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Three methods of characterizing climate-induced changes in extreme rainfall: a comparison study

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ABSTRACT

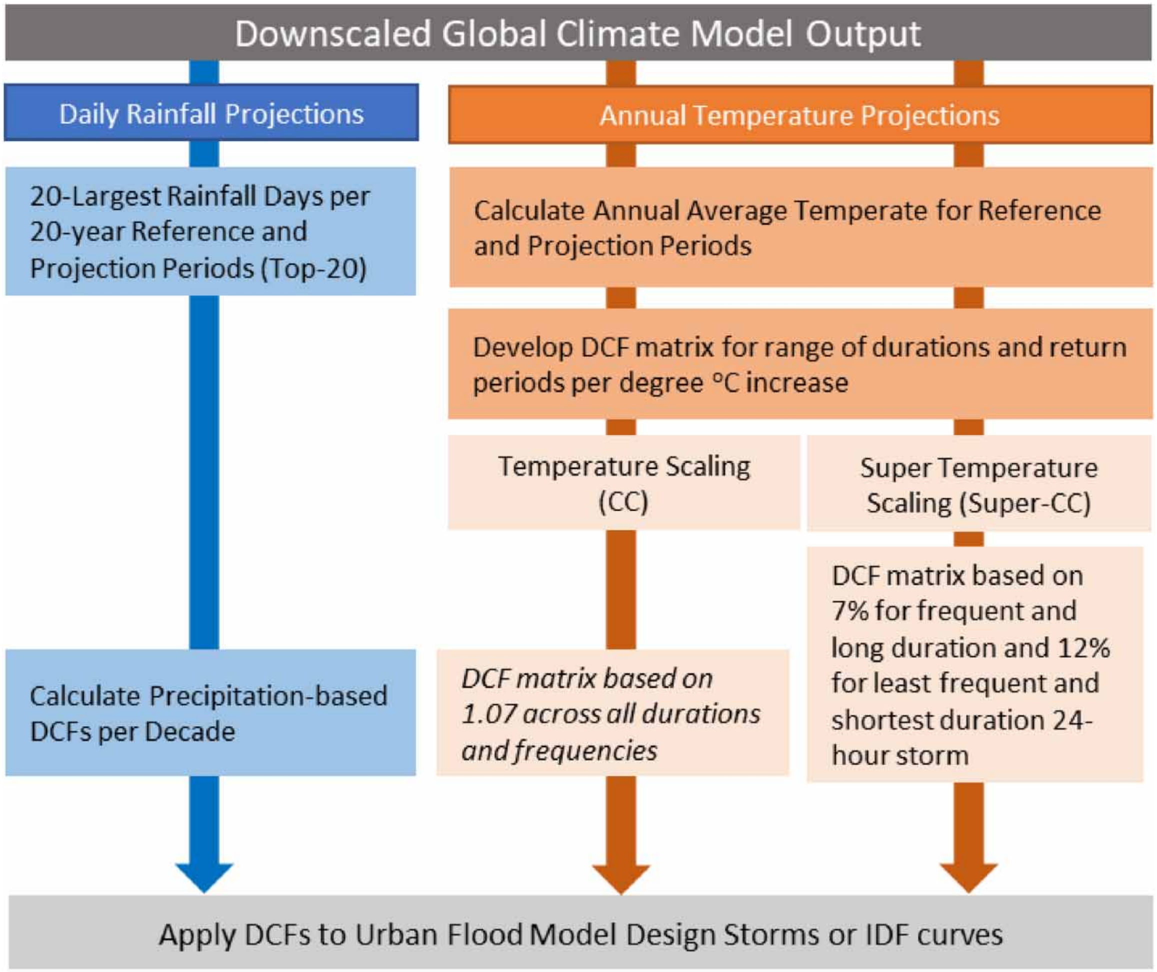
(1) Three practical and easily implementable methods are provided to estimate percent increases in extreme rainfall due to climate change for the period 2020–2090 using Global Climate Model (GCM) output. (2) Methods are designed to bracket the expected range of extreme rainfall intensification for 1–24-h events with return intervals of 1 year to 100 years. (3) One method is based on the 20 largest wet days produced by an ensemble of GCMs, and the other two use GCM projections of temperature and Clausius–Clapeyron assumptions. (4) The results of the case study for the Philadelphia area show that, by the end-of-century, extreme rain event volumes might increase from a low of 18% to a high of 61%, depending on the duration and return interval under consideration. (5) Methods have been benchmarked against existing, publicly available projected rainfall intensities to show the methods that provide an accurate range of extreme rainfall intensification due to climate change.

Key words: Clausius–Clapeyron, climate change, extreme rainfall, flooding, future precipitation projections, global climate model

HIGHLIGHTS

- Three practical methods to assess changes in extreme rainfall are provided.
- Method benchmarked against five publicly available national databases.
- Brackets plausible range of storm intensification for planning and risk assessments.
- Change factors for 1-year to 100-year return intervals for daily and subdaily storm event durations relevant to urban flood applications are provided.
- Case study application for Philadelphia.

GRAPHICAL ABSTRACT



INTRODUCTION

The most recent Intergovernmental Panel on Climate Change (IPCC) report (IPCC 2022) states that human-induced climate change, including more frequent and intense extreme events, has caused widespread adverse impacts and related losses and damages to nature and people. Tabari (2020) states that extreme precipitation is expected to intensify with global warming over large parts of the globe as the concentration of atmospheric water vapor increases in proportion to the saturation concentration at a rate of about 6–7% per degree Celsius rise in temperature. However, changes in atmospheric dynamics can reinforce the thermodynamic effect regionally and modify the extreme precipitation amplification. Li *et al.* (2019) indicate that, due to different interacting drivers of extreme precipitation changes, the changes are not uniform in space and vary by region. The scaling rate of extreme precipitation with land surface temperature is not constant. In wet regions, amplified atmospheric moisture convergence can intensify the effects of extreme precipitation. There is a clear need for methods to quickly estimate the potential range of changes in extreme rainfall that can be applied locally and can be quickly updated as new Global Climate Model (GCM) output becomes available.

This article addresses two challenges. Most methods of assessing climate-induced changes to extreme rainfall rely on the less accurate precipitation projections from the GCMs and thus require complex statistical analysis of downscaled GCM output or other modeling-based methods to attempt to provide localized estimates of future extreme rainfall. For most communities, such complex studies are too resource intensive to carry out, and simpler, effective methods are needed. The second challenge is related to the uncertainty inherent in climate projections and the need to consider a range of future possibilities when it comes to storm intensity. Thus, we offer different methods to generate plausible ranges of low to high estimates for climate-induced changes to extreme rainfall events. These methods are relatively simple to apply, making them accessible to communities with limited technical and/or funding resources that are faced with a myriad of risks related to increasing storm intensities. By providing a range of estimates for changing precipitation extremes, communities can decide where within the spectrum of potential change they wish to plan.

This article presents the results of several years of continuous research focused on translating climate research results into actionable science for urban drainage system planning and flood study applications. Maimone *et al.* (2019) discussed an approach to using downscaled GCM output to create projections of future time series for hydraulic and hydrologic modeling applications. Maimone & Adams (2023) presented an approach to estimating changes in extreme rainfall intensification. In this paper, they expanded three practical approaches to estimating future changes in extreme rainfall. For the purposes of the article, extreme rainfall events are limited to durations of 1–24 h for return intervals of 1 year to 100 years. The intent is not to suggest that changes in future extreme rainfall can be accurately predicted using GCM output and scenario-based projections but rather to develop planning level estimates of extreme rainfall changes that likely bracket the best available projections.

The physical mechanisms linking climate change and extreme storms can result in variable responses, making detection and attribution of trends in extreme storm characteristics difficult. Some of these include available precipitable water, temperature during storm event, topography, and degree of urbanization. Projecting changes in severe storms is also challenging because of GCM limits on grid size that make it hard to capture and represents the small-scale, highly local physics of extreme storms.

There are several emerging approaches to analyze changes in extreme storms using existing Regional Climate Models (RCMs) and GCMs. The simplest approach is to analyze GCM output using only the most extreme precipitation projections and calculating changes. This approach can also include fitting a generalized extreme value (GEV) equation to annual maximum or partial duration daily wet days from GCMs and RCMs. More complex approaches use the parameterization of output by examining vertical profiles of temperature, humidity, precipitable water, and wind as a proxy for actual severe thunderstorm occurrences. Other methods use GCM temperature projections and a relationship of moisture holding capacity to estimate changing precipitation amounts and intensities. There is currently no consensus on a best approach, and all are useful methods for assessing the likelihood of various types of extreme precipitation probabilities and intensities in a future climate. Most methods, however, are complex data and time-intensive statistical approaches.

Three approaches have been developed to estimate projected changes in the intensity of the most extreme storms due to climate change. These approaches are intended to bracket the range of uncertainty inherent in projections and be relatively simple to implement and update. The results of the extreme rainfall projected changes are presented as low, medium, and high projections of percent change in extreme rainfall for a variety of storm durations and frequencies. The results of the three methods are supported by a comparison with a variety of results from five other available studies carried out by the Department of Defense (DOD 2020), U.S. Environmental Protection Agency (U.S. EPA 2021), the NJ Department of Environmental Protection (NJDEP 2020), the RAND Corporation in cooperation with MARISA (RAND 2021), and the U.S. National Oceanic and Atmospheric Administration (NOAA) as part of their Atlas-15 research (NOAA 2022).

EXTREME RAINFALL SUPPORTING RESEARCH

Research and application of GCMs has, for decades, supported the conclusion that GCMs, commonly with atmospheric resolution ranging from 100 to 200 km (1–2°), are not sufficient to resolve the most extreme precipitation events. Finer resolution models, which do a better job of reproducing large rain events, generally can reproduce observed rainfall events with 24-h or more duration. For short duration and extreme rainfall events, underestimation of the intensity and volume is still likely when relying on GCM or RCM output (Wehner *et al.* 2010, 2014; O'Gorman 2015; Van der Wiel *et al.* 2016; Bador *et al.* 2020; Jong *et al.* 2023).

It is generally acknowledged that GCMs and RCMs are much more accurate in reproducing changes in temperature than in rainfall. Randall *et al.* (2007) indicated that confidence in model estimates is higher for temperature than for precipitation, and that temperature projections have consistently provided a robust and unambiguous picture of significant climate warming in response to increasing greenhouse gases. Nourani *et al.* (2022) found that downscaled temperature was 78–97% more accurate compared to downscaled precipitation. Both the IPCC (2013, 2022) reports have also supported this conclusion. Results from these reports indicate that, with few exceptions, the absolute error (outside polar regions and other data-poor regions) is less than 2 °C for temperature projections. Some of the larger errors may result simply from mismatches between the model topography and the actual topography. Even as far back as the early 2000 version GCMs, IPCC (2013) concluded that models can account for a very large fraction of the global temperature pattern. The correlation coefficient between the simulated and observed spatial patterns of annual mean temperature is typically about 0.98 for individual models. This supports the view that major processes governing surface temperature climatology are represented with a reasonable degree of fidelity by the models.

Padulano *et al.* (2019) suggest that much research has indicated that the physical consequence of temperature rise is the general increase in precipitation extremes due to the increase in atmospheric water retention. This is supported by a significant body of research (Tsanis *et al.* 2011; Bao *et al.* 2017; Barbero *et al.* 2017; Ganguli & Coulibaly 2017). Ali *et al.* (2021) discuss that the Clausius–Clapeyron (CC) relationship has been effectively used as a benchmark to interpret change to extreme precipitation (O'Gorman 2015; Fischer & Knutti 2016). This relation links air temperature and atmospheric humidity when the air is saturated, giving an increase in humidity of 6–7% per degree warming (Trenberth *et al.* 2003). Under the assumption of constant relative humidity, which is partly supported by climate modeling results and physical reasoning at least over (relatively) wet surfaces, the actual humidity of the air increases at the same rate. Recent studies have confirmed an approximately CC rate of increase in long-term trends in observations and projections of daily extreme rainfall when averaged globally or over large regions and mostly using large-scale temperature rise or even global temperature rise (Fischer & Knutti 2016; Scherrer *et al.* 2016; Rajczak & Schär 2017; Guerreiro *et al.* 2018; Zhang *et al.* 2019).

To investigate the relationship between warming and the intensification of shorter duration, more infrequent rainfall extremes, a common approach uses scaling between surface air temperature and precipitation extremes. This approach is referred to as 'apparent' scaling following the terminology introduced by Bao *et al.* (2017). Results of studies using apparent scaling have shown a wide range of behavior. Often, behavior close to the CC rate is obtained (Wasko *et al.* 2016; Ali *et al.* 2018; Gao *et al.* 2018). However, for some regions, signs of super CC behavior, exceeding the CC rate, have been found for subdaily (mostly hourly) precipitation (Lenderink & Van Meijgaard 2010; Lenderink *et al.* 2011; Berg *et al.* 2013; Park & Min 2017).

Ali *et al.* (2021) found that hourly precipitation extremes can intensify with temperature at higher rates than the expected from thermodynamic increases explained by the CC relationship. They found scaling rates per degree Celsius varied across the USA, with an average of 6.2–12% per degree Celsius for the temperate climate zone common to five of six regions of the USA where hourly precipitation gauge data are available. Scaling curves follow at least the CC rate in all regions for hourly precipitation. Using daily dew point temperature, a direct proxy of absolute humidity, the research estimated at-gauge local scaling across six macro-regions for a global data set of over 7,000 hourly precipitation gauges. The research found scaling rates ranging from CC to twice the CC at more than 60% of gauges. Moreover, regional scaling rates show surprisingly universal behavior at around CC. Importantly for impacts, hourly scaling is persistently higher than scaling for daily extreme precipitation. Results from Ali *et al.* (2021) indicated greater consistency in global scaling than those from previous work usually at or above the CC rate. Fowler *et al.* (2021) found that, globally, heavy rainfall extremes have been shown to be intensifying with warming at a rate generally consistent with the increase in atmospheric moisture, for accumulation periods from hours to days. However, in some regions, high-resolution modeling trends and observed temperature dependencies indicate stronger increases in short-duration extreme rainfall intensities that can be expected from atmospheric moisture increases alone. It has been established that at least some of this enhancement of rainfall intensities are from local in-storm effects and urbanization. Interestingly, they found that scaling curves for Europe follow $2 \times$ CC for temperatures above 12°C. Examining the distribution of scaling rates estimated at rain gauge-level, most European stations exceed the CC rate, and a small fraction of stations even exceed $2 \times$ CC. Moreover, the median scaling is greater than CC for gauges in wet and dry regions.

Recent research (NOAA 2022) associated with the development of Atlas-15 statistical approaches to estimating future extreme precipitation used three different statistical downscaling approaches for GCM data. Results indicated that the projected increases in storm intensity by 2075 were greater for 24-h storms with a 100-year return interval than for storms with a 2-year return interval in the Northeast of the USA. Jong *et al.* (2023), using a high-resolution model, found that the increasing rate of extreme storms is not uniform, with the frequency of 10 cm events increasing by a factor of 3, while the larger, less frequent 15 cm events would increase by a factor of 6.

Finally, Fowler *et al.* (2021) found that globally, heavy rainfall extremes have been shown to be intensifying with warming at a rate generally consistent with the increase in atmospheric moisture for accumulation periods from hours to days (Ali *et al.* 2018, 2021). However, in some regions, high-resolution modeling (Lenderink *et al.* 2017) showed trends and observed temperature dependencies indicating stronger increases in short-duration extreme rainfall intensities that can be expected from atmospheric moisture increases alone (Guerreiro *et al.* 2018; Wasko *et al.* 2018). It has been established that at least some of this enhancement of rainfall intensities are from local in-storm effects and urbanization (Li *et al.* 2020). Ombadi *et al.* (2023) recently found increases in extreme rainfall tied to elevation and the change from snow to rain in mountainous regions of up to 15% per degree Celsius. This supports the concept that shorter duration rainfall events will show greater intensity increases than longer duration events.

METHOD

There are several key principles related to extreme rainfall projections produced by climate models that stem from the physical relationship between temperature and rainfall, which are often supported by observed trends in extreme rainfall. It is critical to have a basic understanding of these principles when it comes to developing and applying appropriate rainfall projections for water resource applications.

1. **GCM underestimation of extreme rainfall events**: As discussed above, GCMs and finer resolution models, which do a better job of reproducing large rain events, cannot simulate observed data for events with 24 h or less durations. This indicates that for short duration and extreme or low frequency rainfall events, underestimation of the intensity and volume is likely when relying on GCM or RCM output.
2. **GCM temperature accuracy:** Research results indicate that GCMs can account for a very large fraction of the global temperature pattern, with a correlation coefficient between the simulated and observed spatial patterns of annual mean temperature typically about 0.98 for individual models.
3. **CC assumption:** Research has indicated that the physical consequence of temperature rise is the general increase in precipitation extremes due to the increase in atmospheric water retention. This relation results in an increase in humidity of 6–7% per degree Celsius warming in long-term trends of daily extreme rainfall when averaged globally using large-scale temperature rise or even global temperature rise.
4. **Super CC assumption:** Results of studies using apparent scaling have shown a wide range of behavior. Often, behavior close to the CC rate is obtained, however, for some regions; signs of super CC behavior, exceeding the CC rate by a factor of 2, have been recorded. This has been found for subdaily (mostly hourly) precipitation.
5. **Extreme, low-frequency storm underestimation:** Recent research from downscaled GCM output supports the principal that the less frequent extreme events will increase more than the more frequent, smaller rainfall events.
6. **Shorter duration storm underestimation:** High-resolution modeling and observed temperature dependencies indicate that shorter duration rainfall events show greater intensity increases than longer duration events.

These key principles are used to develop three approaches for estimating a range of climate-induced changes in extreme rainfall as discussed below. Key principle 1 is important as it underlies all attempts to use GCM output to estimate future changes to extreme rainfall events. Key principles 2 and 3 form the basis for our medium projection approach. Key principles 4–6 form the basis for our high projection approach.

Actionable approaches to bracket extreme rainfall estimates

The three approaches discussed in this paper to estimate projected changes in the intensity of the most extreme storms due to climate change take the six key principles explained above into consideration. The approaches further aim to fulfill the following objectives critical for use in utility planning and design.

- Develop an easily implemented approach to making projections of climate-related changes to storm intensity for a range of durations and frequencies most applicable to water and stormwater utility needs. These can range from extreme storms of 24-h duration which are often the cause of riverine flooding, down to short-duration intense bursts of rainfall that typically cause flooding in urban areas where sewer capacity is quickly exceeded by hourly or even sub-hourly extremely intense rainfall.
- Acknowledge the significant uncertainty in all the current approaches by creating a low–medium–high set of projections to bracket the expected range of extreme storm intensification projections.
- Develop a high scenario that acknowledges the body of research that shows the possibility of super CC intensification for short duration (under 24-h) and low frequency (greater than 1-year) events.
- Develop approaches that are practical and can be easily and quickly updated with the most recent downscaled daily GCM data as it becomes available.

The City of Philadelphia was used as a case study for these methods. All three methods make use of Coupled Model Intercomparison Project Phase 5 (CMIP5) GCM projections based on the Local Constructed Analogs (LOCA) downscaling technique made available through the downscaled CMIP5 Climate and Hydrology Projections website: https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/ for grid cells covering the City of Philadelphia. The example uses the representative concentration pathway (RCP) 8.5 emission scenario, which is the planning scenario that the city uses for many of their planning activities. The approach is equally applicable to other projection scenarios, including the newer ones from the most recent Coupled Model Intercomparison Project Phase 6 (CMIP6) results. These are available from the IPCC. The latest iterations of scenarios, used for CMIP6 (2016–2021) and featured in the IPCC Sixth Assessment Report (2021), are based on a set of shared socio-economic pathways.

Results from this case study and characteristics of the three practical methods are described in further detail below. All results are framed as delta change factors (DCFs). These are factors that multiply baseline storm volumes/intensities by a given percent increase to represent projected future storm volumes/intensities based on GCM scenario daily output.

Low estimate: 20-storm approach

The CDM Smith/PWD low estimate based on a 20-storm approach is described in detail in Maimone & Adams (2023). The approach calculates DCFs based on 32 GCM-based runoff projections for watersheds across the USA. The method involved calculating change factors using the average of the 20 largest precipitation days and associated runoff as simulated by the GCMs and variable infiltration capacity models, respectively. The coverage area for Philadelphia consists of 25 grid cells and generated output is on a decadal scale for 2020 through 2090 for the RCP 8.5 emission scenario. The basic steps in the process are as follows (for more detail, see Maimone & Adams 2023).

- For each of the 32 GCMs, at each of the 25 grid cells covering central and southern Philadelphia, the 20 largest daily runoff events are found for the baseline period 1986–2005 and for each 20-year rolling average decade (e.g. 2020 has the 20 largest daily runoff events within the period 2010–2030).
- The 20 largest runoff days are averaged for each grid cell, each model, each 20-year decadal window, and the baseline period.
- DCFs are generated by calculating the percent increase for each of the decadal average runoff values from the baseline value. This is done for each 20-year window centered by decade for each GCM, each of 25 grid cells, under RCP 8.5.
- For each GCM, the spatial median of the DCFs is calculated by taking the median of the grid cells. This provides median DCFs per model per decade.
- The final DCFs for the city, by decade, are calculated as the mean of the spatial median DCFs across all 32 GCMs, one for each decade.
- The same DCFs were applied to all durations and return intervals. Because this method relies on GCM precipitation output, known to underestimate extreme rainfall events, this method is considered to provide a low estimate of expected increases in intensity.
- The low approach ignores the principle of higher return interval events having higher intensification increases by assuming equal DCFs across the six return intervals.

The DCFs for each decade can then be applied to any published design storm or intensity–duration–frequency (IDF) curve (e.g. the current Atlas-14 values) for a variety of durations and return intervals. This approach provides a low estimate of future extreme rainfall projections.

Medium estimate: temperature scaling (CC approach)

The temperature scaling approach is based on a simple application of the CC principal to the average annual temperature increase. For this, the results from a study by the Philadelphia Water Department were used, which estimated the average, year-by-year temperature increases from nine GCMs under RCP8.5. The study included 16 grid cells covering Philadelphia, slightly fewer than the low method described above. By taking the average temperature for the baseline period across the 16 grid cells and for each of the future 20-year decadal windows, the temperature increase multiplied by 1.07 provides a decade-by-decade DCF for precipitation amounts. Note that with this approach, the DCFs do not vary by storm duration and frequency. This approach provides a medium estimate of future extreme rainfall projections.

High estimate: super temperature scaling (super CC approach)

This method also relies on the application of the CC principle; however, a more nuanced approach is taken to account for increased intensification for low-frequency, shorter duration events. The underlying assumptions are:

- The minimum increase per degree Celsius is represented by the CC value of 7%. This is applied to the most frequent (1-year) and longest duration (24-h) event.
- The greatest increase is referred to in the literature as the super CC value, and has been cited in the range of 12–14% per degree Celsius. A 12% increase per degree Celsius is applied to the least frequent (100-year and above) and shortest duration (1-h) duration events.
- All other percent increases at the intersects of duration and frequency are interpolated between these values following the two principles stated above.

The resulting table of applied percentage increases per degree Celsius is shown in Table 1.

Sub-hourly precipitation

Downscaled GCM output can be accessed only down to a daily time step. In the methods presented, the use of DCFs generally assumes that change factors can be applied down to a 1-h time step to make estimates of future storm volumes, or modified to account for the shorter durations as discussed for the high method. Because most rain gauge data are, at best, available down to 1-h duration, it is common practice for climate and weather bureaus to use factors to adjust rainfall volumes from 1-h durations down to shorter durations (*n*-minute ratios). This is important for many urban water resources applications, as daily or hourly time steps do not suffice to meet end user requirements. For example, urban stormwater models typically run sub-hourly simulations at a 15- or even 5-min time steps. To address this issue, sub-hourly simulations can be created using *n*-minute ratios that relate sub-hourly intensities to hourly intensities. An example, provided in NOAA Atlas 14 for 5, 10, 15, and 30-min durations, is shown in Table 2. Ratios from Table 2 can be used to estimate projected increases in precipitation depths for sub-hourly durations from the results of the three methods found for 1-h duration events. We recognize that sub-hourly events may change in intensity due to climate change, thus changing the *n*-minute ratios used; however, we found insufficient research to address this.

Table 1 | DCFs used in the high approach by duration and frequency

Estimated DCFs percentages per degree Celsius

	Average recurrence interval (%)									
Duration	**1-year**	**2 years**	**5 years**	**10 years**	**25 years**	**50 years**	**100 years**	**200 years**	**500 years**	**1,000 years**
1 h	10.0	10.3	10.7	11.0	11.3	11.7	12.0	12.0	12.0	12.0
2 h	9.4	9.8	10.1	10.5	10.9	11.2	11.6	11.6	11.6	11.6
3 h	8.8	9.2	9.6	10.0	10.4	10.8	11.2	11.2	11.2	11.2
6 h	8.2	8.6	9.1	9.5	9.9	10.4	10.8	10.8	10.8	10.8
12 h	7.6	8.1	8.5	9.0	9.5	9.9	10.4	10.4	10.4	10.4
24 h	7.0	7.5	8.0	8.5	9.0	9.5	10.0	10.0	10.0	10.0

Table 2 | NOAA Atlas-14 *n*-minute ratios

	Average recurrence interval						
Duration	**1 year**	**2 years**	**5 years**	**10 years**	**25 years**	**50 years**	**100 years**
5 min	0.287	0.271	0.271	0.262	0.251	0.243	0.236
10 min	0.459	0.434	0.434	0.419	0.400	0.387	0.375
15 min	0.577	0.549	0.549	0.530	0.507	0.490	0.474
30 min	0.797	0.790	0.780	0.768	0.751	0.738	0.726

RESULTS

The results are verified by comparing them to other sources of similar projected changes to extreme rainfall. This is done for 24-h duration events, as well as for shorter events where comparable studies have been carried out for the Philadelphia area.

Results for 24-h event comparison

A search of the literature showed that there have been a number of studies that compare downscaling techniques and their ability to match precipitation data. However, no studies that compared projections using a variety of statistical approaches from official government sites were found. A comparison with a recent (Jong *et al.* 2023) regional model study showed that in the Northeastern USA, 99th percentile and above extreme rain events have increased significantly since 1960. Their modeling results projected, for example, that a 200 mm 24-h storm, currently estimated to be a 1 in 330-year event, will be a 1 in 58-year event by 2100. For the 100-year event, this represents a shift from approximately 125 to 150 mm or a 20% increase. This puts this within the low to medium range (see Table 5) presented in this paper.

A comparison of results was made between the three methods presented in this paper and four publicly available datasets from other agencies for 24-h duration events. Details of each approach are summarized in Table 3. The comparison datasets used are:

1. USEPA: CLIMATE RESILIENCE EVALUATION AND AWARENESS TOOL (CREAT): https://epa.maps.arcgis.com/apps/MapSeries/index.html?appid=3805293158d54846a29f750d63c6890e Working group of utilities, professional associations, climate science and risk assessment experts, and federal partners.
2. USDOD: Strategic Environmental Research and Development Program (SERDP/Department of Defense). https://precipitationfrequency.ncics.org/about.html (partnered with North Carolina Institute for Climate Studies, NCICS).
3. New Jersey Extreme Precipitation Projection Tool, https://njprojectedprecipitationchanges.com Working group of NJ Departments, supported by Rutgers University.
4. MARISA/Rand: Projected IDF Curve Data Tool for the Chesapeake Bay Watershed and Virginia, https://midatlantic-idf.rcc-acis.org/ Developed by Carnegie Mellon University, Northeast Regional Climate Center at Cornell University, and RAND corporation.

Each dataset uses different assumptions, methods, and differs in climate models used. Thus, the comparison should be considered as an approximate benchmarking exercise to identify where the three simple and practical methods discussed in this paper fall with respect to more sophisticated data processing techniques. The different datasets used mainly differ in:

- Years used for baseline periods as well as future periods,
- Averaging periods (i.e. 20–50 years),
- Variation in extreme projection durations selected,
- Calculation methods and types of CCMs/RCMs used.

Despite the differences, a comparison in projected DCFs could be made for mid-century and end-of-century projections (2050 and 2080s, respectively) for 24-h storm events. Results are shown in Tables 4 and 5, which provide estimates of DCFs for 'mid- and end-of-century' for a variety of return intervals for each method where results are available. Note that the USEPA Create tool results are for the 'stormy' or wetter scenario.

The results of the 24-h duration storm comparison of DCFs lead to a number of observations about how each of the CDM Smith/PWD methods compares to the other available methods.

Low: 20-storm method

- The CDM/Smith low method approach produces a mid-century DCF of 1.10, within the range of the other methods that had a low estimate (0.92–1.15).
- This method produces an end-of-century DCF of 1.18, which is slightly higher than the range from the other methods that had a low estimate (0.97–1.15).
- The RAND/MARISA low results for both mid- and end-of century were lower than all the other methods over almost all return intervals, including the results of the CDM Smith/PWD low method. For some of the low frequency results, the RAND/MARISA approach actually estimated decreasing intensities (DCFs of 0.97–1.06).
- The NJDEP low method (10th percentile) was generally higher than the CDM Smith/PWD low method for mid-century but lower than the CDM Smith/PWD low method for end-of century.

Table 3 | A summary of the various approaches to estimating climate-related changes in extreme rainfall

Extreme storm projection approach comparison

	PWD low	PWD medium	PWD high	U.S. EPA	U.S. DOD	NJ DEP (low, medium, high)	Marisa Chesapeake (low, medium, high)
Developer/ owner	CDM Smith/PWD	CDM Smith/PWD	CDM Smith/PWD	U.S. EPA	U.S. DOD, EPA, DOE	NJDEP	Marisa Chesapeake
Climate models	32 GCMs	9 GCMs (temperature data °C)	9 GCMs (temperature data °C)	22 GCMs	32 GCMs	31 GCMs with LOCA, 25 RCMs	BCCA 21 GCMs, MACA 20 GCMs, LOCA 32 GCMs, NA-Cordex 10 RCMs
Climate model generation	CMIP5	CMIP5	CMIP5	CMIP5	CMIP5, selection of CMIP6	CMIP5	CMIP5, selection of CMIP6
Downscaling method	Localized constructed analogs	Localized constructed analogs	Localized constructed analogs	Bias-corrected spatial disaggregation	Localized constructed analogs	Localized constructed analogs, dynamic downscaling	Bias-corrected spatial constructed analogs, localized constructed analogs, multivariate constructed analogs, dynamic downscaling
Emission scenario	RCP8.5	RCP8.5	RCP8.5	RCP8.5	RCP8.5 and 4.5	RCP8.5 and 4.5	RCP8.5 and 4.5
Baseline period	1986–2005 32 GCMs	1986–2005 (temperature 9 GCMs)	1986–2005 (temperature 9 GCMs)	1981–2010 (various GCMs and RCMs)	Atlas-14 by DOD location	Atlas-14 1950–2019	Recalulated Atlas-14 1950–2000
Projection periods	2020, 2030, 2040, 2050, 2060, 2070, 2080, 2090 (20-year average)	2020, 2030, 2040, 2050, 2060, 2070, 2080, 2090 (20-year average)	2020, 2030, 2040, 2050, 2060, 2070, 2080, 2090 (20-year average)	mid-points 2035, 2060 (20-year average)	2035, 2045, 2055, 2065, 2075 2085 (30-year average)	2020–2069 (mid-century) 2050–2099 (late century) (50-year average)	2020–2070 (mid-century) 2050–2100 (late century) (50-year average)
Climate model selection	Full suite of models	Full suite of models	Full suite of models	Stormy (wettest 5 GCMs), less stormy (driest 5 GCMs)	Full suite of models	Full suite of models	Full suite of models
Storm durations provided	2 h, 3 h, 6 h, 12 h and 24 h	2 h, 3 h, 6 h, 12 h and 24 h	2 h, 3 h, 6 h, 12 h and 24 h	24 h	1, 2, 3, 6, 12, 24 h, 2, 3, 4, 7, 10, 20, and 30 days	24 h	5 min through 60 min, 2 h, 3 h, 6 h, 12 h and 24 h; 2 days, 3 days, 4 days and 7 days
Storm frequencies provided	2, 5, 10, 25, 50, 100 and 200 years	2, 5, 10, 25, 50, 100 and 200 years	2, 5, 10, 25, 50, 100 and 200 years	100 years	1, 2, 5, 10, 25, 50,100 years	2, 5, 10, 25, 50,100 years	2, 5, 10, 25, 50, 100 years
Methodology	Use 20-largest wet days per 20-year period using 32 GCMs over 25 grid cells	Uses average annual temperature change per decade and 7% increase per °C	Uses average annual temperature change per decade and 7–12% increase per °C for different frequency estimates	DCFs based on rainfall for each °C within each GCM, developed and applied to events of same return interval	Blended approach using GEVs of GCM output, and more complex analysis of changes to metereological factors	Largest events of all models fitted to GEV, stochastically generate 1,000 sets, smooth results, calculates percentiles	GEV to calculate 24-h IDF curves for all models and RCPs including the stochastic approach for 24 hour only. Uses same DCF for all durations and frequencies

Table 4 | Mid-century comparison of DCFs for a 24-h duration event for all methods under RCP8.5

DCF comparisons for 2050 for a 24-h event

Return Interval	Method source										
	CDM Smith/PWD					NJDEP			Rand/Marisa		
	Low	Medium	High	DOD	EPA	Low	Medium	High	Low	Medium	High
2 years	1.10	1.23	1.25	1.13	1.06	1.06	1.23	1.39	1.02	1.12	1.19
5 years	1.10	1.23	1.26	1.13	1.09	1.09	1.24	1.33	1.02	1.12	1.19
10 years	1.10	1.23	1.28	1.15	1.16	1.11	1.23	1.30	1.01	1.11	1.22
25 years	1.10	1.23	1.30	1.16	-	1.14	1.22	1.27	0.99	1.10	1.25
50 years	1.10	1.23	1.31	1.17	1.16	1.15	1.20	1.27	0.95	0.95	1.28
100 years	1.10	1.23	1.33	1.18	1.16	1.15	1.19	1.25	0.92	1.11	1.34

Table 5 | End-of-century comparison of DCFs for a 24-h duration event for all methods under RCP8.5

DCF comparisons for 2080 for a 24-h event

Return Interval	Method source										
	CDM Smith/PWD					NJDEP			Rand/Marisa		
	20-storm	CC	Super CC	DOD	EPA	Low	Medium	High	Low	Medium	High
2 years	1.18	1.35	1.38	1.24	-	1.06	1.23	1.39	1.06	1.18	1.28
5 years	1.18	1.35	1.40	1.25	1.16	1.09	1.24	1.33	1.06	1.17	1.28
10 years	1.18	1.35	1.43	1.27	1.16	1.11	1.23	1.30	1.05	1.18	1.32
25 years	1.18	1.35	1.45	1.28	-	1.14	1.22	1.27	1.02	1.18	1.35
50 years	1.18	1.35	1.48	1.30	1.16	1.15	1.20	1.27	1.00	1.17	1.37
100 years	1.18	1.35	1.50	1.31	1.16	1.15	1.19	1.25	0.97	1.17	1.40

- The CDM/Smith low method ignores the principle of higher return interval equals higher intensification DCFs by having equal DCFs across the six return intervals.
- Some methods can result in projections that contradict principle, with lower frequency events showing a lower DCF than more frequent events.
- The NJDEP low approach meets the principle of higher return interval events having higher intensification DCFs.

The CDM Smith/PWD low approach is likely to underestimate extreme storm intensification because it violates the two principles (same DCF for all return intervals), and is based solely on GCM output, which is known to not estimate extreme events very accurately. The RAND/MARISA and the NJDEP low approaches are also likely an underestimation of storm intensification.

Medium: Clausius–Clapeyron

- The medium approach produces a mid-century DCF of 1.23, which is higher than the range of the other methods (0.95–1.23).
- The medium approach produces an end-of-century DCF of 1.35, which is higher than the range of the other methods (1.16–1.31).
- The DOD and EPA approaches had only one set of values, which are most appropriately compared with the CDM Smith/PWD medium method.
- The RAND/MARISA mid-results for mid-century were lower than all other methods over almost all return intervals. For a 50-year return interval, the RAND/MARISA approach estimated lower intensities (DCFs of 0.95).

- The NJDEP medium method was comparable to the CDM Smith/PWD medium approach for mid-century but lower than the CDM Smith/PWD medium approach for end-of-century as the NJDEP uses the same change factors for mid- and end-of-century.
- The CDM Smith/PWD medium method was generally comparable or higher than all other methods.
- The DOD approach meets the principle of greater intensification for greater return intervals.
- The CDM Smith/PWD medium method and the EPA method both ignore the principle of higher return interval having higher intensification DCFs by having equal DCFs across the six return intervals and all durations.
- Some approaches produce lower DCFs for lower frequency events having a lower DCF than the more frequent events.

The CDM Smith/PWD medium method appears to be at the higher end of the other extreme storm intensification estimates because it uses GCM temperature data, which is known to be more accurate than GCM precipitation data. It does compare well with the DOD data, being only slightly higher. Results from the CDM Smith/PWD medium method are likely to be the most defensible current estimate as compared to the other methods presented in this paper though could still represent an underestimation of future extreme rainfall intensification.

High: super Clausius–Clapeyron

- The CDM Smith/PWD high method produces a range of mid-century DCFs of 1.25–1.33, depending on the return interval. This is at the high end of the range of the DOD and EPA results but fairly similar to the range of high results for both NJDEP and the RAND/MARISA studies.
- The CDM Smith/PWD high method produces a range of end-of-century DCFs across durations and return intervals of 1.38–1.50, which is above or at the higher end of the range of the RAND/MARISA high approach and the NJDEP high approach.
- The RAND/MARISA high results for mid-century bracketed the range of the NJDEP high method and were also quite comparable to the CDM Smith/PWD high method.
- The RAND/MARISA high results for end-of-century bracketed the range of the NJDEP high method results but were lower than the CDM Smith/PWD high method.
- The NJDEP high method was comparable to the CDM Smith/PWD high method for mid-century but lower than the CDM Smith/PWD high method for end-of-century.
- The CDM Smith/PWD high method and the RAND/MARISA approach both met the principle of higher return interval events having higher intensification DCFs.
- The NJDEP high approach does not conform to the principle, with lower frequency events showing a lower DCF than more frequent events.

The CDM Smith/PWD high method may be at the higher end of extreme storm intensification estimates because it uses the GCM temperature data and the two principles mentioned above (low-frequency and short-duration events will become more intense). It is not, however, that much higher than the RAND/MARISA approach probably represents a plausible high estimate for extreme rainfall.

Results for a range of storm durations and return intervals

Both the RAND/MARISA and DOD studies contained results for a range of storm durations from 60 min to 24 h for return intervals of 2–100 years. In Table 6, the range of the low to high projections of DCFs for the CDM Smith/PWD methods and the RAND/MARISA method are provided, as well as the DOD estimate which are applied to all return intervals and durations.

- Both DOD and RAND/MARISA results, as well as the CDM Smith/PWD low and medium results, provide constant values across all durations, while the CDM Smith/PWD high method varies by storm intensity and duration.
- RAND/MARISA low estimate is consistently lower by a significant margin than both the DOD and the CDM Smith/PWD low results.
- The CDM Smith/PWD three method results consistently bracket the DOD results.
- The CDM Smith/PWD high results are higher than RAND/MARISA and DOD results across all storm durations and return intervals.

Table 6 | Comparison of the CDM Smith/PWD low-to-high method with DOD and RAND/MARISA results for storm durations of 1 h through 24 h and return intervals of 2–100-year

Summary comparison of DCFs for RCP8.5 end-of-century

	Return interval								
	2 years			5 years			10 years		
Duration	DOD	RAND/MARISA	CDM Smith/PWD	DOD	RAND/MARISA	CDM Smith/PWD	DOD	RAND/MARISA	CDM Smith/PWD
60 min	1.24	1.06–1.28	1.18–1.52	1.25	1.06–1.28	1.18–1.54	1.27	1.05–1.32	1.18–1.55
2 h	1.24	1.06–1.28	1.18–1.49	1.25	1.06–1.28	1.18–1.51	1.27	1.05–1.32	1.18–1.53
3 h	1.24	1.06–1.28	1.18–1.46	1.25	1.06–1.28	1.18–1.48	1.27	1.05–1.32	1.18–1.50
6 h	1.23	1.06–1.28	1.18–1.44	1.25	1.06–1.28	1.18–1.46	1.27	1.05–1.32	1.18–1.48
12 h	1.24	1.06–1.28	1.18–1,41	1.25	1.06–1.28	1.18–1.43	1.27	1.05–1.32	1.18–1.45
24 h	1.24	1.06–1.28	1.18–1.38	1.25	1.06–1.28	1.18–1.40	1.27	1.05–1.32	1.18–1.43

Summary comparison of DCFs for RCP8.5 end-of-century

	Return interval								
	25 years			50 years			100 years		
Duration	DOD	RAND/MARISA	CDM Smith/PWD	DOD	RAND/MARISA	CDM Smith/PWD	DOD	RAND/MARISA	CDM Smith/PWD
60 min	1.28	1.02–1.35	1.18–1.57	1.30	1.00–1.37	1.18–1.59	1.31	0.97–1.40	1.18–1.61
2 h	1.28	1.02–1.35	1.18–1.55	1.30	1.00–1.37	1.18–1.57	1.31	0.97–1.40	1.18–1.59
3 h	1.28	1.02–1.35	1.18–1.52	1.30	1.00–1.37	1.18–1.54	1.31	0.97–1.40	1.18–1.56
6 h	1.28	1.02–1.35	1.18–1.50	1.30	1.00–1.37	1.18–1.52	1.31	0.97–1.40	1.18–1.54
12 h	1.28	1.02–1.35	1.18–1.48	1.30	1.00–1.37	1.18–1.50	1.31	0.97–1.40	1.18–1.52
24 h	1.28	1.02–1.35	1.18–1.45	1.30	1.00–1.37	1.18–1.48	1.31	0.97–1.40	1.18–1.50

Results of comparison with Atlas-15 research methods

The United States National Oceanic and Atmospheric Administration publication (NOAA 2022) provided preliminary results from a study prepared in preparation for updating their Atlas-14 IDF curves. Appendix 2 of NOAA (2022) provides results from a study by the University of Illinois Urbana-Champaign and the University of Wisconsin-Madison (UW). The study uses CMIP5 models and explores the different results from a number of statistical and dynamical downscaling methods. Dynamical downscaling is available from NA-CORDEX, which is the North American component of the international CORDEX (Coordinated Regional Downscaling Experiment) program sponsored by the World Climate Research Program. Results for the dynamical downscaling (NA-CORDEX), and from two statistical downscaling approaches, LOCA and a new University of Wisconsin Probabilistic Downscaling (UWPD) method, are provided for the Northeastern USA. Table 7 shows a comparison of the CDM Smith/PWD three methods for 24-h events at the end-of-century with the three downscaled results from the NOAA (2022) study. The table contains results for a 24-h event with a 2-year and 100-year return interval, and the only results are readily available in the NOAA appendix.

Table 7 | Comparison of the CDM Smith/PWD low–high method 24-h events with NOAA (2022) Atlas-15 research results using three different downscaling approaches

DCF comparisons for 2075–2080 for a 24-h event

Return Period	CDM Smith/PWD methods			Atlas-15 methods		
	Low	Medium	High	LOCA	NA-CORDEX	UWPD
2 years	1.18	1.35	1.38	1.18	1.18	1.21
100 years	1.18	1.35	1.50	1.25	1.19	1.29

- The CDM Smith/PWD low method is almost identical to the three downscaling approaches of the NOAA study for a 2-year return interval.
- The CDM Smith/PWD low and medium approaches bracket the three NOAA approaches, which are significantly lower than the CDM Smith/PWD high method.
- Note that the Atlas-15 methods are developed directly from downscaled GCM precipitation output, which means that the underestimation inherent in GCM precipitation output for extreme storms is clearly reflected in the NOAA results.

DISCUSSION

This paper introduces three, relatively straightforward methods to use GCM downscaled daily precipitation and temperature data to estimate projected changes in extreme rainfall. Extreme rainfall is here defined as rainfall events of 24-h or less, with return intervals of greater than 1-year. A comparison with widely available, US-based websites that provide projections of future rainfall intensification shows that the three methods presented here:

- compare well with both regional results and more complex statistical studies by various agencies,
- match with recent regional modeling results for the US Northeast,
- are compatible with national or regional extreme rainfall statistics such as NOAA Atlas-14, local station data, and international available datasets including ERA5-Land gridded datasets,
- provide a reasonable range of results for planning purposes, and
- are easily applied to any downscaled climate projection datasets.

The approach of using a range of expected changes to extreme rainfall through the end of this century will provide municipalities and water management agencies with critical planning information to help plan and design for future conditions in a changing climate.

Method limitations

First and foremost, it is important to understand that the intent of these methods is not to predict changes in future storm intensity but to provide a plausible range of climate change-related intensification for design storms and IDF curves. This range, which brackets from low to high the changes to storm intensity, can provide critical planning information to assess future risks related to extreme storm and the accompanying flooding concerns.

Actual changes to any given infrequent, extreme storm intensity are influenced by an array of factors that can include actual temperature at the moment of the storm, available water, antecedent conditions, topography, and land use.

In addition, it must be understood that the methods are designed to produce DCFs that are then applied to locally based design storms. They do not directly produce design storm volumes.

Some of the limitations of the CDM Smith/PWD low method include the following:

- It is well established that GCMs, and consequently VIC runoff estimates, underestimate extreme, convective storm events. This makes it difficult to assess whether the GCM changes to extreme storms are similarly underestimated.
- The DCFs based on the 20 largest storms are sensitive to the period from which the storms are selected. We recommend the period includes storms over a 20-year period.
- The method is also sensitive to the number of GCMs used. We recommend using all available GCM output.
- The method is less stable than the temperature-based methods and can result in DCFs that might not always be lower than the CDM Smith/PWD medium method.
- The CDM Smith/PWD low method DCFs are calculated using an approach that selects only the largest events as simulated by the GCMs. These larger events are subject to considerable instability and randomness. Much of this is smoothed out by averaging across 32 GCMs, using 20-year averaging periods, and using the spatial mean. Nevertheless, some anomalous results still appear.
- The method was applied to CMIP5 GCM output. If CMIP6 GCM output is used, the results may be less stable due to the higher sensitivity of CMIP6 GCMs compared to CMIP5 GCMs.
- The method does not account for differing projected future intensities based on storm duration and frequency.

Some of the limitations for the temperature-based CDM Smith/PWD medium and high methods include the following:

- The methods rely on changes to annual average temperature based on GCM projections and the selected climate change scenario. This approach does not account for the temperature and available moisture for any given storm. Thus, the temperature-based DCFs are intended as a possible intensification for future storms but do not represent the temperature profile at the actual moment of any one storm.
- The methods assume that the change in moisture holding capacity will change with temperature, thus assuming that water availability is not a constraint.
- The CDM Smith/PWD medium method does not acknowledge the body of research that suggests that shorter duration infrequent extreme events will intensify more than longer duration, more frequent events.
- The CDM Smith/PWD high method is based on research that has explored the idea that changes to storm intensity can actually exceed the physically based 7% per degree Celsius estimate, up to 12–14%. This is an area of continuing research, and its use for the high method is intended as an upper bound for risk assessments that focus on high value/critical assets in need of a reasonable margin of safety.
- The methods can use the NOAA *n*-minute factors to estimate sub-hourly storm intensities; however, additional research is required to assess if sub-hourly factors need to be increased further due to the shorter durations.

Despite these caveats, these results should help to understand and explain the extreme storm events that are already occurring, and to help to reset our hydrologic assumptions in the face of current and projected climate change.

CONCLUSION

Projecting changes in severe storms is challenging because of GCM limits on grid size that make it hard to capture and represent the small-scale, highly local physics of extreme storms.

This paper describes three practical methods that can be used to estimate extreme rainfall intensification due to climate change using the GCM output. The three methods were developed by using results from research papers published from modeling and data analysis studies. Research supporting the three methods proposed in this memorandum covers several areas of climate change impacts to extreme rainfall.

The three methods developed in this paper provide a useful range of projected change factors for extreme rain events that can provide water resource managers, water suppliers, and stormwater lanners with practical factors that can be applied to current design storms. The results of the case study for the Philadelphia area show that, by the end-of-century, extreme rain event volumes might increase from a low of 18% to a high of 61%, depending on the duration and return interval under consideration. This range captures the variety of results available for this area from several nationally available websites, as well as for the expected range from research that is supporting the development of updated US IDF curves.

Results show that the three methods presented here

- are relatively simple to implement and develop projections that are comparable to more sophisticated statistical analytical methods,
- provide practical, planning level extreme rainfall projections ranging from low to high values that are vital for including climate change in flood-related planning and design projects,
- provide estimates for durations of 1–24 h for return intervals of 1-year to 100 years that can meet a variety of flood-related and risk assessment applications, and
- are easy to implement and update as new GCM projections emerge.

When used appropriately as planning projections, these practical, easy to implement methods for assessing changes to extreme rainfall can provide a great value in understanding, assessing, and accounting for climate-induced changes in extreme rainfall.

DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories.

1. GCM Projections website: https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/.
2. USEPA: CLIMATE RESILIENCE EVALUATION AND AWARENESS TOOL (CREAT): https://epa.maps.arcgis.com/apps/MapSeries/index.html?appid=3805293158d54846a29f750d63c6890e.

3. USDOD: Strategic Environmental Research and Development Program (SERDP/Department of Defense). https://precipitationfrequency.ncics.org/about.html.
4. New Jersey Extreme Precipitation Projection Tool, https://njprojectedprecipitationchanges.com.
5. MARISA/Rand: Projected Intensity-Duration-Frequency (IDF) Curve Data Tool for the Chesapeake Bay Watershed and Virginia, https://midatlantic-idf.rcc-acis.org/.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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