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Developing PIDF Curves From Dynamically Downscaled WRF Model Fields to Examine Extreme Precipitation Events in Three Eastern U.S. Metropolitan Areas

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Abstract

Extreme precipitation events influence watershed, agriculture, and urban management. The probability of extreme precipitation is estimated for storm water management using precipitation intensity-duration-frequency (PIDF) curves. This study explores developing PIDF curves from dynamically downscaled 36- and 12-km simulations using the Weather Research and Forecasting (WRF) model. Three modeled data sets are examined: 36-km WRF model forced with 2.5° (~275-km) NCEP–DOE AMIP-II Reanalysis (R2); 36-km WRF model forced with 0.75° (~80-km) ERA-Interim; and 12-km WRF model forced with ERA-Interim. The WRF outputs are verified against historical observations for three cities in the Eastern United States using a 23-year period (1988–2010). The 36-km WRF data set driven by R2 produced PIDF curves that were acceptable at the 12- to 24-hr durations, but those WRF data could not realistically simulate extremes represented by the high-intensity, short-duration precipitation events. Increasing the resolution of WRF's driving data from R2 to ERA-Interim did not improve WRF's representation of precipitation events. Using 12-km grid spacing enhances WRF's ability to reproduce PIDF curves developed from observations. Finer grid spacing dramatically improves the frequency and intensity of the 1- to 3-hr events and improves the 6- to 24-hr events. However, improvements with the 12-km WRF data did not apply equally to all study sites, suggesting further modifications to the WRF configuration and/or methodology are necessary. Although imperfect, the results here lend confidence to using modeled data to construct PIDF curves, which could be valuable for projecting changes to parameters used in urban and environmental planning.

Keywords

Extreme precipitation; PIDF curves; WRF; downscaling

1. Introduction

Extreme precipitation events result in major floods and erosive runoff that can adversely affect human health, ecosystems, agriculture, infrastructures, and the economy. Across the United States, there has been a well-documented increasing trend in the frequency and intensity of extreme precipitation events of durations ranging from hourly to a few days

(Alexander et al., 2006; Groisman et al., 2004, 2005, 2012; Karl et al., 1996; Karl & Knight, 1998; Kunkel et al., 2003; Karl et al., 2009; Kunkel et al., 2013). For example, from 1895 to 2010, the extreme precipitation frequency index in the Southeast increased by 11% and in the Midwest by 21%, with the largest increases occurring in the fall (Kunkel et al., 2013). Changes in global extreme precipitation during the past several decades have been linked to changes in climate conditions (Min et al., 2009, 2011). Changes in radiative forcing associated with increasing greenhouse gas emissions to the atmosphere warm the Earth's surface, increasing the capacity of the atmosphere to hold water vapor and leading to increased precipitation extremes (e.g., Trenberth et al., 2003). Karl and Trenberth (2003) demonstrated that, in general, for the same annual or seasonal precipitation totals, warmer climates generate more frequent and more intense extreme precipitation events than cooler climates. Heavy rainfall rates greatly exceed the evaporation rates and depend on low-level moisture convergence, which increases the water vapor mixing ratio. Therefore, the precipitation intensity should also increase at about the same rate as the moisture increases, which may lead—if regional conditions allow—to fewer but more intense precipitation events (Hennessy et al., 1997; Trenberth et al., 2003).

Another changing characteristic of rainfall events is a change in the precipitation distribution within the storm itself. Wasko et al. (2016) suggest that in addition to storm intensification at warmer temperatures, the moisture in any given storm would be redistributed from the storm boundaries to the storm center, which would spatially concentrate the rainfall. Changes in the storm patterns greatly impact urban areas, where existing storm water infrastructure has become insufficient. Unlike rural areas, urban areas typically lack sufficient soil and green infrastructure to mitigate runoff, stressing the capacity of the urban area drainage and resulting in flooding. Urban areas can also locally affect weather by substantially changing the transfer of heat, moisture, momentum, and aerosols between the surface and atmosphere (Shepherd, 2005, 2013). Locally, higher temperatures over cities can force a thermally driven circulation pattern with enhanced convergence and induce more rainfall over the city (Sarangi et al., 2018). Studies of observed changes in extreme precipitation over several urban areas in Europe, India, and the United States showed that the frequency and magnitude of extreme precipitation may increase substantially over cities (Ali et al., 2014; Cheng et al., 2011; Golroudbary et al., 2017; Kishtawal et al., 2010; Mishra & Lettenmaier, 2011; Niyogi et al., 2017). These local effects over urban areas can be obscured in global studies, but they play crucial role in storm water management and urban planning, raising the need to examine modeled extreme precipitation using methods tailored for metropolitan areas.

The design, operation, and maintenance of water infrastructure are based on precipitation intensity-duration-frequency (PIDF) curves. PIDF curves graphically represent the probability that extreme events will occur based on the historical record of observed precipitation events. PIDF data are fundamental for the adequate and economical design of urban storm water systems, farm-terrace and drainage systems, highway and railway culverts, municipal storm-sewer systems, and other engineering works that must care for storm runoff (Yarnell, 1935). In the United States, each municipality manages storm water in compliance with federal and state regulations, with the primary objective of controlling peak runoff. Municipalities provide requirements and guidelines on the precipitation frequencies

and durations to use in designing storm water infrastructure and applying best management practices (John Loperfido, personal communication, 9 August 2018).

Since the 1960s, U.S. engineers and urban planners have typically used PIDF values acquired from series of NOAA Atlas publications (e.g., Bonnin et al., 2006; Hershfield, 1961a, 1961b; Perica et al., 2013). NOAA Atlas 14 (“ATLAS”) is a collection of 11 volumes covering groups of states and territories, and it provides the most recent PIDF values across the United States that are derived from precipitation observations collected by the National Weather Service Cooperative Observer (COOP) network (www.weather.gov/coop). Like many other data networks, observation sites in the COOP network are irregularly spaced, and the records are limited by the length and completeness of the observational data record at each COOP site (Kunkel et al., 2012, 2013). Subsequently, in ATLAS, data from the COOP network are aggregated to provide regional estimates of the precipitation distribution trends on ungauged locations and create full coverage across the CONUS (Bonnin et al., 2006; Hershfield, 1961a, 1961b; Hosking & Wallis, 1997; Perica et al., 2013). The method used to derive PIDF curves assumes temporal stationarity, which inherently ignores changes in the occurrences and intensity of convective precipitation (mesoscale and isolated thunderstorms) in a warming climate (Easterling et al., 2017), and the evolutions of the characteristics of extreme rainfall over time. Additionally, the method ignores changes in the stochastic and heterogeneous distribution of storms.

Given the spatial gaps in observational data networks and the discontinuities in the data records, using model-based weather data could be an attractive alternative, provided model-based data would represent a suitably long historical record. Numerical weather prediction (NWP) models are commonly used to generate gridded reconstructions of historical weather conditions (i.e., “reanalysis”) on both the global scale (e.g., Dee et al., 2011; Kanamitsu et al., 2002) and the regional scale (e.g., Mesinger et al., 2006). NWP models can produce continuous long-term data across spatial scales using a physics-based framework with hourly output. Currently available gridded models based on observational data, such as PRISM (Daly et al., 2008), do not supply subdaily data. The hourly output from NWP models could then be used to generate PIDF curves. If acceptable accuracy is demonstrated in representing precipitation—particularly extreme events—with NWP models, they could then be applied to project changes to PIDF curves under various environmental futures.

One common and readily available NWP model is the Weather Research and Forecasting (WRF) model (Skamarock & Klemp, 2008). WRF has thousands of users worldwide, and it can reliably produce continuous hourly weather data while accounting for changes in topography and land use. In the last decade, subdaily precipitation from WRF has been explored to produce PIDF curves by examining different spatial and temporal resolutions of the output data (Cardoso et al., 2013; Gao et al., 2012; Gao et al., 2015; Liew et al., 2014a, 2014b; Prein et al., 2017; Vu et al., 2017); however, the procedure to develop PIDF curves from the modeled data is not well established. Similarly, there are ongoing efforts to refine the development of PIDF curves from observational data with focuses on data stationarity (Cheng & AghaKouchak, 2014; DeGaetano & Castellano, 2018), data spatial interpolation and ungauged station representation (Bonnin et al., 2006; Guo, 2006; Hamidi et al., 2017; Perica et al., 2013; Schardong et al., 2018), and methods of computing PIDF curves (Bonnin

et al., 2006; DeGaetano & Castellano, 2018; Millington et al., 2011; Perica et al., 2013). Using modeled gridded data to represent point observational data for PIDF curves is also a challenge that has not been addressed (e.g., Cardoso et al., 2013; Chan et al., 2014).

The purpose of this study is to explore the viability of using dynamically downscaled hourly output from the WRF model to develop PIDF curves for 1- to 24-hr duration extreme events. Here, we explore methods of developing PIDF curves from modeled data using WRF for three metropolitan areas in the Eastern United States. The metropolitan areas were chosen to give the study the best chance of success with using WRF data to develop PIDF curves, with the assumption that if we could not use WRF model output at those three cities, then we would have no chance of developing realistic PIDF curves for metropolitan areas with more complex topographical and mesoscale characteristics. The study focuses on the spatial representation of precipitation across the metropolitan areas in observed and modeled data sets and how different data aggregation techniques alter subdaily precipitation frequencies.

2. Methods

Developing PIDF curves from either observed or modeled data is not a uniformly applied procedure. Within every metropolitan area, several observation locations regularly record precipitation at various intervals (either daily or subdaily). These observations sites are irregularly spaced, and the data can be compromised by differing lengths of historical records, as well as by missing data. In addition, there is no consensus on how to relate observational point data to modeled gridded data across a metropolitan or any given area. In this study, various methods were explored to develop PIDF curves from collections of observations, as well as from gridded modeled data. Statistical procedures were employed to determine how to use a suite of observation sites and how to pair those data with gridded modeling data across a metropolitan area to create PIDF curves to represent that city. Additional emphasis was placed on quality assurance and quality control of both types of data sources, as well as on how to use both data sources to develop PIDF curves for a given location.

a. Creating PIDF Curves

PIDF curves simultaneously illustrate the interplay of the three aspects of precipitation: intensity, duration, and frequency. In a PIDF curve, intensity (I) refers to an amount of precipitation falling per unit time (mm/hr), duration (t) refers to time unit (hr) during which there was continuous precipitation at that intensity (mm), and return period (T ; also called the “frequency” or “recurrence interval”) expresses a probability of how often a storm of a given duration and intensity occurs (Dunne & Leopold, 1978; Trenberth et al., 2003). PIDF curves are created using at least 20 years of recorded hourly precipitation from a monitoring station (Bonnin et al., 2006; Hershfield, 1961a; Perica et al., 2013).

In this study, precipitation duration from both observed and modeled data was based on hourly events with a minimum accumulation of 1 mm/hr to exclude trace amounts of precipitation (Salinger & Griffiths, 2001; Gao et al., 2015). Precipitation was accumulated with a rolling summation for the 2-, 3-, 6-, 12-, and 24-hr rain durations. The annual precipitation maximum (the highest annual accumulation) for each duration was used to

develop an annual maximum series (AMS) for the study period. For each study location, the AMS data were examined at the beginning and end of each year (1 January and 31 December, respectively), and none of the annual maxima occurred on either of those days in any year, which ensures that the maximum precipitation events are all self-contained within the individual years. Using AMS data, the intensities of annual extreme events were calculated for 2-, 3-, 6-, 12-, and 24-hr durations using equation 1.

$$I = \frac{P}{t} \quad (1)$$

where I is the precipitation intensity in mm/hr, P is the accumulated precipitation in mm, and t is the duration of precipitation in hr.

The AMS were fit to six probability distributions to estimate precipitation quantities for each duration using extreme value (EV) analysis. The EV analysis usually requires an estimate of the probability of events that are more extreme than any that have been observed. EV theory provides a framework that enables extrapolation from known values (Coles et al., 2001). One of the applications of EV theory is Regional Frequency Analysis (RFA; Hosking & Wallis, 1997). The RFA applies EV theory to a region composed of different sites characterized by similar event frequencies and is weighted by the length of the data record at each station. The RFA method is used in ATLAS (Bonnin et al., 2006; Perica et al., 2013).

In this study, two methods are used to derive PIDF curves. At-site EV analysis and RFA were performed to generate the probability of high-intensity precipitation for different data optimization scenarios (Hosking & Wallis, 1997; Coles et al., 2001; Eslamian & Feizi, 2007). The distributions were tested for goodness of fit (GOF), and the RFA method was tested for homogeneity and dissimilarity. The following probability distributions were considered: Gumbel, generalized extreme value (GEV), Gamma, Pearson Type III, normal, and lognormal (Gumbel, 1958; Coles et al., 2001; Bonnin et al., 2006; Perica et al., 2013). The selection of distribution functions was based on the GOF tests using Kolmogorov-Smirnov, Anderson-Darling, and root mean square error (RMSE; Boessenkool, 2017; Hosking & Wallis, 1997; Laio, 2004; Massey, 1951); see Table S2 in the supporting information. The probability distribution with the best GOF was fitted to each selected duration data series to extrapolate the observed data to the return periods (T) of 2, 5, 10, 25, and 50 years.

b. Modeled Data

The goal of this research is to determine whether modeled meteorological data can be used to create realistic PIDF curves in the absence of observational data (e.g., following future scenarios). The dynamically downscaled meteorological data used here illustrate the sensitivity of the resultant PIDF curves to the spatial scale of the large-scale driving data and the spatial scale of the WRF model. Historical simulations are used in this study so that the resultant PIDF curves can be evaluated against observed weather events. To analyze the impact of the WRF driving data, the study used initial conditions and lateral boundary conditions from two global-model reanalysis (GMR) products of different resolutions. The resolutions of the GMRs are comparable to the global models that informed the

Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC, 2013), the most recent international synthesis of the state of knowledge on climate change. The influence of the spatial scale of downscaling was characterized using two horizontal grid spacings with WRF: 36 and 12 km. The 36-km grid spacing is typical of many dynamical downscaling exercises within the past several years (e.g., Spero et al., 2016, among several others), and it is comparable to the grid spacing used in the Coordinated Regional Downscaling Experiment (Giorgi & Gutowski, 2015). The 12-km grid spacing is emerging more commonly, as computing power has increased.

The study examined the following simulations: (1) "R2_36," where the $2.5^\circ \times 2.5^\circ$ NCEP-DOE AMIP-II Reanalysis (R2; Kanamitsu et al., 2002) was downscaled to 36-km horizontal grid spacing; (2) "ERA_36," where the $0.75^\circ \times 0.75^\circ$ European Centre for Medium-Range Weather Forecasts Interim Reanalysis (ERA-Interim; Dee et al., 2011), was downscaled to 36-km; (3) "ERA_12," where ERA-Interim was downscaled to 12-km horizontal grid spacing. Trenberth et al. (2017) emphasized the importance of using high temporal resolution precipitation data to better capture the individual events and understand the intermittency of those events. This study used hourly precipitation totals from each WRF simulation to construct PIDF curves.

WRF was used to simulate historical conditions over the CONUS with an initialization at 00 UTC 1 November 1987 to provide a 2-month spin-up period prior to the 23-year study period, 00 UTC 1 January 1988 to 00 UTC 1 January 2011. Boundary conditions were updated every 6 hr. The downscaling methodology with WRF follows Otte et al. (2012). Although historical simulations were used, no additional observational data were blended with the GMR driving data set so that the WRF simulations emulated a regional climate downscaling exercise. R2 was downscaled using WRFv3.4.1 with the same WRF simulations used in Seltzer et al. (2016). Similar configurations of WRF driven by R2 were evaluated by Bowden et al. (2012), Otte et al. (2012), and Bowden et al. (2013). Both simulations driven by ERA-Interim were downscaled using WRFv3.9 with some modeling advances beyond what was used in R2_36 including changes to the methods of constraining WRF toward the driving data (Spero et al., 2014, 2018) and to the modeling of the land-surface exchanges (Mallard & Spero, 2019). The ERA_36 and ERA_12 use one of the modeling configurations evaluated in Mallard and Spero (2019). The WRF configurations used for the three simulations are provided in Table 1.

c. Observational Data

For consistency in our analysis, the observational data in this study cover the same 23-year period used for the WRF modeling. The data record used here meets the minimum record length of 20 years recommended by ATLAS to develop PIDF curves (Bonnin et al., 2006; Hershfield, 1961a; Perica et al., 2013). However, this length of data may be considered a limitation of this study because longer data records are typically used in ATLAS. The observed data used in the study were compared with the longer record lengths used in ATLAS (Figure S1), and the differences were primarily attributed to the magnitudes of extreme events occurring in the different data records and to the number of stations that

influenced the PIDF curves. Note that the conclusions of this study are drawn from the relative comparison of the observed and modeled data sets.

In this study, ATLAS methodology was applied to develop PIDF curves from the 23-year observational data record rather than comparing modeled results to the PIDF values in ATLAS that were often developed from longer records. The COOP network provides verified precipitation data across the CONUS, and it is a major source of data used by NOAA to produce PIDF curves (Bonnin et al., 2006; Perica et al., 2013). The COOP historical record varies in length between different stations; thus, using a longer study period here would reduce the number of stations with a complete record available. Previous studies demonstrated that COOP data can be used to detect trends in the frequency and intensity of extreme precipitation events, and they stressed a need to minimize sampling uncertainty by including a minimum number of stations (Kunkel et al., 2012, 2013).

Hourly precipitation data for 137 COOP stations (Table S1) were acquired from NOAA's National Centers for Environmental Information (NCEI) for 1988–2010 (NOAA, 2017). The observational data were evaluated for quality and consistency by considering NCEI measurement and quality flags, and they were organized by fraction of missing valid precipitation observations (Table S1). After reviewing the possible study locations in the Southeast and Midwest United States, three stations with valid hourly precipitation observations for 100% of the 23-year study period were selected: Cincinnati, Ohio; Raleigh, North Carolina; and Atlanta, Georgia (Figure 1). Each of these cities is located at least 100 km from the coast and mountains to minimize the influences of steep topographical gradients and land-water interfaces, which could further affect the heterogeneity of the distribution and accumulation of precipitation when compared with modeled data. Although these cities were selected primarily based on the completeness of the observational data record, the absence of complex terrain and coastlines at these locations enables comparison of modeled data at different grid spacings, and examination of the potential to develop PIDF curves from modeled data under the most favorable conditions. These cities are also more than 500 km apart, which minimizes the potential overlap in the meteorological conditions experienced at these locations and represents three regions of natural climatic variabilities.

d. Data Optimization

Quantifying maximum precipitation is an important aspect of developing PIDF curves. Thus, precipitation for each city is represented using observed precipitation from 10 stations across the metropolitan area. Hourly precipitation at each COOP station is collected from rain gauges representing precipitation at a point in space and time. Precipitation observations can vary wildly across any given metropolitan area due to complex landscapes with different microclimates, influences of topography, and the stochastic nature of convective rainfall. Any network of irregularly spaced gauges is likely insufficient to capture all extreme events across any metropolitan area, especially in areas that are more prone to heterogeneous distributions of rainfall from predominantly stochastic convective events. Additionally, the observations are incomplete, which is not always identified by the NCEI measurement and quality flags. The hourly data, collected by automated rain gauges, often miss maximum

precipitation during extreme events because the automated gauges are vulnerable to power interruptions or other interferences during violent storms or hurricanes.

To examine the effects of missing data on the representation of the intensities, durations, and frequencies of precipitation, PIDF curves developed from both complete and incomplete observational data sets are compared. This comparison also explores challenges associated with comparing incomplete observation data sets to modeled data (which always has 100% completeness for a period of record). All available data from 10 stations are used in RFA to develop PIDF curves (OBS_RFA) to compare with four data clusters described in Table 2: EV_IDW, RFA_75, EV_site, and EV_mean.

The Inverse Distance Weighting (IDW) method applied in EV_IDW data sets assumes that precipitation values closer to the city center are more representative than those at distant locations (Dunne & Leopold, 1978). IDW was calculated using a weighting function from Shepard (1968).

$$f(x) = \frac{\sum_{i=1}^N w_i(x) u_i}{\sum_{i=1}^N w_i(x)}, \quad (2)$$

$$f(x) = \frac{1}{d(x, x_i)^p} \quad (3)$$

In equation 2, the value at location x is determined from a weighted interpolation of N observed data points u_i at each location x_i . The distance-based weights w_i are calculated with equation 3 (where $x = x_i$) and are assigned to each observation location as a function of the distance d between x_i and x . If $x = x_i$, then $w_i(x) = 1$. The distance weighting is adjusted using the power parameter p , which is a positive real number that is set to 2 here (Shepard, 1968; Figure 1 and Table S1).

Modeled data were optimized by considering three spatial representations of the metropolitan area using gridded data: a single cell that contained the major station representing the city (C01), a nine-cell patch centered on C01 (C09), and a 25-cell patch centered on C01 and expanding on C09 (C25; Figure 1). Additional analysis focused on how to use the modeled precipitation from those grid cells to best match PIDF curves derived from the observational data (OBS_RFA) corresponding to the gridded area. As was done for observations, the EV method was applied to the central cell at C01 (EV_C01) and then to data sets aggregated by IDW and mean methods (EV_IDW and EV_mean, respectively) to represent the metropolitan area using WRF output. EV_IDW for modeled data was used in C09 and C25 by considering the distance from the center of each WRF grid cell to C01, which contains the primary observation for the city (Figure 1).

For WRF output, EV_mean involved averaging the n highest hourly values (i.e., $2 \leq n \leq 9$ in the C09 patch, and $2 \leq n \leq 25$ in the C25 patch) from the subsets of each scenario so the outcome data would have best fit to the observations (Table 3); several different settings of n were examined for C09 and for C25 (not shown). The best fit was determined using a suite

of statistical measures: coefficient of determination (R^2), mean percent bias (PBIAS), and RMSE. The best-performing subsets of the modeled data were then compared for the distribution of precipitation intensities at the chosen durations and tested for best probability distribution function. The results were then plotted into PIDF curves (described below). This study also examined seasonal precipitation patterns using a percentage change between observed and modeled data.

3. Results

a. Observational Data

The observational data from Atlanta (Figure 1) were used to test methods of developing PIDF curves from observations. PIDFs of observations for Atlanta were examined using five methods (Table 2). To examine the effects of missing data within an observational record, the PIDFs derived from all data available at 10 stations, using RFA (OBS_RFA), were compared with the PIDFs derived using RFA from the observational data set for Atlanta with 75% completeness (i.e., 25% of the valid observations randomly removed, RFA_75). Further, two data sets were considered where 25% of the data at the central station were randomly removed, and data from surrounding stations filled the missing data gaps using either EV_IDW or EV_mean. In addition, methods of representing the metropolitan area were examined by comparing the results from all data sets with PIDFs derived from 100% completeness at the central station (EV_site; Figure 2).

Figure 2 illustrates the effects of missing data on an observational record. This comparison is a noteworthy contrast to using modeled data, which always have 100% completeness and data coverage for any study. In Figure 2, the comparison of PIDF curves for 2-year return period from OBS_RFA (plotted with 90% confidence intervals [CI]) with EV_site revealed statistically insignificant differences between data sets ($p > 0.05$), with the values from a central station generally 2% higher than those derived via RFA (OBS_RFA). RFA_75 underestimated precipitation depth at all durations (PBIAS = -13%, $p < 0.05$), with underestimation increasing with duration length. This result shows that using hourly precipitation observations with missing data will produce depreciated PIDF values. Thus, the PIDF curves derived from complete data sets (i.e., modeled) may have higher values than those derived from observed data.

The EV_mean data set performed the poorest (PBIAS = +53%, $p < 0.05$), indicating that replacing missing data with the mean of hourly precipitation at the surrounding stations compromises the precipitation distributions and significantly overestimates high-intensity precipitation in all durations. EV_mean also introduces error from duplicate counting of precipitation events that traverse the metropolitan area, increasing the PIDF bias with duration. This method also violates the independence between different events' precipitation records.

Distance-weighted averaging of hourly precipitation (EV_IDW) reproduced the PIDF curves from OBS_RFA and EV_site data sets with no statistically significant difference between data sets ($p > 0.05$) and less than 0.3% PBIAS. Figure 2 suggests that the completeness of the observational record has greater impact on the PIDF curves than the method used to

develop PIDF curves. For the remainder of the paper, PIDF curves are derived from observations using RFA (OBS_RFA) to better align with the methodology employed in ATLAS.

b. Optimizing WRF Model Output to Develop PIDF Curves

PIDF curves define the probabilistic return periods for maximum precipitation amounts (the highest annual accumulation over each given duration for a metropolitan area) to be accommodated in storm water planning. Precipitation totals can vary wildly across a metropolitan region, especially during convectively driven precipitation events. Therefore, modeled data should be used in a way that could capture this heterogeneous distribution of precipitation and not necessarily weigh the precipitation totals at each model grid cell equally for each event. Here, various methods are explored using hourly modeled data to reproduce PIDF curves developed from observations.

The WRF output is extracted for different spatial subsets to determine the best representation of each metropolitan area and the best fit to the observations. The gridded patches (see Figure 1) were processed in various ways to match the observation sites. EV theory was applied to C01, and both the EV_mean and EV_IDW methods were applied to C09 and C25, which contain several grid cells. EV_IDW method for data aggregation and EV_C01 were examined to determine the best match of the modeled data to the observations (Table 3). Additionally, the RFA method was applied to the C09 and C25 grid subsets, where each cell was treated as a separate station (Table S3).

In EV_mean, the mean in C09 and C25 is represented by the average of the n maximum hourly precipitation values recorded at a subset of the cells within those patches. To explore this issue, EV_mean was applied to the n highest values in the patch in each scenario. Results were tested against the observational data for statistical performance. Table 3 summarizes the statistical comparisons of the three gridded patches (C01, C09, and C25) with both EV_IDW and EV_mean to represent the three cities shown in Figure 1. The coefficient of determination and bias were improved by increasing the resolution of the driving data between R2_36 and ERA_36 (Table 3). There is variability in model fit among the cities, especially in R2_36, where the best data fit occurs for Cincinnati. At 12-km grid spacing, ERA_12 has the best data fit for Cincinnati. The differences in model fit values between EV_IDW and EV_mean were inconclusive (Table 3). However, the results show that EV_IDW produced lower biases than EV_mean (Table 3), with R2_36 producing the lowest error for the Atlanta C09 subset; ERA_36 model producing lowest error for the Cincinnati C09 subset; and ERA_12 for the Atlanta C09 subset (Table 3).

Figure 3 shows results derived from different cell subsets. The data from different models for EV_IDW_C09, EV_IDW_C25, RFA_C09, and RFA_C25 were compared to EV_C01, which is plotted with 90% CI. In R2_36, there is a significant difference in EV_C09 and RFA_C09 only in Raleigh ($p < 0.05$; RMSE = 1 mm; PBIAS = -6%), which exceeded lower 90% CI. Other data sets were not significantly different from EV_C01. In ERA_36 all values stayed within the 90% CI of the EV_C01 and were not significantly different from the EV_C01 values. In ERA_12, the EV_C09 and EV_C25 were not significantly different from EV_C01. The RFA_09 differed significantly from EV_C01 only in Atlanta ($p < 0.05$;

RMSE = 1 mm; PBIAS = -5%), underestimating the values below the lower 90% CI of EV_C01. The RFA_25 in Atlanta differed significantly from EV_C01 ($p < 0.05$; RMSE = 15 mm; PBIAS = -6%), with the poorest performance recorded in RFA_C25 for Cincinnati ($p < 0.05$; RMSE = 5 mm; PBIAS = -33%), significantly underestimating the precipitation intensity values. RFA, regardless of good dissimilarity and homogeneity tests (Table S3), tends to underestimate values in modeled data. Thus, for the modeled data, the study uses cell subsets representing the metropolitan area (Figure 1) aggregated with IDW.

In R2_36 and ERA_36, there is a large difference in area represented by C09 and C25 (see Figure 1), which is reflected in the values that are aggregated using IDW. C09 was preferred over C01 because C09 can account for spatial and temporal precipitation variability and the spatial extent of the metropolitan area (see Figure 1). C09 was preferred over C25 because the total size of C25 greatly exceeds the size of the urban area. Similarly, to best match the spatial extent of the metropolitan areas, the ERA_12 was analyzed using C25.

Based on presented analysis and considering the spatial extent of the metropolitan areas, EV_IDW was chosen to represent modeled precipitation because it more appropriately considers the heterogeneous spatial distribution of precipitation, it accounts for representativeness of proximate grid cells, and it gives reasonable statistical performance relative to the other methods evaluated (Table 3; Figure 3). Based on the analysis in the previous section, these modeled data sets are compared against the OBS_RFA data set.

c. Hourly Precipitation Distribution

Comparisons of the intensities of precipitation at six durations from the modeled output were made against the observations at each of the three cities (Figure 4) to determine if WRF could reproduce rainfall distribution and intensity. The observations were assembled using RFA (OBS_RFA) to reflect a methodology used in NOAA Atlas14. The modeled output was selected using the EV_IDW data set for C09 (EV_C09) from the R2_36 and ERA_36 simulations and using the EV_IDW for C25 (EV_IDW_C25) from ERA_12. The hourly precipitation distribution of EV_IDW (Figure 4) illustrates the spatial variability in precipitation intensity at all durations between the three cities. Precipitation intensity and frequency are lower in Cincinnati than in Atlanta and Raleigh. The Atlanta precipitation attains higher intensities and frequencies than the other metropolitan areas.

R2_36 and ERA_36 underestimate high intensities and overestimate low intensities in short-duration rain events (1 and 3 hr). In the 6- to 24-hr durations, the frequency distributions do not reflect distributions of the observed data, but the intensities are better represented than in the shorter durations. In Cincinnati, the precipitation intensities are better represented in the 6- to 24-hr durations by increasing the resolution of the GMR by using ERA_36 instead of R2_36. The change in the input data resolution decreased model performance in Raleigh and Atlanta (Figure 4).

Decreasing the horizontal grid spacing in WRF to 12 km dramatically improved the representation of shorter-duration events compared to the 36-km simulations at all three cities. Distribution of frequencies in ERA_12 matches the observed data in all durations; however, intensities at the 1-hr duration are still underestimated in Cincinnati and Atlanta.

The observations were best reproduced by ERA_12 in 3- to 24-hr durations, in Cincinnati and Atlanta. ERA_12 overestimated intensities in all durations in Raleigh and in the 6- and 24-hr durations in Atlanta (Figure 4).

d. Fitting PIDF Curves to Optimized Modeled Data

For the three locations in this study, the selection criteria for probability functions were determined by the GOF values, and the GEV distribution was adopted across all stations and for all durations (Table S2). All of the distributions failed to reject the null hypothesis, which confirms that data followed the specified distribution (Table S2). The GEV distribution is used in ATLAS (Coles et al., 2001; Bonnin et al., 2006; Perica et al., 2013). The GEV distribution is a three-parameter distribution where location parameter (ξ), scale parameter (α), and shape parameter (κ) were calculated using the L-moments estimation method from the extRemes and lmomRFA R packages (Gilleland & Katz, 2016; Hosking, 2019). The parameters were then applied to calculate at-site precipitation intensity estimates (Q_T) using equation 4 for return periods (T) of 2, 5, 10, 25, and 50 years (Hershfield, 1961a, 1961b) following Hosking and Wallis (1997) and Millington et al. (2011).

$$Q_T = \xi + \frac{\alpha}{\kappa} \left(1 - \left(-\ln \left(\frac{T-1}{T} \right)^\kappa \right) \right) \quad (4)$$

The GEV distribution and L-moments were also used in RFA using the lmomRFA R package (Hosking, 2019; Table S3). The package provides functions that utilize Monte Carlo simulation to estimate the distribution of heterogeneity and goodness-of-fit measures for RFA (where our estimates are based on 1,000 simulations) and to compute 90% CI for estimated quantiles (regsimh and regsimq, respectively; Hosking, 2019).

The distribution of intensities at different durations (Figure 4) is reflected in using AMS to fit probability distributions into the modeled data. In each of the three cities, the 1- to 3-hr events were greatly underestimated by the R2_36 and ERA_36 simulations, and in both 36-km simulations, the 18- to 24-hr events were overestimated in Raleigh and underestimated in Atlanta (Figures 5 and 6). Decreasing the horizontal grid spacing of WRF to 12-km in ERA_12 improved the comparison of the modeled PIDF curves to those derived from observations (Figure 5). Marked improvements were gained in the modeled PIDF curves by using ERA_12 compared with ERA_36, especially in the intensities of the short-duration events. However, ERA_12 still underestimates annual maxima in the shortest durations (Figures 4 and 5), which suggests that even finer grid spacing may be needed to reproduce the highest intensities at the shortest durations.

The improvements with 12-km WRF simulations are also shown in Figure 6. For the 2-year return period, the probabilities are well represented at all durations in ERA_12 in Cincinnati and Atlanta. However, ERA_12 overestimates 2- to 24-hr durations in Raleigh. Both 36-km simulations follow similar pathways in 1- to 24-hr durations in Cincinnati and Atlanta, with ERA_36 underestimating intensities relative to R2_36. In Raleigh, R2_36 agrees with the observed data (within the 90% CI) for 12- and 24-hr durations. ERA_36 underestimates intensities all durations at all three locations.

e. Seasonality

The seasonal precipitation patterns in all three model simulations deviate least from observations during the winter (Figure 7) when there is more synoptically driven precipitation that is more uniform in spatial coverage and accumulation. R2_36 shows spatial variability between stations. Typically, the modeled precipitation for Atlanta is drier than the observations, while Cincinnati and Raleigh are wetter, especially in the summer. Finer-resolution input from ERA-Interim, which drives ERA_36, resulted in overall drier seasons than R2_36, with occasional overestimation of precipitation in the spring and summer in Cincinnati and Raleigh. Figure 7 is consistent with the PBIAS values in the analyses of monthly data (Table 3), with larger and negative PBIAS in ERA_36. ERA_12 overestimated precipitation in all three cities during spring and summer, but the overestimated precipitation in all seasons in ERA_12 is smaller for Cincinnati than for Raleigh. Atlanta shows some precipitation overestimation in the summer and underestimation in the other seasons. The seasonal biases may be addressed with more sophisticated modeling in WRF.

4. Discussion

This study explored the potential of using hourly precipitation output from dynamically downscaled WRF simulations to develop PIDF curves for 1- to 24-hr duration. We focused on the spatial representation of metropolitan areas and developing a methodology to fit the modeled data, while trying to emulate national standards used in ATLAS. This analysis recommends that multiple observations and multiple WRF grid cells should be used to develop PIDF curves for a given metropolitan area.

We used Atlanta to develop the methodology to use observations to represent an urban area. The spatial and temporal characteristics of the observed precipitation for Atlanta were best represented by the EV_site and EV_IDW methods, which marginally overestimated precipitation maxima in 6- to 24-hr durations (Figure 3). RFA was explored for the observed data to supplement missing data (RFA_75), but it underestimated PIDF values and did not reproduce maximum precipitation intensities in 3- to 24-hr durations (Figure 3). The results shown in Figure 2 demonstrate that the completeness of the observational record has a greater influence on the resultant PIDF curves than the method used to develop PIDF curves.

IDW is attractive for capturing spatial precipitation variability and the temporal nonstationarity of storms. However, using data from multiple observation sites or from multiple grid cells in IDW can inadvertently and artificially accentuate precipitation events both temporally and spatially. For example, a moving storm that affects multiple sites around urban areas in IDW over a given duration could be counted multiple times with this method, which may lead to underestimation of short-duration, high-intensity events and overestimation of long-duration events. The analysis shows that for developing PIDF curves, multiple stations could be used over a large urban area but only when using EV_IDW with a 100% data coverage at the central station. EV_IDW should be used with caution to supplement gaps in the observed data record and only to supplement the data during missing periods. However, in this study, the OBS_RFA was preferred over the EV_IDW and EV_site to compare against modeled data sets and for consistency with the ATLAS methodology.

Surprisingly, using RFA for the modeled data, where each cell was considered as a separate station, underestimated the PIDF values. One major advantage of using RFA is developing the PIDF values for regions larger than the cities used here, and from data of different record lengths. Unlike for observations, IDW is used for the modeled data to compensate for the NWP model's reduced temporal and spatial accuracy over large metropolitan areas, where convective activity could be predicted by the model to occur at approximately the same time and place as was observed but does not align perfectly in space and/or time. Therefore, this study tested the fit of different subsets of modeled data and ultimately used a subset that roughly aligned with the spatial extent of the metropolitan area. The 36-km WRF data set driven by 2.5° R2_36 produced acceptable duration distributions and maximum intensities in the 6- to 24-hr durations in Raleigh and 12- to 24-hr durations in Atlanta, but those WRF data could not reproduce the high-intensity, short-duration precipitation events or the long-duration precipitation events (Figures 4, 5, and 6). Increasing the resolution of the global driving data for WRF resulted in underestimated intensities in PIDF curves obtained from 36-km WRF simulations in Cincinnati and Raleigh (Figures 5 and 6).

Neither of the 36-km simulations could capture the spatial and temporal characteristics of precipitation over the cities. Decreasing the horizontal grid spacing of WRF to 12-km was necessary to improve the representation of the duration distribution and maximum intensities in the short-duration events, which illustrates that WRF can reproduce extreme precipitation over metropolitan areas. These simulations strongly suggest that 12-km simulations could generate viable PIDF curves throughout the 1- to 24-hr duration range. However, additional analysis is required to refine the 12-km simulations and to determine if 12-km grid spacing is sufficient for developing PIDF curves for more challenging meteorological cases (such as along coastlines or in complex terrain) and if finer grid spacing (such as 4 km) is advanced enough to handle those challenges. It is unclear whether finer-resolution WRF simulations could be sufficiently accurate and incrementally more skillful than 12-km WRF to justify the additional computational expense.

Although WRF is a very credible model, there is room for improvement. Underestimating 1-hr precipitation is not unique to the WRF simulations used here; for example, it has been reported by Hanel and Buishand (2010) at 25-km grid spacing in WRF driven by 2.5° ERA-40 and by Liew et al. (2014a, 2014b) in studies using 6-hr data from a 30-km WRF simulation driven by ERA-40. Underestimating the intensities could be addressed with a delta method correction to the modeled data for historical periods (Liew et al., 2014a, 2014b; Vu et al., 2017). Gao et al. (2012) showed that their 4-km configuration of WRF missed more than 20 hurricane events, resulting in less-extreme (lower-intensity) precipitation events; they attributed the underrepresentation of extreme events to the global driving data used in their study. Cardoso et al. (2013) showed that WRF at 27- and 9-km grid spacings driven by ERA-Interim overpredicted light precipitation and underrepresented heavy precipitation; however, their study showed that skill improved—especially in areas of complex topography—in the higher-resolution simulation.

While the WRF configuration (Table 1) will influence the specifics of the PIDF curves, the shape of the PIDF curves derived from WRF output (especially the ability to capture the extremes) is predominantly the horizontal grid spacing used in the WRF model. The

configurations of the two 36-km WRF simulations in this study used different input data sources (2.5° R2 vs. 0.75° ERA-Interim) had differences in WRF model version, and several differences in the physics and nudging options. However, the PIDF curves developed from the 36-km simulations were not appreciably different (see Figures 4, 5, and 6). By contrast, identical configurations of WRF input data source, model version and executable, and physics options were used to simulate 36- and 12-km output. In the latter runs, the PIDF curves were dramatically improved by decreasing the horizontal grid spacing in WRF. The short-duration, high-intensity events were much better reflected in PIDF curves generated using 12-km WRF than with 36-km WRF.

More development is needed to improve the resultant PIDF curves, either through modifications to the methods of using modeled data or through scientific improvements to WRF. Although the 12-km simulation shown here qualitatively improved the PIDF curves relative to the 36-km simulations, it degraded the summertime precipitation for Raleigh (Figure 7) and the resultant PIDF curves for Raleigh from that simulation (Figure 5). Because summertime precipitation is predominantly convective, this result strongly implicates the convective parameterization used in WRF. Consequently, follow-on research will consider scale-aware convective schemes in WRF to refine the simulation of precipitation at 12 km in the Southeastern United States and to ultimately support 4-km simulations. An additional 23-year WRF simulation at 12 km was conducted (not shown) using the MSKF convective scheme (He & Alapaty, 2018; Zheng et al., 2016), and the preliminary analysis indicates that the shapes of the PIDF curves are similar between the two 12-km simulations. The 12-km simulation with MSKF improved the precipitation and PIDF curves for Raleigh, as well as for coastal cities (not shown). These preliminary results provide impetus to refine the WRF configuration at 12 km to develop PIDF curves.

This study used methods that were chosen to align closely with the ATLAS. However, this study is not intended to replace or compete with ATLAS. Yet the results here can be compared to ATLAS with some caveats that highlight the differences between the methods. First, the PIDF curves in ATLAS are developed from the longest data record available for any given location, while this study was limited to the data record for 1988–2010. Second, unlike ATLAS, this study was limited to observations from 10 stations to represent a single station.

Although imperfect, these WRF data can be used toward the development of PIDF curves that could inform storm water management. This research serves as a proof-of-concept that PIDF curves can reliably be developed from modeled meteorological data provided the grid spacing is sufficiently fine enough. In addition, this research lends confidence to using these data and modeling techniques to assess potential changes to extreme precipitation under various future scenarios without access to observations to construct PIDF curves. Eventually, these techniques will contribute PIDF curves to the EPA's Storm Water Management Model and Climate Resilience Evaluation and Awareness Tool, allowing public communities to use these data and techniques in storm water management planning, thereby avoiding negative economic impacts.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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References

- Alexander LV, Zhang X, Peterson TC, Caesar J, Gleason B, Tank AK, Haylock M, Collins D, Trewin B, Rahimzadeh F, & Tagipour A. (2006). Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research*, 111, D05109. 10.1029/2005JD006290
- Ali H, Mishra V, & Pai DS (2014). Observed and projected urban extreme rainfall events in India. *Journal of Geophysical Research: Atmospheres*, 119, 12–621. 10.1002/2014JD022264
- Boessenkool B. (2017). extremeStat: Extreme Value Statistics and Quantile Estimation. R package version 1.4.0. <https://CRAN.R-project.org/package=extremeStat>
- Bonnin GM, Martin D, Lin B, Parzybok T, Yekta M, & Riley D. (2006). NOAA Atlas 14, Volume 2, Version 3.0, Precipitation-Frequency Atlas of the United States. Silver Spring, MD: NOAA, National Weather Service.
- Bowden JH, Nolte CG, & Otte TL (2013). Simulating the impact of the large-scale circulation on the 2-m temperature and precipitation climatology. *Climate Dynamics*, 40(7-8), 1903–1920. 10.1007/s00382-012-1440-y
- Bowden JH, Otte TL, Nolte CG, & Otte MJ (2012). Examining interior grid nudging techniques using two-way nesting in the WRF model for regional climate modeling. *Journal of Climate*, 25, 2805–2823. 10.1175/JCLI-D-00167.1
- Campbell PC, Bash JO, & Spero TL (2018). Updates to the Noah land surface model in WRF-CMAQ to improve simulated meteorology, air quality, and deposition. *Journal of Advances in Modeling Earth Systems*, 11, 231–256. 10.1029/2018MS001422
- Cardoso RM, Soares PMM, Miranda PMA, & Belo-Pereira M. (2013). WRF high resolution simulation of Iberian mean and extreme precipitation climate. *International Journal of Climatology*, 33(11), 2591–2608. 10.1002/joc.3616
- Chan SC, Kendon EJ, Fowler HJ, Blenkinsop S, Roberts NM, & Ferro CA (2014). The value of high-resolution met office regional climate models in the simulation of multihourly precipitation extremes. *Journal of Climate*, 27(16), 6155–6174. 10.1175/JCLI-D-13-00723.1
- Chen F, & Dudhia J. (2001). Coupling an advanced land surface-hydrology model with the Penn State–NCAR MM5 modeling system. Part I: Model implementation and sensitivity. *Monthly Weather Review*, 129(4), 569–585. 10.1175/1520-0493(2001)129<0569:CAALSH>2.0.CO;2
- Cheng CS, Li G, Li Q, & Auld H. (2011). A synoptic weather-typing approach to project future daily rainfall and extremes at local scale in Ontario, Canada. *Journal of Climate*, 24(14), 3667–3685. 10.1175/2011JCLI3764.1
- Cheng L, & AghaKouchak A. (2014). Nonstationary precipitation intensity-duration-frequency curves for infrastructure design in a changing climate. *Scientific Reports*, 4, 7093 10.1038/srep07093 [PubMed: 25403227]

- Coles S, Bawa J, Trenner L, & Dorazio P. (2001). An introduction to statistical modeling of extreme values (Vol. 208). London: Springer 10.1007/978-1-4471-3675-0
- Daly C, Halbleib M, Smith JI, Gibson WP, Doggett MK, Taylor GH, Curtis J, & Pasteris PP (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 28(15), 2031–2064. 10.1002/joc.1688
- Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S, Andrae U, Balmaseda MA, Balsamo G, Bauer DP, & Bechtold P. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 137(656), 553–597. 10.1002/qj.828
- DeGaetano AT, & Castellano C. (2018). Selecting time series length to moderate the impact of non-stationarity in extreme rainfall analyses. *Journal of Applied Meteorology and Climatology*, 57, 2285–2296. 10.1175/JAMC-D-18-0097.1
- Dunne T, & Leopold LB (1978). *Water in Environmental Planning*. New York: Freeman 10.1002/esp.3290040322
- Easterling DR, Kunkel KE, Arnold JR, Knutson T, LeGrande AN, Leung LR, Vose RS, Waliser DE, & Wehner MF (2017). Precipitation change in the United States In Wuebbles DJ, Fahey DW, Hibbard KA, Dokken DJ, Stewart BC, & Maycock TK (Eds.), *Climate Science Special Report: Fourth National Climate Assessment, Volume I* (pp. 207–230). Washington, DC, USA: U.S. Global Change Research Program 10.7930/J0H993CC
- Eslamian SS, & Feizi H. (2007). Maximum monthly rainfall analysis using L-moments for an arid region in Isfahan Province, Iran. *Journal of Applied Meteorology and Climatology*, 46, 494–503. 10.1175/JAM2465.1
- Gao P, Carbone GJ, & Guo D. (2015). Assessment of NARCCAP model in simulating rainfall extremes using a spatially constrained regionalization method. *International Journal of Climatology*, 36(5), 2368–2378. 10.1002/joc.4500
- Gao Y, Fu JS, Drake JB, Liu Y, & Lamarque JF (2012). Projected changes of extreme weather events in the eastern United States based on a high resolution climate modeling system. *Environmental Research Letters*, 7(4), 044025. 10.1088/1748-9326/7/4/044025
- Gilleland E, & Katz RW (2016). extRemes 2.0: An extreme value analysis package in R. *Journal of Statistical Software*, 72(8), 1–39. 10.18637/jss.v072.i08
- Giorgi F, & Gutowski WJ Jr. (2015). Regional dynamical downscaling and the CORDEX initiative. *Annual Review of Environment and Resources*, 40, 467–490. 10.1146/annurev-environ-102014-021217
- Golroudbary VR, Zeng Y, Mannaerts CM, & Su ZB (2017). Detecting the effect of urban land use on extreme precipitation in the Netherlands. *Weather and Climate Extremes*, 17, 36–46. 10.1016/j.wace.2017.07.003
- Groisman PY, Knight RW, Easterling DR, Karl TR, Hegerl GC, & Razuvaev VN (2005). Trends in intense precipitation in the climate record. *Journal of Climate*, 18(9), 1326–1350. 10.1175/JCLI3339.1
- Groisman PY, Knight RW, & Karl TR (2012). Changes in intense precipitation over the central United States. *Journal of Hydrometeorology*, 13(1), 47–66. 10.1175/JHM-D-11-039.1
- Groisman PY, Knight RW, Karl TR, Easterling DR, Sun B, & Lawrimore JH (2004). Contemporary changes of the hydrological cycle over the contiguous United States: Trends derived from in situ observations. *Journal of Hydrometeorology*, 5(1), 64–85. 10.1175/1525-7541(2004)005<0064:CCOTHC>2.0.CO;2
- Gumbel EJ (1958). *Statistics of extremes*, (p. 247). New York: Columbia University Press.
- Guo Y. (2006). Updating rainfall IDF relationships to maintain urban drainage design standards. *Journal of Hydrologic Engineering*, 11(5), 506–509. 10.1061/(ASCE)1084-0699(2006)11:5(506
- Hamidi A, Devineni N, Booth JF, Hosten A, Ferraro RR, & Khanbilvardi R. (2017). Classifying urban rainfall extremes using weather radar data: An application to the greater New York area. *Journal of Hydrometeorology*, 18(3), 611–623. 10.1175/JHM-D-16-0193.1
- Hanel M, & Buishand TA (2010). On the value of hourly precipitation extremes in regional climate model simulations. *Journal of Hydrology*, 393(3–4), 265–273. 10.1016/j.jhydrol.2010.08.024

- He J, & Alapaty K. (2018). Precipitation partitioning in multiscale atmospheric simulations: Impacts of stability restoration methods. *Journal of Geophysical Research: Atmospheres*, 123, 10,185–10,201. 10.1029/2018JD028710
- Hennessy K, Gregory J, & Mitchell J. (1997). Changes in daily precipitation under enhanced greenhouse conditions. *Climate Dynamics*, 13, 667. 10.1007/s003820050189
- Hershfield DM (1961a). Estimating the probable maximum precipitation. *Journal of the Hydraulics Division*, 87(5), 99–116.
- Hershfield DM (1961b). Rainfall frequency atlas of the United States for durations from 30 minutes to 24 hours and return periods from 1 to 100 years. U.S. Department Commerce Technical Paper, 40, 1–61.
- Herwehe JA, Alapaty K, Spero TL, & Nolte CG (2014). Increasing the credibility of regional climate simulations by introducing subgrid-scale cloud-radiation interactions. *Journal of Geophysical Research: Atmospheres*, 119, 5317–5330. 10.1002/2014JD021505
- Hong S-Y, & Lim J-OJ (2006). The WRF single-moment 6-class microphysics scheme (WSM6). *Journal of the Korean Meteorological Society*, 42, 129–151.
- Hong S-Y, Noh Y, & Dudhia J. (2006). A new vertical diffusion package with an explicit treatment of entrainment processes. *Monthly Weather Review*, 134(9), 2318–2341. 10.1175/MWR3199.1
- Hosking JRM (2019). Regional frequency analysis using L-moments. R package, version 3.2. URL: <https://CRAN.R-project.org/package=lmomRFA>.
- Hosking JRM, & Wallis JR (1997). Regional frequency analysis: An approach based on L-moments. Cambridge: Cambridge University Press 10.1017/CBO9780511529443
- Iacono M, Delamere JS, Mlawer EJ, Shephard MW, Clough SA, & Collins WD (2008). Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *Journal of Geophysical Research*, 113, D13103. 10.1029/2008JD009944
- IPCC (2013). In Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, et al. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, (p. 1535). Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.
- Kain JS (2004). The Kain-Fritsch convective parameterization: An update. *Journal of Applied Meteorology*, 43(1), 170–181. 10.1175/1520-0450(2004)043<0170:TKCPAU>2.0.CO;2
- Kanamitsu M, Ebisuzaki W, Woollen J, Yang SK, Hnilo JJ, Fiorino M, & Potter GL (2002). NCEP–DOE AMIP-II Reanalysis (R-2). *Bulletin of the American Meteorological Society*, 83(11), 1631–1644. 10.1175/BAMS-83-11-1631
- Karl TR, & Knight RW (1998). Secular trends of precipitation amount, frequency, and intensity in the United States. *Bulletin of the American Meteorological Society*, 79(2), 231– 242. 10.1175/1520-0477(1998)079<0231:STOPAF>2.0.CO;2
- Karl TR, Knight RW, Easterling DR, & Quayle RG (1996). Indices of climate change for the United States. *Bulletin of the American Meteorological Society*, 77(2), 279–292. 10.1175/1520-0477(1996)077<0279:IOCCFT>2.0.CO;2
- Karl TR, Melillo JM, Peterson TC, & Hassol SJ (Eds) (2009). *Global climate change impacts in the United States*. Cambridge: Cambridge University Press.
- Karl TR, & Trenberth KE (2003). Modern global climate change. *Science*, 302(5651), 1719–1723. 10.1126/science.1090228 [PubMed: 14657489]
- Kishné AS, Yimam YT, Morgan CLS, & Dornblaser BC (2017). Evaluation and improvement of the default soil hydraulic parameters for the Noah Land Surface Model. *Geoderma*, 285, 247–259. 10.1016/j.geoderma.2016.09.022
- Kishtawal CM, Niyogi D, Tewari M, Pielke RA Sr., & Shepherd JM (2010). Urbanization signature in the observed heavy rainfall climatology over India. *International Journal of Climatology*, 30(13), 1908–1916. 10.1002/joc.2044
- Kunkel KE, Easterling DR, Kristovich DA, Gleason B, Stoecker L, & Smith R. (2012). Meteorological causes of the secular variations in observed extreme precipitation events for the conterminous United States. *Journal of Hydrometeorology*, 13(3), 1131–1141. 10.1175/JHM-D-11-0108.1

- Kunkel KE, Easterling DR, Redmond K, & Hubbard K. (2003). Temporal variations of extreme precipitation events in the United States: 1895–2000. *Geophysical Research Letters*, 30(17), 1900. 10.1029/2003GL018052
- Kunkel KE, Karl TR, Brooks H, Kossin J, Lawrimore JH, Arndt D, Bosart L, Changnon D, Cutter SL, Doesken N, Emanuel K, Groisman PY, Katz RW, Knutson T, O'Brien J, Paciorek CJ, Peterson TC, Redmond K, Robinson D, Trapp J, Vose R, Weaver S, Wehner M, Wolter K, & Wuebbles D. (2013). Monitoring and understanding trends in extreme storms: State of knowledge. *Bulletin of the American Meteorological Society*, 94(4), 499–514. 10.1175/BAMS-D-11-00262.1
- Laio F. (2004). Cramer-von Mises and Anderson-Darling goodness of fit tests for extreme value distributions with unknown parameters. *Water Resources Research*, 40, W09308. 10.1029/2004WR003204
- Li D, Bou-Zeid E, Barlage M, Chen F, & Smith JA (2013). Development and evaluation of a mosaic approach in the WRF-Noah framework. *Journal of Geophysical Research: Atmospheres*, 118, 11,918–11,935. 10.1002/2013JD020657
- Liew SC, Raghavan SV, & Liong SY (2014a). Development of Intensity-Duration-Frequency curves at ungauged sites: Risk management under changing climate. *Geoscience Letters*, 1(1), 1–12. 10.1186/2196-4092-1-8
- Liew SC, Raghavan SV, & Liong SY (2014b). How to construct future IDF curves, under changing climate, for sites with scarce rainfall records? *Hydrological Processes*, 28(8), 3276–3287. 10.1002/hyp.9839
- Mallard MS, & Spero TL (2019). Effects of mosaic land use on dynamically downscaled WRF simulations of the contiguous U.S. *Journal of Geophysical Research: Atmospheres*, 124, 9117–9140. 10.1029/2018JD029755
- Massey FJ Jr. (1951). The Kolmogorov-Smirnov test for goodness of fit. *Journal of the American Statistical Association*, 46(253), 68–78. 10.1080/01621459.1951.10500769
- Mesinger F, DiMego G, Kalnay E, Mitchell K, Shafran PC, Ebisuzaki W, Jovi D, Woollen J, Rogers E, Berbery EH, Ek MB, Fan Y, Grumbine R, Higgins W, Li H, Lin Y, Manikin G, Parrish D, & Shi W. (2006). North American regional reanalysis. *Bulletin of the American Meteorological Society*, 87(3), 343–360. 10.1175/BAMS-870-3-343,
- Millington N, Das S, & Simonovic SP (2011). The comparison of GEV, Log-Pearson Type 3 and Gumbel distributions in the Upper Thames River Watershed under global climate models. *Water Resources Research Report*, 40 <https://ir.lib.uwo.ca/wrrr/40>
- Min SK, Zhang X, Zwiers FW, Friederichs P, & Hense A. (2009). Signal detectability in extreme precipitation changes assessed from twentieth century climate simulations. *Climate Dynamics*, 32(1), 95–111. 10.1007/s00382-008-0376-8
- Min SK, Zhang X, Zwiers FW, & Hegerl GC (2011). Human contribution to more-intense precipitation extremes. *Nature*, 470(7334), 378–381. 10.1038/nature09763 [PubMed: 21331039]
- Mishra V, & Lettenmaier DP (2011). Climatic trends in major US urban areas, 1950–2009. *Geophysical Research Letters*, 38, L16401. 10.1029/2011GL048255
- Niyogi D, Lei M, Kishtawal C, Schmid P, & Shepherd M. (2017). Urbanization impacts on the summer heavy rainfall climatology over the eastern United States. *Earth Interactions*, 21(5), 1–17. 10.1175/EI-D-15-0045.1
- NOAA. (2017). NOAA's National Centers for Environmental Information (NCEI) <https://www.ncdc.noaa.gov/cdo-web/search>
- Otte TL, Nolte CG, Otte MJ, & Bowden JH (2012). Does nudging squelch the extremes in regional climate modeling? *Journal of Climate*, 25(20), 7046–7066. 10.1175/JCLI-D-12-00048.1
- Perica S, Martin D, Pavlovic S, Roy I, Laurent MS, Trypaluk C, Unruh D, Yekta M, & Bonnin G. (2013). NOAA Atlas 14, Volume 9, Version 2, Precipitation-Frequency Atlas of the United States, Southeastern States (Vol. 18). Silver Spring, MD: NOAA, National Weather Service.
- Prein AF, Rasmussen RM, Ikeda K, Liu C, Clark MP, & Holland GJ (2017). The future intensification of hourly precipitation extremes. *Nature Climate Change*, 7(1), 48–52. 10.1038/nclimate3168
- Salinger MJ, & Griffiths GM (2001). Trends in New Zealand daily temperature and rainfall extremes. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 21(12), 1437–1452. 10.1002/joc.694

- Sarangi C, Tripathi SN, Qian Y, Kumar S, & Ruby Leung L. (2018). Aerosol and urban land use effect on rainfall around cities in Indo-Gangetic Basin from observations and cloud resolving model simulations. *Journal of Geophysical Research: Atmospheres*, 123, 3645–3667. 10.1002/2017JD028004
- Schardong A, Gaur A, Simonovic SP, & Sandink D. (2018). Computerized tool for the development of intensity-duration-frequency curves under a changing climate. Technical Manual. www.idf-cc-uwo.ca
- Seltzer KM, Nolte CG, Spero TL, Appel KW, & Xing J. (2016). Evaluation of near surface ozone and particulate matter in air quality simulations driven by dynamically downscaled historical meteorological fields. *Atmospheric Environment*, 138, 42–54. 10.1016/j.atmosenv.2016.05.010
- Shepard D. (1968). A two-dimensional interpolation function for irregularly-spaced data. In *Proceedings of the 1968 23rd ACM national conference*, pp. 517–524. ACM 10.1145/800186.810616.
- Shepherd JM (2005). A review of current investigations of urban-induced rainfall and recommendations for the future. *Earth Interactions*, 9(12), 1–27. 10.1175/EI156.1
- Shepherd JM (2013). Impacts of urbanization on precipitation and storms: Physical insights and vulnerabilities. *Climate Vulnerability*, 5, 109–125. 10.1016/B978-0-12-384703-4.00503-7
- Skamarock WC, & Klemp JB (2008). A time-split nonhydrostatic atmospheric model for weather research and forecasting applications. *Journal of Computational Physics*, 227(7), 3465–3485. 10.1016/j.jcp.2007.01
- Spero TL, Nolte CG, Bowden JH, Mallard MS, & Herwehe JA (2016). The impact of incongruous lake temperatures on regional climate extremes downscaled from the CMIP5 archive using the WRF model. *Journal of Climate*, 29(2), 839–853. 10.1175/JCLI-D-15-0233.1
- Spero TL, Nolte CG, Mallard MS, & Bowden JH (2018). A maieutic exploration of nudging strategies for regional climate applications using the WRF model. *Journal of Applied Meteorology and Climatology*, 57(8), 1883–1906. 10.1175/JAMC-D-17-0360.1
- Spero TL, Otte MJ, Bowden JH, & Nolte CG (2014). Improving the representation of clouds, radiation, and precipitation using spectral nudging in the Weather Research and Forecasting model. *Journal of Geophysical Research: Atmospheres*, 119, 11,682–11,694. 10.1002/2014JD022173
- Trenberth KE, Dai A, Rasmussen RM, & Parsons DB (2003). The changing character of precipitation. *Bulletin of the American Meteorological Society*, 84(9), 1205–1218. 10.1175/BAMS-84-9-1205
- Trenberth KE, Zhang Y, & Gehne M. (2017). Intermittency in precipitation: Duration, frequency, intensity, and amounts using hourly data. *Journal of Hydrometeorology*, 18(5), 1393–1412. 10.1175/JHM-D-16-0263.1
- Vu MT, Raghavan VS, & Liong SY (2017). Deriving short-duration rainfall IDF curves from a regional climate model. *Natural Hazards*, 85(3), 1877–1891. 10.1007/s11069-016-2670-9
- Wasko C, Sharma A, & Westra S. (2016). Reduced spatial extent of extreme storms at higher temperatures. *Geophysical Research Letters*, 43, 4026–4032. 10.1002/2016GL068509
- Yarnell DL (1935). Rainfall intensity-frequency data (No. 204). Washington, DC: U.S. Government Printing Office.
- Zheng Y, Herwehe JA, Del Genio AD, & Niyogi D. (2016). Improving high-resolution weather forecasts using the Weather Research and Forecasting (WRF) model with an updated Kain-Fritsch scheme. *Monthly Weather Review*, 144(3), 833–860. 10.1175/MWR-D-15-0005.1

Figure 1.

On the left, cities examined in this study, each of which has 100% data completeness for 1988–2010. On the right, COOP stations selected to represent Atlanta. Overlaid are the graphical representations of the urban area using WRF grid cells, and radii (R) used in station selection criteria.

Figure 2. Comparison of PIDF curves derived from observational data for Atlanta for a 2-year return period at 1-, 2-, 3-, 6-, 12-, and 24-hr durations. The OBS_RFA data set has 90% confidence intervals indicated by the gray area.

Figure 3. Comparison of PIDF curves derived from data based on different cell subsets, using EV and RFA methods, for Cincinnati (left column), Raleigh (middle column), and Atlanta (right column). Each panel corresponds to data from different model. The EV_site data set has 90% confidence intervals indicated by gray area.

Figure 4.

Precipitation intensity distributions for Cincinnati (left column), Raleigh (middle column), and Atlanta (right column) for six durations (in rows). The precipitation intensity is plotted on a logarithmic scale for 1-, 2-, 3-, 6-, 12-, and 24-hr durations.

Figure 5.

PIDF curves for Cincinnati (left column), Raleigh (middle column), and Atlanta (right column) developed from OBS_RFA observations data set (top row) and developed using EV_IDW for 36-km WRF C09 subset simulations driven by R2_36 (second row), 36-km WRF C09 subset simulations driven by ERA-Interim (third row), and 12-km WRF C25 subset simulations driven by ERA-Interim (bottom row).

Figure 6.

PIDF curves from observations and three model simulations isolated by return period for Cincinnati (left column), Raleigh (middle column), and Atlanta (right column). Each panel shows the PIDF curves developed from OBS_RFA observations data set (solid black line) with 90% confidence intervals in gray; R2_36 C09 subset (yellow dashed line), ERA_36 C09 subset (light blue dashed line), and ERA_12 C25 subset (blue dash-dot line). Rows represent 2-, 5-, and 50-year return periods.

Figure 7.

Seasonal differences in precipitation from each model simulation (along rows) and at each city (in columns) within each year of the 23-year simulation period. Differences are expressed as percent (%) difference ($-100 \times [\text{observed seasonal precipitation} - \text{modeled seasonal precipitation}] / \text{observed seasonal precipitation}$) for each year.

Table 1.**WRF Model Options Used for the Three Simulations**

	R2_36	ERA_36 and ERA_12
WRF version	WRFv3.4.1	WRFv3.9
Input data source	NCEP–DOE AMIP-II Reanalysis (“R2”)	ERA-Interim
Input data spacing	$2.5^{\circ} \times 2.5^{\circ}$	$0.75^{\circ} \times 0.75^{\circ}$
Horizontal grid spacing	36 km	ERA_36: 36 km ERA_12: 12 km
Vertical coordinate	34 sigma (eta) layers	34 hybrid sigma-pressure layers
Model top	50 hPa	50 hPa
Longwave radiation	RRTMG (Iacono et al., 2008)	RRTMG (Iacono et al., 2008)
Shortwave radiation	RRTMG (Iacono et al., 2008)	RRTMG (Iacono et al., 2008)
Explicit microphysics	WSM6 (Hong & Lim, 2006)	WSM6 (Hong & Lim, 2006)
Convection	Kain-Fritsch with radiative feedbacks (Herwehe et al., 2014; Kain, 2004)	Kain-Fritsch with radiative feedbacks (Herwehe et al., 2014; Kain, 2004)
Planetary boundary layer (PBL)	YSU (Hong et al., 2006)	YSU (Hong et al., 2006)
Land-surface model	NOAH (Chen & Dudhia, 2001)	NOAH (Chen & Dudhia, 2001) with six mosaic categories (Li et al., 2013) and updated soil and vegetation properties (Campbell et al., 2018; Kishné et al., 2017) ^a
Land use	USGS	NLCD-MODIS
Nudging	Spectral nudging above the PBL toward horizontal wind components, potential temperature, and geopotential at $3.0 \times 10^{-4} \text{ s}^{-1}$	Spectral nudging above the PBL toward horizontal wind components, potential temperature, and geopotential at $3.0 \times 10^{-4} \text{ s}^{-1}$ and water vapor mixing ratio (Spero et al., 2014) ^b at $1.0 \times 10^{-5} \text{ s}^{-1}$

^aThe updated soil and vegetation properties (Campbell et al., 2018; Kishné et al., 2017) are available in WRFv4.1.

^bThe option for spectral nudging toward water vapor mixing ratio (Spero et al., 2014) is available in WRFv4.0.

Table 2.

Data Sets and Methodology Used to Quantify the Impact of Missing Data on PIDF Curves in Atlanta

Data set	Description
OBS_RFA	PIDF results derived with RFA from all available data from 10 stations.
RFA_75	PIDF results derived with RFA from the data set with 25% of the observations randomly removed at each station. This data set has 75% completeness.
EV_site	PIDF results derived using at-site EV theory based on the data set from a single site with 100% completeness.
EV_IDW	PIDF results derived using at-site EV theory based on the data set where 25% of missing observations at the central station were supplemented by the average of precipitation from other stations at a given hour, weighted by distance from the central station using IDW.
EV_mean	PIDF results derived using at-site EV theory based the data set where 25% of missing observations at the central station were supplemented by average of precipitation available at each station at a given time (hour), under the assumption that data from all stations are equally representative of the city center and are equally plausible.

Table 3.Statistics for Monthly Precipitation Compared With Observational Data: R^2 , PBIAS, and RMSE

	Cincinnati					Raleigh					Atlanta, GA				
	C01	C09		C25		C01	C09		C25		C01	C09		C25	
	R2_36					R2_36					R2_36				
		IDW	Mean (8)	IDW	Mean (21)		IDW	Mean (9)	IDW	Mean (23)		IDW	Mean (7)	IDW	Mean (18)
Correlation	0.38	0.38	0.39	0.39	0.41	0.25	0.26	0.30	0.25	0.30	0.66	0.7	0.71	0.67	0.69
R ²	0.14	0.15	0.15	0.15	0.17	0.06	0.07	0.09	0.06	0.09	0.44	0.4	0.50	0.45	0.47
PBIAS (%)	2	0	−2	−2	−3	18	15	−1	13	−2	0.8	−3	−5	−5	−1
MAE	127	121	121	116	121	204	194	179	189	178	148	143	130	144	137
RMSE (mm)	151	149	151	148	152	297	281	218	268	213	183	181	174	186	173
	ERA_36					ERA_36					ERA_36				
		IDW	Mean (7)	IDW	Mean (18)		IDW	Mean (6)	IDW	Mean (16)		IDW	Mean (5)	IDW	Mean (13)
Correlation	0.36	0.37	0.43	0.37	0.43	0.37	0.38	0.38	0.38	0.37	0.75	0.75	0.75	0.74	0.77
R ²	0.13	0.14	0.18	0.14	0.19	0.14	0.14	0.15	0.15	0.14	0.56	0.56	0.57	0.55	0.59
PBIAS (%)	−7.9	−11	−5	−13	−4	−21	−23	−4	−25	0	−33	−35	−7	−37	1
MAE	178	179	161	179	160	230	244	157	255	172	383	409	164	430	173
RMSE (mm)	216	220	200	227	202	276	289	220	301	236	415	438	225	456	227
	ERA_12					ERA_12					ERA_12				
		IDW	Mean (9)	IDW	Mean (25)		IDW	Mean (9)	IDW	Mean (25)		IDW	Mean (9)	IDW	Mean (24)
Correlation	0.73	0.73	0.72	0.70	0.70	0.46	0.46	0.45	0.49	0.48	0.49	0.49	0.50	0.50	0.50
R ²	0.53	0.53	0.52	0.49	0.49	0.21	0.21	0.21	0.24	0.23	0.24	0.24	0.25	0.25	0.25
PBIAS (%)	18	18	14	23	10	50	50	48	50	46	8	8	1	4	−1
MAE	204	204	166	250	145	502	502	489	501	474	189	189	169	166	171
RMSE (mm)	225	225	196	277	176	581	581	567	573	543	258	258	231	235	236

Note.

The number in parentheses for the EV_mean data sets is the number of WRF grid cells in the patch used in the mean method that yielded best fit for each data set.