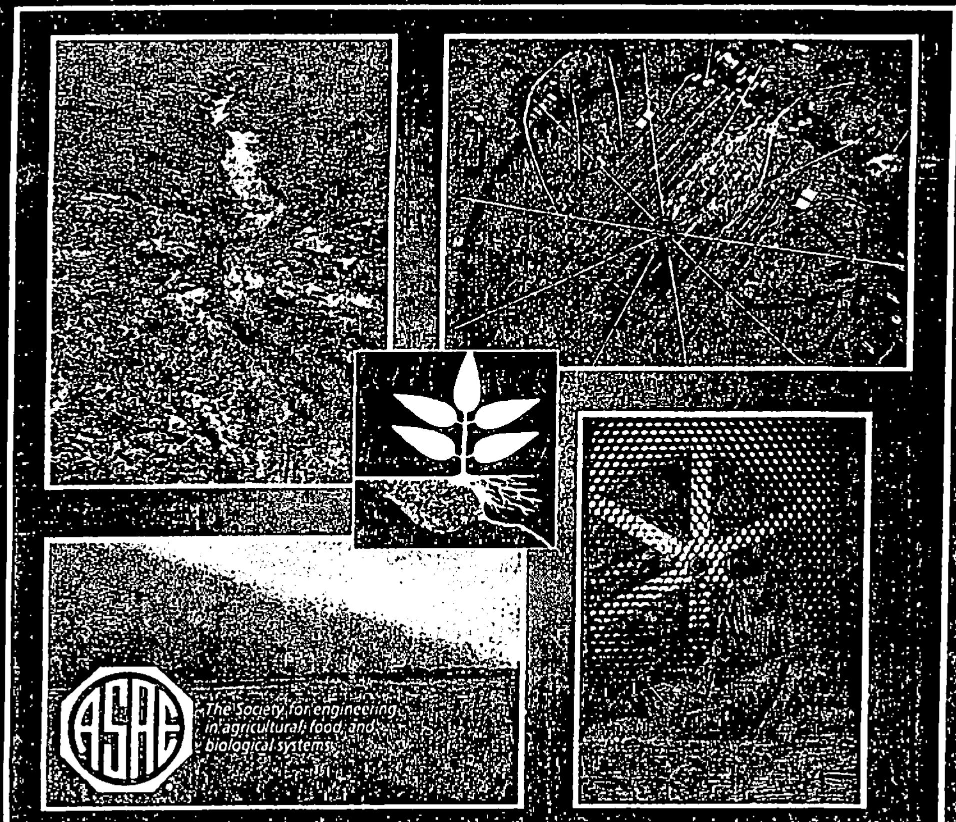
Soil Erosion Research for the 21st Century



Proceedings of the International Symposium

January 3-5, 2001
Honolulu, Hawaii

SOIL EROSION RESEARCH FOR THE 21ST CENTURY

Proceedings of the International Symposium

3-5 January, 2001
Honolulu, Hawaii, USA

Edited By
James C. Ascough II
Dennis C. Flanagan

Symposium Sponsored and Published By
American Society of Agricultural Engineers
2950 Niles Rd., St. Joseph, Michigan, 49085-9659 USA

An Empirical Model of Hydraulic Roughness for Overland Flow

C. J. Lopez-Sabater, K. G. Renard and V. L. Lopes[1]

Abstract

Physically based runoff and erosion simulation models usually rely on the representation of watersheds using cascades of planes and channels, and on the solution of 1-D flow equations. Often, the effect of microtopography and spatial variability of surface properties on overland flow is considered indirectly by derivation of an effective roughness parameter using optimization procedures. Research reported here developed a mathematical model of hydraulic roughness to be used as an integral part in an overland flow model. The hydraulic roughness is described using a neural network model, as a function of the soil surface configuration and flow characteristics. The neural network provides estimates of the hydraulic roughness (Darcy-Weisbach's, Chezy's and Manning's roughness coefficients). In addition, the neural network model assisted in selecting a method to characterize the soil surface configuration.
Keywords. Overland flow, hydraulic roughness, mathematical models, neural networks.

Introduction

Microtopography, soil cover, roughness and infiltration capacity are some of the surface characteristics that influence overland flow and erosion. Hydraulic roughness, or friction, represents the resistance to flow caused by roughness elements, including soil particles and aggregates, rocks, vegetation and microrelief. The term also incorporates the retardance effects of impacting raindrops. The effect of microtopography and spatial variability on hillslope surface properties has been usually considered by the derivation of effective roughness coefficients using optimization procedures with simulation models. However, as a result of this practice the roughness parameter becomes model-dependent and may perhaps help to hide errors in model structure.

The conventional resistance equations relating friction coefficients to Reynolds number cannot be used in general to estimate roughness coefficients under field conditions. Abrahams, Parsons and Luk (1986) showed that an increase in discharge on a surface with a complex microtopography would result first in a rise of the friction coefficient, and then, as the discharge and the Reynolds number continue increasing, in a decline of the roughness parameter. However, Baird, Thornes and Watts (1993) maintain that as long as the hydraulic radius is properly estimated, rather than being replaced with the average depth, the problem of variable cross section can be accommodated as it is in conventional river models.

Neural networks have been used in many fields of science and engineering to approximate unknown nonlinear relationships to any desired degree of accuracy. Schaap, Leij and van Genuchten (1998) used neural network models to predict saturated hydraulic conductivity and water retention parameters from commonly measured soil properties. Shayya and Sablani (1999) developed non-iterative neural network models to predict Darcy-Weisbach and Chezy roughness coefficients using Reynolds number and relative roughness as the independent variables. It was the objective of this study to develop neural networks to predict hydraulic roughness coefficients for overland flow models, based on surface and flow characteristics.

Materials and Methods

Experimental Setup

A metal flume 2 m long and 0.5 m wide, with a 1 m long removable central section, was used to carry out the experiment. Five surfaces with different degrees of roughness were placed on the central section. The surfaces were shaped using concrete to avoid changes in surface configuration. Surface configurations ranged from nearly flat to rough (visual perception) and had different degrees of surface storage. Each surface was placed in the flume and an initial experiment was carried out to find out the relationship between the average flow velocity

[1]Carlos J. Lopez-Sabater, Graduate Student, Dept. of Agricultural and Biosystems Eng., University of Arizona, Tucson, AZ; Kenneth G. Renard, Hydraulic Engineer, USDA-ARS Southwest Watershed Research Center, Tucson, AZ; Vicente L. Lopes, Associate Professor, Watershed Management, University of Arizona, Tucson, AZ. **Corresponding author**: Carlos J. Lopez-Sabater, Dept. of Agricultural and Biosystems Eng., Shantz Building Room 403, Tucson, AZ 85721; tel.: (520) 621-4363; e-mail: <lopezsab@u.arizona.edu>.

and the velocity of the edge of a cloud of dye. This was done for a range of slopes between 0.5 and 21.1% and discharges between 0.03 and 0.43 l $m^{-1}s^{-1}$.

Once the velocity relationship was known the surface was coated with sand having an average diameter of 0.629 mm (collected using sieves of 0.417 and 0.841 mm openings). The sand was glued to the concrete surface (no water repellency was observed due to the glue). After removing excess sand, the surface was scanned using a laser scanner (Huang and Bradford, 1990). A scan file consisted of 200 longitudinal profiles 2 mm apart, each one including 900 elevation measurements 1 mm apart. Following scanning, the surface was placed back on the flume for collection of flow data. After setting the flume slope and making sure the flow discharge was constant, a cloud of dye was dropped at the upstream end of the central section of the flume, and the travel time of the dye edge along a 90 cm segment monitored. A computer automatically recorded the average flow discharge, dye velocity and water temperature during the time it took the edge of the dye cloud to cover the 90 cm distance. Dye velocities were subsequently converted to average velocities using the relationships previously derived. This procedure was repeated for a combination of slopes and discharges. After the flume run, the surface was allowed to dry and then coated again with coarser sand. Three more sand fractions with the following average sieve diameters were tested: 1.004 mm, 1.584 mm and 3.334 mm. Twenty different combinations of surface configuration and sand coating were scanned and tested on the flume.

Data Set

The roughness coefficients were computed from the recorded data using standard procedures:

$$f = \frac{8gRS}{V^2} \tag{1}$$

$$n = \frac{1}{V} R^{2/3} S^{1/2} \tag{2}$$

$$C = \frac{V}{\sqrt{RS}} \tag{3}$$

where f is the dimensionless Darcy-Weisbach roughness coefficient, n [T $L^{-1/3}$] is Manning's roughness coefficient, C [$L^{1/2}$ T^{-1}] is Chezy's coefficient, R [L] is the hydraulic radius, S [L L^{-1}] is the flume slope, and V [L T^{-1}] is the average flow velocity. The hydraulic radius was computed dividing the flow discharge by the average velocity, thus equaling the average depth. The roughness coefficients so computed implicitly account for the deviation of the actual hydraulic radius from the average depth.

Different functions are available to represent the scale-dependent roughness configuration of a surface (Huang, 1988). Variogram (γ_k [L^2]), mean absolute elevation difference (ΔZ_k [L]) (MAED), and power spectral density ($C(\omega)$ [L^2 L rad^{-1}]) (PSD) were computed from the scanned longitudinal profiles. For each combination of surface and sand coating, the computed functions from the 200 profiles were pooled in a single ensemble function. A Markov-Gaussian model was fitted, using least squares, to the ensemble variogram, by changing the values of the parameters σ^2 [L^2] (variance of the height measurements) and L [L] (correlation length),

$$\gamma_k = \sigma^2\left(1 - e^{-k/L}\right) \tag{4}$$

where k represents the lag distance. The linear relationship between $1/\Delta Z_k$ and $1/k$ proposed by Linden and van Doren (1986) was fitted to the ensemble MAED by changing the parameters LD [L] (limiting elevation difference) and LS [L L^{-1}] (limiting slope),

$$\frac{1}{\Delta Z_k} = \frac{1}{LD} + \frac{1}{LS}\frac{1}{k} \tag{5}$$

A power function was fitted to the ensemble PSD by changing the parameters B [L^2 (L $rad^{-1})^{(1-p)}$] and p,

$$C(\omega) = B\,\omega^p \tag{6}$$

where ω [rad L^{-1}] is the angular frequency. Both $c(\omega)$ and ω were log-transformed before fitting B and p.

The data set consisted of 1827 vectors. Each one contained the following information: surface sand diameter in mm, σ^2 in mm^2, L in mm, LD in mm, LS (dimensionless), B in $mm^2(mm\ rad^{-1})^{(1-p)}$, p (dimensionless), flow discharge in ml m^{-1} s^{-1}, flume slope (%), water temperature (°C), f (dimensionless), n in s $m^{-1/3}$, and C in $m^{1/2}s^{-1}$.

Neural Network Models

Feed-forward back-propagation neural networks with one hidden layer were used in this study. This type of neural network is a nonlinear data transformation structure consisting of input and output nodes connected to a number of hidden nodes by adaptable coefficients. The number of input and output nodes corresponds to the number of input and output variables. The number of hidden nodes depends on the complexity of the underlying problem, and is determined empirically. Each input vector consisted of six variables (six input nodes); six hidden nodes were used in the hidden layer; and a single node in the output layer yielded the estimated roughness coefficient. The hidden and the output layers had a sigmoid and a linear transfer function respectively.

The coefficients were obtained in an iterative calibration procedure, called training, based on the Levenber-Marquardt algorithm and the minimization of the mean square error objective function, using the neural network toolbox of MATLAB (version 5.3, MathWorks Inc). The data set was divided into two subsets. The larger one, with 80% of the vectors, was used to train the networks and the smaller one was used to test their performance. Training of the networks stopped when the mean square error of the validation set reached a minimum.

Nine neural networks were constructed, three to predict each one of the three roughness coefficients. All the networks shared four input variables: sand grain diameter, flow discharge, flume slope and water temperature. One of the three networks used to predict each roughness coefficient used the two variogram parameters σ^2 and L as the remaining two input variables, the second network used LD and LS, and the third network used B and p. All the input data and target values (measured roughness coefficients) were normalized so that they had zero mean and unity standard deviation. The neural network predictions were evaluated in terms of the correlation coefficient (r) between predicted roughness coefficients and those derived from the flume measurements.

Results and Discussion

The maximum and minimum values of the parameters used to describe the surface configuration are listed in Table 1. All the surfaces showed different sets of parameters, but only the parameters from the power equation describing the PSD responded to the differences in sand diameter. Both B and p generally increased with coarser sand coatings.

Table 1. Value ranges for the coefficients describing the surface roughness configuration.

	σ^2 [mm^2]	L [mm]	LD [mm]	LS	B [mm^2(mm rad^{-1})$^{(1-p)}$]	p
Minimum	2.43	36.47	1.93	0.050	0.058	-1.31
Maximum	78.45	163.53	10.28	0.725	0.440	-2.40

Computed f coefficients ranged from 0.357 to 90.8 an in general had a linear trend with the logarithm of the Reynolds number. n coefficients ranged from 0.027 to about 0.48 s m$^{-1/3}$, and also showed a linear trend with the logarithm of the Reynolds number. C coefficients varied between 0.31 and 4.69 m$^{1/2}$ s^{-1} and displayed a linear relationship with Reynolds number. Tap water temperature ranged from 15.4 to 25°C.

Table 2. Summary of results from the evaluation of the nine neural network models.

Surface Function	Variogram			MAED.			PSD		
Output Variable	f	n	C	f	n	C	f	n	C
Correlation Coefficient	0.895	0.939	0.948	0.777	0.925	0.949	0.84	0.896	0.938
Best Linear Fit Slope	0.811	0.884	0.893	0.562	0.848	0.894	0.694	0.796	0.877
Best Linear Fit Intercept	1.17	0.0102	0.17	2.28	0.014	0.173	1.52	0.0172	0.204

A summary of the evaluation of the nine network models is presented in Table 2. The relationship between target and network-predicted roughness coefficients was linear and close to a 1:1 line in all cases except when the parameters LD and LS were used to predict f. In this case, the network clearly did not perform as expected. Predictions of f and n based on the variogram parameters σ^2 and L outperformed the predictions based on the other two surface functions. Predictions of C based on the variogram and on the MAED parameters were equally good and outperformed those based on the PSD parameters.

The neural networks that predict C coefficients consistently performed better than the networks predicting f and n. For all three surface description functions, these networks produced the highest correlation coefficient between the target (measured) and the network-predicted values, and the slope of the best linear fit was closer to one. Networks predicting n performed in all cases better than those predicting f. A possible reason for this difference in performance is that C coefficients are more homogeneously distributed within their range of variation, while n coefficients, and especially f coefficients, are clustered near the lower end. This heterogeneous distribution was caused by the relationship that both f and n displayed with the Reynolds number and the flow discharge. Figure 1 demonstrates this point.

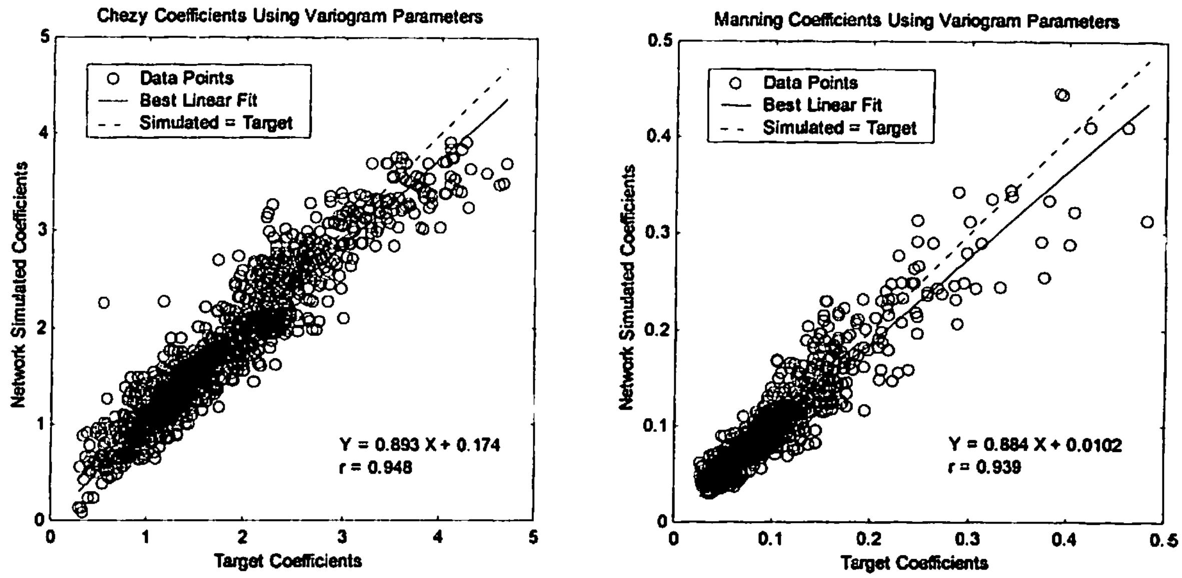


Figure 1. Evaluation of the performance of neural networks to estimate roughness coefficients using the variogram parameters σ^2 and L as input variables: a. Chezy's coefficients, b. Manning's coefficients.

Conclusions

1. Neural networks have been successfully used to predict Darcy-Weisbach, Manning and Chezy hydraulic roughness coefficients using surface characteristics, flow discharge and water temperature as input variables.
2. Neural networks based on the variogram parameters σ^2 and L produced better estimates of the roughness coefficients than those based on the mean absolute elevation difference or power spectral density functions.
3. Chezy's roughness coefficients were more closely predicted by the neural network models than Manning's or Darcy-Weisbach coefficients.

Acknowledgments

This research was possible thanks to a scholarship by the Inter-ministerial Commission for Science and Technology (CICYT) of Spain.

References

Abrahams, A. D., Parsons, A. J. & Luk, S. H. (1986). Resistance to overland flow on desert hillslopes. *J. Hydrol.*, 88: 343-363.

Baird, A. J., Thornes, J. B. & Watts G. P. (1993). Extending overland-flow models to problems of slope evolution and the representation of complex slope-surface topographies. In: A. J. Parsons & A. D. Abrahams (Eds.), Overland flow: Hydraulics and erosion mechanics. Chapman & Hall, New York, pp. 199-223.

Huang, C. (1998). Quantification of soil microtopography and surface roughness. In: P. Baveye, J. Y. Parlange & B. A. Stewar (Eds.), Fractals in soil science. CRC Press, Boca Raton, Fla., pp. 153-168.

Huang, C. & Bradford, J. M. (1990). Portable laser scanner for measuring soil surface roughness. *Soil Sci. Soc. Am. J.*, 54: 1402-1406.

Linden, D. R. & van Doren, D. M. (1986). Parameters for characterizing tillage-induced soil surface roughness. *Soil Sci. Soc. Am. J.*, 50: 1560-1565.

Schaap, M. G., Leij, F. J. & van Genuchten, M. Th. (1998). Neural network analysis for hierarchical prediction of soil hydraulic properties. *Soil Sci. Soc. Am. J.*, 62 (4):847-855.

Shayya, W. H. & Sablani, S. S. (1999). Use of artificial neural networks in the noniterative calculation of the friction coefficients in closed pipe and open channel flow. Presented at the 1999 ASAE/CSAE-SCGR Annual International Meeting, Paper No. 99-3011. ASAE, 2950 Niles Road, St. Joseph, MI 49085-9659 USA.