Jurnal Keteknikan Pertanian

ISSN 0216-3365

Terakreditasi "A"
SK No. 395/DIKTI/Kep/2000

VOL. 19, No. 2
AGUSTUS 2005

Perhimpunan Teknik Pertanian Indonesia
Indonesian Society of Agricultural Engineering

Technical Paper

Estimation Of Soil Hydraulic Properties From Particle Size Distribution Using Artificial Neural Network

Rudiyanto[1] and Budi Indra Setiawan[2]

Abstract

Information of hydraulic properties of agricultural soils is very important for better water management. However, direct measurements of these properties are tedious and time consuming. In this paper, we present techniques to estimate the properties using artificial neural network (ANN). One technique was used to estimate water retention curves and the other to estimate unsaturated hydraulic conductivity curves. The data used in this study varied from sandy to clay soils. In general, the technique gained considerable results but more data for training is still necessary.

Keywords: Soil hydraulic properties, artificial neural network.

A. BACKGROUND

Soil has important role as a favorable medium for plant growth. The soil must be able to store and supply water and nutrients and be free of excessive concentrations of toxic agents. In fact, movement of water and solute through the soil is strongly dependent upon soil particles corresponding to the soil texture, aggregation and density.

Most of the process involving soil-water interaction in the field, and particularly the flow of water in the rooting zone of most crop plants, occur while the soil is in unsaturated condition. Unsaturated flow process is complicated and difficult to describe quantitatively since they often entail changes in the state and content of soil water. Such changes involve complex relations among soil wetness, suction and conductivity.

Many researchers have studied the water flow in unsaturated soil. Setiawan (1998), Saleh (2000) and Hermantoro (2003) studied the water flow under the application of pitcher irrigation in dry land. Bresler *et al*, (1971[a]) and Bresler *et al*, (1971[b]) developed theoretical considerations and mathematical tools to analyze multidimensional transient infiltration and simulated water flow from trickle irrigation.

The soil hydraulic properties (i.e., the water retention curve and hydraulic conductivity) are needed in the study of

[1] Master Student of Agricultural Engineering Sciences, Graduated School, Bogor Agricultural University, Email: lupusae@yahoo.com

[2] Chairman of Graduate Program of Agricultural Engineering Sciences, Graduated School, Bogor Agricultural University, PO BOX 220, Bogor 16002, Indonesia, Email: budindra @ipb.ac.id

water flow and solute transport in vadose (unsaturated) zone. There are many methods of direct measurement that can be used to determine soil hydraulic properties in the field or in the laboratory. The limitation of direct measurement is subjected to specific ranges of applicability with respect to the soil type and saturation and generally quite cumbersome and requires a substantial investment in both time and money. Furthermore, it is impossible to measure soil hydraulics conductivity in many vadose zones with large areas of land that may have lateral, spatial and temporal variability. So, it is of interest to develop the alternative method for estimating soil hydraulic properties.

One of the methods for estimating soil hydraulic properties is pedotransfer functions (PTFs). PTFs transfer basic information from soil surveys into other laborious and expensively determined soil properties. McBratney *et al.* (2002) defined PTFs as predictive soil properties from other easily-, routinely-, or cheaply-measured properties.

In this paper we estimate soil hydraulic properties (water retention and hydraulic conductivity curves) by using PTFs approach. Here, the water retention and hydraulic conductivity curves were estimated from particle size distributions using artificial neural network (ANN) along with Genuchten model and Setiawan model, respectively.

B. THEORETICAL CONSIDERATIONS

Particle Size Distributions

Soil particle covers an extreme size range, varying from stones and rock (exceeding 0.25 m in size) down to submicron clays (< 1μm). Various systems of size classification have been used to define arbitrary limits and ranges of soil particle size (i.e., USDA, CSSC, ISSS and ASTM). Particle size analysis data can be presented and used in several ways, the most common being a particle size distribution that the percentage of particles less than a given particle size is plotted against the logarithm of effective particle diameter. Particle size analysis is often used in soil science to evaluate soil texture. Soil texture is based on different combinations of sand, silt and clay separates that make up the particle size distribution of a soil sample (Gee and Baudar, 1986).

Shiozawa and Campbell (1991) used the unimodal log-normal and bimodal model to model the particle size distribution. Bimodal model gives best fit the data better than unimodal model. Setiawan and Nakano (1993) introduced a model of the particle size distribution as

$$\sigma = 100 - \frac{100}{\left(1+(a1\,\Phi)^{b1}\right)^{c1}} \qquad (1)$$

where σ is percentage particle smaller than Φ, Φ is diameter of particles (mm) and *a1*, *b1*, and *c1* are parameters. This model gives good fits to the particle size distributions of most soil types.

Soil Hydraulic Properties Model

There are three widely used soil hydraulic properties models i.e., Gardener-Russo model, Brooks-Corey model and Genuchten model. Genuchten (1980) identified S-shaped function that fits water-retention characteristics of many types of soil very well. Subsequently, Genuchten model has become most widely used for characterizing soil hydraulic properties. Genuchten model of soil water retention curve can be expressed as follows:

$$\theta(\psi) = \theta_r + \frac{\theta_s - \theta_r}{\left(1 + \left(\frac{abs(\psi)}{\alpha}\right)^n\right)^m} \quad (2)$$

where $\theta(\psi)$ is volume wetness (cm^3/cm^3), θ_r is residual volume wetness (cm^3/cm^3), θ_S is saturated volume wetness (cm^3/cm^3), Ψ is pressure head (cm H_2O) and α, n and m are parameters.

Genuchten model combined the soil water retention function with pore size distribution model of Mualem (1976) and obtained the following relationship of hydraulic conductivity in terms of effective degree of saturation (S_e)

$$k(S_e) = k_s S_e^l \left[1 - \left(1 - S_e^{n/(n-1)}\right)^{1-1/n}\right]^2 \quad (3)$$

and

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} \quad (4)$$

where k_S is the saturated hydraulic conductivity (cm/s), S_e is the effective degree of saturation, and l is a parameter that account for the dependence of the tortuosity and the correlation factors on the water content estimated, to be about 0.5 as an average of many soil.

Setiawan and Nakano (1993) developed unsaturated hydraulic conductivity as a function of volume wetness. Herewith, the model is referred as Setiawan model. Performances of Setiawan model have been tested elsewhere Setiawan and Nakano (1993) and Saleh (2000). The Setiawan model is given by:

$$k(\theta) = k_s \exp\left(-a2(\theta_s - \theta)^{b2}\right) \quad (5)$$

where $k(\theta)$ is unsaturated hydraulic conductivity (cm/s), k_S is saturated hydraulic conductivity (cm/s), θ is volume wetness (cm^3/cm^3), θ_S is saturated volume wetness (cm^3/cm^3), and, $a2$ and $b2$ are parameters.

Artificial Neural Network

Developments of PTFs using ANN have increased rapidly in recent years (Pachepsky *et al.*, 1996; Schaap and Bouten, 1996; Tamari *et al.*, 1996; Minasny and McBratney, 2002). An advantage o f ANN, as compared to traditional PTFs, is that ANN requires no a priori model concept.

Feed forward neural network have been applied successfully to solve some difficult and diverse problems by training the network in a supervised manner with a highly popular algorithm known as the error back propagation algorithm. This algorithm is based on the error-correction learning rule and it may be viewed as its generalization. Basically, error back propagation learning consists of two phases performed through different layers of network: a forward pass and backward pass (Kantardzic, 2003).

In the forward pass, input data vector is applied to the input nodes of network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. We may thus write

$$v_j(n) = \sum_{i=1}^{m} w_{ij}(n)\, x_i(n) \quad (6)$$

Table 1 Summary of retention curve data

Soil type	Ranges of retention curve data	
	Hydraulic conductivity (cm/s)	Volumetric wetness (cm^3/cm^3)
Clay loam	-16000~0	0.255~0.445
Fine sand	-16000~0	0.042~0.365
Light clay	-16000~0	0.215~0.453
Loam	-16000~0	0.098~0.503
Loamy fine sand	-16000~0	0.060~0.439
Medium coarse sand	-16000~0	0.017~0.365
Medium fine sand	-16000~0	0.023~0.350
Sandy clay loam	-16000~0	0.180~0.432
Sandy loam	-16000~0	0.061~0.465
Silt loam	-16000~0	0.092~0.509
Silty clay loam	-16000~0	0.185~0.475
Silty clay	-16000~0	0.257~0.507

$$y_j(n) = \varphi\left(v_j(n)\right) \qquad (7)$$

where $x_i(n)$ is the input data, $w_{ij}(n)$ is weight, φ is the activation function, m is the number of inputs for j_{th} neuron, $y_j(n)$ is output of neuron at j_{th} neuron and n is number of iterations.

During the backward phase, the weights are all adjusted in accordance with an error-correction rule. The principle is minimization of the function $E(n)$. The correction $\Delta w_{ij}(n)$ applied to $w_{ij}(n)$ is defined by the delta rule as follows:

$$\Delta w_{ij}(n) = \eta\delta_j(n)x_i(n) \qquad (8)$$

$$\delta_j(n) = \frac{\partial E(n)}{\partial w_{ij}(n)} \qquad (9)$$

$$E(n) = \frac{1}{2}\sum\left(d_j(n) - y_j(n)\right)^2 \qquad (10)$$

where η is learning rate and $d_j(n)$ is the output target for j_{th} neuron. A simple method of increasing the rate of learning yet avoiding the problem of instability is to modify the delta rule by including a momentum (α) term:

$$\Delta w_{ij}(n) = \eta\delta_j(n)x_i(n) + \alpha\Delta w_{ij}(n-1) \qquad (11)$$

Having computed the adjustment $\Delta w_{ij}(n)$, the updated value of weight is determined by:

$$w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n) \qquad (12)$$

Table 2 Summary of hydraulic conductivity data

Soil type	Range of hydraulic conductivity curve data	
	Hydraulic conductivity (cm/s)	Volumetric wetness (cm^3/cm^3)
Clay loam	9.72×10^{-7}~1.16×10^{-5}	0.411~0.445
Fine sand	3.90×10^{-6}~5.79×10^{-4}	0.196~0.365
Light clay	7.11×10^{-6}~4.05×10^{-5}	0.360~0.453
Loam	5.74×10^{-6}~5.79×10^{-5}	0.420~0.503
Loamy fine sand	5.73×10^{-6}~3.07×10^{-4}	0.179~0.437
Medium coarse sand	1.16×10^{-8}~3.47×10^{-3}	0.095~0.353
Medium fine sand	3.47×10^{-7}~1.27×10^{-3}	0.155~0.350
Sandy clay loam	7.97×10^{-6}~2.72×10^{-4}	0.338~0.432
Sandy loam	1.16×10^{-7}~1.91×10^{-4}	0.260~0.453
Silt loam	1.02×10^{-5}~7.52×10^{-5}	0.461~0.509
Silty clay loam	1.62×10^{-6}~1.74×10^{-5}	0.372~0.475
Silty clay	5.21×10^{-7}~1.50×10^{-5}	0.463~0.507

C. MATERIALS AND METHODS

Materials

The soils that used were 10 types of soil base on USDA classification system i.e., clay loam, sand (fine sand, medium coarse sand and medium fine sand), clay (light clay), loam, loamy sand (loamy fine sand), sandy clay loam, sandy loam, silt loam, silty clay loam and silty clay (de Laat, 1991). For each soil type the pressure head was given for thirteen values (0, -10, -20, -31, -50, -100, -250, -500, -1000, -2500, -5000, -10000, -1600 cm) for retention curve data. For each soil type the pressure head was given for six values (0, -10, -20, -31, -50, -100 cm) for hydraulic conductivity curve data. The summary of soils for retention curves and hydraulic conductivity data are shown in Table 1 and 2, respectively.

Parameter Optimization

Parameters optimization of particle size distribution model (a1, b1 and c1), Genuchten model (θ_r, θ_s, a, n and m) and Setiawan model (k_s, a2, and b2) were done using Marquardt algorithm (Marquardt, 1963 and Setiawan and Shiozawa, 1992). The algorithm is powerful method to solve a nonlinear curve fitting. The Optimized parameters of Genuchten and Setiawan model are then referred here as original parameters.

First, ANN was developed to estimate the Genuchten parameters from the parameters of particle size distribution model. The structure of ANN is shown in Figure 1. Second, ANN was developed to estimate the Setiawan model parameters from the parameters of particle size distribution model and saturated volume wetness (Figure 2).

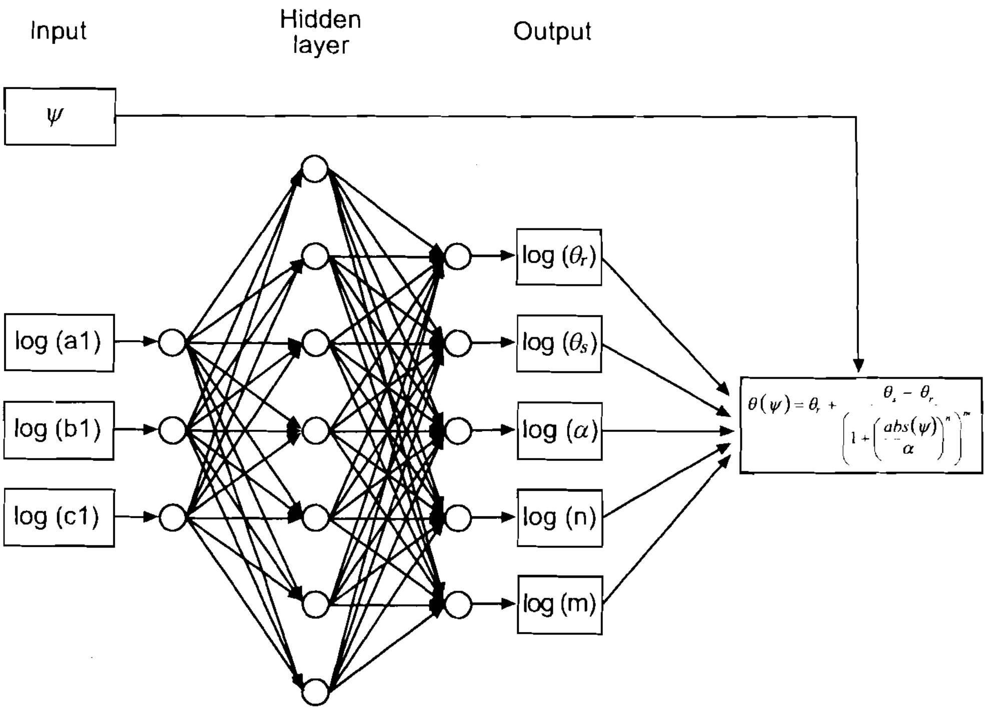


Figure 1. The structure of ANN to estimate Genuchten model parameters

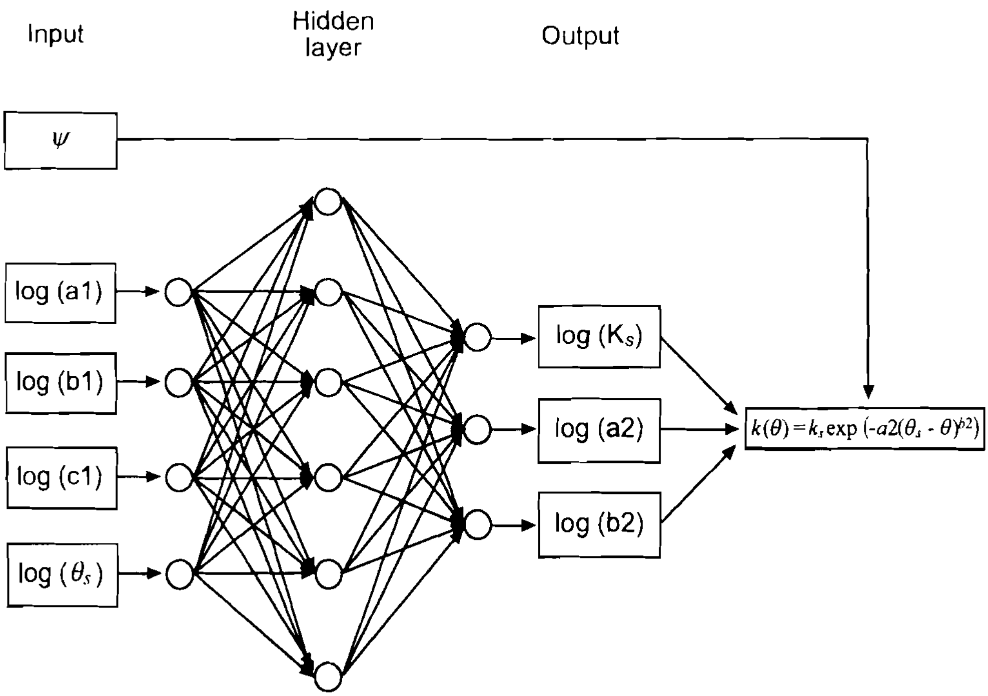


Figure 2. The structure of ANN to estimate Setiawan model parameters

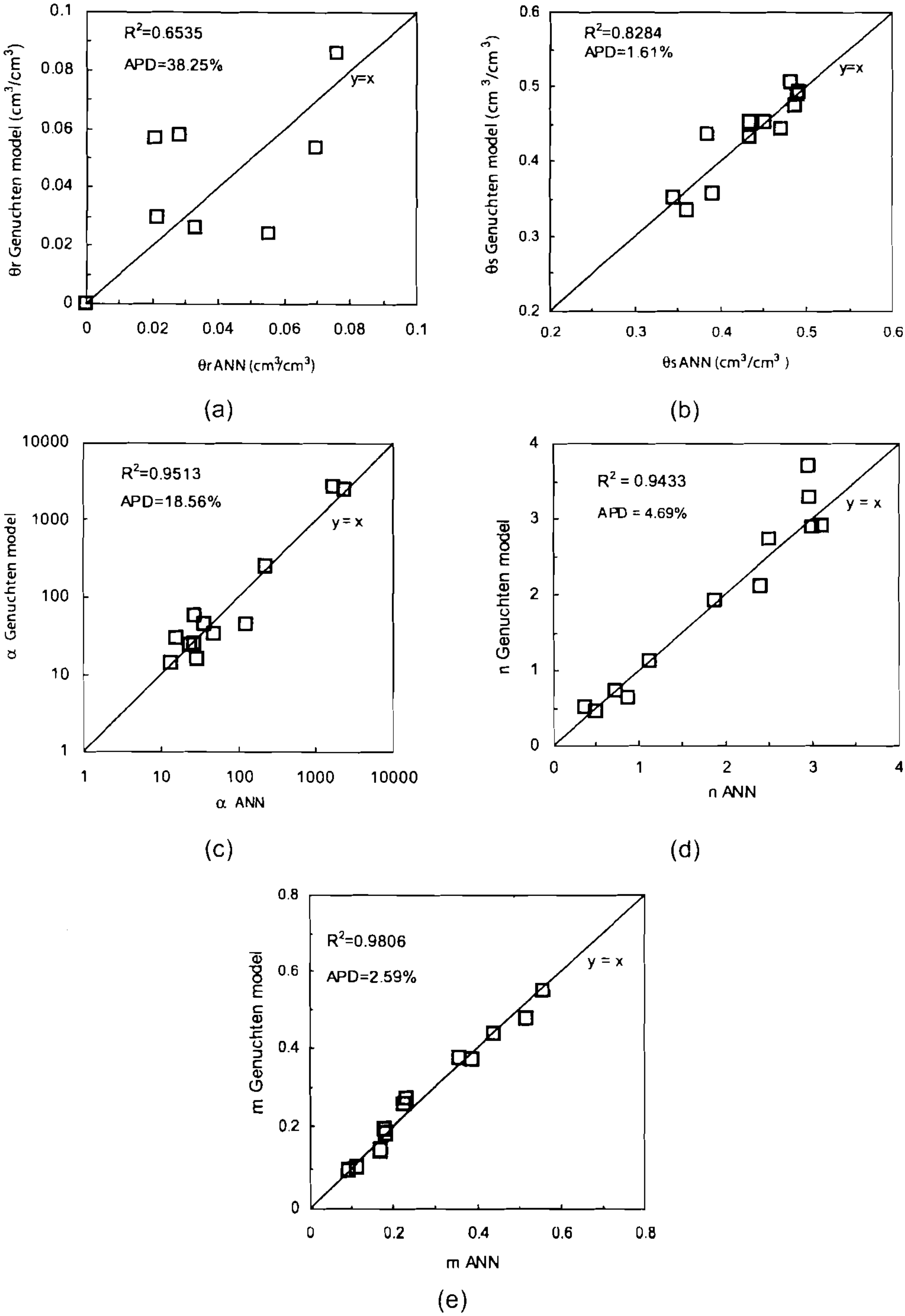
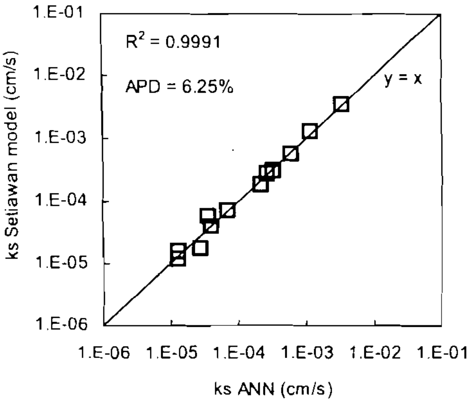
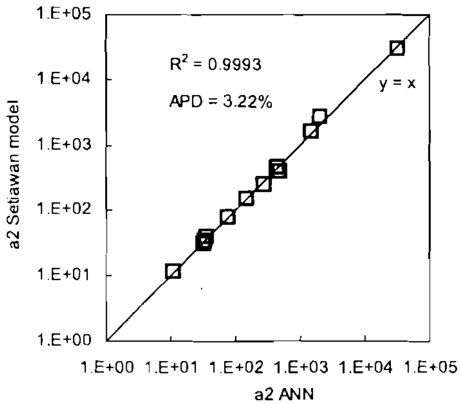


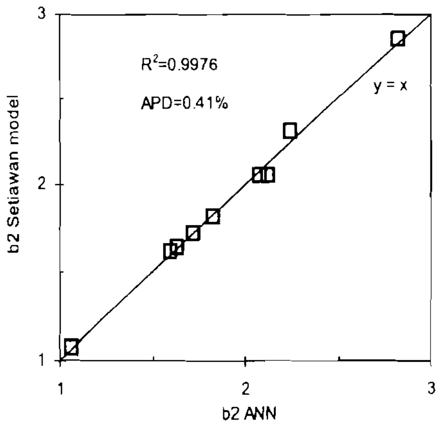
Figure 3 Comparison between parameters by Genuchten model with by ANN: (a) Residual volume wetness (θ_r), (b) Saturated volume wetness (θ_S), (c) α-parameter, (d) n-parameter, and (e) m-parameter



(a)



(b)



(c)

Figure 4 Comparison between parameters by Setiawan model with by ANN:
(a) Saturated hydraulic conductivity (ks), (b) a2-parameter, and (c) b2-parameter

Estimated parameters from ANN are then referred here as estimated parameters. The learning process was carried out using the following parameters: learning rate (η) = 0.9, momentum (α) = 0.9, and, gain =0.9.

ANN Performance

The accuracy of ANN to estimate Genutchten and Setiawan model parameters were analyzed by coefficient of determination (R^2) and average percentage of deviation (APD). Coefficient of determination is defined as ratio of variation of data explained by model to the total variation. APD is defined as a fraction of deviation of the original data value the model (Stoecker, 1989).

D. RESULT AND DISCUSSION

Estimation of Water Retention Curves

Figure 3 shows comparison of parameters estimated by ANN and the original of Genuchten model. It can be seen that the estimation is generally good for all parameters but not for θ_r. The highest of coefficient of determination is for m parameter followed by α, n, θ_S, and θ_r. The lowest APD is for θ_S followed by m, n and α parameter and θ_r parameter.

Figure 5 presents five comparisons of water retention data and Genuchten model with original and estimated parameters. There was generally good agreement between measured data and Genuchten model with original and estimated parameters. Moreover, Genuchten model with original parameters gives well fitted for all soil

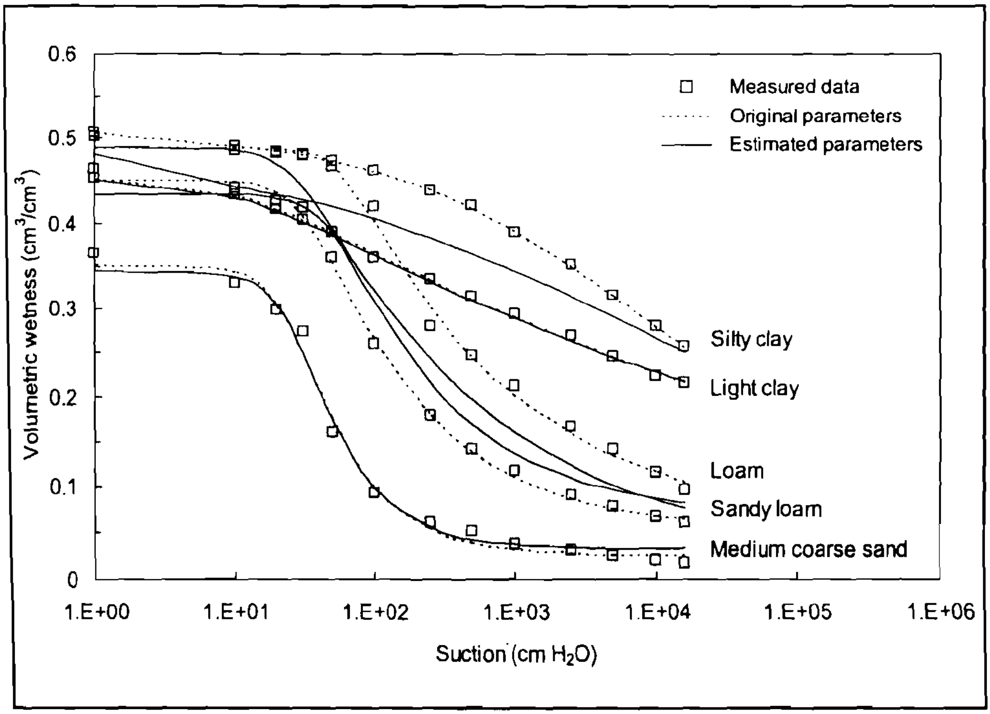


Figure 5. Water retention data and Genuchten model with original and estimated parameters

type but Genuchten model with estimated parameters gives better estimation for water retention curve especially for sand and clay soil type. Genutchen model with estimated parameters underestimates for silty clay and loam soil type.

Estimation of Hydraulic Conductivity Curves

Figure 4 shows comparisons of parameters estimated by ANN and the original of Setiawan model. Parameters estimation by ANN produced good result. It can be seen that the coefficient of determination for all parameter reach 0.99. The APD for k_S, a2, and b2 parameter are 6.25%, 3.22%, and 0.41%, respectively.

Figure 6 shows comparisons of hydraulic conductivity data and Setiawan model with original and estimated parameters. We present hydraulic conductivity curves for five soil type. It can be seen that Setiawan model with original parameters can be so closer than Setiawan model with estimated parameters to the hydraulic conductivity data. Setiawan model with original and estimated parameters is better fitted the hydraulic conductivity data more than 1.E-6. Moreover, Setiawan model with estimated parameters has good agreements especially for light clay soil type and underestimates for loam soil type.

E. CONCLUSION

Techniques to estimate water retention and hydraulic conductivity curves have been developed using artificial neural network. The results were considerably satisfied but more data training is deemed necessary for better achievement.

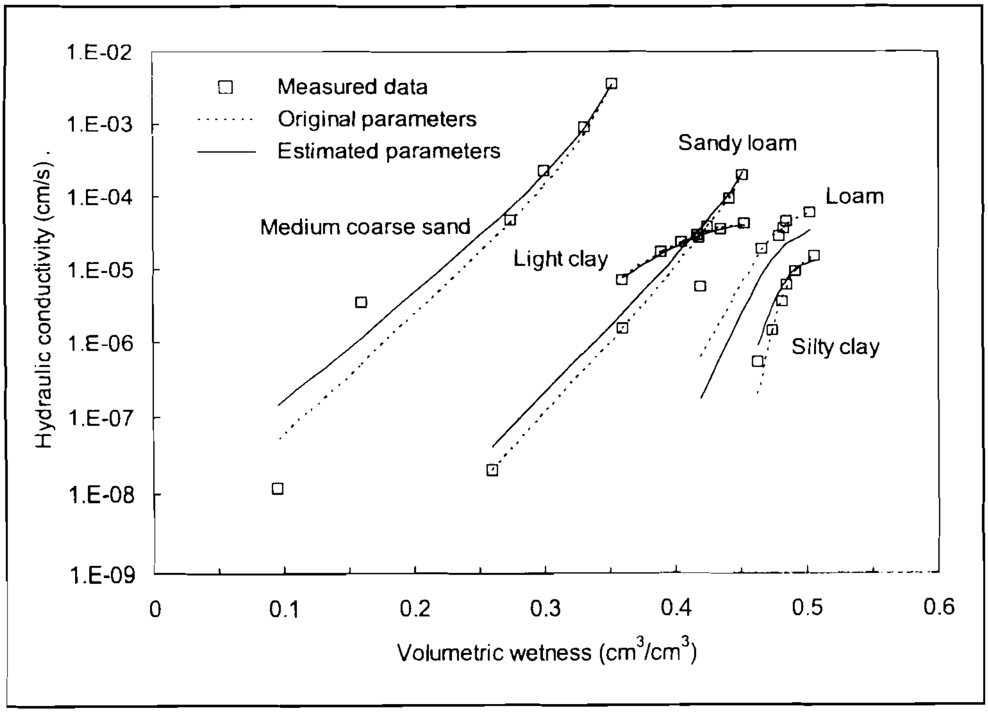


Figure 6. Hydraulic conductivity data and Setiawan model with original and estimated parameters

REFERENCES

Bresler, E. J. Heller, N. Diner, I. Ben-Asher, A. Brandt, and D. Goldberg. 1971[a]. Infiltration from a Trickle Source: I. Mathematical Model. Soil Sci. Soc. Amer. Proc., Vol. 35: 675-682.

Bresler, E. J. Heller, N. Diner, I. Ben-Asher, A. Brandt, and D. Goldberg. 1971[b]. Infiltration from a Trickle Source: II. Experimental Data and Theoretical Predictions. Soil Sci. Soc. Amer. Proc., Vol. 35: 683-689.

de Laat, P.J.M. 1991. Agricultural Hydrology. 2nd edition. IHE Delft.

Gee, G. W., and J. W. Bauder. 1986. Particle-size Analysis. Agronomy monograph no. 9. 2nd edition. Madison.

Hermantoro. 2003. The Effectiveness of Pitcher System on Bush Paper Crops. Dissertation. Bogor Agricultural University. Bogor. (in Indonesia).

Kantardzic, M. 2003. Data Mining, Concepts, Model, Method, and Algorithm. A John Wiley & Sons, Inc., Publication. Hoboken, NJ.

McBratney, A.B., Minasny, B., Cattle, S.R., Vervoort, R.W. (2002). From Pedotransfer Function to Soil Inference System. Geoderma 109, 41-73.

Marquardt, D.W. 1963. An Algorithm for Least-Squares Estimation of Non-Linear Parameters. J. Soc. Ind. Appl. Math. 11:431-441.

Minasny, B and A.B., McBratney, 2002. Neural Networks Package for fitting Pedotransfer Functions Technical Note Version 1.0. The University of Sydney.

Mualem, Y. 1976. A New Model Predicting the Hydraulic Conductivity of Unsaturated Porous Media. Water Resour. Res. 12:513-522.

Pachepsky, Ya.A., D. Timlin, and G. Varallyay. 1996. Artificial Neural Networks to Estimate Soil Water Retention from Easily Measurable Data. Soil Sci. Soc. Am. J. 60:727-733.

Saleh, E. 2000. The Performance of Pitcher Irrigation System for Crop in Dry Land. Dissertation. Bogor Agricultural University. Bogor. (in Indonesia).

Schaap, M.G. and W. Bouten. 1996. Modeling Water Retention Curves of Sandy Soils Using Neural Networks. Water Resour. Res. 32:3033-3040.

Setiawan, B.I. and S. Shiozawa. 1992. Marquardt Algorithm in Pascal. The University of Tokyo. Tokyo.

Setiawan, B.I., and M.Nakano. 1993. On the Determination of Unsaturated Hydraulic Conductivity from Soil Moisture Profiles and from Water Retention Curves. Soil Sci. Soc. Am. J. 156(6):389-395.

Setiawan, B.I. 1998. Pitcher Irrigation System for Vegetables in Dry Land. Bogor Agricultural University. Bogor. (in Indonesia).

Shiozawa, S. and G. S. Campbell. 1991. On The Calculation of Mean Particle Diameter and Standard Deviation From Sand, Silt, And Clay Fractions. Soil Science Vol. 152 : 427-431.

Stoecker, W.F. 1989. Design of Thermal Systems. McGraw-Hill. Kogakusha, Ltd. Tokyo.

Tamari, S., J.H.M. Wösten, and J.C. Ruiz-Suárez. 1996. Testing an Artificial Neural Network for Predicting Soil Hydraulic Conductivity. Soil Sci. Soc. Am. J. 60:1732-1741.

van Genuchten, M.Th. 1980. A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils. Soil Sci. Am. J. 44:892-898.