Incorporating uncertainty from downscaled rainfall projections into climate resilience planning in U.S. cities

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Abstract

The planning, design, and maintenance of stormwater infrastructure must be informed by changing rainfall patterns due to climate change. However, there is little consensus on how future climate information should be used, or how uncertainties introduced by use of different methods and datasets should be characterized or managed. These uncertainties exacerbate existing challenges to using climate information on local or municipal scales. Here we analyze major cities in the U.S., 48 of which developed climate adaptation and resilience plans. Given the prevalence of depth duration frequency (DDF) curves for planning infrastructure for rainfall, we then assessed the underlying climate information used in these 48 plans to show how DDF curves used for resilience planning and the resulting outcomes can be affected by stakeholders’ methodological choices and datasets. For rainfall extremes, many resilience plans varied by trend detection method, data preprocessing steps, and size of study area, and all used only one of the available downscaled climate projection datasets. We evaluate the implications of uncertainties across five available climate datasets and show the level of climate resilience to extreme rainfall depends on the dataset selected for each city. We produce risk matrices for a broader set of 77 U.S. cities to highlight how local resilience strategies and decisions are sensitive to the climate projection dataset used in local adaptation plans. To help overcome barriers to using climate information, we provide an open dataset of future daily rainfall values for 2-, 5-, 10-, 25-, 50-, and 100 years annual recurrence intervals for 77 cities and compare resilience outcomes across available climate datasets that each city can use for comparison and for robust resilience planning. Because of uncertainty in climate projections, our results highlight the importance of no-regret and flexible resilience strategies that can be adjusted with new climate information.

1. Introduction

Anthropogenic greenhouse gas (GHG) emissions have altered climate patterns across the world, and these changes will continue with increased emissions. Global mean near-surface atmospheric temperature and maximum annual rainfall in many regions has increased while sea levels have risen (IPCC 2021). Under continued and increasing GHG emissions, rainfall and extreme storms will become more intense in many regions (Prein et al. 2017, Emanuel 2017, IPCC 2021), and global mean temperature will continue to increase (IPCC 2021).

The impacts of climate change require fundamental changes in planning, design, and management of systems where human-climate interactions exist. For example, infrastructure designed with U.S. standards (Lopez-Cantu and Samaras 2018, Wright et al. 2019, Stoner et al. 2019, Underwood et al. 2017, Bartos and Chester 2015, Markolf et al. 2020) based on historical records is unlikely to perform as intended over the multiple decades or more that infrastructure is in use (Chester et al. 2020). In the U.S., local governments have a primary role in enabling climate resilience, and local knowledge about city-specific vulnerabilities and costs...
Environ. Res.: Infrastruct. Sustain. 2 (2022) 045006

T Lopez-Cantu et al

(Cook et al 2020) increases the effectiveness of adaptation efforts (Fünfgeld 2015). In many U.S. cities, local climate adaptation efforts start with the development of a climate adaptation plan (or climate resilience plan) to evaluate local vulnerabilities and outline strategies to enable climate resilience (Bierbaum et al 2013, Woodruff and Stults 2016). For example, New York City has had resilience plans and guidelines to address climate change impacts since 2013 (Freedman 2013).

Although local adaptation efforts are moving forward in many areas along with research on how to improve climate information that meets decision-makers’ needs (Galford et al 2016, Briley et al 2015, Hewitt et al 2017, Lai and Dzombak 2019, Gardiner et al 2019, Lemos et al 2012, Lai et al 2022), developing effective resilience plans with successful implementation guidance (Woodruff and Stults 2016) remains challenging for many local governments. Developing locally-relevant information requires navigating increasingly available sources of climate projections. Appropriately applying this information at a local scale with little guidance (Kirchhoff et al 2019) is among the challenges previously identified as barriers to pursuing successful adaptation efforts (Bierbaum et al 2013, Moss et al 2019, Hewitt et al 2017, Beauchamp et al 2020).

Another important consideration is to ensure equity throughout the adaptation planning process. Low- and middle-income communities face a double burden of inequality: while contributing least to climate change, these communities face disproportionate effects of extreme weather events, extreme heat events, storm surge, and coastal flooding, among other impacts (Reckien et al 2017, Collins et al 2019, Lieberman-Cribbin et al 2020). A city’s municipal resources, institutional capacity, governance, and available knowledge can considerably help or hinder efforts to adapt to climate change impacts, leading to inequitable distribution of adaptive capacities (Araos et al 2016, Shi et al 2016, Thomas et al 2019). Without consideration of equity and impacts for disadvantaged and frontline communities, adaptation strategies can quickly become maladaptive strategies for vulnerable populations (Anguelovski et al 2016, Pelling and Garschagen 2019, Siders et al 2019, Schipper 2020). For example, a seawall was constructed in Fiji to protect communities from sea level rise driven flooding events. Research conducted to evaluate the seawall’s effectiveness revealed that the design and construction of the asset not only did not meet its purpose, but became an origin of more flooding events and health issues for a larger population (Piggott-McKellar et al 2020).

Extreme rainfall patterns have increased in most regions in the U.S. due to climate change (Kunkel et al 2012, Trenberth et al 2003, Hoerling et al 2016), and future projections show that these increases will continue throughout the 21st century (Prein et al 2017, Lopez-Cantu et al 2020a, Wu et al 2019). Because stormwater infrastructure is in service for many decades, climate resilience strategies for new and existing stormwater infrastructure systems are required (Cook et al 2020, DeGaetano and Castellano 2017, Mailhot and Duchesne 2010, Prein et al 2017, Chester et al 2021). Stormwater infrastructure is a critical contributor to climate resilience outcomes in cities and communities, as this infrastructure collects and conveys stormwater runoff during rainfall events, prevents flooding and damage, and allows safe travel through the transportation network (Markolf et al 2020, Underwood et al 2020).

Much of the existing stormwater infrastructure capacity needs are determined based on standards determined from historical records, and do not consider changing climate conditions that might occur over the infrastructure’s lifetime (Cook et al 2017, Lopez-Cantu and Samaras 2018, Underwood et al 2020, Wright et al 2019, 2021). However, given large uncertainties in the magnitude of projected changes, in some instances ranging from no change to up to four times its present value, including this information in intensity–duration–frequency (IDF) or depth–duration–frequency (DDF) curves that summarize precipitation characteristics and used in the design and operation of infrastructure, poses some challenges (Cook et al 2020, Lopez-Cantu et al 2020a). Rainfall events can be characterized by their average probability of occurrence or frequency (e.g. 25 years storm or 4% annual exceedance probability), and the duration of a rainfall event (often measured over 24 h). For a given recurrence interval and duration, IDF curves summarize rainfall intensity per unit of time (mm h$^{-1}$), and DDF curves summarize rainfall depth (mm). For example, for stormwater standards requiring a 25 year return period, a stakeholder in Pittsburgh, PA using historical climate information would design for 89 mm of rainfall. Using future climate projections from one of the available datasets, the median rainfall depth for this return period is 105 mm, hence a system designed for the historical climate would likely flood or fail if it experiences this 25 years storm under climate change (Cook et al 2017).

While there has been substantial progress on investigating methods and strategies to increase stormwater infrastructure resilience, there has been less focus on the generation and use of the technical climate information that provides the basis for city-level vulnerability assessments and resilience strategies. The mismatch between the conditions for which infrastructure are designed for and the ones they will withstand during their service life has motivated cities to evaluate local vulnerabilities and outline strategies organized in climate resilience and adaptation plans (Bierbaum et al 2013, Kirchhoff et al 2019, Woodruff 2016).

Using climate information to inform infrastructure requires multiple decisions and methods by practitioners, that can compound uncertainties and affect the results (Lai et al 2022). For example, the choice of downscaled climate projections can affect infrastructure design decisions and that using different sources of
climate projections can lead to different required stormwater pipe sizes (Cook et al. 2017, 2020). In the U.S., there are publicly available downscaled climate projections that are different in output temporal and spatial resolution, downscaling methodology, number of downscaled global climate models (GCMs), among other differences (Lopez-Cantu et al. 2020a). These products include statistically downscaled projections from the localized constructed analogues (LOCAs), multiadaptive constructed analogues (MACAs), the bias-corrected constructed analogues (BCCAs) version 2 and the dynamically downscaled products from the NA-CORDEX (Mearns et al. 2017, Abatzoglou and Brown 2012, Maraun et al. 2010, Pierce et al. 2014).

In this paper we analyze the use of climate information in city climate adaptation plans, characterize methodological choices to produce climate information and show when and where differences in these choices need to be included in the adaptation decision-making process. We analyze climate resilience plans or climate assessment reports from cities in the continental U.S. with a population greater than 300,000 people, as well as the most populous city in each state. We assess the underlying climate information used in 48 plans, and give the prevalence of DDF curves for planning for stormwater infrastructure design, we show how updated DDF curves used for planning and resulting climate resilience can be different under stakeholders’ methodological choices and the datasets used. To summarize these findings, we produce updated DDF curves for a broader set of 77 cities and provide tools to highlight how local resilience strategies and decisions are sensitive to the climate projection dataset used in local adaptation plans.

2. Methods

2.1. Compilation of climate adaptation plans developed by U.S. Cities

We analyzed the climate resilience plans from U.S. cities with a population larger than 300,000 in 2019 (see table S1 (https://stacks.iop.org/ERIS/2/045006/mmedia) for a list of the cities) (US Census Bureau 2019). To ensure each state is represented even if they do not contain large cities, we also included the most populous city for each U.S. State in the Continental U.S. according to the same dataset, which includes 18 cities with a population less than 300,000.

For each of the 87 cities, we assessed whether the city’s government has published an adaptation plan. We used the pattern ‘(city name) climate adaptation plan’ in a Google-based search. We also substituted the word ‘adaptation’ with ‘resilience’ to account for commonly used terms in the climate adaptation and resilience field. We complemented the search by individually looking for climate adaptation plans published on each the local government’s website under the sustainability, environment, or similar office, and also included all adaptation and resilience plans for any of the 87 cities that were identified in the Georgetown Climate Center database (Georgetown Climate Center 2020). This search also revealed climatic assessments or action plans for some cities. This search was completed in May 2020, and we generated a single document archiving the complete plans that we assessed (Lopez-Cantu et al. 2020b). We did not include climate action plans as these documents focus on GHG emissions mitigation.

While there is often little difference between local climate assessment reports and adaptation or resilience plans, we identified three categories: (1) adaptation plan only, (2) assessment report only, (3) adaptation plan and assessment report. Adaptation plans include a list of actions or strategies that the city is planning given changing climate conditions. A summary of changing climate conditions is also often included, which comes from assessment reports commissioned by the local government or other national and international reports. On the other hand, an assessment report lists changes in climate variables at the city location and often also include a vulnerability analysis, however, no specific actions are recommended. Finally, an adaptation plan can also include a detailed assessment of the observed and future changes in climate variables at the city. We included climate assessment reports in our analysis because these contain information that is used in adaptation plans to support decision-making. We refer collectively to all these documents as adaptation plans in this paper.

The main question that drove the analysis of climate information in each plan was: what are the sources of climate information the adaptation plans are based on? We then collected more detailed information based on questions such as, what type of climate information or change metrics does the adaptation plan use? and, what are the implications for local resilience of the methodological choices to derive the climate information used in the adaptation plan? This required narrowing down the analysis to a single climate variable. Although we focus on rainfall extremes to characterize what methods and input data adaptation plans use to characterize historical and future changes, similar methodological choices are faced in the analysis of other climate variables (Ekström et al. 2016, Kulp and Strauss 2019, Abadie et al. 2020), and our questions are applicable to other climate variables for future work. We focused on exploring the different sources of uncertainty, mainly the implications of uncertainties across different downscaled climate projection data sets. This uncertainty source, along with other uncertainties, are faced by resilience managers and local planners face when outlining strategies using
available climate information. Table 1 lists each aspect that we collected from adaptation plans to answer each question and an example, and we produced a data file, included in the SI, containing this information for each adaptation plan analyzed.

2.2. Implications of methodological choices in future extreme rainfall changes analyses

We used five commonly used sources of climate projections that, while downscaling CMIP5 GCMs, their spatial structure and magnitude of the projected change in rainfall extremes is widely different (Lopez-Cantu et al 2020a). These products are often used in climate change impacts assessments [e.g. (Cook et al 2017, Kuo et al 2015, Martinich and Crimmins 2019)] and we found that they are also referred to for discussing climate change impacts in these adaptation plans. Figure 1 shows the methodology used to analyze the implications of choosing one of these climate projections for future extreme rainfall.

We analyzed the implications of choices of source of climate projections by producing an open data set of local projected rainfall extremes information (Lopez-Cantu et al 2020c). The data set provides updated DDF curves that could be used to inform decisions because (1) they incorporate information about how a hazard (extreme rainfall) will intensify under climate change (DeGaetano and Castellano 2017), (2) they can be used to analyze existing vulnerability given that these curves have been the standardized method to design stormwater infrastructure resilience since the early 1960s (Lopez-Cantu and Samaras 2018, Perica et al 2013b, Testik and Gebremichael 2013), and (3) can be coupled with simulations of adaptation and resilience strategies to investigate if these options can mitigate negative consequences (Kirshen et al 2015, Rosner et al 2014, Urich and Rauch 2014).

To update historical DDF curves from city station records (see section S4), we used the delta-change method. This method computes a percent change factor per quantile of the extreme rainfall distribution from model output [e.g. ratio between future/historical simulations for different average recurrence interval (ARI) events] and apply these to the historically observed rainfall at a station. This method has been applied in previous studies to provide updated IDF curves for planning purposes in New York (DeGaetano and Castellano 2017). For each source of climate projections to examine changes in rainfall extremes, following the delta-change method, we proceeded with collecting historical rainfall records from stations in each city vicinity. The delta-change method is based on computing the percent change (or change factor) per quantile of the extreme rainfall distribution between a historical period and a future period simulated by the GCM, and downscaled according to the method associated to each dataset source. This ratio or change factor is then applied to the IDF curves derived from the historical station records, as follows:

$$D^h_{\text{future}} = D^h_{\text{historical}} \frac{D^G_{\text{GCM, future}}}{D^G_{\text{GCM, historical}}}$$

where $D^h$ is the rainfall depth for the design storms (2-, 5-, 10-, 25-, 50-, and 100 years) estimated using the station records, and $D^G_{\text{GCM}}$ the rainfall depth for the same design storms estimated using downscaled climate model output.

To generate historical station DDF curves, we extracted annual maximum series (AMS) for the period between 1951 to 2006 from rainfall time series from global historical climate network (GHCN) stations listed in section S4. These stations were chosen using the following criteria: (1) proximity to the city center and (2) record coverage. We only used station records that had fewer than five days missing over a year and more than 50 years of data. We used these filters to minimize the uncertainty when fitting the statistical model. Then, to model extreme rainfall we fitted a generalized extreme value (GEV) distribution, which is commonly used to describe extremes (Coles 2001, DeGaetano and Castellano 2017). Typically, engineers and planners would refer to NOAA Atlas 14 to retrieve IDF values at a desired location, however, it was not possible to simply use Atlas 14 values as inputs to the delta-change method for several reasons. First, Atlas 14 was released in different volumes covering different parts of the U.S. and second, the station records used span different time periods. It has been shown that the selection of historical period in station data when producing updated DDF curves is a significant source of uncertainty, therefore, it is preferable that the historical station and historical simulated timeframes match (Fadhel et al 2017). The change factors from each GCM downscaled in the datasets we used in this study were retrieved from the dataset described in (Lopez-Cantu et al 2020a). This dataset constitutes a collection of change factors for the continental U.S. from five different downscaled climate projections.

We briefly describe here the method employed in (Lopez-Cantu et al 2020a) and refer the reader to that paper for additional details. Precipitation time series at each grid were remapped to a common 0.44° × 0.44° resolution, and AMS were extracted from a historical reference period (1951 to 2006) and a future period (2044 to 2099). Again, a GEV distribution was fitted to both historical and future AMS to model extreme rainfall. Finally, for each annual recurrence interval, the change factor is equal to the ratio between the x-year
| Characteristic or metric                                                                 | Examples                                                                                   |
|----------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------|
| Availability of climate assessment reports at the state level                                                                   | Yes, no                                                                                  |
| Discussion of equity-related search terms: Equity/justice/diversity/disability/vulnerable                                        | Yes, no                                                                                  |
| AROUND(2) population OR community income AROUND(2) low                                                                            |                                                                                           |
| Source of climate overview                                                                                                      | National climate assessment, NOAA RISA program reports, state climate assessment reports |
| Analysis of rainfall extremes                                                                                                    | Yes, no                                                                                  |
| Definition of extremes in observed changes analysis                                                                            | Number of days with rainfall events above a threshold, rainfall volume falling in events above a percentile of the total annual rainfall distribution |
| Source of rainfall records                                                                                                       | Global historical climate network, (GHCN), PRISM                                           |
| Type of rainfall record data                                                                                                     | Stations, gridded observations                                                            |
| Spatial scale of historical assessment                                                                                           | State, climate division                                                                   |
| Historical assessment timeframe                                                                                                  | Starting in 1960 and finishing in 2012                                                     |
| Method to detect historical rainfall changes                                                                                     | Linear regression, Sen’s slope robust estimator                                           |
| Definition of extremes in future changes analysis                                                                               | Return periods using extreme value distributions, number of days with rainfall events above a threshold, rainfall volume falling in events above a percentile of the total annual rainfall distribution |
| Source of downscaled GCM projections (if applicable)                                                                             | Number of days with rainfall events above a threshold, rainfall volume falling in events above a percentile of the total annual rainfall distribution |
| Type of future data                                                                                                              | CMIP3 GCMs, CMIP5 GCMs                                                                   |
| Future assessment timeframe                                                                                                       | Three different periods (2010–2039, 2040–2069, 2070–2099)                                  |
| Method to detect future rainfall changes                                                                                         | Change factor, direct comparison with historical values                                     |
| Source of downscaled GCM projections (if applicable)                                                                             | LOCA (statistical downscaling method), NARCCAP (dynamical downscaling method)             |
Figure 1. Methodological steps followed to generate updated DDF curves at each city analyzed and quantify sources of uncertainty. Sources of climate projections were 5, LOCA, MACA, BCCAv.2 and two different resolutions of the NA-CORDEX dataset, 44 degree by 44 degree and 22 degree by 22 degree.

future period rainfall volume and historical period. As mentioned previously, given that the change factor dataset uses a reference historical period 1951–2006, the historical station series were also extracted for the same period, and might result in DDF values that deviate from NOAA Atlas 14 (Perica et al. 2013b).

We then applied the change factors from (Lopez-Cantu et al. 2020a) to the historical DDF curves constructed from station records to generate future IDF curves for each station. Both the AMS and the updated 24 h DDF curves can be accessed in the supplementary materials.

Finally, we characterized uncertainty in future DDF curves by estimating the variability stemming from (1) the selection of downscaled climate projections, and (2) selection of emission scenario. These sources of uncertainty are additional to the GEV model fitting in both historical station and GCM-simulated AMS, but we did not explore this uncertainty in this study.

Given that previous research has shown that decision outcomes are dependent on the characteristics of climate data input to carry out the analysis of future DDF curves (Cook et al. 2020, Switzman et al. 2017), and that some city resilience plans have already made a choice of data input to support the strategies in the plan and others are explicitly consider updating IDF curves, we analyzed the implications of selecting one dataset over other, by estimating the increase or decrease in the risk of exceedance of n event T under conditions described by other dataset than the one used to create a future IDF curve. The risk of exceedance, or that a given event with T year return period will be equaled or exceeded over n years is,

$$R_n = 1 - \left(1 - \frac{1}{T}\right)^n.$$  \hspace{1cm} (2)

This definition corresponds to the standard definition of stationary risk in hydrology textbooks (Read and Vogel 2015), and assumed a stationary risk because updated IDF curves already embed changes in rainfall extremes projected by the selected climate projections dataset.

3. Results and discussion

3.1. Analysis of climate adaptation plans

We found that only 48 (55%) of the total 87 cities that we assessed have produced adaptation plans that account for changes in climate variables. Out of the 48 cities with adaptation plans, 42 are city-level standalone plans,
Figure 2. Status of climate adaptation plans in U.S. cities comprising our assessed sample of 87 cities with population greater than 300,000 as well as the most populous city in each state, as of May 2020. More populous cities tend to have adaptation plans, while many city-scale plans have been developed in states without statewide adaptation plans. The assessment report in Manchester, NH includes the southeastern New Hampshire region. Statewide plans included climate adaptation plans, climate action plans and climate assessment plans (full list in table S1). Sacramento, CA and Tampa, FL completed adaptation plans since 2020 and are not included here (see table S2).

5 are county-level plans, an one is a regional plan. Additionally, there were a few cities with climate assessment reports (5 out of 48 at the city-level and 3 out of 48 at the county-level), but did not have an adaptation plan. However, we included city- and county-level climate assessments in the analysis as adaptation plans because these are used to inform local decision-making (Kirchhoff et al. 2019). Although the remaining cities (39 out of 87, about 45%) did not have adaptation plans or city-scale assessments, there exists some state-level guidance in 16 out of these 39 locations. Since this search was completed in 2020, we are aware that there might be more plans presently available or in development. However, our contribution is focused on the uncertainty associated with downscaled dataset choice for climate adaptation plans, and we provide results for all 87 major cities in our study, whether or not they have an adaptation plan. Our collection of adaptation plans is broadly representative of the current efforts in cities within the continental U.S., and what the existing challenges that these cities are facing or could be facing during resilience planning, since we found that most of these plans were published in the last 5 years.

From the 48 city adaptation and resilience plans we assessed, we categorized three general aspects of each city’s adaptation plan: source of climate projections, methods to characterize changes in a climate variable (see tables 1 and S3), and resilience strategies relevant to stormwater infrastructure. 39 cities out of 48 (about 81%) developed standalone plans (focused on adaptation planning under climate change only), while the remaining cities (9 out of 48, about 19%) developed plans along with other goals such as climate action or sustainability goals or as part of emergency response planning (figure 2).

Additionally, because climate change adaptation and equity are closely intertwined (Bulkeley et al. 2014, Reckien et al. 2017, Revi et al. 2014, Wilson et al. 2010), we also examined if climate adaptation plans noted the challenges that climate change pose to vulnerable communities. We found that 44 out of 48 plans (about 92%) refer to equity in some capacity (see table 1 for search parameters). Some cities have taken concrete actions to counter inequity, and others have established criteria to identify vulnerable populations and evaluate equity considerations in adaptation strategies. The most common climate change impacts discussed with respect to low-income communities or vulnerable populations were increasing temperatures and the urban heat island effect, energy costs or energy burdens, affordable housing, and flooding due to storm surge, sea level rise, and changes in rainfall patterns. Some examples include Indianapolis, IN and Louisville, KY, where equity was incorporated in creation and preparation stages of plans through facilitation of participatory processes and community input. In Dallas, TX, each adaptation action is evaluated based on equity considerations for ‘whether and (and how) an action would specifically benefit or burden vulnerable communities’. In San Francisco, CA, potential strategies can be evaluated using 24 criteria, six of which are related to equity and health. Cities have also taken other actions to counter inequity, such as the creation of Climate Action Working Groups to address equitable implementation and community engagement in Flagstaff, AZ, the vulnerability indices created in Indianapolis, IN, to highlight vulnerable neighborhoods for implementation, and the climate equity screening tool created to operationalize the commitment to climate equity in San Antonio, TX.
3.2. Adaptation plans use different sources of climate information for rainfall

While not all adaptation and resilience plans that we assessed were primarily concerned with rainfall extremes, many included information about changing rainfall patterns for their region or their locality. The main sources of climate information used in the 48 climate adaptation plans we assessed include worldwide organizations such as the IPCC (2 out of 48, about 4%), and national organizations (e.g. U.S. Global Change Research Program, EPA, or NOAA; 14 out of 48, 29%), whereas other plans cite sources of information at a regional scale (16 out of 48, about 33%), such as regions within the Regional Integrated Sciences and Assessment (RISA) Programs (e.g. GLISA and NECIA) or State Climate Assessments.

This diversity of climate information used in these reports likely is a result of availability, ease-of-use, and credibility of sources. Decision-makers might prefer local information for planning at the city scale because the global and regional scales (Vardy et al 2017) in these assessments often are too large to be locally relevant (Galford et al 2016). However, not all decision-makers have access to localized information because there exist few local resources that that have been produced by boundary organizations (e.g. RISAs), which ensures a comparable credibility to that of national and global assessments without compromising saliency (Kirchhoff et al 2019, Galford et al 2016, Briley et al 2015). Therefore, localized assessments often provide little guidance on use, and often do not prioritize credibility (Kirchhoff et al 2019). While producing new information is one challenge, once the local new information is produced, other difficulties can arise. Smaller organizations might not be able to conduct revisions and updates with the same frequency of national and global assessments, because of a lack of resources (Kirchhoff et al 2019). Infrequent updates can be problematic in places where climate change signals have become stronger since the production of the latest climate assessment or climate information source cited (Lopez-Cantu and Samaras 2018, Wright et al 2021). For example, the Miami-Dade county stormwater vulnerability assessment adopted NOAA Atlas 14’s (Perica et al 2013b, p 9) conclusion on the lack of evidence of non-stationary conditions, however, there is evidence of increasing rainfall extremes if longer station records and different methods are used (Wright et al 2019).

The Fourth U.S. National Climate Assessment recognizes the lack of resources and guidance needed to produce locally relevant data and this and other reports and national tools are beginning to facilitate the exploration of climate data, including raw local station observations, trends and downscaled climate projections (Gardiner et al 2019).

3.3. How city adaptation plans differ in accounting for changes in rainfall extremes

We found that 28 out of 48 plans included a section that discussed extreme rainfall changes. To analyze observed changes in rainfall extremes, most plans use similar metrics to define extreme rainfall events in the historical record (e.g., days with rainfall above different thresholds or the fraction of the total annual rainfall volume that occurs during severe events, such as heavy events where the total rainfall accumulation is above the 95th percentile of the rainfall distribution) (see table S3). However, they are considerably different in the methodology used to characterize the change trend and the spatial scale of the trend analysis (e.g., state-wide or regional). Many adaptation plans (12 out of 28, about 43%) do not explicitly state the methodology used to estimate the trends included in their plans. We found that those that do describe their methodology rely on linear regression (5 out of 28, about 18%), direct comparison between two periods (6 out of 28, about 21%), and a small fraction uses the Sen’s slope robust estimator coupled with the Mann–Kendall trend test and Pearson correlation coefficient to verify the existence of trends in the data (3 and 1 out of 28, about 11% and about 4%, respectively).

Adaptation plans use future projections that are different in two ways. First, most of the adaptation plans we assessed use future projections produced by statistical downscaling methods (13 out of 21, about 62%), whereas a few plans use dynamically downscaled projections (3 out of 21, about 14%). In the remaining fraction of city plans, the source of climate projections was not explicitly stated. Second, even though statistically downscaled projections are most commonly used by adaptation plans, these were produced using different statistical downscaling methods, including the asynchronous regional regression model, multivariate MACAs, BCCAs, and the LOCAs.

3.4. Using a single downscaled climate dataset for stormwater neglects uncertainties in future rainfall extremes

We found that cities are planning for future rainfall extremes using only one of the commonly-used public downscaled projection datasets, without accounting for the differences in the change signal projected by (Lopez-Cantu et al 2020a), therefore neglecting uncertainties in future rainfall extremes. If a city makes resilience decisions based on climate information from one of these datasets, but future conditions under the same emissions scenario end up being closer to projections in another dataset, the city’s decision may not provide the same level of intended resilience protection. Figure 3 shows the distribution of the 100 years, 24 h rainfall volume under RCP 8.5 from downscaled future climate projections in these five datasets for five U.S.
Figure 3. The selection of a single downscaled climate projection dataset to inform resilience decisions has resilience implications for different cities. Density estimates of the distribution of future (2044–2099) 100 years, 24 h precipitation volume compared to historical (1951–2006) for five cities in the U.S. with adaptation plans that use a specific source of downscaled climate projections in their future rainfall analysis. The distribution is from the projected future values from available downscaled simulations in five downscaled climate projection datasets [LOCA, MACA, NA-CORDEX (22 km (high) and 44 km (low)) and BCCAv.2].

cities that have chosen one of the five datasets in their climate adaptation plans. We note that the variance of the distribution differs among cities, depending on how much the downscaled simulations agree or disagree about future change. Assuming that each future under an emissions scenario is equally likely to occur, the decisions in these cities (e.g., selecting the ensemble median of one dataset) position them at either side of the resilience spectrum. For example, the choice used by Boise, ID covers a large range of the distribution, but this is not the case in the remaining cities. In Philadelphia, PA, the future value under the dataset selected lies to the left of the mean of the distribution. In most cities, selecting a single dataset statistic leads to neglecting more extreme scenarios. Planning for future rainfall volumes that are less than more extreme future rainfall volumes could lead to undersized stormwater infrastructure at increased risk of failure, while providing the appearance of resilience being appropriately included (Lopez-Cantu and Samaras 2018).

To illustrate the implications of a city using a single dataset, we use the adaptation action of increasing the capacity of an existing green or gray stormwater infrastructure asset to convey projected rainfall volumes (Cook et al. 2020). This specific action requires determining an asset’s rainfall conveyance capacity based on the probability of a rainfall exceedance event (i.e., risk) or the probability that an exceedance event will not occur (i.e. reliability) over an asset lifetime, along with establishing a risk tolerance threshold. For stormwater infrastructure design, rainfall event characteristics are drawn from IDF or DDF curves published in government-issued precipitation documents for historical conditions (Perica et al. 2013a). To account for future changes, these curves are updated using a change factor derived from an ensemble statistic of climate projections (Cook et al. 2017, Underwood et al. 2020). For this example, we use the ensemble median change factor from the downscaled climate projections datasets (e.g., LOCA, NA-CORDEX, etc) used in the assessed plans.

An event with an ARI of 100 years should have approximately a 40% probability of occurring at least once over a 50 year period. Figure 4 shows the updated DDF curves for 2044–2099 in Los Angeles, CA using five different available downscaled climate projections datasets (figure 4(a)) and the probability that a 100 years event will be exceeded over a 50 year period under different combinations of future conditions if a city bases resilience decisions on a specific dataset (rows) but the future conditions resemble another dataset (columns) (figure 4(b)). The results from figures 4(a) and (b) for 77 major cities that met input data requirements can be found in the SI text. If the intended 100 years ARI resilience protection, (approximately a 40% probability of exceedance over 50 years) is to be maintained, for any future condition in figure 4(b) with a value greater than
Figure 4. The success of local resilience strategies is sensitive to the climate projection dataset used in local adaptation plans. Los Angeles, CA uses LOCA data for its adaptation plan, and future rainfall DDF and resilient infrastructure decisions informed by a single dataset could result in insufficient protection depending on future conditions defined by the other datasets. Panel (a) shows updated DDF curves for the 24 h rainfall event using five different publicly available climate projection datasets. In this example for Los Angeles, a 100 years event in the chosen dataset (LOCA) is equivalent to a 50 years event in the projections from another dataset (MACA). Panel (b) shows the increase or decrease in the probability of exceedance of a 100 years event over a 50 years time period for a dataset selected (row) for climate decisions in Los Angeles under different futures defined by the other datasets (columns). Values greater than 40 percent indicate a degradation in intended resilience protection. Values for 77 cities assessed are provided in the SI.

40%, the capacity of a city’s newly designed resilient infrastructure would have to increase and/or surrounding land use must change to accommodate future conditions under climate change. Over the same 50 year period, a probability of exceedance lower than 40% is associated with a smaller ARI (e.g., below 100 years). For the remaining 11 cities that were also part of our analysis but for which we do not provide future DDF values due to unavailability of station records that matched our filtering criteria, we recommend using different approach to estimate historical DDF curves than the one used in this study, such as undertaking a regional analysis, in which several stations’ records are pooled to balance the lack of long historical records or stochastic storm transposition (Hosking and Wallis 2005, Wright et al 2020).

We find that under the conditions defined by the other datasets (columns in figure 4(b))—an infrastructure asset in Los Angeles that was upgraded for a storm event with a 40% probability of exceedance in 50 years under LOCA, the same event has a 58%, 59% and 61% chance of exceedance in three future conditions described by the datasets that are not considered in Los Angeles’ resilience plan. For one potential future scenario described by the BCCAv.2 dataset, the 40% chance drops to 21%—implying infrastructure upgraded potentially past the desired resilience performance, suggesting a potential overdesign using LOCA data. Including other datasets in resilience plans can support and improve the decision-making process. For example, including and managing uncertainty in resilience plans could elicit questions such as: is a 59% probability of exceedance versus the originally intended 40% acceptable for stakeholders? Under which conditions would this exceedance be acceptable? Which other structural and non-structural strategies can be considered to reduce the risks associated with the uncertainties around extreme rainfall events?

The same pattern shown in figure 4 for Los Angeles occurs at the other cities we assessed, many of which have not yet produced a climate adaptation plan or analyzed future local rainfall extreme changes (see figures S2–S77 for results for the other 76 cities). However, the dataset that projects the largest and smallest increases in rainfall extremes is not the same across cities, even within the same state, which discourages guidance based on information larger than the local scale. It is not possible to determine which outcome (with its associated dataset) is more likely before selecting any given dataset. By assuming that future conditions defined by all datasets are similarly plausible, this enables stakeholders to understand plausible differences between future scenarios and can encourage the re-evaluation of strategies to increase their flexibility and robustness.
4. Conclusion

4.1. Pathways to increase climate resilience in city climate adaptation plans

We found that while nearly half of major cities in the U.S. do not have a climate adaptation plan, and those cities with local adaptation plans inform local decision-making about changing climate conditions at usable scales use different sources of climate information. The understanding of future climate change impacts is also advancing, with newer methods and simulations emerging as well methods to communicate these to non-climate science experts (Hewitt et al 2017, Galford et al 2016, Gardiner et al 2019, Eyring et al 2016), resulting in a massive growth in resources to analyze changes in climate. We found all city climate resilience plans only use one of the available downscaled climate projection datasets, and that specific choices of methods, data, and resources used in adaptation plans can affect resilience strategies and outcomes. Therefore, it is required to account for uncertainty among increasingly available information to increase the robustness of resilience strategies at local scales and ensure that developed resilience strategies protect the public.

We characterized differences in rainfall values and resilience outcomes from future downscaled projections across five available climate datasets for 77 U.S. cities and showed that characterizing uncertainties about climate information in a resilience plan and including other datasets can encourage an examination of strategies that meet locally desired levels of risk. This step is crucial for both robust and dynamic decision-making frameworks that incorporate uncertainties and reveal adaptation strategies that balance their effects via policies or actions (Herman et al 2020, Hall et al 2012). For example, preserving and maintaining natural areas across individual watersheds and accommodating green infrastructure to enhance rainfall capture and storage can increase the success of upsizing infrastructure capacity and hedge uncertainties arising from different sources of climate information. Additionally, this approach can be coupled with regular revisions of the adaptation plan or specific resilience actions can be separated into different terms (e.g., short-, mid- and long-term) as it is currently done in some cases (e.g. City of Boston climate adaptation plan). In these cases, more detailed guidance from impacts modelers and city planners in terms of their modeling choices and risk preferences can enable a better integration of uncertainties. To facilitate this process, we have also made available for each of the 77 cities, the updated future 24 h DDF curves for the 2-, 5-, 10-, 25-, 50-, and 100 years annual recurrence intervals as well as resilience outcomes using each of the five available downscaled datasets and emissions scenarios RCP4.5 and RCP8.5 as supplemental data. Stakeholders, planners, and decision-makers at these cities can use these data to develop relevant information that supports and improves local climate adaptation efforts. Cities often do not have the time and resources to assess future precipitation estimates across multiple downscaled datasets, and in providing these data and assessments we have removed this barrier for stakeholders.

In conclusion, we found that cities are incorporating climate information into their climate resilience and adaptation plans, but the abundance of sources of climate projections with different characteristics poses challenges for ensuring local resilience. Specifically, we found that choice of climate projections for updating climate information used in infrastructure design can affect resilience design decisions such as stormwater infrastructure sizing. We showed this by updating DDF curves used in stormwater infrastructure design with five different sources of climate projections, which represent possible different future climate trajectories but remain uncertain. There is no single correct climate projection data set to use to plan for future impacts. Yet, if cities are only assessing climate impacts with one climate projection dataset, there is a likelihood that the extremes of other projections, or even the medians, are not accounted for in their resilience assessment. This means a city may be making stormwater design decisions for climate resilience that might not protect against future rainfall volumes. Stakeholders can use our open dataset for 77 cities to assess climate resilience for stormwater strategies across five commonly used downscaled datasets, especially for critical infrastructure projects where a higher level of resilience is desired. Because of uncertainty in climate projections, our results highlight the importance of no-regret and flexible resilience strategies that can be adjusted with new climate information. Additional research on methods to incorporate uncertainty and optimize decisions while accounting for multiple future scenarios is needed.

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Author contributions

TL-C, MKW, and CS conceived the research plan. TL-C and MKW analyzed and prepared the data. TL-C, MKW, and CS interpreted the data and contributed to writing the manuscript.

Data availability statement

Data associated with this paper is available in an open data repository. Adaptation plans assessed in this analysis have been merged into a single PDF document (Lopez–Cantu et al 2020b). Information that was collected from each city adaptation plan is provided in .CSV format and provided as supplementary materials. Data for the updated DDF 24 h curves for each of the 77 cities in the SI and Los Angeles are provided in .CSV format (Lopez–Cantu et al 2020c). Instructions on how to access the adaptation plans PDF and how to interpret the .CSV file have been included as separate sections (sections 1 and 2 respectively) in the supplementary materials.

Conflict of interest

The authors declare no conflicts of interest. This research was conducted while TLC and CS were affiliated with Carnegie Mellon University. The opinions expressed in this article are the authors’ own and do not reflect the view of the United States Government or any other organization.

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