FIELD EXPERIMENT AND OBSERVATIONS OF RUNOFF GENERATION PROCESSES IN A FORESTED MOUNTAINOUS CATCHMENT, TONO AREA, JAPAN

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The present paper shows the relevance of a new approach of using back propagation neural network (BPNN) in storm runoff estimation by using near surface soil moisture. Intensive field observation and field experiment conducted to observe the behavior of a forested catchment in Tono area is presented. The results obtained by numerical experiment using BPNN were tested by the field experiment and catchment observations. Both the experiment and field observations supported the results of the previous studies. The field experiment showed that the importance of litter layer in the direct contribution to runoff was not so significant. It was observed that the highly conductive soil layer underlying the litter layer and overlying the less macroporous soil zone with low hydraulic conductivity was the chief contributor to the total runoff in the study area. The field observation showed that the main contribution to the total storm runoff was from the channel system that received the runoff from such layers as in the field experiment.

Key Words: *Runoff analysis, Back propagation neural network, Soil moisture, Runoff generation processes*

1. INTRODUCTION

At the small catchment and hillslope scales, soil moisture is a function of topography, vegetation and soil characteristics (Western et al.[1]). The role of soil moisture in the runoff generation is important in a steep forested catchment even in humid region due to rapid movement of subsurface flow (both translatory and macropore). Watanabe[2] has mentioned the role of near surface flow in the forested catchment and modeled storm runoff using three-dimensional finite element technique. However, the extensive data requirement and huge computational time required make such fully distributed physically based models (Beven[3]; Grayson et al.[4]) less popular in practical uses. Artificial neural network (ANN) models have been recently reported in the literatures as being simple yet useful in many situations. Recently, Gautam et al. [5] has generalized these available ANN models for runoff studies into two categories. These include, (a) autoregressive type ANN models which utilize past observed discharges and (b) pseudo rainfall-runoff type ANN models which make use of past observed discharges as well as past observed rainfall for future runoff estimation. Both of these categories of models cannot be used for design and planning purposes as no catchment characteristics are included in the input data sets of such models (Liong et al. [6]). The present paper reviews the present authors' recent new approach of applying ANN by utilizing catchment-based data. Such recent past studies by authors, although important, lack the substantial field observations and experimental studies to support the selected model and hypothesis on which it is based (**Fig. 1**). The test of models in the past study was mainly done by the evaluation of the models in the testing phase. The present paper is mainly concerned with enhancement of the verification process with the help of direct field observations and experiment.

Among other important aspects of the runoff study in hydrology, the storm runoff generation process is highly controversial in the perspective of pathways followed by the storm runoff (Pearce et al.[7]). In the present study, we present the importance of soil moisture in the runoff generation processes without going much into the controversy of the runoff pathways. With these themes this paper is organized into the following sections. First, the inferences from the soil moisture data from our study of variation of soil moisture and results obtained from the numerical experiments (Gautam et al.[5]) will be briefly presented. In the subsequent sections we present our detailed field observation and small-scale field experiment carried out at a new sub-catchment in the Tono area.

2. RUNOFF MODELING WITH BPNN

Researchers such as Watanabe[2] have mentioned the importance of near surface soil moisture in the storm runoff generation. Recently Gautam et al.[5] have made storm runoff generation study in the Tono area located in Gifu prefecture of Japan. In one of the subcatchment of the Tono area, the authors analyzed the soil moisture data of various depths in different locations along a hillslope. For the runoff estimation purpose, they found the importance of 40-cm soil moisture depth at downmost slope location over other locations and depth in the normal storm condition (extreme events excluded). Numerical experiments were carried out with the formulation of BPNN models. The application of BPNN was made in the premise that its use is considered a favorable choice when the relationship between input and output is not so clear and particularly when the problems are of non-linear nature (Hsu et al.[8]). In the field of hydrology where the non-linearity is pervasive, neural network modeling can be of substantial worth. The general modeling approach adopted in the study in using BPNN is shown in **Fig. 1**. A brief introduction of BPNN is given below. However, the details of BPNN modeling approach in the hydrological runoff estimation perspectives can be found in Hsu et al.[8], Minn and Halls[9], Gautam[10], Dawson and Wilby[11] and Tingsanchali and Gautam[12),13]. A more detailed information about theory and applications of BPNN in the general perspective can be found in Ebberhart and Dobbins[14] and Hecht-Nielsen[15].

(1) Neural Network modeling approach

Three layer feed forward network based on back propagation algorithm has remained popular in the field of hydrology, runoff analysis in particular. The network consists of an input layer consisting of node(s) representing various input variable(s), the hidden layer consisting of many hidden nodes, and an output layer consisting of output variable(s). The number of hidden nodes is determined by trial and error process. Input data are often normalized with suitable methods. The output data is usually normalized in the range of 0.1 and 0.9 when logistic activation function is used. The input nodes pass on the input signal values to the nodes in the hidden layer unprocessed, which is distributed to all the nodes in the hidden layer depending on the

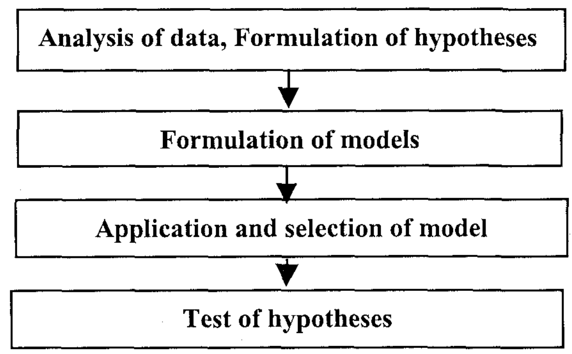

Fig. 1 Flow chart showing modeling approach using BPNN

connection weights between the input node and the hidden nodes. In the hidden nodes the inputs ($0 \ldots n_i$) from the input layer are summed (**Eq. 1**). The summed input (x_j) is then processed using an activation function. The logistic function, which is widely used in ANN applications, yields the output (X_j) at that node (**Eq.2**).

$$x_j = \sum_{i=0}^{n_i} I_i w_{ij} \qquad (1)$$

In the **Eq. 1**, I_0 represents input from bias node and has the value of 1.

$$X_j = \frac{1}{1+e^{-x_j}} \qquad (2)$$

In the analogous manner the processed signals from the hidden nodes are distributed to the output nodes ($1 \ldots n_o$) where all the incoming signals from the hidden nodes ($0 \ldots n_h$) are summed and processed. Finally, the actual and network outputs are compared, the squared of the error is computed and summed for all available patterns . The computed error is propagated backward from the output nodes to the hidden nodes and from the hidden nodes to the input nodes based on the gradient delta rule. The connection weights are then updated to minimize the total network error. In the weight updating, two parameters namely momentum and learning parameter are introduced. The function of the learning parameter and the momentum rate is to speed up the training process and avoid oscillation. However, there is no specific rule for selection of the values of these parameters and the determination is subjected to trial and error estimation. Adopting one set of value, the training process is started and depending upon the characteristic of the training process i.e. whether the error reduction of the network is slow or rapid or the network is oscillating, these parameters are adjusted by trial and error process. Once the training process is satisfactorily completed, the final weights are saved and used for the evaluation of the models in the testing phase.

with other inputs. Sensitivity analysis was carried out with 40-cm soil moisture content by formulating more ANN models with the addition of some other inputs namely discrete precipitation data and other

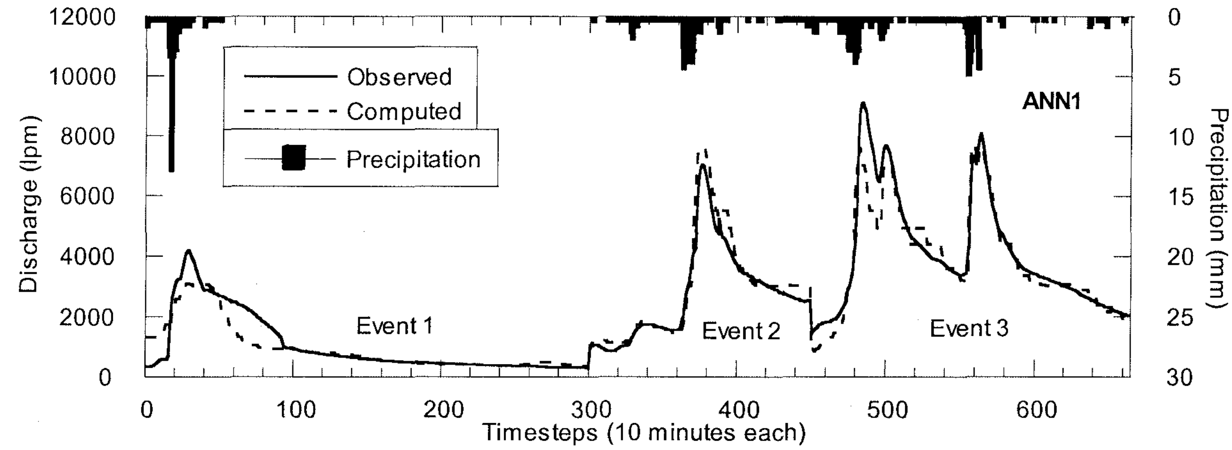

Fig. 2 Comparison between observed and computed discharge, training phase. The figure represents multiple-events joined end to end. (Event 1: 1-300; Event 2: 301-450; Event 2: 451: 665 timesteps).

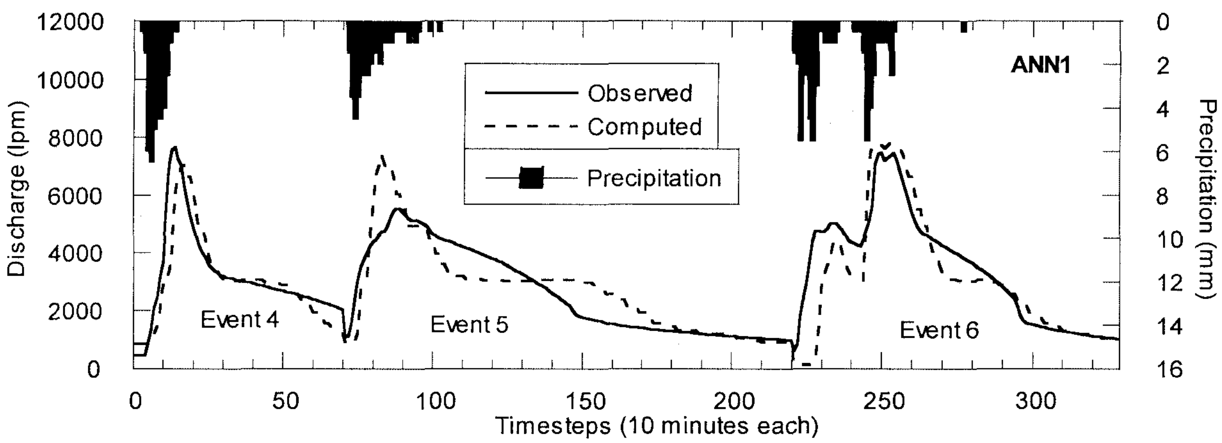

Fig. 3 Comparison between observed and computed discharge, testing phase. The figure represents multiple-events joined end to end. (Event 4: 1-70; Event 5: 71-219; Event 6: 220: 330 timesteps).

(2) Application of BPNN in recent runoff study

Six separate major runoff events were considered in the study: 3 in the year 1997 and remaining 3 in the year 1998. Split record procedure was adopted and runoff events of the year 1997 and 1998 were considered for training and testing phase respectively.

Many ANN models were formulated based on different inputs in the input layer. The inputs considered included soil moisture content at various locations and depth along a hillslope and discrete precipitation data. It was found that the consideration of discrete precipitation alone resulted into poor simulation both in training and testing phase. This indicated that discrete precipitation data alone cannot furnish enough information for runoff estimation for this catchment. It was observed that the consideration of 40-cm depth soil moisture at downmost location gave better results compared

catchment data (soil moisture at other depth and locations). These new models were trained and tested in the similar way. It was found that, the consideration of other inputs decreased the model performance. Thus with these numerical experiments the importance of 40-cm soil moisture

Table 1 Average Training and Testing phase EI of Models

Model Name	Input (soil moisture)	Training Phase EI	Test Phase EI
ANN1	(t-Δt) 40D	0.87	0.70
ANN2	(t-4Δt) 40M	0.62	0.63
ANN3	(t-Δt, t-2Δt, t-3Δt, t-4Δt) 40D	0.63	0.48
ANN4	Average of (t-Δt, t-2Δt, t-3Δt, t-4Δt, t-5Δt, t-6Δt) 20D	0.88	0.46

content data at downmost location was concluded. The importance of such soil moisture data at downmost location signifies two things-the importance of soil moisture and the contribution of upslope contribution area. Such a consideration of the soil moisture nearer to the river valley side is useful in the catchment study as it gives an integrated effect of soil, vegetation and topographic contribution of the upslope area. The Nash and Sutcliffe efficiency index (EI)[Nash and Sutcliffe[16)]] of the selected models considered in the numerical experiments are shown in **Table 1**. In this Table, D and M refer to the downmost location and midslope location respectively; 't' refers to the time for which runoff estimation is made and Δt represents timestep, which in the present study was taken as 10 minutes. **Fig. 2** and **Fig. 3** represent the results of ANN1 model for training and testing phase respectively. Due to limitation of space, only the results of ANN1 model could be shown here.

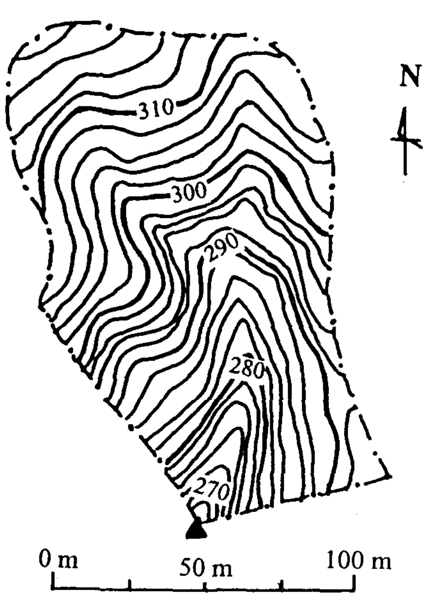

Fig. 4 Topographic map of Shomasama Subcatchment (Elevation is in meter and contour interval is 2 m)

3. FIELD OBSERVATIONS AND DISCUSSIONS

In a very recent study the above results in other area in Tono was tested with the help of intensive field observation and small-scale field experiment in Shomasama sub-catchment (shown in **Fig.4**) located also in the same Tono area. This sub-catchment has an area of about 1.5 ha and has an average slope of about 42%. The western part of this sub-catchment is less steeper than the headwater and eastern part.

The authors' observation in the sub-catchment and along the stream during both storm period and non-storm period revealed following features.

(a) The tributaries and main channel starting from the headwater part was the chief contributor to the storm runoff. The contribution from the stream bank could be seen but not as significant as the tributaries which were shallow and received mainly the contribution of near surface layer underlying the litter layer (consisting mainly of dead leaves, decayed leaves and dense small root zones). It was however, observed that in a rather quick time, the soil moisture condition along the stream bank changed.

(b) Importance of return flow due to presence of low conductivity zones was observed at many locations. At many locations soil profile consisted of the litter layer underlain by very shallow soil overlying the weathered gravel with very low hydraulic conductivity.

(c) The contribution of deep groundwater flow to the stream runoff could not be found in this watershed. A similar finding was observed by Gautam et al.)[5] in another sub-catchment in the Tono area by analyzing the deep water table data.

(d) In the rainfall events during the intensive field study, it was observed that the litter layer with its high hydraulic conductivity underlaid also by high conductivity layer did not contribute much to the stream runoff.

(e) The walking trail in the area was only found to be the contributor of the Hortonian overland flow. However, the main walking trail did not contribute to the sub-catchment under consideration.

Channels (tributaries) formed along the pathways created along hillslope hollows reflect the importance of topographic characteristics. The characteristics of the soil profile on the other hand reflect the general soil moisture variability along the vertical profile and importance of soil moisture at near the surface soil following the litter layer. It may be said that there exists a correlation between the near surface soil moisture condition along the tributaries and the wetness condition along the downslope location along the bank of the stream. As such, the soil moisture measured near to the side of the river may be used for runoff estimation. However, a better approach for runoff estimation using BPNN can be to consider soil moisture at various locations along such hillslope hollows at downslope positions.

As mentioned above, return flow was observed in the field at many locations and thus can be said to be important in this sub-catchment. The soil along the sub-catchment consisted of upper 8-10 cm thick litter layer underlain by the soil consisting of many root holes and some gravels. This is followed by gravelly soil. But as mentioned above, in this steep sloped catchment, at many locations different type of soil profiles consisting of litter layer underlain by low conductive soil zone were observed. In such case, water seeping down will form a saturated wedge which due to absence of lateral flow pathways returns back to surface and travels along the surface along the path defined by topography. In the process it infiltrates again till it reaches the channels or stream through highly conductive near-surface layer, thus again making soil moisture along such hillslope location important.

4. FIELD EXPERIMENT AND DISCUSSIONS

The major purpose of the experimental study was to study the reason of better performance of ANN models in the previous study and to get insight into the physical processes of the runoff generation in the area.

Although extreme caution is needed in extending the result of the small-scale field experiment to the catchment scale or hillslope scale, this kind of simple field experiment can provide some qualitative information about the catchment characteristics for runoff generation.

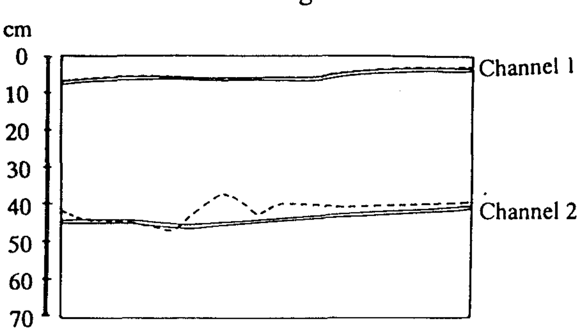

Fig. 5 Front view of the experimental site with position of two layers of troughs shown.

A 1.1 x 1.6-m pit was dug nearer to the ridge location. As shown in **Fig. 5** a collection trough was set at distinct interface between organic humus layer and the soil underneath and another trough was set at a location above a layer of Seto group comprising of relatively recent deposit of land slided materials . Seto group belongs to Pliocene age and consists mainly clay and unconsolidated conglomerates as its chief constituents. Due to large boulders and gravels of Seto layer in the experimental plot, it was not so easy to form water tight collection trough at the junction and the water collected at the bottom of the pit was significant. Such water collected at the bottom of the pit was in effect a contribution from the leakage around the second trough location and also to some extent from the underlying layer below this trough location. On the day of 30 July 1999, with sunny weather, artificial rain of intensity 40 mm/hour was applied for about 102 minutes. The initial condition of soil could be considered as moist due to the artificial rain experiment on the previous day and wet antecedent precipitation condition due

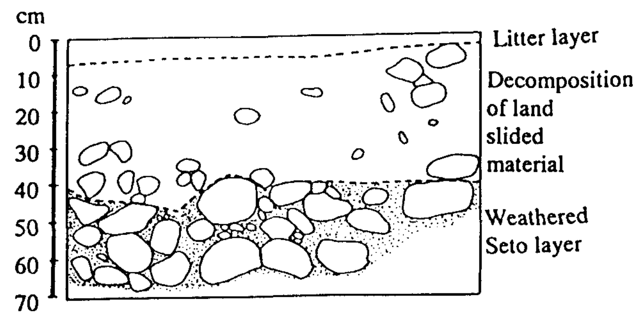

Fig. 6 Distribution of gravels in the soil profile at the experimental site (Front view).

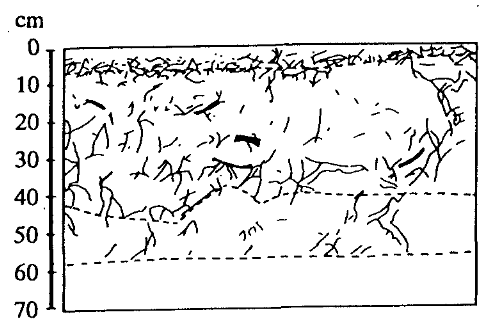

Fig. 7 Distribution of root zones in the soil profile at the experimental site (Front view).

to rainfall on days before.

It was observed that the contribution started from the lower layer, which was due to formation of saturation wedge around the low conductive boulders of Seto layer. The contribution of upper layer was nominal compared with the lower layers. This may not be unusual given the high vertical hydraulic conductivity of this zone followed by the high conductive macroporous soil zone. The gravel and root zone distributions at the experiment site shown in **Fig. 6** and **7** respectively supports this behavior of the soil profiles. It was further observed that the lower horizon started to contribute earlier than the litter layer.

The total contribution of litter layer was much smaller than the lower layers. **Figure 8** shows the throughflow contribution from the litter layer and lower layer (excluding leakage). The contribution from this layer was just about 0.275 % of total rainfall input compared to 21.1 % from the lower layer (inclusive of leakage and loss from the bottom of the pit).

In the backdrop of controversy regarding importance of macropore flow, observation of contribution of the macropores was made during

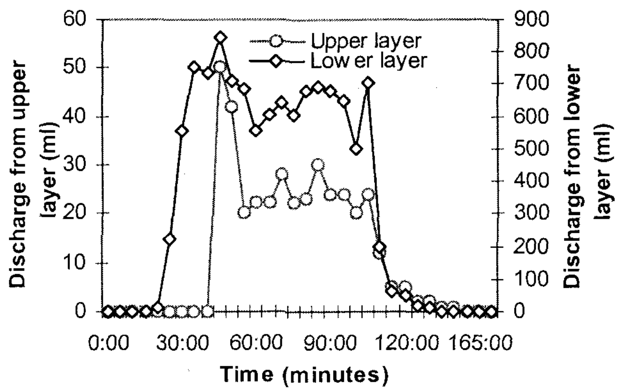

Fig. 8 Throughflow collected at two different depths due to 40 mm/hour artificial- rainfall.

artificial rainfall experiment. It was observed that pores as rootholes etc. of size of the range 8 mm only were able to provide a flow pathway that at after sufficient time of rainfall. This is due to the reason that it takes some time to prevail saturated condition along the macropore pathways provided by the bigger sized rootholes. Under the high intensity rainfall condition, the rootholes of size of the order of 8 mm contributed flow along the root zone pathways. Roots of size smaller than this was found to have little influence in the direct contribution to the runoff.

The flow stopped just about 30 minutes after cessation of rainfall. The cessation of flow immediately after stoppage of rainfall was due to the nature of soil and high rate of evaporation on the sunny day of experiment.

5. CONCLUSIONS

Intensive field observation along with field experiment was conducted to observe the behavior of one of the forested catchments in Tono area. The field experiment and catchment observations were quite helpful to provide justification to the results of previous results of storm runoff estimation using BPNN model that utilized soil moisture data.

The direct contribution of the litter layer to runoff was not significant, as was found by both field experiment and observations. Instead, the highly conductive soil layer underlying the litter layer and overlying the less macroporous soil zone with low hydraulic conductivity was found to be the main contributor to the stream runoff. The observation of sub-catchement during rainfall period showed that the channel system, which carried runoff chiefly from such layers (as in the field experiment), were the main contributors to the total storm runoff. In the process of estimation of runoff by BPNN models, the soil moisture at downmost slope location or hillslope hollow locations at the depth below litter layer and above the relatively less conductive layer can be said to have substantial importance.

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