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A DECISION-SUPPORT TOOL FOR ASSESSING CLIMATE CHANGE IMPACTS ON DESIGN AND MANAGEMENT OF URBAN WATER SYSTEMS

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Abstract: Global and regional climate models have been extensively used in many climate change impact studies. However, due to the current limitations on detailed physical modelling and computational capability, outputs from these models are commonly provided at coarse spatial and temporal scales. Consequently, these outputs are not suitable for impact assessment studies at short time scales (e.g., sub-daily durations) for a given local site or for small urban catchments. In particular, for urban drainage system design, it is necessary to develop the linkage between the large-scale climate variability and the local observed characteristics of short-duration extreme rainfalls over a given urban watershed. If this linkage could be established, then the projected change of climate conditions available at global or regional scales could be used to predict the resulting change of the local precipitations and the resulting urban runoff characteristics. This paper presents therefore a decision-support tool (referred herein as SMExRain) for assessing the climate change impacts on extreme rainfall processes for locations with or without historical data. Results of an illustrative application has indicated the feasibility and accuracy of the proposed tool using observed extreme rainfall data over Ontario region in Canada and based on climate simulation outputs from 21 global climate models that have been downscaled by NASA to a regional 25-km scale for different climate change scenarios.

1. INTRODUCTION

In recent years, climate change has been recognized as having a profound impact on the hydrologic cycle at various spatial and temporal scales. The temporal scales could vary from a very short time interval of a few minutes (for urban water cycle) to a yearly time scale (for annual water balance computation). The spatial resolutions could be from a few square kilometers (for urban and rural watersheds) to several thousand square kilometers (for large river basins). In particular, the intensity and frequency of extreme precipitation events in most regions will be likely increased in the future (Shephard et al. 2014, Zhang et al. 2017). Hence, there exists an urgent need to assess the possible impacts of climate variability and climate change on the extreme rainfall intensity-duration-frequency (IDF) relations in general and on the design storm in particular for improving the design of urban drainage systems in the context of a changing climate (Willems et al. 2012, CSA 2012, Madsen et al. 2014, Simonovic et al. 2016).

To assess the potential impacts of climate change and climate variability, the global and regional climate models have been extensively used in many studies. However, due to current limitations on the detailed physical modelling and computational capability, these models could only provide output scenarios at the macro and meso scales and on a daily time step which are ineffective to inform decision-making at the micro (or local) scales (Nguyen and Nguyen 2008, 2018). Thus, resolving the spatial and temporal scale issues are crucial for reliable assessment of climate change impacts, so that local decision makers can possibly evaluate what the likely climate change impacts are, such as maximum rainfalls, at the urban or local scales.

To resolve the scale discrepancy issues, different spatial downscaling techniques have thus been proposed (Maraun et al. 2010, Werner and Cannon 2016, Gooré Bi et al. 2017). Of particular importance for urban drainage system design are those procedures dealing with the linkage of the large-scale climate variability to the local-scale historical observations of short-duration extreme rainfall processes over a given urban watershed (Nguyen and Nguyen 2008, Khalili and Nguyen 2016). If this linkage could be established, then the projected change of climate conditions available at global or regional scales could be used to predict the resulting change of the local precipitations and the resulting urban runoff characteristics. Furthermore, assuming this linkage could be established, outputs from these climate models are mostly available at the daily time step because of the current limited ability in the detailed modelling of the atmospheric processes and the current limitation in the computational capabilities. Hence, one of the main challenging tasks in rainfall modeling is to develop an improved approach to simulating extreme rainfall processes over a wide range of time scales (e.g., from several minutes to one day) in order to be able to estimate the sub-daily extreme rainfalls from the available daily data (Nguyen and Nguyen 2019b).

In view of the above issues, the present paper proposes a decision-support tool (herein referred to as SMExRain) to address these issues. The tool has been first developed to consolidate the weather extreme data and to help visualize the descriptive and predictive scenarios of different probability distribution models commonly-used in modeling extreme hydrologic processes. This aids the decision-makers in identifying the most suitable probability models for performing rainfall frequency analyses in general and for constructing IDF relations in particular. Furthermore, the tool is also capable of establishing the linkage between climate projections of climate change available at large-scale to local scales (i.e. to see smaller regional impacts of climate change) with or without empirical data. Details on SMExRain structure and its methodology are described in section 2. The feasibility and accuracy of the tool for assessing climate change impacts on local extreme rainfall processes for gaged and ungaged sites are presented in section 3 and section 4 respectively. Model performances were evaluated based on the climate simulation outputs from 21 global climate models (GCMs) that have been downscaled by NASA to a regional 25-km scale for different representative concentration pathway scenarios and the observed extreme rainfall data over Ontario region, Canada.

2. THE DECISION-SUPPORT TOOL: SMEXRAIN

2.1 General description

SMExRain has been coded in the Matlab environment and equipped with a user-friendly ribbon interface. It can independently run without any requirement of a Matlab version. However, it requires the installation of the free-of-charge Matlab Compiler Runtime (Mathworks 2016). The structure of SMExRain is shown in Figure 1. Inputs for SMExRain are historical annual maxima of different specified rainfall durations at a site of interest. For the climate change impact assessment studies, SMExRain also requires the projected extreme rainfall series available at the regional scales. In the data screening and preliminary analysis steps, SMExRain provides users with several computed common statistical properties. In addition, it also generates many useful graphs for statistical analyses, including the histogram plot for empirical probability density function analysis, the time series plot for trend analysis, and the boxplot for outlier detection. Furthermore, three statistical tests are included for testing the independence and stationarity of the input data series: the Mann-Whitney test for homogeneity and stationarity (jumps), the Mann–Kendall test for trend detection, and the Wald-Wolfowitz test for independence and stationarity (WMO 2009).

2.2 Estimation of extreme rainfall values for the design and management of urban water systems

The extreme design rainfall values necessary for the design and management of urban water systems at a given small urban watershed could be computed based on the rainfall frequency analyses of historical extreme rainfall values available at that location or at the nearby locations. The frequency analysis could be carried out by first selecting an appropriate distribution and parameter estimation method among many candidates available and then fitting the selected distribution to the observed dataset to estimate the design rainfall quantiles corresponding to the desired return periods.

SMExRain includes several common probability distributions that have been selected based on their popularity in hydrologic frequency analyses: Gumbel (GUM), Generalized Extreme Value (GEV), Generalized Pareto (GPA), Pearson Type III (PE3), Log-Pearson Type III (LP3), Generalized Normal (GNO), Generalized Logistic (GLO), Beta-K (BEK), Beta-P (BEP), and Wakeby (WAK) distributions. Other special cases of these distributions, such as normal (NOM) and exponential (EXP) are also included in the tool. Regarding the parameter estimations, the method of L-moments is used for all distributions (Hosking and Wallis 1997) except for the BEK and BEP models that are estimated by the method of maximum likelihood. GEV parameters are estimated by both the L-moments (denotes as GEV) and non-central moments (denotes as GEV*) methods (Nguyen et al. 2017, Nguyen and Nguyen 2019a).

SMExRain relies on the systematic procedure proposed by Nguyen et al. (2017) for identifying the best-fit probability distribution. This systematic approach has been shown to be more efficient and more robust than the traditional model selection method since it was based on two main steps: (i) a detailed evaluation of both descriptive and predictive abilities of a probability model as well as its uncertainty (rather than only the descriptive ability as in most previous studies); and (ii) a systematic comparison of the accuracy and robustness of all candidate models based an extensive set of graphical and numerical performance criteria. Descriptive ability relates to the goodness-of-fit of the theoretical probability model to the empirical frequency distribution given by the observed extreme rainfall data while the predictive ability is concerned with the accuracy and robustness of the extreme rainfall quantile estimates given by the selected model using the rainfall data in the validation period (that are different from those data used in the calibration of the selected model). Note that for convenience, SMExRain allows users to perform the assessment and comparison of multiple probability distributions (up to twelve models) simultaneously rather than to evaluate a single distribution at a time. An illustrative numerical application using a large number of IDF data from 84 rain gages located in the province of Ontario, Canada, could be found in Nguyen and Nguyen (2019a).

2.3 Assessment of climate change impacts on extreme rainfalls at gaged and ungaged sites

2.3.1 Linking the projected regional climate simulations to local daily extreme rainfalls

In SMExRain, the spatial linkage between the extreme rainfalls available at a regional scale $\hat{X}$ and at a given local site X_i could be established using different statistical models based on two different manners. The first approach is based on the use of a scaling factor η_i to correct the mean of the regional data and the mean of the at-site data as shown by Eq. [1]. The second method is relied on a bias correction function $e(F)$ to correct the differences between the empirical cumulative distribution functions of regional and at-site daily extreme rainfalls as indicated by Eq. [2]. This bias correction function can be represented by a regression model (i.e., a second-degree polynomial function) as shown by Eq. [3] (Nguyen and Nguyen 2008, Willems et al. 2012). For gaged sites, both approaches could be used and estimated based on the empirical data at the study sites (Nguyen and Nguyen 2019b). For ungaged sites, where observed data is unavailable, the scaling factors at a given location could be computed based on the interpolated mean at that site transferred from those of the neighboring stations located within a same homogeneous region (Nguyen et al. 2018).

[1] $$X_i(F) = \delta_i \cdot \hat{X}(F) \;;$$

[2] $$X_i(F) = \hat{X}(F) + e(F) \;;$$

[3] $$e(F) = c_o + c_1 \cdot \hat{X}(F) + c_2 \cdot [\hat{X}(F)]^2 + \varepsilon$$

where $X_i(F)$ is the adjusted daily extreme rainfall at the local site of interest i; $\hat{X}(F)$ is the daily regional ER at the grid containing that site; F is the cumulative probability of interest; $\delta_i = \mu_i/\hat{\mu}$ is the scaling factor at site i; μ_i and $\hat{\mu}$ are respectively the mean of the daily extreme rainfalls at the local site i and the mean of the regional values at the grid containing that particular site; $e(F)$ is the bias correction function associated with $\hat{X}(F)$; $c_o, c_1, and\ c_2$ are the coefficients of this function and ε is the error term.

2.3.2 Linking the estimated local daily to sub-daily extreme rainfalls

In SMExRain, the temporal linkages between local daily and sub-daily extreme rainfalls are performed based on the scale-invariance models. Scale invariance implies that the statistical properties of extreme rainfalls over different time scales are related to each other by an operator involving only the scale ratio and the scaling exponent. In particular, the distributions of sub-daily extreme rainfalls are derived using the scale-invariance probability weighted moment-based Generalized Extreme Values (GEV/PWM) model. The GEV/PWM model has been recently shown to perform superior than other existing scale-invariance models (Nguyen and Nguyen 2018). More specifically, the quantile, X_T, corresponding to a given return period $T = 1/(1-F)$, of the GEV model can be estimated once the parameters are known as in Eq. [4]. These parameters could be estimated based on the method of PWM (Hosking and Wallis, 1997). For a simple scaling process, it can be shown that the r^{th}-order PWMs β_r of rainfalls and parameters and quantiles of the GEV distribution for two different rainfall durations t and λt can be related as in Eqn. [6]-[7]. For gaged sites, the scaling exponents could be computed based on the empirical data at the study sites (Nguyen and Nguyen 2019b). For ungaged sites, where observed data is unavailable, the scaling exponents at a given location could be interpolated from those of the neighboring stations located within a same homogeneous region (Nguyen et al. 2018)

[4] $$X_T = \xi + \frac{\alpha}{\kappa}\{1 - [-\ln(F)]^{\kappa}\}$$

[5] $$\beta_r = M_{1,r,0} = E[X\,\{F(X)\}^r] = (r+1)^{-1}\left(\xi + \frac{\alpha}{\kappa}\{1-(r+1)^{-\kappa}\,\Gamma(1+\kappa)\}\right)$$

[6] $$\beta_r(\lambda t) = \lambda^{\eta_r}\beta_r(t) = \lambda^{\eta}\beta_r(t)$$

[7] $$\alpha(\lambda t) = \lambda^{\eta}\alpha(t);\ \xi(\lambda t) = \lambda^{\eta}\xi(t);\ \kappa(\lambda t) = \kappa(t);\ \ X_T(\lambda t) = \lambda^{\eta}X_T(t);$$

in which $\xi, \alpha,$ and κ are the location, scale, and shape parameters respectively; and F is the cumulative probability of interest. $\Gamma(.)$ is the gamma function and r must be non-negative; $\eta_r = \eta$ is the scaling exponent and can be estimated based on the mean $E\{X\}$ (that is, the PWM of order $r = 0$).

2.4 Extreme rainfall intensity-duration-frequency (IDF) relations

The estimated extreme design rainfall values are often summarized and presented in the form of IDF relations for convenience in the design and management of urban water systems. In SMExRain, IDF relations are provided in both tabular and graphical forms for the computed rainfall intensities (or depths) for different durations (usually from five minutes to one day) and for different return periods of interests (commonly from two to a hundred years). Depending upon the empirical mathematical model selected for representing the IDF relations, the coefficients (parameters) of this model are computed using the least-square technique. In general, the mathematical form of the empirical model is chosen such that it can facilitate the interpolation of rainfall intensities for a given observed duration or interpolated (unobserved) duration. SMExRain supports many popular regression equations in both real-space (with two or three coefficients) and log-space (with polynomial up to order 6).

Optimization	Formula
Real-space least squares	$RI = \frac{a}{t^b}$; $RI = \frac{a}{t^b + c}$; $RI = \frac{a\,T}{t^b + c}$; $RI = \frac{a}{(t+c)^b}$; $RI = \frac{a + b.\log(T)}{(1+t)^c}$
Log-space least squares	$\log(RI) = \sum_{k=1}^{p+1} C_k\,(\log t)^{p+1-k} = C_1(\log t)^p + C_2(\log t)^{p-1} + \cdots + C_p(\log t) + C_{p+1}$

where RI is the average precipitation intensity, that is, depth per unit time, generally expressed in mm/hr, t is the precipitation duration in minutes or hours, T is the return period in years, p is the polynomial order (the supported lowest and highest orders are $p = 1$ and $p = 6$ respectively) and $a, b,\ c$, and C_k ($k = 1,2,\dots,p$) are coefficients varying with the locations and return periods.

3. NUMERICAL APPLICATION FOR GAGED SITES

3.1 Study sites and data

To assess the feasibility and accuracy of the tool in reproducing the statistical properties of the historical data at a gaged site as well as to study the climate change impacts on the short-duration extreme rainfalls, the climate simulation outputs from 21 GCMs conducted under the Coupled Model Inter-Comparison Project Phase 5 (CMIP5) and the observed IDF data from a network of seven rain gages located in Ontario, Canada, were used for this study. The climate simulation outputs were statistically downscaled by NASA from the global scales (a few degrees or 10^2 km) to the regional scale (approximately 25 km x 25 km) for the Representative Concentration Pathways 4.5 scenario (i.e. RCP 4.5) based on the bias-correction spatial disaggregation approach (Thrasher et al. 2012). Each of the precipitation projections contains data for the periods from 1950 through 2005 ("Retrospective Run") and from 2006 to 2100 ("Prospective Run"). The observed IDF data at each site contained annual maxima of nine different durations (ranging from 5 to 1440 minutes). These data have been provided by Environment Canada to produce the at-site IDF relations for the various practical engineering application purposes (Environment Canada 2014). The selection of the stations relied on the quality of the data, the adequate length of available historical extreme rainfall records, and the representative spatial distribution of the rain gages. Note that for the calibration process, only the at-site historical and regional data for the 30-year period from 1961 to 1990 were used for estimating the scaling factors, η_i, of the spatial linkages and the scaling exponents of the temporal linkages. While for the validation of these estimations, the data for the 15-year period from 1991 to 2005 were employed.

3.2 Results

3.2.1 Derivation of local daily and sub-daily extreme rainfalls at gaged sites

For the purpose of illustration, Figure 2 shows the probability plots of the computed extreme design rainfalls X_T (mm) for different durations at the London CS Station for the calibration 1961-1990 period. The yellow markers show the empirical cumulative distribution function (CDF) of the observed data, while the red discontinuous lines and cross markers show the theoretical CDF based on the at-site frequency analysis. The gray lines and boxplots show the estimated CDF of the local short-duration extreme rainfalls derived using the SMExRain tool and the NASA regional daily climate-projections data. Uncertainties associated with the estimation of the extreme design rainfalls are also displayed in the form of standard boxplots. It can be seen that the distributions of the estimated local short-duration extreme rainfalls highly agree with the observed data.

A numerical comparison was conducted to evaluate the feasibility and accuracy of the spatio-temporal downscaling using the SMExRain tool based on the three dimensionless GOF indices, including the root mean square relative error (RMSEr), mean absolute relative deviation (MADr), and correlation coefficient (CC). Results for each individual study site are presented in Table 1. The low values of RMSEr and MADr as well as the high values of CC indicate that the proposed SMExRain tool is feasible and accurate in estimating extreme design rainfalls for a given location. The SMExRain tool was then used for assessing the changes on the local short-duration extreme rainfall series for future periods using the daily "Prospective Run" data for each site.

3.2.2 Assessment of climate change impacts on short-duration extreme rainfalls

Figure 3 shows the projected extreme rainfalls at London CS Station for three different return periods (T= 10, 50, and 100 years) and three different rainfall durations (D=5, 60, and 1440 minutes) for future periods 2020s (2011-2040), 2050s (2041-2070), and 2080s (2071-2100) under the RCP 4.5 scenario as compared to the extreme rainfalls for the reference "baseline" period (1961-1990). It can be seen that, as compared to the baseline, there was an increase in the future extreme rainfalls for all return periods and durations. The relative changes of projected extreme rainfalls for all rainfall durations at all seven study locations are also presented in Figure 4 for 100-year and 10-year return periods respectively. These results indicated an increase between 3% to 20% in the projected rainfall amounts from low to high return periods, except for

Winsor A Station where a slight increase in rainfall amounts was observed for the 10-year return period and a slight decrease for 100-year return period.

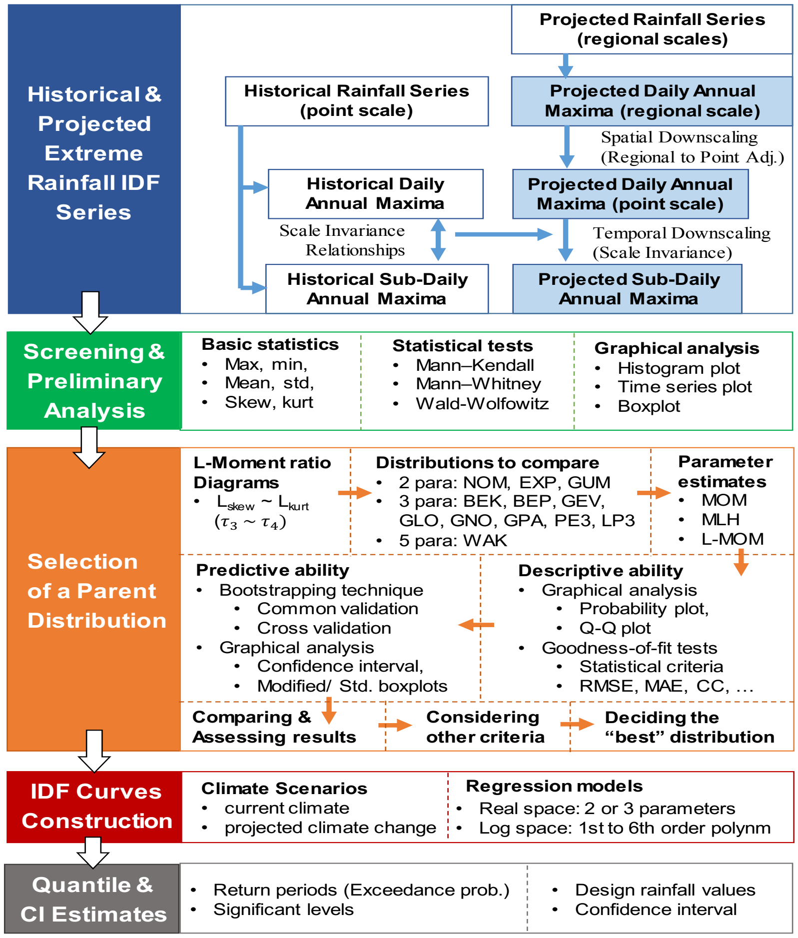


Figure 1: The structure of the decision-support tool SMExRain

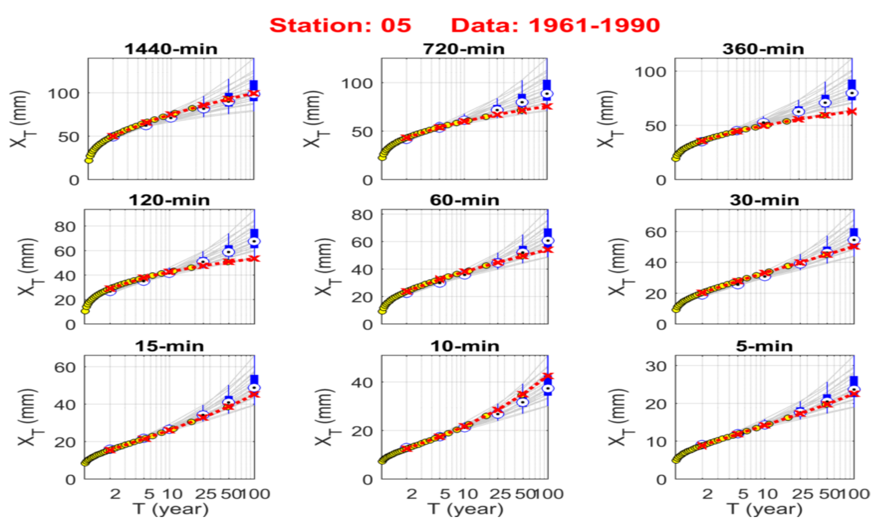


Figure 2: Cumulative distribution function (CDF) plots of the computed extreme design rainfalls X_T (mm) for different durations at London CS Station.

Table 1: GOF results of the estimated and observed IDF data at each study site

Stn	Calibration period 1961-1990			Validation period 1991-2005		
	RMSEr	MADr	CC	RMSEr	MADr	CC
1	0.136	0.109	0.989	0.207	0.165	0.932
2	0.120	0.102	0.987	0.123	0.106	0.985
3	0.137	0.121	0.991	0.241	0.198	0.987
4	0.065	0.051	0.995	0.159	0.138	0.984
5	0.086	0.064	0.980	0.198	0.165	0.956
6	0.169	0.128	0.973	0.169	0.135	0.948
7	0.176	0.147	0.967	0.241	0.189	0.968

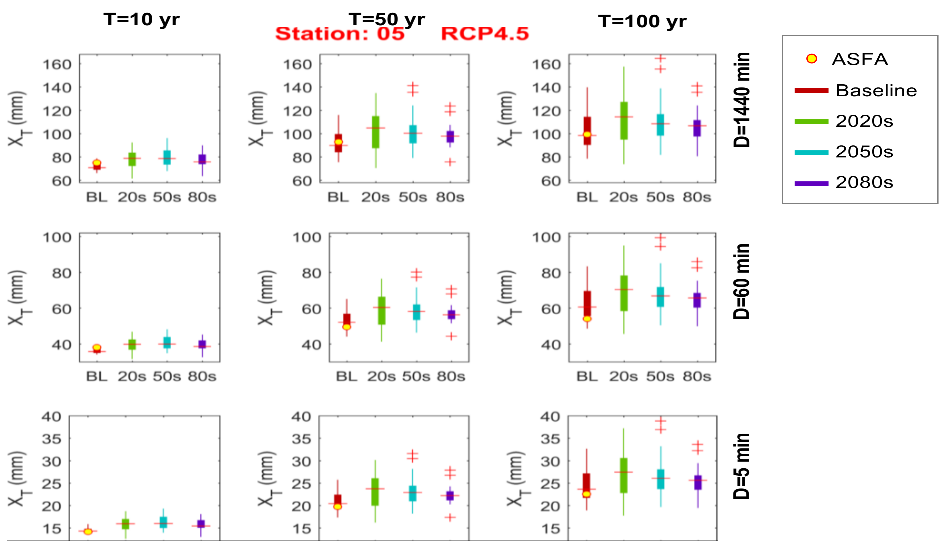
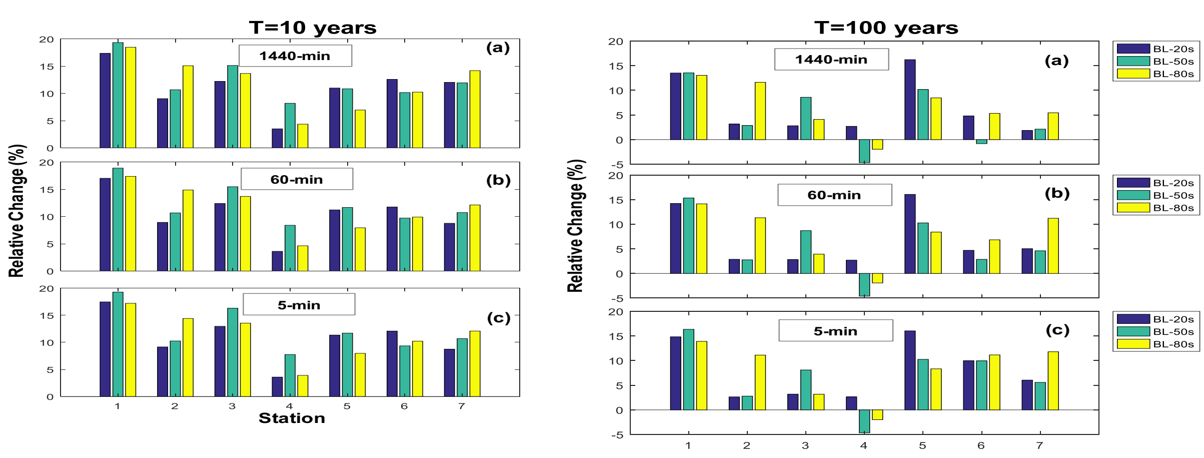


Figure 3: Projected short-duration extreme rainfalls at London CS Station using data for the current period of 1961-1990 (Baseline), and for future periods 2011- 2040 (2020s), 2041-2070 (2050s), and 2071-2100 (2080s) under the RCP 4.5 scenario. Yellow circles show the at-site frequency analysis (ASFA) values



(a) (b)

Figure 4: Comparison of relative changes (%) in the future extreme design rainfalls of duration D=5, 60, and 1400 minutes (baseline-2020s, baseline-2050s, and baseline-2080s) for (a) T=10 and (b) T=100 years

4. NUMERICAL APPLICATION FOR UNGAGED SITES

This section only focuses on the evaluation of the feasibility and accuracy of SMExRain in reproducing the statistical properties of the historical data at an ungaged location. The assessment of climate change impacts on local extreme rainfalls could be done similar to section 3.2.2.

4.1 Study sites and data

To assess the feasibility and accuracy of the tool in reproducing the statistical properties of the historical data at an ungaged site, similarly, the NASA climate simulation outputs from 21 global climate models conducted under the CMIP5 and the observed IDF data in the period of 1961-2005 from a network of 15 raingages located in the Ontario province, Canada, were selected for this study (Environment Canada 2014). The jackknife technique was used to represent the ungaged site condition at the study sites. In addition to these sites, IDF data from other 69 neighbouring stations were also used for the interpolation of the means and scaling exponents at the ungaged sites. Selection of these stations relied on the quality of the data, the adequate length of available historical extreme rainfall records, and the representative spatial distribution of raingages. Data of 1961-1990 were used for the calibration of the scaling factors and scaling exponents, while those of 1991-2005 were used for the validation of the calibrated estimations.

4.2 Results

To transfer the NASA extreme rainfalls at the 25-km regional scale, $\hat{X}$, to a given ungaged site, scaling factors were used. Figure 5 shows the comparisons of different GOF test results between the daily estimated (i.e., regional and the bias-corrected values) and the daily observed extreme rainfalls for both the calibration (1961-1990) and the validation periods (1991-2005). It is important to note that there was a systematic bias between the extreme rainfalls at the regional scale and at a local site. Indeed, the correlation coefficients between the regional and observed values are high (higher than 0.9) but the errors are also large (about 30%) for both the calibration and validation periods. The use of a transfer function (i.e. a scaling factor or areal-reduction factor) is thus necessary. Furthermore, it can be clearly seen that the bias-corrected (areal-reduction adjustment) extreme rainfalls derived for an ungaged site using the estimated scaling factor produced lower values of RMSEr and MADr as well as higher values of CC as compared to the raw data (i.e. 25x25 km regional values) obtained directly from NASA. In addition, the low values of RMSEr and MADr (about 10% and 15% or less for the calibration and validation respectively) and high values of CC (about 0.95 or higher) have indicated the feasibility and accuracy of the proposed spatial downscaling (or areal-reduction adjustment using scaling factors) approach in the estimation of extreme design rainfalls for an ungaged location.

To obtain the sub-daily extreme rainfall series from the daily extreme rainfall series at a given site, the proposed scale-invariance GEV/PWM method was applied. Different graphical visualization and goodness-of-fit (GOF) tests were used to evaluate the feasibility and accuracy of this method. For purpose of illustration, Figure 6a presents the probability plots of the computed extreme design rainfalls X_T (mm) for two different durations at station #13 – the Hamilton RBG CS station for both the calibration (1961-1990) and validation (1991-2005) periods respectively. Uncertainty associated with the estimation of the extreme design rainfalls is displayed in the form of standard boxplots. It can be seen that the distributions of the estimated sub-daily extreme rainfalls derived based on the distribution of local daily extreme rainfall (adjusted from regional values) using SMExRain agreed well with the observed data. Figure 6b shows the Q-Q plots of the estimated extreme design rainfalls derived from the NASA regional data using SMExRain and the at-site frequency analysis using the GEV distribution for different rainfall durations and return periods for all 15 selected stations. Note that the median values of the results from 21 GCMs were used for the computation. A numerical comparison was conducted to evaluate the results using the three selected dimensionless GOF indices (i.e. RMSEr, MADr, and CC) for all sites as shown in Table 2. The low values of RMSEr and MADr as well as the high values of CC have indicated the feasibility and accuracy of the proposed temporal GEV/PWM statistical downscaling in the estimation of the extreme design rainfalls for a given ungaged location. Note that, for accuracy, only the estimated quantiles within the twice sample lengths (i.e. up to 50-year and 25-year return periods for the calibration and validation respectively) were used for comparisons.

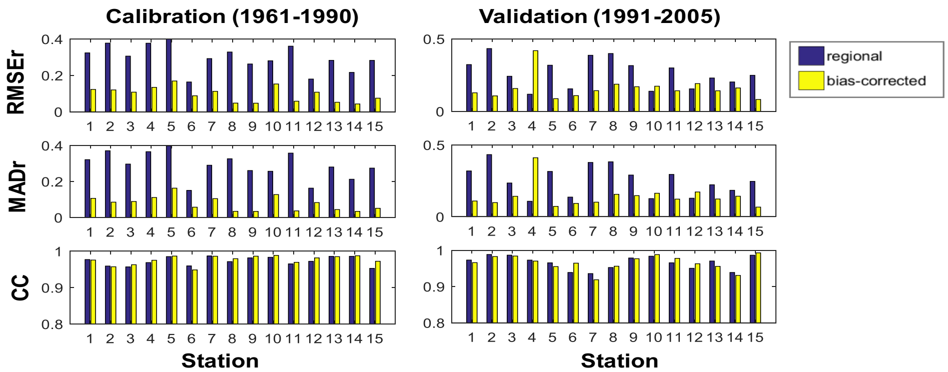
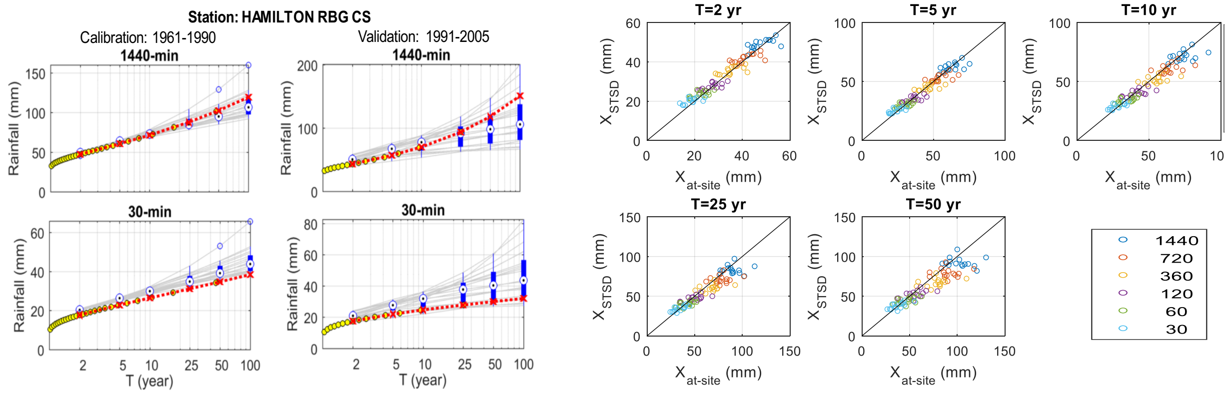


Figure 5: GOF results between observed and estimated (i.e., regional and bias-corrected) extreme rainfalls at the 15 study sites for the calibration (1961-1990) and validation (1991-2005) periods



(a) (b)

Figure 6: (a) CDF plots of the computed extreme design rainfalls X_T (mm) for two different durations (D=30 and 1440 minutes) at the Hamilton RBG CS station for both the calibration (1961-1990) and validation (1991-2005) periods, and (b) Q-Q plots of the estimated extreme rainfalls using SMExRain (X_{STSD}, mm) and the at-site frequency analysis ($X_{at\text{-}site}$, mm) for different rainfall durations (D=30 to 1440 minutes) and for different return periods (T=2 to 50 years).

Table 2: Goodness-of-fit test results for both calibration and validation periods

	Calibration period 1961-1990					**Validation period 1991-2005**			
T (year)	**2**	**5**	**10**	**25**	**50**	**2**	**5**	**10**	**25**
RMSEr (%)	10.3	10.3	11.4	13.9	16.3	15.9	15.2	16.5	20.2
MADr (%)	8.0	8.1	9.3	11.8	13.8	13.4	12.5	12.8	15.9
CC (dmnl)	0.965	0.958	0.950	0.931	0.910	0.929	0.903	0.885	0.866

5. CONCLUSIONS

This paper presents an innovative decision-support tool SMExRain for assessing the climate change impacts on extreme rainfalls for design and management of urban water systems. More specifically, it has been demonstrated that the proposed tool was able to describe accurately the linkage between the climate change information at large spatial and temporal scales given by global (or regional) climate models and the short-duration extreme rainfalls at a local site where observed historical rainfall record are available (a gaged site) or unavailable (an ungaged site). To evaluate the feasibility and accuracy of the proposed SMExRain, the climate simulation outputs from 21 global climate models and the observed extreme rainfall data over Ontario region, Canada were used. These climate simulations have been downscaled by NASA to a regional 25-km scale for different climate change scenarios. Results of these numerical applications have indicated the feasibility and accuracy of the SMExRain in the assessment of the climate change impacts on the extreme rainfalls at a given gaged or ungaged site. Furthermore, it can be noted that the SMExRain tool can be used to assist the decision-makers in identifying in an efficient and objective manner the most suitable probability models for modeling the extreme rainfall processes at a given location as described in detail by Nguyen et al., (2017) and Nguyen and Nguyen (2019a). Finally, the inferences made in this paper are based upon case studies using the observed extreme rainfall IDF data from Ontario (Canada) and the daily downscaled climate projections available at the 25-km regional scale from NASA. Similar studies should be carried out to assess the feasibility and accuracy of the proposed SMExRain tool based on available data in other regions with different climatic conditions.

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