Modeling of Fine Resolution Precipitation Data Using GAME Data Product and Validating Against the Spatial Patterns of HUBEX-IOP-EEWB Data

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Abstract

Multiplicative Random Cascade (RC) method is a stochastic tool to model a fine resolution precipitation data, which is based on assumption that the precipitation structure is Multifractal. The random process involved within it, which often causes the results either to differ largely in between repeated trials or to differ from a measured one, dominates existing RC method. This weakness is necessary to remove before adopting the method as a reliable tool of modeling the fine resolution precipitation field. Noticing that the spatial rainfall field contains spatial correlation, we attempted to include this information in a RC method. First, we evaluate a reference matrix, which accounts for the spatial correlation effect of a coarse precipitation field and the distance from the nearest point of coarse grid to the center of a grid at the fine resolution. Then, this reference matrix assists to find the location of a cascade generator by comparing the hierarchical order. It also assists to re-allocate the statistically filtered peak values to a proper location. This method, named as Multiplicative Random Cascade with Hierarchical and Statistical Adjustment (RCHSA) method, was used to model the fine resolution precipitation data (10-arc minute resolution) using GAME Reanalysis 1.25 degree data as the input. Comparing the spatial patterns of over 40,000 test outputs from the RCHSA method against the spatial patterns of the HUBEX-IOP-EEWB data, it revealed that the RCHSA method was largely successful to remove the weakness of the RC method. The overall performance was improved to 0.6 from 0.34 after including the HSA method. This has helped us to use the GAME 1.25 degree data product in hydrological simulations of catchments as small as of 2000 sq. km. scale successfully.

Keyword: rainfall downscaling, random cascade method, HSA method, spatial correlation.

1. Introduction

Precipitation data are the important binding forcing to understand space time variability of meteorological and hydrological conditions, and to drive small to large-scale and short to long-term simulations in both sectors. GAME Re-analysis project, started in 1999 in Japan with a joint effort of Meteorological Research Institute Numerical Prediction Division / Japan Meteorological Agency and Earth Observation Research Center, had aimed to obtain higher quality data using the most updated assimilation system, the 4DDA, and the off-line data collected during GAME-IOP period. This project released the GAME re-analysis data in September, 2000. Before the release, it conducted the case study of heavy precipitation in the Yangtze River in addition to comparison of the re-analyzed data with ECMWF and NCEP products (Yamazaki et al., 2000). This is an example of use of the precipitation data `to evaluate the performance of a numerical model in meteorological data acquisition system.

Three different sets of the GAME re-analysis product were released in its version 1.1 package having different horizontal resolutions, 2.5-degree, 1.25-degree and 0.5-degree including 3-dimensional analyzed fields and two dimensional forecasted fields. The data have covered the summer of 1998. The effort of releasing multi-resolution data product was appreciable realizing the fact that what we observe at a scale does not necessarily be true at another scale, though there remained an unanswered question "how many different resolutions are to release?" Provided a finer resolution data, there is comparatively little trouble in getting a coarser resolution data which have averaged intensity in a wider region and smoother spatial pattern. But to obtain a finer resolution data, in terms of the precipitation data, from a coarser resolution data is a challenging task as it needs to describe the sub-grid scale variability, particularly in the subtropical and temperate monsoon regions of East Asia, where the energy and water cycle is characterized largely by the Baiu front in summer. Various scales of cloud/precipitation systems associated with the complex processes between air and land-surface are formed in this frontal zone and they play a major role in this region making it hard to describe the sub-grid scale variability.

Attempts to obtain a sub-grid scale spatial variability of the precipitation are headed toward two major directions. The first direction is mainly developed in meteorology literature describing the atmospheric dynamics and thermodynamics. There are some practical difficulties to obtain finer resolution outputs over long timescale due to complexities of nesting boundary conditions, unknown parameterization for convective precipitation, and multiscale variability of deep convection through this direction (Giorgi and Mearns, 1991; Houze, 1997; Chen *et al.,* 1996). Also, there are many unknowns in describing the microphysics of the intermittent precipitation mechanism in finer resolution. The second direction is mainly developed in hydrology literature that leads to the description of spatial organization of the precipitation in terms of intensity at multiple scales. In this discipline, the recognition of the hidden sub-grid scale features from the coarse fuzzy information has become a major key to disaggregate the precipitation data into finer resolution using probabilistic models of space-time rainfall.

The second approach is based on the scaling invariance features of observed spatial rainfall fields

(Schertzer and Lovejoy, 1987; Lovejoy and Schertzer, 1990; Gupta and Waymire, 1990) with extreme variability and strong intermittence (Georgakakos and Krajewski, 1996), which has yielded a multiplicative random cascade theory (Lovejoy and Schertzer, 1990; Gupta and Waymire, 1993). Due to the scaling invariance or self-similarity concept in this approach of space-time rainfall modeling, the parameterization is parsimonious and valid over a wide range of scales (Lovejoy and Schertzer, 1990; Gupta and Waymire, 1993; Over and Gupta, 1994; Foufoula-Georgiou and Krajewski, 1995; Olsson, 1996).

The objective to obtain further finer resolution precipitation data than that of the currently available one has multi-purpose attraction either in research or in application studies. In this study, we present the results of out attempt to model the fine resolution precipitation data using the GAME 1.25-degree two-dimensional forecast field. We compare the outcome of the model with the spatial patterns of HUBEX IOP EEWB data (Kozan *et al.* 2001

2. Description of the model

A multiplicative cascade treatment based on the statistical theory of turbulence (Mandelbrot, 1974) offers a concrete way of modeling these fields (Schertzer and Lovejoy, 1987) as the kinetic energy transfer is seen in the cascade of turbulent eddies from a large energy scale to smaller dissipation scales. Similarly, in the cascades of precipitation modeling, an area of higher intensity precipitation is embedded in larger areas of lower intensity precipitation, which are again a part of even larger areas but of even lower intensity. This can be described either in continuous or in discrete form of multiplicative cascades. Debates are ongoing on suitability of approaches to form the multiplicative random cascade whether the continuous or discrete. The continuous form of multiplicative random cascades has the major advantage of developing cascades over a continuous interval of scales instead of only a discrete set (Marsan *et al.,* 1996); however, the discrete form of multiplicative random cascade has ability to separate rainy and non-rainy area (Gupta and Waymire, 1993; Over and Gupta, 1994) and can be adopted to respect the discrete sub catchment partitioning of the landscape by the drainage network of a catchment (Gupta *et al.,* 1996; Over and Gupta, 1996). We choose here a discrete multiplicative random cascade method, so called the beta lognormal model developed by Over and Gupta (1994, 1996) and apply a method to improve the shortcoming of the model. This is called as the multiplicative random cascade HSA method (Shrestha et al., 2004)

2.1. The beta lognormal model

In the beta lognormal model, the cascade construction process successively divides a two-dimensional region into equal parts at each step, and during each subdivision (say n = 2) the mass (or volume) of rainfall over the region obtained at the previous step (n = 1) is distributed into the b subdivisions (for the case of d = 2; b = 4) by multiplying by a set of "cascade generators" W, as shown schematically in Figure 1.

For an area at level 0, denoted by Δ_0^0, has the outer length scale of L_0 and average precipitation intensity of R_0. The initial volume $\mu_0(\Delta_0^0)$ becomes $R_0 L_0^d$. At level 1, the volume $\mu_0(\Delta_0^0)$ divides into b = 4 sub-areas denoted as Δ_1^i, (i = 1, 2, 3, 4) and the sub-area volume $\mu_1(\Delta_1^i)$ is $R_0 L_0^d b^{-1} W_1^i$, (i = 1, 2, 3, 4). At level 2, each of the sub-area volume is further subdivided into b = 4, all together b^2 = 16 sub sub-area, denoting them as Δ_2^i, (i = 1, 2, ..., 16) and the corresponding volume $\mu_2(\Delta_2^i)$ is $R_0 L_0^d b^{-1} W_1^i W_2^i$, ($i$ = 1, 2, ..., 16). The process of sub-division is continued further until the n^{th} level up to b^n sub-areas, which are denoted as Δ_n^i, (i = 1, 2, ..., b^n). At the n^{th} level, the volume in the sub-areas can be expressed as

$$\mu_n(\Delta_n^i) = R_0 L_0^d b^{-n} \prod_{j=1}^{n} W_j^i \quad ; (i = 1,2,..., b^n) \qquad (1)$$

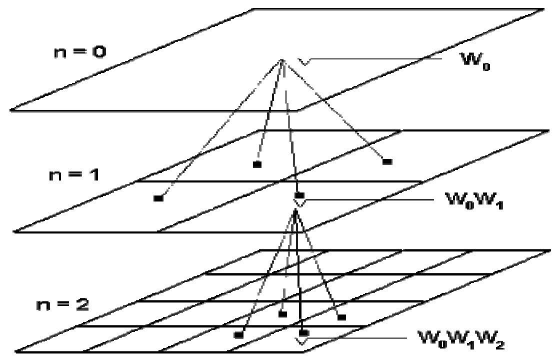


Fig. 1: Schematic of cascade branching

The cascade generators W are non-negative random values with $E[W]$ = 1, which is imposed to ensure the mass conservation from one discretization level to the next (see Over and Gupta, 1996). To get the cascade generator W values, Over and Gupta (1994, 1996) has proposed a model called beta-lognormal model such that

$$W = BY \qquad (2)$$

Here, B is a generator from the "beta model" that separates the rainy and non-rainy zone on the basis of discrete probability mass function and Y is obtained from lognormal distribution (Gupta and Waymire, 1993) in the form of $Y = b^{\left(\sigma X - \frac{\sigma^2 \ln b}{2}\right)}$, where X is standard normal random variate and σ^2 is a parameter equal to the variance of $\log_b Y$. The value of W is evaluated as

$$W = \begin{cases} 0 & when \quad P(B=0) = 1 - b^{-\beta} \\ b^{\beta + \sigma X - \frac{\sigma^2 \ln b}{2}} & when \quad P(B = b^{\beta}) = b^{-\beta} \end{cases} \qquad (3)$$

This model consists of only two parameters, β and σ^2. The parameter estimation method is proposed by Over and Gupta (1994, 1996) by using the Mandelbrot-Kahane-Peyriere (MKP) function, named after Madelbrot (1874) and Kahane and Pyeriere (1976), which characterizes the fractal or scale-invariant behavior of the multiplicative cascade process.

This method is largely dependent on the spatial structure of generators, which is a random process within this method. The random nature of the generators often causes the results either to differ largely in between repeated trials or to differ from a real one. To remove the weakness, the following method has been employed in this study.

2.2. The HSA method

In smaller spatial scale, the precipitation fields have strong spatial correlation. This phenomenon was appeared in the GAME 1.25 degree precipitation data too, although the data is of coarse resolution. Figure 2 shows the spatial correlation of the precipitation data.

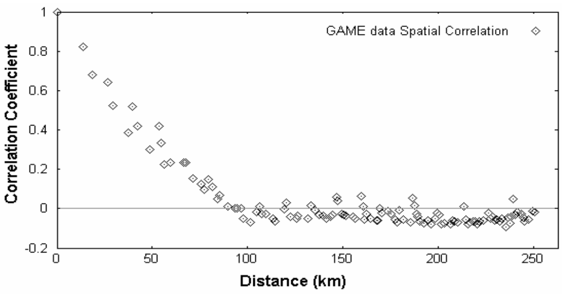


Fig. 2: Spatial Correlation of the precipitation data

The spatial correlation gradually decreases upon increase of distance. The decaying shape of the spatial correlation function may be represented by a logarithmic function (equation 8). This is given by

$$\rho_Z = \begin{cases} \alpha + \kappa \log_\lambda Z & \text{if } \left(\rho_Z > 0 \text{ and } Z < Z_0\right) \\ 0 & \text{if } \left(\rho_Z < 0 \text{ or } Z > Z_0\right) \end{cases} \tag{8}$$

$$Z_0 = anti \log_\lambda \frac{\rho_Z - \alpha}{\kappa}, \text{ for } \rho_Z = 0 \tag{9}$$

where, Z is distance in kilometers; ρ_Z is the spatial correlation value at Z; Z_0 is the threshold beyond which the spatial correlation remains zero by the use of the logarithmic spatial correlation function with α , κ and λ parameters.

In the process of cascading down of a two dimensional (d = 2) spatial field, the b^n numbers of sub-areas, named as, (i = 1, 2, ..., b^n) are obtained at the n^{th} level with the grid dimension L_0 / d^n . For each of these sub-areas, a spatial correlation reference index H is evaluated, which works as a spatial guide matrix. The reference index H is influenced by the average rain intensities R_m of the surrounding eight coarse scale grids (m = 1, 2, …, 8) and corresponding distances of the sub-area from the referred neighbor grid Z_n^m . For n^{th} level, the reference index H can be represented as,

$$H_n^{jk} = \sum_{m=1}^{8} R_m \rho_{Z_n^m} \quad ;\text{for} \quad \begin{matrix} j = 1,2,...,d^n \\ k = 1,2,...,d^n \end{matrix} \tag{10}$$

$$Z_n^m = \sqrt{\left(x_m - x_j\right)^2 + \left(y_m - y_k\right)^2} \tag{11}$$

where, H_n^{jk} is the non-negative reference index at n^{th} level for jk^{th} sub-area; R_m is the rainfall of m^{th} neighbor cell; $\rho_{Z_n^m}$ is the spatial correlation with the m^{th} neighbor viewed from jk^{th} location at n^{th} level, from where the distance up to the m^{th} neighbor becomes Z_n^m . For the sub-area, the x_j and y_j represents the central point of the sub-area.

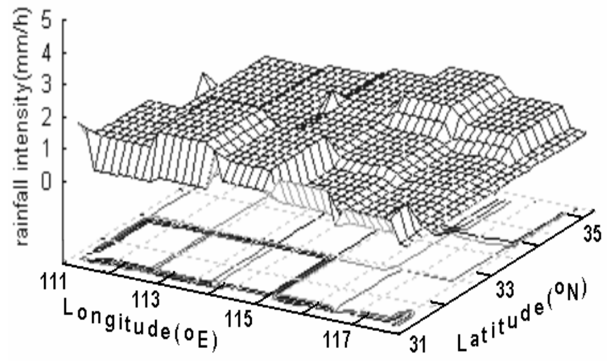
The multiplicative random cascade HSA method assigns the W_n^i values by preserving the spatial correlation structure of the precipitation field such that,

$$W[\bullet] = BY \tag{12}$$

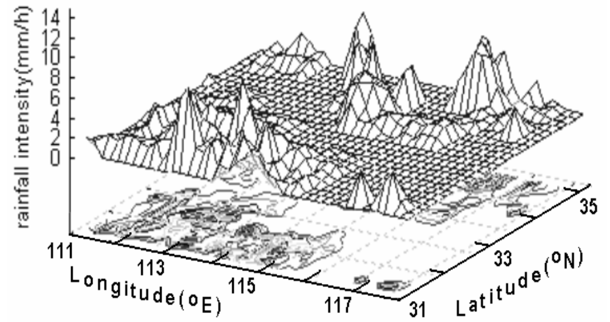
where, $W[\bullet]$ represents the W with its spatial address $[\bullet]$. The reference index H_n^{jk} is used to obtain the spatial address $[\bullet]$ using its two dimensional spatial reference j and k inside the sub-dividing region.

At every additional level (n+1), four more random cascade generators, $W_{n+1}^{i'}$ (i' = b^{n+1}-3, b^{n+1}-2, b^{n+1}-1, b^{n+1}) appear for newly disaggregated sub-area $\Delta_{n+1}^{i'}$ from Δ_n^i , ($i = b^n$). Their spatial address $[\bullet]$ is determined on the basis of comparison between the reference indexes $H_{n+1}^{j'k'}$ and the random cascade generators $W_{n+1}^{i'}$. The $W_{n+1}^{i'}$ may need to reshuffle its location within $\Delta_{n+1}^{i'}$ in order to attain same hierarchy of $H_{n+1}^{j'k'}$ locations. This process includes a spatial correlation structure into the cascade generators in successive progress of disaggregation.

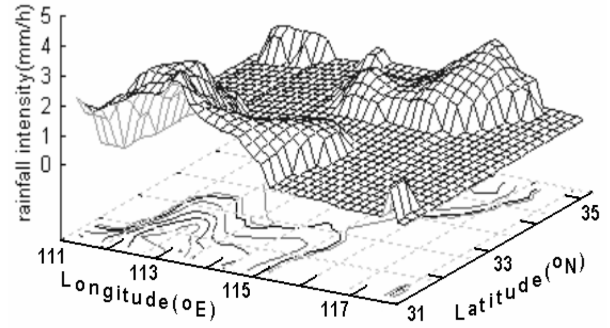
The spatial H_n field is a smooth gradient surface and its shape is based on the surrounding coarse grid average rainfall. The lowest and highest zones of the H_n field are most possibly the non-rainy and rainy zones respectively. If the peak rainy cells of the $\mu_n(\Delta_n)$ field are not in accordance with the rainy zones of H_n field and vice versa, a statistical filter is applied to improve it. Though these extreme high and low value cell numbers may not be significant to influence spatial statistics, they might have practical significance. Therefore at the n^{th} level, spatial locations of the extreme $\mu_n(\Delta_n)$ values are re-adjusted following hierarchical order of H_n field after statistical separation of extreme high and low values from both fields. The statistical adjustment is omitted if the correlation of H_n field and $\mu_n(\Delta_n)$ field is found higher than a target correlation, which is adapted 80% arbitrarily in this case.



(a) GAME 1.25-degree data



(b) Fine resolution data obtained by the model



(c) HUBEX-IOP EEWB data

Fig. 3: Spatial patterns of the precipitation data obtained from a) GAME 1.25-degree precipitation data; b) output of the modeling of fine resolution precipitation data using the GAME data; and c) HUBEX-IOP EEWB precipitation data used to compare the result of the model

3. Results and Discussion

The experiment was successful to produce a fine resolution precipitation data. Figure 3 shows a typical result of this kind. Figure 3a is the GAME 1.25-degree data and Figure 3b is the 10-minute resolution precipitation data. The results were compared with the spatial patterns of the precipitation data collected by the HUBEX-IOP during the same period (Figure 3c). Comparison of the spatial patterns shows good match in between the two precipitation data sets. In another test without the HSA method, so-called as the RC method, the fine resolution precipitation data were found having very different spatial pattern from that of the HUBEX-IOP EEWB data. While the performance of the RC method yielded 0.34 in the test of spatial covariance between the HUBEX-IOP EEWB data and the modeled fine resolution data using the RC method, the RCHSA method, as described in this study, yielded 0.6. This confirms the improved ability of modeling fine resolution data using the GAME 1.25-degree product. The modeled fine resolution precipitation data may not necessarily represent a true precipitation pattern even though it perfectly match with the HUBEX-IOP EEWB data because there could be uncertainty within the HUBEX-IOP EEWB data itself. Their ground based observation data, however, provides the most detailed spatial structure of the precipitation data in the study region. We foresee the possibility of using the modeled data in hydrological simulation of smaller catchments, much smaller than the size of a grid-cell that the GAME 1.25-degree data have, if the modeled fine resolution data can generate similar data as that of the observed one. The HUBEX-IOP EEWB precipitation data provides a smooth spatial pattern, which is the obvious result of interpolation that was employed to make the spatially distributed data from a network of point observed precipitation data (Kozan *et al.*, 2001). The modeled results are not as smooth as the interpolated field. Even being the modeled outputs able to preserve the spatial pattern in terms of separation of rainy zones and non-rainy zones, they include a higher degree of spatial heterogeneity. Definitely, this is the effect of the random generators. The rainfall magnitudes at a particular cell, however, do not remain exactly same in the repeated trials, as they depend upon the generators based on the cascade of multiplication of the random numbers inside the model despite their superb capability of preserving the same spatial patterns. We argue this as a beneficial point of the suggested method to infer the probability of uncertainty in rainfall phenomenon, which might help to understand the consequences of rainfall uncertainty in rainfall-runoff modeling.

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