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Multisite rainfall downscaling and disaggregation in a Tropical Urban Area

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ABSTRACT

A systematic downscaling-disaggregation study was conducted over Singapore Island, with an aim to generate high spatial and temporal resolution rainfall data under future climate-change conditions. The study consisted of two major components. The first part was to perform an inter-comparison of various alternatives of downscaling and disaggregation methods based on observed data. This included (i) single-site generalized linear model (GLM) plus K-nearest neighbor (KNN) (S-G-K) vs. multisite GLM (M-G) for spatial downscaling, (ii) HYETOS vs. KNN for single-site disaggregation, and (iii) KNN vs. MuDRain (Multivariate Rainfall Disaggregation tool) for multisite disaggregation. The results revealed that, for multisite downscaling, M-G performs better than S-G-K in covering the observed data with a lower RMSE value; for single-site disaggregation, KNN could better keep the basic statistics (i.e. standard deviation, lag-1 autocorrelation and probability of wet hour) than HYETOS; for multisite disaggregation, MuDRain outperformed KNN in fitting interstation correlations. In the second part of the study, an integrated downscaling-disaggregation framework based on M-G, KNN, and MuDRain was used to generate hourly rainfall at multiple sites. The results indicated that the downscaled and disaggregated rainfall data based on multiple ensembles from HadCM3 for the period from 1980 to 2010 could well cover the observed mean rainfall amount and extreme data, and also reasonably keep the spatial correlations both at daily and hourly timescales. The framework was also used to project future rainfall conditions under HadCM3 SRES A2 and B2 scenarios. It was indicated that the annual rainfall amount could reduce up to 5% at the end of this century, but the rainfall of wet season and extreme hourly rainfall could notably increase.

Key words: downscaling; disaggregation; GLM; KNN; HYETOS; MuDRain.

1. Introduction

High-resolution spatial and temporal rainfall data is essential for studies of water resources management, hydrological modeling, and flood risk assessment. This is especially true for tropical urban areas where highly complex rainfall patterns exist (Abustan *et al.*, 2008). The previous studies on climate variables and their implications to runoffs have highlighted the necessity to have input data at short timescales for many hydrological models (Mezghani and Hingray, 2009). However, high-resolution data is limited at many regions due to restrictions of cost, technical capability and physical geographic condition. It is also challenging to conduct high-resolution impact studies for hydrological systems under climate change, due to the coarse resolution of general circulation models (GCMs). Using statistical methods (such as spatial downscaling and temporal disaggregation methods) to generate high-resolution rainfall data has demonstrated a viable alternative and the number of the related studies has increased dramatically in the past years.

The fundamental concept of statistical downscaling is to build a linkage between the variables of GCMs at a large scale (predictors) and local observed weather information (predictands) (Fowler, *et al.*, 2007). The widespread used downscaling models could be classified into three types: (i) linear regression models, such as statistical downscaling model (SDSM) (Wilby *et al.*, 2002), generalized linear model (GLM) (Chandler and Wheater, 2002), and automated statistical downscaling tool (ASD) (Hessami *et al.*, 2008); (ii) non-linear regression models, such as artificial neural network (ANN) (Zorita and von Storch, 1999) and support vector machine (SVM) (Tripathi *et al.*, 2006); (iii) weather generators, such as Long

Ashton research station-weather generator (LARS-WG) (Racsko *et al.*, 1991), 'Richardson' type weather generator (WGEN) (Wilks, 1992), and agriculture and agri-food Canada-weather generator (AAFC-WG) (Hayhoe, 2000). Among many alternatives, GLM is an effective stochastic rainfall model based on linear regression, and has proved to be advantageous in addressing issues of spatial correlation, site effect, and seasonal variations etc. Chandler and Wheater (2002) applied GLM to downscale atmospheric predictors at western Ireland, where logistic regression and gamma distribution were used for occurrence and amount modeling, respectively. Yang *et al.* (2005) employed GLM to generate daily rainfall at southern England, and showed that the model could reproduce properties at a scale ranging over 2,000 km^2. Tisseuil *et al.* (2011) used GLM, generalized additive model (GAM), aggregated boosted trees (ABT), and multi-layer perceptron neural networks (ANN) to downscale precipitation and evaporation at southwest France. The results showed that the three non-linear models had a better performance than GLM for modeling fortnightly flow percentiles. Beuchat *et al.* (2012) applied GLM with weighting schemes for downscaling rainfall at 27 sites covering Switzerland. The results showed that the downscaled rainfall exhibited a spatially coherent pattern at seasonal timescale, although spatial independence was assumed by the GLM method.

Many studies also focused on generation of rainfall at a finer timescale using different disaggregation methods. The major types include stochastic point process models (Rodriguez-Iturbe *et al.*, 1987; Rodriguez-Iturbe *et al.*, 1988; Khaliq and Cunnane, 1996; Heneker *et al.*, 2001; Debele *et al.*, 2007; Engida and Esteves, 2011), non-parametric resampling models (Prairie *et al.*, 2007; Nowak *et al.*, 2010; Kalra and Ahmad, 2011) and others (Gyasi-Agyei, 2005; Gyasi-Agyei 2011; Beuchat *et al.*, 2011). Among these models, HYETOS and K-nearest neighbors (KNN) were widely used. Koutsoyiannis and Onof (2001) developed a hybrid model based on the Bartlett-Lewis rectangular pulses model, called HYETOS. It added an adjustment procedure to assure the sum of disaggregated hourly data be consistent with the given daily data. Debele *et al.* (2007) applied HYETOS to disaggregate daily rainfall to hourly ones at Cedar Creek watershed in US. Prairie *et al.* (2007) explored a stochastic nonparametric method, KNN, for spatial-temporal disaggregation of stream flows, and indicated that the KNN method could guarantee the simulation of statistical properties in the original space (historical record). Kalra and Ahmad (2011) applied KNN nonparametric method to generate seasonal precipitation by disaggregating annual precipitation, and the study results indicated that the KNN method performed better than the first-order periodic autoregressive parametric approach, and the seasonal precipitation reproduced on winter and spring seasons was more satisfactory. These studies focused on single-site disaggregation. For multiple sites, the cross-correlation becomes an important factor to be considered. Some studies attempted development of stochastic weather generators for multi-site rainfall generations (Wilks, 1998; Burton et al. 2008; Jennings et al., 2010), but most of them were not able to deal with disaggregation at the same time. As a viable attempt, Koutsoyiannis *et al.* (2003) developed a method, called MuDRain, by combining a simplified multivariate rainfall model and transformation model to disaggregate daily rainfall to hourly ones at multiple sites. In the study of Debele *et al.* (2007), MuDRain model was applied and showed an outperformed result for reproduction of expected statistical properties (e.g. average hourly rainfall, standard deviation, probability of wet hour and skewness) with small RMSE values, especially for the reproduction of peak value and temporal distribution; more importantly, the inter-site cross-correlation could be captured very well.

Based on the above review, it is recognized that many hydrological applications require a full spatial distribution of rainfall at finer timescale. This is especially true for climate change impact studies, where the global circulation models could only offer projections at coarse spatial and temporal resolutions. Hence, integrated downscaling and disaggregation effort is necessary as it provides rainfall data with both high spatial and temporal resolutions to meet the requirement of hydrological modeling. There are relatively few studies in such an area. Segond *et al.* (2006) proposed a combined spatial-temporal downscaling and disaggregation approach using GLM, HYETOS and an artificial profile multisite transformation method. In this approach, the daily data was generated by GLM for multiple sites; HYETOS was used for disaggregating daily data to hourly ones at the master station which contained a historical hourly record; then, the disaggregated hourly data pattern was projected to other sites (i.e. satellite stations) using the artificial profile method. The disaggregation results showed that the desired statistical properties were maintained at acceptable levels, while the inter-site correlation was somewhat overestimated. Mezghani and Hingray (2009) developed another combined downscaling-disaggregation approach for both temperature and rainfall over the Upper Rhone River basin in the Swiss Alps. GLM was used for downscaling mean areal weather variables (including total precipitation, rainfall and temperature) from GCM model, and KNN was used for disaggregating them to sub-daily and sub-regional scales. The study results showed a good performance of the proposed method in generating statistical relationship, including spatial cross-correlations.

Generally, the integration of spatial downscaling and temporal disaggregation could offer high-resolution rainfall data projected from GCM scenarios, and has great potential to help examine the impact of climate change on rainfall patterns and hydrological systems. From reviewing the recent research works, it turns out that such studies are relatively limited. Essentially, there is a lack of an inter-comparison study that could show the advantages or limitations of various options of single-site or multisite rainfall downscaling and disaggregation techniques that could keep the key statistics at different time scales, particularly in connection with the output from a downscaling model. In addition, most of the previous studies focused on a relatively larger scale watershed or basins. There are limited efforts on integrated downscaling and temporal disaggregation for the urban areas at Southeast Asia, which is characterized by tropical climate with rainfalls showing high temporal-spatial variations.

Therefore, the objective of this research work is to conduct a systematic rainfall downscaling-disaggregation study at a tropical urban area (i.e. Singapore Island). An inter-comparison study will be performed first to evaluate various options in implementing single and multiple site downscaling and disaggregation, based on statistical indicators (at daily and hourly scales) and observed data. Downscaling will essentially be based on GLM model as it has already been proved as an advantageous tool in keeping many key daily statistics of rainfall (Yang *et al.*, 2005). Options of KNN, HYETOS, and MuDRain will be tested for temporal disaggregation. Based on the comparison result, the deemed best option of downscaling-disaggregation framework will be used for projecting high-resolution rainfall patterns under future climate conditions for the Singapore Island. The paper will be structured as follows: the study area and data will be introduced first, followed by a description of the general methodology; results and discussions will be given afterwards, followed by a conclusion.

Study area and data

Singapore, with an area of about 723 km^2, locates at the equator pluvial region. Most of the surface elevation over the island is below 15 m, and the highest point is Bukit Timah hill which has a height of 165 m at the central region. The small hill leads to a 'rain shadow' phenomenon (Whiteman, 2000) that induces slight disparities of weather distribution on the western and eastern sides of the island (e.g. the western side of Singapore is wetter than the eastern one). Singapore has a rich precipitation, with an average annual rainfall amount being more than 2,400 mm. The highest record of daily rainfall was near 520 mm which happened at the wettest month, December. There are two monsoons occurring each year: the Northeast Monsoon from December to early March, and the Southwest one from June to September (NEA, 2009). Other months range in period between the two monsoons and have relatively less rainfall. Figure 1 shows the map of the study region and locations of eight rainfall stations that will be used in this study.

Six variables from National Centre for Environmental Prediction (NCEP) reanalysis data (Kistler *et al.*, 2001), re-gridded on Hadley Centre Coupled Model, version 3 (HadCM3) grids (Collins *et al.*, 2001) are used as the predictors to build the statistical relationship to local station data. They include: mean sea level pressure (*mslp*), 500 hPa geopotential (*p500*), 850 hPa geopotential (*p850*), near surface relative humidity (*rhum*), relative humidity at 500 hPa height (*r500*), relative humidity at 850 hPa height (*r850*), and near surface specific humidity (*shum*). The data has been pre-processed through standard normalization and are obtained from CCCSN (Canadian Climate Change Scenarios Network) project of Environment Canada (Dibike, *et al.*, 2008). In terms of predicands, 31-years continuous daily and hourly rainfall record from 1980-2010 at eight stations over the island are available.

For the downscaling study, the NCEP reanalysis data from 1980 to 2000 is used for training (or building) the GLM model. Then, the HadCM3 modeled data from 1980 to 2010 based on the established GLM model will be used to evaluate the validity of HadCM3 in simulating the historical rainfall patterns. The future HadCM3 projected data (from 2011 to 2100) is applied to predict the rainfall amounts under changing climatic conditions. For disaggregation study, 21-years hourly data (from 1980 to 2000) is used for calibrating the disaggregation models, and the rest (from 2001 to 2010) is used for verification. For future predictions, all available data (from 1980 to 2010) is used for building the disaggregation model.

Place Figure 1 here

Methodology

There are four methods to be used in this study: GLM (Chandler and Wheater, 2002), HYETOS (Koutsoyiannis and Onof, 2001), KNN (Prairie *et al.*, 2007) and MuDRain (Koutsoyiannis *et al.*, 2003). Two types of downscaling strategies are employed: (i) single-site GLM downscaling plus KNN for spatial disaggregation (denoted as S-G-K) and (ii) multisite GLM downscaling (denoted as M-G). S-G-K means, a single-site GLM is implemented to downscale the summation of daily rainfalls from eight stations; then KNN method is used to downscale spatially from daily rainfall summation to individual stations. Such an idea is similar to the one proposed by Mezghani and Hingray (2009). M-G means the rainfall will be downscaled for multiple sites at the same time, with inter-site correlation being taken into consideration. The inter-comparison study include: (i) S-G-K vs. M-G for multisite daily rainfall downscaling, (ii) HYETOS vs. KNN for single-site hourly rainfall disaggregation, and (iii) KNN vs. MuDRain for multisite hourly rainfall disaggregation. Based on the comparison results, a relatively better framework of performing an integrated downscaling and disaggregation for the study region will be identified. Then, it will be used to project future sub-daily rainfall patterns. In the entire framework, a number of basic statistical indicators (including mean, standard deviation etc.) and spatial cross-correlation at both daily and hourly timescales will be evaluated. Figure 2 shows the structure of the study methodologies. Detailed introduction on individual components will be given in the following sections.

Place Figure 2 here

Generalized linear model (GLM)

GLM is a popular method to build flexible and veracious relationship between predictors and local observed rainfall data. It simulates the daily rainfall based on two sub-models. The first one is the occurrence model depending on logistic regression (Coe and Stern, 1982; Stern and Coe, 1984; Chandler and Wheater, 2002):

$$\ln\left(\frac{p_i}{1-p_i}\right)=x_i^T\beta \tag{1}$$

where p_i is the probability of rain for the i^{th} day, x_i is the predictor for the i^{th} day, β is the coefficient, and T means the transpose of matrices. The rainfall-amount distribution of wet day is assumed in gamma distribution with mean μ_i, given by (Chandler and Wheater, 2002):

$$\ln\mu_i=\varepsilon_i^T\gamma \tag{2}$$

where ε_i is the predictor and γ is the coefficient. Another added parameter for rainfall amount model is dispersion coefficient v for all gamma distribution, which assumed having a common shape (Yang *et al.*, 2005; Segond *et al.*, 2006). The atmospheric predictors affecting rainfall process may not be independent, and generally interact with each other. Therefore, the interaction parameters are added into the model framework. The response of occurrence and amount model are both linked with non-linearly transformed predictors. A joint distribution for the rainfall of the next day at all stations is built by the spatial dependence of model construction. Normally, the covariate selection and coefficient calculation are both estimated by likelihood methods. Otherwise, the effect of monsoon season specifically for this region also is considered into model. More detailed descriptions can be found in Chandler and Wheater (2002), Yang *et al.* (2005), and Segond *et al.* (2006).

HYETOS

HYETOS is used for disaggregation of single-site based on two versions of Bartlett-Lewis rectangular pulse (BLRP) model. The original version was developed by Rodriguez-Iturbe *et al.* (1987, 1988); the modified BLRP (MBLRP) model was proposed by Onof and Wheater (1993). This study is mainly based on MBLRP. There are several assumptions in such a model: (i) the rainfall occurrence and rain-cell arrival both follow Poisson processes; (ii) the duration of rainfall event and rain-cell both follow exponential distributions; (iii) the rain-cell intensity (depth of rectangular pulse) follows an exponential or gamma distribution. The method of moments (MOM) is used to fit MBLRP model parameters. An adjustment procedure is added into the framework of HYETOS model. The HYETOS model would be applied within the maximum tolerance distance in the adjusting procedure, where the tolerance distance *d* was defined as (Koutsoyiannis and Onof, 2001):

$$d = \left[\sum_{i=1}^{L} \ln^2 \left(\frac{Y_{Mi} + c}{\tilde{Y}_{Mi} + c} \right) \right]^{1/2} \tag{3}$$

where Y_{Mi} and $\widetilde{Y_{Mi}}$ are the original and modeled daily rainfall data respectively, L is the number of wet day in sequence, c is a constant (threshold, 0.1 mm here). The model would run continuously until the simulated daily depths match the sum of whole sequence of daily data within *d*. There are four levels of repetition procedure in HYETOS model to minimize error. For details, readers are referred to Koutsoyiannis and Onof (2001) and Segond *et al.* (2006).

MuDRain

The MuDRain model is a simplified multivariate autoregressive model of rainfall and the major equation can be written as (Koutsoyiannis *et al.*, 2003):

$$X_t = aX_{t-1} + bV_t \tag{4}$$

where X_t is the hourly rainfall at time *t* and *n* location, and could be written as $X_t = [X_t^1, X_t^2, \ldots, X_t^n]$; *a* and *b* are parameters as $[n \times n]$ matrixes; V_t is an independent identically distributed sequence of size *n* vectors of innovation random variables (Debele *et al.*, 2007). A transformation procedure is adopted to adjust the output from multivariate rainfall model to reduce error of stochastic properties. Koutsoyiannis *et al.* (2003) provided the following method to calculate the cross-correlation for satellite stations:

$$r_{ij,h} = \left(r_{ij,d}\right)^m \tag{5}$$

where $r_{ij,h}$ is the hourly cross-correlation coefficient, $r_{ij,d}$ is the daily cross-correlation coefficient, and *m* is a constant need to be estimated. If the hourly data for multiple stations is available, the actual correlation coefficients can be applied into the model; if the hourly data is not available, m value could be assumed in the range from 2 to 3 (Koutsoyiannis *et al.*, 2003; Debele *et al.*, 2007). In this study, the actual correlation coefficients based on hourly data of the studied stations are used.

K-Nearest Neighbors

KNN, as a nonparametric method, is used for both spatial and temporal disaggregation in this study. The spatial disaggregation is to project from the daily rainfall summation from eight stations (whole region) to each single station (sub-region). The temporal disaggregation is to generate hourly rainfall from daily record, for single site or multiple sites (Nowak, *et al.*, 2010). The nearest neighbor of Z should be computed from the observed daily record matrix $\boldsymbol{W}$ with $1 \times n$ dimensions. The 'neighbors' are selected among the potential candidates using Euclidean distance, given by (Deza and Deza, 2013):

$$E[(x,y),(a,b)] = \sqrt{(x-a)^2 + (y-b)^2} \tag{6}$$

where (x, y) and (a, b) are the coordinates of two points. Lall and Sharma (1996) provided a method based on heuristics to define the weight scheme of neighbors:

$$W_i = \left(\frac{1}{i}\right) \Bigg/ \left(\sum_{i=1}^{K} \frac{1}{i}\right) \tag{7}$$

where the K is the number of the nearest neighbors, i is the 'index of neighbor', W_i is the weight scheme of i^{th} index of neighbor; when $i = 1$, the index refers to the closest of the nearest neighbors. The candidates of daily or region data could be selected as the 'nearest neighbor' based on the arranged weight scheme based on a decreasing kernel function. Then, the sub-daily or sub-region data from the candidates are converted to a proportion of the candidate. Let *T* be the target daily or region data which need to be disaggregated. *P* is the selected candidate daily or region data with *m* number of sub-daily or sub-region records. Then, *P* could be converted to a sub-record proportion vector matrix *Z* with dimension $1 \times m$. Finally, the disaggregated sub-daily or sub-region data of *T* could be calculated by *T* multiplying matrix *Z*.

Instead of using a stochastic selection scheme for generating multiple ensembles, an optimization scheme to choose the best ensemble is adopted in this study (Mezghani and Hingray, 2009). This is for the benefit of reducing uncertainty and easiness of comparing with other methods (Khan *et al.*, 2006). The optimization steps are given by (i) selecting 10 nearest neighbors based on Euclidean distance; (ii) arranging equivalent weight to each neighbor (potential disaggregated candidate), and dividing them into ten ensembles based on distance; (iii) using minimization of the objective function to estimate the optimal candidate from the ten ensembles. The objective function (OF) is given by:

$$OF = \frac{\sum_{i=1}^{N} MAPE_i}{N} \tag{8}$$

where *MAPE* means the mean absolute percentage error (Ghosh and Katkar, 2012), *i* means the statistical properties, including mean, standard deviation, lag-1 autocorrelation, lag-2 autocorrelation, probability of wet hour and skewness for single-site disaggregation; another property, cross-correlation is added for multisite disaggregation; N is the number of properties (six for single-site disaggregation, and seven for multisite disaggregation in this study). Figure 3 shows the test result of the objective function value vs. the number of K for single-site disaggregation at station S24. It is found that, when K equals to 5, the objective function would reach its minimum. Similar results were found for other stations.

Place Figure 3 here

Results and discussions

Model configurations

Six statistical indicators (reflecting rainfall characteristics) are used for evaluating model performances: rainfall mean ($\mathrm{Mean_h}/\mathrm{Mean_d}$), standard deviation of rainfall ($\mathrm{STD_h}/\mathrm{STD_d}$), lag-1 autocorrelation of hourly rainfall ($\mathrm{AC1_h}$), probability of wet hour/day ($\mathrm{Pwet_h}/\mathrm{Pwet_d}$), skewness of hourly rainfall ($\mathrm{Skewness_h}$), maximum daily rainfall ($\mathrm{Max_d}$) and cross-correlation coefficients (r_d/r_h), where the subscripts of d and h represent daily and hourly, respectively. The simulated statistical indicators will be evaluated by standard deviation (S_e), relative bias (R_b), change in standard deviation (ΔS), significant test (*Test*) (Debele, *et al.*, 2007), root-mean-square-error (*RMSE*) (Armstrong and Collopy, 1992), mean absolute percentage error (*MAPE*) (Ghosh and Kathar, 2012) and cross correlation coefficient (Liu *et al.*, 2011). The equations are given by:

$$S_e = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(x_{sim,i} - x_{obs,i}\right)^2} \tag{9}$$

$$R_b = \frac{e}{\overline{x_{obs}}} \tag{10}$$

$$\Delta S = \frac{S_{sim} - S_{obs}}{S_{obs}} \tag{11}$$

$$Test = \frac{abs\left(\overline{x_{obs}} - \overline{x_{sim}}\right)}{2S_e} \tag{12}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{obs,i} - x_{sim,i}\right)^2}{N}} \tag{13}$$

$$MAPE = \frac{\sum_{i=1}^{n} abs\left(x_{obs,i} - x_{sim,i}\right)}{N} \tag{14}$$

$$CC = \frac{\sum_{i=1}^{n}\left(x_{obs,i} - \overline{x_{obs,i}}\right)\left(x_{sim,i} - \overline{x_{sim,i}}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_{obs,i} - \overline{x_{obs,i}}\right)^2 \sum_{i=1}^{n}\left(x_{sim,i} - \overline{x_{sim,i}}\right)^2}}$$

where $x_{obs,i}$ is the observed rainfall data, $x_{sim,i}$ is the simulated rainfall data, $\overline{x_{obs}}$ is the mean of observed data, $\overline{x_{sim}}$ is the mean of simulated data, S_{obs} is the standard deviation of observed data, S_{sim} is standard deviation of simulated data, and N is the number of record.

Multisite downscaling based on GLM

Two strategies of multisite downscaling based on GLM, namely S-G-K and M-G, are compared in this section. The large-scale predictors are from NCEP reanalysis data ranging from 1980 to 2000. Twenty ensembles are generated by each method to form envelops of the downscaled results. Figure 4 shows the downscaled results vs. the observed data for four statistical properties ($Mean_d$, STD_d, $Pwet_d$ and Max_d) at station S46. The results indicate that the S-G-K and M-G methods perform fairly close for standard deviation (Figure 4a1). S-G-K shows a slightly better result in terms of daily maximum data (Figure 4d1) but is inferior to M-G with reference to other two indicators. However, both methods show somewhat underestimation of rainfall frequency, especially at the northeast monsoon season (as shown in Figures 4c1 and 4c2). Table 1 shows the average cross-correlation coefficients which are calculated from twenty ensembles. It is indicated that the two methods could both capture the spatial structure well. Overall, the multisite GLM method performs slightly better than single-site GLM plus KNN.

Place Figure 4 and Table 1 here

KNN vs. HYETOS for single-site disaggregation

In this section, the observed hourly rainfall from 1980 to 2000 is used to build the disaggregation model; the observed record from 2001 to 2010 is used for model verification. Figure 5 shows the statistical properties of disaggregated hourly data using KNN and HYETOS during the verification period at two stations. It shows that, KNN and HYETOS could both keep the standard deviation of the disaggregated results. From Figures 5b and 5c, HYETOS illustrates a notable underestimation for the $AC1_h$ and $Pwet_h$ at the two stations; KNN shows a better performance in fitting the observed data, especially for the reproduction of rainfall frequency. Hanaish *et al.* (2011) applied HYETOS to disaggregate daily rainfall in Southeast Asia (Malaysia) and the results also showed that the HYETOS had a lower accuracy in reproducing of Pwet. However, there are also a slight underestimation by KNN at the two wettest months, i.e. January and December. The reason is that KNN does not consider the seasonal effects due to limited number of samples for individual months. Reproduction of skewness is useful for assessing the extreme-event representation for the disaggregation models. From Figure 5d, KNN method performs better in terms of skewness at S24 than that at S46; HYETOS shows an opposite result.

Figure 6 presents the quantile-quanile plot for the extreme data at two stations for quantitative examination. The threshold of a large rainfall event is defined as the rainfall intensity being greater than 30 mm/hour. At S24 station (Figure 6a), HYETOS illustrates an overestimation for almost the entire range of rainfall data, and the error would increase with the increase of rainfall intensity; while, KNN shows a closer trend to the observed data. For S46 station, KNN provides a better fit than HYETOS when the rainfall is below around 70 mm/hour. However, a significant overestimation for peak value is seen by KNN (Figure 6b). This may because the KNN method resamples the historical extreme record for calibration period, but the twenty-four hours rainfall distribution of peak daily rainfall in the verification period does not follow the same distribution in the found 'nearest neighbors' in the calibration period.

Table 2 illustrates the summary of goodness of fit for each month at S24 station. It shows that the bias and the value of significant test for two models are both small. The absolute average values of RMSE, Rs and ΔS for KNN are 2.699, 1.274 and 0.097, respectively; those for HYETOS are 2.964, 1.415 and 0.131, respectively. Similar results are also observed for S46 station (not shown). Generally, the closer the values of RMSE, Rs and ∆S to zero, the better the models are (Debele, *et al.*, 2007). Overall, by comparing the MAPE values and other indicators in Table 2, KNN is considered to perform generally better than HYETOS for single-site disaggregation.

Place Figures 5 and 6, Table 2 here

KNN vs. MuDRain for multisite disaggregation

KNN and MuDRain both need a master station that has historical hourly rainfall record to disaggregate hourly data to satellite stations. In this section, S46 station is used as the master station due to its central location. The performance assessment of multisite disaggregation should also consider the interstation cross-correlation. Figure 7 shows a comparison between KNN and MuDRain in terms of STD_h, $AC1_h$, $Pwet_h$ and $Skewness_h$ at one of the satellite stations (S24) for the verification period. From Figure 6a, the standard deviation of the disaggregated rainfall by MuDRain is somewhat underestimated from January to November. KNN generally performs better than MuDRain except for January. For $AC1_h$, different from the result of single-site disaggregation, KNN shows a poorer performance (with MAPE level at 0.22) compared with MuDRain (0.08). From Figure 7c, both methods well capture the rainfall frequency. However, similar to those in single-site disaggregation, January and December are also underestimated (perhaps due to extreme rainfall patterns in this two month). For skewness, MuDRain shows a much better fitting at the first six months from January to June; but for the rest four months, KNN outperforms MuDRain (Figure 7d). For other stations, the MuDRain generally shows a better result for Pwet, Skewness and AC1; but KNN performed generally better in terms of standard deviation. Table 3 shows the summary of goodness-of-fit of downscaled results at station S24 using other measurement criteria. The absolute average values of RMSE, Rs and ΔS for KNN are 2.772, 1.312 and 0.093, respectively; those for MuDRain are 2.432, 1.139 and 0.148, respectively. It shows that KNN could better reflect rainfall variation, but MuDRain has a smaller error in overall fitting of the rainfall time series.

Interstation correlation is another important factor that should be considered for model assessment in multisite disaggregation. Table 4 illustrates the correlation coefficients against master station (S46) for the observed and disaggregated hourly rainfall data in each month. MuDRain seems to generate fairly close correlation coefficients in comparison to observed ones; whereas, KNN shows a notable underestimation. The reason is that KNN is incapable of addressing spatial correlation as the satellite stations rely heavily on the historical record from the master station. MuDRain has the capability to keep the correlation by the optimization procedure based on the input cross-correlations matrix. Overall, MuDRain model could reproduce most of the statistical properties reasonable well, especially for the extreme data and interstation correlation. It is selected for multisite disaggregation in further studies.

Place Figure 7, Tables 3 and 4 here

Integrated downscaling-disaggregation

From inter-comparison study, the multisite GLM, KNN and MuDRain are selected to be included in an integrated downscaling-disaggregation framework. GLM is established by using NCEP reanalysis data for multisite spatial downscaling and future projections are based on HadCM3 predictors.

(1) Spatial downscaling

GLM model is used for spatial downscaling at eight stations. The observed daily data and NCEP reanalysis data during the period from 1980 to 2000 have been used for establishing the GLM model. Then, HadCM3 modeled predictors with a period from 1980 to 2010 are linked with the GLM model for verifying the quality of the modeled data. Figure 8 shows the observed and simulated monthly statistical properties (i.e. $Mean_d$, STD_d, $Pwet_d$, and Max_d) for station S46 during the verification period 1980-2010. From Figure 8, all observed indexes are generally fall between the envelop curves generated by GLM (with 20 ensembles), especially for the simulation of standard deviation (Figure 8b). Figure 8(c) shows a slight underestimation for the rainfall frequency in two months of wet season, November and December. For the extreme data, except an underestimation for March, the observed data is well covered by the simulated envelops (as shown in Figure 8d). Overall, it is indicated that the GLM model and HadCM3 predictors could generally offer acceptable reproduction and prediction of rainfall patterns for the historical condition. Figure 9 shows the spatial cross-correlation coefficients vs. inter-gauge distances for both observed and simulated rainfalls. GLM shows a good performance for keeping the spatial correlation, and the average values of 20 ensembles are much close to observed ones (CC equal to 0.99).

Place Figures 8 and 9 here
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(2) KNN single-site disaggregation at master station

KNN is selected for single-site disaggregation based on the output of GLM model. As the error of mean is mainly from input data in the disaggregation procedure, Figure 10 only presents standard deviation, lag-1 autocorrelation, probability of wet hour and the skewness at the hourly scale. From the figure, most of the observed properties fall within envelop of the simulated series. The simulation of rainfall frequency (probability of wet hour) is slightly underestimated. This may be caused by errors of the downscaled results and KNN does not consider the seasonal effect. Regarding the prediction of extreme data (i.e. skewness), the simulated envelopes mostly cover the observed data.

Place Figure 10 here
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(3) MuDRain multisite disaggregation at satellite stations

MuDRain is used for multisite disaggregation at seven satellite stations. The input data include the downscaled daily data for all stations and disaggregated hourly data for the master station. Figure 11 compares the disaggregated and observed statistical properties (STD_h, $AC1_h$, $Pwet_h$ and $Skewness_h$) at station S24. The standard deviation from disaggregated data shows a tendency of underestimation. There are slight overestimations for the probability of wet hour in April to June and the underestimations for January and December. Overall, the range of disaggregated data also presents good performance to cover most of the observed statistics. Other stations show similar trends. Figure 12 shows the cross-correlation coefficients for four selected months (February, June, September and December), which distribute in dry/wet seasons and two monsoon seasons, respectively. From the figure, the correlation coefficients from disaggregated data could well cover the observed data for the four months. Based on the average value of 20 ensembles, the correlation coefficients to the observed data are generally over 0.98, which demonstrates an acceptable performance of multisite disaggregation.

Based on the above-mentioned results, the integrated downscaling-disaggregation framework based on GLM, KNN and MuDRain could offer reasonable simulations of hourly rainfall at multiple sites for the Singapore, using HadCM3 as the predictors. The approach shows the framework's high capability in capturing the average rainfall amount and extreme data, and maintaining spatial correlations at both daily and hourly timescales. The reason of a relatively poorer performance for Pwet is mainly affected by the downscaled results. The limited number of samples in different seasons for this study also affects KNN's performance in simulation of rainfall frequency.

Place Figures 11 and 12 here
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(4) Projected hourly rainfall to the future condition

Through the validation of GLM model and HadCM3 predictors, this section presents the projected rainfall for next century for the study region under the climate change conditions. The SRES A2 and B2 scenarios are used for downscaling model to assess rainfall variation during period of 2011-2100. Figure 13 illustrates the mean and maximum hourly rainfall for Singapore island during the baseline period (1980-2010) and three future periods including 2030s (2011-2040), 2050s (2041-2070) and 2080s (2071-2100). It is indicated that, the annual average rainfall would increase (about 2%) in the first period (2030s) slightly, but drop in 2050s and 2080s. The annual rainfall amount would be expected to drop about 5% at the end of this century. For each month, the rainfall in the Northeast Monsoon season would generally increase (December, January and February); in the Southwest Monsoon season, the rainfall tend to reduce and the highest decreasing rate (more than 40%) would be occurring at September. This result is somewhat consistent with the findings in IPCC Fourth Assessment Report (2007), which points out a decreasing trend in precipitation over Southeast Asia, and HadCM3 projections presented in LARS-WG (Semenov and Barrow, 1997). Regarding the extreme rainfall amount, the results (Figure 13a2, b2 and c2) show a generally increasing tendency. Under A2 emission scenario, only August and September would have a decreasing trend of rainfall at the end of this century; other months, on the contrary, demonstrate notable increases. The maximum rainfall would reach up to 181 mm/hr in December, which is about 60% higher than the baseline level. Under B2 emission scenario, the increasing trend of maximum rainfall is generally milder than that in A2 scenario. At the end of this century, the maximum increase rate is about 47% in June, but the peak value (139 mm/hr) is still expected to occur in December. Overall, the projected results imply that the annual rainfall amount would have a slight reduction, but the extreme rainfall events and the rainfall in the wet season could increase notably.

It should be noted that, the projection results are largely determined by the type of GCMs selected. A multiple run of the integrated framework under various models and emission scenarios is essential for reaching a more reliable conclusion. This is especially important when the related results are to be used in adaptation planning. This study aims to demonstrate the validity of the proposed methodology, only one GCM with two emission scenarios is used. Furthermore, the integrated spatial downscaling and temporal disaggregation model is established based on the historical observed data. It is a common difficulty to exam the stationarity of the statistical relationship between local data and large scale predictors under the future climate-change conditions. Two potential ways might be helpful to mitigate such a problem. Firstly, the high-resolution regional climate model (e.g. WRF) could consider to be coupled with the statistical method to predict future rainfall. This method could both consider the physical process and statistical adjustment. Secondly, if the observed dataset is sufficient, the rainfall data at different periods could be selected to examine the changing trend of the statistical relationship and the related information could potentially be used to update or improve the statistical models. Nevertheless, the integrated multisite downscaling and disaggregation framework investigated in this study is a viable way to investigate future rainfall patterns and uncertainties. Most importantly, the hourly rainfall data, with essential statistical properties being kept, will be particularly useful for urban hydrological impact studies. It is also noted that if the method is to be applied in other regions with a large area, the cross-correlation may not be of a serious concern and the framework could be largely simplified by assuming gauge independence.

Place Figure 12 here

Conclusions

With an aim of generating high spatial and temporal resolution rainfall data at multiple sites over Singapore Island under future climate-change conditions, a systematic downscaling-disaggregation study was conducted. The framework was based on multisite spatial downscaling, master-station-based disaggregation and multisite disaggregation models. The study was divided into two major components. The first one was to evaluate various alternatives of spatial downscaling and temporal disaggregation methods based on observed data. The results revealed that, for multisite downscaling, the direct multisite GLM method performs better than single-site GLM combined with KNN spatial disaggregation. For single-site disaggregation, KNN could better keep the basic statistics (STD, AC1 and Pwet) than HYETOS, especially for the reproduction of rainfall frequency. For multisite disaggregation, KNN and MuDRain showed comparable performance in terms of STD, Pwet and Skewness. However, only MuDRain could keep a good fit for interstation correlations, while KNN made significant underestimations.

In the second component of study, an integrated downscaling-disaggregation framework based on GLM, KNN, and MuDRain was used to predict rainfall patterns under future climate change conditions. HadCM3 model predictors were firstly evaluated for reproducing the current rainfall condition. The results indicated that downscaled and disaggregated rainfall data based on multiple ensembles from HadCM3 for the period from 1980 to 2010 could well cover the mean rainfall amount and extreme data, and also keep reasonable spatial correlations at both daily and hourly timescales. However, the results showed a relatively lower accuracy for simulation of rainfall frequency. The framework was also used to project future rainfall under HadCM3 SRES A2 and B2 scenarios. It indicated that the annual rainfall amount would have a slight increase in the period of 2011-2040, and would reduce at a rate about 5% at the end of this century. However, the rainfall in wet season and extreme events would notably increase.

The major contributions of this study include: (i) it made an inter-comparison on the performance of multiple downscaling and disaggregation tools; (ii) it proposed an integrated downscaling-disaggregation framework that could offer a cost-effective alternative for generating high-resolution rainfall data in tropical areas. The study outputs could help decision makers evaluate future rainfall patterns in tropical urban areas and examine the impacts of climate change on urban hydrological systems. The methodology can also be used for other regions where spatial correlations among multiple stations are high. Due to the limited number of predictors or accuracy of the general circulation models in the tropical region, the performance of statistical models is subjected to a certain level of uncertainties. It is necessary to use multiple GCMs or regional climate models (RCM) to improve the performance of the related downscaling and disaggregation models in future studies.

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Table List

Table 1: Comparison of average cross-correlation coefficients between single-site GLM plus KNN and multisite GLM method based on NCEP reanalysis data in the period of 1980-2000.

Distance	Station	OBS	S-G-K	M-G
3.3	S46-S69	0.74	0.72	0.73
4.65	S40-S69	0.67	0.70	0.68
6.3	S40-S66	0.64	0.70	0.66
7.85	S46-S40	0.63	0.62	0.60
9.13	S55-S69	0.51	0.53	0.55
9.55	S46-S55	0.54	0.55	0.58
10.2	S46-S60	0.52	0.51	0.54
10.71	S66-S69	0.50	0.54	0.53
10.9	S24-S55	0.56	0.58	0.60
11.7	S40-S55	0.50	0.54	0.52
11.8	S44-S66	0.46	0.50	0.46
13.3	S40-S44	0.49	0.51	0.49
13.52	S60-S69	0.44	0.42	0.46
13.6	S46-S66	0.50	0.52	0.48
13.73	S44-S69	0.46	0.47	0.46
14.2	S46-S44	0.51	0.51	0.52
16.1	S55-S60	0.42	0.43	0.45
17.8	S55-S66	0.41	0.45	0.42
17.9	S40-S60	0.43	0.42	0.41
19.2	S46-S24	0.48	0.51	0.50
19.2	S44-S60	0.46	0.44	0.46
19.8	S24-S69	0.41	0.44	0.43
21.6	S24-S60	0.44	0.46	0.47
22.6	S24-S40	0.44	0.45	0.43
22.9	S44-S55	0.38	0.40	0.39
23.14	S60-S66	0.36	0.40	0.36
28.5	S24-S66	0.38	0.40	0.38
33.4	S24-S44	0.38	0.38	0.38

Note: Average cross-correlation correlations are calculated from twenty ensembles.

Table 2: Goodness-of-fit statistics of disaggregated hourly rainfall at S24 station based on KNN and HYETOS.

S24	Method	RMSE	R_s	ΔS	Test
Jan	KNN	3.566	1.316	0.099	0.001
	HYETOS	3.994	1.474	0.181	<0.001
Feb	KNN	2.219	0.88	-0.12	<0.001
	HYETOS	1.971	0.949	-0.051	<0.001
Mar	KNN	2.575	1.372	0.116	<0.001
	HYETOS	2.625	1.398	0.071	<0.001
Apr	KNN	2.674	1.344	-0.078	<0.001
	HYETOS	2.717	1.365	0.041	<0.001
May	KNN	2.582	1.206	-0.162	<0.001
	HYETOS	2.826	1.32	-0.113	0.002
Jun	KNN	2.11	1.391	0.065	<0.001
	HYETOS	2.327	1.534	0.195	<0.001
Jul	KNN	2.276	1.322	0.006	<0.001
	HYETOS	2.494	1.448	0.07	0.002
Aug	KNN	2.422	1.195	-0.149	<0.001
	HYETOS	3.145	1.552	0.195	<0.001
Sep	KNN	2.315	1.317	-0.024	<0.001
	HYETOS	2.773	1.578	0.219	<0.001
Oct	KNN	2.665	1.304	-0.075	<0.001
	HYETOS	2.88	1.41	0.107	<0.001
Nov	KNN	3.365	1.241	-0.085	<0.001
	HYETOS	3.757	1.386	-0.008	<0.001
Dec	KNN	3.626	1.404	0.184	0.003
	HYETOS	4.055	1.571	0.325	0.002

Table 3:Goodness-of-fit statistics of rainfall from KNN and MuDRain at S24 station.

S24	Method	RMSE	Rs	ΔS	Test
Jan	KNN	4.11	1.52	0.33	<0.001
	MuDRain	3	1.11	-0.08	<0.001
Feb	KNN	2.2	0.9	-0.1	<0.001
	MuDRain	2.19	0.86	-0.14	<0.001
Mar	KNN	2.78	1.48	0.21	<0.001
	MuDRain	2.27	1.21	-0.15	<0.001
Apr	KNN	2.49	1.25	0.05	<0.001
	MuDRain	2.53	1.27	-0.15	<0.001
May	KNN	2.69	1.26	-0.05	<0.001
	MuDRain	2.61	1.22	-0.14	<0.001
Jun	KNN	2.15	1.42	0.08	<0.001
	MuDRain	1.64	1.08	-0.13	<0.001
Jul	KNN	2.33	1.35	-0.04	<0.001
	MuDRain	1.95	1.13	-0.1	<0.001
Aug	KNN	2.73	1.35	-0.04	<0.001
	MuDRain	2.3	1.13	-0.26	<0.001
Sep	KNN	2.36	1.34	-0.04	<0.001
	MuDRain	1.88	1.07	-0.23	<0.001
Oct	KNN	2.85	1.39	0	<0.001
	MuDRain	2.27	1.11	-0.24	<0.001
Nov	KNN	3.1	1.14	-0.08	<0.001
	MuDRain	3.39	1.25	-0.13	<0.001
Dec	KNN	3.47	1.34	0.1	<0.001
	MuDRain	3.15	1.22	0.03	<0.001

Table 4: Comparison of spatial correlation coefficients between station S46 and station S24.

	OBS	KNN	MuDRain
Jan	0.43	0.12	0.47
Feb	0.10	0.04	0.10
Mar	0.27	0.05	0.32
Apr	0.16	0.04	0.07
May	0.29	0.06	0.16
Jun	0.36	0.01	0.54
Jul	0.31	0.01	0.38
Aug	0.28	0.01	0.38
Sep	0.30	0.01	0.41
Oct	0.39	0.03	0.27
Nov	0.25	0.09	0.14
Dec	0.29	0.10	0.34
Average	0.29	0.05	0.30