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Update of intensity-duration-frequency (IDF) curves under climate change: a review

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ABSTRACT

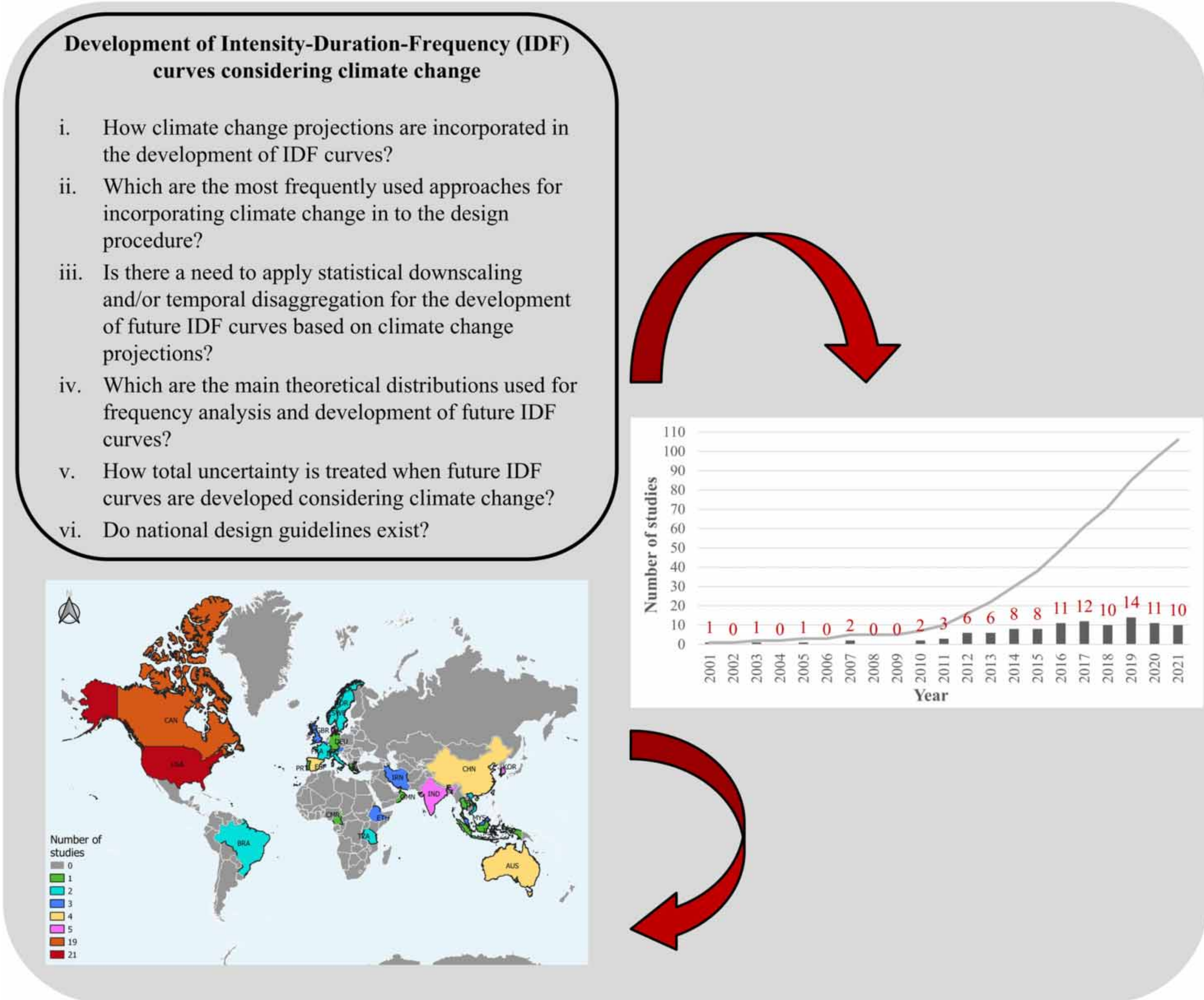
Land use and land cover changes, population growth, urban sprawl and climate change are expected to augment the pressure on natural environment and on existing infrastructure. As a result, update of intensity-duration-frequency (IDF) curves considering climate change is essential for adaptation of water-related structures to climate change. The present work reviews the main challenges regarding the update of IDF curves considering climate change. A wide literature search was conducted in scientific databases. More than 100 articles published between 2001 and 2021 have been reviewed and are summarized and discussed. The main aims of the present work were to: (i) identify the state-of-the-art scientific approaches regarding IDF curve update under climate change projections; (ii) assess whether or not these approaches incorporate uncertainty (i.e., uncertainty related to climate models, statistical downscaling techniques, temporal resolution of data, theoretical distribution selection etc.); and (iii) propose general guidelines for updating IDF curves based on climate projections. First, the motivation is presented that makes IDF curve renewal a global issue. Second, current practices are described and reviewed and the main impacts of climate change on short precipitation extremes around the world are briefly discussed. Finally, limitations and future research needs are discussed.

Key words: climate change, GCM/RCM, stationary and non-stationary IDF curves, statistical downscaling-bias correction, temporal disaggregation, total uncertainty

HIGHLIGHTS

- Over 100 published papers are summarized.
- Approaches for updating IDF curves considering climate change are reviewed.
- Climate change impacts on future IDF curves are summarized.
- Uncertainty quantification methods are discussed.
- General guidelines for updating IDF curves are proposed.

GRAPHICAL ABSTRACT



INTRODUCTION

The natural environment and the infrastructure are expected to be influenced by the combined impacts of climate change, land use and land cover changes, population growth and urban sprawl (Alfieri *et al.* 2016; Patra *et al.* 2018; Kourtis *et al.* 2019). Impacts of climate change are well documented for different sectors and for several hydrological systems, both at regional and sub-regional scales of the globe (e.g., Arnbjerg-Nielsen *et al.* 2013; Breugem *et al.* 2020; Kundzewicz *et al.* 2020; Tramblay *et al.* 2020; Walsh *et al.* 2020).

In water resources engineering and management, intensity-duration-frequency (IDF) curves constitute one of the most commonly adopted tools for planning, design and operation of a wide range of water resources related projects (e.g., Kourtis *et al.* 2020). Development of IDF curves is based on extreme value analysis of observed timeseries, extracted using the annual maxima series (AMS) method or the peak over threshold (POT) method (also called partial duration series method; Mimikou *et al.* 2016). Commonly, historical data are used under the assumption that the same underlying processes will govern future rainfall patterns (Agilan & Umamahesh 2016). However, the non-stationarity assumption of rainfall extremes, due to climate change projections, is expected to influence the hydrological cycle (Shrestha *et al.* 2014; Bayazit 2015; Theodossiou 2016; Chandrakar *et al.* 2017; Chattopadhyay *et al.* 2017; Ouhamdouch & Bahir 2017; Dahal *et al.* 2018; Dubey & Sharma 2018; Ramteke *et al.* 2020; Dau *et al.* 2021). An increase of future rainfall intensities will result in increased flood risk

(Fowler *et al.* 2021c) and increased risk for agriculture. As a result, adaptation and renewal of IDF curves must be incorporated in the design procedure to reduce vulnerability of existing and/or new infrastructure projects. Economic losses, flood catastrophes and human casualties may increase as a result of the projected increase in the intensity and frequency of extreme storm events. Consequently, a major challenge emerges for most countries and regions of the world to develop or update IDF curves (Ombadi *et al.* 2018) under the assumption of climate change.

Climate change impact assessment and update of IDF curves are mainly based on climate projections from general circulation models (GCMs). However, the spatiotemporal scale of GCMs is too coarse and their spatial scale and temporal resolution must be enhanced based on dynamic and/or statistical approaches (Themeßl *et al.* 2012; Kourtis & Tsihrintzis 2021). Dynamic downscaling refers to using regional climate models (RCMs) forced by GCMs under different climate scenarios (representative concentration pathways – RCPs or special report on emissions scenarios-SRES). Fowler *et al.* (2021a) stated that observed short rainfall extremes can only be compared with the simulations provided by RCMs and/or convention permitting climate models (CPMs). RCM biases, coarse spatial scale and temporal resolution (Willems *et al.* 2012a, 2012b), along with their inability to accurately represent convective storms (Berg *et al.* 2012, 2018) affecting sub-daily scales, results in needing further spatial and temporal downscaling. Statistical downscaling refers to spatial downscaling using climate analogs, and bias correction using perfect prognosis or model output statistics (Eum *et al.* 2020). Overall, statistical downscaling and/or bias-correction and temporal disaggregation must always be practiced with caution (Kourtis & Tsihrintzis 2021).

The new generation of climate models, CPMs, are based on meteorological forecasting models and they are able to better simulate short rainfall extremes (up to sub-hourly scales; Vergara-Temprado *et al.* 2021) operating with horizontal resolution less than 4 km. However, CPMs tend to suffer from biases, and bias correction is proposed to take place before using rainfall data for extreme value analysis (Kendon *et al.* 2014; Berthou *et al.* 2020). However, it must be stated that ongoing research is undertaken regarding calibration and improvement of CPM schemes in order to address biases (Kendon *et al.* 2021). The wide use of CPM simulations is constrained due to the high computational cost (computations can take place only for small regions and for short reference periods). As a result, the only way to estimate return periods with low probability of occurrence when updating IDF curves is the use of future climate projections from a single model with a rather short reference period (e.g., 10–20 years) and extrapolation from the fitted theoretical distribution. However, this can lead to severe epistemic uncertainty. The interested reader is refereed to Kendon *et al.* (2021) for more information regarding CPMs.

Climate model uncertainty and sensitivity leads to future climate projections with a large variability. Climate models and scenarios, initial conditions and internal variability are the main reasons for the uncertainty of the climate projections. It must be stated that the uncertainty is also compounded by downscaling techniques (dynamic and statistical), bias correction methods and disaggregation approaches (Willems *et al*. 2012b). It is essential not to treat climate projections neither as future visualizations nor as predictions.

The aim of the present paper is threefold: (i) provide an overview of the approaches used for the development and/or update of IDF curves considering climate change projections; (ii) summarize the methods and the research findings from over 100 peer-reviewed articles to assess how these findings will influence the update of IDF curves in the future; and (iii) identify gaps and propose general guidelines for updating IDF curves that can be easily accessible and implemented in different regions around the globe for both design and operational purposes.

REVIEW METHODOLOGY AND DATASET

The present review is aiming to address the issue of updating IDF curves under the assumption of climate change by answering six questions. The main questions tried to be answered are: (1) How are climate change projections incorporated in the development of IDF curves? (2) Which are the most frequently used approaches for incorporating climate change in the design procedure? (3) Is there a need to apply statistical downscaling and/or temporal disaggregation for the development of future IDF curves based on climate change projections? (4) Which are the main theoretical distributions used for frequency analysis and development of future IDF curves? (5) How is total uncertainty treated when future IDF curves are developed considering climate change? And (6) Do national design guidelines for updating IDF curves exist?

A systematic literature review was undertaken, based on the recently reported guidelines of Moher *et al.* (2009), for collecting studies regarding the development and/or update of IDF curves considering climate change. Up-to-date studies were included in the present search. Scopus and Google Scholar were the main search engines used for collecting relevant studies. The main keywords used were: (i) intensity-duration-frequency or IDF curves; (ii) climate change; (iii) stationary and non-stationary IDF curves. The collected articles were screened for inclusion and the most relevant were identified first through title, abstract and conclusions, and then through full-text review (Supplementary Material, SM; Figure SM1a). Conference proceedings, usually, do not undergo rigorous peer review, and, as a result, it was decided not to include them in the present review study. The focus was to cover as many peer-reviewed articles published as possible. The decision on whether or not to include an article was based on the level of detail presented in each article regarding the development and/or update of IDF curves including future climate projections. A total of 456 records were identified (Figure SM1a), and finally, the full texts of 195 articles were assessed for eligibility. Ultimately, 106 studies were considered relevant to IDF curves development and/or update considering climate change (Figure SM1b).

ASSESSMENT OF STUDIES UPDATING IDF CURVES UNDER CLIMATE CHANGE

Researchers have reported an increase in extreme rainfall intensities, based on in-situ observations for different regions around the globe (e.g., Groisman *et al.* 2012; Hao *et al.* 2013; Kunkel *et al.* 2013). Several studies have argued that IDF curves must be updated to account for climate variability (e.g., Cheng *et al.* 2014; Bhatkoti *et al.* 2016; Ren *et al.* 2019; Fowler *et al.* 2021a; Kourtis & Tsihrintzis 2021; Kourtis *et al.* 2021). A number of studies have reported differences in the frequency and/or intensity of future short rainfall extremes for Europe (e.g., Skougaard Kaspersen *et al.* 2017; Hosseinzadehtalaei *et al.* 2018, 2020; Kourtis *et al.* 2021), North and South America (e.g., Ganguli & Coulibaly 2019; Cook *et al.* 2020; Butcher *et al.* 2021; Requena *et al.* 2021a, 2021b; Silva *et al.* 2021), Australia (e.g., Herath *et al.* 2016), Asia (e.g., Andimuthu *et al.* 2019; Binesh *et al.* 2019; Uraba *et al.* 2019; Zhou *et al.* 2019; Kim *et al.* 2020) and Africa (e.g., de Paola *et al.* 2014; De Paola *et al.* 2018; Gebru 2020). Limited data availability has led the research community to use relatively short periods of observations, which may result in augmented uncertainty due to natural variability.

Frequency analysis of rainfall may be categorized as of local, regional or grid scale, depending on whether information from a single station, from several hydrologically similar stations or from grid-based precipitation products is used for estimating quantiles. Various approaches have been presented developing local (e.g., Cook *et al.* 2020), regional (e.g., Bermúdez *et al.* 2020), or grid scale (e.g., Hosseinzadehtalaei *et al.* 2020) IDF curves in the context of climate change. Regional IDF curves are mainly developed based on the methodology of Hosking & Wallis (1997).

The comparison of results reported in different studies is not always easy due to the application of different frameworks and different methodologies, different data sets, and different periods of analysis. For example, studies are focusing on different scales, e.g., local (e.g., Cook *et al.* 2020), regional (Bermúdez *et al.* 2020), national, continental and worldwide (e.g., Hosseinzadehtalaei *et al.* 2020). Researchers use SRESs (e.g., Kuo *et al.* 2015) while others use the most recent RCPs (e.g., Khazaei 2021). Others use future climate projections from GCMs (e.g., Kuok *et al.* 2016), while others use future climate projections derived from RCMs (e.g., Padulano *et al.* 2019; Ren *et al.* 2019). The results of climate projections are used without statistical downscaling and/or bias correction (e.g., Nunes Carvalho *et al.* 2020) while in other studies statistical downscaling and/or bias correction is performed prior to the derivation of IDF curves (e.g., Hu & Ayyub 2019; Gebru 2020; Li *et al.* 2021). Temporal resolution of climate models is still too coarse for deriving AMS or POT timeseries (i.e., 1–3 h and in most times daily), especially at the urban basin level, and as a result, temporal disaggregation techniques are applied. Different disaggregation techniques have been proposed and used for temporal downscaling of the coarse resolution of climate models (Kourtis & Tsihrintzis 2021). Researchers employ temporal disaggregation techniques (e.g., Binesh *et al.* 2019; Bermúdez *et al.* 2020; Costa *et al.* 2020; Butcher *et al.* 2021; Zahmatkesh *et al.* 2021; Zhao *et al.* 2021) or not (Andimuthu *et al.* 2019; Martínez-Gomariz *et al.* 2019; Cook *et al.* 2020) prior to the development of IDF curves. Sub-hourly rainfall extremes (e.g., 5 min) are needed for the development of accurate IDF curves as those are an essential part of the design procedure of various infrastructure works (e.g., sewers).

Different theoretical distributions (e.g., Gumbel, generalized extreme value – GEV, generalized Pareto distribution – GPD, log-normal, log pearson type III, exponential) are used in frequency analysis (e.g., Forestieri *et al.* 2018; Ganguli & Coulibaly 2019; Bermúdez *et al.* 2020; Hosseinzadehtalaei *et al.* 2020, 2018). AMS and/or POT methods (e.g., Hosseinzadehtalaei *et al.* 2020) are frequently employed for extracting peak precipitation time series. Tabari (2021) investigated the effect of using AMS or POT method in extreme value analysis under climate projections. They concluded that both methods agree on the signal of change; however, they disagree on the magnitude, especially for return periods with low probability of occurrence. IDF curves are derived for different durations, ranging from 1 min to 30 days (e.g., Zhou *et al.* 2012; Hosseinzadehtalaei *et al.*

2018) and for different exceedance probabilities (return periods), ranging from 0.2 months to 1,000 years (e.g., Rodríguez *et al.* 2014; Zhou *et al.* 2018).

Uncertainty of climate projections and frequency analysis methods is quantified (e.g., Ganguli & Coulibaly 2019; Hosseinzadehtalaei *et al.* 2020, 2018; Butcher *et al.* 2021; Zahmatkesh *et al.* 2021) based on different schemes (e.g., Zhu *et al.* 2013; So *et al.* 2017; Zhou *et al.* 2019; Kim *et al.* 2020) or overlooked (Alfieri *et al.* 2015; Jaiswal *et al.* 2015; da Silva *et al.* 2018; Kristvik *et al.* 2018; Andimuthu *et al.* 2019; Hu & Ayyub 2019; Uraba *et al.* 2019; Costa *et al.* 2020; Khazaei 2021; Zhao *et al.* 2021).

Overall, it must be stated that it is advisable to address and quantify uncertainty to inform planners and decision makers regarding climate change adaptation options. Finally, there is no general agreement on how to treat no-stationarity assumption, for example researchers have proposed and applied frameworks using a moving 30-year time window (e.g., Hu & Ayyub 2019; Uraba *et al.* 2019; Zhao *et al.* 2021), Bayesian inference frameworks coupled with GEV distribution with location and/or scale parameters varying in time (Ragno *et al.* 2018; Ganguli & Coulibaly 2019; Ren *et al.* 2019; Silva *et al.* 2021; Zahmatkesh *et al.* 2021). Overall, extrapolation from short, observed and/or simulated, rainfall records is not advisable as it may compound uncertainty. In addition, it must be mentioned that as the shape parameter of GEV distribution is sensitive and more difficult to estimate, it should not be used under non-stationary frequency analysis.

Table SM1 presents the 106 studies reviewed in the present article. More specifically, full details are provided regarding: (i) the study area; (ii) the climate model used (GCM or RCM); (iii) the climate scenario (RCPs or SRESs); (iv) the use of statistical downscaling technique-bias correction or not; (v) the application of temporal disaggregation or not; (vi) the duration of the IDF curves developed; (vii) the distribution used in frequency analysis; (viii) the return period of the developed IDF curves; (ix) the method used to extract peak rainfall series; (x) the quantification of uncertainty or not; and (xi) the scale of the developed IDF curves (local-station, grid or regional). The geographical distribution of the 106 studies reviewed in the present work is presented in Figure SM2.

Comparison of the studies, methods and corresponding approaches provided useful insights and helped answering the main questions raised in the present review study. Moreover, the comparison allowed us to identify the main limitations and propose a general framework associated with the development of IDF curves based on future climate simulations.

Figures 1–7 present the results of the 106 publications reviewed in the present work and summarized in Table SM1. More specifically, the assessment was based on: (i) the type of climate model used (Figure 1); (ii) the future climate scenario used

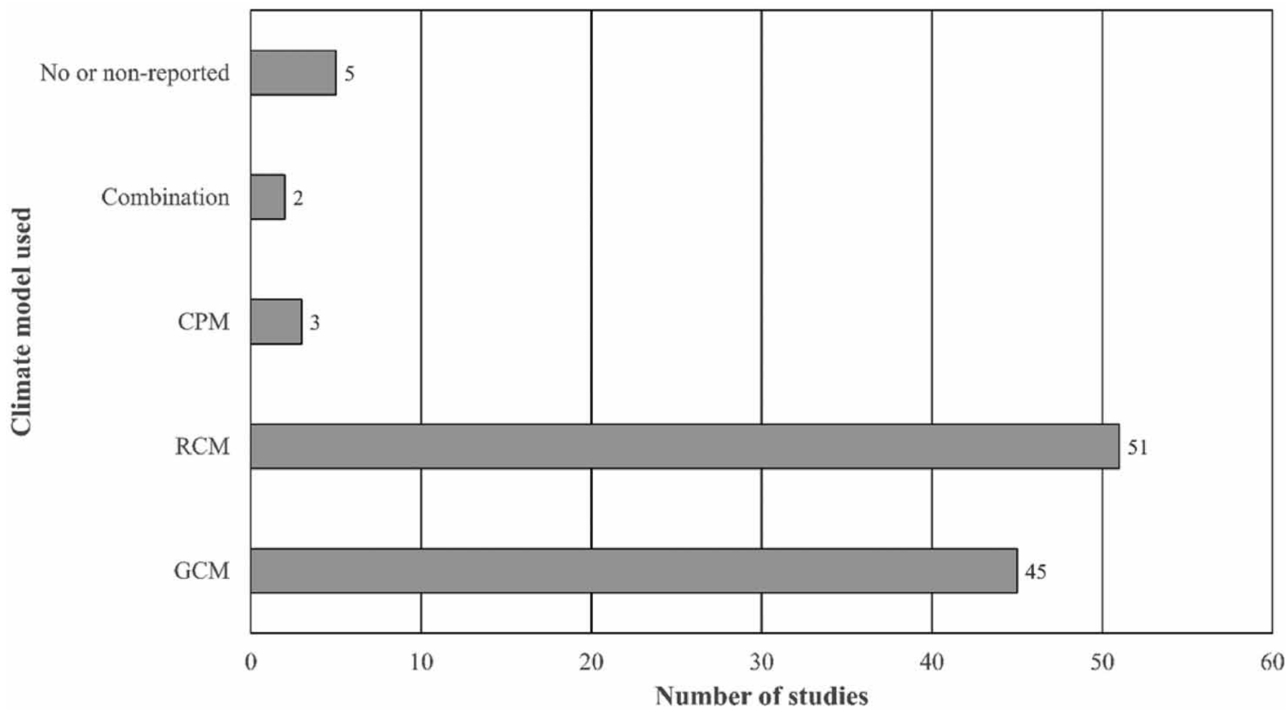


Figure 1 | Number of studies using various climate models in the 106 reviewed publications.

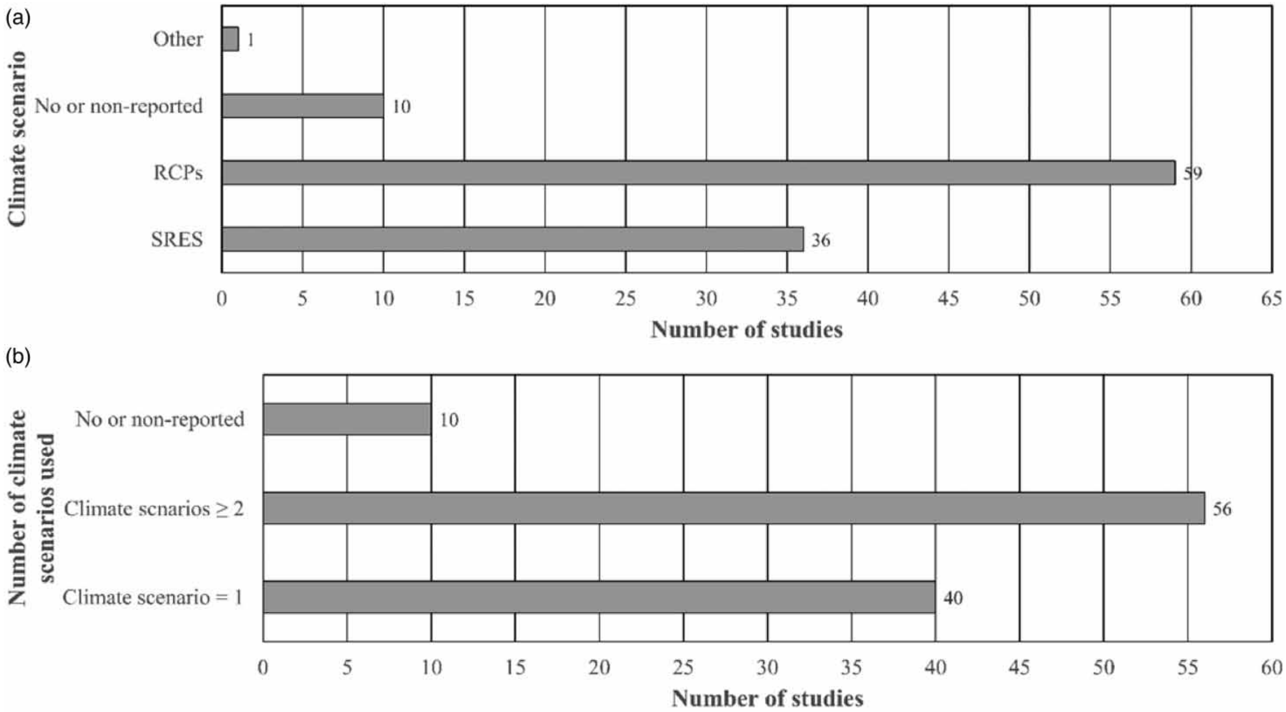


Figure 2 | (a) Number of studies using different climate scenarios; and (b) number of studies using one or two or more future climate scenarios in the 106 reviewed publications.

(Figure 2(a)) and the use or not of an ensemble of climate scenarios (Figure 2(b)); (iii) the method used for extracting annual extreme values (Figure 3(a)), the main theoretical distributions used (Figure 3(b)) and the method used for extracting annual extreme values along with the selected theoretical distribution used for modeling annual extremes (Figure 3(c)); (iv) the main approaches used (i.e., stationary and non-stationary; Figure 4(a)) and the most widely used methods (methods for extraction of annual extreme values and the main theoretical distribution used) for each approach (Figure 4(b)); (v) the application of

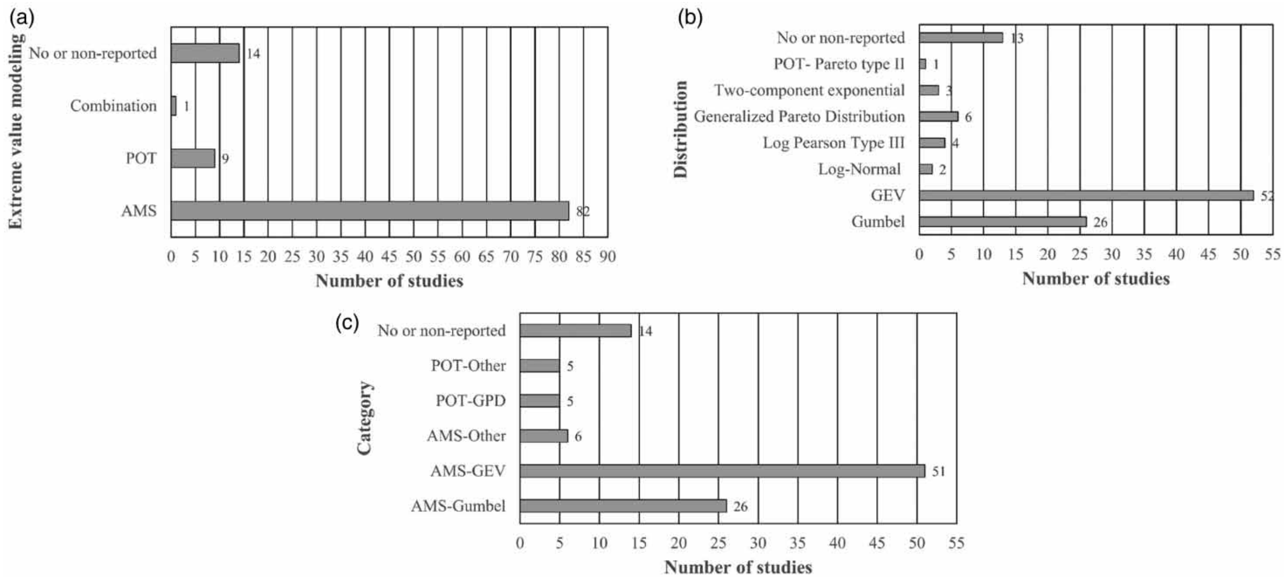


Figure 3 | (a) method used for extracting annual extreme values; (b) main theoretical distributions used; and (c) method and distribution used for the development of IDF curves.

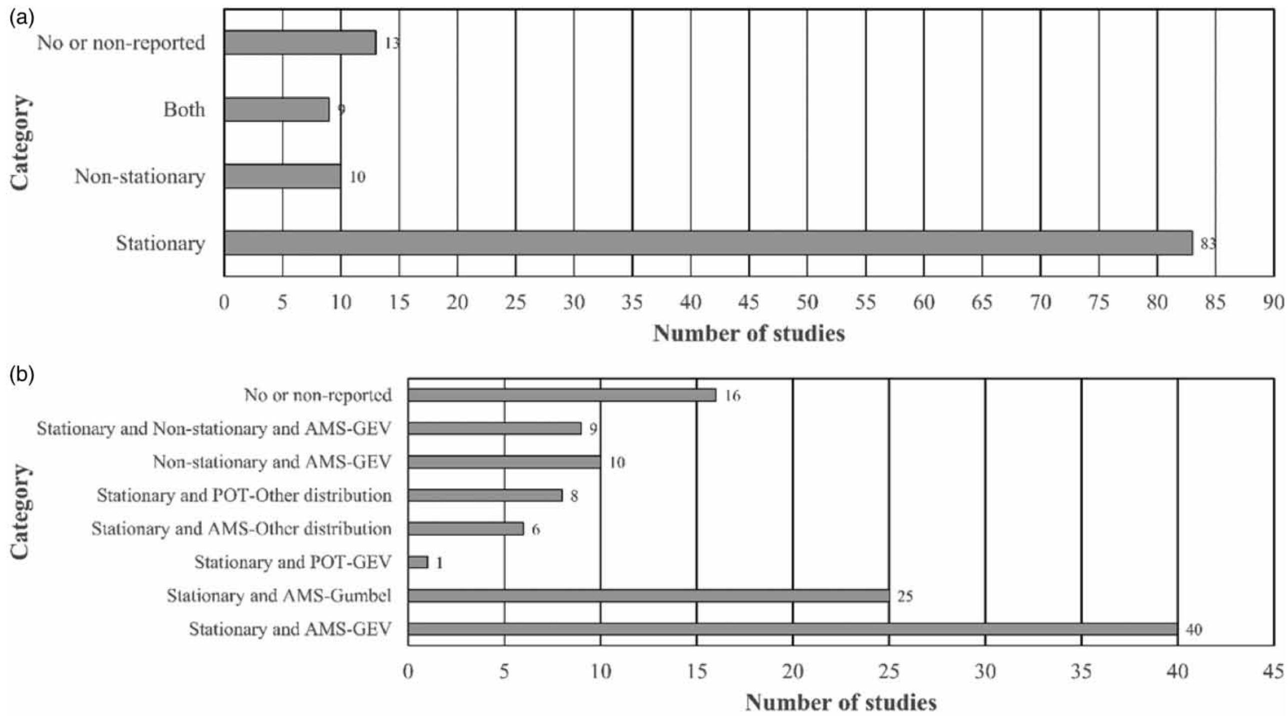


Figure 4 | (a) Approach (i.e., stationary or non-stationary); and (b) approach, method for modeling annual extremes and theoretical distribution used for developing future IDF curves in the 106 reviewed publications.

statistical downscaling (Figure 5(a)) and temporal disaggregation (Figure 5(b)); (vi) the minimum time scale used for developing future IDF curves (Figure 6); and (vii) the total number of studies that have assessed uncertainty and the corresponding years (Figure 7).

Frameworks used

Based on the climate model used, we grouped the 106 studies into five categories: (i) GCM; (ii) RCM; (iii) CPM; (iv) combination of climate models; and (v) no use of a climate model (i.e., use of a simple scale factor) or non-reported (Figure 1). The majority (91%) of the studies reviewed used future climate projections from GCMs and/or RCMs, while only three and two studies (3 and 2%) used the new generation of climate models (i.e., CPMs) and/or a combination (e.g., GCM and CPM), respectively.

Raw data from climate model simulations tend to underestimate/overestimate design rainfalls and present a wide variability (a wide range of possible outcomes) because of the inherited uncertainty and sensitivity of the climate models and climate scenarios. Uncertainty is inherited from internal variability of the system and climate projections (forcing scenario), and is compounded by climate modeling and spatial downscaling and temporal disaggregation techniques. To this end, the use of a multi-member ensemble (e.g., different climate models, different climate scenarios and the same models with different initial conditions) is proposed. However, we must acknowledge that due to limited resources (e.g., time and computational power) this may not be feasible for CPMs.

Based on the climate scenario used, we grouped the 106 studies into four categories (Figure 2(a)): (i) use of the previous generation of climate scenarios (i.e., SRESs); (ii) use of the latest generation of climate scenarios (i.e., RCPs) (iii) no use of a climate scenario or non-reported; and (iv) other. The majority (56%) of the studies examined used RCPs, while only ten studies (9%) did not use a climate scenario or did not report the scenario used. Moreover, based on if the 106 studies used more than two climate scenarios, we grouped them into three categories (Figure 2(b)): (i) one climate scenario used; (ii) two or more; and (iii) no climate scenario used or non-reported. The majority (53%) of the studies examined used two or more future climate scenarios. The main reason for using more than one climate scenario is for assessing and/or quantifying the uncertainty associated with those scenarios. However, it must be stated that in a rather vast number of studies (38%)

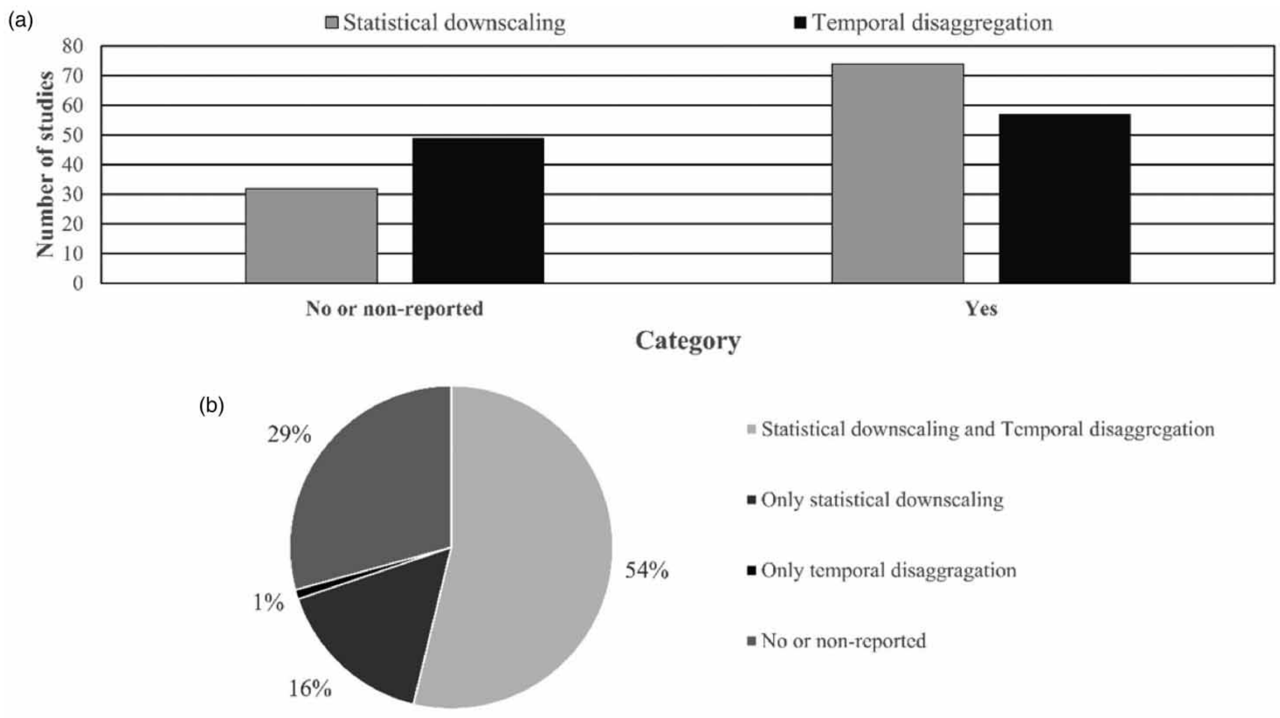


Figure 5 | (a) Number of studies statistical downscaling and temporal disaggregation; and (b) percent of studies employing statistical downscaling along with temporal disaggregation, only downscaling, only temporal disaggregation or none of the above in the 106 reviewed publications.

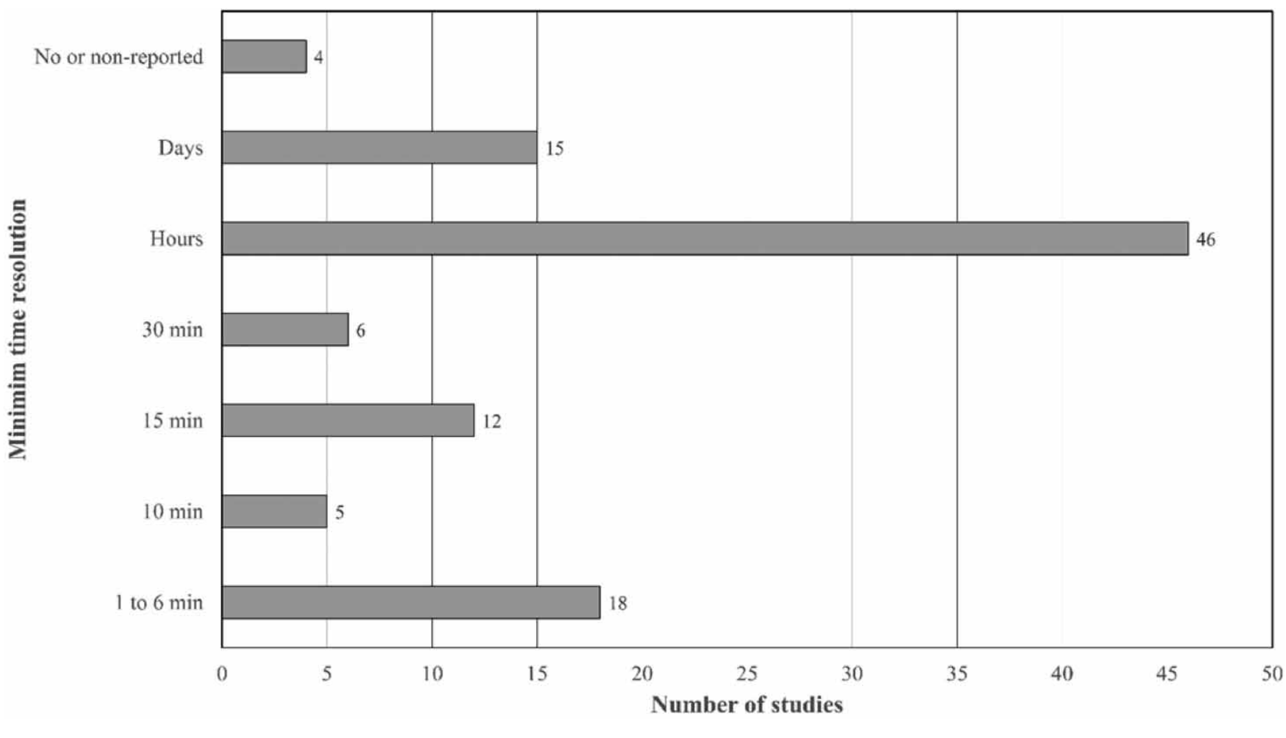


Figure 6 | Minimum time resolution used for the development of future IDF curves in the 106 reviewed publications.

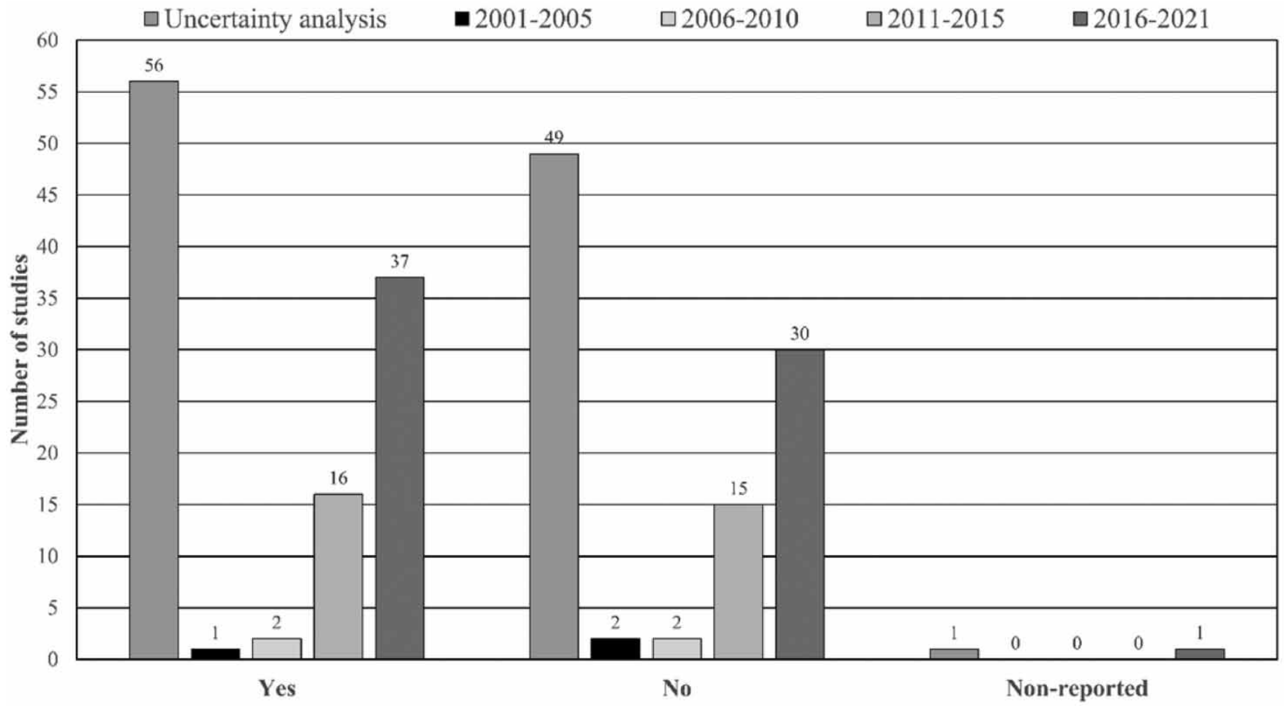


Figure 7 | Number of studies that included uncertainty and number of studies that included uncertainty throughout the years in the 106 reviewed publications

the uncertainty is not treated and future IDF curves are developed based on solely one future climate scenario. As already stated, to treat uncertainty of future climate scenarios the use of multiple (at least two) climate scenarios are proposed.

Different researchers and countries have adopted a simplified methodology (scaling factor) for assessing the impacts of climate change on future rainfall extremes. For example, Niemczynowicz (1989) and Defra (2006) used an uplift factor varying from 10 to 30%, and Semadeni-Davies (2004) used an uplift factor varying from 10 to 40%. Most countries have not addressed the issue of updating IDF curves and there are not specific guidelines. Moreover, where there exist guidelines, they vary significantly from country to country and are subjective (Hailegeorgis & Alfredsen 2017). Madsen *et al.* (2014) reviewed existing design flood and precipitation guidelines for Europe, concluding that most countries have not incorporated climate change impact assessment in the design procedure. Requena *et al.* (2021a) proposed a framework and technical guidelines for the development of IDF curves under the assumption of climate change for Canada.

Another approach, based on Clausius-Clapeyron relationship scaling of rainfall extremes and temperature, can provide a starting point for IDF updating under future climate change projections. According to the Clausius-Clapeyron equation, assuming a constant relative humidity, one-degree Celsius increase of temperature leads to about 7% increase in water vapor availability (Fowler *et al.* 2021a, 2021b). Based on future climate projections of rainfall extremes from climate models, the Clausius-Clapeyron relationship has reported to hold even for regions were a decreasing trend of future rainfall is projected (e.g., Aalbers *et al.* 2018). Researchers (e.g., Fischer & Knutti 2016) have reported similar rates for observed daily rainfall extremes. On the other hand, observed short duration rainfall extremes (e.g., hourly rainfall) analysis has revealed that the 7% increase is far exceeded (Westra *et al.* 2014) as short rainfall extremes tend to be sensitive based on rainfall duration, the region and the region topography, observed temperatures, moisture availability and the scaling approach used (Prein *et al.* 2015; Hodnebrog *et al.* 2019; Vanden Broucke *et al.* 2019; Helsen *et al.* 2020; Vergara-Temprado *et al.* 2021). Moreover, other researchers have expressed concerns regarding extrapolation of future short rainfall extremes for observed temperature scaling (e.g., Chan *et al.* 2015).

Figure 3(a) compares the number of studies that used AMS, POT and/or a combination. It can be observed that the vast majority of the studies examined herein (77%) used the AMS approach. The main reason is associated with the difficulty and/or uncertainty of a suitable threshold needed for using the POT approach. Figure 3(b) presents the main theoretical distributions used for modeling rainfall extremes. It can be observed that Gumbel (24% of the examined studies) and GEV

(49% of the examined studies) distributions are the main theoretical distributions used. This is expected as Gumbel and more recently GEV are proposed from national guidelines around the globe for modeling annual rainfall extremes. Finally, Figure 3(c) presents the method used for extracting annual extreme values along with the selected theoretical distribution used for modeling annual extremes. In most studies reviewed herein, the AMS approach with Gumbel distribution (24%) and the AMS approach with GEV distribution (48%) are selected for the development of IDF curves considering the effects of climate change. Overall, it must be concluded that in the literature there is no general agreement upon the best theoretical model for performing extreme value analysis. Suitability of a given theoretical distribution is highly dependent on: series length, analysis method (i.e., annual maxima, partial duration series) and the examined variable. To this end, it is proposed to also assess other distributions prior to the development of IDF curves.

It is proposed that different theoretical distributions be tested via statistical tests (e.g., chi-square test) prior to the development of IDF curves. In addition, researchers and practitioners should be careful when trying to develop IDF curves from short rainfall records. For instance, in many regions around the globe, especially in developing countries, adequate rainfall records are not available for various reasons, i.e., limitation in spatial coverage, short rainfall records and low quality of data. To this end, other data sources such as re-analysis data sets, radar data etc. and or data from similar (climatologically) regions can be used for the development of IDF curves. However, rainfall derived from satellite products tends to underestimate and/or overestimate rainfall frequency. As a result, prior to the application of other precipitation data sources for deriving IDF curves, errors must be examined and corrected (bias-correction). Overall, it must be stated that it is both crucial and essential to develop approaches that are able to incorporate new scientific advancements (e.g., satellite-based precipitation data sets) in the design, planning and operational procedure of water related infrastructure.

Most research efforts of Table SM1 updated IDF curves based on one future period. For example, Noor *et al.* (2018) applied their framework for modeling climate change impacts on future IDF curves, for Malaysia, for the period 2006–2099. Their results suggested an increase in future rainfall intensities especially for short durations, and uncertainty of projections was also found to increase as duration decreased. Hosseinzadehtalaei *et al.* (2018) assessed the impact of climate change on IDF curves for central Belgium. They used a large ensemble of RCM (88) projections forced by two RCPs (4.5 and 8.5). Bias correction of climate model projections and temporal disaggregation was not considered and the results were only compared with in-situ observations. Hosseinzadehtalaei *et al.* (2020) proposed a framework for updating IDF curves under the assumption of climate change on continental scale. They applied their methodology for developing continental future and current IDF curves for Europe. They utilized *in situ* rainfall observations (Uccle and De Bilt), remote-sensing based rainfall data and re-analysis rainfall data (CMORPH, MSWEP, E-OBS) in conjunction with a multi-model RCM ensemble (EURO-CORDEX). Their results demonstrated that the intensification of sub-daily events would be greater than for the events with low return period and it depends on the duration studied. Kim *et al.* (2020) updated the IDF curves for Korea based on an ensemble of 16 future climate projections. Their results suggested that future change in rainfall intensities varies significantly (from about −40 to about 140%) based on the study site, the return period and the duration examined. Moglen & Rios Vidal (2014) assessed climate change effects in Washington, DC, USA on 2-year and 10-year precipitation depth return periods for various durations. They used four different RCMs forced by two different GCMs. Results of the climate model simulations indicated considerable variability of precipitation projections. For example, they reported that the 24-h duration precipitation depth increased from about −2 to 37% compared to NOAA Atlas 14, and the return period assessed (2 and 10 years). Vu *et al.* (2017) reported for Hanoi, Vietnam, an increase of future 1-hour rainfall intensity for all return periods studied ranging between 34 and 48%. However, to temporally disaggregate projected rainfall values, they used one forcing scenario and a simple scaling approach, assuming scaling invariance.

Climate projections and time windows of 30-year future periods (e.g., 2020–2051, 2069–2100) is an alternative procedure for updating IDF curves. Employing this approach, the stationary frequency analysis is undertaken for both the baseline and the future periods. For example, Rodríguez *et al.* (2014) studied climate change impacts on extreme precipitation for the city of Barcelona, Spain. They used five GCMs under four SRESs. Their results demonstrated an increase (i.e., at least 4%) in daily rainfall with return periods greater than 20 years. They also reported an increased sensitivity to the climate model and the referred observational data used. Chandra *et al.* (2015) used an ensemble of 26 GCMs under four RCPs in modeling IDF curves under climate change and the associated uncertainties for the city of Bangalore, India. Kao & Ganguly (2011) developed IDF curves for various climate model simulations forced with several climate scenarios (i.e., SRESs) based on re-analysis data sets (instead of observations). Extreme value analysis of AMS was undertaken based on GEV distribution and parameters were estimated (MLE method) successively, using a 30-year window to account for non-stationarity of climate. They argued that the computed differences between climate model simulations and reanalysis data sets are large and as a result uncertainty must be quantified prior to decision making. Moreover, they concluded that water management must not rely on the stationarity assumption, similarly to the conclusion reported by Milly *et al.* (2008). Fadhel *et al.* (2017), for bias correction of climate model simulations and developing IDF curves for Yorkshire, UK, utilized 11 RCMs under one SRES and eight different reference periods of 30 years. They concluded that for the majority of the reference periods studied and for all durations, rainfall intensity increased. Moreover, they suggested the use of an ensemble of reference periods used for bias correction. Forestieri *et al.* (2018) studied the impacts of climate change on the IDF curves of Palermo and Catania in Sicily, Italy. They used an ensemble of 11 RCMs driven by RCP 8.5 scenario. Their results suggested an increase in the future rainfall depth, compared to the observations, ranging from about 17 to 86% based on the duration, the exceedance probability and the area studied. Moreover, they reported that variability of future IDF curves increases as the horizon and return period examined increases. Wang *et al.* (2013) studied the impacts of climate change on IDF curves at the Apalachicola watershed in Florida, USA. They utilized an ensemble from seven nested GCM-RCM simulations. Moreover, they assessed the performance of the seven nested GCM-RCMs on the simulation of precipitation temporal variation, and found that two of the RCMs presented good skills regarding the generation of high-intensity precipitation events. Next, they employed two bias correction methods to bias correct the selected RCMs and assess climate change impacts on future IDF curves. Uncertainty of RCMs and the associated IDF curves were only discussed and not qualified. The average future 2-year, 3-hour (24-hour) rainfall of the two RCMs was found to range from −11% (11%) to 153% (788%) based on the station studied. Shrestha *et al.* (2017) utilized the simulations from nine GCMs driven by two SRES scenarios for modeling climate change impacts for the city of Bangkok, Thailand. They reported that the percent change in future rainfall intensity ranges between −18 and 50% based on the return period, the duration, the climate model and the scenario examined.

Researchers have argued that examining the non-stationarity of future IDF curves based on a moving time window framework is misguiding, and proposed the use of a non-stationary framework where parameters of GEV distribution are considered time variant. The non-stationary nature of extreme precipitation events is investigated by introducing covariates such as time, maximum, minimum and mean temperature, and different climate indices and physical processes varying in time (Silva *et al.* 2021).

During the past 20 years, the concept of non-stationarity, which introduces time and/or other physical processes and climate indices as covariates of the parameters of the used statistical distribution of future rainfall extremes, has received much attention. However, different studies have criticized and/or raised concerns regarding the aforementioned concept (e.g., Lins & Cohn 2011; Matalas 2012; Koutsoyiannis & Montanari 2014; Serinaldi & Kilsby 2015). Figure 4(a) presents the number of studies which apply a stationary framework (78%), a non-stationary framework (9%), both approaches (8%), and no method (12%). In addition, Figure 4(b) shows the number of studies which used a stationary or a non-stationary approach along with the method used for extracting extreme rainfall values and the main distributions used. It can be observed that the vast majority (35%) of the reviewed studies employed a stationary framework coupled with the AMS approach and GEV distribution (Figure 4(b)). In addition, the non-stationary approach is also used with AMS and GEV distribution (Figure 4(b)).

Overall, in the literature, different approaches have been proposed for non-stationary frequency analysis of extreme rainfall events. Trend analysis, prior to the selection of a stationary and/or a non-stationary model for modeling rainfall extremes, must be applied in order to identify deterministic mechanisms (Serinaldi & Kilsby 2015). As a result, non-stationary frequency analysis must always be practiced with caution as observed trends may not be similar to future trends. In addition, the non-stationary modeling approach introduces another level of uncertainty that must always be assessed. We believe that trend analysis and shift detection must be performed prior to the application of a stationary and/or a non-stationary framework for developing IDF curves. However, as Serinaldi & Kilsby (2015) stated, trend analysis must be undertaken to determine deterministic mechanisms and not to detect changes.

Combined with Bayesian inference, these frameworks account for both non-stationarity of climate and the associated uncertainties. Yan *et al.* (2021) reviewed recent advancements regarding update of IDF curves. They mainly focused in the two most widely used approaches: the stationary approach based on simulations of climate models and the non-stationary approach where different covariates are used. Silva *et al.* (2021) introduced a framework for updating IDF curves under the non-stationarity assumption of climate. In the proposed framework several non-stationary GEV models were constructed and several trend combinations with time as covariate, which were compared with a stationary GEV model. The results for the Moncton station suggested a trend in the location parameter of GEV distribution, while the stationary model was found to be acceptable only for short durations (<10 min). However, the results for the Shearwater station suggested that the stationary GEV model is acceptable for all the durations studied except for the 24-hour. Overall, the authors reported that the exceedance probability may be reduced in the future as a result of climate change; however, the reduction ratio greatly varies with duration, return period, study site and modeling options (stationary or non-stationary). Ganguli & Coulibaly (2019) updated IDF curves for Southern Ontario, Canada, using stationary and non-stationary GEV models. Their results suggested that IDF curves with high probability of occurrence (up to 10 years) are projected to increase for all scenarios examined. On the other hand, for return periods of up to 25 years, only for the non-stationary scenario a change in the projected IDF curves was reported (Ganguli & Coulibaly 2019). Ragno *et al.* (2018) proposed a framework for updating IDF curves based on GCM projection driven by RCPs 4.5 and 8.5. They applied the proposed framework in 18 cities across the USA, and, based on the mean of the multi-model ensemble utilized, they argued that extreme precipitation events in the USA may increase up to 20% and be twice more frequent compared to the historical period. Silva *et al.* (2021) updated IDF curves for six stations in Canada. They used climate projections from 24 GCMs, produced for the Coupled Model Intercomparison Project Phase 5 (IPCC 2014), driven by three RCPs (2.6, 4.5 and 8.5). In modeling the non-stationary behavior of future rainfall extremes, they used time as a covariate, allowing parameters of GEV distribution to vary in time, and tested nine different combinations of GEV parameters, based on the Akaike criterion, and parameter estimation was carried out using the method of maximum likelihood. They reported an increase in the frequency of extreme rainfall events, under the non-stationary model, which varies according to the study area, duration and the return period. Zahmatkesh *et al.* (2021) updated IDF curves for the greater Toronto area, Canada. They utilized future climate projections from Ontario Climate Change Data Portal and the study of Ganguli & Coulibaly (2019) driven by RCP 8.5. The results suggested a higher flood probability under the non-stationary assumption. However, it has been argued that non-stationary frequency analysis can potentially be influenced by the use of different covariates and the type of the covariates (Vu & Mishra 2019). In order for a non-stationary framework to be reliable, the deterministic processes leading to time variant must be understood (Hertig *et al.* 2015; Ragno *et al.* 2018). Most studies are employing covariates as a time function in the scale and location parameter of GEV distribution. An exact estimation of the shape parameter of GEV distribution is difficult, and as a result, in most cases, it is not considered as a covariate of time. For more information regarding the non-stationary models using covariates the reader is referred to Yan *et al.* (2021).

CPMs have opened an important window into hourly and sub-hourly duration computations, which are critical to IDF curve development and for extreme value analysis of future rainfall. GCMs have a very limited usefulness for IDF curve development as they do not represent sub-daily precipitation very well. To this end, the new approach for updating IDF curves is based on future climate projections from CPMs. CPM future simulations of short duration rainfall extremes tend to produce larger increases compared to GCMs and/or RCMs (Kendon *et al.* 2021). Based on future climate projections from CPMs, different researchers have reported an increase in daily and sub-daily rainfall extremes for different areas around the globe (e.g., Cannon & Innocenti 2019; Vanden Broucke *et al.* 2019; Ban *et al.* 2020; Fosser *et al.* 2020). Helsen *et al.* (2020) used two different CPMs and reported an intensification of future hourly extremes with small differences observed between the two climate models, concluding that intensification of hourly future rainfall intensity is region-dependent. Martel *et al.* (2020) used future climate projections from two large ensembles GCMs for investigating climate change impact on daily rainfall. They reported a decrease in the return period for events with return period of 100 years. Fosser *et al.* (2020) concluded that rainfall uncertainties, resulting from parameterization of deep convection schemes, can be reduced by CPMs. Kendon *et al.* (2019) employed a CPM with horizontal resolution of 4.5 km for an Africawide domain in simulating future 3-hour precipitation (10-year period towards the end of the century and climate scenario RCP8.5). They compared their results with those produced from an RCM with horizontal resolution of 25 km. They concluded that future rainfall extremes simulated with the CPM are greater than the ones simulated with the RCM. Intensification of future rainfall projections has been reported to stay below the Claus Clausius-Clapeyron relationship (Ban *et al.* 2015; Hodnebrog *et al.* 2019; Vergara-Temprado *et al.* 2021); however, others have reported increases larger than the Claus Clausius-Clapeyron relationship (e.g., Mantegna *et al.* 2017; Hodnebrog *et al.* 2019; Fosser *et al.* 2020; Knist *et al.* 2020; Lenderink *et al.* 2021).

Cannon & Innocenti (2019) updated IDF curves based on future climate projections from a single CPM for the North America domain. They reported largest increases in the return periods of short rainfall extremes compared to daily. Their results are in accordance with the results reported by other researchers (e.g., Westra *et al.* 2014; Martel *et al.* 2020; Fowler *et al.* 2021a). Mantegna *et al.* (2017) developed future IDF curves for two stations in Australia based on future climate projections from a high-resolution convection-parameterizing RCM forced by six GCMs under A2 SRES scenario. They argued that climate projections from RCMs can be used instead of CPMs for future projections of short rainfall extremes. Tabari *et al.* (2016) compared climate change projections, derived by different climate models (GCMs, RMs and CPMs), with observations (Uccle station, Belgium) and reanalysis rainfall data (E-OBS dataset), at different spatiotemporal scales, with respect to extreme rainfall statistics (i.e., IDF curves and empirically developed return periods). They concluded that the resulting future climate projections derived by CPMs are more accurate than climate projections derived by GCMs. Moreover, a number of studies have addressed the impact of climate change on short rainfall extremes based on CPM simulations (e.g., Kendon *et al.* 2014, 2017, 2019; Ban *et al.* 2015; Hodnebrog *et al.* 2019; Vanden Broucke *et al.* 2019; Fosser *et al.* 2020; Helsen *et al.* 2020; Knist *et al.* 2020; Luu *et al.* 2020; Lenderink *et al.* 2021; Pichelli *et al.* 2021; Vergara-Temprado *et al.* 2021). However, in the aforementioned studies, IDF curves were not developed (i.e., extreme value analysis by fitting a theoretical distribution is not undertaken) and the impact of climate change on short rainfall extremes was assessed based on empirically extracted precipitation percentiles (e.g., 95, 99, 99.9 etc.). As a result, those studies were not further investigated and not included in the present review article.

Overall, the majority of studies assessing the impact of climate change on future sub-daily and daily rainfall extremes using climate projections from CPMs are based on one CPM and one, relative short, future period for updating IDF curves. As a result, this can lead to severe structural and epistemic uncertainty. To deal with uncertainty of climate projections, a large multi-member ensemble is proposed to be used for updating IDF curves. However, the main drawback of the proposed scheme are the computational power and time needed. Overall, it can be concluded that CPMs are able to provide improved estimates of extreme sub-daily precipitation compared to GCMs and RCMs. Moreover, research has focused on advancing those climate models and, in combination with the advancements of high-performance computing, it is likely that estimates will considerably be improved in the future and statistical downscaling and/or bias correction may not be needed. Overall, to treat internal variability and epistemic uncertainty, it is recommended to use both multi-member and multi-model ensembles.

To the best of our knowledge, the only freely available decision support tool for updating IDF curves based on climate projections is the IDF_CC Tool (Simonovic *et al.* 2016b). However, this tool is only available for Canada. The methodology of the IDF_CC tool consists of spatial and temporal downscaling and frequency analysis of AMS using Gumbel or GEV theoretical distributions. However, uncertainties of climate models and future scenarios, of spatial downscaling and temporal disaggregation, and those associated with the frequency analysis scheme are not taken into account. To this end, a tool incorporating trend analysis, different spatio-temporal disaggregation techniques, various theoretical distributions, both stationary and non-stationary models and uncertainty quantification is proposed to be developed.

Statistical downscaling

Climate change projections from climate models (GCMs, RCMs and CPMs) are often biased, and as a result, post-processing by means of bias correction is needed. According to Fowler *et al.* (2007), statistical downscaling can be categorized as follows: (i) regression models; (ii) weather generators; and (iii) weather classification schemes. Several studies have reviewed and compared several downscaling and bias correction techniques (e.g., Fowler *et al.* 2007; Dixon *et al.* 2016; Maraun 2016; Maraun & Widmann 2018; Gutiérrez *et al.* 2019), while novel statistical downscaling techniques are still being developed and applied (Zennaro *et al.* 2021). Overall, various methods exist, and new methods are developed and proposed. However, there is not a single best method; hence, it is proposed that at least two statistical downscaling methods be used to incorporate the uncertainty associated with these approaches.

Figure 5(a) presents the number of studies that employed statistical downscaling and temporal disaggregation prior to the development of future IDF curves. The vast majority of the studies examined (70%) performed statistical downscaling for removing bias from the future climate projections. Moreover, more than half of the examined publications (54%) applied temporal disaggregation (e.g., scaling of AMS, cascade models etc.). This is to be expected as the spatiotemporal scale of climate models (i.e., GCMs and RCMs) is not adequate for developing high-resolution IDF curves. However, 46% of the examined studies did not apply a temporal disaggregation technique; hence, the time scale of developed IDF curves matches the time scale of the projections. In case of GCMs and RCMs, this is not adequate for small basins where the time of concentration is in the range of hours. On the other hand, if the projections from CPMs are to be used for the development of future IDF curves, the temporal scale (e.g., 3 h or less) may be adequate for small or medium rural basins. However, in case of small rural basins and/or urban basins, the temporal scale of those future simulations is not appropriate for the development of future IDF curves and the researcher/designer must employ at least one technique for temporal disaggregation.

Li *et al.* (2017) studied the effects of climate change on IDF curves and compared nine methods for bias correcting the results of an RCM driven by one SRES. They concluded that raw data overestimated design rainfall but the results tend to be sensitive to the method used. The quantile mapping approach constitutes a model output statistics technique and is the most frequently used method for statistical downscaling (e.g., Cook *et al.* 2020; Kim *et al.* 2020; Li *et al.* 2021). For example, Willems (2013) revised urban drainage design parameters for Uccle, Belgium, based on a large ensemble of climate models (i.e., 44 RCMs and 69 GCMs). Spatial downscaling and bias correction took place employing the quantile perturbation method. Results were derived for the 2071–2100 future period with 1961–1990 control period. They argued that climate change factors of future precipitation strongly depend on the return period and the location of the study area. They also reported an increase of future rainfall compared to the observed ranging from 15 to 50%, for the high-end climate scenario, based on the return period examined. So *et al.* (2017) proposed a copula Bayesian downscaling scheme for the assessment of future IDF curves in South Korea. The quantile mapping method was used for bias correction while uncertainties of climate projections were quantified based on a Bayesian framework. They utilized various CORDEX-RCM future climate simulations driven by RCPs 4.5 and 8.5. They concluded that an increase in future rainfall intensities under the RCP 8.5 scenario is to be expected ranging from 5 to 30% for the 50-year return period. Moreover, they argued that uncertainty associated with climate projections decreases as the duration studied increases. In general, a 10 to 20% increase in rainfall intensity was observed. Simonovic *et al.* (2016a) updated IDF curves considering climate change for Canada. They used the IDF_CC tool (Simonovic *et al.* 2016b), which utilized simulations from GCMs and an equidistant quantile mapping approach for statistical downscaling and bias correction. Frequency analysis of AMS was based on Gumbel theoretical distribution with parameters estimated using the maximum likelihood method. The results reported are based on climate projections from a multi-model ensemble and a GCM for the distant future (2100) driven by three RCPs (2.6, 4.5 and 8.5). The median results from the multi-model ensemble showed less variability compared to the results obtained using only one GCM.

Several weather generators and stochastic rainfall generators have been proposed and used to simulate future rainfall for the development of future IDF curves (e.g., K-Nearest Neighbor, LARS-WG, Neyman-Scott rectangular pulse model etc.). Chandra *et al.* (2015) used WGEN weather generator and Shrestha *et al.* (2017) used LARS-WG weather generator for spatial downscaling of precipitation. Lu & Qin (2020) employed an integrated framework for studying the effects of climate change on short rainfall extremes in urban drainage networks. The framework combined a weather generator (LARS-WG) and a scaling approach for disaggregating daily rainfall to hourly. The weather generator was forced by five GCMs driven by RCP 8.5. The Gumbel distribution was used to project future rainfall and generate IDF curves while designed storms were developed using Huff distribution. They reported decreased intensities for all the scenarios and return periods examined, and observed significant variability of the projected rainfall intensities. Moreover, they reported that the decrease in rainfall intensity is larger for the greater exceedance probabilities. Mamo (2015) used future climate projections from GCMs under three emission scenarios as an input to a stochastic weather generator (LARS-WG) for updating IDF curves in Astoria Heights, New York, USA. The suitability of different theoretical distributions was evaluated using various statistical tests. The results suggested a general increase in future rainfall intensities resulting in the need for new design standards for the development and update of IDF curves incorporating climate change projections. A similar conclusion has been drawn by other researchers (e.g., Simonovic *et al.* 2016a, 2016b; Bermúdez *et al.* 2020; Cook *et al.* 2020; Kourtis & Tsihrintzis 2021; Requena *et al.* 2021a). Khazaei (2021) employed Neyman-Scott rectangular pulse model to assess the impact of climate change projections (two GCMs forced by RCPs 2.6, 4.5 and 8.5) for two basins (five stations) in Iran. IDF curves were developed for durations ranging from 1 day to 10 days and for return periods of 2, 5, 20, 50, 100 and 500 years. The results suggested an increase in future rainfall extremes for all durations and return periods studied; however, the variability of the increase (average increase ranging from 22 to 206%) was significant. Bermúdez *et al.* (2020) updated IDF curves for the city of Betanzos, Spain using an ensemble of nineteen GCM projections forced by two RCMs (4.5 and 8.5). Spatial downscaling of future climate projections took place employing a weather type scheme (SD-B-7). They reported an increased future rainfall intensity for all durations studied indicating a need for updating IDF curves, and acknowledged that GCM future climate projections suffer from significant uncertainties. Agilan & Umamahesh (2016) developed future IDF curves for the city of Hyderabad, India, utilizing simulations derived from twenty-four GCMs driven by various RCMs and further downscaled using K-Nearest Neighbor weather generator. Moreover, they compared future IDF curves, derived from GCM simulations; with IDF curves developed using five covariates. The covariates used for the development of the non-stationary IDF curves were ENSO cycle, urbanization, global warming, local temperature changes and Indian Ocean Dipole. For the first future period studied (2015–2056), they reported that the maximum increase, for the 98th percentile, was 17% while for the second period (2057–2098) the increase, in the 100th percentile of rainfall, was estimated at 37%.

Temporal disaggregation

Figure 6 presents the number of studies reviewed and the minimum time resolution used for the development of future IDF curves. The results suggest that the majority of the studies examined developed future IDF curves based on hourly (43%) daily (14%) time scales. However, as already discussed, sub-hourly data are needed for the development of accurate IDF curves. The present literature review revealed that only a small number of studies used AMS with sub-hourly time scales, i.e., 5 min or less (17%) or 10 min (5%). The main reason is the need for long-term observations with high temporal resolution from a dense network of stations, which in most regions around the globe are missing. On the other hand, long-term daily and/or hourly data are more readily available. As already stated, in cases of limited data, the use of other data sources (e.g., re-analysis data sets, radar data etc.) is proposed. Moreover, the use of temporal disaggregation techniques is proposed to overcome the aforementioned limitations.

In the literature, a wide variety of both stochastic (e.g., Gaume *et al.* 2007) and deterministic (e.g., Ormsbee 1989) methods have been employed for temporal disaggregation of rainfall. Stochastic methods are the most widely used approach and a wide variety of temporal disaggregation schemes have been proposed based on: (i) scale invariance theory; and (ii) rectangular pulse stochastic rainfall models. Artificial neural networks and chaotic models are also used for temporal disaggregation of rainfall (Willems *et al.* 2012b). We point the reader to Serinaldi (2010), Müller & Haberlandt (2018) and Willems *et al.* (2012b) for more information.

Nguyen *et al.* (2007) proposed a method based on scale invariance theory for spatiotemporal downscaling of future climate projections. The method was applied on 15 rain-gauge stations in Quebec, Canada. They used climate projections from two GCMs under one SRES (A2). Their results suggested increased variability of future rainfall extremes based on the climate model used, the study site, the duration and the return period examined. Rodríguez *et al.* (2014) employed temporal disaggregation of daily rainfall projections using two methods (i.e., the daily change factor was applied to sub-daily and a scaling method). The results suggested that change factors calculated using the temporally disaggregated rainfall (i.e., 1-hour) are higher than the ones obtained by using the daily rainfall. Chandra *et al.* (2015) also used scale invariance theory for temporal disaggregation of rainfall. Hassanzadeh *et al.* (2019) investigated potential impacts of climate change on future rainfall extremes. They assessed three quantile-based downscaling of AMS approaches (i.e., quantile-quantile down-scaling method, equidistance quantile matching and scale-invariance method). All three methods were used for the spatiotemporal downscaling of extreme rainfall quantiles. They used daily climate projections from 20 GCMs (NEX-DDP) under two RCPs (4.5 and 8.5). They reported that none of the downscaling methods was able to perfectly represent observations; moreover, results suggested that the selection of downscaling method greatly influences future extreme rainfall events. They argued that an ensemble of climate models and downscaling techniques must be used for impact assessment studies. They also stated that future rainfall extreme with high probability of occurrence may increase, while those with low (e.g., 100 years) may decrease. Noor *et al.* (2018) and Mirhosseini *et al.* (2014) used artificial neural networks for temporal disaggregation.

Sun *et al.* (2019) updated IDF curves for Singapore utilizing *in situ* observations coupled with high-resolution (i.e., 1-hour) remote sensing rainfall data. HyetosR package (Kossieris *et al.* 2018) was used for temporal downscaling of future climate projections from daily to hourly. A generalized IDF curve based on the empirical formulae of Sherman (1931) was developed. Frequency analysis was conducted fitting GEV distribution on AMS. Shrestha *et al.* (2017) used Hyetos software for temporal disaggregation of rainfall. They concluded that future rainfall is expected to increase in the study area. Zhao *et al.* (2021) proposed a novel bias-correction approach named normalized quantile mapping and compared it with two widely used methods (quantile mapping and delta quantile mapping). They also used an artificial neural network for temporal disaggregation of daily rainfall to hourly and the results were compared with Hyetosminute software. They reported that future rainfall intensity varies between −1 and 73% with respect to the historical period based on the return period, the duration and the study site examined. Li *et al.* (2017) compared different bias correction and temporal disaggregation methods for removing biases from RCM projections. The goal was to update IDF curves for the Greater Sydney, Australia. The quantile mapping approach was used for bias correcting the entire timeseries of rainfall and the AMS. The method of fragments was used for temporal disaggregation of rainfall. Regional frequency analysis was employed fitting GEV distribution to AMS using the L-Moments method. They reported an increased variability and differences in the projected rainfall extremes between the examined approaches, with a general consensus for a projected increase in storm rainfall extremes for the study area.

Temporal disaggregation, especially for studies focusing at the urban basin level, is essential. A wide variety of methods have been proposed in the literature but there is no general agreement which methods perform best. Overall, the application of temporal disaggregation must be practiced along with uncertainty analysis as it may give rise to additional uncertainties.

Uncertainty

Finally, Figure 7 presents the number of studies that assessed uncertainty of future IDF curves. More than half (53%; Figure 7) of the examined studies included and quantified uncertainty of future IDF curves. Uncertainty stems from various sources, as already discussed, and is not always easy to address and quantify all these sources; as a result, 46% of the studies reviewed (Figure 7) have not included uncertainty quantification. Moreover, various approaches and frameworks (e.g., Bayesian, bootstrapping etc.) have been proposed and used. Overall, there is no general agreement regarding a general approach for treating uncertainty. It is, thus, crucial to develop future IDF curves based on sub-hourly AMS of various time scales and include uncertainty quantification when trying to update and or develop future IDF curves employing either a stationary and/or a non-stationary approach.

Updating IDF curves considering climate change encompasses various sources of uncertainty. It has been argued that uncertainty of future climate projections is larger than the uncertainty associated with past projections (Willems *et al.* 2012b). The uncertainties arise from: (i) internal variability; (ii) initial conditions of GCM model; (iii) climate model uncertainty; (iv) climate scenario uncertainty; (v) spatial downscaling uncertainty; (vi) bias correction uncertainty; (vii) temporal disaggregation uncertainty; and (viii) uncertainty of the parameter estimation method. In order To account for structural uncertainties (i-iv), it has been proposed to use a multi-model ensemble with various initial conditions, different GCMs and RCMs and various climate scenarios. Shahabul Alam & Elshorbagy (2015) quantified uncertainty stemming from various sources and concluded that climate models are the main source of uncertainty followed by climate scenarios and the choice of the downscaling technique. Hagedorn *et al.* (2005) and Mirhosseini *et al.* (2013) stated that combining several models can reduce uncertainties and biases associated with any individual model.

Kim *et al.* (2020) quantified uncertainty for an ensemble of climate projections based on two GCMs, four RCMs and two climate scenarios (RCPs). They also applied the quantile mapping method in AMS for correcting the bias in RCM future climate projections and the scale invariance method for temporal disaggregation of rainfall projections. Gumbel distribution was used as a probability density function for frequency analysis. Parameters of the theoretical distribution were calculated based on the probability weighted moments method. They argued that the use of a large number of models for constructing the ensemble may not always result in reduced uncertainty. Hailegeorgis *et al.* (2013) examined uncertainty associated with various sources (i.e., tendency, homogeneity, distribution and sampling uncertainty). Chandra *et al.* (2015) quantified uncertainty of future climate projections using a Bayesian approach (i.e., the reliability ensemble average method). They reported that the major source of uncertainties related to IDF curves are poor data quality and insufficient quantity of data. Hailegeorgis & Alfredsen (2017) used a balanced bootstrapping scheme for quantifying uncertainty of climate projections. Fadhel *et al.* (2017) suggested using a moving window reference period for bias correction of climate projections. They used eight reference periods for the bias corrections of climate projections. However, they only used one bias correction method; hence, only the uncertainty due to the selection of the adopted reference period was taken into account. They argued that the percent of change varies from 0.32 to 30.31% for a 5-year return period according to the reference period and the rainfall duration (i.e., 5 min to 24 h) examined. Hosseinzadehtalaei *et al.* (2020) argued that if CORDEX simulations are to be used for updating IDF curves then uncertainty of different bias correction techniques must be considered and quantified. Li *et al.* (2021) assessed future changes in extreme precipitation events over China, in both frequency and intensity terms, based on a large ensemble derived from one GCM (Canadian Earth System Model) driven by RCP 8.5. Bias correction was undertaken employing empirical quantile mapping technique. Before bias correction the authors interpolated the areal values of future precipitation using the inverse distance weighting method and corrected wet day frequency employing the local intensity scaling method. Extreme precipitation events were modeled using GEV distribution and uncertainty analysis was conducted employing a bootstrap scheme. They concluded that the raw ensemble exhibits bias that must be corrected before the impacts of climate change on extreme precipitation events are studied. Cook *et al.* (2020) developed IDF curves by fitting GEV theoretical distribution to the historical and future AMS with maximum likelihood estimation method. Uncertainty was quantified for the parameters of the GEV distribution, spatial resolution of the climate model and uncertainty arising from the downscaling technique employed. They used three future climate projections from high-resolution RCMs and for two spatial resolutions driven by RCP 8.5. They also used three spatial downscaling approaches called the kernel density distribution mapping approach, parametric AMS mapping/equidistant quantile mapping and the change factor approach. Cook *et al.* (2020) argued that modeling choices for the method used for updating IDF curves are a major source of uncertainty. They also concluded that the parameters of the updated IDF are significantly affected by the spatial resolution of the RCM and the spatial downscaling scheme employed. Zhu *et al.* (2013) studied the impacts of climate change on IDF curves for eight sites (i.e., Portland, Burbank, Las Vegas, Denver, St. Paul, Dallas, Albany and Orlando) in the USA. Uncertainty of IDF curves was assessed based on Bayesian model. They reported model uncertainty as the dominant source of uncertainty. Moreover, they reported an increase in future rainfall extremes varying significantly from 2 to 24% for all sites studied. Lima *et al.* (2018) provided regional IDF curves for the Han river watershed using observations from 18 stations in South Korea. They used climate projections from a GCM forced by two climate scenarios (RCPs 6.0 and 8.5) bias corrected using the smoothing spline-based bias correction method. Future IDF curves were developed using scaling property of rainfall coupled with a Bayesian framework for modeling uncertainty. Hosseinzadehtalaei *et al.* (2018) reported large uncertainties for the changes in extreme precipitation events mainly associated with GCMs.

Kristvik *et al.* (2018) studied the effects of climate change for the city of Bergen, Norway. Their analysis was based on an integrated approach combining spatial downscaling and temporal disaggregation with the GEV distribution for updating IDF curves. They used RCM future climate data under RCP 4.5 and 8.5. The results indicated that temporal disaggregation is the main source of uncertainty. Mailhot *et al.* (2007) developed grid-scale and station-scale future IDF curves for southern Quebec, Canada. They reported an increasing trend in future rainfall extremes and an increased uncertainty as duration and return period increases. Monette *et al.* (2012) developed regional future IDF curves for 21 Canadian watersheds. They used future climate projection from an RCM ensemble driven by A2 SRES. Uncertainty was investigated in terms of the coefficient of variation. They reported an increased variability (−30 to 40%) between the climate projections and the historical data for the reference period. A multi-model ensemble approach is usually used to address uncertainty stemming from climate models and scenarios; however, the uncertainty associated with spatial downscaling, bias correction, temporal disaggregation, and frequency analysis of rainfall is overlooked in most studies. Nwaogazie & Sam (2020) reviewed the development of IDF curves based on the stationary and non-stationary assumption; however, uncertainty, stemming from different sources, and the schemes applied in the literature for uncertainty quantification were briefly discussed. Arnbjerg-Nielsen *et al.* (2013) reviewed the impacts of climate change projections on short rainfall extremes and urban drainage systems, and Kourtis & Tsihrintzis (2021) reviewed the measures for climate change adaptation proposing a blueprint accounting for uncertainty. It is not always easy to quantify total uncertainty as it stems from various sources. Moreover, the various sources of uncertainty make it difficult to rely solely on future climate projections for updating IDF curves. Nevertheless, updating of IDF curves must include uncertainty quantification, especially for climate change adaptation scenarios.

CONCLUSIONS

The present review study aims to: (i) summarize the main approaches employed for updating IDF curves considering climate change; (ii) assess how the non-stationarity assumption is incorporated in the context of future IDF curves; and (iii) identify gaps and suggest some future research needed.

Development of IDF curves is based on the stationarity assumption. Climate projections challenge this assumption. It is proposed that decision makers and designers not solely rely on outdated guidelines for the design of critical water related infrastructure. Climate change projections from GCMs, RCMs and/or CPMs would be useful as a starting point for updating IDF curves. However, future climate projections must be treated as hypothetical future scenarios, for future impact studies, and not as future predictions.

The projected impacts of climate change on IDF curves are a subject of ongoing research; however, there is not a general consensus in the literature regarding the impacts of climate change on future extreme storm events. Results suggested that future change in rainfall intensities varies significantly, from −40 to 788%, based on the climate model, the climate scenarios, the spatiotemporal downscaling approaches, the duration, the return period and the location examined. Methods for estimating future precipitation changes, incorporating total uncertainty for fine spatial and temporal scales are rather limited in the literature. National guidelines for updating IDF curves considering climate change do not exist, except of very few.

There is a need for high-quality long-term data with high temporal resolution from a dense network of gauging stations to capture the spatial patterns of precipitation. In most countries, especially developing ones, this is not the case. As a result, it is rather difficult if not impossible to estimate future changes in IDF curves. Researchers have attempted to estimate regional parameters and thus regional IDF curves for ungauged or poorly gauged sites. Recent literature is mainly focusing on the uncertainties related to the projections of climate models and the selection of the best bias correction technique. A limited number of studies has addressed total uncertainty. New approaches that address uncertainty must be introduced to the design procedure.

Finally, due to the high uncertainties, mainly associated with climate projections, a continuous procedure, based on high-quality long-term monitoring data and new re-analysis rainfall products is proposed. The proposed approach must systematically update and assess the developed IDF curves based on historical observations and the most robust climate scenarios and models, statistical downscaling techniques and temporal disaggregation methods. General recommendations for the update of IDF curves can be summarized as follows: (i) acquisition of high-resolution observations, at least hourly for at least 20 years; (ii) use of a multi-model ensemble incorporating several GCMs, RCMs and climate scenarios or use of a multi-model ensemble from CPMs; (iii) use more than one statistical downscaling-bias correction technique; (iv) use more than one temporal disaggregation approach; (v) uncertainty quantification and estimations and reporting of the confidence intervals (e.g., 95, 90%) for the current and future IDF curves; (vi) assessment of spatiotemporal downscaling and comparison with the observations. In case high-resolution climate projections from CPMs are available and employed for IDF update, steps (iii and iv) may be skipped. However, a careful analysis of the present-day climate (e.g., trend analysis) must be undertaken prior to the selection of a stationary or a non-stationary approach for modeling rainfall extremes.

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DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Material Information.

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