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STATISTICAL DOWNSCALING METHODS FOR CLIMATE CHANGE IMPACT ASSESSMENT ON URBAN RAINFALL EXTREMES FOR CITIES IN TROPICAL DEVELOPING COUNTRIES – A REVIEW

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ABSTRACT

Results of most global and regional climate model simulations cannot be directly applied in future change impacts and adaptation studies of urban drainage and flood risk management. A form of downscaling is required to increase the spatial and temporal resolution of the modelled rainfall data. This paper provides a critical review of the current state of the art statistical downscaling techniques that can be applied to quantify climate change impacts on urban rainfall extremes. Emphasis is placed on delta change methods and Poisson cluster stochastic rainfall models. The paper discusses the applicability and key limitations of statistical downscaling in climate impact and adaptation studies for cities in tropical developing countries. From the review, it can be concluded that simpler statistical downscaling techniques with modest resource requirements such as climate impact sensitivity analyses, use of simple Markov chain or semi-empirical models, construction of climate analogues and spatial interpolation of grid point data are appropriate for scoping of climate impacts and evaluation of mitigation and adaptation strategies at the city scale. Emerging resilience based approaches that combine both scenario based climate model projections and acceptability thresholds defined by key flood risk management stakeholders are promising for application in climate impact and adaptation studies for cities in tropical developing countries.

KEYWORDS

Climate change, tropical developing countries, delta change, stochastic rainfall models

1. INTRODUCTION

The impact of climate change on local extreme rainfall patterns and flood risk in urbanised catchments is a subject of current research (Chen and Djordjević, 2012; Djordjević. et al., 2011). Global climate model (GCM) projections indicate that climate change can lead to changes in frequency and intensity of extreme rainfall events which consequently impacts urban drainage and flood risk management decisions (Butler and Davies, 2011; IPCC, 2007a). Climate change has the potential to exacerbate flood risk particularly in cities in tropical developing countries due to the anticipated increase in extreme rainfall events, finite design capacity of existing systems and changing socio-economic trends among other urbanisation challenges (Djordjević et al., 2011; IBRD/WB, 2009). However, results of global and regional climate model simulations exhibit coarse spatial and temporal resolutions and hence cannot be directly applied in urban drainage and flood risk studies (Onof and Arnbjerg-Nielsen, 2009; Willems, Arnbjerg-Nielsen et al., 2012). Statistical downscaling techniques offer a viable approach to generate accurate and reliable high spatial and temporal resolution rainfall data that is relevant for urban drainage and flood risk management (Bates et al., 2008; Chen and Djordjević, 2012; Onof and Arnbjerg-Nielsen, 2009; Sunyer et al., 2012; Willems, Olsson, et al., 2012).

This paper therefore provides a critical review of the current state of the art on statistical downscaling techniques that can be applied to quantify climate change impacts on urban rainfall in tropical developing countries. The paper differs from previous review papers on downscaling such as Willems, Arnbjerg-Nielsen, et al., (2012); Wilby and Wigley (1997); Wilby et al., (2004) and Fowler et al., (2007) which have not specifically addressed its applicability in the context of urban areas and cities in tropical developing countries. In this review, emphasis is placed on two promising statistical downscaling methods with relatively limited resource requirements: delta change methods (Olsson et al., 2012) and Poisson cluster stochastic rainfall models i.e. the Bartlett-Lewis Rectangular Pulse (BLRP) and the Neyman-Scott Rectangular Pulse (NSRP) models (Burton et al., 2008; Butler and Davies, 2011; Onof and Arnbjerg-Nielsen, 2009; Sunyer et al., 2012). A comparative assessment of the downscaling methods for urban rainfall extremes is made with respect to their suitability for application in cities in tropical developing countries.

2. EVIDENCE OF CLIMATE CHANGE IMPACTS ON EXTREME RAINFALL EVENTS

Results of global and regional climate modelling experiments suggest a general trend towards more frequent and intense extreme rainfall events especially in tropical and high latitude regions (IPCC, 2007a; Olsson et al., 2012; Willems, Olsson, et al., 2012). In Northern Europe, climate model projections indicate a clear tendency towards increases in both annual mean winter precipitation and extremes of daily precipitation (IPCC, 2007a; Jenkins et al., 2009; Willems, Olsson, et al., 2012). Jenkins et al., (2009) projected an increase of up to 33% in winter precipitation in western UK and up to 40% decline in summer precipitation in South England by 2080 in UK against the 1961-1990 baseline using probabilistic multi-model projections. In tropical and high latitude regions such as East Africa, South, East and South East Asia, climate model projections indicate a general increase in both annual mean precipitation and an increase in the frequency and intensity of extreme precipitation events (Bates et al., 2008; IPCC, 2007b). Such climatic trends have vital implications for urban drainage and flood risk management particularly in cities and urbanised areas in tropical developing countries that are highly vulnerable to future change impacts. Consequently, high spatial and temporal resolution rainfall data sets are required by impact modellers for climate impact assessments, proposition and evaluation of context specific mitigation and adaptation measures at the city scale (Butler and Davies, 2011; Sunyer et al., 2012; van Vuuren et al., 2011; Willems, Olsson, et al., 2012).

3. STATISTICAL DOWNSCALING METHODS

Downscaling offers an appropriate methodology that can be used to generate high spatial and temporal resolution data of between 1 - 5 km and 5 - 15 minutes respectively, which satisfies the data requirements of urban drainage and flood risk studies (Butler et al., 2007; Onof and Arnbjerg-Nielsen, 2009). Two main approaches that can be employed to refine coarse climate model data to generate high resolution data include dynamic and statistical downscaling. Dynamic downscaling utilises Regional Climate Models (RCM) set up for specific regions of interest and nested within a Global Climate Model (GCM) to simulate local scale climate features such as orographic precipitation, extreme climate events and regional scale climate anomalies at high spatial (between 12 – 50 km) and temporal (daily time step) resolutions using a physically based approach (Fowler et al., 2007; Sunyer et al., 2012; Willems, Arnbjerg-Nielsen, et al., 2012). In a recent study, Kendon et al. (2012) used a very high resolution convection-permitting RCM with a spatial scale of 1.5 km and compared it with a 12 km RCM to study the realism of simulated hourly heavy rainfall events in the UK. However, RCM model results inherit biases of the driving GCM, and increase with increasing intensity of rainfall events (Kendon et al., 2012). Furthermore, the use of RCMs may still necessitate an extra statistical downscaling step to attain the necessary spatial and temporal resolution for urban drainage studies (Fowler et al., 2007; Sunyer et al., 2012; Willems, Arnbjerg-Nielsen, et al., 2012).

Statistical downscaling methods on the other hand can be used to generate ensembles of daily climate that evolve in line with the transient, large scale changes of the host climate model (Diaz-nieto and Wilby, 2005). Statistical downscaling is premised on the concept that regional climates are fundamentally a function of the large scale atmospheric state and that the relationship can be expressed as a stochastic or deterministic function between the large scale atmospheric variables and the local or regional climate variables (Fowler et al., 2007; Sunyer et al., 2012; Wilby et al., 2004). This approach further assumes that the ratios of large scale (spatial) to local point statistics remains constant under climate change, an assumption that is considered a major limitation to the approach (Diaz-nieto and Wilby, 2005; Fowler et al., 2007; Onof and Arnbjerg-Nielsen, 2009; Sunyer et al., 2012). Statistical downscaling methods can be broadly classified into four main groups: delta change, regression based, weather typing (re-sampling) methods and stochastic rainfall models (Fowler et al., 2007; Onof and Arnbjerg-Nielsen, 2009; Sunyer et al., 2012; Willems, Arnbjerg-Nielsen, et al., 2012). Figure 1 below graphically illustrates the respective methods and their interrelationships.

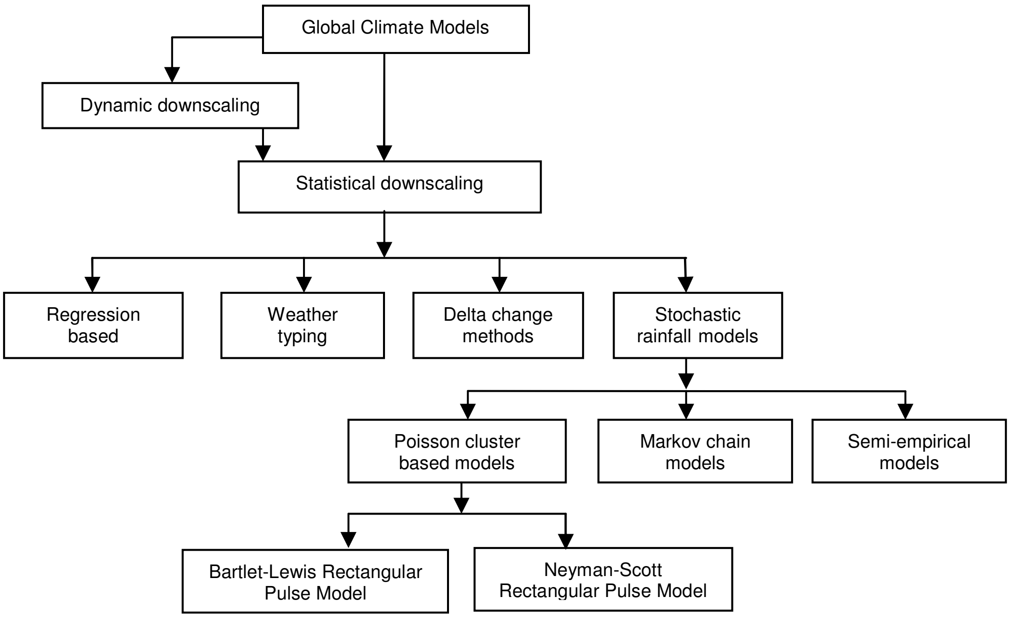

Figure 1: Overview of downscaling techniques

In this paper, emphasis is placed on delta change methods and the use of stochastic rainfall models which have received greater prominence in recent studies on downscaling of extreme rainfall for urban drainage impact studies (Onof and Arnbjerg-Nielsen, 2009; Sunyer et al., 2012). The other methods i.e. regression based methods and weather typing methods have been found to be inadequate for simulation of extreme events mainly due to their inadequacy in representing extreme events (Fowler et al., 2007; Wilby et al., 2004).

3.1 Delta change methods

In this method, change factors (CF) are used to quantify changes in rainfall frequencies and intensities between a control period and a future period for specified return periods (Olsson et al., 2012). The computed change factors can be applied to baseline observations by simply adding or scaling the mean climatic change factor to each period. In order to account for annual variability, change factors can be computed separately for each month or season (Olsson et al., 2012; Sunyer et al., 2012). The main advantage of this approach is the ease and speed of application and the direct scaling of the scenario in line with the changes resulting from the climate model results (Diaz-nieto and Wilby, 2005). Climate change factors are dependent on both the aggregation level (temporal scale) and the return period (rainfall intensity level) and can be formulated using various statistical distributions e.g. probability distributions of rainfall intensities, rainstorm cumulative volumes and wet and dry spell lengths (Willems, Olsson, et al., 2012).

The method can be applied for both continuous and event based applications. In the continuous case, short term precipitation from climate projections is analysed using the partial duration series method to estimate delta change factors associated with different percentiles in the frequency distributions of non-zero intensities. In the event based case, Intensity-Duration Frequency (IDF) curves for a given location can be downscaled using extreme value analysis of annual maxima series.

Semadeni-Davies et al., (2008) computed climate change factors for 6-hour rainfall intensities based on two RCM model runs to study the combined effects of climate change and urbanisation on sewer flows in Helsingborg, Sweden. The computed monthly change factors varied from a 50% decrease to over 500% increase in rainfall intensity for the future period 2071 - 2100. Olsson et al., (2009) extended the delta change methodology to downscale rainfall time series of Kalmar city, Sweden by calculating changes in the probability distribution of rainfall intensities and modelling the delta change factors as a percentile function. The results of the assessment indicated that summer and autumn rainfall intensities would increase by 20% to 60% and would lead to an increase of 20% to 45% in the number of surface floods the year 2100.

In a recent study, Olsson et al., (2012) applied the delta change method to both continuous time series and event based analytical applications using precipitation data from climate model results for Linz, Austria and Wuppertal, Germany. In the continuous time series case, delta change factors were obtained by computing the ratio between a certain percentile in the future period by the same percentile in the reference period. In the event based case, delta change factors were computed by dividing the Gumbel estimate for a certain return period in a future period by the same estimate in a reference period. The computed change factors were thereafter used to estimate future design storms as illustrated in Figure 2 (Olsson et al., 2012).

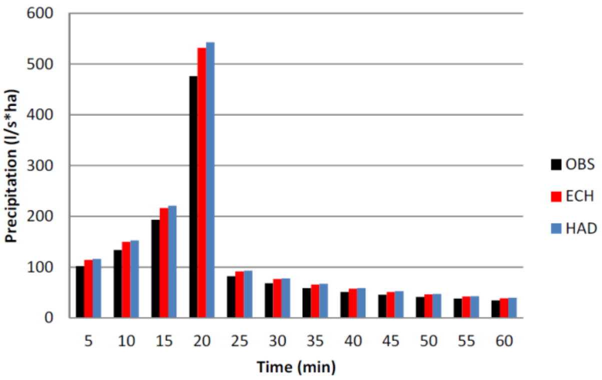

Figure 2: Example of historical 30 year 1-hour EULER II design storm for Wuppertal (OBS) and downscaled version based on future climate model projections (ECHAM5 and HADCM3 denoted as ECH and HAD respectively) (Olsson et al., 2012)

The main limitations of the delta change method include its deterministic nature, dependence on the reliability of the driving GCM and RCM climate models, requirement of equivalent climate model and observational data sets and assumption that the number of wet and dry days remains constant under climate change (Diaz-nieto and Wilby, 2005; Olsson et al., 2012; Sunyer et al., 2012). These limitations can be tackled either by making the delta change approach entirely event based or by using probabilistic multi-model (ensemble) projections to account for uncertainty (Fowler et al., 2007; Olsson et al., 2012).

3.2 Stochastic rainfall models

Stochastic rainfall models (also referred to as weather generators) are used to simulate plausible daily or hourly rainfall series of any length conditioned upon large-scale atmospheric information. The statistical parameters of the stochastic model are computed based on statistical analysis of time series of observed data and climate model results (Kilsby et al., 2007; Onof and Arnbjerg-Nielsen, 2009; Willems, Arnbjerg-Nielsen, et al., 2012). Recent studies argue that stochastic rainfall models are more appropriate for extreme event generation and hence are very relevant for urban drainage modelling studies (Sunyer et al., 2012; Willems, Olsson, et al., 2012).

The first rainfall models were simplified and based on Morkov chain models and semi empirical models for wet and dry periods. First order Markov chain models simulate rainfall occurrence and amounts using transition probabilities and gamma distributions respectively. Second and third order Markov chain models were aimed at improving simulation of precipitation occurrence and persistence. Markov chain models are generally inefficient in modelling the clustered nature of rainfall occurrence (Fowler et al., 2007). Semi-empirical weather generators on the other hand use partly empirical distributions (e.g. histograms with uniform distributions and a fixed number of intervals) to separately describe precipitation occurrence and volume and the length of wet and dry spells (Sunyer et al., 2012).

Poisson-cluster based models which have been extensively developed and evaluated over the last 25 years offer a plausible physically based approach to stochastic rainfall modelling (Onof and Arnbjerg-Nielsen, 2009). Such models assume that any rainfall event is triggered by arriving ‘storm origins’ that generate a sequence of ‘rain cells’ clustered using rectangular pulses (Butler and Davies, 2011). Rectangular pulse models generally assume that each storm origin arrives and generates a random number of rain cells according to statistical Poisson processes. Clustering of the rain cells is accomplished using either the Bartlet Lewis Rectangular Pulse (BLRP) or the Neyman-Scott Rectangular Pulse (NSRP) models (Butler and Davies, 2011; Kilsby et al., 2007; Onof et al., 2000).

3.2.1 Bartlett-Lewis Rectangular Pulse Model

The Bartlett-Lewis Rectangular Pulse (BLRP) model assumes that each storm arrive in a Poisson process with rate λ, and that within each storm, cells arrive according to another Poisson process with a rate β, and the duration of activity of the storm is a random variable. Each cell is assigned a random depth and duration and the total rainfall at time, t is the sum of the contributions of all the cells alive at that time. The duration of the activity of the storm is exponential (parameter, γ) and the number of cells has a geometric distribution, $\mu_c = 1+\beta/\gamma$. The cell depth and duration are also exponentially distributed with parameters $1/\mu_x$ and η respectively and all model variables are mutually independent (Kilsby et al., 2007; Onof & Arnbjerg-Nielsen, 2009; Onof et al., 2000).

Butler et al., (2007) applied *Balerep*, a six parameter BLRP model to the study the impacts of climate change on storm sewer tank design. The model was used to downscale results of rainfall data sets generated by Hadley RCM for 10 year control (1980 – 1990) and future (2080 – 2090) periods. The results of the study indicated a 35% increase in the number of storm events that fill the tank and a 57% increase in the required average storage volume. Segond et al. (2007) used a statistical multi-site Generalized Linear Model combined with a six parameter BLRP model, a disaggregation model and inverse distance weighting function to downscale multi-site daily rainfall to hourly time series for Dalmuir, UK. Although some bias was detected in the proportion of dry day results, the simulation generally preserved the rainfall properties of the observed statistics. Onof and Arnbjerg-Nielsen, (2009) used an 8 parameter BLRP model in combination with a multi-scaling disaggregator to downscale rainfall data from an RCM model for Holbaek, Denmark. The parameters were fitted using the generalised method of moments for both observed rainfall time series and RCM model results on a monthly basis. The results of the study indicated an increase of between 2% and 15% in extreme rainfall in Holbaek, in the next 80 years (Onof and Arnbjerg-Nielsen, 2009).

3.2.2 Neyman-Scott Rectangular Pulse Model

The Neyman-Scott Rectangular Pulse (NSRP) Model is based on similar assumptions as the BLRP model. The following differences between the two models can be identified. Unlike the BLRP model, rain cells within each storm in the NSRP model arrive randomly according to a geometric or Poisson process with mean, μ_c and the number of cell arrivals are independent and identically distributed around the storm centre. The intensity of each rain cell is exponentially distributed with parameter ξ and is equal to the sum of the intensities of all active cells at that instant. The NSRP model ably represents changes in extreme rainfall amounts for both single site and multi-site applications, explicitly represents skewness of extreme rainfall events and is capable of producing high resolution rainfall time series of arbitrary lengths (Onof et al., 2000; Sunyer et al., 2012; Willems, Olsson, et al., 2012).

The NSRP model parameters can be estimated by minimizing the weighted sum of squared differences followed by optimisation, validation and temporal downscaling of the simulation results (Kilsby et al., 2007). The model has undergone significant development and currently forms the basis for standard UK urban drainage design software (Jones et al., 2007). In the recent UK climate projections report (UKCP09), a weather generator based on the NSRP model was applied in combination with monthly change factors to simulate synthetic rainfall time series with a 5 km spatial resolution for the UK (Jones et al., 2009). The requirement of an adequately long observed time series data set for use in model parameter estimation, fitting and validation is the main limitation of this approach (Fowler et al., 2007).

4. APPLICATIONS IN URBAN AREAS IN TROPICAL DEVELOPING COUNTRIES

Most climate change impacts and adaptation studies employing statistical downscaling have been carried out using case study cities in temperate and mid-latitude regions (Chen and Djordjević, 2012; Olsson et al., 2012; Semadeni-Davies et al., 2008) and only a few studies of a similar nature have been carried out using case studies areas in semi-arid or tropical regions (Fowler et al., 2007; Wilby et al., 2004). A recent impact study on a city scale applied results of a coupled climate model (ECHAM5/MPI-OM) to assess the impacts of climate change on urban water supply and drainage infrastructure in Khulna city, Bangladesh (ADB, 2011). Other recent studies in tropical developing countries were not focused on a city scale but a regional scale and included Cowden et al., (2008) who applied both a first order Markov Chain and a stochastic weather generator (LARS-WG) to assess the potential for domestic rainwater harvesting in West Africa and Kigobe et al., (2011) who developed and applied a stochastic rainfall model based on the Generalised Linear Modelling (GLM) approach to infill and extend and historical rainfall data sets in Uganda.

In all these studies closely related issues that limit the application of statistical downscaling in urban areas in tropical developing countries can be identified. First of all, most statistical downscaling methods use results of global and regional climate models and therefore are limited by their resource (i.e. people, time and computational) intensity, uncertainties cascading from the parent models and less reliability in regions where local convective processes greatly influence local climate (Cowden et al., 2008; Pouget et al., 2011; Willems, Olsson, et al., 2012). Secondly, statistical downscaling require long observed rainfall times series data (up to 30 years) with comparable spatial-temporal resolution as the regional climate model results (Willems, Olsson, et al., 2012). However, most urban areas in tropical developing countries have limited or incomplete observed climate data sets which is attributed to sparse gauge networks, limited or no automation of weather stations, equipment down time, funding challenges and operator absence among others (Cowden et al., 2008). Thirdly, existing research and commercial stochastic rainfall models have been developed for application in temperate climates which presents a considerable challenge in adapting the models to other climatic regions (Semadeni-Davies et al., 2008; Willems, Arnbjerg-Nielsen, et al., 2012).

Consequently, climate impact and adaptation studies in cities in tropical developing countries require context appropriate tools and methodologies. Cowden et al., (2008) and Wilby et al., (2004) argue in favour of less sophisticated statistical downscaling techniques such as simple Markov Chain models and semi-empirical models (e.g. LARS-WG) due to their limited input data requirements, fast computations and ease of use. Other approaches with modest resource requirements include spatial interpolation of grid point data, climate sensitivity analysis of impact models, construction of climate analogues using historical data (Wilby et al., 2004, 2009). The delta change approach could also be favourable in the case of availability of reliable observed and climate model data sets such as those provided by Climate Information Portal hosted by the Climate Systems Analysis Group (CSAG, 2013) and the CORDEX Africa experiments (Hernández-Díaz et al., 2012)

Statistical downscaling techniques can generally be categorised as top-down (scenario led) in nature. An emerging and promising approach that could be suitable for application in cities in tropical developing countries is the use of resilience based approaches which combine elements of both top down and bottom up approaches for decision making under uncertain future conditions (Gersonius, 2012; Wilby and Dessai, 2010). Resilience based approaches such as the robust adaptation framework (Wilby and Dessai, 2010) and adaptive policy making (Haasnoot et al., 2013) among others do not entirely rely on climate model projections but also incorporate acceptability thresholds predefined by key flood risk management stakeholders.

5. CONCLUSIONS

Statistical downscaling techniques offer a suitable approach to estimate changes in extreme rainfall events at high spatial-temporal resolution. The above challenges notwithstanding, simple and straight forward statistical downscaling techniques that include climate impact sensitivity analyses, use of simple Markov chain models, construction of climate analogues and spatial interpolation of grid point data are appropriate for use in urban drainage and flood risk management studies for cities in tropical developing countries. The general applicability of statistical downscaling could be improved through measures aimed at increasing availability and dissemination of pre-processed regional climate model data, increased stakeholder engagement and through development of suitable guidelines and decision support tools to guide selection and matching of available methodologies to the requirements of specific impact studies (Fowler et al., 2007; Wilby et al., 2009). From this review, the need to develop resilience based approaches for application in impacts and adaptation studies in cities in tropical developing countries is also evident.

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