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PREDICTION OF THE OCCURRENCE OF DEBRIS FLOW AND A RUNOFF ANALYSIS BY THE USE OF NEURAL NETWORKS

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ABSTRACT

Debris flows are feared for their potential to cause severe disasters, therefore studies on the occurrence and runoff of debris flows are needed. Several practical methods for forecasting a debris flow have been proposed to forecast the debris flow, however, the accuracy of these methods is not enough for practical use. Neural networks are introduced into the prediction of the occurrence of the debris flow and a runoff analysis. The method was verified by applying it to the Mizunashi River in the Unzen volcanic area. The results of this application led to the conclusion that the neural network model can be used to predict of a debris flow. The neural network model also is useful for identifying the critical condition for such a flow. The neural network model, which calculates the hydrograph of debris flow from the time series of rainfall, was verified by the observed data.

1. INTRODUCTION

Debris flows cause severe damage in downstream by depositing large amounts of sand and stone. Consequently, the characteristics of debris flow must be clarified and a predicting method established to prevent against disasters. Several practical methods have been proposed for forecasting debris flows due to heavy rainfall. But their accuracy is not sufficient for practical use, mainly because they lack a theoretical basis and are inadequate in terms of procedures. In a previous study [1], a system analysis technique was recommended to improve these defects. The conditions under which a debris flow occurs were analyzed to obtain the critical rainfall needed to cause such a flow, and a mathematical runoff model which predicts the hydrograph of a debris flow was proposed. In this study, neural networks are introduced into the prediction of debris flows occurrence and runoff analysis. Neural networks are computing methods which operate in manner analogous to that of biological nervous systems. Such models also can be used for classification and functional approximation. The prediction and analysis models proposed here have been applied to the data for the Mizunashi River in the Unzen Volcano area, in Kyushu, western Japan. The volcano began erupting in 1990 after 198 years of dormancy. Since then, debris flows have been frequent in the Mizunashi River and have caused severe disasters.

2. CRITICAL RAINFALL FOR OCCURRENCE OF DEBRIS FLOW

2.1. Occurrence Criteria for a Debris Flow

On a slope of deposits shown in Fig. 1, the shear stress, τ, at a point in the deposit is given by

$$\tau=\{C_*(\sigma-\rho)a+\rho(h_o+a)\}g\ \sin\theta \tag{1}$$

KEYWORDS: Debris flow, Neural networks, Critical rainfall, Runoff analysis, Unzen Volcano

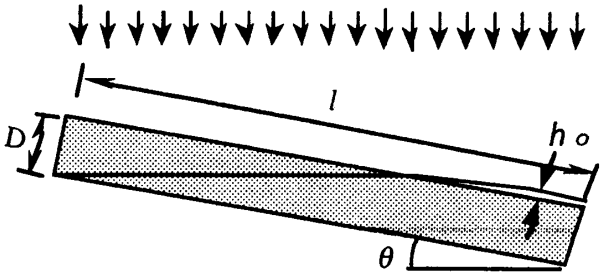


Fig. 1. Schematic sketch of a slope.

where, C_* is the concentration of deposited material, σ and ρ respectively, are the density of the deposits and water, a is the distance from the surface, h_o the depth of the surface flow, g the gravitational acceleration and θ the angle of the slope.

The resisting stress, τ_L, at the point is expressed as

$$\tau_L = c + C_*(\sigma - \rho) a g \cos\theta \tan\phi \tag{2}$$

where c is the adhesive force, and ϕ the angle of internal friction.

As the critical condition is $\tau = \tau_L$, the critical angle of a slope, θ_c, for the occurrence of a debris flow. is obtained from Eqs. (1) and (2) as

$$\tan\theta_c = \frac{c/(\rho g a \cos\theta_c) + C_*(\sigma/\rho - 1)\tan\phi}{C_*(\sigma/\rho - 1) + 1 + h_o/a} \tag{3}$$

Substituting the common values of $C_* = 0.6$, $\tan\phi = 1.0$, $\sigma/\rho = 2.65$, and $c = 0$ for the sandy materials in Eq. (3) and considering that a and h_o should be larger than grain size d to cause a debris flow (Takahashi [1]), $\theta_c = 14.8°$ is obtained. This value is supported by field as well as flume data.

Accordingly, a debris flow will occur on a slope steeper than θ_c when the depth of the surface flow exceeds the grain size. On the basis of the theory, two approaches are used to obtain the critical rainfall.

2.2. Critical Rainfall Intensity

One approach gives the discharge of a surface flow, in which the depth is equal to the grain diameter of the deposits as the critical discharge (Ashida et al. [2]). The critical discharge, Q_c, is derived by setting $h_o = d$ and $Q_c = Buh_o$ as

$$Q_c = \sqrt{\frac{8 \sin\theta}{f_o \kappa^3} B^2 g d^3} \tag{4}$$

where B is the width of the flow, u the velocity of surface flow, f_o the resistance coefficient, κ the ratio of h_o and d close to unity, and d the grain diameter of the deposits.

Applying the Rational Formula to Eq. (4), the critical rainfall intensity r_T is

$$r_T = \frac{1}{T}\int_0^T r\,dt \geq \frac{Bd}{fA}\sqrt{\frac{\sin\theta}{f_o \kappa^3} g d} \tag{5}$$

where T is the time of concentration, f the runoff coefficient, and A the catchment area.

The other approach is to assume that the occurrence of surface flow as the trigger of debris flow. Because the irregularity of the slope surface is larger than the grain size, the depth of the surface flow will exceed some part of the slope when a surface flow appears on the slope. Consequently, a debris flow will occur when a surface flow appears on a slope due to heavy rainfall.

On the slope shown in Fig. 1, the momentum and continuity equations of subsurface flow are expressed by

$$\frac{\partial(\lambda h)}{\partial t}+\frac{\partial(vh)}{\partial x}=r\cos\theta \quad \text{and} \quad v=k\sin\theta \tag{6}$$

where λ is the porosity, h the depth of the subsurface flow, t the time, v the velocity of the flow, x the coordinate taken in the downstream direction, r the rainfall intensity, and k the hydraulic conductivity.

Solving Eq. (6) using the kinematic wave theory, gives the occurrence conditions of surface flow as

$$l\geq kT\sin\theta/\lambda \quad \text{and} \quad \lambda D\leq\int_0^T r\cos\theta\, dt \tag{7}$$

where l is the length of the slope, T the time of concentration, and D the depth of the deposits.

Assuming that a debris flow occurs when a surface flow appears on a slope, the occurrence condition for a debris flow is derived from Eq. (7) as

$$r_T=\frac{1}{T}\int_0^T r\, dt\geq\frac{Dk}{l}\tan\theta \tag{8}$$

The applicability of this equation was verified by experiment (Hirano et al. [4]).

Substituting $h_o=0$ and the above values mentioned above to Eq. (3) gives $\theta_c=21.7°$. Therefore, debris flow is possible before the appearance of a surface flow on a slope steeper than this angle. The critical conditions for this case are given by

$$r_T=\frac{1}{T}\int_0^T r\, dt\geq\frac{H_c k}{l}\tan\theta \tag{9}$$

$$\frac{H_c}{D}=\frac{c/(\rho g D\cos\theta_c)+C_*(\tan\theta-\tan\phi)\sigma/\rho}{\tan\theta+C_*(\tan\theta-\tan\phi)} \tag{10}$$

where H_c is the depth of the seepage flow under which a slope failure occurs.

Although Eqs. (5), (8), and (9) are derived differently, the right sides of these equations are the same. These equations indicate that a debris flow will occur when the rainfall intensity within the time of concentration exceeds a particular value determined by the properties of the slope.

2.3. Estimation of Critical Rainfall

With Eqs. (2) and (6), it may be possible to estimate the critical rainfall and calculate the flow rate of a debris flow by measuring the hydraulic conductivity, and the depth, length and gradient of the slope. But the values are not obtained accurate enough for practical use due to the errors in the measurements, even though the theory might be perfect.

Hirano et al. [5] proposed the system analysis technique to identify the parameters for the prediction of a debris flow. To estimate the time of concentration, T, and the critical rainfall, R_c,

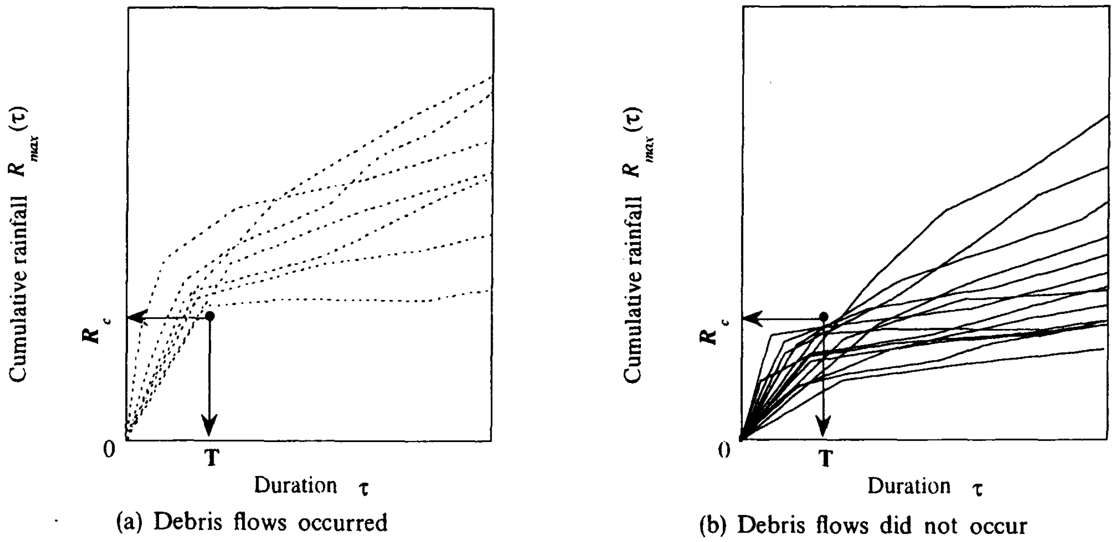


Fig. 2. Schematic illustrations of the curves of maximum cumulative rainfall $R_{max}(t)$.

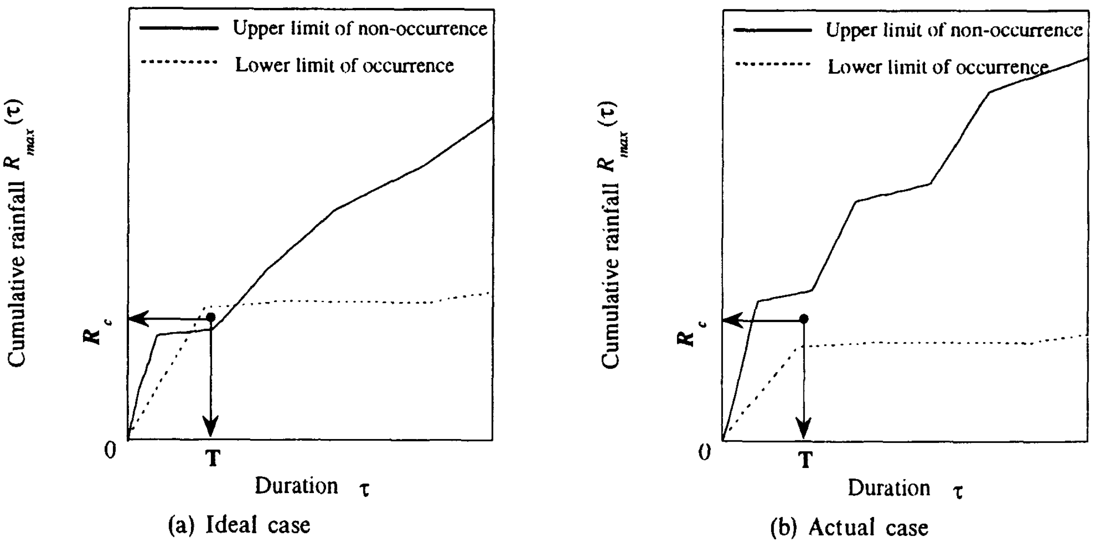


Fig. 3. Upper limit of non-occurrence and lower limit of occurrence.

R_c, the cumulative rainfall, $R(t,\tau)$, defined as

$$R(t,\tau)=\int_{t-\tau}^{t} r\,dt \tag{11}$$

$$R_{max}(\tau)=max[R(t,\tau)] \tag{12}$$

The maximum values of $R(t,\tau)$ for each time, $R_{max}(\tau)$, are plotted against τ. If there are no errors in the data or in the theory, the plotted lines should exceed the point $R_{max}(T)=R_c$ when debris flow occurs, and not exceed that point when debris flow does not occur, as shown schematically in Fig. 2.

Consequently, the upper limit line for non-occurrence and the lower limit line for occurrence should cross near point, (T,R_c), as shown in Fig. 3 (a), but because of errors in the data and unsteady field conditions, the upper limit of non-occurrence and lower limit of occurrence will not cross but be separated like the two lines shown in Fig. 3 (b). The point at which the difference between the two curves is the local minimum is estimated to be the time of concentration.

The application to various field data shows that this method does not always give a good estimation due to errors in the data or to unsteady field conditions. A neural network should predict the occurrence/non-occurrence of debris flow without giving unclear occurrence criteria.

3. APPLICATION OF NEURAL NETWORKS

3.1. Multi Layer Neural Network with Back Propagation Learning

Artificial neural networks or simply "neural networks" are mathematical models that operate analogously to biological nervous systems. Typically they consist of a set of layered processing units and weighted interconnections. Neural networks learn the examples presented to the networks and adjust themselves by some learning rule. There are various neural network models and learning procedures [6]. Multi-layer neural networks, the most widely used, are feed-forward networks with one or more layers of units between the input and output units. Fig. 4 shows a three-layer network. The simplest unit forms a weighted sum of N inputs, subtracts the internal threshold, θ, from it and passes the result through a non-linear function (Fig. 5).

The sigmoid function given below is commonly used as the activation function of the unit.

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

The above equation varies continuously and monotonically from 0 to 1 as shown in Fig. 6. Typically, real values for training data are normalized from 0 to 1 and are given to neural networks.

Multi-layer networks are trained by means of the back propagation method [7]. Learning involves modification of the connections. The learning algorithm is an iterative gradient algorithm designed to minimize the mean square error between the actual output of the network and the

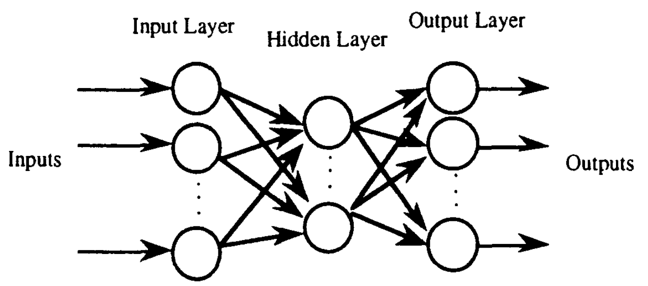


Fig. 4. Typical three-layer network.

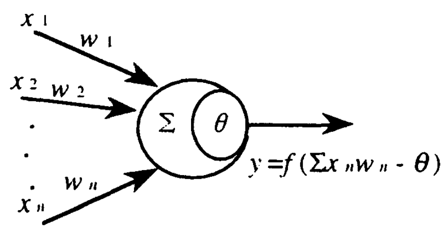


Fig. 5. Processing unit.

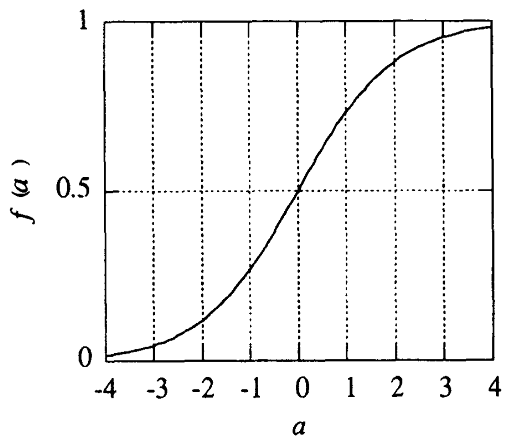


Fig. 6. Sigmoid function.

desired output given by

$$E_p=\frac{1}{2}\sum_k(d_{pk}-z_{pk})^2 \qquad (10)$$

where d_{pk} is the desired response of the k-th unit of the output pattern produced by presentation of pattern and z_{pk} the k-th unit of the actual output pattern produced by presentation of pattern p. The criterion function to be minimized is the sum of $E=\Sigma E_p$. In the case of a three-layer network, weight, w_{jk}, which connects the j-th hidden unit to the k-th output unit, is modified by Eq. (11).

$$w_{jk}^{new}=w_{jk}^{old}+\frac{1}{P}\sum_p\Delta w_{jk} \qquad (11)$$

where $\Delta w_{jk}=\varepsilon\delta_k y_j$, $\delta_k=z_k(1-z_k)(d_k-z_k)$, and ε is the learning rate.

Thereafter, weight w_{jk} which connects the i-th input unit to the j-th hidden unit is modified by Eq. (12).

$$w_{ij}^{new}=w_{ij}^{old}+\frac{1}{P}\sum_p\Delta w_{ij} \qquad (12)$$

where $\Delta w_{ij}=\varepsilon\delta_j x_i$ and $\delta_j=(1-y_j)\sum_k\delta_k v_{jk}$.

The weights typically are initialized to small random values. The final weights of successfully trained neural networks represent its knowledge about a set of input/output pairs.

Here the input/output sets are normalized to an input range between -1.0 and 1.0 and an output range between 0.2 and 0.8. The initial weights are random values between -0.2 and 0.2. The learning rate e is from 0.4 to 0.8. The number of units in the hidden layer empirically is determined as about half of the input units in the case of one output unit.

3.2. Prediction of the Occurrence of a Debris Flow by the Use of Neural Networks

Neural network model to predict the occurrence of a debris flow

A set of rainfall time series is characterized by the maximum cumulative rainfall ,$R_{max}(\tau)$, expressed by Eq. (2). The various cumulative rainfalls, $R_{max}(\tau_1)$, $R_{max}(\tau_2)$,$\cdots$,$R_{max}(\tau_n)$, are given as input data to the input units in the prediction model. The desired output is the degree of risk 1 when a debris flow occurs, and the degree of risk 0 when no debris flow occurs. The neural network model for learning of the occurrence and non-occurrence of a debris flow is shown in Fig. 7.

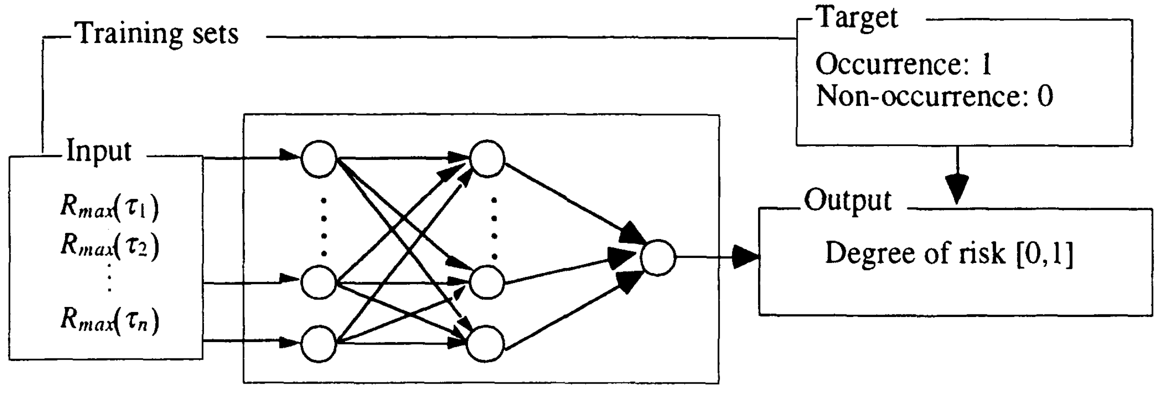


Fig. 7. Learning model for the occurrence and non-occurrence of debris flows.

Application to the Mizunashi River in the Unzen Volcano area

To check the applicability of the neural network model to the prediction of the occurrence of a debris flow, the model is applied to the Mizunashi River in the Unzen Volcano area. Cumulative rainfalls are calculated from the ten-minute rainfall data collected at the Unzen Meteorological Observatory.

The data for each year are given to the neural networks as input. After learning the data for a year, the degree of risk for the rainfall the next year is calculated by the model as the prediction. For example, the degree of risk for 1992 is calculated by the neural networks which learned the data for 1991. When the degree of risk exceeds 0.5, occurrence is predicted. Table 1 shows the results of prediction, where correct prediction corresponds a debris flow for which the output of the model exceeds 0.5. When a debris flow did not occur and the output is less than 0.5, the prediction also is correct, but these events are not included in Table 1. When debris flow did not occur but the output exceeds 0.5, the result is defined as a wrong prediction. A missed prediction is counted for the event of debris flow when the output is less than 0.5. The ratio of correct prediction to the total of correct, wrong, and missed predictions also is shown in Table 1. Except for 1994, fairly good results were obtained. In Fig. 8, 60 minute rainfalls from 1991 to 1995 are plotted and divided between occurrence and non-occurrence. From the figure, a sudden change in occurrence criteria is seen in June, 1993. This change in results in a worse prediction for 1994. In 1995, good results again are obtained.

Estimation of the time of concentration and critical rainfall

The time of concentration is estimated by plotting the upper limit of non-occurrence and the lower limit of occurrence, as shown in Fig. 3. The curves before and after June 1993 are plotted in Fig. 8 for the Mizunashi River. From the figure, the time of concentration is estimated to be about an hour, and the critical rainfall to be about 8 mm using the closest point of the two curves for the data from May, 1991 to June, 1993. The time of concentration is 40 minutes and the critical rainfall about 10.5 mm for the data from June, 1993 to July 1995. As uncertainty remains in this estimation, neural networks give a better estimation by examining fluctuation of outputs [8].

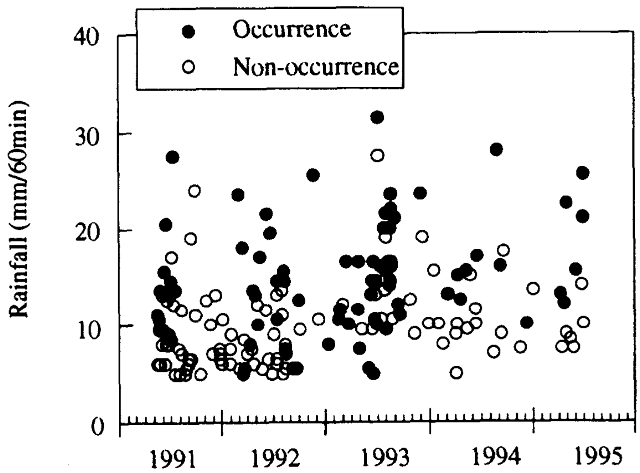
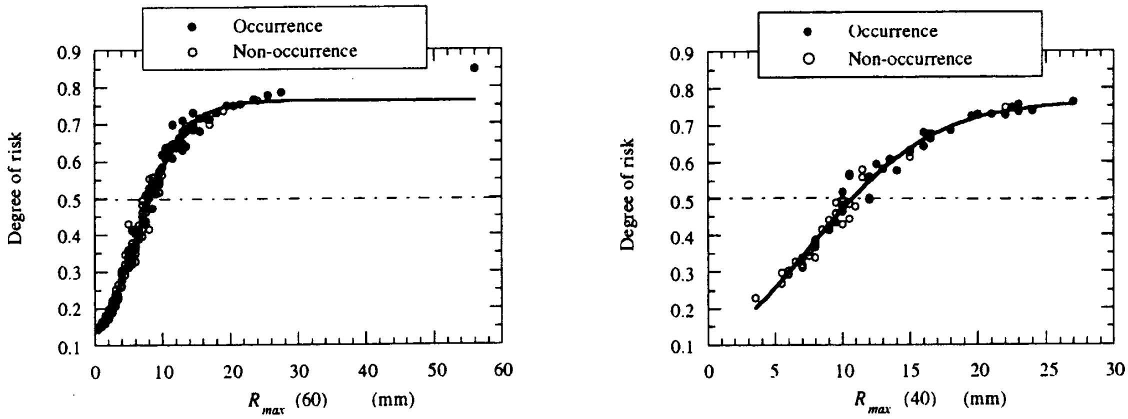


Fig. 8. Hourly rainfall and the occurrence of debris flows.

Table 1. Prediction results for the next year.

Year	Occurrence	Prediction			
		Correct	Wrong	Missed	Rate
1991	15	-	-	-	-
1992	21	15	12	6	45.5
1993	34	32	14	2	66.7
1994	8	3	4	5	25.0
1995	6	6	3	0	66.7



(a) May, 1991 - June, 1993 (b) June, 1993 - July, 1995

Fig. 9. Estimation of the critical rainfall.

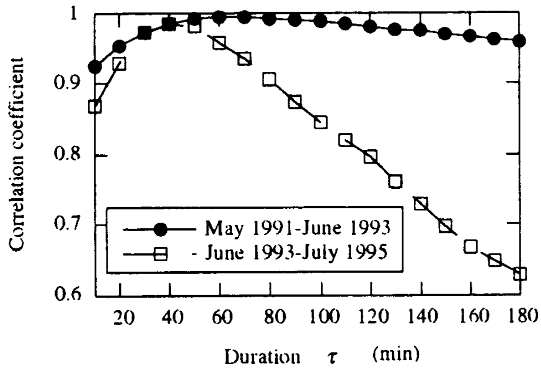
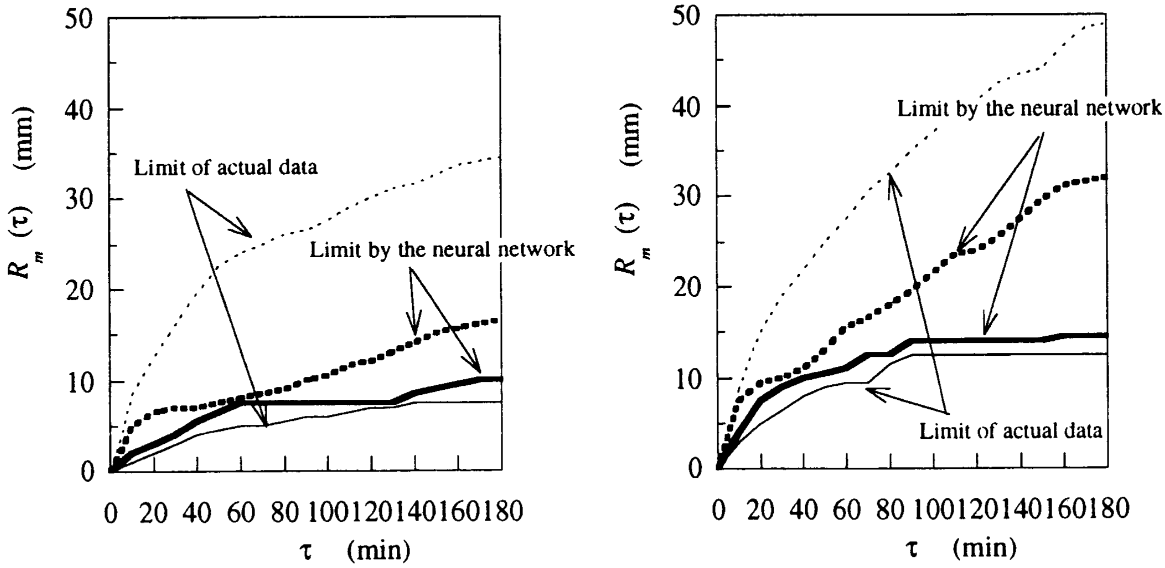


Fig. 10. Estimation of the time of concentration.



(a) 1991 - June, 1993 (b) June, 1993 1995

Fig. 11. Occurrence criteria of the actual data and the output from the neural network.

If the relation between the output values and rainfall of a certain duration shows the least fluctuation, the duration is considered to correspond to the time of concentration. When the number of the learning data is large and the occurrence criteria is unclear, output values of the neural networks against every input factors can be approximated by the transfer function of the output unit. In Fig. 9, the output values of the learned models are plotted against the rainfall. The curves on the figure are the sigmoid function determined to obtain the best fit. The correlation between the outputs and the best fitting curves, calculated for various durations of rainfall, is plotted in Fig. 10. The duration that corresponds to the highest correlation is considered the time of concentration. As is clear from this, the time of concentration is estimated to be 60–70 minutes before June 1993 and 40 minutes after that time.

This estimation method for occurrence criteria can be demonstrated by the upper limit curve of non-occurrence and the lower limit curve of occurrence. The upper and lower limits assumed by the neural networks are plotted in Fig. 11. The assumed upper limit of non-occurrence is given from the rainfall curves of non-occurrence for which the neural network output is a degree of risk less than 0.5, and the assumed lower limit of occurrence is given from the rainfall curves of occurrence for which the output exceeds 0.5. Although the limit curves for the actual data are widely separated and the local minimum points of both lines are unclear, the limit curves obtained by the neural networks show the ideal patterns (Fig. 3).

3.3. Runoff Analysis of Debris Flow by Use of Neural Networks

Neural network model for runoff analysis of debris flow

A neural network model is developed to predict the hydrograph of debris flow from rainfall. As input data, ten-minute rainfall is given to the input units in the prediction model, as shown in Fig. 12. The desired output is the discharge of the debris flow. In this figure, τ_l is the lag time of debris flow runoff equal to 20 minutes in the model.

Application to the Mizunashi River in the Unzen Volcano area

The data for the velocity and surface height of the debris flow respectively were collected with a radar velocimeter and a super sonic gage, at the Mizunashi River on 12–13 June, 1993. From the data, the hydrograph of the debris flow shown in Fig. 13 was obtained. At clear relation between the discharge of the debris flow and the ten-minute rainfall is seen in the figure, and the lag time between hyetograph and hydrograph seems to be 20 minutes.

A neural network is used to construct a runoff model of debris flow. For learning, the discharge of the debris flow, $Q(t)$, and the ten-minute rainfall 20 to 70 minute ahead, $r(t-20)$, $r(t-30),\cdots,r(t-70)$, are the input data. In Fig. 13, the computed values for discharge are compared with the measured ones. The recognized values show close agreement with the observed ones.

No hydrograph of other events reliable enough to use for verification of the model has been obtained at the Mizunashi River. The amounts of the deposits, however, were measured by Nagasaki Prefecture and the Ministry of Construction Japan. The applicability of our model could

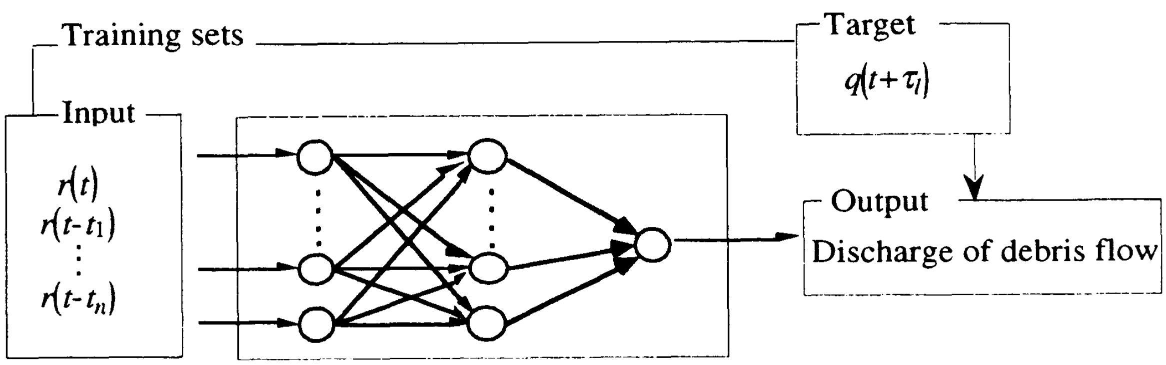


Fig. 12. Learning model of the discharge of debris flows.

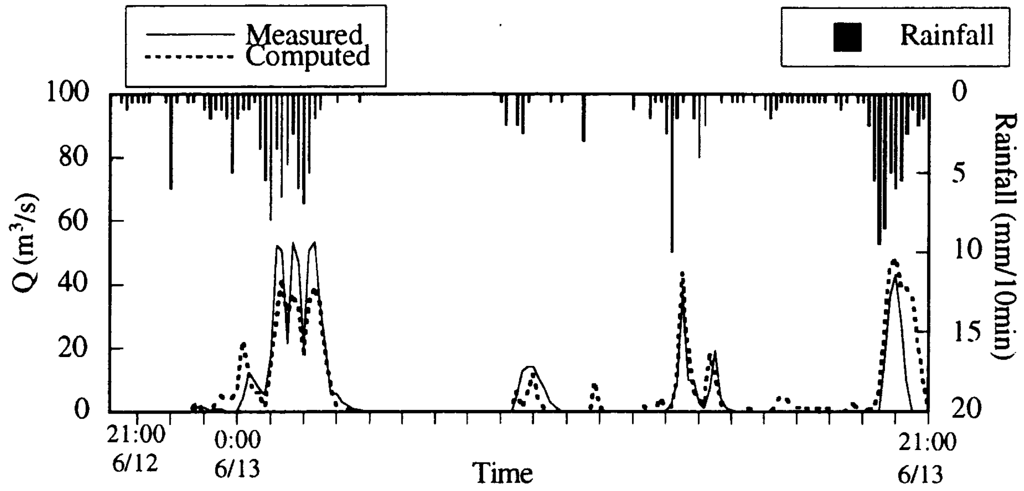


Fig. 13. Comparison of the computed and observed hydrographs of debris flow.

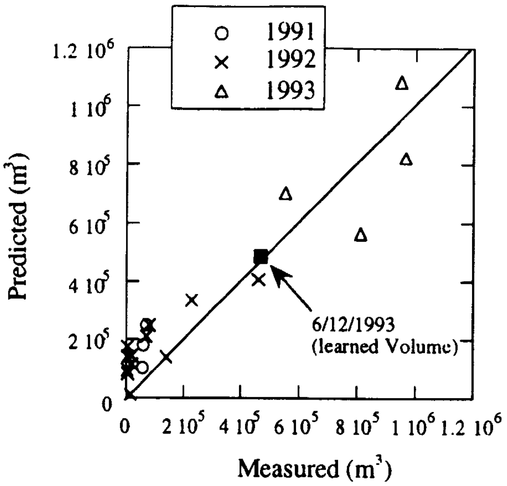


Fig. 14. Measured and predicted volumes of debris flow deposits.

be checked by comparing the calculated total amounts of debris flow with the measured amounts of the deposits. Figure 14 shows the volume of the debris flow integrated from the predicted hydrographs and the measured volume of deposits. The predicted volumes are in fairly good agreement with observed ones.

4. CONCLUSIONS

Neural networks were introduced into the prediction of the occurrence and runoff analysis of a debris flow and verified by applying them to the Mizunashi River in the Unzen Volcano area. Results of the application show that

(1) Neural networks can be used to forecast the occurrence of debris flow.

(2) A more objective estimation of the time of concentration is possible by the use of neural networks.

(3) The hydrograph of debris flow can be calculated by the time series of rainfall, therefore, neural networks are useful for making runoff analyses of debris flows.

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