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Prediction of Precipitation by Aneural Network Method

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ABSTRACT

A neural network method to reduce natural disasters (particularly, avalanches, slush flow, and melting snow in snow hazards) was used to predict precipitation on the ground. Based on computation cost and similar pattern two types of simulations were made. Two methods were used to evaluate precipitation, mean square error which is superior for evaluating the strength of precipitation over the prediction range and Critical Success Index (CSI) evaluation used to judge the existence of precipitation. Results were compared with prediction results from the short time precipitation forecast method used by the Japan Meteorological Agency. Mean square error was about 0.1 to 0.2 mm/h toward the term when there was much precipitation whether rain or snow. In the CSI evaluation, the neural network method gave high values as compared with the short time precipitation forecast method for the strong winter characteristics. Results of these two evaluations show that our method can adequately predict for the subsequent hour and is a practical tool for reducing snow hazards.

1. INTRODUCTION

Changes in precipitation distribution are complicated, being affected by meteorological and geographical factors. The method of predicting precipitation distribution for several hours is called short-time rainfall prediction, consisting of topographical methods, the rainfall conception model and the meso-scale model (Nakakita et al; 1996, 1999). The most typical prediction method has been the short time precipitation forecast used by the Japan Meteorological Agency. It consists of complicated equations involving various factors. One of the main problems with this method is that error is produced when the strength and movement of precipitation change nonlinearly with time. Private weather companies have started predicting weather, by nonlinear methods (e.g. neural networks) (Shinozawa et al; 1995, Ochiai et al; 1998).

There have been two methods for predicting rainfall and snowfall with a neural network. One is the prediction of daily fresh snowfall at a specific point after determining the snowfall pattern from past history (Amenomori and Hashiyama, 1993; Yamada et al., 1997). The other, local short-range prediction of cloud movement that brings snowfall, uses mesh data for a radius of a few kilometers (Asuma et al., 1984; Maeda and Amenomori, 1999). The latter can deal with complicated movement (development, decline, and appearance) because of being a nonlinear method. In reality, the prediction of rainfall and snowfall on the ground is more useful for the reduction, prediction, and investigation of natural disasters (in particular, the avalanches, slush flow, and melting snow seen in snow hazards), because conditions in the sky differ from those on the ground. Moreover, because it uses a large number of learning patterns (precipitation patterns), it requires a large amount of calculation time to sufficiently reduce error. Based on past examples, only 5 to 25 input neurons were obtained. Therefore, we have attempted to increase the number of input neurons to reduce prediction error by classifying a few snowfall patterns during the snowy season, ignoring the computation cost and to predict snowfall on the ground by use of function produced through the learning process. We then compared our results those predicted results as calculated by the Japan Meteorological Agency.

2. DATA USED

Mesh data for the Kanto and Chubu areas of eastern Japan were used (see Fig.1-a). Precipitation data was obtained from the Japan Weather Association. Data, recorded hourly consisted of 14400 (120x120) pixcels, with a 5km x 5km range for each pixcel. Based on the actual precipitation, we chose a classification range of 1 to 15 strength levels (0 to 13 mm/h) of precipitation. More than 16 strength levels were combined to make the 15th level (Table 1). The prediction and learning ranges of these simulations by neural network methods were based on an area of 21x39 pixcels (about 105 x 195 km) in the Jouetsu and Chuetsu areas, Niigata Prefecture, Japan (Fig.1-b). This data collected by the Japan Meteorological Agency, is generally available to the public for

KEY WORDS: neural network, precipitation, maximum cross correlation, mean square error, CSI evaluation, short time precipitation forecast

prediction. It consists of synthetic radar data made up of the precipitation at AMeDAS observation points and the estimated precipitation on the ground in order to supplement echo strength in the sky at points not covered by the observations. Full details are given in section 3.1.

Fig. 1 (a)

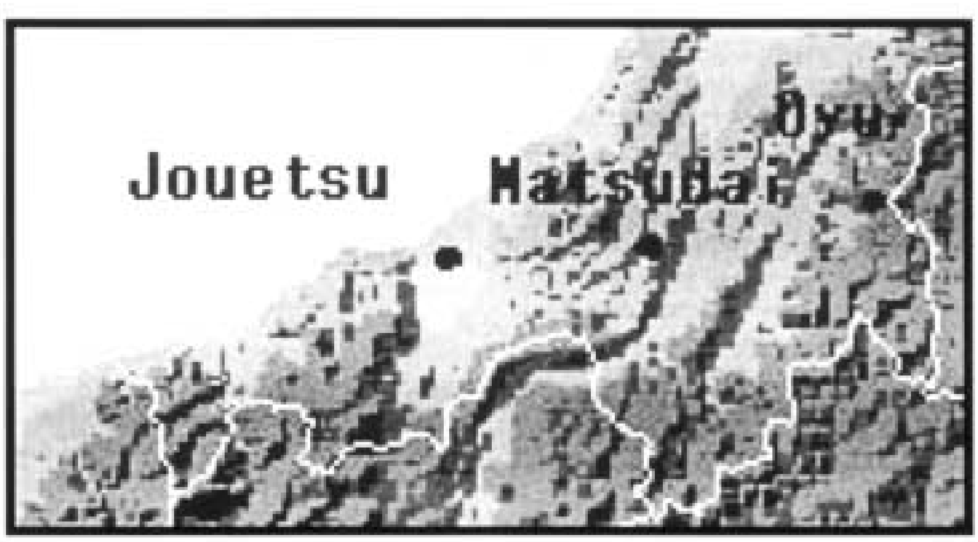


Fig. 1 (b)

Fig. 1 (a) Range of mesh data for the Kanto and Chubu areas in eastern Japan and (b) the learning and prediction range

3. SIMULATION

3.1 Short time precipitation forecast method

Predicted results, based on precipitation data over a wide area, gathered by the Japan Weather Association, were compared with results provided by the neural network method.

The mesh prediction data for a wide area are computed by a method called short time precipitation forecast used by the Japan Meteorological Agency and are provided the Agency to private meteorological companies. The prediction equations used in the short time precipitation forecast method estimate complicated movement (development, decline, and appearance) by combining movement vectors of precipitation areas and adding topographical terms. This movement vector is not obtained from the entire prediction range, but from various vectors in each subrange by the use of a complicated equation involving the moving precipitation range.

3.2 Neural Network Method

(1) Preparation

Hourly maximum cross correlations between the precipitation distribution for the present hour and that for the next hour were

Table 1. Correspondence table of the supplemented strength of precipitation

Data value	Class value	Typical value	Supplemented value
0	No observation		
1	0・0.1mm/h	0 mm/h	1
2	0.2 − 0.4 mm/h	0.3 mm/h	2
3	0.5 − 1.4 mm/h	1.0 mm/h	3
4	1.5 − 2.4 mm/h	2.0 mm/h	4
·····	·····	·····	·····
14	11.5 − 12.4 mm/h	12.0 mm/h	14
15	12.5 − 13.4 mm/h	13.0 mm/h	15
16	13.5 − 14.4 mm/h	14.0 mm/h	15
17	14.5 − 15.4 mm/h	15.0 mm/h	15

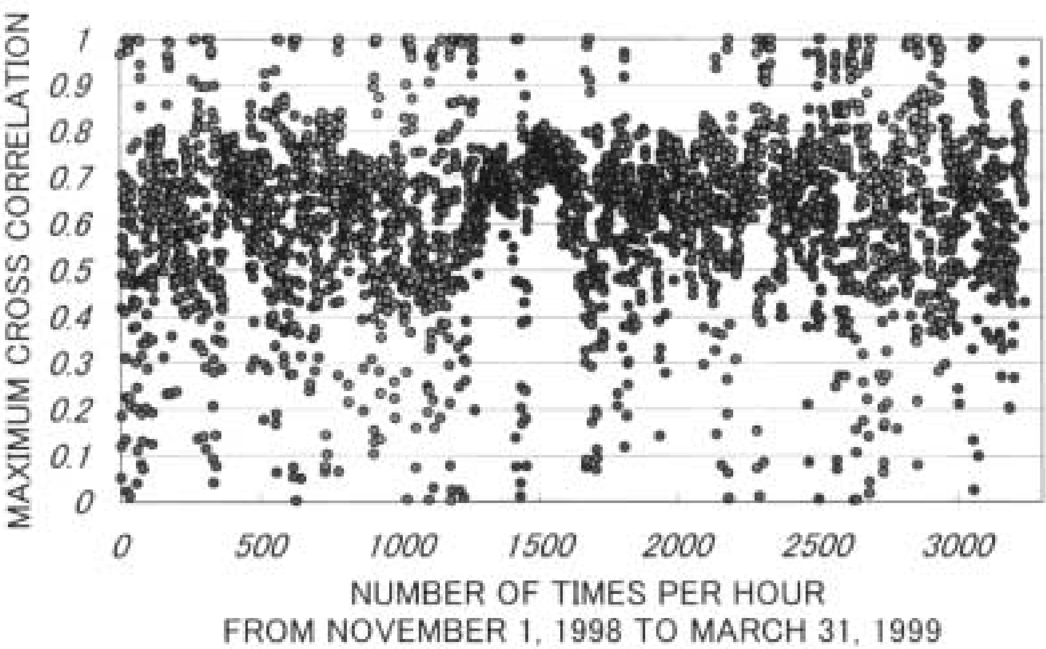


Fig. 2 Hourly distribution map of the maximum cross correlation (November 1, 1998 to March 31, 1999)

calculated from November 1, 1998 to March 31, 1999 to determine the optimal input neuron combination of the network.

Fig.2 shows the maximum cross correlation distribution for each hour from November 1, 1998 to March 31, 1999. The hourly maximum cross correlation mean was about 0.6 to 0.8 throughout this snowy season period, and generally was high.

The movement vector throughout this snowy season period was calculated based on Fig.2. The equations that produced the movement vector (Vy,Vx) are

$$Vy=(Y+m)\Delta y/\Delta T, \tag{1}$$

$$Vx=(X+n)\Delta x/\Delta T, \tag{2}$$

$$m=2(\sigma_{-y}-2\sigma_0+\sigma_{+y})/(\sigma_{-y}-\sigma_{+y}), \tag{3}$$

$$n=2(\sigma_{-x}-2\sigma_0+\sigma_{+x})/(\sigma_{-x}-\sigma_{+x}). \tag{4}$$

where

m and n	= interpolation point
σ_0	= value of maximum cross correlation;
σ_{-y}, σ_{+y}, σ_{-x} and σ_{+x}	= nearby cross correlation values of σ_0;
Δy and Δx	= pixcel size;
ΔT	time interval;
Y and X	coordinate of σ_0.

Distribution of the movement vector was widely extended,

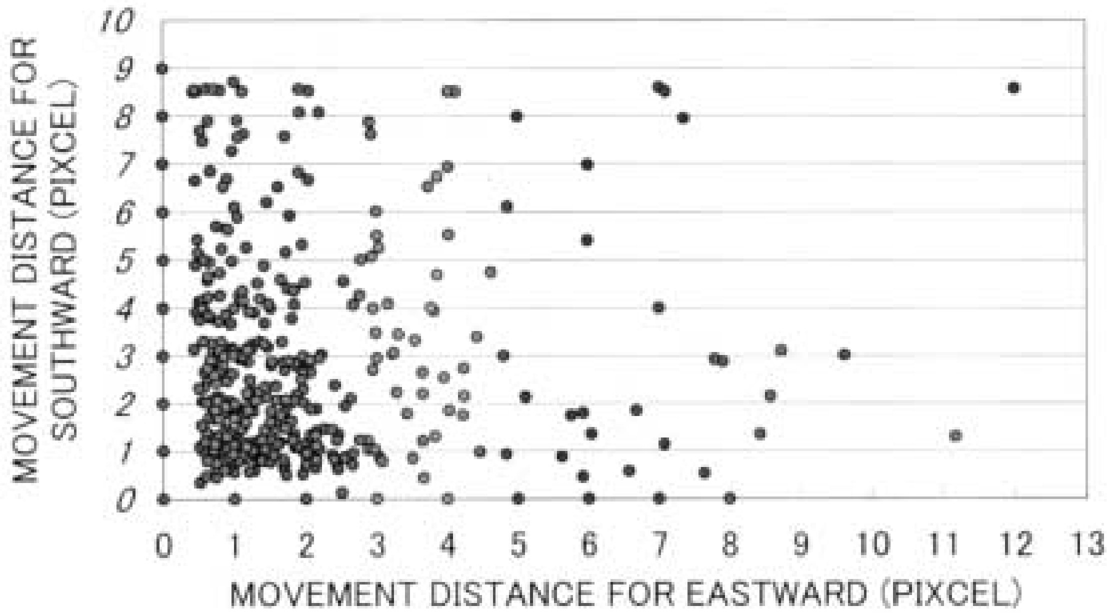


Fig. 3 Distribution map of the movement vectors of precipitation for maximum cross correlation (November 1, 1998 to March 31, 1999)

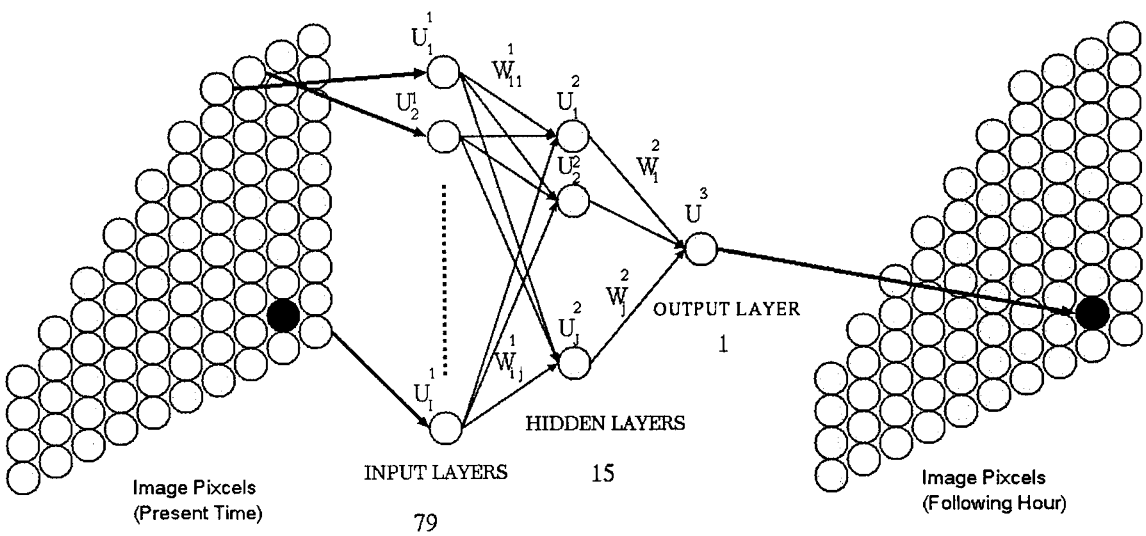


Fig. 4 Structure of the neural network model used (a) pixcels of the concentrated maximum cross correlations, (b) pixcels of the southern and eastern directions in the case of movement of the precipitation range by low pressure

about 8x8 = 64 pixcels (Fig.3). Consequently, we made 79 input layers that were parts of the concentrated maximum cross correlations (a), for the southern and eastern directions in the case of movement of the precipitation range by low pressure (b), that were based on the Cross Correlation-Neural Network hybrid method (Maeda and Amenomori, 1999) (see Fig.4). Fifteen hidden layers also were made from results of several experimental, and lastly one output layer was predicted for the next hour.

The Jacobs Hybrid Algorithm (Jacobs, 1986), which is 10 to 100 times faster than traditional neural networks, was used to reduce error. This faster convergent algorithm consists of the following steps:

Step1 Set the initial weights $\mathbf{w}[0]$, the initial learning rate diag(η [0]), its increment and decrement factors, κ , ϕ , and the Momentum factor α ,; then set coefficient θ used to smooth the partial derivative.

Step2 Calculate the forward step. As the output function to each layer, use the Sigmoid function (Eq.5).

$$F(S)=1/(1+\exp(-\beta * S)) \quad (5)$$

Step3 Calculate the backward step. Calculate gradient $\mathbf{g}[t]$ and $\delta[t]=(1-\theta)*\mathbf{g}[t]+\theta*\delta[t-1]$. Modify the learning rate based on the sign δ 1[t-1];

$$\eta i[t]=\eta i[t-1]+\kappa \qquad \text{if } \delta i[t-1]*\mathbf{g}[t]>0 \quad (6)$$

$$\eta i[t]=\eta i[t-1]*\phi \qquad \text{if } \delta i[t-1]*\mathbf{g}[t]<0 \quad (7)$$

$$\eta i[t]=\eta i[t-1] \qquad \text{otherwise.} \quad (8)$$

Then calculate

$$\Delta w[t] = -\mathrm{diag}\,\eta\,[t])*\mathbf{g}[t]+\alpha*(\mathbf{w}[t]-\mathbf{w}[t-1]) \quad (9)$$

Step4 Change the weights and return to step2

$$\mathbf{w}[t+1]=\mathbf{w}[t]+\Delta\mathbf{w}[t]. \quad (10)$$

The initial parameters of these simulations were η =0.05, β =0.01, α =0.9, κ =0.01, ϕ =0.9 and θ =0.7.

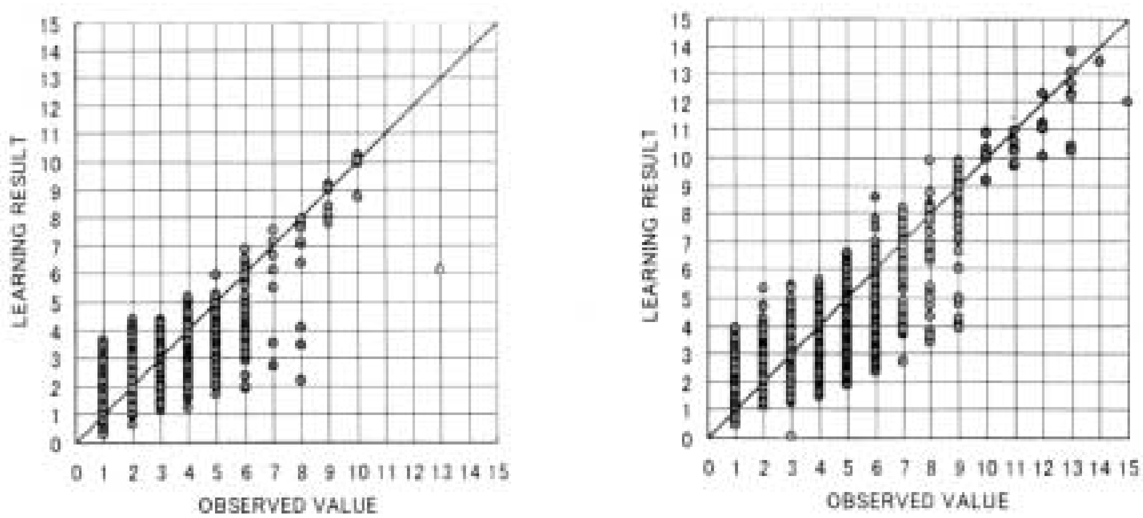
(2) Learning Process

We tested two types of simulations; (A) the period of a typical pressure pattern for winter during heavy snowfall in the mountainous region and (B) the period of a typical pressure pattern for winter during heavy snowfall in the plain region based on data for the snowy season (November 1998 to March 1999). Both types were tested because of computation cost and similar patterns based on the results given in Section-3.2.1. The number of acquired learning patterns (number of precipitation patterns) was 30000 to 50000. As the learning iterations increase, errors in the learning process decrease, but if the learning iteration is increased too much, there is high possibility that the produced prediction equation will become fixed on specific precipitation patterns. On the basis of various experimental results, a learning iteration of 30000 steps therefore was selected.

In simulation (A), precipitation patterns which had winter characteristics during heavy snowfall in the mountainous region for about one week in early January 1999 were used, and in (B) those which were characteristic of winter during heavy snowfall in the plain region near the end of January and early in February 1999 were used. For both the (A) and (B) simulations, the learning results obtained gave high evaluations, even when there was much precipitation (Fig.5). Moreover, the mean square errors were about 0.5 - 0.6 mm for both simulations.

3.3 Prediction results

Data from November 1998 to March 1999 were used as the learning patterns, to predict the hourly distribution of precipitation from November 1999 to March 2000 based on the function pro-



(A) (B)

Fig. 5 Learning results of characteristics of winter during heavy snowfall in (A) the mountainous region and (B) the plain region (Numbers in these figures indicate precipitation strength) duce after learning the results.

To assess the prediction, two evaluation methods were used; the mean square error (MSE) that is excellent for evaluating the strength of precipitation over the prediction range calculated from equation (11), and the CSI (Critical Success Index) evaluation that is used to judge the existence of precipitation calculated from equation (12). Moreover, the correspondence of symbol N in equation (12) is shown in Table 2.

$$\boldsymbol{MSE} = \left(\Sigma(\boldsymbol{A}_{ij}-\boldsymbol{B}_{ij})^2\right)^{1/2} \tag{11}$$

$\boldsymbol{A}_{ij}$ is the real value, $\boldsymbol{B}_{ij}$ the predicted one.
($1< \boldsymbol{i} < 39$, $1< \boldsymbol{j} <21$)

$$\boldsymbol{CSI}(\%) = \boldsymbol{N}_{11} / (\boldsymbol{N}_{01}+\boldsymbol{N}_{10}+\boldsymbol{N}_{11}) \tag{12}$$

Table 2. Correspondence of ***N*** symbols in the CSI evaluation

Symbol	Precipitation: real image	Precipitation: prediction image
N_{11}	existent	existent
N_{10}	existent	non-existent
N_{01}	non-existent	existent
N_{00}	non-existent	non-existent

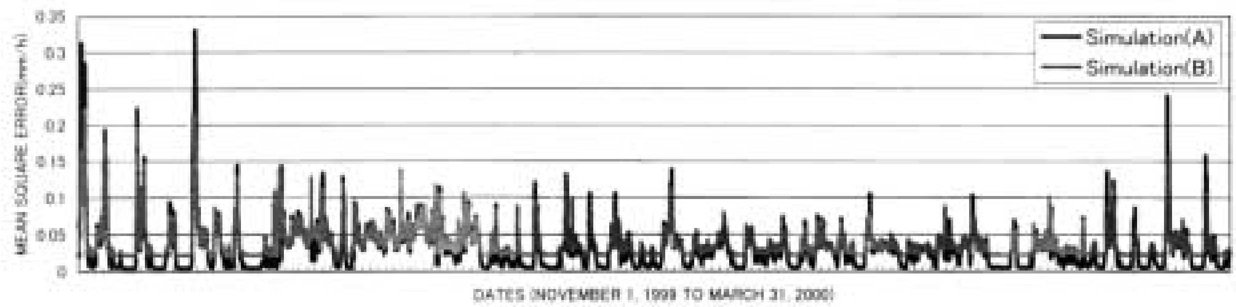


Fig. 6 Hourly prediction evaluation from November 1, 1999 to March 31, 2000

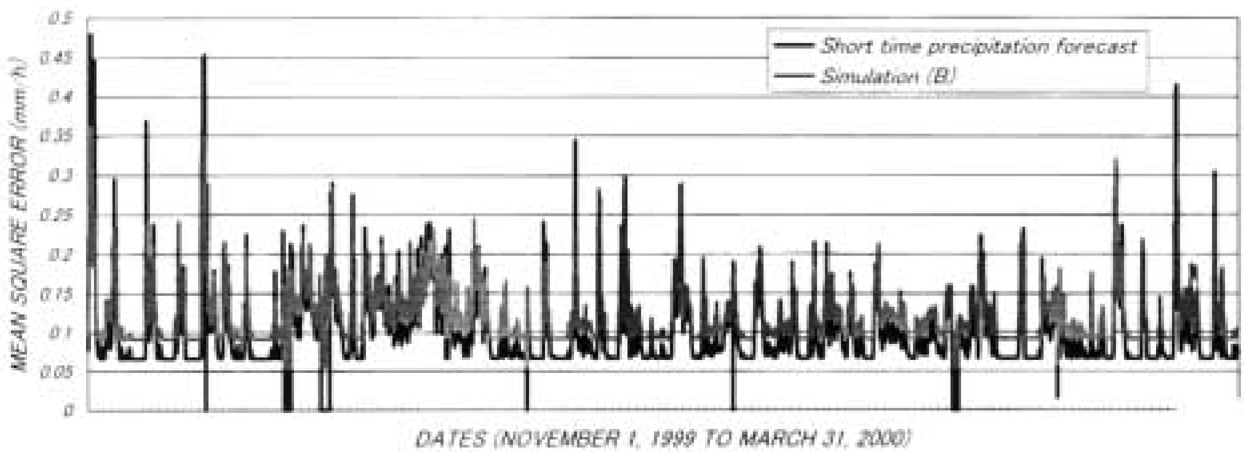


Fig. 7 Comparison of prediction results of the short time precipitation forecast and neural network method in simulation-(B) by the mean square error (November 1, 1999 to March 31, 2000)

(1) Mean Square Error

Results of the preceding two simulations and of the short time precipitation forecast method of the Japan Meteorological Agency were evaluated by the mean square error. The prediction's precision in the winter season of the following year based on learning results had a mean square error average of about 0.05, although the values at the beginning and end of winter were larger than the midterm value (MSE = 0.1 - 0.2) (Fig.6), evidence of satisfactory prediction results.

Fig.7 shows the comparison with the mean square error for the neural network method in simulation-(B) and the short time precipitation forecast method. Results were compared with the daily precipitation at Takada, Jouetsu City, Niigata Prefecture (Fig.8), throughout the winter season. The mean square errors showed that there was little error in the comparison of the prediction evaluation of the short time precipitation forecast method with that of the

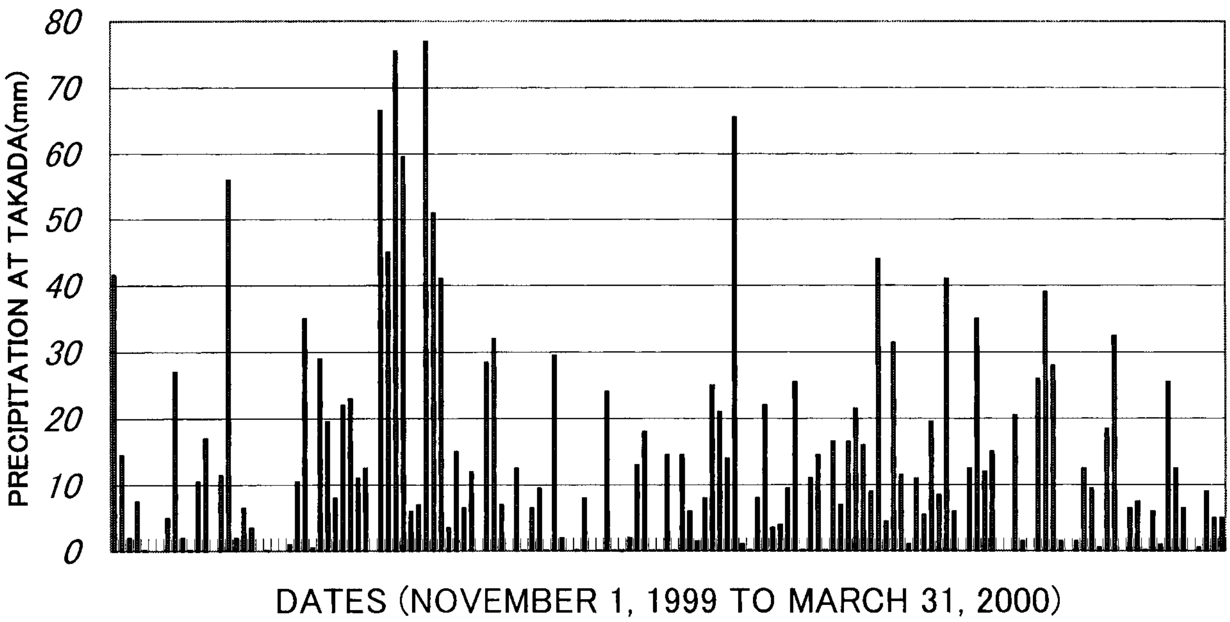


Fig. 8 Daily precipitation (mm) at Takada, Jouetsu City, Niigata Prefecture from November 1, 1999 to March 31, 2000

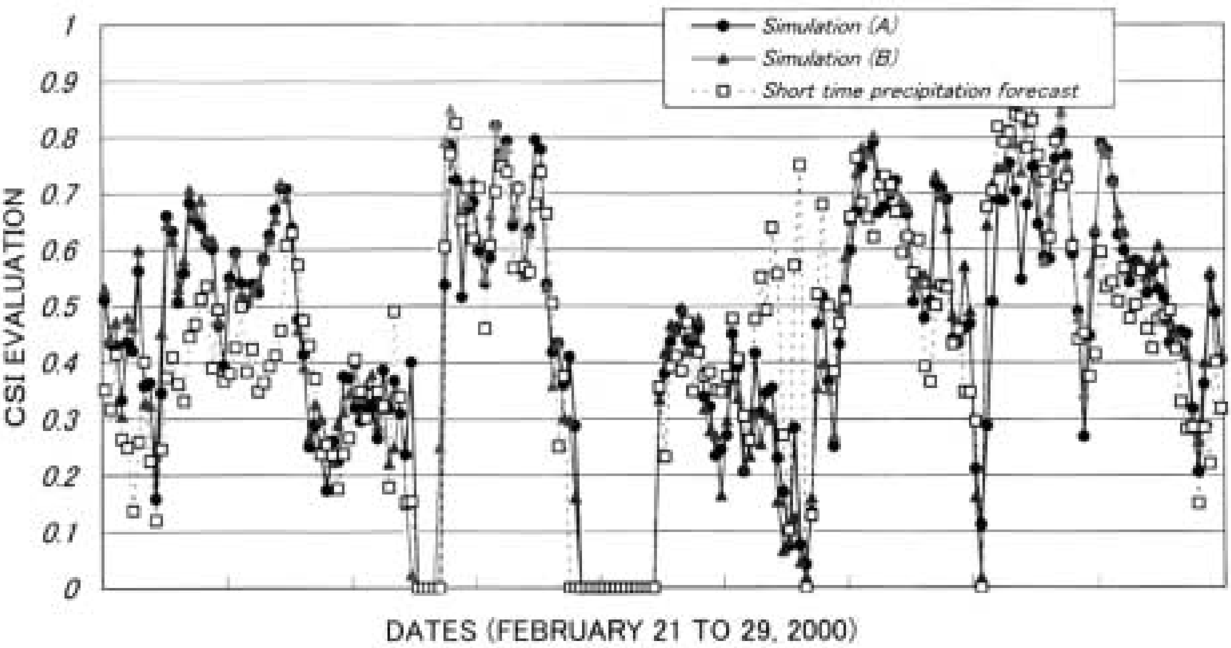


Fig. 9 CSI evaluation during each simulation near the end of February 2000

neural network methods on days when there was little or no precipitation at Takada. On days when there was much precipitation, whether rainfall or snowfall, however, the neural network methods could sufficiently reduce error, in particular when the error was large as in the case of the short time precipitation forecast method.

(2) CSI Evaluation

In the CSI evaluation, the results of precipitation predictions by the short time precipitation forecast method were a little higher than those by the neural network methods throughout the winter season but particularly during the periods of early and end of winter. Fig.9 shows a comparison of the CSI evaluations for the

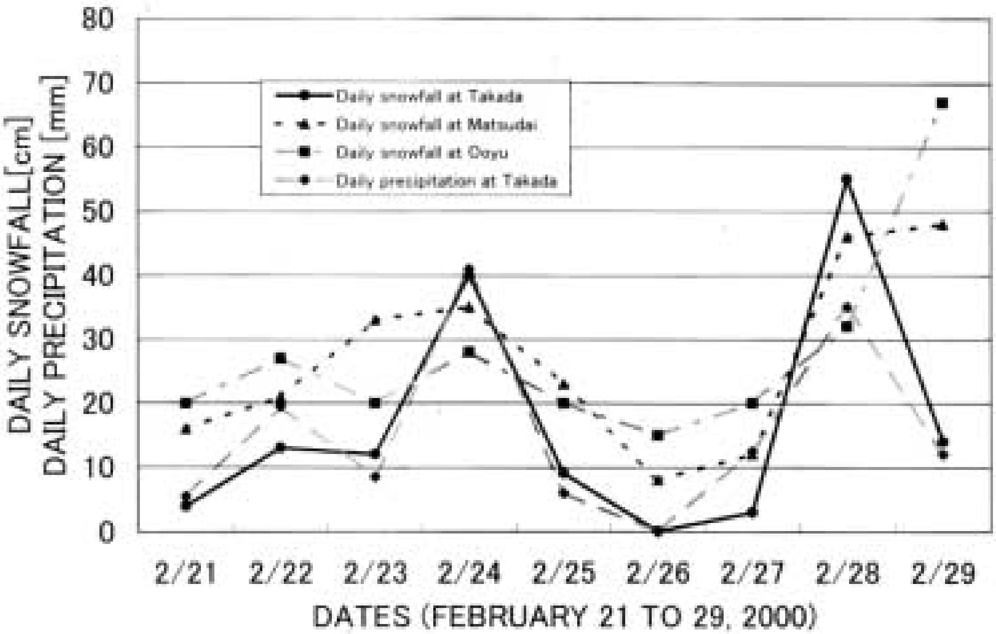


Fig. 10 Daily snowfall (cm) at Takada, Matsudai Town, and Oyu. Daily precipitation at Takada, Niigata Prefecture

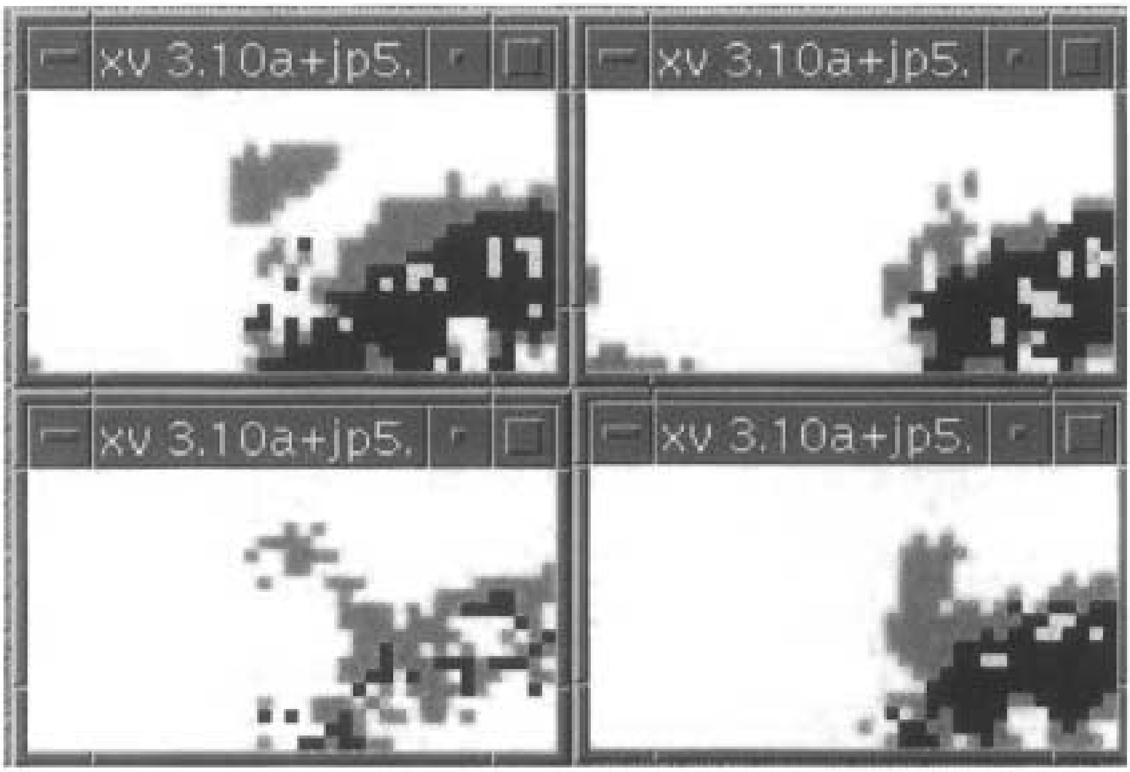


Fig. 11 (a)

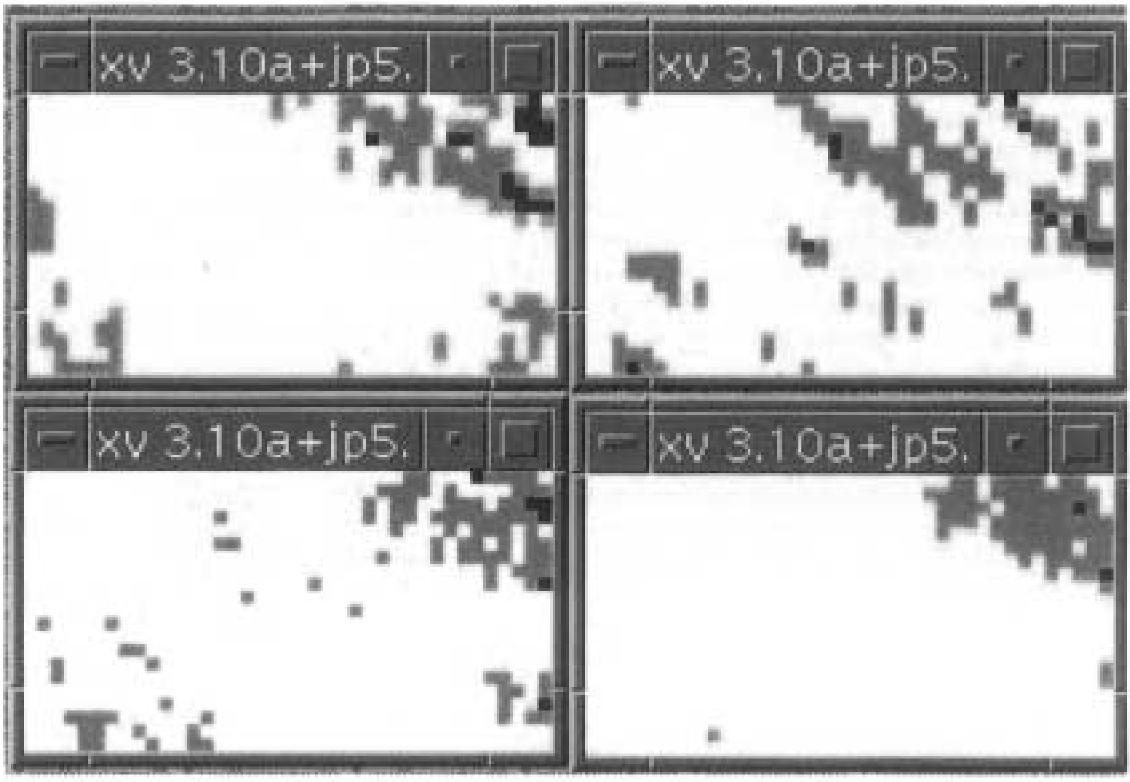


Fig. 11 (b)

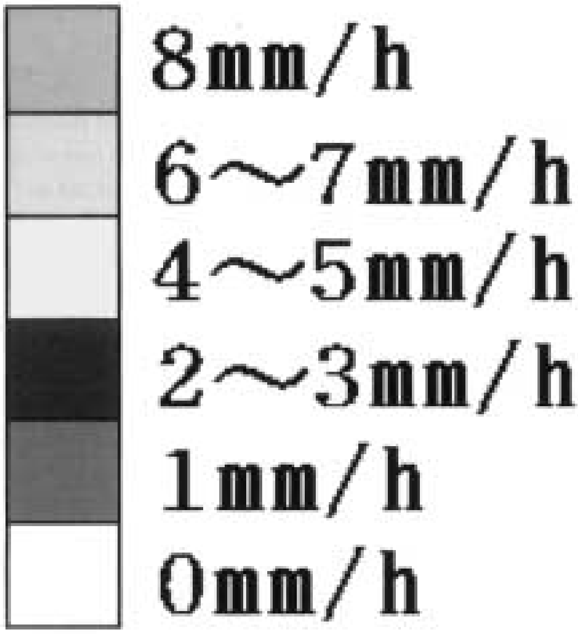


Fig. 11 (c)

Fig. 11 Prediction images of simulations by neural network methods
(a) characteristic of heavy snowfall in the plain region
(b) characteristic of heavy snowfall in the mountainous region
upper left: real image at the present time
upper right: real image after an hour
lower left: prediction image after an hour made with the function produced after learning the characteristics of heavy snowfall in the mountainous region
lower right : prediction image after an hour made with the function produced after learning the characteristics of heavy snowfall in the plain region
(c) precipitation strength

(A),(B) neural network and short time precipitation forecast methods near the end of February, 2000 when both types of winter characteristics were present.

Fig.10 shows predictions for February 21 to 23 when there were weak winter characteristics during heavy snowfall in the mountainous region; for February 24 and 28 when there were winter characteristics during heavy snowfall in the plain region (40 to 55cm deep at Takada.); and for February 29 when there were strong winter characteristics during heavy snowfall in the mountainous regions (about 50cm deep at Oyu and Matsudai Town, Niigata Prefecture.), evidence that the two neural network methods have high prediction precision as compared to the short time precipitation forecast method.

Except for the typical pressure pattern characteristics of winter, there was close similarity to the winter term characteristics including the results of the CSI evaluation. The evaluation for the short time precipitation forecast method generally was better than for the neural network methods, but when there was much snowfall, the neural network methods also were useful for prediction. The mean values of the CSI evaluation when there was precipitation frequently were more than 0.6 for all the methods. This prediction method therefore is concluded to have high precision except when there is almost no precipitation (CSI evaluation values were 0.).

Furthermore, Fig.11 shows prediction images for (a) when there was heavy snowfall in the plain region (0:00, February 24, 2000) and (b) when there was heavy snowfall in the mountainous regions (0:00, February 29, 2000), and for the following hour when the function obtained from the learning process in the 1998 to 1999 winter season was used. The prediction images were compared with the real images for the following hour. For both (a) and (b) there was little difference in the distribution of the precipitation range in regard to the prediction images when a different simulation type function was used. When prediction images used the same simulation type function, (a) was superior for predicting the distribution and strength of precipitation, whereas (b) was superior for the output of a narrow precipitation range. Consequently, the precipitation for the actual following hour can be predicted.

4. CONCLUSION

Prediction of precipitation on the ground was predicted by a neural network method, because this type of prediction is very useful for reducing the chances of a natural disaster in the winter. To determine the input layers, the maximum cross correlation between present time and following hour first were calculated. The values were high, the mean being about 0.6 to 0.8 throughout the winter.

Because, however, the movement vector of the precipitation ranges of the total radar images produced the maximum cross correlation, which showed a wide distribution, many input neurons and further calculations were needed.

The precision of this neural network method's learning process could reduce error sufficiently, producing good results, even for strong precipitation strength values in both the (A) and (B) simulations.

On the prediction evaluations, the neural network methods and the short time precipitation forecast method used by the Japan Meteorological Agency were compared. In some cases the mean square error is more useful for judging the evaluation of precipitation strength. In early winter and at the end all the methods compared have few high errors in comparison with the coldest period, but about 0.1 to 0.2 mm/h toward the term there was much precipitation whether rain or snow. Although the CSI evaluation is more useful for determining the existence of precipitation, the neural network methods gave high values in comparison with the short time precipitation forecast method during the strong winter characteristics. These two evaluations gave results that can sufficiently cope with prediction for the following hour. As for the output of prediction image, in cases that used the same type function, the distribution and strength of precipitation could be predicted almost exactly, and the output for prediction of the narrow precipitation range also was almost exact. Furthermore, only after the learning process, Can the function produced be used to reduce the prediction value immediately. This method therefore is practical for reducing snow hazards.

In the further, a method for the automatic separation of the (A) and (B) simulations needed to be developed and the errors in all the methods must be evaluated.

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REFERENCES

Amenomori, M. and Hashiyama, H., 1993. Prediction of daily snowfall depth obtained from neuro computing method. Journal of the Japanese Society of Snow and Ice, 55; 191-196 (in Japanese).

Asuma, Y., Kikuchi K. and Kon, H., 1984. A method for estimating the advection velocity of radar echoes using a simple weather radar system. Geophysical Bulletin of Hokkaido University, 44; 23-34 (in Japanese).

Asuma, Y., Kikuchi K. and Kon, H., 1984. Experiments for a very-short-range prediction of snowfall using a simple weather radar system Part 1. Outline and possibility. Geophysical Bulletin of Hokkaido University, 44; 35-51 (in Japanese).

Nakakita, E., Yagami, T., Suzuki, Y. and Ikebuchi, S., 1999. Characteristic of generation and propagation of localized heavy rainfall over southern Tohoku and northern Kanto region. Annuals of Disaster Prevention Research Institute, Kyoto University, 42, B-2; 153-168 (in Japanese).

Nakakita, E., Ikebuchi, S., Nakamura, T., Kanmuri, M., Okuda, M., Yamaji, A. and Takasao, T., 1996. Short-term rainfall prediction method using a volume scanning radar and GPV data from numerical weather prediction. Journal of Geophysical Research, 101, No.D21; 26, 181-26,197.

Jacobs, R. A., 1988. Increased rates of convergence through learning rate adaptation. Neural Networks, 1; 296-307.

Maeda, N. and Amenomori, M., 1999. Local short-range prediction of cloud images of weather radar by a neural network method. Journal of the Japanese Society of Snow and Ice, 61; 197-205 (in Japanese).

Ochiai, K., Suzuki, H., Suzuki, S., Sonehara N. and Tokunaga, Y., 1998. Rainfall and snowfall prediction from images of weather radar with artificial neural networks. The Transactions of the Institute of Electronics, Information And Communication Engineers, J81, D-II; 1631-1638 (in Japanese).

Shinozawa, K., Fujii, M. and Sonehara, N., 1995. A weather radar image prediction method in local parallel computation. The Transactions of the Institute of Electronics, Information And Communication Engineers, J78, D-II; 1144-1149 (in Japanese).

Yamada, Y., Iwanami, K., Maeda, N., Amenomori, M. and Michigami, M., 1997. Are neural networks a distinct tool for prediction and estimate of newly fallen snow?, In Snow Engineering: Recent Advances, eds. Izumi, M., Nakamura, T. and Sack, Ronald L. A. A. Balkema, Rotterdam; 125-128.