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Updating Intensity-Duration-Frequency curves for urban infrastructure design under changing environment

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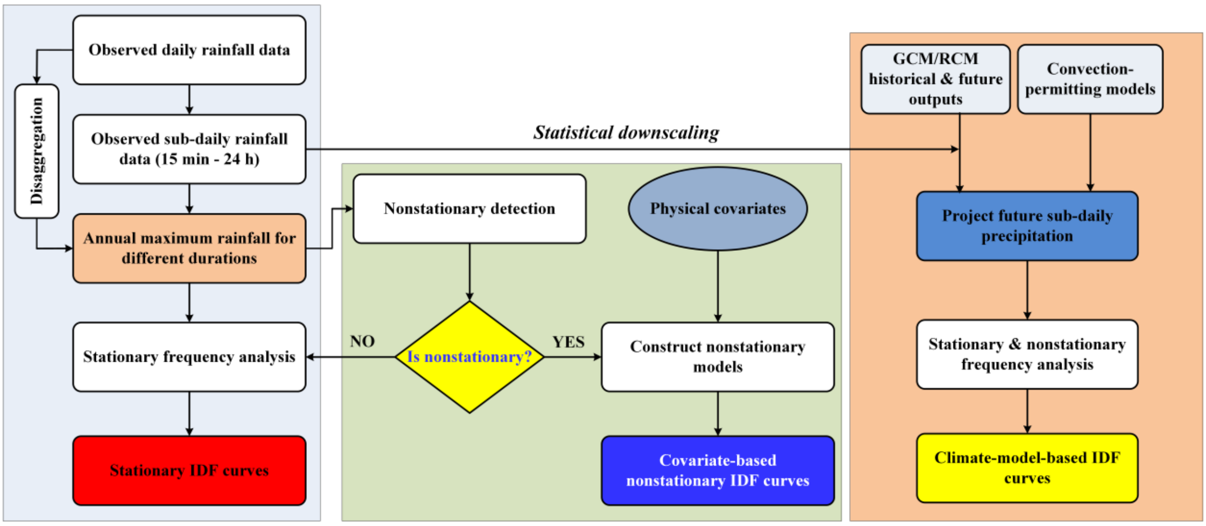
Abstract

Over the past century, the intensity and frequency of extreme precipitation are increasing due to changing climate. Moreover, many studies have revealed that short-duration extreme precipitations are likely to become more and more severe, particularly in urban areas, thus raising a question whether our urban infrastructures have been designed adequately to cope with these changes for future climate. Currently, Intensity-duration-frequency (IDF) curves, which summarize relationships between the intensity and frequency of extreme precipitation for different durations, are recommended as criterion for urban infrastructure design and storm water management. However, climate change is thought to have invalidated the stationary assumption employed in deriving IDF curves, thus making that current IDF curves may underestimate future extreme precipitation. Therefore, it is necessary to update current IDF curves to consider the possible changes in probabilistic behaviour of extreme precipitation. ~~We~~ first summarize observed changes in urban short-duration extreme precipitation and explore the physical mechanisms associated with these changes, including thermodynamic mechanism due to the increase in moisture and dynamic mechanism due to changing vertical motions. Then we introduce~~d~~ two major approaches for updating IDF curves, namely the covariate-based nonstationary

IDF curves and climate-model-based IDF curves. Advances in these two updating approaches for IDF curves are our review focus, including the investigation of physically-based covariates associated with nonstationary modeling of extreme precipitation, the nonstationary precipitation design strategies, the statistical downscaling methods and numerical prediction models for projecting future high-quality short-duration precipitation, and the derivation of future IDF curves based on climate simulations. Finally, future research challenges and opportunities are summarized on how to better characterize the probabilistic behaviour of short-duration extreme precipitation for IDF design considerations.

Graphical/Visual Abstract and Caption



Schematic diagram of updating current stationary IDF curves under changing environment

1. INTRODUCTION

Over the past century, we have witnessed an increase in the global temperature as a result of human activities and associated anthropogenic greenhouse gas emission (Hansen, Ruedy, Sato, & Lo, 2010; Meinshausen et al., 2009). The increasing temperature is expected to boost the water-holding capacity of air at a rate of approximately 7%℃$^{-1}$, governed by the Clausius-Clapeyron (C-C) curves (Feng et al., 2016; Guerreiro et al., 2018; Herath, Sarukkalige, & Van Nguyen, 2018; Lenderink & Fowler, 2017). Higher water-holding capacity can intensify the extreme precipitation and probable maximum precipitation (PMP) (Ben Alaya, Zwiers, & Zhang, 2020; Chen, Hossain, & Leung, 2017; Kunkel et al., 2013), particularly for the short-duration extreme precipitation. As reported by the Fifth Assessment Report (AR5) of Intergovernmental Panel on Climate Change (IPCC), at the end of the 21st century, the frequency and intensity of extreme precipitation are likely to increase in most land areas (IPCC, 2013). Compared with undeveloped and suburb regions, urban areas, particularly the densely-populated and highly-developed megacities are more sensitive to the impacts of climate change because of the Urban Heat Island (UHI), thus leading to more serious economic and social losses. The impacts of urbanization on extreme precipitation have been identified in recent decades (Agilan & Umamahesh, 2016; Golroudbary, Zeng, Mannaerts, & Su, 2019; Gu, Zhang, Li, Singh, & Sun, 2019; Lu et al. 2019; Miao, Sun, Borthwick, & Duan, 2016; Zhang, Villarini, Vecchi, & Smith, 2018). Moreover, at local and global scale, many studies have reported the increase in urban short-duration extreme precipitation in Europe, Asia, America et al., (Barbero, Fowler, Lenderink, & Blenkinsop, 2017; Jakob, Karoly, & Seed, 2011; Lenderink, Mok, Lee, & Van Oldenborgh, 2011; Liang & Ding, 2017; Madsen, Arnbjergnielsen, & Mikkelsen, 2009; Mishra, Ganguly, Nijssen, & Lettenmaier, 2015).

Currently, Intensity-duration-frequency (IDF) curves are typically employed to deal with extreme precipitation and urban flooding in urban infrastructure design and storm water management. IDF curves are designed to reflect statistical characteristics of extreme precipitation and represent the relationships between intensity and frequency of extreme precipitation for different durations. Based on the extreme value theory (EVT), precipitation intensities for different durations (e.g., 15-min, 30-min, 1-hr, 2-hr, 6-hr, 12-hr, and 24-hr) are estimated by fitting a theoretical probability distribution to annual maximum extreme precipitation samples or peaks over threshold samples. Currently, the design concepts of IDF curves are based on the stationary assumption. Under the stationary condition, the statistical characteristics of extreme precipitation are assumed to be invariant over time, thus the probability distribution of extreme precipitation in future period is expected to be the same as in the historical period. However, the stationary assumption is challenged in recent decades since climate change and urbanization are expected to have altered the intensity and frequency of extreme precipitation. To cope with this challenge, nonstationary assumption is proposed in hydrology and climate-related literature (Hu et al., 2018; Lu et al., 2019; Villarini, Serinaldi, Smith, & Krajewski, 2009; Vogel, Yaindl, & Walter, 2011; Xiong et al., 2019; Yan et al., 2019a; Yan, Xiong, Liu, Hu, & Xu, 2017a; Yan et al., 2020).

Under nonstationary condition, the statistical parameters of probability distribution of extreme precipitation are no longer constant but changing with covariate over time. This kind of changing statistical properties of extreme precipitation raises the question of whether the stationarity-based conventional design concepts of urban infrastructures are still adequate under changing environment. Given the observed increase in extreme precipitation, it is recommended that the current IDF curves should be undated to account for the impacts of climate change (Acero et al., 2017; Agilan & Umamahesh, 2017; Cheng & Aghakouchak, 2014; Ganguli & Coulibaly, 2017; Hassanzadeh, Nazemi, & Elshorbagy, 2014; Sarhadi & Soulis, 2017; Singh & Zhang, 2007; Westra et al., 2014; Willems, 2013). In recent years, the nonstationary frequency analysis has become one of the research hotspots in hydrological and climatic fields (Bayazit, 2015; Hao & Singh, 2016; Salas, Obeysekera, & Vogel, 2018). Moreover, more attention has been paid to the nonstationary IDF curves to sustain the reliability of urban infrastructures and storm water management. In this paper, we focus on the construction of nonstationary IDF curves and aim to provide a review of the existing methods as well as discuss future research opportunities.

2. URBAN SHORT-DURATION EXTREME PRECIPITATION

2.1 Observed changes in urban short-duration extreme precipitation

Short-duration extreme precipitation generally refers to extreme precipitation with sub-daily or even sub-hourly durations. For decades, trend analysis is often carried out for daily precipitation due to the scarcity and accessibility of short-duration extreme precipitation. However, many studies have suggested that the intensity of short-duration extreme precipitation is intensifying more rapidly than daily extreme precipitation Westra et al. (2014), which will result in more hazardous flooding in urban areas because of the difficult of proactive warning and rapid emergency response. Therefore, it is important to directly analyse the trend of urban short-duration precipitation to reveal the changing properties of urban short-duration extreme precipitation. Currently, trend analysis for extreme precipitation can be categorized into 3 groups:

- Collect samples of annual maximum extreme precipitation (AMEP) with different durations, and analyze the change of intensity or frequency for AMEP.

- Define different kinds of extreme precipitation index (EPI), and analyze the trend of EPI.
- Split the entire historical precipitation data into sequential subsets and estimate design precipitation or IDF curves for each subset. Finally, analyze the change of design precipitation or IDF curves.

Table 1 summarized some studies concerning trend analysis of urban short-duration extreme precipitation using historical observation data. Generally, the increase of intensity and frequency of urban short-duration extreme precipitation were observed and identified in most cities, although several cities exhibited opposite trend. In addition, the trend of urban short-duration extreme precipitation is related to the length of durations and occurrence seasons. Moreover, the trend of short-duration extreme precipitation is more significant than daily extreme precipitation, and exhibits spatial variability.

Table 1 Summary of trend analysis of urban short-duration extreme precipitation in some regions

2.2 Physical mechanism associated with extreme precipitation

It is crucial to investigate the physical mechanisms associated with extreme precipitation, for the purpose of prediction of extreme precipitation and regional flood control and disaster reduction. The response of extreme precipitation to climate change is ~~dominated by~~ governed by two major physical mechanisms, namely the thermodynamic mechanism and the dynamic mechanism.

2.2.1 Thermodynamic mechanism

Thermodynamic mechanism rules the relationship between water-holding capacity and temperature. Currently, based on the thermodynamic Clausius-Clapeyron (C-C) curves which argues that increasing temperature is anticipated to increase the water-holding capacity of air at a rate of approximately 7%℃$^{-1}$, it is widely accepted that atmospheric moisture can be well characterized by the air temperature, and assumed the extreme precipitation responds directly to the change of atmospheric moisture. Therefore, the precipitation-temperature scaling has become an important approach to study the changing properties of extreme precipitation. Many studies have been carried out worldwide to analyze the relationship between temperature and short-duration extreme precipitation. However, it is found that the extreme precipitation may deviate from the C–C relationship for many regions. In the mid-latitude regions, changes in intensity of subdaily extreme precipitation can be up to twice the C–C relationship (Lenderink et al., 2011; Westra et al., 2014). On the contrary, in some regions, evidence suggests that even decrease of intensity of extreme precipitation with warming is observed (Lenderink & Fowler, 2017). This deficiency is due to the fact that air temperature cannot directly reflect humidity. Thus, Lenderink et al. (2011) explored the relationship between hourly extreme precipitation and dew point temperature, which directly corresponds to humidity, and found that the change of hourly extreme precipitation can be better explained by dew point temperature. However, it is difficult to distinguish cause from effect since both precipitation and temperature are affected by the impacts of atmospheric circulation. In addition, precipitation types and durations are likely to modulate the precipitation-temperature scaling relationship (Berg & Haerter, 2013; Wasko, Sharma, & Johnson, 2015). Therefore, the changes in short-duration extreme precipitation cannot be directly explained using precipitation–temperature scaling method (Lenderink & Fowler, 2017).

2.2.2 Dynamic mechanism

The thermodynamic mechanism is now relatively well understood, while the theory of dynamic mechanism has not been fully developed (O'Gorman, 2015). Dynamic mechanism determines the occurrence of multiscale weather systems (e.g., extratropical cyclones, tropical plumes and tropical cyclones) and their interactions driving the transport of atmospheric moisture (Liu et al., 2020; Trenberth, 1999). To further reveal the dynamic mechanism of changes in extreme precipitation, Pfahl, O'Gorman, & Fischer (2017) employed the measure of condensation in updraft to ~~diagnose~~ the occurrence of extreme precipitation based on the simulation results of 22 global climate models (GCMs) from Coupled Model Intercomparison Project Phase 5 (CMIP5), and ~~accurately~~ reproduced daily extreme precipitation worldwide for the present climate. The good results are benefit from the physical formulation relying on both the atmospheric moisture and the vertical velocity of the air. It should be noted that temporal and spatial resolution of the GCMs used in their study are relatively coarse. Nevertheless, the physical process resulting in urban short-duration extreme precipitation usually occurs at finer temporal and spatial resolution. Thus, although GCMs are able to capture the main physical processes of extreme precipitation, their capabilities are insufficient to model the reality of urban short-duration extreme precipitation.

Under changing environment, both the precipitation-temperature scaling approaches and the physical-based diagnostic methods provide feasible schemes for quantifying the physical mechanisms associated with extreme precipitation. In future, it is essential to improve the observation capabilities of extreme precipitation at finer temporal and spatial resolutions, besides more efforts are needed to develop GCMs which can explicitly resolve convention conditions to further our understanding of urban short-duration extreme precipitation.

3. COVARIATE-BASED NONSTATIONARY IDF CURVES

3.1 Nonstationary models

Under stationary (ST) conditions, the intensities of extreme precipitation corresponding to various design return periods for different durations are estimated based on the EVT. The annual maxima series for different durations (e.g., 15-min, 30-min, 1-hr, 2-hr, 6-hr, 12-hr, and 24-hr) are first fitted by a theoretical probability distribution, and then precipitation intensities corresponding to various design return periods (e.g., 2-yr, 5-yr, 10-yr, 25-yr, 50-yr, 100-yr) are determined. Generalized extreme value (GEV) distribution is often used to model the annual maxima, such as AMEP. For the AMEP z_t $(t=1,\ldots,n)$, the cumulative distribution function (CDF) of stationary GEV (GEV-ST) model is given by

$$\begin{cases} G(z_t \mid \mu,\sigma,\varepsilon) = \exp\left\{-\left[1+\varepsilon(z_t-\mu)/\sigma\right]^{-1/\varepsilon}\right\} \\ 1+\varepsilon(z_t-\mu)/\sigma > 0 \end{cases}, \quad t=1,\ldots,n \tag{1}$$

where, $-\infty < \mu < \infty$, $\sigma > 0$ and $-\infty < \varepsilon < \infty$ are the location, scale and shape parameters of GEV-ST model, respectively. It should be noted that $\varepsilon \to 0$, $\varepsilon > 0$ $\varepsilon < 0$ correspond~~s~~ to Gumbel, Fréchet and Weibull distributions, respectively. Under ST conditions, statistical parameters of GEV are ~~invariant~~. However, under nonstationary (NS) conditions, the statistical parameters of GEV model are time-dependent and can be modeled as a function of covariates, such as time and other physical covariates, to capture the changing properties of AMEP. The CDF of a fully nonstationary GEV (GEV-NS) model is defined as

$$\begin{cases} G_t(z_t \mid \mu_t, \sigma_t, \varepsilon_t) = \exp\left\{-\left[1+\varepsilon_t(z_t-\mu_t)/\sigma_t\right]^{-1/\varepsilon_t}\right\} \\ 1+\varepsilon_t(z_t-\mu_t)/\sigma_t > 0 \end{cases}, \quad t = 1,\ldots,n \tag{2}$$

where $G_t^{-1}(\cdot)$ denotes the time-varying CDF of GEV-NS model. μ_t, σ_t and ε_t are the time-varying location, scale and shape parameters of GEV-NS model, respectively, and t is the time scale. Theoretically, although all the three statistical parameters can be described as time-varying parameters, the shape parameter is sensitive and difficult to estimate (Cheng & Aghakouchak, 2014; Du et al., 2015; Um, Kim, Markus, & Wuebbles, 2017). Thus, the GEV-NS models only consider the changing properties of location parameter and/or scale parameters are widely used in practical applications. This kind of simplified GEV-NS models can yield realistic design precipitation quantiles consistent with the probabilistic behaviour of extreme precipitation (Cheng & Aghakouchak, 2014; Sarhadi & Soulis, 2017).

3.2 What are the best covariates for nonstationary IDF curves

To model the changing properties of nonstationary extreme precipitation, the time-varying statistical parameters should be described as functions of covariates using the generalized linear model (GLM), or generalized additive model for location, scale and shape parameters (GAMLSS) which is more powerful and flexible (Rigby & Stasinopoulos, 2005). Thus, the time-varying location and scale parameters of GEV-NS models are given by

$$\begin{aligned} h(\mu_t) &= \alpha_0 + \sum_{j=1}^{m} \alpha_j x_j^t \\ h(\sigma_t) &= \beta_0 + \sum_{j=1}^{m} \beta_j x_j^t \end{aligned} \tag{3}$$

where $h(\cdot)$ is the link function, such as logarithm function. $\boldsymbol{\alpha}=(\alpha_0,...\alpha_m)$ and $\boldsymbol{\beta}=(\beta_0,...\beta_m)$ are model parameters to describe the trend of μ_t and σ_t, respectively. x_j $(j=1,\ldots,m)$ are the time-dependent covariates employed to explain the changing properties of extreme precipitation, and m is the number of used covariates.

In the implementation of nonstationary models, it is crucial to strengthen the physical meaning of the established statistical model, instead of doing a statistical exercise without paying much attention to the physical process of extreme precipitation (Yan et al., 2019b). Moreover, the prediction of future evolution of the probability distribution of extreme precipitation is one of the most challenging issues in the estimation of nonstationary design precipitation intensities, which heavily depends on the projections of covariates in future period. Therefore, it is essential to select appropriate covariates associated with extreme precipitation. In most recent studies, only time covariate is used to model nonstationarity of extreme precipitation. Cheng and AghaKouchak (2014) proposed a general framework for developing nonstationary IDF curves using GEV-NS model with time covariate for the illustration purpose. Yan et al. (2017b) argued that the covariates used for nonstationary frequency analysis should satisfy two requirements: (i) owning sufficient explanatory power to describe the changing properties of extreme events; and (ii) being able to be reliably predicted in future period. Sarhadi and Soulis (2017) constructed GEV-NS model using both time and Southern Oscillation Index (SOI) in deriving nonstationary IDF curves of the Great Lakes area. Ouarda et al. (2019) developed the nonstationary GEV and Gumbel models using time and the climate indices, such as

Atlantic Multi-decadal Oscillation (AMO) and Western Hemisphere Warm Pool (WHWP) for the stations in Canada, and SOI and Pacific Decadal Oscillation (PDO) for the stations in United States. Agilan and Umamahesh (2017) comprehensively evaluate possible covariates associated with extreme precipitation, namely urbanization, temperature, global warming, El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and time. They found that local process, such as urbanisation and temperature are the best covariates for local short-duration extreme precipitation, while global processes, such as global warming, ENSO and IOD are the best covariates for long-duration extreme precipitation. Besides, time covariate is not recommended for constructing nonstationary IDF curves.

3.3 Nonstationary design methods for estimating precipitation intensities

The statistical parameters of GEV-NS models are described as function of time or other physical covariates. Thus, how to estimate the nonstationary design precipitation with a prescribed return period under nonstationary condition is one of the core questions (Acero, Parey, García, & Dacunha-Castelle, 2018; Acero et al., 2017; Jiang, Xiong, Yan, Dong, & Xu, 2019; Salas & Obeysekera, 2014; Yan et al., 2017b). If we still follow the design concepts under stationary condition, the annual design precipitation associated with a given return period varies over time. Obviously, this kind of time-varying annual design precipitation would be impractical for urban infrastructure design and storm water management under changing environment.

In recent years, several nonstationary design methods have been proposed to tackle the problem of design precipitation estimation under nonstationary condition (Acero et al., 2018; Cheng & Aghakouchak, 2014); Hu et al., 2018; Olsen, Lambert, & Haimes, 1998; Parey, Hoang, & Dacunha Castelle, 2010; Parey, Malek, Laurent, & Dacunha-Castelle, 2007; Rootzén & Katz, 2013; Salas & Obeysekera, 2014; Yan et al., 2017b). Initially, Cheng and AghaKouchak (2014) determined the time-variant location parameter of GEV model using the 95th percentile of the location parameters in observation period, and then the stationary design concepts can be used to derive design precipitation corresponding to a specified return period. Based on different interpretations of return period under nonstationary conditions, expected waiting time (EWT) (Cooley, 2013; Olsen et al., 1998) and expected number of exceedances (ENE) (Parey et al., 2010, 2007) were proposed. In EWT method, the return period m is defined as the expected waiting time until the next precipitation intensity exceeds associated design precipitation $z(m)$, while in ENE method, the return period m is defined as the time period over which the expected number of precipitation intensity exceeding design precipitation $z(m)$ is equal to one. Cooley (2013) provided the mathematical expressions of ENE and EWT methods under both stationary and nonstationary contexts. Hu et al. (2017) compared the difference between EWT and ENE methods in calculating nonstationary design flood. Yan et al. (2020) explored the applicability of the EWT method in nonstationary flood design, and found that the extrapolation time of EWT was influenced by the trend of extreme series and the choice of extreme distributions.

Under changing environment, the design life of a project should be considered in the nonstationary design, since the risk of failure is different for different future periods. In recent years, researchers have developed several well-designed nonstationary design methods considering design lifespan of projects. The concept of design life level (DLL) was proposed by Rootzén and Katz (2013) to communicate the reliability of a project over its design lifespan. However, how to determine the reasonable value of reliability that urban infrastructures will experience over the design lifespan may be a challenging work, for the reason that engineers and decision makers are more familiar with the concept of return period which has served as basis of engineering design for decades. Therefore, Hu et al. (2018) proposed the concept of equivalent reliability (ER). In this method, the reliability over a project's design lifespan under nonstationary conditions is assumed to be identical to the reliability under stationary conditions. Yan et al. (2017b) proposed another nonstationary design method, i.e., average design life level (ADLL), which argued that the annual average reliability over a project's design lifespan under nonstationarity should be equal to that of yearly reliability. To investigate the performance of the above nonstationary hydrological design methods, Yan et al. (2017b) compared the design results estimated by ENE, DLL, ER and ADLL methods, and found ENE, ER and ADLL can yield similar design results using physical-based covariates.

4. CLIMATE-MODEL-BASED IDF CURVES

4.1 Projections of future short-duration precipitation

Different from projecting future IDF curves using nonstationary models, evaluate the potential changes in IDF curves using projections of climate model is more straightforward. However, the temporal and spatial resolution of GCM outputs are still too coarse to directly assess future changes of sub-daily precipitation, despite the progress made by GCMs participated in CMIP5. Therefore, downscaling and bias correction of outputs from GCMs or Regional Circulation Models (RCMs) to the desired spatial resolution (i.e., spatial downscaling) and temporal resolution (i.e., temporal downscaling) for assessing changes in urban short-duration extreme precipitation ~~is~~ necessary, and have becoming one of the demanding topics in recent years (Willems, Arnbjergnielsen, Olsson, & Nguyen, 2012). Researchers have developed a few approaches to generate future short-duration precipitation and update IDF curves with a range of complexities and underlying assumptions. These methods can be categorized into two major groups: (i) statistical downscaling methods (Hassanzadeh, Nazemi, Adamowski, Nguyen, & Van-Nguyen, 2019; Li, Johnson, Evans, & Sharma, 2017; Pastén-Zapata, Jones, Moggridge, & Widmann, 2020; Pui, Sharma, Mehrotra, Sivakumar, & Jeremiah, 2012) and (ii) Numerical prediction models with high spatial and temporal resolutions, such as RCMs and Convention-Permitting Models (CPMs) (Ban, Schmidli, & Schär, 2015; Liu et al., 2017; Prein et al., 2015, 2017; Zittis, Bruggeman, Camera, Hadjinicolaou, & Lelieveld, 2017).

4.1.1 Statistical downscaling methods

Statistical downscaling methods are the most commonly used methods in projecting future sub-daily precipitation. They are typically easier to understand and require less computational efforts than dynamic downscaling methods. Srivastav et al. (2014) reviewed the existing statistical downscaling methods and categorized them into three groups:

- Delta change method. This method is usually used to transfer the signal of climate change from climate models to observations. The change factors of GCM/RCM outputs between baseline period and future period are applied to manipulate observed historical precipitation with different durations (Hosseinzadehtalaei, Tabari, & Willems, 2018; Mailhot, Duchesne, Caya, & Talbot, 2007; Semadeni-Davies, Hernebring, Svensson, & Gustafsson, 2008; Zahmatkesh, Karamouz, Goharian, & Burian, 2015).

- Bias correction methods. In this method, differences between GCM/RCM simulation and observed precipitation for the historical period are firstly estimated, and then used to perturb GCM/RCM outputs in future periods (Hassanzadeh et al., 2019, 2014; Ngai, Tangang, & Juneng, 2017; Pastén-Zapata et al., 2020).

- Downscaling-disaggregation methods. In this method, spatial downscaling and bias correction for GCM/RCM outputs are firstly applied to generate future daily or monthly precipitation, and thereafter temporal disaggregation models are employed to disaggregate future precipitation from daily to sub-daily scales (Li et al., 2017; Mirhosseini, Srivastava, & Stefanova, 2013; Nguyen, Nguyen, & Cung, 2007; Pui et al., 2012). Li et al. (2017) and Pui et al. (2012) reviewed and compared different downscaling-disaggregation methods.

The aforementioned methods differ from each other in the way they simulate the relationship between GCM/RCM outputs and observed daily or sub-daily precipitation for the baseline period and how they utilize the changes between GCM/RCM simulated precipitation for the historical period and future period (Lima, Kwon, & Kim, 2016). The advantages and disadvantages of some above methods have been discussed by researchers (Lehmann, Phatak, Stephenson, & Lau, 2016; Lima et al., 2016; Pui et al., 2012; Srivastav et al., 2014).

4.1.2 Numerical prediction models with high spatial and temporal resolutions

Researchers have also dedicated to develop more powerful climate models to better understand the physical process of extreme precipitation. Such as the higher-resolution RCMs with 10–50 km spatial resolution, which are capable of improving the representation of daily extreme precipitation compared with GCMs. Moreover, researchers have reported that this kind of RCM with 10-50 km spatial resolution can better reproduce the observed sub-daily precipitation and capture the spatial structure of sub-daily precipitation extremes (Evans & Westra, 2012; Lenderink & Van Meijgaard, 2008; Tripathi & Dominguez, 2013; Westra et al., 2014). However, RCMs is still insufficient to reproduce the observed local sub-daily precipitation and represent the spatial characteristics of extreme short-duration precipitation, particularly when the required resolution is lower than 10km (Jiang, Gautam, Zhu, & Yu, 2013; Prein et al., 2015; Westra et al., 2014; Zhang, Zwiers, Li, Wan, & Cannon, 2017).

Currently, the development of Convection-permitting models (CPMs) with spatial resolution less than about 4 km has become one of the hotspots in the field of numerical prediction. CPMs are found to be capable of better modeling the diurnal cycle of convective precipitation, the spatial structure of precipitation, and reproduce the intensities of extra-large extreme precipitation (Langhans, Schmidli, Fuhrer, Bieri, & Schar, 2013; Prein et al., 2017; Westra et al., 2014). Differ from GCMs/RCMs which use convection parameterization schemes to account for the influence of convection over the model grid scale (sources of errors and uncertainties), the improvements of CPMs in projecting future short-duration extreme precipitation are attributed to their explicit resolving of deep convection and better representation of local high-resolution orography and variations of surface fields (Clark, Roberts, Lean, Ballard, & Charltonperez, 2016; Liu et al., 2017; Westra et al., 2014; Zittis et al., 2017). Generally, CPMs can adequately represent the spatial and temporal characteristics of observed hourly extreme precipitation, thus providing effective tools for analysing the changes in future short-duration extreme precipitation.

4.2 Derivation of future IDF curves

Once the future short-duration extreme precipitation is projected, the distribution of extreme precipitation with various durations is determined for future period based on EVT, and then the IDF curves and related changes in them can be easily evaluated. Typically, the most wildly used probability distribution for annual maximum precipitation series is GEV distribution (Agilan & Umamahesh, 2017; Cheng & Aghakouchak, 2014; Ganguli & Coulibaly, 2017; Lu et al., 2019). Researchers have also explored other distributions in building IDF curves. Lima et al. (2016) proposed a Bayesian beta model to derive IDF curves in South Korea based on GCM outputs for future climate. They found that the fitting qualities of the proposed Bayesian beta model are as good as those of conventional GEV models, and the Bayesian beta model can be applied to disaggregate future 24-hour precipitation to finer scales to facilitate the impact analysis of future changes to current IDF curves. Ragno et al. (2018) developed nonstationary models for bias corrected historical and multi-model projected extreme precipitation, and estimate IDF curves and their associated uncertainties using Bayesian inference framework. They found that the intensity is expected to increase 20%, while the occurrence of extreme precipitation is twice as frequent as historical period for densely-populated regions in United States.

In addition to conducting frequency analysis directly on the projected future extreme precipitation with different durations, Alternatively, future IDF curves can also be derived using delta change method based on projection of climate models. Hosseinzadehtalaei et al. (2018) firstly conducted frequency analysis for peaks over threshold (POT) extreme precipitation statistics of both historical and future simulations in EURO-CORDEX project (an ensemble of 88 RCMs) using a two-component exponential distribution. Then they calculated the change factors of precipitation intensities for different return periods and durations, and applied these change factors on IDF statistics of observed extreme precipitation to generate IDF statistics for future period.

5. SUMMARY

Under changing environment, the intensity and frequency of short-duration extreme precipitation are anticipated to increase for future climate, which destroys the stationary assumption in urban infrastructure design and storm water management. Thus, the IDF curves should be updated to account for future changes in extreme precipitation. This study provides a review on the changes in urban extreme precipitation and potential physical mechanisms, and particularly we reviewed current progresses in methods for updating IDF curves for future climate, namely the covariate-based nonstationary IDF curves and climate-model-based IDF curves. The covariate-based nonstationary models provide an avenue to predict future IDF curves based on observed and reliable sub-daily extreme precipitation. However, there is no well-accepted and non-controversial nonstationary modeling approach. Reliable nonstationary modeling requires attribution analysis to identify the physical causes of nonstationarity (Montanari & Koutsoyiannis, 2014; Serinaldi & Kilsby, 2015). Typically, the relationship between statistical parameters and covariates are assumed to be unchanged when projecting distributions of future extremes, which may lead to unreliable results (Luke, Vrugt, AghaKouchak, Matthew, & Sanders, 2017; Ragno et al., 2018; Serinaldi & Kilsby, 2015). The climate-model-based methods highly rely on the projections of local high-resolution extreme precipitation, which inevitable contains different degrees of uncertainties, despite the improvements made in recent years, particularly for urban areas.

There are limited studies comparing the differences and performance of these two methods. For example, Agilan and Umamahesh (2016) firstly developed the IDF curves based on 24 GCMs' simulated precipitation and K nearest neighbour weather generator based downscaling method, and the IDF curves derived using nonstationary models with best physical covariates (i.e., urbanization, temperature, global warming, ENSO and IOD), separately for the Hyderabad city, India. Then they compared the design precipitation with return periods of 2, 5, 10 and 25 years estimated using these two kinds of IDF curves, and found that the covariate-based nonstationary IDF curves are reasonable and able to capture the signal of climate change for at least future 50 years. Therefore, covariate-based nonstationary IDF curves by modeling the trend in observed extreme precipitation are appropriate choices for urban infrastructure design, if the best possible physical covariates are identified properly. From another perspective, Ragno et al. (2018) argued that one drawback of covariate-based nonstationary IDF curves is the dependence of solely observed precipitation records for nonstationary modeling, with an assumption that extrapolates observed trends to future periods, while GCMs outputs can offer plausible scenarios for future climate and can be incorporated for deriving future IDF curves. So, they tried to take advantages of both covariate-based and climate-model-based methods by developing nonstationary models for future projected precipitation.

Despite the increased attention given to update current IDF curves, there is still no well-accepted and non-controversy methodology for updating IDF curves. In fact, there is not even agreement on the need for updating IDF curves. Ganguli and Coulibaly (2017) compared the current stationarity-based IDF curves with the covariate-based nonstationary IDF curves, and no significant differences were found especially for short return period, which is commonly used in urban infrastructure design. Therefore, the signal of nonstationarity does not automatically implies the requirement of updating IDF curves for urban design considerations. Even so, there are some efforts made by government to highlight the need for updating IDF design guidelines. Such as the recommendation by Guidelines for Canadian water resources practitioners (CSA, 2010) to emphasize the necessity to update IDF curves more frequently than previous periods to account for the increase in intensity and frequency of extreme precipitation in Canada.

6. FUTURE CHALLENGES

In future urban design strategies, it is crucial to revisit the current IDF design guidelines and assess possible impacts of future climate. Thus, collaborative and interdisciplinary research efforts with engineers, climate scientists and decision makers et al. are required for updating the design strategies for IDF curves (Cheng & Aghakouchak, 2014; Ganguli & Coulibaly, 2017; Ragno et al., 2018). In the following section, we would like to provide some future research possibilities and challenges in updating IDF curves under changing environment, which we hope will lead to better understanding of changing properties of short-duration extreme precipitation and provide advice for urban infrastructure design.

(1) High-quality subdaily extreme precipitation is essential for impacts analysis of climate change and updating IDF curves for future climate. However, the record lengths of available subdaily precipitation is limited and their qualities are not satisfactory. Moreover, there is commonly no free access to high-quality subdaily precipitation records in most countries. Currently, remotely sensed satellite precipitation products and ground-based radar products provide new avenues to obtain high-quality subdaily precipitation data, in spite of the observation errors associated with them. In future studies, research efforts should be made to improve the observation capabilities and bias correction methods for short-duration precipitation.

(2) Reliable projections of future short-duration extreme precipitation are crucial for either developing climate-based IDF curves or analysis of future changes of short-duration precipitation. However, almost all the climate models are, currently, lack of characterisation for changes in urban underlying surface. For relatively large scale, changes of short-duration may be mainly dominated by climate change, while for urban areas the impacts of underlying surface changes cannot be neglected. To adequately characterize the urban environment in climate models, researchers recommended introduce parameterization scheme of urban canopy into climate models, describe the links between the urban system and aerosols in climate models, and so on (Garuma, 2017; Jin & Shepherd, 2005; Pitman, Arneth, & Ganzeveld, 2012; Wang, Feng, Yan, Hu, & Jia, 2012). Thus, more research efforts are called to improve the capabilities of climate models in modeling the interaction between urban underlying and local atmosphere.

(3) Precipitation extremes are typically described by multi-attribute properties, such as intensity, duration and volume. Thus, univariate frequency analysis is inadequate to fully describe the dependence structure among different attributes (Jiang, Xiong, Yan, Dong, & Xu, 2019). Under stationary conditions, there ~~has~~ been several studies exploring developing copula-based IDF curves using multivariate statistical approaches (Ariff, Jemain, Ibrahim, & Zin, 2012; Bezak, Sraj, & Mikos, 2016; Singh & Zhang, 2007). Under nonstationary conditions, Vinnarasi and Dhanya (2019) derived the time-varying Intensity-Duration relationship to investigate the joint statistical properties of intensity and duration using dynamic Bayesian copula function. In future studies, more research efforts are required to improve the understanding of relationship between intensity and duration of short-duration precipitation extremes using multivariate statistical approaches.

(4) Under changing environment, urban infrastructures are expected to suffer different risk of failure during the service period or design life period due to the changing properties of short-duration extreme precipitation. Therefore, for both covariate-based nonstationary IDF curves and climate-model-based IDF curves, the updated IDF curves should be linked with the design life of urban infrastructures to communicate risk under future climate. In hydrology community, several well-designed nonstationary design approaches have been proposed considering design lifespan of infrastructures, such as DLL, ER and ADLL methods. In future studies, more efforts are needed to test the existing methods worldwide and meanwhile develop more rational design strategies for updating IDF curves.

CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

Tables

Table 1 Summary of trend analysis of urban short-duration extreme precipitation in some regions

Country/region	Data	Methods	Key findings	Reference
Global scale	8326 stations Annual maximum daily precipitation (1900-2009)	The Mann Kendall nonparametric trend test method; Non-stationary generalized extreme values models	The extreme precipitation of nearly two-thirds of stations worldwide exhibits increasing trend.	Westra et al. (2013)
Global scale	217cities 24 h rainfall extreme (1973-2012)	Mann-Kendall test; Theil-Sen’s slope estimation method	10% of annual maximum 24 h rainfall in urban area shows a clear upward trend	Mishra et al. (2015)
China/ Beijing-Tianjin-Hebei, Yangtze River delta	146 cities 24 h rainfall data (1960-2014)	Define 6 extreme rainfall indices; Ordinary least squares method; Principal component analysis	Extreme precipitation in Beijing-Tianjin-Hebei shows a downward trend, while for Yangtze River delta an upward trend is confirmed.	Zhou et al. (2017)
China/ Shanghai	11 stations 1 h rainfall data (1916-2014)	Linear tendency estimation method; Ensemble Empirical Mode Decomposition; Mann-Kendall test	The annual maximum 1 h rainfall shows a significant upward trend	Liang et al. (2017)
China/ Hong Kong	Hong Kong station 1 h rainfall data (1885-1939 and 1947-2010)	Design rainfall based on EVT and generalized Pareto distribution; Sliding window	The 1 h rainfall extremes in the urban area of Hong Kong has shown a clear increasing trend.	Lenderink et al. (2011)
China/ South	2420 stations 1 h precipitation	Student’s t test Mann-Kendall test	There is a clear increasing trend of hourly precipitation	Fu et al. (2016)

	(1982-2012)		extremes in South China	
Indonesia/ Jakarta	Jakarta station 1 h rainfall data (1866-1950 and 1959-2010)	Linear regression 5-year moving window	No significant trend in the 5-year moving average of the annual maximum 1 h rainfall is found	Siswanto et al. (2016)
Japan Nationwide	92 stations Rainfall with duration 10 min, 1 h, 24 h (1951-2010)	Linear regression Annual maxima and 95th percentile	10 min rainfall extremes show the most significant upward trend	Fujibe (2013)
Peninsular Malaysia	25 stations 1 h rainfall data (1975-2010)	Linear regression.	1 h precipitation extremes show an upward trend	Syafrina et al. (2015)
India/ Northwest	33 cities 24 h rainfall data (1971-2005)	Mann-Kendall test Theil-Sen's slope estimation method	Annual maximum 24h rainfall in 18% of cities shows a clear trend	Pingale et al. (2014)
Australia/ Sydney	Sydney station Rainfall data with duration between 6 min and 72 h (1921-2005)	Comparison of the 10-year moving average and the long-term series average	Changes in rainfall frequency and magnitude are closely related to season, duration, and rainfall threshold	Jakob et al. (2011)
Belgium/ Uccle, Brussels	Uccle station 10 min precipitation extremes 107-year time series	Frequency analysis for moving window with 5 and 15 years	10 min precipitation extremes increase significantly	Ntegeka and Willems (2008)
Czech Republic	17 stations 30 min rainfall data (1961-2011)	Theil-Sen's slope estimation method	Precipitation extremes of most stations are increasing	Hanel et al. (2016)
Denmark Nationwide	66 stations Rainfall data with duration between 1 min and 48 h (1979-2005)	Analyze the changes in the estimated IDF curves between 1979-1997 and 1979-2006	10-year design rainfall between 30 min and 3 h increased by more than 15%; Intensity of rainfall over 24 h did not change significantly	Madsen et al. (2009)
United Kingdom Nationwide	1311 stations 1 h rainfall data (1982-2011)	Least squares regression Mann-Kendall test	Average hourly rainfall intensity trend is significant, but the annual extreme rainfall has no significant trend	Blenkinsop and Fowler (2014)
United States Nationwide	more than 6,000 stations Hourly precipitation data (1950-2011)	Mann-Kendall test Pettitt test Nonstationary GEV model	Both hourly and daily rainfall extremes have significantly increased over the last six decades across the U.S.	Barbero et al (2017)

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