A SPATIAL DOWNSCALING MODEL FOR INDIAN RAINFALL

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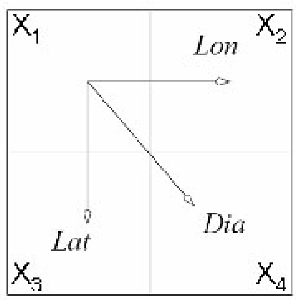
Abstract— In this work, we have focused on the development of a spatial downscaling model using data from the TRMM (Tropical Rainfall Measurement Mission) satellite. Specifically, the 3B42V6 data, which is available at 0.25^0 X 0.25^0 (approximately 25 X 25 km) spatial resolution and 3-hourly temporal resolution, has been considered over the Indian region and scaling laws have been developed, which relate the rainfall variability across a range of spatial scales (25 km to 100 km). The scaling relations are then used to downscale the aggregated (smoothed) satellite fields to smaller scales, compare with the original satellite snapshots and demonstrate the validity and efficiency of the proposed downscaling scheme in terms of being able to reproduce small-scale variability.

1. INTRODUCTION

Over the last few decades, significant progress has been made in forecasting large-scale rainfall with weather and climate models. However, simulation of the meso-scale variability of rainfall, which is useful and important in accurately predicting hydrologic variables such as peak runoff or time of concentration, is still largely beyond the capability of global and regional models. These models operate at a scale which is much coarser than that needed for hydrologic applications. The need to unify descriptions over scales (i.e., rainfall variability over a small area with rainfall variability over a larger scale) and to parsimoniously parameterise subgrid-scale ("small scale") rainfall variability, has prompted the introduction of new ideas and tools for analysing and modeling space-time rainfall patterns: namely, the concept of scale-invariance.

Many studies (e.g., Schertzer and Lovejoy 1987, Gupta and Waymire 1990, Lovejoy and Schertzer 1991, Kumar and Foufoula-Georgiou 1993a, b) have shown the existence of scale-invariance in spatial and temporal rainfall. Scale-invariance in a process suggests that a property of the process (or a related observable) at one (space or time) scale can be statistically related to the property at another (space or time) scale by a simple renormalisation involving just the ratio of scales. Specifically, if P represents a property of the process (e.g., rain-intensity), λ_1 and λ_2 represent the two scales of interest (space or time), and f_P represents the probability density function of P, then the presence of statistical scale invariance in the property suggests that $f_P(\lambda_1) = (\lambda_1/\lambda_2)^H f_P(\lambda_2)$, where H, the so-called scaling parameter, depends on the process - for instance, convective rainfall would have a different H from a stratiform type of rainfall. Moreover, there appears to be evidence suggesting that scaling parameters (when scaling is present) are dependent on the region under study (for instance, mountainous vs. flat terrain; forest vs. urban areas). Scaling relations, if present, can then be used to develop seasonal (i.e., monsoon) downscaling models. The primary goal of statistical downscaling of precipitation fields is to provide an easy way of resolving fine-scale variability which can, in turn, be used to drive hydrologic models. Over the Indian region, such studies, however, have not been done extensively.



$$\bar{X} = X_1 + X_2 + X_3 + X_4$$
$$X_1' = (X_1 + X_2) - (X_3 + X_4)$$
$$X_2' = (X_1 + X_3) - (X_2 + X_4)$$
$$X_3' = (X_1 + X_4) - (X_2 + X_3)$$

$$\xi_i = \frac{X_i'}{\bar{X}} \quad i = 1,2,3$$

Fig. 1: ***Schematic illustrating the construction of the mean and directional fluctuations at each scale. This process is repeated for a range of scales starting from the given resolution.***

In this work, we focus on the downscaling scheme of Perica and Foufoula-Georgiou (1996b). In their studies, they analysed standardised spatial fluctuations of rainfall and showed that scale-invariance exists over a range of 4 to 32 km. Furthermore, they used this aforementioned spatial organisation in developing a spatial downscaling scheme and tested it successfully on many single-site radar-observed data sets. In this work, we will show that scale-invariance in standardised spatial fluctuations can be extended to larger scales, and more importantly, the spatial downscaling scheme can be used to successfully resolve the variability of rainfall at scales of importance to hydrologic applications, i.e., important statistics such as mean, standard deviation and percentage of rainy-area within the observed domain are preserved. Specifically, we utilise satellite observations at 25km spatial resolution and demonstrate via a multiresolution wavelet framework that scaling relations that have been found between 4km and 32km (e.g., see Perica and Foufoula-Georgiou 1996, Venugopal *et al.* 1999) can be extended to larger scales, namely up to and beyond climate scales (~200 to 400 km).

2. Data and Methodology

The rainfall observations that have been used in our study are obtained from the TRMM (Tropical Rainfall Measurement Mission) data archive (e.g., Adler *et al*. 2000, Kummerow *et al*. 1998). These satellite observations are at a nominal spatial resolution of 25 km and a temporal resolution of 3 hours. We first convert the 3-hourly snapshots into daily accumulations at 25 km resolution and explore for scaling relations of the daily accumulations for the summer monsoon period (June through September, hereafter denoted as JJAS). We have analysed the observations for 9 years (1999-2007). In other words, we analyse 122 snapshots (corresponding to 122 days of the monsoon season) per year for scaling relations. The region that has been taken for our analysis is given by the following coordinates: 65-98E, 6N-38N.

The methodology used for our analysis stems from the dyadic multiresolution wavelet framework proposed by Mallat *et al*. (1989) and used by Perica and Foufoula-Georgiou (1996) on radar observations. The main idea is to decompose a given 2-dimensional snapshot into its mean and three components corresponding to horizontal, vertical and diagonal fluctuations. Fig. 1 shows a simple schematic illustrating the procedure. This process is repeated at every scale. For instance, if we have an image of size 128 x 128 pixels, on the first stage of the decomposition/coarsening, we have the mean, and three directional fluctuations (see Fig. 1), each of size 64 x 64. In the second stage of decomposition, the resulting mean and fluctuations will be of size 32 x 32. This process if repeated until we reach a scale where is a sufficient number of samples for any meaningful estimation of the statistics. It has been found that the fluctuations of rainfall are dependent on the local averages, i.e., small fluctuations tend to predominantly associate themselves around small intensities while large fluctuations are associated with large intensities [e.g., see Perica and Foufoula-Georgiou 1996a, Venugopal *et al*. 1999]. To eliminate this dependency, one can form standardised fluctuations, i.e., the fluctuations are normalised by the local averages. In other words, if ξ represents the process of standardised fluctuations, then, following Fig. 1, $\xi_1 = X_1^{'} / \overline{X}$ etc. The distributions of these normalised/standardised fluctuations are then analysed for the presence of scale-invariance.

3. Results and Discussion

We illustrate our analysis and downscaling procedure using the daily accumulation of August 1, 2003 as seen by the TRMM satellites. Starting from the original spatial resolution of 25km, we repeatedly average/smooth the data while retaining the directional fluctuations at each scale. In other words, as discussed in the previous section, gradients of rainfall intensity in the horizontal, vertical and diagonal directions (X_1', X_2', X_3' in Fig. 1) are constructed for a range of scales (50, 100, 200 and 400 km). These fluctuations are then normalised by the local spatial mean to form the standardised fluctuations. Thus, we have the mean and normalised fluctuations at each scale (λ).

The statistics of these normalised fluctuations (ξ_i) are then analysed as a function of scale. In addition to the fact that these normalised fluctuations can be well-approximated by a Gaussian distribution with zero mean (not shown), we observe that there exists scale-invariance in the second moment (standard deviation) of ξ_i (Fig. 2), i.e., the log-log linearity evident from Fig. 2. This also means that given the standard deviation at any scale, one can estimate the standard deviation of the normalised fluctuations at any other scale. Since a Gaussian distribution is completely described by its first two moments, the presence of scaling in the second moment implies that there exists scale-invariance in the distribution. Following the work of Perica and Foufoula-Georgiou (1996), these scaling relations, coupled with the fact that the normalised fluctuations follow a Gaussian distribution, help us develop a spatial downscaling model for the Indian region. The work presented here shows the testing of the conceptual idea of Perica and Foufoula-Georgiou (1996), shown in Fig. 3.

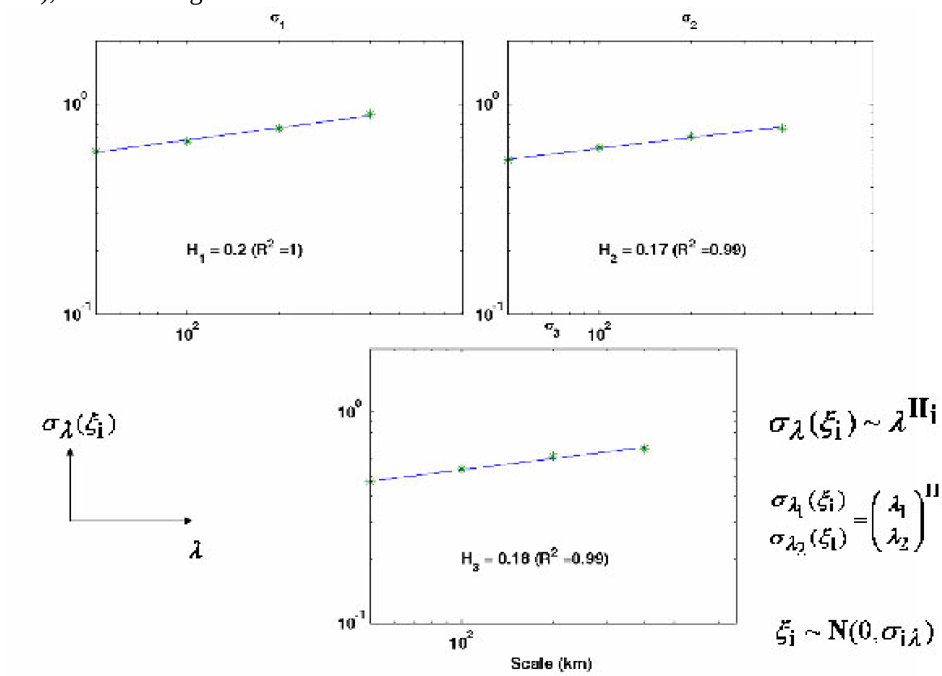


Fig. 2: ***Plot of the standard deviation of the normalised fluctuations as a function of scale (50 km to 400 km) for the daily accumulation of August 1, 2003. The log-log linearity evident from the figures suggests that given the standard deviation at any scale, one can estimate the standard deviation of the normalised fluctuations at any other scale. Another important observation is that the normalised fluctuations follow a Gaussian distribution (figure not***

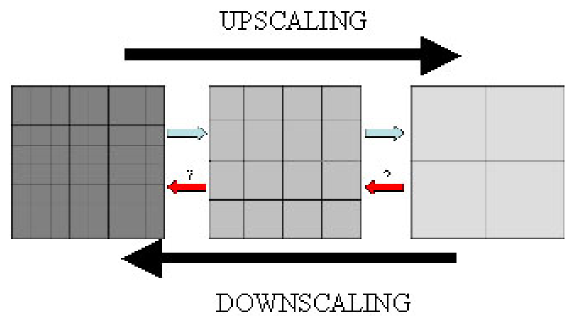


Fig. 3: ***A schematic of the spatial downscaling scheme, following the work of Perica and Foufoula-Georgiou (1996).***

The essence of the downscaling model is the following: The data at some given resolution is coarsened (upscaling; Fig. 3 left to right) up to a scale where there are enough number of samples to reliably estimate statistics, for the purpose of developing scaling relations. If scaling relations exist, then we start from the coarsest scale, say λ (right-most panel of Fig. 3), and generate Gaussian-distributed fluctuations at that scale (with a standard deviation σ_λ (ξ_i)). Then, using a linear combination of these ξ_i with the coarse-grained rainfall (i.e., the spatial rainfall field at λ), one can generate rainfall at a scale twice as fine as λ. This process is repeated till we reach the scale of interest. In other words, if we started with 200 km, one can successively generate stochastic realisations of rainfall at 100, 50, 25 km.

Fig. 4 shows the result of applying this downscaling model to a daily accumulation (August 1, 2003) of satellite snap-shots at a 25km resolution. The “simulated” field at each scale is an average of 10 ensemble members (since the proposed method is a stochastic approach, an ensemble mean is appropriate than choosing a single “best” realisation). This procedure was repeated for the entire month of August 2003.

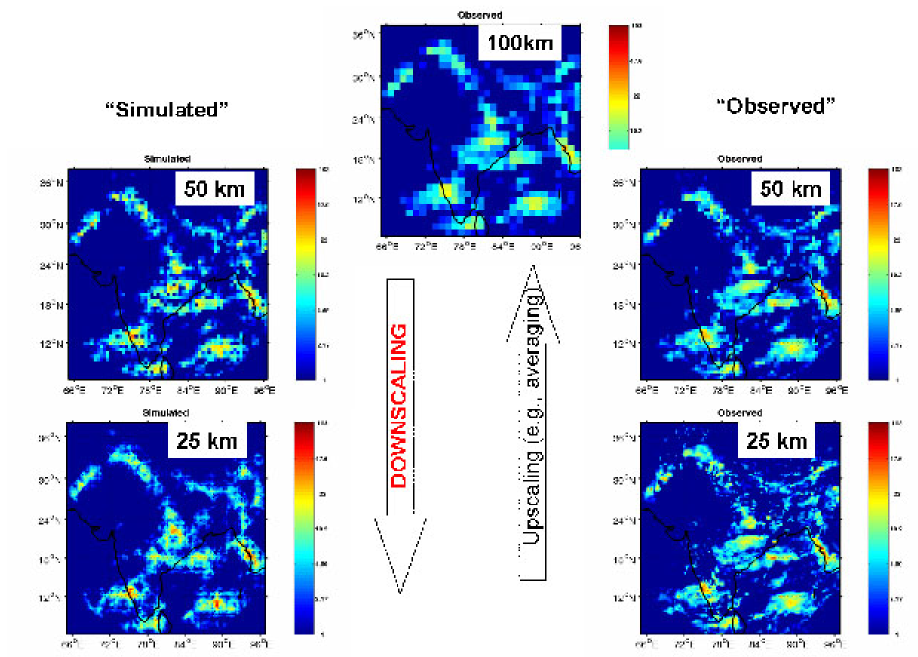


Fig. 4: ***Application of the proposed spatial downscaling scheme to daily accumulations of TRMM 3B42 rainfall data (August 1, 2003), available at 25 km X 25km.***

The comparison of the statistics of the resulting simulated fields (mean, standard deviation and percentage of rain-covered area) with those of the "observed" fields is shown in Fig. 5. Figs. 5a, b show the mean and standard deviation of the simulated and observed rainfall fields. While overall the performance in terms of matching statistics is broadly satisfactory, the one striking downside to the proposed methodology is that the percentage of rainy area is not captured well (Fig. 5c). Upon further investigation, we find that the difference in the simulation of percentage rainy areas comes from the poor simulation of the very low intensity rainfall (figure not shown).

4. SUMMARY

Using satellite-observed precipitation, we have demonstrated that scale invariance, characterising the variability of rainfall, exists over a large range of scales (50-400 km). These scaling relations were then used to develop a spatial downscaling model for rainfall. Preliminary testing of the spatial downscaling model as a conceptual tool by upscaling satellite data and downscaling the coarsened field indicates promise in reproducing the finer-scale statistics.

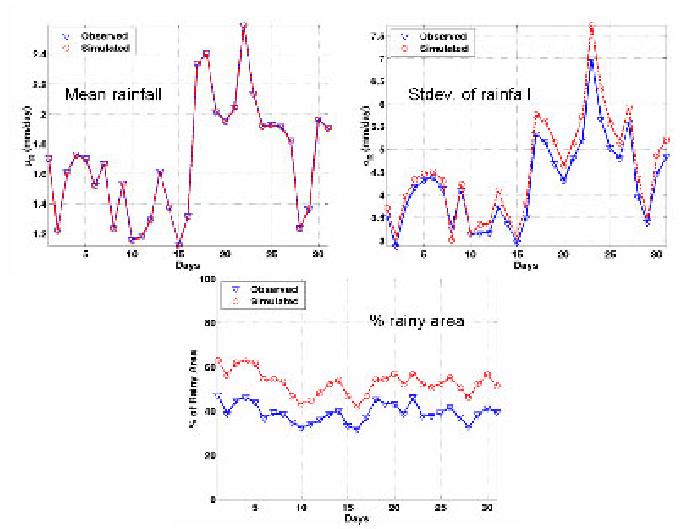


Fig. 5: ***Comparison of the (a) mean, (b) standard deviation and (c) percentage of rainy area of the observed and simulated rainfall fields at a spatial resolution of 25 km, for the month of August 2003.***

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