Applicability of the Neural Network Based Radar Rainfall Estimation in Streamflow Modeling

Chau Nguyen Xuan QUANG 1) Minjiao LU 1)

1) Department of Civil and Environmental Engineering, Nagaoka University of Technology
(1603-1 Kamitomioka nagaokashi Niigata-ken 940-2188)

This study evaluates performance of the neural network based radar rainfall estimation and examines the applicability of the radar rainfall input estimated from the neural network (RNN) in streamflow modeling. The Uono River basin is selected as the study basin. A distributed hydrologic model is driven by using RNN, the radar rainfall input obtained from the Z-R relationship (RZ-R), and the gauge rainfall (RG) respectively. The statistical results of radar rainfall estimation indicate that the radar rainfall product using the neural network is more accurate than that using the operational Z-R relationship. In addition, the streamflow simulation results show that the simulated hydrographs obtained from RNN are more accurate than those obtained from RZ-R. The study concluded that the neural network technique outperforms the existing operational Z-R relationship. The appropriately trained network at the rain gauge sites is accurate, stable, and robust for estimating radar rainfall over the whole basin. The study also suggested that the RNN is an alternative input for hydrologic modeling when the gauge rainfall data is unavailable or insufficient.

Key words: Neural network, radar rainfall estimation, distributed hydrologic modeling, PUB

I. INTRODUCTION

Uncertainty largely limits the applicability of radar rainfall in hydrologic modeling despite of its large areal coverage with high spatial and temporal resolution. Krajewski and Georgakakos (1985) showed that the error of radar rainfall could be as large as about fifty percent. Recent application of radar rainfall in hydrologic modeling indicated that the simulated results derived from radar rainfall are less accurate than those obtained from gauge rainfall (Johnson et al., 1999; Sun et al., 2000; Yang et al., 2003 and Neary et al., 2004). Clearly, the accuracy of hydrologic modeling using gauge rainfall strongly depends on rain gauge density in the study basin. The accuracy of the simulated results decreases at the basins with a low density of rain gauges. In the basins with a dense gauge network, the hydrologic modeling is solely based on the gauge rainfall. On the contrary, in the ungauged or poorly gauged basins, the radar rainfall input can be an alternative for hydrologic modeling. Despite of the given uncertainty, therefore, radar rainfall is still a crucial input for hydrologic modeling in ungauged or poorly gauged basins.

The rainfall intensity (R) is estimated from the radar reflectivity (Z) by using the power law of the form $Z = BR^\beta$ (known as Z-R relationship), where $B$ and $\beta$ are parameters. The Z-R relationship was pioneered by Marshall and Palmer (1948). The performance of radar rainfall estimation mainly depends on a proper choice of Z-R relationship (Anagnostou and Krajewski, 1998). Various methods have been proposed to improve the accuracy of radar rainfall estimation. One of the successful approaches was the neural network based radar rainfall estimation method (Xiao and Chandrasekar, 1997). In this approach, the neural
network was employed to establish a relationship between the radar reflectivity ($Z$) and the ground rainfall intensity ($R$). The neural network was appropriately trained by using the historical data of radar reflectivity and gauge rainfall measurement at the rain gauge sites as input and output of the network respectively. It was concluded that, at the rain gauge sites, the radar rainfall products derived from the trained network are more accurate than those obtained from several existing $Z$-$R$ relationships. However, the accuracy of the neural network based radar rainfall product at the full areal coverage of the radar, which is very important for distributed hydrologic modeling, is unable to be determined due to the lack of the ground truth rainfall data for comparison. It is recognized that the distributed hydrologic modeling using the radar rainfall input estimated by the trained network (hereafter $R_{NN}$) evaluates not only the impact of $R_{NN}$ input on the accuracy of simulated results, but also it is a useful step for implicitly examining the performance of the trained network at the basin scale.

The objective of this research is to investigate if the streamflow modeling with the $R_{NN}$ input could yield a more accurate result than that using the radar rainfall input derived from the existing $Z$-$R$ relationship (hereafter $R_{Z,R}$). Further more, we also seek to examine the comprehensive performance of the trained network at the basin scale. In this study, more attention is paid to the comparison of the results between two radar rainfall products ($R_{NN}$ and $R_{Z,R}$) rather than the comparisons of the results between gauge and radar rainfall. The conclusions were assessed by the statistical results of comparison between the estimated radar rainfall products and between the observed hydrographs and the simulated ones which were obtained from gauge rainfall (hereafter $R_{G}$), $R_{NN}$, and $R_{Z,R}$ respectively. The hydrologic data of six flood events in the Uono River basin was used to verify the research methodology.

II. STUDY BASIN AND DATA

The study basin, the Uono River basin is located in the northern part of Japan, Fig.1. The main stream of this basin is the Uono River, a tributary of the Shinano River which is the longest in Japan. The basin is hilly with an elevation ranging from 100 m to about 2,000 m and a drainage area of about 355 km$^2$. The study area is completely covered by the Yakushidake weather radar. The spatial and temporal resolutions of this radar are three kilometers and five minutes, respectively.

Hydrologic data of six flood events, including five-minute radar reflectivity data, hourly measured rainfall (at ten gauges located inside and nearby the study basin as shown in Fig.1), and hourly observed discharge at the basin outlet were used in this study. The names of ten raingauges are Muikamachi (R05), Ikasawa (R06) Shimizu (R07), Futai (R08) Tuchitaru (R09), Yuzawa (R10), Miyanoshita (R11), Miyamura (R12), Gomisawa (R14), and Ohmine (R16). Detailed description of six flood events is presented in Table 1. Though five-minute radar reflectivity data is available, the hourly simulation was performed because the conventional data of measured rainfall and discharge are hourly measurements.

![Fig. 1 Map of the Uono River basin.](image-url)
III. NEURAL NETWORK FOR RADAR RAINFALL ESTIMATION

1. Neural network

A neural network is a massively parallel-distributed information processing system inspired from our understanding of biological neural processing. Although various paradigms of neural network have been developed in the literature (i.e. Multilayer Feedforward Network (MLFN), Radius Basis Function (RBF), Recurrent Network (RN)), the MLFN trained with the well-known Backpropagation (BP) algorithm is found to be simple and efficient for establishing the nonlinear relationship between input and output in many cases. Therefore, in this study, the MLFN and the BP algorithm were selected to approximate the highly nonlinear relationship between radar reflectivity and ground rainfall intensity.

MLFN is a common neural network consisting of one input layer, one output layer and more than one hidden layers of neurons. The neurons from one layer have weighted connections with neurons in the next layer, but no connection between neurons in the same layer. A typical MLFN is shown as Fig. 2.

The net input $n_j^k$ to node $j$ in layer $k$ can be obtained from:

$$n_j^k = \sum_{i=1}^{m_{k-1}} w_{ij}^{k-1,k} o_i^{k-1} + b_j^k$$

(1)

where $m_{k-1}$ is the number of nodes in layer $k-1$, $n_j^k$ is the net input to node $j$ in layer $k$, $w_{ij}^{k-1,k}$ is the connection weight between node $i$ in layer $k-1$ and node $j$ in layer $k$, $o_i^{k-1}$ is the output of node $i$ in layer $k-1$, $b_j^k$ is the bias of node $j$ in layer $k$.

The sigmoid function is most frequently used to compute the output $o_j^k$ from node $j$ in layer $k$ in case of nonlinear relation modeling as showing in previous research (Chau, 2004). Therefore, the output $o_j^k$ is computed as:

$$o_j^k = \frac{1}{1 + \exp(-n_j^k)}$$

(2)

The error between the network output and target output was defined in the objective function as following:

$$E = \frac{1}{2} \sum_{j=1}^{n} (t_j - o_j)^2$$

(3)

where $t_j$ and $o_j$ are the target and network output of neuron $j$ in the output layer respectively, $n$ is the number of neurons in the output layer.

The BP algorithm adjusts the weight and bias parameters of the neural network based on the iteration procedure. This procedure is terminated when the objective function expressed as Eq. (3) satisfies a target error, or the number of iteration exceeds its maximum, or the over-training occurs.

Table 1 List of the selected flood events.

<table>
<thead>
<tr>
<th>Flood No.</th>
<th>Period</th>
<th>Max. rainfall (mm/hr)</th>
<th>Peak flow (m³/s)</th>
<th>Time lag (hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>890806</td>
<td>1989/08/06-08/07</td>
<td>10.6</td>
<td>286.5</td>
<td>4</td>
</tr>
<tr>
<td>890918</td>
<td>1989/09/18-09/21</td>
<td>11.4</td>
<td>222.8</td>
<td>3</td>
</tr>
<tr>
<td>900919</td>
<td>1990/09/19-09/21</td>
<td>13.9</td>
<td>387.1</td>
<td>2</td>
</tr>
<tr>
<td>901007</td>
<td>1990/10/07-10/09</td>
<td>13.2</td>
<td>279.9</td>
<td>5</td>
</tr>
<tr>
<td>940929</td>
<td>1994/09/29-10/01</td>
<td>9.4</td>
<td>381.5</td>
<td>3</td>
</tr>
<tr>
<td>950915</td>
<td>1995/09/15-09/18</td>
<td>9.5</td>
<td>158.6</td>
<td>5</td>
</tr>
</tbody>
</table>

Fig. 2 A typical multilayer feedforward network.
The training process consists of a series of three sequential steps; presenting input pattern to the input layer; propagating the input pattern from input layer forward to output layer as Eqs. (1) and (2), and then comparing the computed output to the desired output. The connection weights and biases were updated in the back propagating step and their values are computed by using Eqs. (4), (5) and (6) below.

The adjustment value of weight, \( \Delta w_{ij}^{k-1,k} (i+1) \), and bias, \( \Delta b_j^k (i+1) \), within the progress of training are defined as:

\[
\Delta w_{ij}^{k-1,k} (s+1) = \eta \delta_j^k a_i^{k-1} + \alpha \Delta w_{ij}^{k-1,k} (s) \tag{4}
\]

\[
\Delta b_j^k (s+1) = \eta \delta_j^k a_i^{k-1} + \alpha \Delta b_j^k (s) \tag{5}
\]

where \( s \) is the iteration number, \( \delta_j^k \) is the local gradient for node \( j \) in layer \( k \), \( \eta \) is the learning rate parameter, and \( \alpha \) is the momentum parameter. The \( \delta_j^k \) can be calculated as:

\[
\delta_j^k = \begin{cases} 
  a_j (1-a_j)(d_j-a_j) & \text{at output layer 1} \\
  a_j (1-a_j) \sum_{i=1}^{m_{k-1}} w_{ij}^{k-1,k} \delta_j^{k+1} & \text{at hidden layer } k
\end{cases} \tag{6}
\]

### 2. Framework of neural network based radar rainfall estimation

Neural network based radar rainfall estimation consists of two stages, the development stage and the application stage. As for the development stage, there are two periods namely the training period and testing period. The training period establishes the relationship of radar reflectivity and rainfall intensity through the training process. The testing period verifies the performance of the trained network. After the network is well trained at the calibration gauge sites, it is ready for the application stage. The trained network is applied to estimate the radar rainfall for full areal coverage of radar.

For development of a trained neural network, three main steps including network architecture selection, data processing, and network training are carried out as following.

a) **Network architecture selection**

Although the proper choice of neural network architecture significantly affects the accuracy of the result, there are no common rules for this selection. Decisions must be made regarding aspects such as the number of input and output variables, the number of the hidden layers and the nodes within hidden layers. Aside from the output variables, which are the same as the desired outputs, the other selections are mainly based on trial and error, and developer's experiences.

In this study, the output of the network is hourly measured gauge rainfall. The input of the network and the network architecture are determined by several training experiments. For the input selection, the radar reflectivity (\( Z \)) and the radar rainfall product (\( R_{Z,R} \)) are tried as input for training the network in turn. The radar reflectivity (\( Z \)) is the hourly mean value at the grid cell which covers one of ten rain gauge sites. The radar rainfall products (\( R_{Z,R} \)) are converted from the radar reflectivity by means of the \( Z-R \) relationship (\( R_{Z,R} = (Z/B)^{1/\beta} \)) using the operational and optimal parameters of \( B \) and \( \beta \), respectively. The comparison results indicated that the performance of network trained with radar rainfall product (\( R_{Z,R} \)) is slightly better than one trained directly with the radar reflectivity (\( Z \)). Therefore, the radar rainfall product (\( R_{Z,R} \)) is used as input to the network instead of the radar reflectivity (\( Z \)). Furthermore, the comparison results also showed that the performance of network trained with radar rainfall product (\( R_{Z,R} \)) derived from optimal parameters (\( B \) and \( \beta \)) is not quite different with the network trained with the \( R_{Z,R} \) obtained from the operational parameters. The optimization ability of neural network assures the overall performance is almost the same. While the accuracy of two cases is almost the same, the operational parameters should be used here for simplicity reason. Using of the operational parameters, it is not necessary to determine and select the optimal parameters which vary from rainfall events to rainfall events and from estimation methods to
estimation methods (Lu et al., 2001). Here, the operational values of $\beta$ and $B$ are 1.5 and 650 respectively. The value of $B$ is about four times of the normal value because of a hardware mistake. In addition, it is also from this trial experiments, the network architecture of 1-5-4-1 is found to be appropriate for training the neural network.

b) Data processing

The available data set was divided into two separate data sets, the training data set and the testing data set. The training data set includes four flood events no. 890806, 890918, 900919 and 901007, of seven training gauges namely R05, R06, R07, R09, R10, R11, and R14, which were randomly chosen from ten gauge sites. The testing data set includes two other remaining flood events 940929 and 950915 of seven training gauges and all of six flood events at three other remaining gauges, namely R08, R12, and R16. The domains of training and testing data sets are illustrated in Table 2. The selection of testing data ensured that the performance of the trained network can be tested both spatially and temporally.

The data is normalized using following formula before applying for neural network training.

$$r_i = \frac{0.9 (R_i - a)}{A - a} + 0.05$$

(7)

The output is renormalized as the formula:

$$R_i = \frac{(A - a)(r_i - 0.05)}{0.9} + a$$

(8)

Table 2: Illustration of the training and testing data set domains.

<table>
<thead>
<tr>
<th>Rain gauge</th>
<th>Flood events</th>
<th>Training Data</th>
<th>Testing Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>R05</td>
<td>890806</td>
<td>890918</td>
<td>900919</td>
</tr>
<tr>
<td>R06</td>
<td>TRAINING DATA</td>
<td>TESTING DATA</td>
<td></td>
</tr>
<tr>
<td>R07</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R09</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R10</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R11</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R14</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R08</td>
<td></td>
<td>TESTING DATA</td>
<td></td>
</tr>
<tr>
<td>R12</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R16</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

where $R_i$ is the actual value, $r_i$ is the transformed value, $a$ and $A$ is the minimum and maximum value of the time series of input data respectively.

c) Network training

When the training data and network architecture was determined, the training process was implemented to obtain the optimal connection weights and biases. This process was repeated until the error of both the training and testing periods satisfied a target error or number of iterations exceeded the given epochs. The training process will also be prematurely stopped to avoid the ‘overfitting’, a phenomena where the performance of the training period increases but the performance of testing period decreases.

V. SIMPLE DESCRIPTION OF THE DISTRIBUTED HYDROLOGIC MODEL

A distributed hydrologic model developed by Lu et al. (1996a) was applied for the Uono River basin (detailed description of this model refers to Lu et al. (1996a)). The basin was divided into 36,233 grid cells of 100 m x 100 m (slightly larger than officially published drainage area 355 km²). The runoff from the grid cells are calculated by using the conceptual rainfall runoff model, XinAnJiang model, (Zhao, 1992). The generated runoff of a grid cell is considered to concentrate immediately to its center and to flow to one of its eight neighbor cells forming the steepest slope. The flow path between these two grid points (the center of a grid cell) is modeled as an open rectangular channel. Hence the runoff of grid cells can be routed to the basin outlet through this channel network. The flow routing in the channel network is computed by kinematic wave approximation. In order to keep the downstream channel to be routed after the routing of all its upstream channels, Lu et al. (1993, 1996b) developed an automatic algorithm to determine the optimal routing order of channel network. In this study, the model parameters are calibrated by using the gauge rainfall data and are applied to simulation using other rainfall data sources.
V. RESULTS AND DISCUSSION

1. Performance evaluation criteria

The following criteria were used to evaluate the performance of radar rainfall estimation and hydrologic model output.

Correlation coefficient (Coef):

\[
\text{Coef} = \frac{\sum_{i=1}^{n} (O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n} (O_i - \bar{O})^2 \sum_{i=1}^{n} (S_i - \bar{S})^2}}
\]  

(9)

Nash-Sutcliffe efficiency index (EI):

\[
\text{EI} = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}
\]  

(10)

Mean error (ME):

\[
\text{ME} = \frac{1}{n} \sum_{i=1}^{n} (O_i - S_i)
\]  

(11)

Root mean square error (RMSE):

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - S_i)^2}
\]  

(12)

where \(O_i\) and \(S_i\) are observed and simulated value at time \(i\) respectively, \(\bar{O} = \frac{1}{n} \sum_{i=1}^{n} O_i\) is mean observed value, \(\bar{S} = \frac{1}{n} \sum_{i=1}^{n} S_i\) is mean simulated value, and \(n\) is number of data points.

2. Radar rainfall estimation results

The radar rainfall products \((R_{NN}\text{ and } R_{Z-R})\), estimated by the properly trained neural network and the operational Z-R relationship \((R = (Z/650)^{1/1.5})\) respectively, are compared to the measured gauge rainfall at the rain gauge sites. The performance of radar rainfall estimation methods was evaluated by using three statistical criteria including correlation coefficient (Coef), mean error (ME), and root mean square error (RMSE) in Eqs. (9), (11), and (12) respectively. Table 3 presented the statistical comparison results in both the testing and training periods of the training gauge group (R05-R06-R07-R09-R10-R11-R14). Table 4 presented the statistical comparison results in testing period of the training gauge group (R08-R12-R16).

Table 3 and Table 4 show that the statistical indexes of \(R_{NN}\) is better performance than those of \(R_{Z-R}\) for both training and testing periods (except for flood event no.890806). The RMSE and ME values of \(R_{NN}\) are significantly lower than those of \(R_{Z-R}\).
The ME values of $R_{Z,R}$ which are more negative than those of $R_{NN}$ indicate that the $Z-R$ relationship produces overestimated rainfall as compared with the trained network. In addition, the Coef values of $R_{NN}$ are closer to 1.0 than those of $R_{Z,R}$. This means that $R_{NN}$ is more highly correlated to $R_G$ than $R_{Z,R}$. Therefore, with regard to overall performance, it can be concluded that, at the rain gauge sites, the neural network technique estimates more accurate radar rainfall than the operational $Z-R$ relationship despite of the inaccurate results of $R_{NN}$ in flood event 890806.

It is noteworthy from Table 4 that the trained network gives good results in the testing gauge group (R08-R12-R16) though their data are entirely excluded from training data set. This promises that the trained network will perform well for computing radar rainfall for full coverage of the study area. The comprehensive performance of the trained network at the basin scale will be evaluated as following.

The trained network and the operational $Z-R$ relationship are applied for estimating radar rainfall for all grid cells in the Uono River basin. The accumulative basin-average rainfall intensity criterion is used for the preliminary evaluation of the comprehensive performance of the trained network at the basin scale. The results of accumulative basin-average rainfall of $R_G$, $R_{Z,R}$, and $R_{NN}$ were plotted in Fig.3. It can be seen from this figure that the accumulative basin-average rainfall of $R_{Z,R}$ products are still more overestimated than those of $R_{NN}$, a similar situation to the rain gauge sites. This evidences that the trained network is accurate and stable for computing radar rainfall for the overall basin. More assessment on the accuracy of estimated radar rainfall using the trained network at all grid cells is implicitly evaluated by the simulated hydrograph results in the next section. Because of the different spatial distribution between radar and gauge rainfall, the results obtained from $R_G$ are used for reference rather than for comparison. However, it could be also seen that the results of $R_{NN}$ are closer with those of $R_G$ when compared with those of $R_{Z,R}$.

3. Hydrologic modeling results

Since the hydrologic model is calibrated by relying on the gauge rainfall, the calibrated parameters are adjusted to compensate for the spatial distribution of gauge rainfall. These parameters may be inconsistent for applying with the quite different spatial distribution of radar rainfall. This may introduce error to the simulation results when the model is driven by radar rainfall. However, it is important to recall that the focus of study is mainly to compare the simulated results obtained from two radar rainfall sources ($R_{NN}$ and $R_{Z,R}$), rather than to compare with those obtained from gauge rainfall. Therefore, the uncertainty from calibrated parameters will not influence the final conclusions, because both simulation results of $R_{NN}$ and $R_{Z,R}$ are affected implicitly by the same model parameters.

Distributed hydrologic simulations in the Uono River basin were performed by using the $R_G$, $R_{Z,R}$, and $R_{NN}$ respectively. Fig.4 shows a time-series comparison of the hourly simulated streamflows from three different rainfall inputs and the hourly observed streamflows. The statistical comparisons were carried out between the observed and simulated hydrographs by using two statistical criteria including Nash-Sutcliffe efficiency index (EI) and root mean square error (RMSE) expressed as Eqs. (10) and (12) respectively. The statistical comparison results were presented in Table 5. In addition, the total discharge of each flood event was also used for evaluating the water balance between observed and simulated discharges. The
The RMSE and EI results in Table 5, the total discharge results in Table 6 as well as the display of hydrographs in Fig. 4 indicate that the simulation results obtained from $R_{Z,R}$ are extremely poor as compared with the observed ones. For example, the EI in the case of using $R_{Z,R}$ of flood events no. 890918 and 900919 is -20.053 and -9.459 respectively. However, the accuracy of simulation results is significantly improved in the case of using the $R_{NN}$ (except for flood event no. 890806). Specifically, in flood events no. 901007, 940929, and 950915, the results of $R_{NN}$ are more accurate than those of $R_G$. As shown in Table 5, the RMSE and EI in the case of using $R_{NN}$ of these flood events are respectively lower and larger than corresponding values of using $R_G$. The good results of simulated hydrograph derived from $R_{NN}$ in the testing flood events no. 940929, and 950915

### Table 5 Statistical comparison results of hydrologic modeling.

<table>
<thead>
<tr>
<th>Flood events</th>
<th>EI</th>
<th>RMSE (m$^3$/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gauge</td>
<td>$Z$-R relationship</td>
</tr>
<tr>
<td>890806</td>
<td>0.956</td>
<td>0.741</td>
</tr>
<tr>
<td>890918</td>
<td>0.502</td>
<td>-20.053</td>
</tr>
<tr>
<td>900919</td>
<td>0.783</td>
<td>-9.459</td>
</tr>
<tr>
<td>901007</td>
<td>0.736</td>
<td>-1.524</td>
</tr>
<tr>
<td>940929</td>
<td>0.771</td>
<td>-0.690</td>
</tr>
<tr>
<td>950915</td>
<td>0.757</td>
<td>-1.839</td>
</tr>
</tbody>
</table>
(as their rainfall data are entirely excluded in training process) reveal that the trained network estimate radar rainfall well in the testing period.

Though, with regard to overall performance, it can be seen that the simulation results obtained from \( R_N \) is the most accurate one, the \( R_NN \) provides more accurate results than \( R_G \) in some flood events. However, in the viewpoint of water balance, Table 6 shows that \( R_NN \) gives the most accurate results. The sum of simulated discharges of six flood events is overestimated about 70 % by using \( R_{Z,R} \), and underestimated about 10 % and 4.9 % by using \( R_G \) and \( R_NN \) respectively.

As the calibrated parameters is retained for applying with different rainfall input sources (\( R_{N}, R_{Z,R} \), and \( R_G \)), the performance of simulated hydrographs only depends on the quality of the rainfall input. The more accurate the rainfall input, the more accurate result in streamflow modeling can be expected. Therefore, more accurate results of the simulated hydrographs of \( R_{NN} \) when compared with those of \( R_{Z,R} \) proved that \( R_{NN} \) input is better than \( R_{Z,R} \) one. Once again, this confirms that the neural network technique is better method for radar rainfall estimation than the existing operational Z-R relationship. The network trained at the rain gauge sites is accurate, stable, and robust for estimating radar rainfall over the basin. In addition, the superior performance of streamflow simulation by using \( R_{NN} \) suggest that the \( R_{NN} \) can be a better alternative input for hydrologic modeling when the gauge rainfall data is unavailable or insufficient.

The streamflow simulation results show that the simulated hydrographs yielded from \( R_{NN} \) are also more accurate than those yielded from \( R_{Z,R} \). From the results of radar rainfall estimation and streamflow simulation, it can be concluded that the neural network technique is more appropriate method for radar rainfall estimation than the existing operational Z-R relationship. The network trained at the rain gauge sites is accurate, stable, and robust for estimating radar rainfall over the basin. In addition, the superior performance of streamflow simulation by using \( R_{NN} \) suggest that the \( R_{NN} \) can be a better alternative input for hydrologic modeling when the gauge rainfall data is unavailable or insufficient.

### REFERENCES


<table>
<thead>
<tr>
<th>Flood events</th>
<th>( \Sigma Q_{obs} ) (m³/s)</th>
<th>( \Sigma Q_{sim-G} ) (m³/s)</th>
<th>( \Sigma Q_{sim-R} ) (m³/s)</th>
<th>( \Sigma Q_{sim-NN} ) (m³/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>890806</td>
<td>2806.49</td>
<td>2812.88</td>
<td>1978.59</td>
<td>1281.56</td>
</tr>
<tr>
<td>890918</td>
<td>5751.77</td>
<td>3828.46</td>
<td>12148.91</td>
<td>5682.18</td>
</tr>
<tr>
<td>900919</td>
<td>4353.45</td>
<td>4903.52</td>
<td>10044.84</td>
<td>5898.71</td>
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<td>3252.99</td>
<td>5565.66</td>
<td>3792.78</td>
</tr>
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<td>950915</td>
<td>4011.08</td>
<td>3346.71</td>
<td>5746.39</td>
<td>3459.46</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>23138.45</strong></td>
<td><strong>20624.74</strong></td>
<td><strong>39424.56</strong></td>
<td><strong>21995.31</strong></td>
</tr>
<tr>
<td><strong>Error (%)</strong></td>
<td><strong>-0.109</strong></td>
<td><strong>0.704</strong></td>
<td><strong>-0.049</strong></td>
<td><strong>-0.049</strong></td>
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流量予測におけるニューラルネットワーク雨量推定の利用に関する研究

Chau Nguyen Xuan QUANG 1) 陸 愛姣 1)

1)长冈技术科技大学环境·建设系
(〒940-2188 新潟県长冈市土富冈1603-1)

本研究はニューラルネットワークによるレーダー雨量推定技術の評価およびその流量予測への利用について検討するものである。信濃川支川魚野川上流の六日町上流域を対象とし、6洪水の水文データを用いて、ニューラルネットワークによる雨量R_{06}を、ルーチンレーダー方程式による雨量R_{06}と地上雨量計雨量R_{06}を比較する。そしてこれらの雨量を分布型水文モデルに入力し、実測ハイドログラフと各雨量の計算ハイドログラフを統計的に比較検討し、その実用性を確認する。本研究では特にレーダーレグキャストの結果との比較に焦点を置く、ニューラルネットワークがルーチンレーダー方程式より精度の高い雨量を得ることができ、流量予測においてもより実測に近いハイドログラフを得ていることが明らかになった。このことから、適切にトレーニングされたニューラルネットワークは雨量観測地点のみならず、流域平均雨量をも安定的に高精度に推定できることを示され、雨量観測所の少ない、または全くない流域にとって有用な雨量推定手法であると考えられる。

キーワード：ニューラルネットワーク、レーダー雨量、分布型水文モデル、PUB