第II部門 **A new method to improve the downscaling of rainfall field from GCM data**

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INTRODUCTION

General circulation model provides meteorological data at larger scale covering a wide region, which are usually referred as GCM data. The resolution of GCM data is often very coarse such that they cannot be used directly in hydrological model as input information Successful efforts towards a suitable scale change, obviously a down scaling process, may lead towards a promising possibility of using the GCM data in hydrological analysis, which may fulfill the data requirement demand of distributed hydrological model in most of the ungauged basins as well.

Data downscaling by means of random cascade generators are the one among the downscaling processes. Over and Gupta[1] have formulated the procedure using a β-log normal model to disaggregate an average value of a coarse grid cell into finer grids. An improvement is examined in this model by introducing a new method named as HSA method (designated for hierarchical and statistical arrangement method).

The experiment is conducted over a Chinese river basin Huaihe (132350 km^2). Grid precipitation data is taken from GAME Reanalysis 1.25-degree data[2] (Version 1.1) for the period from May1 to August 31, 1998. A finer resolution data called as HUBEX IOP EEWB data[3] (10-minute spatial resolution, called EEWB data hereafter) is referred for spatial pattern of data over the region. A brief description of the findings is presented in this paper.

DATA PREPARATION

A coarse 1.25-degree GAME - Reanalysis data is intended to use in downscaling experiment to obtain a 10-minute resolution data. Since, such finer resolution data is not available, there rises up a problem to verify the obtained result of downscaling afterward. To fill up this gap, the GAME-1.25-degree data is converted to GAME 10-minute data by forcing the spatial pattern of EEWB data. An arithmetic approach is used to incorporate the spatial pattern (equation 1)

$$P_{4j} = \begin{cases} P_{1j@i} + \alpha(P_{2j} + P_{3j@i}); & if \geq 0 \\ 0 & ; otherwise \end{cases} \quad (1)$$

For time j = 1, 2, 3... m.

Here, P_{4j} is GAME 10-minute data; $P_{1j@i}$ is original GAME 1.25-degree data at i – reference resolution; P_{2j} is EEWB 10-minute data; and $P_{3j@i}$ is reference coarse data produced by average of EEWB 10-minute data at the reference resolution i.

The GAME 10-minute data is again aggregated to 1.25-degree resolution to make a coarse resolution data, which has to employ downscaling process. The objective is now to obtain the finer resolution data, from which the coarse one is constructed. The degree of ability to reproduce the finer resolution data examines the effectiveness of downscaling method.

RANDOM CASCADE DOWNSCALING MODEL

Spatial disaggregation of rainfall field can be carried out using the extended discrete random cascade approach[1,4,5]. In this process, a two-dimensional region with known volume of rainfall is successively divided into b equal parts (b = 2^d) at each step and during each subdivision the volume obtained at the previous disaggregation step is distributed into the b subdivisions by multiplication by a set of "cascade generators" W, as shown schematically in Fig.1 (for d = 2 and b = 4).

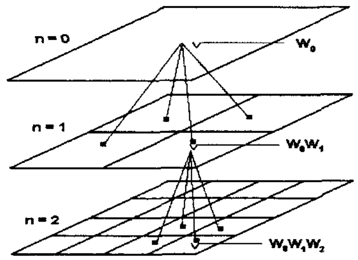

Fig. 1 Schematic of cascade branching

When the process of subdivision is continued, the volume $\mu_n(\Delta_n^i)$ in the sub areas at the nth level of subdivision (Δ_n^i, i = 1, 2, ..., b^n) are given by

$$\mu_n(\Delta_n^i) = R_o L_o^d b^{-n} \prod_{j=1}^{n} W_j^i \quad (2)$$

where for each j level, i represents the sub area along the path to the nth level sub area; R_o is initial average rainfall intensity; L_o is the outer length scale; W_j^i is the jth level cascade generator for ith sub area number, which is given by beta lognormal model as

$$W = BY \quad (3)$$

And, $$B = \begin{cases} 0 & for\ probability\ 1 - b^{-\beta} \\ b^{\beta} & for\ probability\ b^{-\beta} \end{cases} \quad (4)$$

$$Y = b^{-\frac{\sigma^2 \ln b}{2} + \sigma X} \quad (5)$$

Here, b is branching number; β is a parameter; X is normal random variate and σ^2 is a parameter equal to the variance of $\log_b Y$ with condition that $E[Y] = 1$ and $E[W] = 1$.

This model is able to reproduce statistical characteristic and spatial patterns of rainfall field upon downscaling in a longer time range. However, the downscaled results are quite random in almost snapshot comparisons. Tachikawa et. al.[6] tried to incorporate the control effect of altitude in rainfall. This trial also succeeded to reproduce the long-term information only.

INTRODUCING HSA METHOD

A new method is introduced here, which utilize the spatial correlation information of rainfall field to adjust the location of random generators. A decreasing trend of spatial correlation is appeared in rainfall field with increase in distance such that the correlation appears to be negative or zero approximately around 100 km and beyond. Therefore the rain events are not totally random events.

This method principally evaluates correlation reference indexes with respect to the average rain intensities of the surrounding 8 coarse scale grid squares using a correlation relationship. The spatial locations of random cascade generator are then assigned on the basis of hierarchical comparison between the correlation reference indexes and the random cascade generators. This process principally does not introduce any arbitrary bias to the random cascade generators because the generators are independent to the spatial locations unlike the trials introduced by Jothityangkoon et al.[7] and Tachikawa et al.[6] , in which, an additional G component is included to the model of Over and Gupta[1,5]. The controlled assignment of generators on the basis of correlated reference index is just a re-arrangement in another sense. Such arrangements are believed to preserve the existence of hierarchical structure of rain band, which is one major component of meso scale rain cells.

$$G_{ij} = \sum_{k=1}^{8} R_k \rho_{X_k} \qquad (6)$$

Here, G_{ij} is the reference index for ij^{th} cell; R_k is the rainfall of k^{th} neighbor cell; ρ_{X_k} is the correlation with the k^{th} neighbor viewed from ij location, from where the distance up to the k^{th} neighbor becomes X_k.

$$X_k = \sqrt{(i_k - i)^2 + (j_k - j)^2} \qquad (7)$$

As the level of downscaling progresses, the sizes of both the correlation reference indexes' matrix (***G***) and random cascade generators' matrix (***W***) also grow together by 2^n. The statistics such as the mean (μ), standard deviation (σ) and mutual correlations between the ***G*** and ***W*** matrix sets are calculated. If the correlations are not found good between ***G*** and ***W*** matrixes, then the ***W*** values of the cells, whose ***G*** values are above (μ_G + σ_G) in ***G*** matrix are interchanged to the position whose ***W*** values are lying below (μ_W - σ_W) in ***W*** matrix and vice versa. The process is repeated until either the mutual correlation improvement saturates or the mutual correlation improvement is higher than 80%.

RESULT AND DISCUSSION

The Random cascade method included with HSA method is found promisingly successful to produce the spatial pattern as that of the source data (see Fig. 2). Beside this, it is largely successful to reproduce the result in repeated trials. Of course, the magnitude does not remain same, as they depend upon the randomly created generators as that of conventional random cascade downscaling but the spatial patterns are almost similar in repeated trials. This occurs basically due to relocation of the random generators referring the indexes, which gives a feedback of rainfall spatial correlation based on coarse grid information. Upon the downscaling trial of 2952 events, the average correlation is found to be improved to 0.595 from 0.345 between the downscaled data and source data, which shows a good improvement in performance.

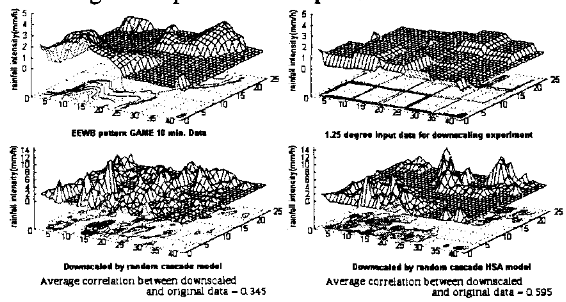

Fig. 2 Comparison of downscaled results

Acknowledgment: The contribution of providing program source code for random cascade generators by Mr. Hiwasa, DPRI, Kyoto University is highly acknowledged.

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