第Ⅱ部門 **Uncertainty assessment of discharge simulation results obtained from the downscaled rainfall data**

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INTRODUCTION

River discharge simulation results using any distributed hydrological models are heavily influenced by the characteristics of rainfall input such as its resolution and spatial patterns[1]. The role of an accurate spatial rainfall field is significant to obtain a successful discharge simulation result. Therefore, the research questions like how to obtain an accurate spatial rainfall field and how to assess the quality of the spatial rainfall field needs to analyze the uncertainty in discharge simulation results. It is necessary to quantify the uncertainty associated with the discharge simulations for quality assessment of the spatial rainfall field and improving the rainfall runoff predictions as well.

In this research, two different sets of downscaled rainfall data are input to a distributed hydrological model with the same parameters. The obtained ensembles of discharge simulations results exhibit different degree of predictive uncertainties. A relation is proposed to quantify the associated uncertainty with the ensemble of river discharge simulations and tested in results comparison. The quality of the downscaled spatial rainfall field may be evaluated using this method as it links with the uncertainty. The experiment is conducted on the Huaihe river basin (132350 km^2), China. Grid precipitation data are taken from the Multifractal downscaled outputs using GAME Reanalysis 1.25-degree data[2] (Version 1.1) for the period from May1 to August 31, 1998. A brief description of the findings is presented in this paper.

BACKGROUND AND OBJECTIVES

In our previous research, an experimental data (10 minute spatial resolution data called hereafter EXPT data) is created referring GAME Reanalysis 1.25 degree data[2] and HUBEX IOP EEWB data[3]. A coarse 1.25-degree data, obtained from aggregating the experimental data, is subjected to downscaling process using the Multifractal method of random cascade generation to get the 10-minute resolution data ensemble. Two different downscaling algorithms are adopted to create the data. First is the random cascade method[4], which uses the β-log normal model, suggested by Over and Gupta (1996) to generate the random generators. The downscaled data from this method is called RC data hereafter. The second algorithm is the random cascades including a modified procedure called as the Hierarchical and Statistical Adjustment (HSA) method[5]. This method modifies the spatial arrangement of the random generators based on spatial correlation of the rainfall field. The downscaled data from this method is called RCHSA data hereafter.

In this research, one of the main objective is to test the rainfall data downscaled by two different methods using a distributed hydrological model. The second objective is to assess the uncertainties of the hydrologic simulation results associated with the rainfall variability using an ensemble of the downscaled realizations as the input.

UNCERTAINTY EVALUATION INDEX

The simulation results may be deviated from an expected value due to heterogeneity in input, landscape or process descriptions. A wider chance of the deviation represents a higher degree of uncertainty. In Figure 1, the uncertainty is higher at t = a than at t = b. Mimicking the concept, an index named as a Relative Uncertainty Index (RUI) is proposed here.

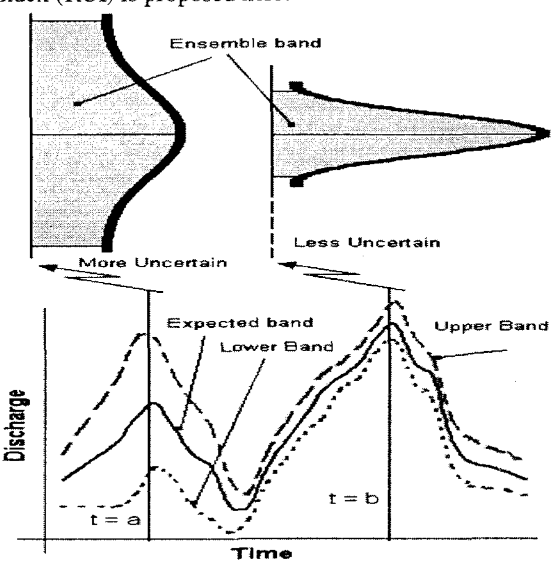

Fig. 1 Schematic figure of predictive uncertainty

The ensemble bandwidth of simulated discharge gives the standard deviation σ as a measure of the uncertainty. The RUI is a measure of deviation in time series, which is given by

$$RUI = \frac{\sum_{t=1}^{n} 6\sigma_t}{\sum_{t=1}^{n} E[X]_t}$$

where, X is the simulation discharge at time t. The RUI measures the uncertainty with respect to the expected value of the ensemble considering the degree of deviation bandwidth. In addition, the bias between the ensemble and observed discharge is necessary to be considered. Recognizing the bias between the ensemble and the observed discharge, an index named as the Index of Uncertainty Estimator (IoUE) is proposed, which is given by

$$IoUE = \frac{\sum_{t=1}^{n} 6\sigma_t}{\sum_{t=1}^{n} E[X]} + \left\{ E_T\left[\left(E[X] - E_T[E[X]]\right)^2\right] + E_T\left[\left(E_T[E[X]] - E[\hat{X}]\right)^2\right] \right\}^{1/2}$$

where, $E[X]$ represents the expectation of the ensemble simulation at any time interval; $E_T[X]$ represents the expectation of the ensemble simulation along the time series; and $\hat{X}$ represents the observed series.

METHODOLOGY

All together 30 set of RC data and RCHSA data are separately made ready for input to the distributed hydrological model. The details of the hydrological model are available in Shrestha *et al.*, 2002.

The simulation is conducted using the EXPT data and the downscaled data. The results from each set of data are observed at Suiping (2093 km^2), Wangjiaba (29,844 km^2) and Bengbu (132,350 km^2). The observed discharge data at these stations are suspected of having anthropogenic influence such as the paddy irrigation and the reservoir storages. Hence, the result obtained from the EXPT data is treated as the observed data and the results obtained from the downscaled data are treated as the simulated data.

RESULT AND DISCUSSION

The discharge simulation results obtained from two different ensemble precipitation shows interesting phenomenon of ensemble prediction. The RC data yields a wider bandwidth of the ensemble discharge than that of the RCHSA data (see Figure 2 and Figure 3). On the other hand, the hydrograph comparison between the expected simulation result and the simulation result from the EXPT data (Figure 4) does not show significant differences. This confirms a larger degree of uncertainty associated with the RC data compared to the RCHSA data. Since both ensemble simulation are conducted just changing the spatial rainfall field, the appeared uncertainty is solely responsible to the accuracy of the spatial rainfall field. In this condition, the measure of performance evaluation is expected to reflect the uncertainty from the ensemble prediction rather than depending on a unique expected simulation.

The proposed criteria seems successful to estimating the associated degree of uncertainty in the discharge simulation results (see Table 1). The RUI is able to show the importance of narrower simulation bandwidth referring lesser uncertainty. The IoUE considers the bias as well as the variance of the ensemble prediction.

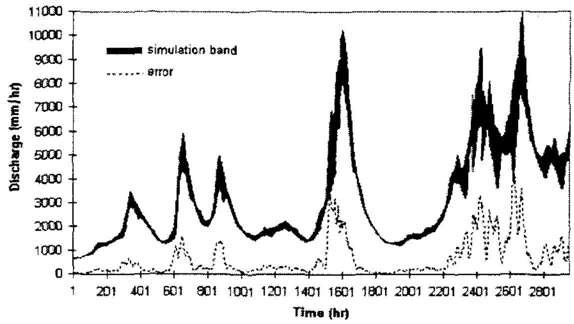

Fig. 2 Discharge ensemble from RC data at Bengbu

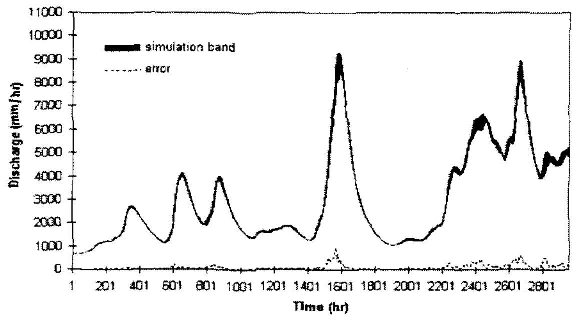

Fig. 3 Discharge ensemble from RCHSA data at Bengbu

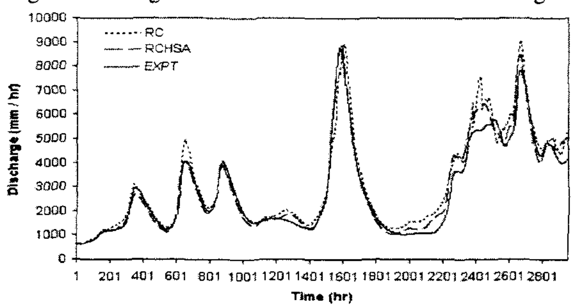

Fig. 4 Comparing expected discharge Vs. EXPT output

Table 1: Summary of Uncertainty assessment indexes

	Bengbu		Wangjiaba		Suiping	
	RUI	**IoUE**	**RUI**	**IoUE**	**RUI**	**IoUE**
RC data	0.374	0.407	0.342	0.379	0.787	0.847
RCHSA	0.095	0.116	0.163	0.239	0.476	0.619

REFERENCES

1) Shrestha, R., Tachikawa, Y. and Takara, K. 2002 : Effect of forcing data resolution in river discharge simulation, *Annual J. Hydraulic Engg.* **46**, 113-144.
2) ftp://hydro.iis.u-tokyo.ac.jp/GAME/GAIN/GAME-REANL/
3) Kozan O., Tanaka K. and Ikebuchi S.: Estimation of Energy and Water Budget in the Huaihe River Basin, China, *Game publication no. 28 pp. 32-35, 2001.*
4) Over, T. M., and V. K. Gupta, 1996 : A space-time theory of mesoscale rainfall using random cascades, *Jour. Geophys. Res.* **101(D21)**, pp. 26,319- 26,331.
5) Shrestha, R., Tachikawa, Y. and Takara, K. 2003 : A new method to improve the performance of downscaling rainfall field from GCM data, *Proc. Annual Conf. Civil Engg, JSCE Kansai Chapter.* ISSN 0285-7324, pp. II-89-1.