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Past and Present Design Practices and Uncertainty in Climate Projections are Challenges for Designing Infrastructure to Future Conditions

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Abstract

Designing infrastructure for a changing climate remains a major challenge for engineers. In popular discourse a narrative has emerged that infrastructures are likely undersigned for the future. Weather-related hazards are directly embedded in the infrastructure design process. Yet the codes and standards that engineers use for this risk analysis have been changing for decades, sometimes increasing and other times decreasing design values. Further complicating the issue is that climate projections show increasing or decreasing intensities depending on the hazard and region. Thus, it is not clear that infrastructure is universally underdesigned. Here, analyses are developed at both regional and national scales using precipitation and roadway drainage systems to answer this question. First, it is shown that modeling uncertainty can pose challenges for using future projections to update region-specific standards. Second, the results show that depending on the historical design conditions and the direction of projections, roadway drainage infrastructure may be designed appropriately in some regions while in others they are possibly underdesigned. Given these uncertainties, the authors believe that there is a need for alternative design paradigms, and these needs are discussed.

Keywords: climate change; infrastructure; resilience; failure; uncertainty

Introduction

Infrastructure systems are the front line of defense against climate and weather-related disruptions. While infrastructure normally operate well when subjected to hazards, extreme events can push systems close to or beyond their capacities, leading to failure in one of two ways:

1) structural, where physical components of the infrastructure break down due to use beyond design expectations: e.g., Oroville dam (ASDSO 2018; Vahedifard et al. 2017) and the San Bernardino, California, Interstate 10 bridge washout; and
2) functional, where despite the structure remaining intact, operating conditions are exceeded and an infrastructure element or system cannot be used as intended: e.g., flooding of Interstate 10 in downtown Phoenix in Fall 2014 (NBC News 2014).

Current engineering design uses a risk-based approach to account for hazards in the operation of infrastructure. Hazards may exist in many forms including loading, use, and climate. Risk-based approaches quantify the uncertainty of the critical factors that affect performance (either indirectly through pre-selected design safety factors or more directly using statistical uncertainty of environmental factors like precipitation or heat), then select acceptable levels of failure, and finally design the physical elements to function to the chosen risk levels.

With respect to climate, current design standards are based on the analysis of historical records under the hypothesis of stationarity (USACE 1996; Olsen et al. 2015; ASCE 2018). While this has been a practical and effective approach to deal with largely unpredictable events, two factors challenge the efficacy of this practice. First, federal and state infrastructure design manuals direct engineers to precipitation frequency atlases to obtain rainfall characteristics. These atlases have been updated over time as new historical climate observations become available and statistical analyses improved (USDOC 1943-1966; Hershfield 1961; Bonnin et al. 2011). As a result, the magnitude of climate variables predicted by these standards for the same level of risk may have changed over time. A recent study by Lopez-Cantu and Samaras (2018) has shown that differences among currently used United States (U.S.) precipitation estimates compared to previously used precipitation estimates obtained by stormwater engineering standards released over the period 1961-2000 are statistically significant in about 90% of the area of the 43 states where data were available. The practical implications of this finding are that (i) existing infrastructure may be over- or underdesigned according to the current standards, and (ii) the risk level of infrastructure that are designed with today's standards may change in the future.

The second factor challenging current risk-based approaches is that theoretical analyses (Trenberth 1999; Emori and Brown 2005) and an increasing number of studies based on observations (e.g., Barros and Evans 1997; Mallakpour and Villarini 2015) and climate model outputs (Milly et al. 2008, IPCC 2014) suggest that climate dynamics may evolve in a nonstationary fashion due to climate change. Some researchers have developed a theoretical background to compute climatological design factors under nonstationary conditions as a function of climate model outputs (e.g., Cheng and Kouchak 2014; Read and Vogel 2015; Salas and Obeysekera 2013). However, several sources of model, data, and scenario uncertainties still prevent the practical and standardized implementation of such methods. For example, the main sources of uncertainties of General Circulation Models (GCMs) are due to model structure (the representation of the physical processes varies across models), forcings (future human activities and natural events influencing climate are unknown), and internal climate variability (climate naturally exhibits fluctuations that can be larger than changes caused by human activities) (Deser et al. 2014). These uncertainties raise two main questions about using climate projections within the traditional design process: 1) what kind of future with respect to greenhouse gases and land use should be considered? and 2) which model(s), and which output values within selected models, within any future scenario should be selected? These choices are often made by climate modelers, by determining which scenarios and models to focus model output. In addition, engineers, researchers, and other stakeholders interpreting climate projections for design process inputs also make these choices, which implicitly project risk preferences and can affect the resulting size and cost of resilient infrastructure (Cook et al. 2020). As a result, traditional risk-based methods may currently be more useful than nonstationary approaches (Serinaldi and Kilsby 2015). It should be mentioned that researchers are exploring how minimum regret, robust decision making, and deep uncertainty approaches can be used to modernize the infrastructure design process as well (Walker et al. 2013; Dittrich et al. 2016)

While there may be utility in the risk-based approaches now, there are strong arguments that because of the large future uncertainties there is a need to transition away from this paradigm. In this paper, this issue is examined by examining two case studies in detail: 1) a regional study of design storms that elucidates the challenges of climate downscaling and uncertainty, and 2) a national scale study of the U.S. Interstate system involving changing design standards relative to future climate forecasts. Both cases are examined through the lens of risk-based analysis to expose the complications with adapting design standards for climate uncertainty with such an approach. These case studies serve as explicit examples to support four specific objectives for this paper:

1) show how the evolution of design standards have created stormwater infrastructure systems with elements that vary with respect to robustness to current and future climate,
2) show that this effect is spatially varied,
3) show the challenges with respect to using GCM outputs for stormwater infrastructure design, and
4) discuss how under future climate projections this inhomogeneous system may create adaptation challenges for designers that rely on risk-based approaches.

The authors believe that the challenges examined in this paper are relevant to most infrastructure and a broad suite of climate hazards; however, the examples in the paper focus on stormwater because these infrastructures are one of the few whose primary purpose is to directly manage the hazard.

Infrastructure Design

Climate Effects on Infrastructure

Infrastructure consists of multiple elements that must work together to reliably deliver services and protect against extreme events. Regardless of the infrastructure system, its elements have a specific role in the overall function and can fail in their own ways, which the design process strives to reduce to a standardized level of risk. For example, major elements of stormwater systems are surface channels, sub-surface pipes, culverts, pumps, storage basins, and drop inlets (Mays 2010). For each of these elements the governing design criteria may differ somewhat, but all ultimately focus on water flow, either in terms of volume, velocity, or both (e.g., Thompson and Kilgore 2006). A key step in the design process is the selection of the design storm, which is defined as the precipitation depth associated with a certain return period occurring over a given duration, in the contributing watershed (McCuen 2005). The design storm is used along with terrain, soil and land use information of the watershed to estimate the flow conditions for design. Depending on flow conditions, structural failures (collapse or undermining of the element support) can occur through foundation/channel scour, physical washing away of the element, and debris related damage. Functional failures (overtopping and bank overflow) can occur when the heavy precipitation results in a maximum peak flow that exceeds the conveyance capacity of the element. Functional failures can also take place due to debris build-up and operational failures in associated systems, such as when pumps are blocked and cause retention basins to overflow their banks.

Design Process using Codes

Regardless of the infrastructure system, the design of individual elements is generally performed with codes and specifications that empirically articulate observed performance measures, analytical/computational structural and functional analysis, and broad engineering experience. These codes vary from one agency to another although, in some cases, multiple agencies may come together to define some aspects of the design protocols. As is often the case, new knowledge, observations of systematic limitations in current strategies, catastrophic failures of infrastructure elements in one location, and reanalysis of previous information lead to revisions to these codes. Under these cases, it is rare that older, functioning infrastructure elements are redesigned and reconstructed. Thus, each element is designed and constructed based on the prevailing standards of the day, which may vary in time and space. For example, agencies may expand into new geographical areas and/or revise their standards due to newly emerging science or statistical reanalysis of historical data. In some cases, this process may take a very long time (Lopez-Cantu and Samaras 2018). For example, the Texas Atlas 14 was just updated in 2018. Prior to its release, the only state-wide analysis was TP40, which means nearly 60 years passed between updated precipitation intensity guidance for the State. Infrastructure, especially stormwater infrastructure, can function in place for many decades or more. Thus, infrastructure systems often contain elements designed using different techniques, assumptions, risk-tolerances, and methods. In many cases, and especially when elements are not physically connected, these differences may be cataloged in a formal way when designing new elements. These differences impart inconsistent risk across the elements of real infrastructure systems and assessing the cumulative risk to the system is therefore difficult or impossible.

The process of updating and adopting new design standards may involve a significant coordination (communication with national and local professional communities, attendance at nationally organized conferences and workshops, etc.) and an analysis of the costs and other impacts from more stringent standards in the technical practice. The findings are then articulated into a formal recommendation to the governing body, which ultimately decides whether to adopt the changes. This process can often take years before mass adoption happens. For most infrastructure, agencies provide technical manuals that articulate this technical guidance. Since these guidelines may not be applicable to every agency, modifications can be used to incorporate local experiences and balance costs-benefits appropriately for the jurisdiction. For example, Lopez-Cantu and Samaras (2018) found large differences in the design storm return periods used by state agencies with respect to roadway hydrological design, even within similar climatic regions. These differences varied by not only stormwater infrastructure element, but also by the type of roadway.

Consideration of Climate

As demonstrated with stormwater systems, climate directly affects infrastructure and since the design process considers these effects by using historical records, any deviation from what was observed in the historical record introduces potential vulnerability. Consistent with the U.S. Department of Homeland Security, vulnerability is defined as a physical feature or operational attribute that renders an entity, asset, system, network, or geographic area open to exploitation or susceptible to a given hazard (DHS 2010). To understand this vulnerability, the evolution of climate records used for design must be examined.

Stormwater infrastructure design is based on precipitation intensity-duration-frequency (IDF) curves, which provide the probability of occurrence of precipitation intensities for a given event duration. This probability is often expressed as return period (Read and Vogel 2015). National guidance for IDF curves has evolved from technical papers (USDOC 1943-1966) (notably TP40), to NOAA Atlas 2 (NOAA-2) (Miller et al. 1973), and now NOAA Atlas 14 (e.g., Bonnin et al. 2011), which was first introduced in 2004. Each of these documents derive the IDF curves across the U.S. by applying different statistical methodologies to records of rain gauges (gauge coverage varies but is most densely concentrated in urban areas). While most states have adopted NOAA Atlas 14 (hereafter referred to simply as NOAA-14 for brevity), some still use previous releases or use their own estimates (Lopez-Cantu and Samaras 2018).

One example of the changes that have occurred from TP40 to NOAA-14 can be seen from the 50-year, 24-hour event for the United States. NOAA-14 applies an updated statistical analysis method to a historical dataset that includes a denser network of gauges with longer records than was used in developing TP40 guidance. These differences, coupled with the changes in observed rainfall events over the longer analysis period, result in changes to the intensity of the 50-year, 24-hour event. In some areas, NOAA-14 produces higher estimates than TP40 (as high as +187%) and in some areas NOAA-14 produces lower estimates than TP40 (as low as -75%). These differences are spatially varied, which can be inferred from Figure 4 that is described in detail later. Differences also exist for other return periods and durations as well (Lopez-Cantu and Samaras 2018). The importance of these changes is the fact that infrastructure systems are designed over multiple decades using guidelines available to engineers at the time of design. In areas where intensities increased from NOAA-14 and TP40, this process may mean that the infrastructure elements designed prior to the adoption of NOAA-14 may be at greater risk of failure than those designed more recently (Lopez-Cantu and Samaras 2018). Of particular importance is the fact that in some regions, estimates have gone down and in others the estimates have gone up, which is an important dynamic when trying to answer the question of whether infrastructure are underdesigned for climate change.

Design events also carry statistical uncertainty from the estimation process due to the sample size and statistical techniques adopted. The uncertainty can be translated into confidence intervals using the mean intensity or the mean return period. For example, the largest value of a record of 50 samples may be assumed as the expected value of the 50-year event. The exceedance probability of this event is often estimated through the Weibull plotting position as (1 – 50/51) = 0.0196, whose 95% confidence interval has been demonstrated to be included between 0.0005 to 0.071 (Serinaldi and Kilsby 2015). These values, in turn, correspond to return periods of 2000 and 14 years, respectively. Similar considerations can be drawn when the sample is analyzed statistically by fitting a probability distribution function. To account for this type of uncertainty, NOAA-14 provides the expected value for the precipitation intensity associated with a given return period and duration and the 90% confidence intervals, a feature that was not provided in previous governmental releases of this precipitation information. Despite this, design is almost always based on mean estimates.

Methods

Two case studies are used here to characterize the challenges associated with infrastructure design and climate uncertainty at national and regional scales. The first study uses the metro area of Phoenix, Arizona to demonstrate how uncertainties in future climate models manifest with respect to design. Phoenix is an interesting study location because it represents a confluence of several important climatological, hydrological, infrastructural, and social variables. The region already experiences severe flash floods during the summer monsoon season that inundate infrastructure (Yang et al. 2014; Mascaro 2018). The second study involves analysis of interstate roadway stormwater infrastructure across the contiguous U.S. This system is compelling because it is very large and governed by a diverse set of agencies, standards, and practices.

Challenges with Climate Uncertainty at Local Scales

Designing infrastructure systems for future climate presents challenges, especially at local scales. These challenges exist because additional uncertainty is introduced as a result of a mismatch between the resolution needed and what is provided by climate models (Fowler et al. 2007; Cook et al. 2017). Precipitation conditions at the Sky Harbor International airport (a centrally located piece of infrastructure in Phoenix) (Figure 1) were used to demonstrate how these challenges complicate the integration of future climate projections into infrastructure design. This case study focuses on the 50-year design storm for a 24-hour duration (P_{50}). The return period of 50 years was chosen because in 1956 the Bureau of Public Roads issued a policy that required a 50-year minimum code for the newly initiated Interstate System and because it continues to be the standard for most states in the U.S. (Lopez-Cantu and Samaras 2018; Supporting Information).The value of P_{50} was derived from the current standard, NOAA-14, along with the associated 90% confidence interval. NOAA-14 estimates are based on the application of a statistical distribution describing annual maxima with parameters estimated through regionalization techniques (Hosking and Wallis 2005; Bonnin et al. 2011). The 90% confidence interval is used for the analysis here because NOAA-14 only provides this significance level, which is commonly adopted for statistical inference (Wilks 2011). To quantify the effects of different statistical methods and lengths of the precipitation records, four additional estimates of P_{50} were obtained. The first two estimates were derived from TP40 and NOAA-2 standards that were previously used in Arizona. The other two values were based on the at-site estimation of P_{50} using the Generalized Extreme Distribution (GEV) and Generalized Pareto (GP) distributions. For each downscaled GCM, the GEV was fit to the annual precipitation maxima extracted at each pixel, and the quantile associated with the return period of 50-year was calculated. The GEV distribution is commonly used to model extremes of climate variables (e.g., Villarini et al. 2011) and was fitted here through the maximum likelihood method (Coles 2011). The GP is an alternative distribution also commonly used to model extremes of climate variables through the peak-over-threshold series (e.g., Mascaro 2018). The GEV and GP distributions were fitted to the daily precipitation observations from NOAA's National Center for Environmental Information database for Sky Harbor airport, available from 1950 to 2010.

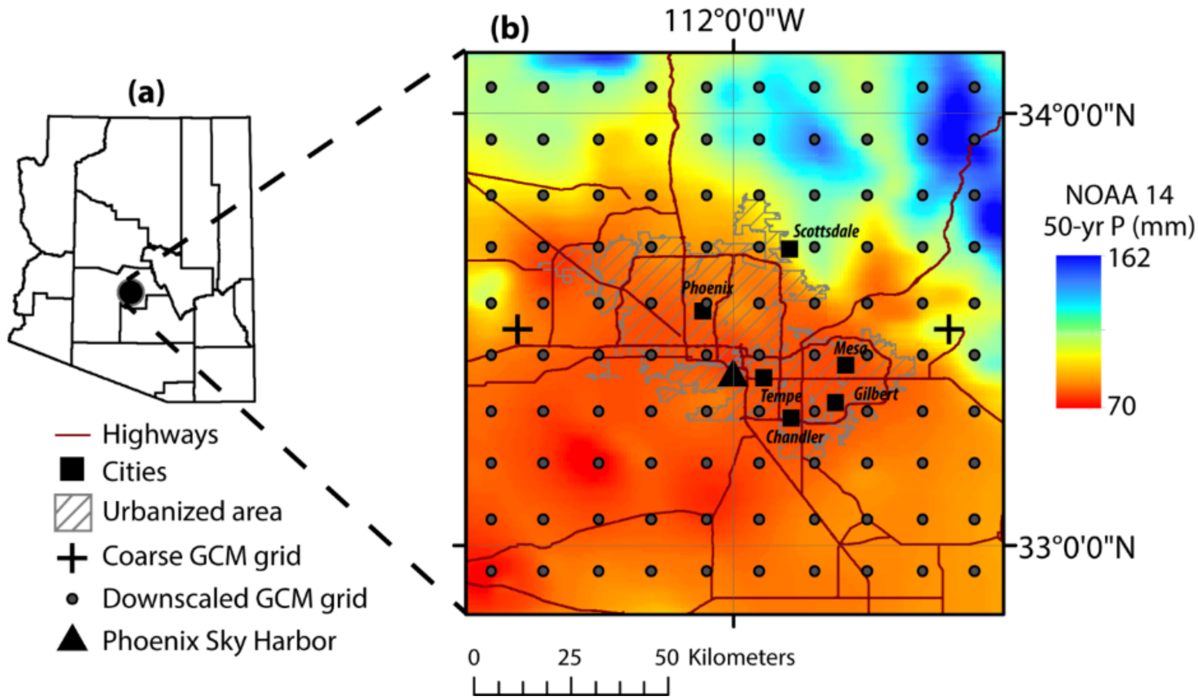

Figure 1. (a) Location of the Phoenix Metropolitan region in the state of AZ, along with the county boundaries. (b) Map of the P50 provided by NOAA-14 in the region, with the centers of the coarse and BCCA GCM grids, as well as the rain gauge at Phoenix Sky Harbor airport.

To quantify potential changes of the design storm in future climate, precipitation outputs from 20 GCMs of the Climate Model Intercomparison Project phase 5 (CMIP5; Taylor et al. 2012) were obtained from the database of Brekke et al. (2013) for the historical period (1950-2010) and the future period (2011-2100) under the Representative Concentration Pathway (RCPs; Vuuren et al. 2011) 8.5 scenario. The outputs of the 20 GCMs were downloaded at the original resolution and downscaled and bias corrected with two techniques, including the Bias-Correction Constructed Analogues (BCCA; Maurer et al., 2010) and the Localized Construct Analogs (LOCA) (Pierce et al. 2014). These two downscaling products are routinely used in climate change impact studies (Gutmann et al., 2014; Cook et al., 2017), and were both downloaded to assess the uncertainty associated with the downscaling methodologies. In doing so, the observed precipitation products of Maurer at al. (2002) and Livneh et al. (2013) that were used as reference in BCCA and LOCA, respectively were also obtained. A table listing the GCMs used in the study is shown in the Supplementary Materials. RCP 8.5 was used for this case because the more extreme predictions best highlight the aforementioned challenges. The original GCM data were provided in a common grid at 1º horizontal spacing (~100-km), which is shown through plus markers in Figure 1 along with the map of the NOAA-14 estimates of P_{50} and the BCCA and LOCA downscaled outputs were obtained at 0.125º and 0.0625º resolution respectively. For each climate model, this calculation involved computing P_{50} multiple times with samples ranging from 1950 to year j, with j = 2010, 2011… 2100. Such analysis is based on a stationary approach, conceptually similar to the ones adopted by NOAA that has the goal of updating the estimate of P_{50} every year as new data become available.

Changing Design Criteria of the U.S. Interstate System

Analyses were conducted to assess the vulnerability of stormwater infrastructure in the U.S. Interstate System. The approach required knowing how infrastructure age varies spatially, associating roadway links with age-appropriate design criteria, and assessing how these design criteria have changed over time and compare to future precipitation forecasts.

The U.S. Interstate System began in 1956 with the signing of the Federal-Aid Highway Act. Precise records of the construction history of the system are difficult to obtain in lieu of the fact that some components were already in place in 1956 (i.e., some parts of the Interstate System were built by simply connecting existing roadways) and the fact that individual states were responsible for construction record keeping. However, an estimate of the construction year was obtained based on published decadal maps of the growth of the system available from the Federal

Highway Administration. Segments shown in the 1960 decadal map were considered to be built prior to TP40 guidance (adopted after 1961) and segments built after the 2000 decadal map were considered to use NOAA-14 (adopted after 2004) standards.

In this case study, the differences in P_{50} from TP40 and NOAA-14 standards were first computed in the states where NOAA-14 is currently available. Digitized TP40 contour maps developed by Lopez-Cantu and Samaras (2018) were acquired from the authors, while NOAA-14 grids at ~500-m resolution were retrieved from the NOAA Hydrometeorological Design Studies Center. Next, the U.S. Geological Survey (USGS) Watershed Boundary Dataset (ten- and twelve-digit hydrologic units) was used to obtain the boundaries of all basins that intersect the Interstate System. The analysis is carried out on the basis of watersheds because the infrastructure is designed based on water volumes computed from analysis of flow across a watershed. For each design standard, the spatial mean P_{50} was computed in each basin to approximate the design storm used to size the infrastructure of the Interstate system located within each watershed.

As a next step, future projections of percent changes in P_{50} were obtained from 32 GCMs from CMIP5 downscaled with LOCA for RCP 4.5 and 8.5 scenarios (see Table in the Supplementary Materials). Note that, for the sake of simplicity and the different goals of these analyses, the downscaled product with the largest number of GCMs, (LOCA) was selected, thus allowing the evaluation of a more robust ensemble (Knutti and Sedlacek 2013). As in the Phoenix case study, the GEV was fit to the annual precipitation maxima extracted at each pixel, and the quantile associated with the return period of 50-year was calculated for each GCM. This analysis was done for the historical experiment and the RCP 4.5 and RCP 8.5 scenarios, thus producing three geospatial datasets of P_{50} for each model. The ensemble means of P_{50} across the 32 GCMs were then calculated and, from these, two maps of percent changes from historical to RCP 4.5 and RCP 8.5 were obtained.

To validate the reliability of the outputs from the downscaled climate models and the analysis approach in general, the spatial distribution of the ensemble mean P_{50} for the historical climate was compared with the map of P_{50} from NOAA-14. As expected, the two datasets did not perfectly match possibly because of errors due to climate models and downscaling technique, differences in the statistical methods used to estimate P_{50}, as well as the scale mismatch between the 6-km gridded observational product used to bias correct the climate models and the point-based records used to generate the NOAA-14 map. Despite the fact that the exact magnitudes did not perfectly agree, the two maps are highly correlated (spatial correlation coefficient of 0.83); thus, GCM projections were incorporated into the analysis by using the change factor approach (Cook et al. 2017). In this method, the percentage difference between (i) the map of P_{50} estimated in the historical experiment and (ii) the map of P_{50} estimated in future scenarios was first computed. This calculation was done for each model individually. Then, this percentage difference was multiplied by the map of P_{50} from NOAA-14 values (used as reference) to compute the predicted future intensity for each model. Finally, the model results were averaged and used for analysis.

Uncertainties and Challenges to Incorporating Forecasts into Design

Differences in the estimation of the design storm associated with a given return period due to the evolution of design manuals represent a complication for engineers. Another important aspect of climate change impacts analyses that may not be well understood by engineers and practitioners in general, is the uncertainty associated with GCM projections (Cook et al., 2017). While this is true for all climate metrics, uncertainties are particularly prevalent with precipitation projections (e.g., Piras et al. 2016). Thus, adoption of GCM projections into design standards is still prevented by a number of challenges, which are discussed through a study in the Phoenix metropolitan area.

Uncertainties in the Definition of the Current Design Storm

At Phoenix Sky Harbor, current and past design standards and the at-site analyses provide a wide range of values for P_{50}. NOAA-14 estimates a mean P_{50} of 74 mm, with a 90% confidence interval from 66 to 83 mm. The older design standards, TP40 and NOAA-2, suggest instead a P_{50} of 107 and 86 mm, respectively, thus above the confidence interval of NOAA-14. Both at-site estimations of P_{50} based on GEV and GP distributions return instead a value of ~65 mm, which is slightly below the lower bound of the 90% confidence interval of NOAA-14. The significant differences among the design standards and the at-site estimates are evidence of the uncertainty in the definition of a single value of the design storm intensity in current conditions (or when the infrastructure was built), which is due to the selected statistical method and the sample length. This uncertainty represents a first challenge for the use of climate projections for future design, because it is not immediately clear which reference value should be used to evaluate the climate models' ability to simulate the historical climate.

Uncertainties in Downscaling and Bias Corrections

Figure 2 presents the time evolution of P_{50} simulated from 2010 to 2100 by the GCM at their original resolution (part a), as well as downscaled with BCCA (part b) and LOCA (part c). In each panel, the mean P_{50} of TP40 and NOAA-2 (shown as dashed lines), as well as the mean and 90% confidence interval (CI) of NOAA-14 (shown as a dashed line and a gray semi-transparent filled band respectively) are reported along with the at-site estimate (Gauge, which is shown as blue points and line). For the GCM model predictions, the time evolution of P_{50} is plotted as the ensemble mean (solid line) and 90% CI (shown as hatched areas) across the 20 models. The value of P_{50} for 2010 accounts for the period 1950-2010 and, thus, is obtained only from the historical simulations. The values after 2010 include additional data from the RCP 8.5 simulations. For the downscaled models in panels (b) and (c), P_{50} estimated from the observed dataset of Maurer et al. (2002) and Livneh et al. (2013), respectively, are used to bias correct and downscaled the GCM outputs. The important items to observe from this figure are how the CI (uncertainty band) changes with downscaling (size of the hatched area between the panels), how the CIs from the GCMs compare with the CI from NOAA-14 (hatched areas versus grayed band), and how the mean of the GCM outputs compare with the TP40, NOAA-2, and NOAA-14 (solid lines versus the different dashed lines).

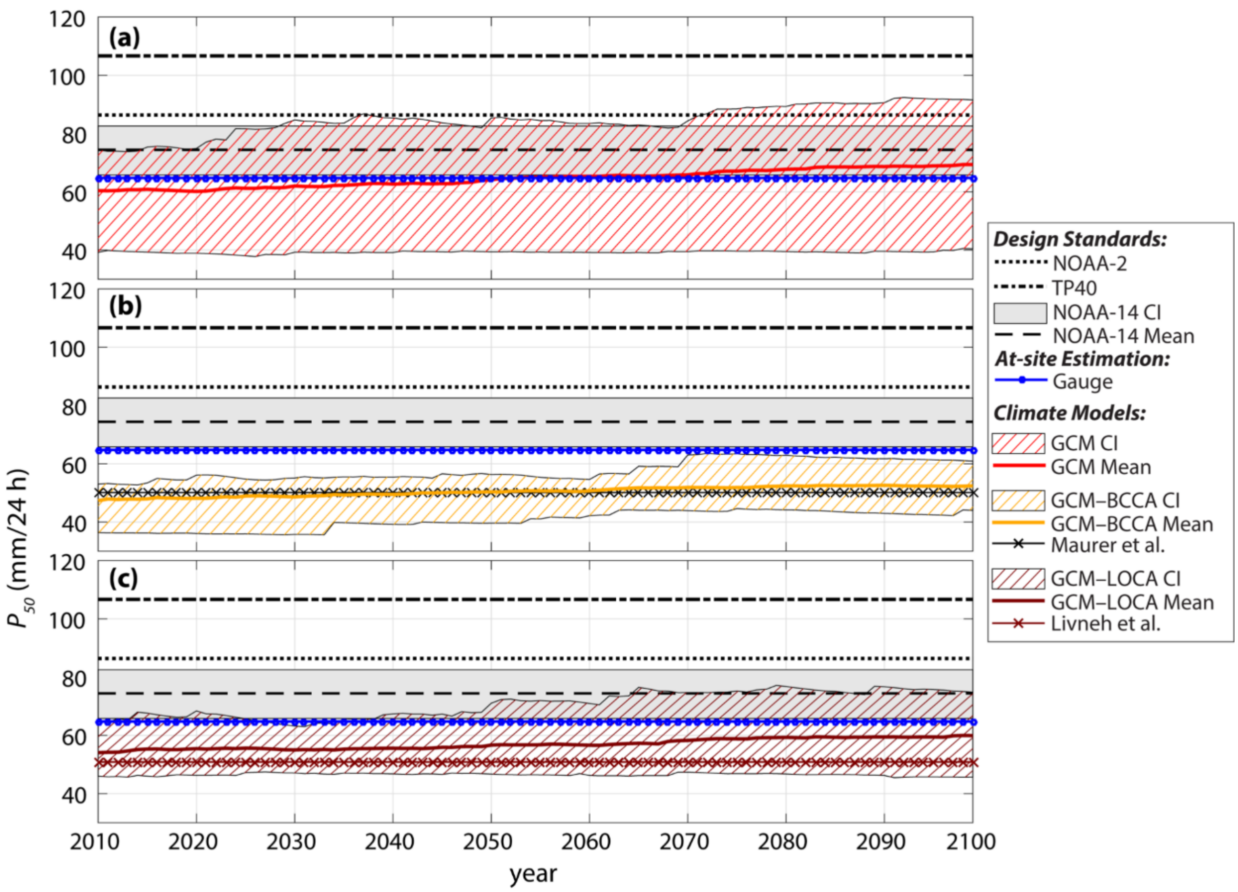

Figure 2. Time evolution of P50 computed for (a) coarse GCMs, (b) GCMs downscaled with the BCCA method (GCM–BCCA), and (c) GCMs downscaled with the LOCA method (GCM–LOCA). In each panel: results of the climate models are shown as ensemble mean and 90% confidence interval (CI); P50 from NOAA-2, the mean and 90% confidence interval of P50 from NOAA-14, and P50 estimated at the gauge are reported. In (b) P50 estimated from the observed dataset of Maurer et al. (2002) is shown and in (c) P50 from Livneh et al. (2013) is shown.

The ensemble mean of the GCMs increases over time from 60 mm in 2010 to approximately 65 mm to 2100, Figure 2(a). However, the inability of the GCMs to capture local precipitation features results in a very large uncertainty, quantified through the width of the CI (39-74 mm in 2010). When the GCM output is statistically downscaled through the LOCA and BCCA methods (Figures 2(b)-(c)), the ensemble mean of P_{50} also increases with time, but the uncertainty across the 36 models is much lower because the downscaling tools act as a filter. For example, in 2010 the range becomes 36-53 mm for BCCA and 45-65 mm for LOCA, respectively. However, since the observed datasets used to apply BCCA and LOCA are negatively biased compared to the local NOAA-14 estimate, the values of P_{50} are significantly lower than the other estimates. As a result, the CIs of these two products do not overlap or only partially overlap with the NOAA-14 confidence interval for most of the future period. From the practical point of view, this outcome does not give enough confidence in the ability of these datasets to reproduce P_{50} in the historical climate, thus limiting the utility of the direct use of its future projections. This finding also reveals that a challenge with applying bias correction and downscaling techniques to support future design is the use of observed products that are consistent with the datasets adopted in current design standards. A simple approach to remove the bias effect is the use of percent differences between future and historical downscaled climate simulations (see Cook et al., 2017 and references therein).

Roadway Infrastructure Design Under Historical and Future Climate

Another challenge in the issue of climate and infrastructure is related to the fact that future climate may not be readily predicted from historical records. The differences between the design storms returned by TP40 and NOAA-14 were first analyzed to characterize the current infrastructure vulnerability. Next, projections of future precipitation changes for the two scenarios were used to analyze the implications on future vulnerability.

Infrastructure Dating

Figure 3(a) shows the cumulative number of centerline interstate system miles built since 1956, while Figure 3(b) shows the estimated age of the individual roadway segments across the U.S. When TP40 was published in 1961, approximately 12,000 miles, or 25% of today's system, had already been built (USDOT 2017). Prior to TP40, guidance for engineering designs requiring rainfall frequency were likely drawn from another series of less comprehensive technical papers released by the U.S. Department of Commerce (Hershfield 1961). However, it is unclear what standard may have been used for interstate segments built between 1956 and 1961. The vast majority, 72%, of the system was built between 1961 and 2004. Here, it was assumed that the drainage infrastructure along these segments were designed using data derived from TP40 and drainage infrastructure was not reconstructed on these segments after 2004, nor designed to values than higher than TP40 because of local factors. The remaining 3% of the system, built between 2004 and present, would have relied on a mix of TP40 and NOAA-14 depending on whether NOAA-14 data had been released for that location and whether the section was newly designed and constructed or redesignation of an existing roadway. Nearly all of the miles added to the interstate system since 2004 are the result of designating existing state and highways as interstates (ex. Interstate 22 brought online in 2012). When this happens, the roadway geometry and safety features are upgraded to the current design standards, but drainage infrastructure may not be updated. Thus, there exists considerable uncertainty about the design standard used for the 3% that has been added since 2004. The overall impact from this assumption is expected to be minimal since, as noted earlier, the vast majority of the interstate was created between 1961 and 2004.

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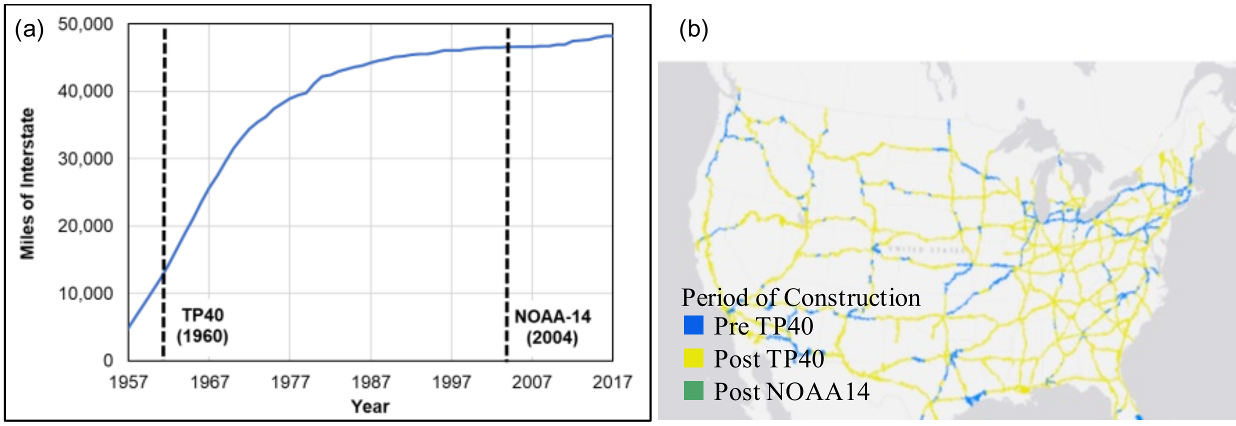

Figure 3. Results of infrastructure dating analysis; (a) cumulative interstate system miles 1956-Present and (b) map showing the design standards by interstate segment.

Over/Underdesign Challenges for Current Climate

Figure 4 shows the absolute change in P_{50} between TP40 and NOAA-14 in the watersheds intersecting the interstate system. In Figure 4, locations shown in red (green) are those where NOAA-14 gives a higher (lower) value for P_{50} when compared to TP40. The differences exhibit both inter and intra-state variability. If NOAA-14 is assumed accurate for the current climate conditions, a conservative assumption given recent heavy storm activity since 2004, stormwater infrastructure designed using TP40 in the coastal regions in the eastern and southern U.S. and in the Midwest are mostly underdesigned. In these areas, changes in P_{50} range up to 98 mm. In contrast, stormwater infrastructure designed with TP40 in the western U.S. and Ohio River valley (with the exception of southeastern California and, western Arizona, and central Colorado) are potentially over-designed, with differences in P_{50} up to -141 mm.

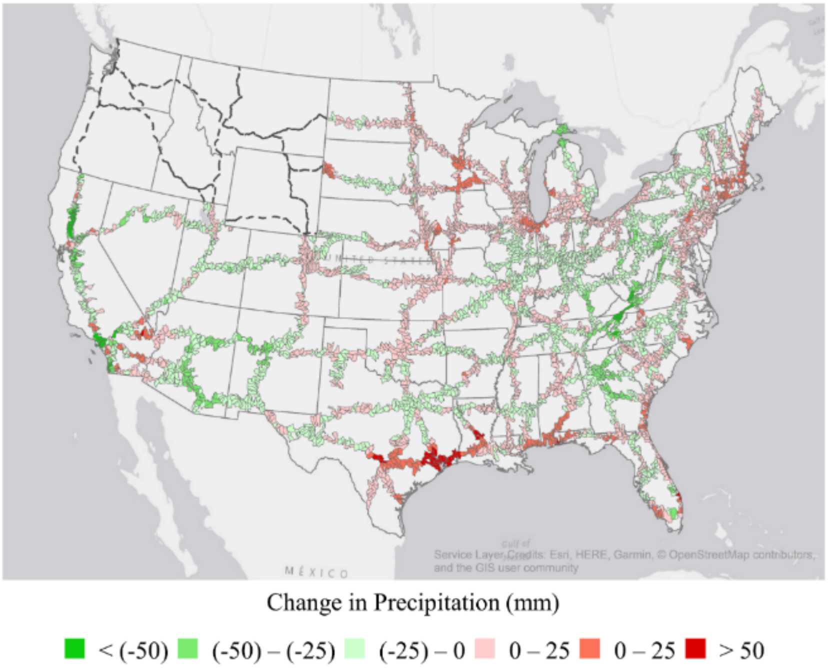

Figure 4 Absolute change in precipitation intensity for P50 between TP40 and NOAA-14. Note: NOAA 14 is not currently available for the Pacific Northwest States (upper left).

At the continental scale, the changes follow a bell-shaped distribution with mean close to zero and standard deviation of ~20 mm (not shown), indicating the lack of a substantial bias and similar chance to observe positive and negative changes. In fact, isolating the road segments assumed to be designed using TP40 precipitation intensity guidelines, 47% of the contributing watersheds are expected to receive the same amount of or larger precipitation for the 50 year-24 hour event based on NOAA-14 mean estimates. As a result, the stormwater infrastructure in these locations may be currently underdesigned. Conversely, 53% of the watersheds (49.8% of the total watershed area) contributing to stream flows that interact with interstate drainage infrastructure are expected to receive less water based on the NOAA-14 estimate, e.g., 53% of watersheds may be overdesigned infrastructure for the current climate. These numbers are based on the mean of the NOAA-14 values, but as the Phoenix study demonstrated, Figure 2, this mean value can have considerable uncertainty. When considering the confidence intervals in the P_{50} values, the number of watersheds with overdesigned infrastructure could be considerably higher or lower. In addition, the percent of watersheds that are potentially over or underdesigned is one metric, but roadway risks under climate change could also be based on average annual daily traffic, or by population living near each segment.

Characterizing Current Capacity to Identify Needs in a Future Climate

Given the consensus that, in the future, rainfall extremes will increase in magnitude and frequency in many regions, a common narrative is that infrastructure is systematically underdesigned to withstand these changes. However, the evidence presented in Figure 4 showing that, while many regions may be underdesigned, in some regions, infrastructure may be over-designed. This may lead to different conclusions about future adaptive decisions. To demonstrate this, future projections of P_{50} were obtained by applying the percent changes in P_{50} derived from the downscaled climate simulations to P_{50} from NOAA-14, which provides the most up-to-date estimate available. These future projections of P_{50} were then compared with TP40, which is the standard that has been used to design most of the Interstate System (Figure 3). The differences between these future and past products are presented in Figure 5 for both RCP 4.5 and 8.5 scenarios.

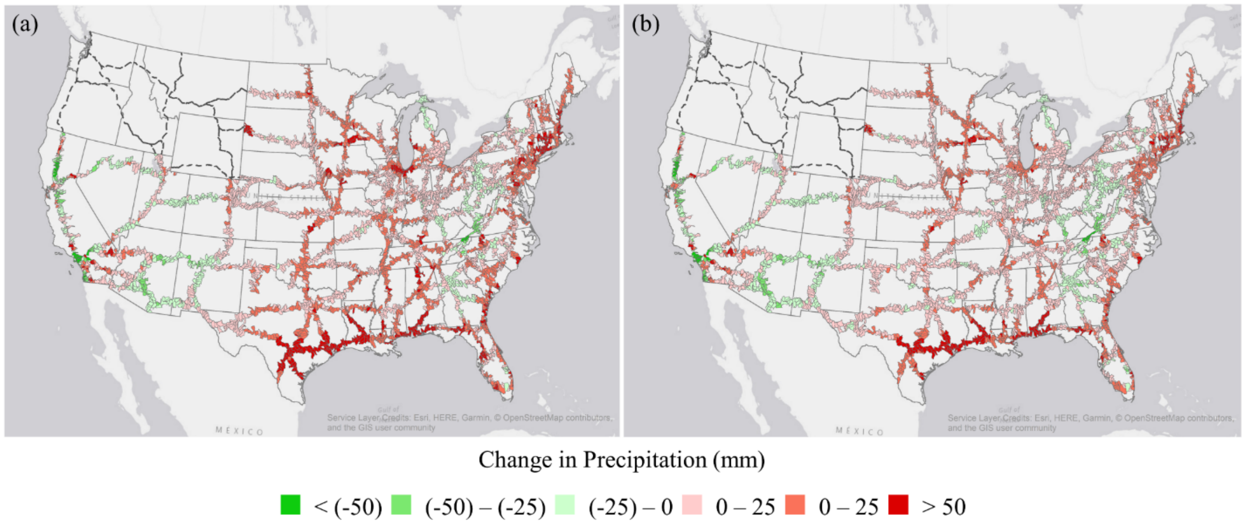

Figure 5. (a) Difference between P50 estimated for the RCP 8.5 scenario and P50 from TP40. (b) Same as (a) but for the RCP 4.5 scenario. Note: NOAA 14 is not currently available for the Pacific Northwest States (upper left)

It is found that, with respect to TP40, P_{50} is expected to rise in the majority of the study area, consistent with the consensus that storm intensity is expected to increase in the future due to climate change. On average, the change between TP40 and RCP 4.5 (RCP 8.5) is 12.5 mm (20 mm), with a range between approximately 125 mm and -100 mm (150 mm and -100 mm). Interestingly, results show that, under RCP 4.5, 23% of the study watersheds (25.6% of the total watershed area) will experience decreased precipitation intensity in the future, while this number reduces to 18% (21.7% of the total watershed area) under RCP 8.5. While it is generally accepted that most civil infrastructure will become more vulnerable to disruption and failure due to climate change, these findings suggest that, if infrastructure was built using TP40 guidance in areas where storm intensity decreases in the future relative to this guidance, it may actually be more robust than the original risk tolerance guidelines called for. Changes in precipitation depths from TP40 to NOAA-14, NOAA-14 to future climate, and TP40 to future climate exhibit both inter- and intra-state variability. For example, parts of the Southwest (including parts of California) and

Appalachia show decreases from TP40 to the future. Conversely, much of the Midwest and East Coast show increases. These changes should again be considered in light of the analysis shown for the Phoenix case study, which demonstrated the considerable uncertainty that can be associated with the GCM projections. There, for a single location, it was found that the GCM model uncertainty can be as high as 50%. Due to the scale and number of watersheds, in this paper the implications of this uncertainty on the probability of over/underdesign for the entire interstate network is not examined in detail. However, were a design to be completed that used projected model ensembles, then accurate assessment of potential risk would need to consider the potentially large uncertainty that the Phoenix study showed.

Discussion

Summary of Results

The Phoenix case study illustrates that using climate projections for infrastructure design presents many challenges. There are additional complications not explicitly found in the results. The analyses presented in Figure 2 has been obtained under the assumption of climate stationarity, which despite research that suggest climate may evolve in non-stationary fashion, is also an assumption found in several other studies (Jain and Lall 2000; Milly et al. 2008; Commission for Hydrology 2012; Cheng and Kouchak 2014). Recent work has refined and adopted this theoretical basis to model stochastically non-stationary hydrologic time series to support engineering design, as done for stationary analyses (Salas and Obeysekera 2013; Cheng and Kouchak 2014). While useful and theoretically sound, methods accounting for non-stationarity add more uncertainty into the estimation process that limits their practical use (Serinaldi and Kilsby 2015) and thus a number of studies suggest that stationary assumptions should still be the default approach (Montanari and Koutsoyiannis 2014).

Similarly, and in simple terms, the science of future climate projections has not been developed enough to produce accurate predictions at the spatial and temporal resolution currently used in the decision making process for many types of infrastructure. To use these climate models into the decision making process therefore introduces additional uncertainty, which would be largely unaccounted for. Yet, omitting climate projections from design decisions also omits the characterization of a changing hazard that is critical to the design. This mismatch between climate model outputs and the input values needed for engineering design means that standards have not yet emerged on how engineers should prepare and use these climate model data (Cook et al. 2017). First, the definition of a single value of the design storm in current conditions is subject to uncertainty. This uncertainty must be properly quantified and considered when evaluating the accuracy of climate models to simulate the past and predict future conditions. It should also be considered when assembling a robust ensemble of models for analysis (Madsen et al. 2017). Second, the spatial resolution of GCM outputs is still too coarse for direct use in design standards. Downscaling via RCMs and statistical techniques are required to increase the resolution and capture local climatological features. Third, when applying downscaling and bias correction tools, it is important to verify that the reference dataset is consistent with the records used in current design standards. Fourth, all sources of uncertainty associated with climate projections (model structure, future projections, climate internal variability, and downscaling techniques) should be taken into account to develop confidence intervals of future design storms. In the Phoenix example, only the uncertainty of model structure was accounted for. Finally, while statistical models based on non-stationary conditions of climate are available, the uncertainty in the definition of the link between model parameters and time is still quite high, thus preventing their immediate use. These challenges were mitigated in the first case study by using the projected change from the multi-model GCM ensemble to simply scale the NOAA-14 IDFs. As a result, it is likely that some infrastructure is adequately robust (i.e., overdesigned) for future climate changes while others are underdesigned.

Alternative Design Paradigm

Considering the challenges identified, engineers are not currently prepared to accurately incorporate GCM outputs for design. The likely adaptation is to consider the worst case scenario with respect to predicted precipitation and develop designs capable of dealing with these demands. However, as the analysis here demonstrates some infrastructure may already be sufficiently designed. Collectively, all of this uncertainty suggests that more complex resilience approaches may be needed in place of traditional risk-based approaches. The examination of NOAA Atlas data and its use to define design parameters that govern against particular failure mechanisms reveals challenges for planning under climate change. First, normative assumptions about the future may create serious problems as 1) there is no consensus as to which climate scenario and corresponding uncertainty to use (Knutti et al. 2013; Knutti and Sedlacek 2013) and 2) the infrastructure will likely persist long into the future and could easily be under- or even over-sized. Over-sized infrastructure is not, in the context of failure, a concern but does have unintended consequences (increases capital, maintenance, and rehabilitation costs at a time when many infrastructure agencies are short on funds, and potentially larger impacts on people and the environment).

The traditional risk-based design process is insufficient in the face of climate change. In this paper, two analyses are presented that demonstrate the substantial uncertainties with incorporating climate projections into traditional design and in interpreting how climate change may affect already in-place infrastructure. Though not shown in this paper, greater uncertainty embeds the need for more robust designs when risk-based approaches are adopted. In place, it is recommended that a fundamental shift towards resilience-based thinking of how infrastructure is planned should occur. A specific outcome of how a resilience-based instantiation of stormwater infrastructure should emerge for climate change is not presented; however, the various characteristics of this approach can be described based on emerging thinking. Because infrastructure are socio-technical systems, these characteristics do not just apply to physical assets. A resilient stormwater system should be able to sense changes in environmental conditions, anticipate the consequences of those changes, adapt structure or function to mitigate or manage the consequences, and learn from the outcomes to improve behavior in the future (Park et al. 2011). These processes could be aided by sensors or social networks, coupled infrastructure simulations that estimate the consequences or failures and the benefits of various adaptation strategies (from hardening and strengthening to green infrastructure), and education programs that support knowledge transfer and cross-disciplinary training. Adaptation is an important component of this overall system. Research has shown that active adaptation in the face of changing climate can have substantial economic impacts (Neumann et al. 2015). In this paper focus is placed on the technical roadblocks related to the uncertainty of climate projections and the historical non-uniformity of engineering standards. However, other technical roadblocks exist, for example the role of infrastructure materials and the effects of potentially increasing numbers of non-critical events on the ability of the infrastructure to withstand less frequent and higher intensity events. Perhaps more importantly there are social roadblocks related to the form and function of the organizations that are responsible for the delivery and management of the infrastructure.

Resilience strategies may take on forms that are atypical to current gray infrastructure solutions. While green infrastructure solutions are possible strategies (e.g., bioswales and green roofs), it may also be the case that safe-to-fail approaches are preferred (Kim et al. 2017). Stormwater management systems that are designed to fail while the consequences of failure are minimized have been successfully implemented. The Phoenix area's Indian Bend Wash is an 18-km greenbelt through the heart of the city filled with parks, golf courses, and public spaces (Scottsdale 1985). During dry times, the wash sees little more than a trickle of water, maybe a meter or two wide. During heavy rains, the wash turns in to a raging river, which can destroy park and public infrastructure in the greenbelt. However, the benefits of this infrastructure design (increased activities and public spaces) far outweigh the small costs of replacing pieces of park infrastructure after some rain events. This is in contrast to a design like the Los Angeles River, where channelized concrete provides little to no value to the city outside of the conveyance functionality and at the same time the costs of failure are high. Again, a particular solution for a resilience-based implementation is not prescribed, but instead emerging thinking around what characteristics these solutions might have is highlighted.

The time scale of climate change is congruent with the infrastructure's lifetime and thus infrastructure deployed today are likely to experience the more intense effects that climate change forecasts predict by mid to end-of-century. As such, there is pressing need to ensure that infrastructure are resilient to climate change and are able to manage the uncertainty that exists today and for several decades from now. Part of the challenge is that today's infrastructure have long lives– they are locked in to particular forms that largely resemble what has been deployed for the past decades if not century. This lock in results from several reasons including financing that focuses on a handful of technologies, increasing interconnectedness with other infrastructure, and a lack of flexibility in components (Chester and Allenby 2018). The implementation of resilient solutions will likely require the breaking of this lock in, targeting not only the form of the physical infrastructure but also the economic, political, and legal forces that perpetuate risk-based designs. New forms of infrastructure that are agile and flexible may provide opportunities to more closely match the replacement time of infrastructure with that of climate change, to reduce concerns of many of the long-term uncertainties associated with climate change (Chester and Allenby 2018).

Climate hazards intersect infrastructure in many ways. In this paper, precipitation, its evolving characteristics, and the effects on stormwater infrastructure have been examined more closely. Precipitation also affects roadways, sanitary sewers (due to interconnectedness with stormwater), water treatment systems, and electrical generation and distribution systems. Each of these systems are designed using the same overall risk-based paradigm discussed earlier and consideration of future weather events would require similar estimation to what is shown here. However, climate hazards are not limited to precipitation and can include temperature (extreme heat and cold, but also mean changes), drought, wildfires, hurricanes, and other effects. The importance of these hazards depends on geographical location, the infrastructure (types of systems but also the specific elements in place), and the assumptions made during design. Similar to precipitation, each hazard involves uncertainties, which are estimated using historical data. Thus, the challenges outlined here can be generalized across multiple climate hazards and infrastructure due to similarities in the way climate is considered in current design methods (i.e., risk-based approaches based on historical measurements). However, detailed analysis similar to the one presented in this paper, but specific to the hazard and infrastructure system in question is warranted to understand and accurately quantify the potential impacts.

Conclusions

Based on the two case studies and analysis in this paper some specific conclusions can be made. The case study in Arizona suggests the following specific conclusions:

- The design standards that have been gradually published over the years as new data and methodologies have become available provide a large range of values for the design storm (from 74 mm to 107 mm for P_{50}), which differ from at-site estimations (65 mm).
- The P_{50} derived from the ensemble mean of both GCMs and downscaled GCMs in the historical period (1950-2010) are, in this site, negatively biased when compared to NOAA-14 (mean value of ~60 mm for the original GCMs and ~50 mm for the two downscaling products).
- The uncertainty of climate projections from GCMs at their native resolution is larger than the uncertainty of downscaled products (almost double), as shown by the width of CIs.
- The mean predicted values from the GCMs at native and downscaled resolutions generally grow in time and the limits of the uncertainty bands vary with time.

This single site study shows that modeling uncertainty and the models inability to be consistent with the datasets adopted in current design standards still poses challenges for using future projections to update region-specific standards because unified methods to deal with these inconsistencies and uncertainties do not yet exist.

From the study involving the U.S. interstate system the following conclusions are made.

- The majority of U.S. interstates were designed at a time when TP40 guidelines formed the basis of hydrological design standards
- The NOAA-14 estimates P_{50} are lower than the P_{50} estimate from TP40 for 53% of the total watersheds that intersect the U.S. interstate system.
- The average and range of change in P_{50} from the RCP 4.5 (RCP 8.5) model ensemble to TP40 P_{50} is 12.5 mm (20 mm) and 125 mm to -100 mm (150 mm to -100 mm) respectively.
- The RCP 4.5 (RCP 8.5) ensemble suggests that 23% (18%) of the study watersheds will experience smaller P_{50} in the future compared to TP40.
- Future climate projections suggest that parts of the Southwest (including parts of California) and Appalachia will see decreases in P_{50} from TP40 while much of the Midwest and East Coast will show increases.

This case study shows that depending on the historical design conditions and the direction of projections forecasts, roadway drainage infrastructure may be designed appropriately in some regions, overdesigned in some, and underdesigned in others.

It must be emphasized that these conclusions and the studies that supported them have limitations that warrant considerations before generalizing these findings across all stormwater infrastructure and across other infrastructures. First, the Phoenix study highlights the uncertainty and challenges for updating regional specific standards, but this study encompassed only a single geographic area. Other areas, particularly those with longer records of measurement may not encounter the exact same challenges and if they do the magnitude of the challenges may be less. Nevertheless, the fact that the study found difficulties for this site, demonstrates that careful attention to the historical and projected records is needed when embarking on an effort to update regionally specific standards. Likewise, the U.S. interstate system study does not consider the "on-the ground" decision making that might have taken place during the delivery of the infrastructure assets nor does it consider other factors that may figure into the design process of individual assets. Thus, while the analysis suggest that some infrastructure are already overdesigned and may have the capacity to absorb future climate stressors, local conditions should be considered before overextending these findings to include all infrastructure everywhere.

Data Availability Statement

Some data, models, or code used during the study were provided by a third party. These items include the downscaled and bias corrected GCM outputs, the raster images used to identify differences in TP40 and NOAA-14 P_{50} values, and the watershed layers used for GIS analysis. Direct requests for these materials may be made to the provider as indicated in the Acknowledgments. Other data are available from the corresponding author by request. These items include the maps overlaying watersheds, roadways, and design standards.

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SUPPLEMENTARY INFORMATION

Table 1. Climate Projection Models Used in this Study.

Modeling Center (or Group)	Institute ID	Model Name
Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	CSIRO-BOM	ACCESS1.0* ACCESS3.0
Beijing Climate Center, China Meteorological Administration	BCC	BCC-CSM1 BCC-CSM1.1*
Canadian Centre for Climate Modeling and Analysis	CCCMA	CanESM2*
National Center for Atmospheric Research	NCAR	CCSM4*
Community Earth System Model Contributors	NSF-DOE-NCAR	CESM1-BGC* CESM1-CAM5
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC	CMCC-CM CMCC-CMS
Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CERFACS	CNRM-CM5*
Commonwealth Scientific & Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-QCCCE	CSIRO-Mk3.6.0*
EC-EARTH consortium	EC-EARTH	EC-EARTH
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University	LASG-CESS	FGOALS-g2
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM3* GFDL-ESM2G* GFDL-ESM2M*
NASA Goddard Institute for Space Studies	NASA GISS	GISS-E2-H GISS-E2-R
National Institute of Meteorological Research/Korea Meteorological Administration	NIMR/KMA	HadGEM2-AO
Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)	MOHC (additional realization by INPE)	HadGEM2-CC HadGEM2-ES
Institute for Numerical Mathematics	INM	INM-CM4*
Institute Pierre-Simon Laplace	IPSL	IPSL-CM5A-LR* IPSL-CM5A-MR*
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, and National Institute for Environmental Studies	MIROC	MIROC-ESM* MIROC-ESM-CHEM* MIROC5*
Max Planck Institute for Meteorology	MPI-M	MPI-ESM-LR * MPI-ESM-MR*
Meteorological Research Institute	MRI	MRI-CGCM3*
Norwegian Climate Centre	NCC	NORESM1-M*

* Models were also used in the analysis used for the Phoenix case study