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PREDICTION OF WATER AVAILABILITY BY USING TANK MODEL AND ARTIFICIAL NEURAL NETWORK
(Case Study at Ciriung Sub-Catchment Serang District)

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ABSTRACT
This study was conducted in Ciriung sub-watershed, Cidanau Watershed in Banten Province. The total area of the sub-watershed is 118.01 ha. The land use is mostly dominated by mix-garden (88.27%), and dry paddy field (11.14%), settlement (0.59%). The purpose of this study is to predict water flow in Ciriung River in the future. Three steps were undertaken. The first step was to find the most effective evapotranspiration model for the area. The second step was to determine parameters of tank models. And, the third step was to forecast future rainfall and potential evapotranspiration values using Artificial Neural Network (ANN). The selected model is a standard tank model, which has four series of tank standing in a vertical arrangement, and twelve parameters are involved, i.e., five parameters are in the surface, three parameters are in the intermediate, three parameters are in the sub-base, and one is in the base tank. One parameter and others are mutually interaction, and Marquardt algorithm was used for finding the optimum parameters. Three-layer of ANN with back-propagation were developed, trained and tested to forecast future rainfall and evapotranspiration. The climatic and the stream flow data were collected with digital instruments (logger).The results show that model Hargreaves along with Turc and Jensen-Haise models are the most effective evapotranspiration models for this location. The optimization technique to Tank model gained fast and accurate results of total flow and flow components. The ANN could forecast rainfall and evapotranspiration when trained on adequately representative data set. The result of forecasting of the future total runoff, there were various due to total rainfall and a-year daily rainfall distribution.

Key words: Tank model, parameters. rainfall, evapotranspiration, artificial neural network

BACKGROUND

River flow data is one of the hydrology data the importantness in order to be known, because the data can be used as base planning of catchment development. Problem which was often faced isn't stream data, to get the stream data can be used by approach of hydrology model. Catchment is an system of hydrology hence planning and management of resources which there is in it more accurate when analysed pursuant to phenomenon of hydrologi, one of the indicator of is water balance a catchment.

One of the hydrology models able to be used for the prediction of river discharge is tank model. According to Sugawara (1961) the tank model is a non-linear method based on a hypothesis that is runoff and infiltration is function of the amount of water stored in the soil. Applying of the tank model for dynamic water balance study a catchment have executed many (Et al Fukuda et al. 2001; Heryansyah, 2001; I Sutoyo et al. 2000). Applying of the tank model conducted to daily data in the form of rain data, evapotranspiration, and runoff data, later then the data used to determine parameter of the tank models. Assorted of method to get parameter model tanks have been done, and most using trial-error. Setiawan et al.

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(2003) expressing that to get parameter the tank models assumed by black-box perceived when getting change of parameter. Observation conducted with system of optimization use algorithm of Marquardt. The Algorithm very and effective in finding optimum parameter although for models which is non-linear.

Evapotranspiration data can be calculated pursuant to climates parameter, various model of evapotranspiration have been developed (Penman model, Hargreaves, Jensen-Haise, Penman-Monteith, Radiation, Turc, and Makkink model). Penman and Penman-Monteith model complicated relative, because requiring climates parameter which many and conversions set of complex. Penman model require five climates parameter that is: temperature, humidity relative, speed of wind, saturation vapor pressure, and netto radiation (Doorenbos and Pruitt, 1977). While Model of Hargreaves, Jensen-Haise, Radiation, Turc and Makkink model are model of evapotranspiration the simpleness, with required data only two climates parameter that are temperature and sun radiation (Capece et al.,2002). Applying of the model adapted for the availibility of data, to get efficient model namely simple calculation and have high correctness require to be done by model test.

Problems which often happened if analyse evapotranspiration a region is his incomplete of climates parameter data, though the data very need to process analysis on the land surface. To overcome the problem, can be made model for prediction of climates parameter pursuant to other climates parameter. One of the models able to for prediction is model of Artificial Neural Network (ANN).

Research target is prediction availability of water Ciriung sub-catchment, in detail the target of research shall be as follows: a). Testing effectiveness evapotranspiration model, b). Getting parameters the tank model by optimization technique, and d). Rain and evapotranspiration prediction use ANN to know water avaibility.

THEORETICAL APPROACH

Stream Data Analysis

River discharge measured by sharp crest weir, equation to calculate discharge shall be as follows (Raju, 1981):

$$Q = \frac{2}{3} K_1 K_3 B \sqrt{2g} \left[0.611 + C_1 \frac{H_1}{W} \right] H_1^{\frac{3}{2}} \qquad (1)$$

where Q is discharge (m^3/s); K_1 is coefficient which the was value of influenced by height of water face, gravitation, water specific weight and viskositas.; $K3$ = 0.95; B is width of weir (m); g = gravitation (9.8); $C1$ is coefficient influenced by wide comparison of weir and wide of channel.; H_1 water level of channel (m); W height of weir (m).

Daily stream depth in set of mm / day, obtained from totalizing daily stream volume divided by catchment area with equation like following (Chow *et al.*, 1988):

$$Vd = \sum_{n=1}^{N} Qn \Delta t \qquad (2)$$

$$rd = \frac{Vd}{L} 1000 \qquad (.3)$$

where Vd is volume of direct runoff (m^3). Qn is discharge (m^3/s), Δt = time interval (s), rd = depth of direct runoff (mm), L catchment area (m^2).

Evapotranspiration Model

Evapotranspiration is unique natural phenomenon that is aliance between evaporation of water at surface of water and land, also transpiration of vegetation. Qiu *et al.* (1998) expressing that especial difficulty of evaporation evaluation of land is accuration estimate from aqueous vapour movement resistensi. The difficulty can overcome temperature factor surface of dry land for estimation.

Configuration of land surface have an in with interaction between atmosphere and land, that is sun radiation, clammy devisit and air temperature, and wind of turbulensi, rain and cloud, and also the nature of and soil and vegetation. Based on survey air stream and balance of energy land surface, at homogeneous topography of interaction between land surface and atmosphere almost same (Raupach et al., 1997).

Level of value of evapotranspiration to an area of vegetated influenced by local climate like temperature, wind speed, sun radiation and humidity of air. Process transpiration besides determined by climate, is also influenced by crop type. Evaporation of land surface determined by type, properties and level of soil humidity (Doneen et al., 1988).

Evapotranspiration model is approach of empirical formula to determine the level of potential evapotranspiration (ETp). Various model of ETp have been developed, models of ETp which studied at] this research shall be as follows:

Penman Model (Doorenbos and Pruitt, 1977):

$$ETp = c[WxRn + (1-W)f(u)(ea-ed)] \qquad (4)$$

Hargreaves Model (Wu, 1997):

$$ETp = 0{,}0135(T+17{,}78)Rs \qquad (5)$$

Jensen-Haise Model (Jensen, 1981):

$$ETp = C_T(T-T_x)Rs \qquad (6)$$

Radiation Model (Doorenbos dan Pruitt, 1977):

$$ETp = c(W.Rs) \qquad (7)$$

Penman-Monteith Model (Capece *et al.*,2002):

$$ETp = \frac{\Delta(R_n - G)}{\lambda(\Delta+\gamma^*)} + \frac{\gamma^* M_w(e_a - e_d)}{R\Theta r_v(\Delta+\gamma^*)} \qquad (8)$$

Turc Model (Capece *et al.*,2002):

$$ETp = 0.013\left(\frac{T}{T+15}\right)(R_s+50) \qquad (9)$$

Makkink Model (Capece *et al.*,2002):

$$ETP = 0.61\left(\frac{\Delta}{\Delta+\gamma}\right)\frac{R_s}{58.5} - 0{,}12 \qquad (10)$$

where:

ETp	=	Potential evapotranspiration (mm/d).
W	=	weight factors related to temperature.
Rn	=	Netto sun radiation equivalent evaporation (mm/d).
f(u)	=	Function related to wind.
(ea-ed)	=	Difference between saturated vapour pressure at mean air temperature with vapour pressure of actual air mean (mbar)
c	=	Correction factor
T	=	Mean temperature (°C)
Rs	=	Sun radiation equivalent evaporation (mm/d).
Δ	=	function saturated vapo(u)r pressure slope. (Pa/°C).
G	=	Heat flow into soil (kW/m²).
*γ**	=	Psychometric constanta. (Pa/°C).

Artificial Neural Network (ANN) Model

Artificial Neural Network attempt to mathematically simulate the functioning of human brain (biological neuron) by means of massively parallel processing artificial neurons and a learning rule. Pham (1995) expressing that ANN has the character of flexible to data input and yield respon the consistence. Network which consists of some layers (multilayers) can show the perfect to solve various problems. Study of ANN can finish parallel calculation for complicated dutieses, such us prediction and modeling; recognition pattern and classification; and optimization.

ANN basically lapped over from some layers that is: input layer, hidden layer, and output layer. At each layer there is node that is an simplest computing unit and attributed to node at next layer, relation between node expressed by an number is so-called weight. Each node at input layer become input at next layer to the last output layer (Toth et al., 2002).

Fu (1994) expressing that elementary concept of graphical theory of neural network described as one arrow sign and node A node designates a neuron, and arrow sign is symbol of direction process between neuron. The neural network can be depicted mathematically and the activity process can be conducted digitally computer and analogue computer, depended from data type, scheme example learning of ANN model presented at Figure 1. Neural Networks solve problems by self-learning and self-organization. They derive their intelligence from the collective behavior of simple computational mechanisms at individual neurons. Computational advantages offered by neural networks include: a). neural networks can perform generalization, abstraction, and extraction of statistical properties from the data, b). neural network can create their own representation by self-organization, c). neural networks can carry out computation in parallel, d). the system performance degrades gracefully in response to errors.

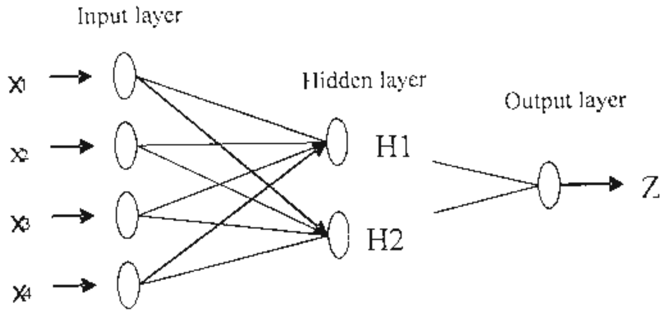


Figure 1. Network scheme for Backpropagation

Solution of calculation of ANN model used by equations following (Patterson, 1996)

$$H_j = \sum_i v_{ji} x_i \qquad j = 1, 2, \ldots, h \qquad (11)$$

$$I_k = \sum w_{kj} y_j \qquad k = 1, 2 \ldots, m \qquad (12)$$

Hj is the combined or net input to hidden layer unit j, while I_k is the net input to unit k of the output layer. Outputs computed by unit j of the hidden layer and unit k of the output layer are given by:

$$y_j = f(H_j) \qquad j = 1, 2, \ldots, h \qquad (13)$$

$$z_k = f(I_k) \qquad k = 1, 2, \ldots, m \qquad (14)$$

Respectively, where *f* is an arbitary, bounded, differentiable function. For output unit k the following response to an input pattern x

$$z_k = f(I_k) = f\left(\sum_j w_{kj} y_i\right) = f\left(\sum_j w_{kj} f(H_j)\right) = f\left(\sum_j w_{kj} f\left(\sum_i v_{ji} x_i\right)\right) \qquad (15)$$

Learning procedure of the model was generated by optimallizing recognized function value by using equation as follow:

$$E = \frac{1}{2}\sum_{k=1}^{m}\left(t_k^p - z_k^p\right)^2 \qquad I_k = \sum_j w_{kj} y_j \text{ and } z_k = f(I_k) \quad \text{.......... (16)}$$

where t is target and z is ANN output.

Focussing first on the weight updates for the output units, we can use the actual errors to find the update rule, that is

$$\frac{\partial E}{\partial w_{kj}} = \frac{\partial E}{\partial I_k}\frac{\partial I_k}{\partial w_{kj}} = \frac{\partial E}{\partial I_k}\left(\frac{\partial}{w_{kj}}\sum_j y_i w_{kj}\right) \quad \text{where } \frac{\partial}{w_{kj}}\sum_j y_j w_{kj} = y_k \quad \text{.......... (17)}$$

The updating procedure at hidden layer is presented as follow:

$$\Delta w_{kj} = \eta \partial_k y_j = \eta(t_k - z_k) f'(I_k) y_j \quad \text{Where } \partial_k = (t_k - z_k) f'(I_k) \quad \text{.......... (18)}$$

The updating rule for the hidden layer unit as

$$\Delta v_{ji} = \eta \partial_j x_i = \eta x_i f'(H_j) \sum_k \partial_k w_{kj} \quad \text{Where } \partial = f'(H_j) \sum_k \partial_k w_{kj} \quad \text{.......... (19)}$$

To summarize, we repeat the two update rules for output and hidden layer units, respectively:

$$w_{kj}^{new} = w_{kj}^{old} + \Delta w_{kj} = w_{kj}^{old} + \eta y_j (t_k - z_k) f'(I_k) \quad \text{.......... (20)}$$

$$v_{ji}^{new} = v_{ji}^{old} + \Delta v_{ji} = v_{ji}^{old} + \eta x_i f'(H_j) \sum_k \partial_k w_{kj} \quad \text{.......... (21)}$$

Tank Model

Tank model is constructed of four vertical reservoirs, of which from top to bottom parts representst the Surface Reservoir (*A*), Intermediate Reservoir (*B*), Sub-base Reservoir (*C*), and Base Reservoir (*D*). In this concept, water can fill the underneath reservoir, and can go reversibly if evapotranspiration is so predominant. The horizontal outlet reflects the outflow, consisting of Surface Flow (*Ya2*), Subsurface Flow (*Ya1*), Intermediate Flow (*Yb1*), Sub-base Flow (*Yc1*), and Base Flow (*Yd1*). Each outflow only occurs when the water level at each reservoir (*Ha,Hb, Hc* and *Hd*) is higher than
11) its outlet (*Ha1, Ha2, Hb1* and *Hc1*). The outflow
12) at each outlet is also influenced by the characteristics of the outlet, i.e., *A0, A1, A2, B0, B1, C0, C1,* and *D1*, which further are called as the parameters of the Tank Model to be determined. All in all there are 12(twelve) parameters (Figure 2).

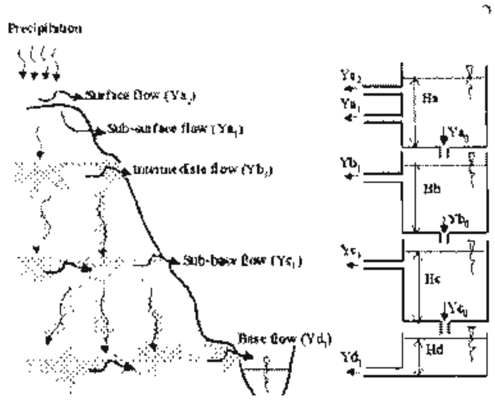


Figure 2. Schematic Standard Tank Model

Globally, the water balance equation can be written as follows:

$$\frac{dH}{dt} = P(t) - ET(t) - Y(t) \quad \text{.......... (22)}$$

13) Where, *H* is water level (mm), *P* is precipitation (mm/day), *ET* is evapotranspiration
14) (mm/day), *Y* is total flow (mm/day), and *t is* time (day).
The total flow is the summation of the flow components that can be written as follows:

$$Y(t) = Ya(t) + Yb(t) + Yc(t) + Yd(t) \quad \text{.......... (23)}$$

15) The water balance in each reservoir in more detail can be written as:

$$\frac{dHa}{dt} = P(t) - ET(t) - Ya(t) \quad \text{.......... (24)}$$

$$\frac{dHb}{dt} = Ya_0(t) - Yb(t) \qquad (25)$$

$$\frac{dHc}{dt} = Yb_0(t) - Yc(t) \qquad (26)$$

$$\frac{dHd}{dt} = Yc_0(t) - Yd(t) \qquad (27)$$

Where, *Ya*, *Yb*, *Yc* and *Yd* are the horizontal flow components from each reservoir, and *Ya*0, *Yb*0 and *Yc*0 are the vertical components.

MATERIAL AND METHOD

The research was conducted in Ciriung sub-catchment Serang regency, which cover area of 118,01 ha. The field survey was done from January 2002 until June 2003. Materials and equipment research are as follows: a). Thermo TR-71S, b) Thermo TR-72S, c) Sun radiation used Voltage VR-7 d) CTD-DIVER, e) Weir, f) soil and tophography map, g) meteorogical data

Test of ETp Model

The efficientness of ETp model was verified by comparing between models. To test model used three mistake indicators thus are 1). Root Mean Square Error (RMSE) 2). Mean Absolute Error (MAE), and 3) Logaritmic RMSE (LOGARITHM). Along with thus comparation, coefficient of determination (R2) was olso applied to verify model. The model is considered to effective if the value error is small, hight R2, and small climates parameter required for calculation.

Optimization Technique

It is of interest to design an optimization technique capable of facilitating each structure of the Tank Model. Such optimization technique must not require detail information in every Tank Model. Herewith, the Tank Model is assumed as one Black Box and its behavior is observable when receiving updated parameters. We applied Marquardt algorithm, which in a simple case it is very quick and effective in finding the optimum parameter even for extremely non-linear equations (Marquardt, 1963; Setiawan and Shiozawa, 1992). Aside from that, it also has been equipped with maximum and minimum values for each parameter. Considering the basic structure of a Tank Model, the algorithm is reconstructed so it can receive the data of total outflow and calculation results from the model. With the Tank Model having 4 (four) reservoirs, an algorithm in the form of **procedure** is constructed the following considerations: 1) It has an input argument for receiving all parameters (**B**); 2) It has an input argument for receiving net of rainfall data minus evapotranspiration (**X**); and; 3) It has an output argument for transferring the calculation outflow of the Tank Model (**Yc**).

Herewith, in Pascal language, the **procedure** can be written as follows:

```
procedure TankModel(B:ArrayM; X:single; var Yc:single);
begin
...
end;
```

The Marquardt1 algorithm is constructed with the following considerations:

1) It has an input argument for receiving Minimum Value (**Bmin**) and Maximum Value(**Bmax**) parameters;

2) It has an input argument for receiving net of rainfall and evapotranspiration (**X**);
3) It has an input argument for receiving debit data (**Yd**); and
4) It has an input/output argument for receiving and transferring parameter (**B**).

Herewith, the designed **procedure Marquardt** is written as:

procedure Marquardt (Bmin,Bmax:ArrayM; X,Yd:ArrayN; var B:ArrayM);
begin {Main of Marquardt}
...
end;{End of Marquardt}

The **procedure Marquardt** consists of **procedure derivative** with the function to carry out first derivation of the Tank Model numerically, **procedure least square** for minimizing error, and **procedure gauss** for the calculation of the renewed parameters.

By giving initial approximation of the parameters, iteration process continued until the sum of absolute changes of updated parameters reached a tolerable value, good conformity and less discrepancy of water balance. The last updated parameters then are considered as the final solutions.

Updating all parameter values for each iteration was done was terminated after the absolute
total of the changes in all parameters was less than the given tolerance value, i.e., 0.00001.The successfulness of the optimization technique was shown using coefficient of correlation (*R*) and 7 (seven) error indicators, i.e., 1) *Root Mean Square Error* (*RMSE*), 2) *Mean Absolute Error* (*MAE*), 3) *Logarithmic RMSE* (*LOG*), 4) Standard χ, 5) Squared Standard $\chi 2$; 6) Relative Error (*RE*), and 7) Squared Relative Error (*RR*), which are written as the following equations:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Qci - Qoi)^2} \quad \text{....... (28)}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Qci - Qoi| \quad \text{....... (29)}$$

$$LOG = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\log Qci - \log Qoi)^2} \quad \text{....... (30)}$$

$$\chi = \frac{1}{N}\sum_{i=1}^{N}\frac{|Qc_i - Qo_i|}{\sqrt{Qo_i}} \quad \text{....... (31)}$$

$$\chi^2 = \frac{1}{N}\sum_{i=1}^{N}\frac{|Qc_i - Qo_i|^2}{Qo_i} \quad \text{....... (32)}$$

$$RE = \frac{1}{N}\sum_{i=1}^{N}\frac{|Qc_i - Qo_i|}{Qo_i} \quad \text{....... (33)}$$

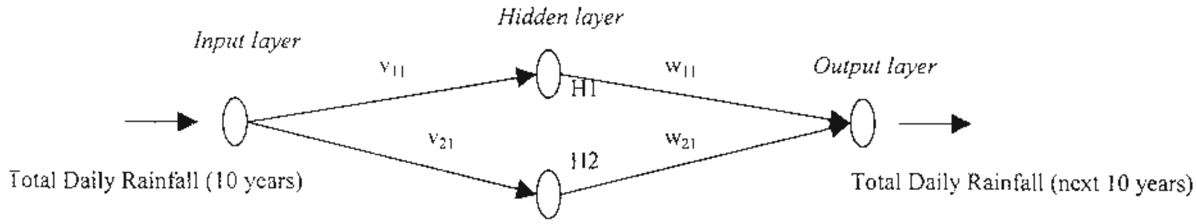


Figure 5. Scheme of ANN Model for 10 years daily rainfall prediction.

ANALYSIS OF RESULTS

Depth of Runoff

Data recorded by CTD-DIVER logger is fluctuation of pressure due to water level fluctuation. This research is used 2 loggers to measure change of underwater pressure and free on the air as control. Data of Logger the analyzed is recorded pressure difference underwater logger and free logger on the air (Pw-Pa). The graph depicting relation between pressure and river water level presented at Figure 6 Stream discharge time to time was calculated by equation 1 dan Figure 6. The depth of runoff caculated by equation 2 and 3. The depth of runoff (Figure 7) used for the analysis of determination of tank model parameters in Ciriung sub-catchment.

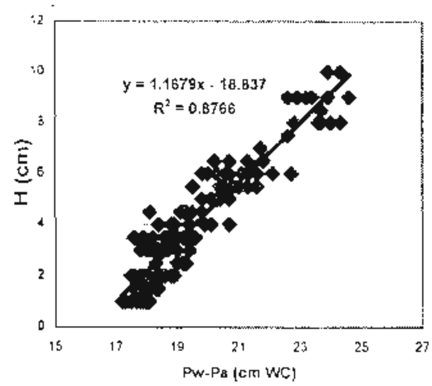
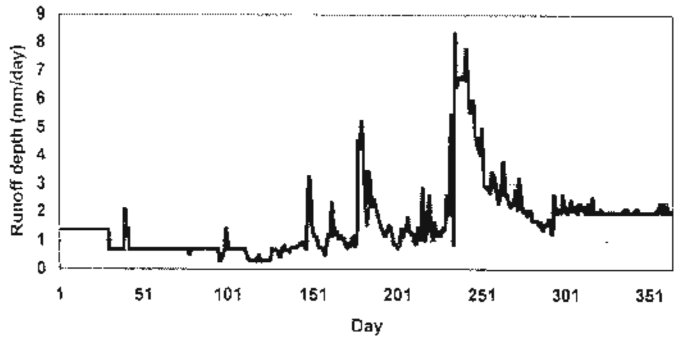


Figure 6. Presure vs water level



Figur 7. The Runoff depth

ETp Model

According to three errors indicator that is RMSE, MAE, and LOGARITHM there are four models having mistake indicator values which is small. Penman model, Jensen-Haise, Hargreaves, and Turc model. Penman model with Jensen-Haise model (RMSE = 0,6924, MAE = 0,5515, LOGARITHM = 0,0601), Penman with Hargreaves (RMSE = 0,44, MAE = 0,4031, LOGARITHM = 0,0597), and Penman model with Turc model (RMSE = 0,3631, MAE = 0, 2937, LOGARITHM = 0,0682). Beside have small mistake indicator values, ad for the model have value of R^2 the big enoughness. Penman model with Jensen-Haise model assess R^2 = 0.8599, Penman with Hargreaves R^2 = 0,9425, and Penman with I Turc model R^2 = 0,9615. Four model have value (RMSE, MAE, LOG) small and big R^2, this matter indicate that the models have same correctness to prediction ETP.Thereby to prediction ETp in Ciriung sub-catchment can be used by simple models which only requiring two climates parameter that are air temperature and sun radiation. Relation between Penman models with Hargreaves model presented at] Figure 8. For the input of tank model the ETp corrected with crop factor (kc= 0.86). Value of ETp corrective presented at Figure 9.

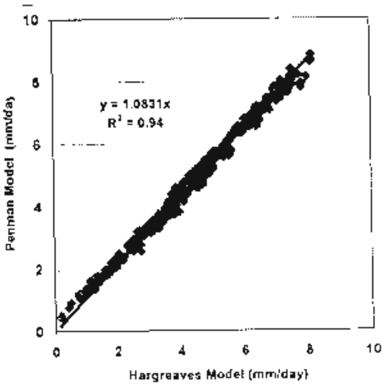


Figure 8. Penman model vs Hargreaves model

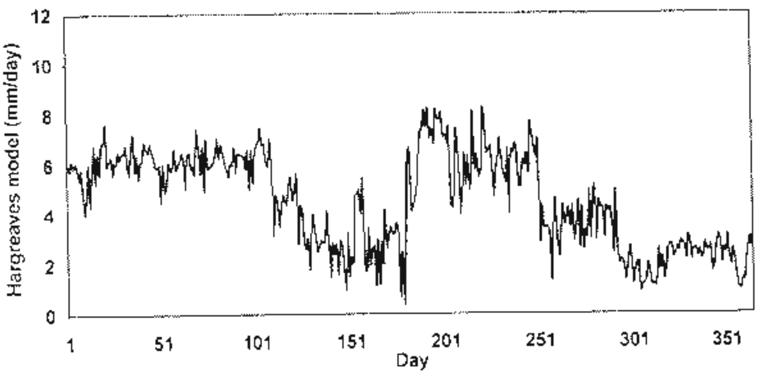


Figure 9. ETc of Ciriung sub-catchment July 2002 to June 2003

Rainfall data

The parameters of Tank models determined with daily rain data input. Daily rainfall data got by automatic recorder from July 202 to June 2003. The rainfall data of Ciriung sub-catchment used for the input of tank model presented at Figure 10.

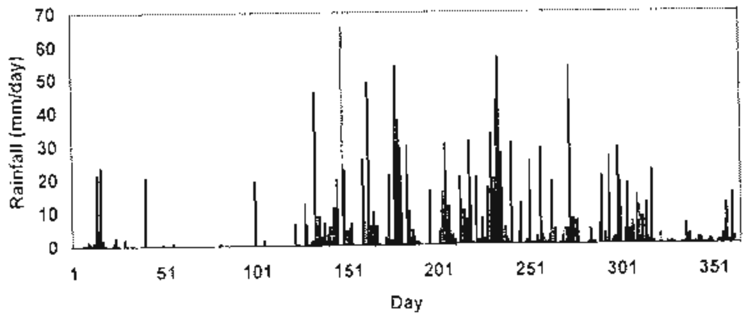


Figure 10. Rainfall data of Ciriung sub-catchment July 2002 to June 2003

Tank Model

The Optimization Technique was tested to determine the parameters of the Standard Tank Model in Ciriung sub-catcment; daily data of rainfall, evapotranspiration, and water discharge were well from July 2002 through June 2003. Table 1 shows the optimum parameter after going through optimization process for Ciriung sub-catchment. At the catchment, the Standard Tank Model resulted in very good water balance where the occurred discrepancy approaching zero. As such, the coefficient of correlation (***R***) was over 0.82, whilst the other error indicator was almost less than one except for ***RMSE*** which was over 1 repectively (Figure 11).

Table 1. Parameters of tank model Ciriung sub-catchment

No	Parameter	Nilai	No	Parameter	Nilai
1	A_0	0,047	7	C_1	0,001
2	A_1	0.002	8	D_1	0,001
3	A_2	0,025	9	H_{a1}	15,00
4	B_0	0.006	10	H_{a2}	60,00
5	B_1	0,012	11	H_{b1}	0.001
6	C_0	0,001	12	Hc1	0.221

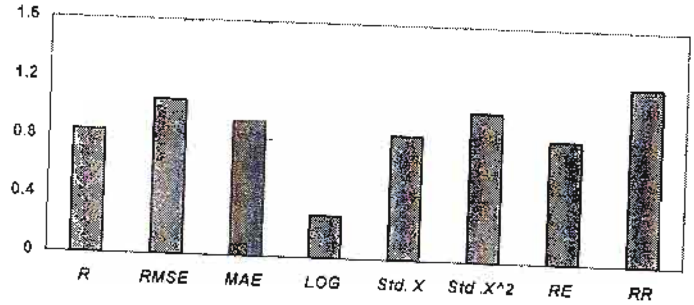


Figure 11. Performance indicators of tank model in Ciriung sub-catchment

Figure 12 shows the hydrographic for Ciriung River. Ciriung River in theearly year shows somewhat high discharges. But in the middle of the year starting from the end of June up to the early December of 2002 (dry season), it shows a decreasing discharges. Here, the Standard Tank Model seems to be successful in approaching the peak discharges as compared to its nearness to the low discharges.

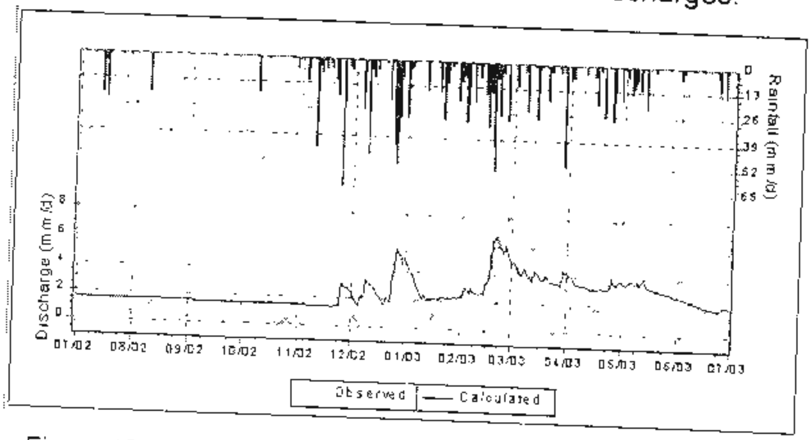


Figure 12 Hydrograph for Ciriung sub-catchment in 2002/2003

Rainfall and ETp Prediction

The learning process of ANN model to calculate ETp used climates parameter data in 1990 through 1992. Table 2 shows the weight value after going backpropagation learning process at Ciriung sub-catchment in 1990 through 1992. The weight value used for prediction of ETp in 1993 through 2002. Figure 13 shows the verification of ANN model and observation, and Figure 14 shows ETp calculated in 1990 through 2002.

Table 2 The weight value for ETp prediction in 1992 to 2002

Weight	Value	Weight	Value
v_{11}	-0,22875	v_{23}	-1,01520
v_{21}	1,85274	v_{14}	0,61738
v_{12}	-1,09670	v_{24}	1,30867
v_{22}	-0,72136	w_{11}	-2,46920
v_{13}	0,70853	w_{21}	1,67847
RMSE = 0,000893			

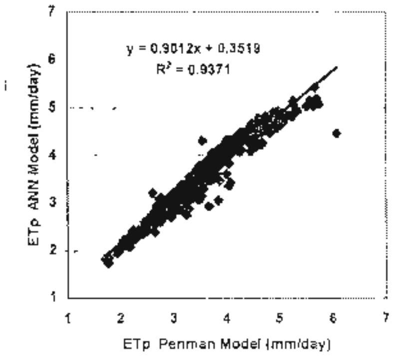
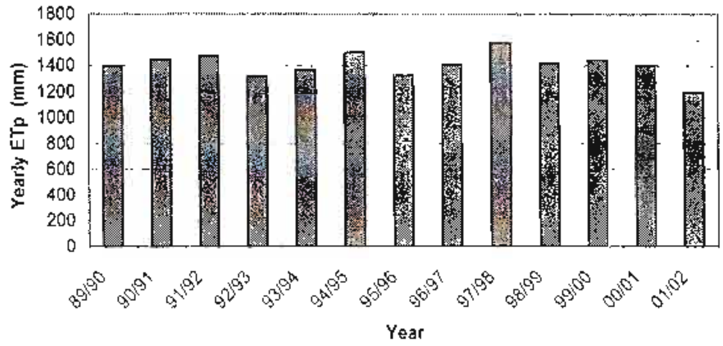


Figure 13. Penman model Vs ANN model



Figur 14. ETp Calculated in 1990 to 2002

The future ETp (2004 through 2010) calculate based on the past ETp (1990 through 2002). Data of ETp used learning process of ANN model is 10 year totalizing daily ETp. The training data used three sets data that are 1989 to 1999, 1990 to 2000, and 1991 to 2001. Table 3 shows the weight value after going backpropagation learning process with 10 year totalizing daily ETp, and Figure 15 shows the verification ANN model and calculated. The learning process continues to be conducted, then the result for prediction of ETp next year. Table 4 shows the weight value after going backpropagation learning process for prediction of ETp in 2004 through 2010, Figure 16 shows ETp in 2004 through 2010.

Table 3. Weight value for training data 10 year totalizing

Pembobot	Nilai
v_{11}	-2,0672
v_{21}	1,9248
w_{11}	-3,7432
w_{12}	1,3222
RMSE	1,17E-03

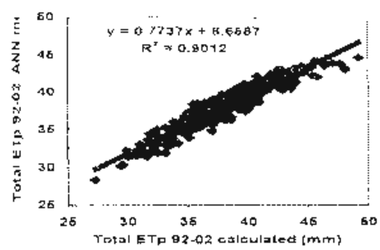


Figure 15. ANN model vs calculated (Totalizing ETp 10 years)

Table 4. The weight value for prediction ETp in 2004 through 2010

	For prediction						
Weight	2004	2005	2006	2007	2008	2009	2010
v_{11}	2,3620	1,5612	-1,4167	-1,3323	1,8699	-1,3424	1,6166
v_{21}	-2,2239	-0,9656	1,7957	1,5850	-1,4866	1,7286	-1,4546
w_{11}	1,5132	0,9856	-2,4351	-2.0268	1,2099	-2,1688	1,1452
w_{21}	-4,2453	-1,6672	1,1786	1,0930	-2,5228	1,1286	-2.2452
RMSE	0,0002	0,0054	0,0030	0,0039	0,0027	0,0037	0,0032

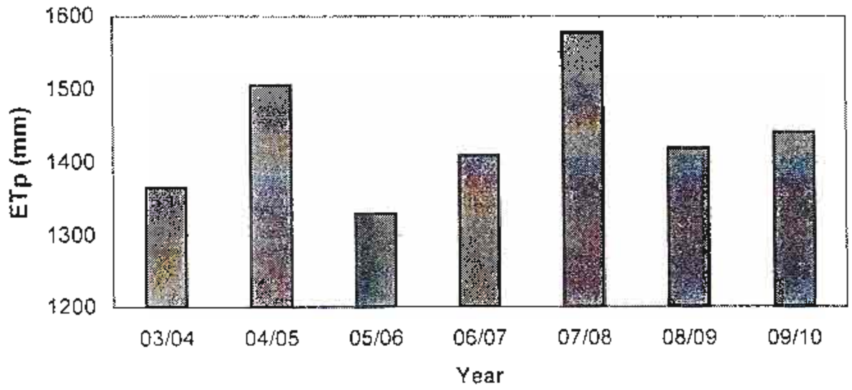


Figure 16. ETp in 2004 through 2010 Cinung sub catchment

The future rainfall (2004 through 2010) calculates based on the past rainfall (1990 through 2002). Data of rainfall used learning process of ANN model is 10 year totalizing daily rainfall. The training data used three sets data that are 1989 to 1999, 1990 to 2000, and 1991 to 2001. Table 5 shows the weight value after going backpropagation learning process with 10 year totalizing daily rainfall, and Figure 15 shows the verification ANN model and calculated. The learning process continues to be conducted, then the result for prediction of rainfall next year. Table 6 shows the weight value after going backpropagation learning process for prediction of rainfall in 2004 through 2010, Figure 17 shows rainfall in 2004 through 2010.

Tabel 5. Nilai pembobot hujan 10 tahun

Weight	Value
v_{11}	-3,2251
v_{21}	-5,46E-02
w_{11}	-3,056067
w_{21}	0,666136
RMSE	2,40E-03

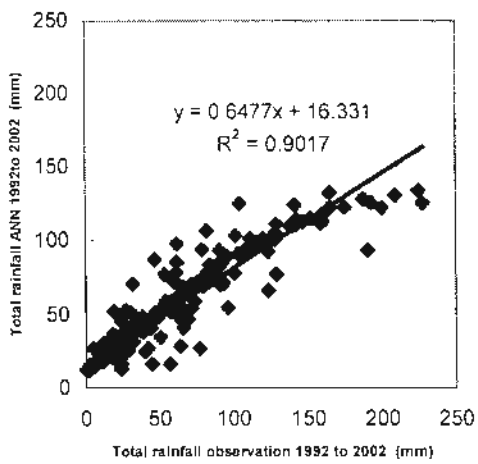


Figure 16. ANN model vs calculated (10 years Totalizing Rainfall)

Table 6. The weight value for prediction rainfall in 2004 through 2010

	For prediction						
Weight	2003/04	2004/05	2005/06	2006/07	2007/08	2008/09	2009/10
v_{11}	-4,5452	-3,0505	-4,2101	-3,2038	-3,8043	-3.3102	-4,5533
v_{21}	-1,4838	1,2137	-3,9512	0,7035	-0,0361	0,9563	-4,1600
w_{11}	-3,3144	-4,1197	-1,4253	-3,8460	-3,7764	-4,0062	-1,5084
w_{21}	0,6070	1,3460	-1,0898	1,0850	0,9632	1,2166	-0,9901
RMSE	0,0014	0,0002	0,0029	0,0003	0,0004	0,0021	0,0036

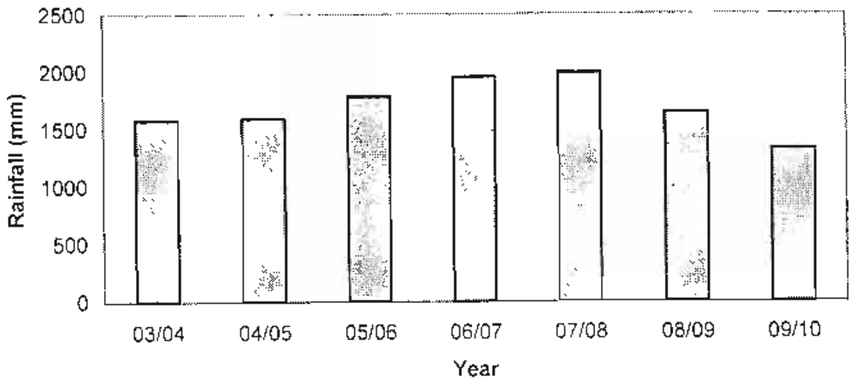


Figure 17. Rainfall in 2004 through 2010 Ciriung sub catchment

According to tank model parameters (Table 1) the availability water can predicted by daily rainfall and evapotranspiration data input. Figure 18 shows availability water at Ciriung sub-catchment in 2003 through 2010.

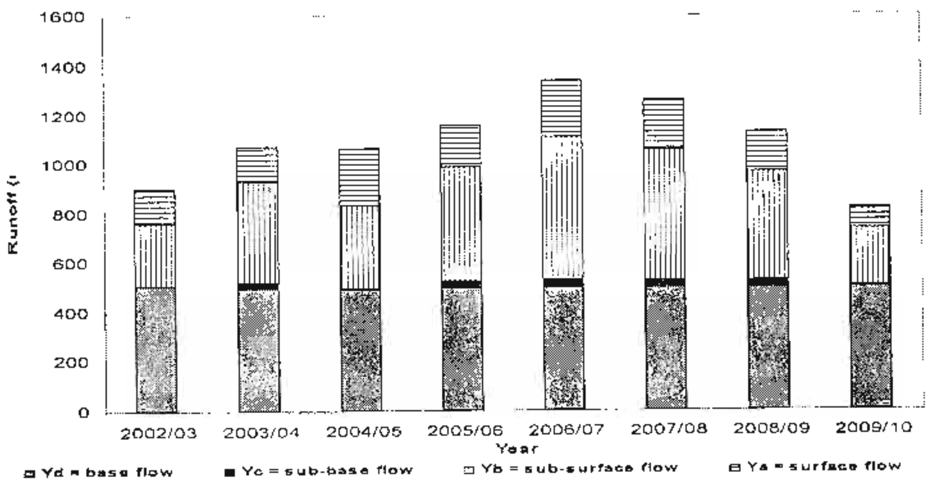


Figure 17. Availability water Ciriung sub-catchment in 2003 through 2010

CONCLUSION

1. The seven models were applied to determine ETp based on daily climatic data collected in one year using automatic weather station located at the Ciriung sub cacthment.The error indicators to evaluate the effectiveness of the ETp models are Root Mean Square Error (RMSE), Mean Average Error (MAE), and Logaritmic RMSE (LOG), and the determination coefficient (R^2). The result shows that Hargreaves model is the most effective along with Turc and Jensen-Haise models.
2. The optimization technique to Tank Model gained fast and accurate results of total flow and flow components
3. Results revealed that the ANN networks were able to well learn the events they were trained to recognize. Moreover, they were capable of effetively generalize their training by predicting potential evapotranspiration for sets of unseen cases. The ANN can forecast rainfall and evapotranspiration when trained on adequetely representative data set
4. Result of tank model analysis and ANN model was able to clarify water availability in sub-catchment of Ciriung in dry season. Thus, irigated field area can be acounted.

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