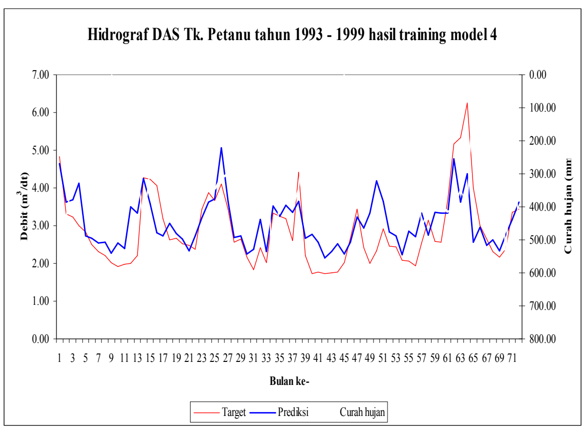


Training (architecture 3)

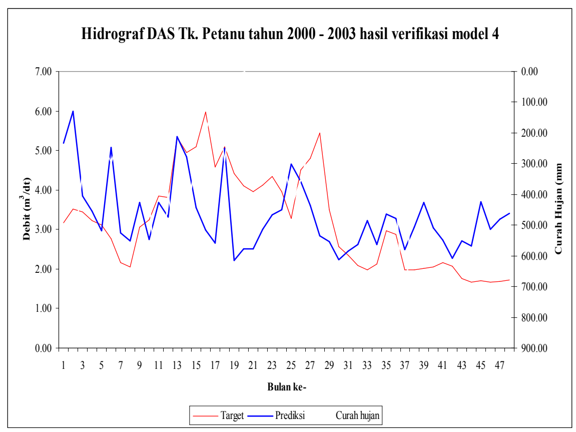


Testing (architecture 3)

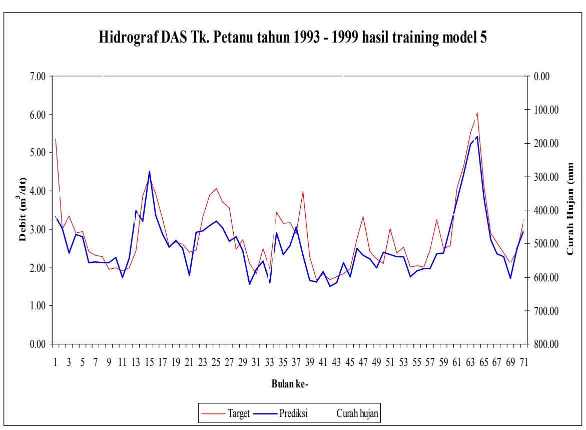
Figure 3.a Comparison *training* and *testing* (architecture 1 - architecture 3) for Tukad Petanu Watershed



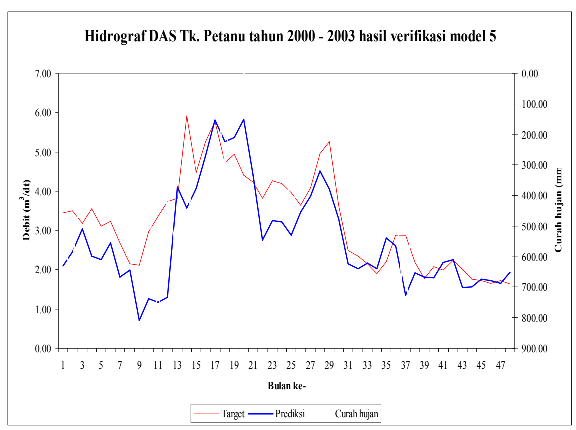
Training (architecture 4)



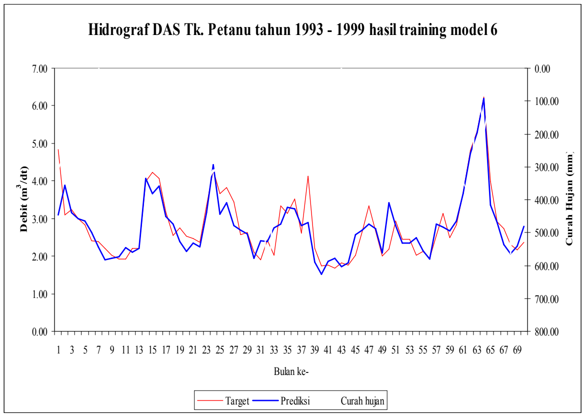
Testing (architecture 4)



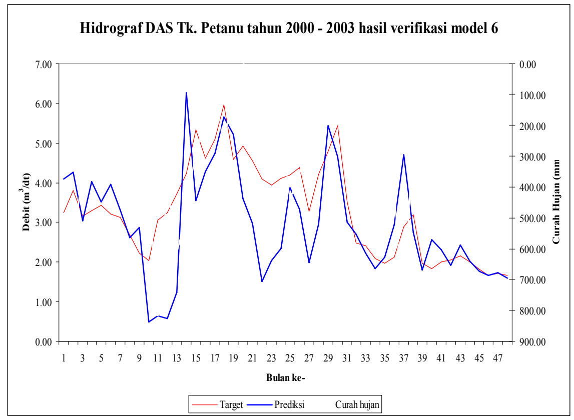
Training (architecture 5)



Testing (architecture 5)



Training (architecture 6)



Testing (architecture 6)

Figure 3.b Comparison *training* and *testing* (architecture 4 - architecture 6) for Tukad Petanu Watershed

Table 1. Model performance for Tukad Petanu Watershed

Model	Tukad Petanu Watershed								
	MSE network	Training				Testing			
		r	MSE	RMSE	AAE	r	MSE	RMSE	AAE
Model 1	0,109887	0,5753	1067,545	32,6733	0,1836	0,166	2710,854	52,0659	0,2957
Model 2	0,075641	0,7365	96,490	9,8229	0,1539	0,3156	27690,432	166,4044	0,3752
Model 3	0,0554063	0,8175	538,295	23,2012	0,1373	0,7123	2174,985	46,6367	0,2122
Model 4	0,093106	0,7006	904,565	30,0760	0,1971	0,2274	3083,212	55,5267	0,3581
Model 5	**0,0558376**	**0,8688**	**542,469**	**23,2910**	**0,1322**	**0,7536**	**1608,729**	**40,1090**	**0,1971**
Model 6	0,0350548	0,8913	340,538	18,4537	0,0999	0,6045	2492,68	49,9267	0,2398

According to graph (Figure 3.a and 3.b) and table 1, best network performance level given by the model 6 which is equal to 0.035. Model 6 with a 4-10-5-1 architecture, AAE value of 0.099 and the highest correlation coefficient of 0.8913 or 89.13% of all the models that have made the learning process. In the testing process, models 5 with architectural 3-10-5-1, AAE scores of 0.197 and a correlation coefficient is 0.7536 or 75.36%. From the results of the analysis to get the level of performance models, feed forward back propagation neural network method 3-10-5-1 architecture (model 5) provide the most optimum results to describe the rainfall-runoff relationships that occur in the watershed Tukad Patanu (stable score in "r" and "AAE" between training and testing process). From Figure 3.a and 3.b on the comparison of training and testing for the model 1 to model 6 shows that the pattern of the target line (red) with the prediction line (blue) shows a pattern close to each other, which means it has a balance between the process of memorization and generalization of network.

4.2 Drought Forecasting

Hydrological drought is associated with the effects of periods of precipitation (including snowfall) shortfalls on surface or subsurface water supply (i.e., streamflow, reservoir and lake levels, groundwater). The frequency and severity of hydrological drought is often defined on a watershed or river basin scale. The value for drought affected by the duration of a deficit. Dry (drought) called when the discharge was dried under normal discharge/runoff or median of the data flow for each year, where the deficit is the difference between the volume of water shortages and threshold. Duration is the total time of the deficit.

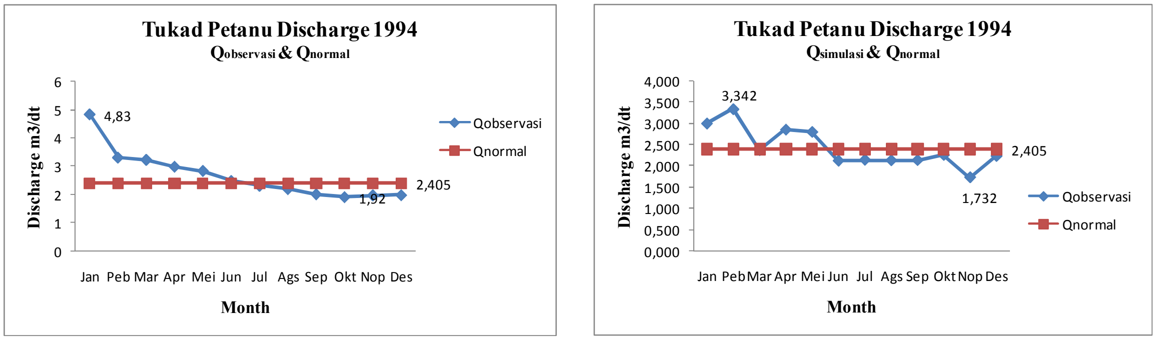


Figure 4.a. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (1994)

The result based on $Q_{observasi}$, value of Q_{normal} in 1994 = 2,405 m^3/dt with maximum discharge in January as big as 4,83 m^3/dt, under Q_{normal} in October in the amount of 1,92 m^3/dt and 0,485 m^3/dt for deficit value. Whereas based on $Q_{simulasi}$, maximum discharge in February as big as 3,342 m^3/dt, under Q_{normal} in November in the amount of 1,732 m^3/dt and 0,673 m^3/dt for deficit value.

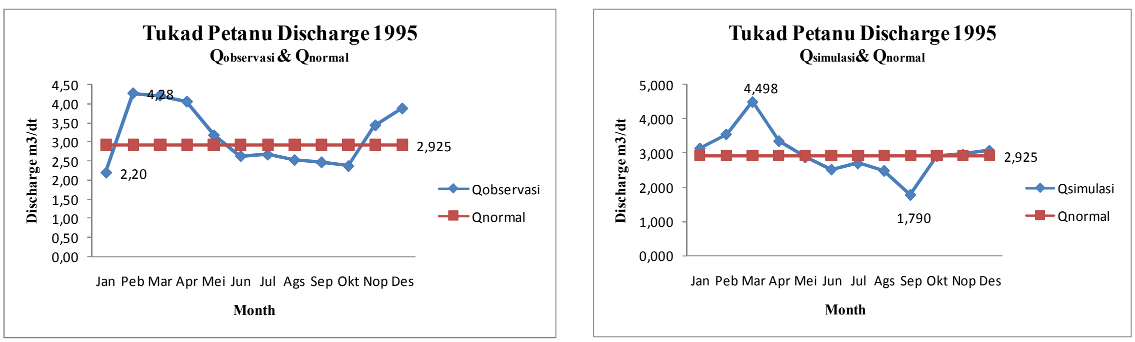


Figure 4.b. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (1995)

The result based on $Q_{observasi}$, value of Q_{normal} in 1995 = 2,925 m^3/dt with maximum discharge in February as big as 4,28 m^3/dt, under Q_{normal} in January in the amount of 2,20 m^3/dt and 0,725 m^3/dt for deficit value. Whereas based on $Q_{simulasi}$, maximum discharge in March as big as 4,498 m^3/dt, under Q_{normal} in September in the amount of 1,790 m^3/dt and 1,135 m^3/dt for deficit value.

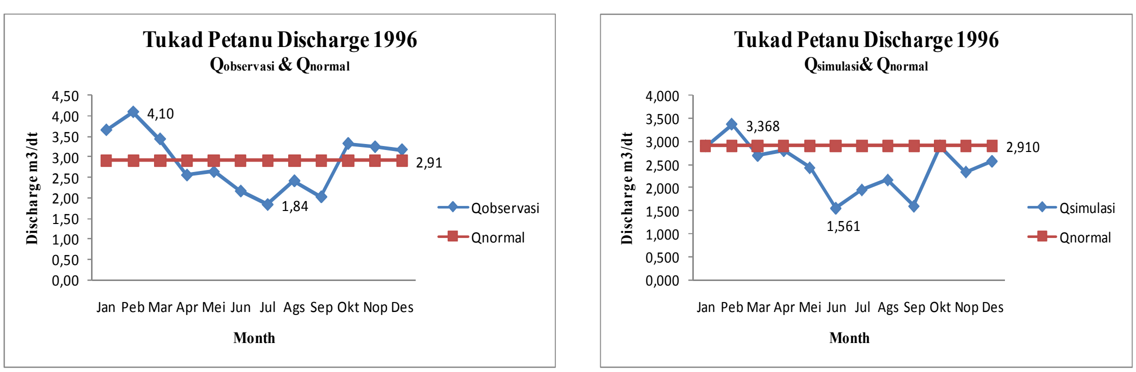


Figure 4.c. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (1996)

The result based on $Q_{observasi}$, value of Q_{normal} in 1996 = 2,91 m^3/dt with maximum discharge in February as big as 4,10 m^3/dt, under Q_{normal} in Juli in the amount of 1,84 m^3/dt and 1,07 m^3/dt for deficit value. Whereas based on $Q_{simulasi}$, maximum discharge in February as big as 3,368 m^3/dt, under Q_{normal} in June in the amount of 1,561 m^3/dt and 1,349 m^3/dt for deficit value.

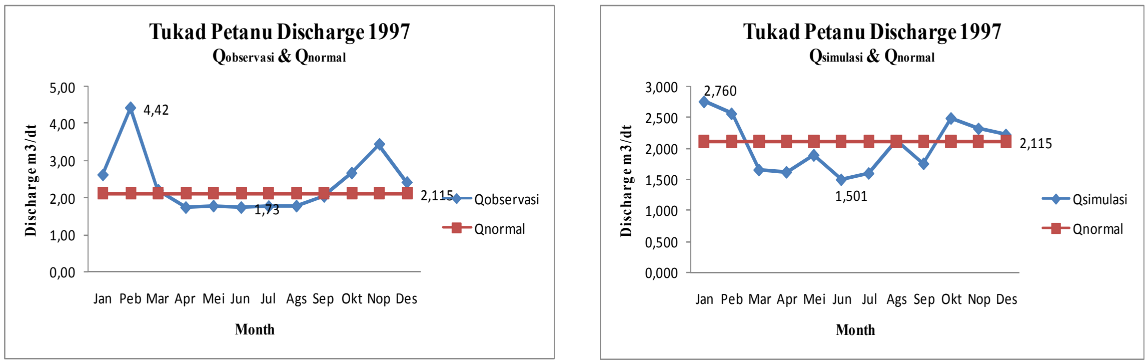


Figure 4.d. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (1997)

The result based on $Q_{observasi}$, value of Q_{normal} in 1997 = 2,115 m^3/dt with maximum discharge in February as big as 4,42 m^3/dt, under Q_{normal} in April and June in the amount of 1,73 m^3/dt and 0,385 m^3/dt for deficit value. Whereas based on $Q_{simulasi}$, maximum discharge in January as big as 2,760 m^3/dt, under Q_{normal} in June in the amount of 1,501 m^3/dt and 0,614 m^3/dt for deficit value.

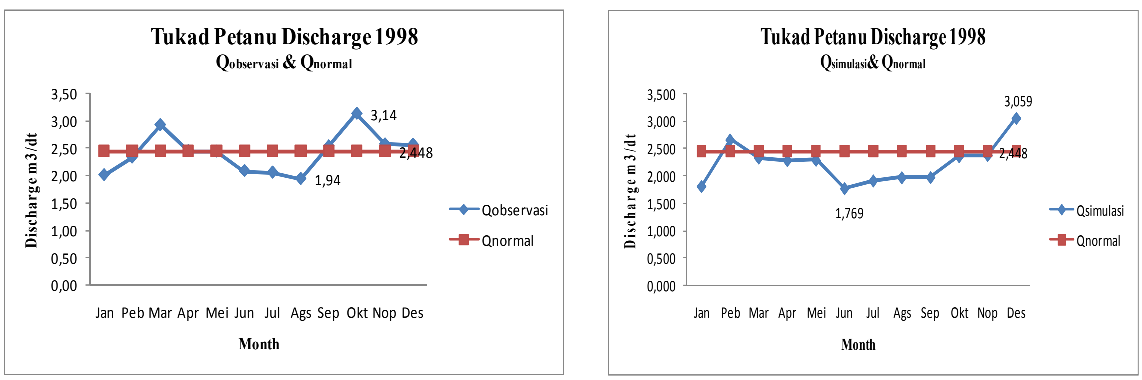


Figure 4.e. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (1998)

The result based on $Q_{observasi}$, value of Q_{normal} in 1998 = 2,448 m^3/dt with maximum discharge in October as big as 3,14 m^3/dt, under Q_{normal} in August in the amount of 1,94 m^3/dt and 0,508 m^3/dt for deficit value. Whereas based on $Q_{simulasi}$, maximum discharge in Desember as big as 3,059 m^3/dt, under Q_{normal} in June in the amount of 1,769 m^3/dt and 0,679 m^3/dt for deficit value.

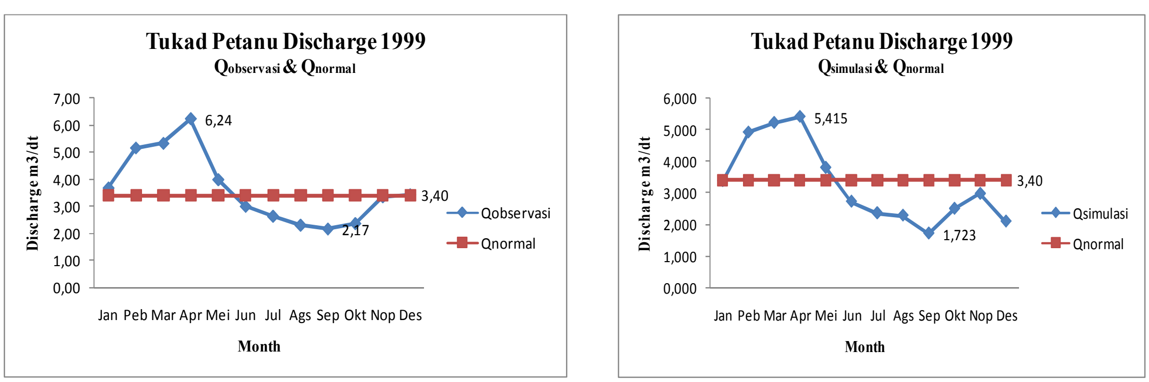


Figure 4.f. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (1999)

The result based on $Q_{observasi}$, value of Q_{normal} in 1999 = 3,40 m^3/dt with maximum discharge in April as big as 6,24 m^3/dt, under Q_{normal} in September in the amount of 2,17 m^3/dt and 1,23 m^3/dt for deficit value. Whereas based on

$Q_{simulasi}$, maximum discharge in April as big as 5,415 m^3/dt, under Q_{normal} in September in the amount of 1,723 m^3/dt and 1,677 m^3/dt for deficit value.

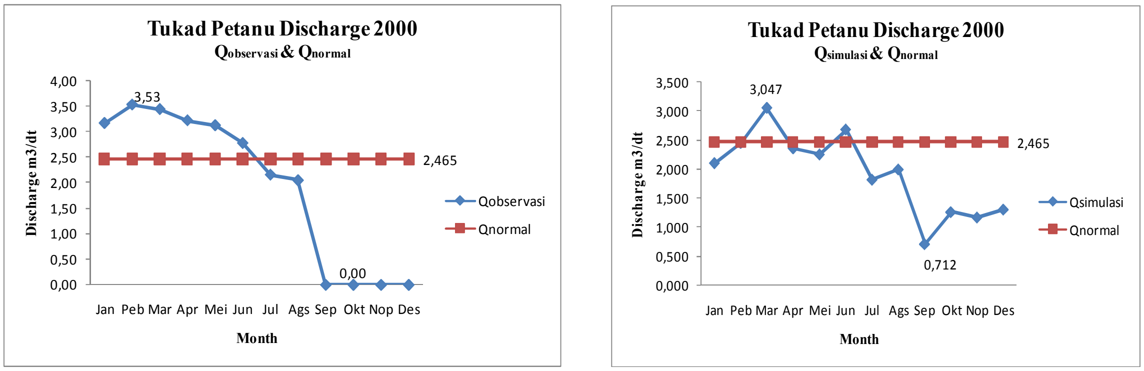


Figure 4.g. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (2000)

The result based on $Q_{observasi}$, value of Q_{normal} in 2000 = 2,465 m^3/dt with maximum discharge in February as big as 3,53 m^3/dt, under Q_{normal} in September until December in the amount of 0,00 m^3/dt and 2,465 m^3/dt for deficit value. For this year (2000), had a missing data for September until December which supply 0,00 m^3/dt for discharge. Whereas based on $Q_{simulasi}$, maximum discharge in March as big as 3,047 m^3/dt, under Q_{normal} in September in the amount of 0,712 m^3/dt and 1,753 m^3/dt for deficit value.

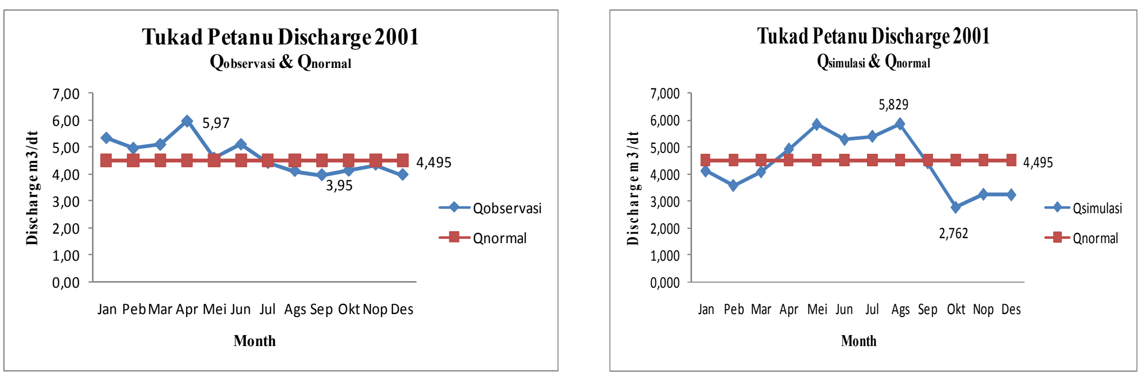


Figure 4.h. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (2001)

The result based on $Q_{observasi}$, value of Q_{normal} in 2001 = 4,495 m^3/dt with maximum discharge in April as big as 5,97 m^3/dt, under Q_{normal} in September in the amount of 3,95 m^3/dt and 0,545 m^3/dt for deficit value. Whereas based on $Q_{simulasi}$, maximum discharge in August as big as 5,829 m^3/dt, under Q_{normal} in September in the amount of 2,762 m^3/dt and 1,733 m^3/dt for deficit value.

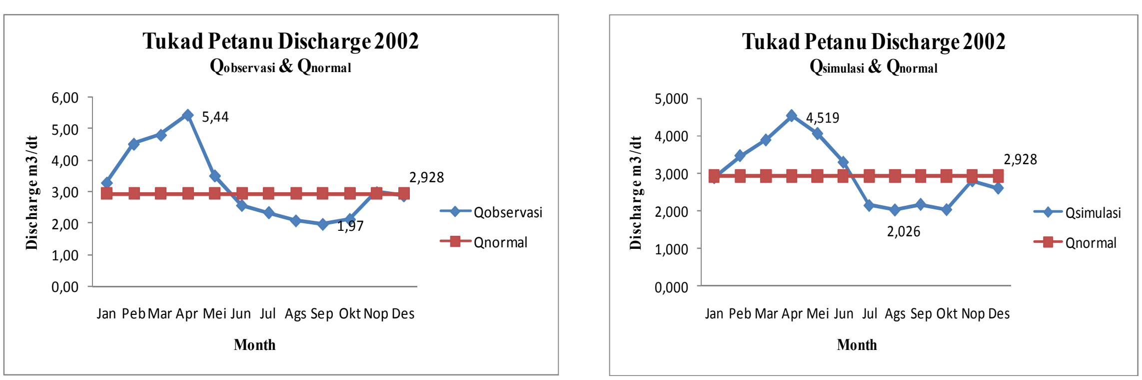


Figure 4.i. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (2002)

The result based on $Q_{observasi}$, value of Q_{normal} in 2002 = 2,928 m^3/dt with maximum discharge in April as big as 5,44 m^3/dt, under Q_{normal} in September in the amount of 1,97 m^3/dt and 0,958 m^3/dt for deficit value. Whereas based on $Q_{simulasi}$, maximum discharge in April as big as 4,519 m^3/dt, under Q_{normal} in August in the amount of 2,026 m^3/dt and 0,902 m^3/dt for deficit value.

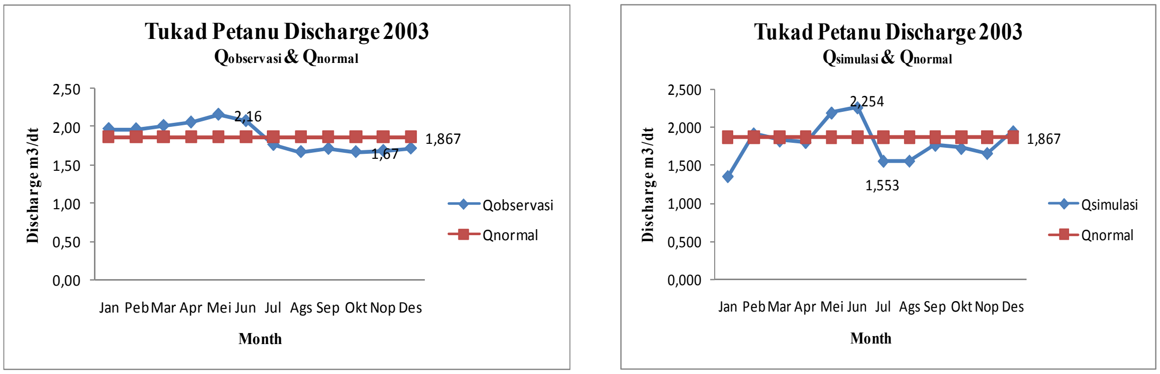


Figure 4.j. Comparison $Q_{observasi}$ & Q_{normal} and $Q_{simulasi}$ & Q_{normal} in Tukad Petanu Watershed (2003)

The result based on $Q_{observasi}$, value of Q_{normal} in 2003 = 1,867 m^3/dt with maximum discharge in May as big as 2,16 m^3/dt, under Q_{normal} in October in the amount of 1,67 m^3/dt and 0,197 m^3/dt for deficit value. Whereas based on $Q_{simulasi}$, maximum discharge in June as big as 2,254 m^3/dt, under Q_{normal} in July in the amount of 1,553 m^3/dt and 0,314 m^3/dt for deficit value.

From analysis of drought can be seen that the results between the $Q_{simulasi}$ and $Q_{observasi}$ compared to Q_{normal} showed a significant difference. This can be seen in the duration of the drought that occurred on average for a year. Based $Q_{observasi}$, average drought duration obtained for 5.8 months while based $Q_{simulasi}$, average drought duration obtained during 7.3 months. As for the dry months, based on the two analyzes ($Q_{observasi}$ and $Q_{simulasi}$), the month began to dry starting with the average in July and ends in December. By using the data of the rainfall-runoff tranformation from feed forward backpropagation neural network analysis, for drought forecasting process can be done next month. The results of the calculations in this paper is forecasting drought for the next two years (2004 and 2005).

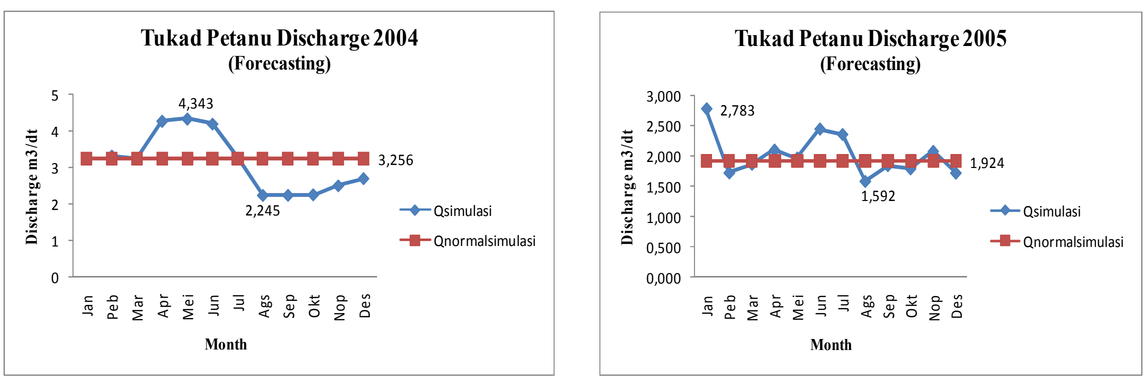


Figure 5. Discharge Forecasting in Tukad Petanu Watershed

Drought forecasting shown in Figure 5. From the analysis result obtained, in 2004 $Q_{maximum}$ will occur in May as big as 4,343 m3/dt and in August the discharge in the amount of 2,245 m^3/dt. Dry (drought) season will start in July and will end in December. The value of the deficit amounted to 1,011 m^3/dt. in 2005 $Q_{maximum}$ will occur in January as big as 2,783 m3/dt and in August the discharge in the amount of 1,592 m^3/dt. Dry (drought) season will start in July and will end in December. The value of the deficit amounted to 0,332 m^3/dt.

5. Summary and Conclusion

A non-linear rainfall-runoff forecasting model was developed for the Tukad Petanu watersheed using feed forward back-propagation neural network algorithm. From this analysis, model 5 with architectural 3-10-5-1, AAE scores of 0.197 and a correlation coefficient is 0.7536 or 75.36%. From the results of the analysis to get the level of performance models, feed forward back propagation neural network method 3-10-5-1 architecture (model 5) provide the most optimum results to describe the rainfall-runoff relationships that occur in the watershed Tukad Petanu (stable score in “r” and “AAE” between training and testing process). Finally, discharge for next year forecasted using the developed model for planning drought mitigation strategies. This study found that on the basis of the developed discharge forecasting model, there is an opportunity of developing a drought watch system for mitigating impacts of droughts in a large-scale irrigation and clean water scheme supplied by water from Tukad Petanu.

6. References

Anonymious, 1998, The Disaster Handbook, Institute of Food and Agricultural Sciences University of Florida

Anonymious, 2005, Drought Assessment And Forecasting, World Meteorological Organization

Anonymious, 2011, *Peraturan Presiden Republik Indonesia Nomor 45 Tahun 2011 Tentang Rencana Tata Ruang Kawasan Perkotaan Denpasar, Badung Gianyar, Dan Tabanan*, download from www.bpkp.go.id

Barua, S., 2010, Drought Assessment and Forecasting Using a Nonlinear Aggregated Drought Index, Dissertation, Victoria University, Australia

Dawson, C.W. and Wilby, R.L., 2001, Hydrological Modelling Using Artificial Neural Networks, Progress in Physical Geography, 25-1: 80-108.

Doddy Heka Ardana, P., 2010, Artificial Neural Network Application in Rainfall-Runoff Modelling, Thesis, Udayana University – Bali, Indonesia

Fausett, L., 1994, Fundamental of Neural Networks, Prentice Hall, Engelwood Cliffs, New Jersey.

Fu, LiMin, 1994, Neural Networks In Computer Intelligence, McGraw-Hill Inc., Singapore.

Harto, S., Br., 1993, Analisis Hidrologi, PT. Gramedia Pustaka Utama, Jakarta.

Hadiani, R., et.al, 2009, Hydrologic Drought Analysis (Case Study in DAS Kali Asem Lumajang), Proceeding, D51-D61

Hu, T.S., Lam, K.C., and NG, S.T., 2001, 2001, River Flow Time Series Prediction With a Range-Dependent Neural Network, Journal of Hydrological Sciences, 46: 729-745.

Joorabchi, A., H. Zhang, M. Blumenstein, 2007, Application of Artificial Neural Networks in Flow Discharge Prediction for the Fitzroy River, Australia, Journal of Coastal Research, Australia.

Junsawang, P., Asavanant, J., Lursinsap, C, 2007, Artificial Neural Network Model for Rainfall-Runoff Relationship, ASIMMOD, Chiang Mai, Thailand.

Illeperuma, G. and Sonnadara, U., 2009, Forecasting Droughts using Artificial Neural Networks, Procceding National Symposium on Disaster Risk Reduction & Climate Change Adaptation

Kusumadewi, S., 2004, Membangun Jaringan Syaraf Tiruan Menggunakan MATLAB dan Excel Link, Graha Ilmu, Yogyakarta.

Sohail, A., Watanabe, K., Takeuchi, S., 2008, Runoff Analysis for a Small Watershed of Tono area Japan by Back Propagation Artificial Neural Network with Seasonal Data, Water Resour Manage, 22: 1-22

Triatmodjo, B., 2008, Hidrologi Terapan, Beta Offset, Yogyakarta

Yulianto, F.E., et.al, 2014, Rainfall Runoff Modelling For Drought Analysis In DAS Temon, “MATRIKS” Civil Engineering e-Journal Vol. 2 No. 1, 100-107