NCHRP Project 15-61

Applying Climate Change Information to Hydrologic and Coastal Design of Transportation Infrastructure

Design Practices

PREPARED FOR

THE NATIONAL COOPERATIVE HIGHWAY RESEARCH PROGRAM

TRANSPORTATION RESEARCH BOARD

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TRANSPORTATION RESEARCH BOARD OF
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Part I: Introduction

Chapter 1. Overview

Planners and engineers require tools to account for global climate change within hydrologic and coastal design practices for transportation infrastructure. Current hydrologic and coastal design procedures use historical data that planners and engineers assume represent future conditions (McCuen et al. 2002, Douglass and Krolak 2008). With a changing climate, the assumption that historical patterns can be satisfactorily used to analyze future conditions may not be a responsible assumption for the planning and design of transportation infrastructure. A changing climate may result in new risks, such as sea level and temperature rise, and changes in the magnitude, timing, and distribution of precipitation, snowpack, and snowmelt (USGCRP 2017, 2018). Failure to account for these changing risks may compromise the operational characteristics of existing and future transportation infrastructure.

This *Guide* addresses these changes and is intended for experienced hydrologic and hydraulic (H&H) engineers and coastal engineers responsible for the planning, design, operation, and maintenance of transportation infrastructure. Less experienced H&H and coastal engineers, transportation planners, and managers will also benefit from this *Guide*.

This *Guide* provides a comprehensive framework for considering and, where appropriate, incorporating climate change into inland hydrology and coastal analyses. To the extent possible, this *Guide* is independent of specific tools and datasets. Though it is applicable to the tools and datasets available today, it is not tied to them. This *Guide* recognizes that new tools and datasets will be available in the future and is structured so that it remains relevant when those new tools and datasets become available.

1.1. What Does it Mean to Design for Climate Change?

Before even considering climate change, planners and engineers strive to create transportation infrastructure components and systems that are ***resilient***, that is, are capable of maintaining or rapidly recovering functionality in response to changing conditions or disruptions. Planning and designing for climate change means recognizing that the future may not look like the past. It means using climate information from the past along with projections about the future to design resilient transportation infrastructure. Resilient design principles include reducing vulnerability of infrastructure through lowering the probability of failure, experiencing less severe consequences when failure occurs, and enabling faster recovery times from failure or damage.

Traditionally, H&H engineers have used various data and techniques to characterize the historical patterns of storm and flood events, ranging from the frequent to the extreme, in order to understand and design for the probability that such events may occur in the future. Similarly, coastal engineers characterize historical patterns of water levels, winds, waves, and sediment transport in order to understand and design for the probability that those events may also occur in the future. In both contexts, engineers have traditionally relied on historical conditions to be reasonable predictors of future conditions; that is, they rely on ***stationarity***. However, a changing climate undermines this assumption, so that precipitation patterns, water levels, and other climate-driven parameters of the future may not be as reliably estimated from the past. This is known as ***nonstationarity***.

In both inland hydrology and along the coast, designing for climate change means augmenting what is known about the historical occurrence of extreme events with changes in the magnitude and frequency of these events associated with climate change. This means adapting existing tools and techniques to incorporate information from the climate science community. This *Guide* describes how and under what circumstances H&H engineers and coastal engineers may design for climate change.

This *Guide* is based on the current state of knowledge and understanding of possible future conditions developed by the climate science community. However, climate science and modeling is a dynamic field that is continually advancing and changing. Therefore, this *Guide* is intended to be flexible so that when new climate science products are available, they can be incorporated into the planning and design process.

> *BOTTOM LINE: Planning and designing for climate change means recognizing that the future may not look like the past and using information from the past, along with future projections, to design* ***resilient*** *transportation infrastructure.*

1.2. Scope

The emphasis in this *Guide* is on practices applicable to inland hydrology and the coastal environment. It is divided into three parts. Part I is a general introduction. This chapter provides an overview of the scope and use of the *Guide*. Chapter 2 introduces the planner and engineer to recommended decision frameworks for considering climate change in hydrologic and coastal engineering applications. The decision frameworks recognize that not all projects and studies require the same attention.

> AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:
>
> §1.2 General Considerations
>
> §1.3 Specific Considerations
>
> §11 Highways along Coastal Zones and Lakeshores

Part II addresses inland hydrology. Inland hydrology involves the analysis of precipitation, runoff (discharge), infiltration, evaporation, soil moisture, groundwater, temperature, and other factors affecting runoff in a watershed. Climate change can affect all of these hydrologic processes, but the focus of this *Guide* is on precipitation and runoff. Chapter 3 provides guidance on the selection and use of information from Global Climate Models (GCMs), and Chapter 4 provides an overview of basic tools for incorporating climate change into hydrologic analysis and design. The next five chapters address specific tools and their applications. Chapter 5 addresses the identification and use of trends in historical discharges in gauged watersheds. Chapter 6 provides tools for estimating projected precipitation for use in rainfall/runoff models in ungauged watersheds. Chapter 7 and Chapter 8 provide guidance for the use of regression techniques and index approaches, respectively, for estimating future discharges. Chapter 9 provides guidance on the use of continuous simulation models under projected precipitation and temperature conditions.

Part III addresses coastal applications. Planning and design in the coastal environment involves water levels, winds, waves, sediment transport, and other factors. As with inland hydrology, climate change may affect all of these, but the focus of this *Guide* is on sea level rise and storm-related coastal hazards. Chapter 10 addresses overall guidance for incorporating climate assessment in coastal applications. Chapter 11 focuses on guidance for selecting sea level rise for analysis and design. The final chapter, Chapter 12 provides guidance on combining coastal hazards, primarily water levels and waves, with climate change information.

1.3. How to Use this Guide

This *Guide* is designed to be read in its entirety for maximum benefit, but it is also designed for quick reference by topic. Incorporating climate change in design is complex, so this *Guide* lays out each procedure in a step-by-step manner, including example applications. This *Guide* was derived from the final report of the National Cooperative Highway Research Program (NCHRP) project 15-61 "Applying Climate Change Information to Hydrologic and Hydraulic Design of Transportation Infrastructure" (Kilgore et al. 2019). The interested reader is encouraged to consult the final report for background information on the topics in this *Guide*.

This *Guide* is most effectively used by reviewing the described methodologies and accompanying examples so that the techniques can be applied for a given project. In some cases, this *Guide* provides recommended procedures that a state Department of Transportation (DOT) may choose to implement to support hydrologic design or coastal assessment statewide.

In addition, users of this *Guide* for inland hydrology (Part II) are encouraged to be familiar with *Highways in the River Environment – Floodplains, Extreme Events, Risk, and Resilience,* Hydraulic Engineering Circular No. 17 (HEC-17) (Kilgore et al. 2016). Users of this *Guide* for coastal applications (Part III) are similarly encouraged to be familiar with *Highways in the Coastal Environment: Assessing Extreme Events,* Hydraulic Engineering Circular No. 25 (HEC-25) (Volume 2) (Douglass et al. 2014).

Finally, this *Guide* is intended to augment state DOT guidance and procedures. To this end, this *Guide* indicates related sections in the American Association of State Highway and Transportation Officials (AASHTO) Highway Drainage Guidelines (HDG) for the tools and techniques presented (AASHTO 2007). The objective of this *Guide* is not to replace existing state DOT or other guidance and practices, but to provide additional tools for evaluating the potential effects of climate change on transportation infrastructure.

> *The objective of this Guide is NOT to replace existing state DOT or other guidance or tools, but to provide additional tools for evaluating the potential effects of climate change on transportation infrastructure.*

1.4. Terminology

The climate science and engineering communities use some familiar terms differently. For example, there are important differences in analytical context, technical solutions, and quantitative methods in the use of the word "extreme." The climate science community generally defines an extreme event as "the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable" (IPCC 2012a). Extremes are commonly defined in terms of thresholds, percentiles, or return periods relative to a historical period of 30 years or longer.

H&H engineers generally define an extreme as an exceedance threshold estimated from the tail of an assumed probability distribution for the hydrological measurements. For example, a precipitation extreme is expressed as either the percent chance of annual occurrence (i.e., 1%

annual exceedance probability (AEP)) or as the average period between occurrences (i.e., 100-year event), and it is estimated from an assumed probability distribution fit to the observations under the assumption of stationary distribution parameters. Commonly-used thresholds are 25-, 50-, 100-, and 500-year return periods and 4%, 2%, 1%, and 0.2% AEPs, respectively. Similarly, coastal engineers frequently define extreme events based on AEPs or return periods.

The majority of "extreme" indices used in hydrologic and coastal engineering, while similar in definition, tend to be rarer than those commonly used in climate science. For example, considering extremes in daily precipitation, engineers typically think of "extreme" as quantities that occur no more than once every 5 to 10 years, while a climate scientist frequently will use extreme for quantities that occur more frequently. Both uses are correct within their context.

As needed, this *Guide* provides explanations for terms that may be unfamiliar to engineers as they are used. Special attention is given to common terms with different meanings in the engineering and climate science communities. The ***Glossary*** is a useful reference tool.

1.5. When Should You Include a Climate Scientist on Your Team?

There is a growing repository of tools, methods, and resources available to H&H and coastal engineers for considering and incorporating the effects of climate change into hydrologic design and coastal assessment of transportation infrastructure. This *Guide* refers to many of these resources and provides tools for H&H and coastal engineers to incorporate considerations of climate change in their analyses and designs. However, there are circumstances where additional climate science expertise is needed to effectively meet project needs.

One indicator that additional expertise in climate science may be needed is based on the costs, risks, and vulnerability to climate change associated with an infrastructure project. This *Guide* recognizes that all projects do not require the same attention to a changing climate and introduces the concept of *levels of analysis* for different projects in Chapter 2. The lower (less involved) levels of analysis are intended to be successfully completed by experienced H&H and coastal engineers and their project teams. The higher levels of analysis may require increasing expertise in climate science, hydrologic modeling, or coastal modeling. As stated in this *Guide*, the highest levels of analysis require the services of a qualified climate scientist to meet the specific climate needs of a given project. Chapter 2 discusses this topic in general terms. Levels of analysis are discussed in greater detail in Chapter 4 for inland hydrology (Part II) and in Chapter 10 for coastal applications (Part III).

Chapter 2. Decision-Making Frameworks

> AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:
>
> §1.2.4 General Considerations/Related Considerations

This *Guide* considers two decision-making frameworks within which planning and design of transportation infrastructure may be conducted: 1) traditional (top-down) and 2) threshold (bottom-up). As suggested by its name, traditional (top-down) design is the dominant approach for designing transportation infrastructure projects today. Threshold (bottom-up) design has been more frequently used in larger system design and vulnerability assessment and is increasingly being considered for infrastructure design when future uncertainties, such as climate change, are important.

Traditional (top-down) design is a process where designers apply a defined set of information, design procedures, and design criteria to determine an appropriate plan or design for a new project or to evaluate an existing project plan or design. The process is typically sequential, and uncertainty in the inputs may be considered. A factor of safety is sometimes incorporated as an acknowledgement of uncertainty. In the context of climate change, traditional (top-down) design can be characterized as a "predict, then act" approach. A relevant question is "what is likely to happen under the future design conditions?" The goal, then, is to design the infrastructure to perform for those future conditions. In the context of climate change, traditional design seeks to predict the future, or at least a likely range of futures, and then plan or design infrastructure to perform according to standards for those future conditions. Section 2.1 provides a more detailed description of the traditional (top-down) decision-making framework.

Threshold (bottom-up) design is a process where the vulnerabilities of existing or proposed infrastructure are identified so that potential conditions that expose those vulnerabilities can be quantified. The conditions under which the infrastructure becomes vulnerable are called "thresholds." In threshold design, the process is to assess vulnerabilities and develop plans or designs that address those vulnerabilities. The evaluation seeks to identify the greatest vulnerabilities across a range of possible future conditions, and then planners and designers select from alternative approaches those that perform reasonably well under those futures. The goal is to assess vulnerabilities, to seek robust solutions that minimize regret in decision making. Relevant questions under this paradigm are, "how does my system work?" and "under what circumstances might it fail?" In the context of climate change, threshold design identifies vulnerabilities first and then examines how alternative future scenarios expose those vulnerabilities. Planning and design choices are focused on what outcomes are acceptable or unacceptable, rather than defining and relying on a likely range of futures. Section 2.2 provides a more detailed description of the threshold (bottom-up) decision-making framework.

Decision makers may experience ***regret*** in one of two forms. One is regret associated with insufficiently investing in infrastructure to prepare for changes in climate. In this case, the results are excessive damages and negative effects on the public health, safety, and welfare. The second form is regret associated from overinvesting and consuming resources that could be better used elsewhere. Since the future is unknown, planners and designers cannot objectively "minimize" regret. However, this *Guide* provides tools and procedures that promote an understanding of the uncertainty associated with projecting future conditions and integrating that with the uncertainty associated with existing data, tools, and models for hydrologic and coastal design.

A probabilistic risk framework can be applied within either traditional or threshold decision frameworks to evaluate consequences and potential regret. A probabilistic risk framework is one in which the joint probabilities of different types of events (e.g., hurricane) and their responses (e.g., storm surge) are determined, and where those results are used to make risk-based decisions.

With the context of these design-making frameworks, this *Guide* describes how planners and engineers can adapt existing tools for analysis and design to address the potential effects of a changing climate. The remainder of this chapter provides additional description of the decision-making frameworks and introduces the concept of levels of analysis. Guidance for selecting a decision-making framework is provided in Section 2.3

2.1. Traditional (Top-Down) Framework

Transportation infrastructure design teams typically follow a traditional (top-down) design approach with varying ***levels of analysis*** depending on the nature of the project. The project design team bases the selection of an appropriate level of analysis on the criticality of the project, expected service life, the vulnerability of the project to climate change, the functional classification of the project (roadway, bridge, or tunnel), regulatory requirements, and the resources available for the project. These factors are not independent. For example, available project resources are usually linked to, and often dictated by, the type of environmental review process required for the project. The environmental review process is often closely tied to a particular funding program.

A higher level of analysis requires more effort (resources) to conduct and also incorporates more information about historical and possible future climate as shown in Figure 2.1. The goal of using higher levels of analysis is a more informed basis for decision making for those projects for which the investment is justified. The following sections provide an overview of levels of analysis for inland hydrology and coastal projects, respectively.

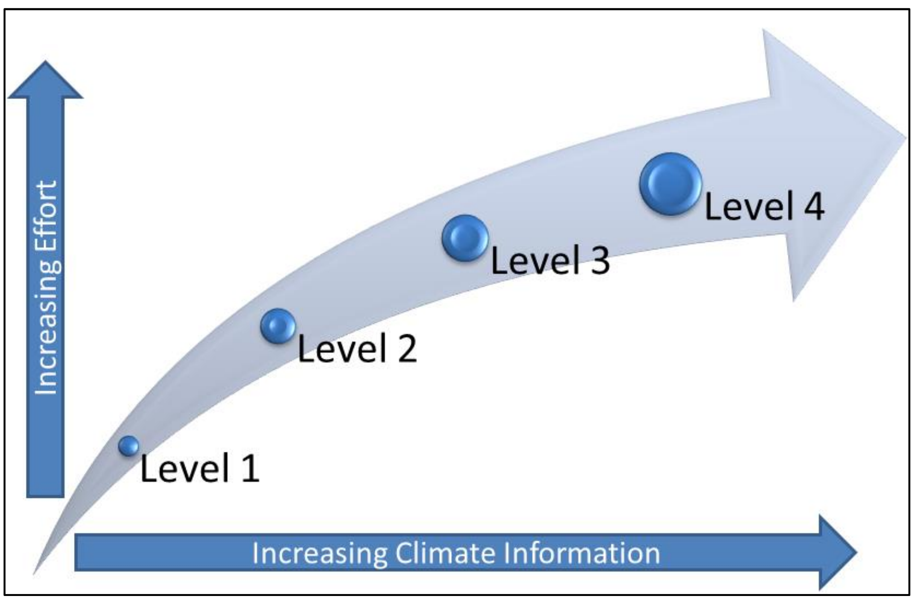

Figure 2.1. Levels of analysis, effort, and climate information.

2.1.1 Inland Hydrology

HEC-17 describes a generalized hierarchy of traditional (top-down) analyses for inland hydrology (Kilgore et al. 2016). These levels, ordered from least to most intensive, not only apply to specific bridges, culverts, or other hydraulic structure projects, but also to plans that may include multiple hydraulic structures or other natural or constructed features.

At each level of analysis, the design team chooses the hydrologic tools and methods appropriate for the project and site-conditions given the governing guidance and appropriate design practice. Beginning at Level 2, the concept of ***confidence limits*** for estimating discharge is employed. Confidence limits define a range in which the true value of discharge is expected to lie with a given probability. The levels of analysis for inland hydrology are summarized as follows:

Level 1 – Design discharge based on historical data. The design team applies the appropriate hydrologic design techniques based on historical data to estimate the design discharge. In addition, the design team qualitatively considers possible changes in the estimated design discharge based on future changes in land use and climate, e.g., precipitation.

Level 2 – Design discharge based on historical data/confidence limits. The design team performs all Level 1 analyses. In addition, the design team quantitatively estimates a range of discharges (confidence limits) based on historical data to evaluate plan/project performance.

Level 3 – Design discharge based on projected information/confidence limits. The design team performs all Level 2 analyses. In addition, the design team obtains and applies existing quantitative projections of changes in land use and climate, where feasible. The design team performs hydrologic analyses using land use and climate projections, as applicable, to estimate projected design discharges and their associated confidence limits.

Level 4 – Design discharge based on projected information/confidence limits/custom evaluation. The design team performs the equivalent of the Level 3 analyses, but augments the analyses with customized projections of land use and climate and/or customized hydrologic modeling techniques. Customization usually requires augmenting the typical design team to include appropriate expertise in climate science and/or land use planning to secure site-specific projections and/or expertise in advanced hydrologic modeling techniques.

Each level of analysis represents increasingly involved project processes and builds on the information developed at lower levels of analysis. At levels 1 and 2, the design team conducts analyses with general skills and expertise that are characteristic of existing project design and planning teams. Moving to a Level 3 analysis requires the retrieval and analysis of projected climate information, which may require the addition of expertise to the project team. By definition, a Level 4 analysis will require additional tools and expertise. Section 4.1 provides guidance for selecting the appropriate level of analysis for inland hydrology projects.

2.1.2 Coastal Applications

HEC-25 Volume 2 describes a generalized hierarchy of traditional (top-down) analyses for coastal applications (Douglass et al. 2014). These levels, ordered from least to most intensive, not only apply to specific tunnel, bridge, and road projects, but also to plans or projects that may include multiple structures or other natural or constructed features.

Coastal vulnerability assessments and design activities may range from broad planning overviews to highly detailed investigations employing state-of-the-art modeling tools. This *Guide* presents techniques for different levels of analysis for these assessments. As with inland hydrology, the detail and degree of complexity grow with each subsequent level of analysis, with the intention that the quality and comprehensiveness of the assessment also increases. Suggested levels of analysis for coastal applications are as follows:

Level 1 - Use of existing data and resources. The design team uses existing inundation, e.g., Federal Emergency Management Agency (FEMA) or tsunami hazard maps, to determine the exposure of infrastructure under selected sea (lake) level change scenarios, and sensitivity to depth-limited wave or wave run-up processes.

Level 2 - Original modeling of storm surge and waves. The design team performs all Level 1 analyses for the initial assessment. The design team also performs original modeling of surge and wave fields for specified storm and climate change scenarios, or modeling of tsunami inundation under climate change scenarios, to provide more detailed information on water levels, waves, etc. for the specified conditions.

Level 3 - Modeling in a probabilistic risk framework. The design team performs original modeling of surge, sea levels, currents, and waves, or tsunamis, including the potential effects of climate change, in a probabilistic risk framework. The specified storms and climate change scenarios are expanded from Level 2.

Each level of analysis represents increasingly involved project processes and builds on the information developed in the lower levels of analysis. Section 10.1 provides guidance for selecting the appropriate level of analysis for coastal applications.

2.2. Threshold (Bottom-Up) Framework

The numerous sources of uncertainty involved in climate modeling and sea level rise projections, inland hydrologic analyses, and coastal hydrodynamic analyses represent a significant challenge for traditional (top-down) approaches. For that reason, planners and designers are increasingly considering alternative ***threshold (bottom-up)*** decision-making frameworks for inland and coastal applications. In such a framework, the goal can be summarized as "assess vulnerabilities and seek robust solutions to minimize regret." In the threshold (bottom-up) paradigm, the relevant questions are, "how does my system work?" and "under what circumstances might it fail?"

In a threshold (bottom-up) framework, the first step is to identify the vulnerabilities or thresholds of a location or system. For example, in the case of a tunnel, the planning/design team identifies at what elevation a coastal or riverine flood would begin to enter the tunnel affecting its performance. Other potential vulnerabilities are also identified.

Next, the planning/design team evaluates the possibilities of those conditions occurring. This process could include the development of "climate narratives" that capture projected future conditions. These narratives are evaluated to see which of the vulnerabilities identified are exposed by the climate narrative and to identify the consequences of that exposure.

Finally, the planning/design team considers the vulnerabilities and the exposure consequences from various climate narratives to evaluate or design infrastructure intended to serve its function for a certain service life. The team identifies a range of policies, plans, or designs that perform reasonably well across that range of climate narratives, minimizing expected regret in decision making. Regret may be in the form of not preparing for climate change and bearing the consequences if projected conditions occur or, alternatively, in the form of over preparing for climate change if projected conditions do not occur.

The threshold (bottom-up) approach can be used for:

- Evaluating existing transportation infrastructure such as roads, bridges, and tunnels, and their associated hydraulic structures, to assess which possible future outcomes may unacceptably threaten the transportation infrastructure.
- Designing new elements of the transportation infrastructure to assess which possible future outcomes may unacceptably threaten the transportation infrastructure.
- Evaluating the value of the threshold (bottom-up) approach itself, in contrast to traditional (top-down) approaches, in the form of pilot studies.

2.3. Selecting a Decision-making Framework

Both traditional and threshold frameworks have advantages and limitations. The choice depends on many factors including the project goal, the perspective of the project team, project context, and potential adaptability of the project. Figure 2.2 summarizes these factors and illustrates that they exist on a continuum, with one side favoring traditional decision making and the other favoring threshold decision making. However, planners and designers should recognize that these are general characterizations only.

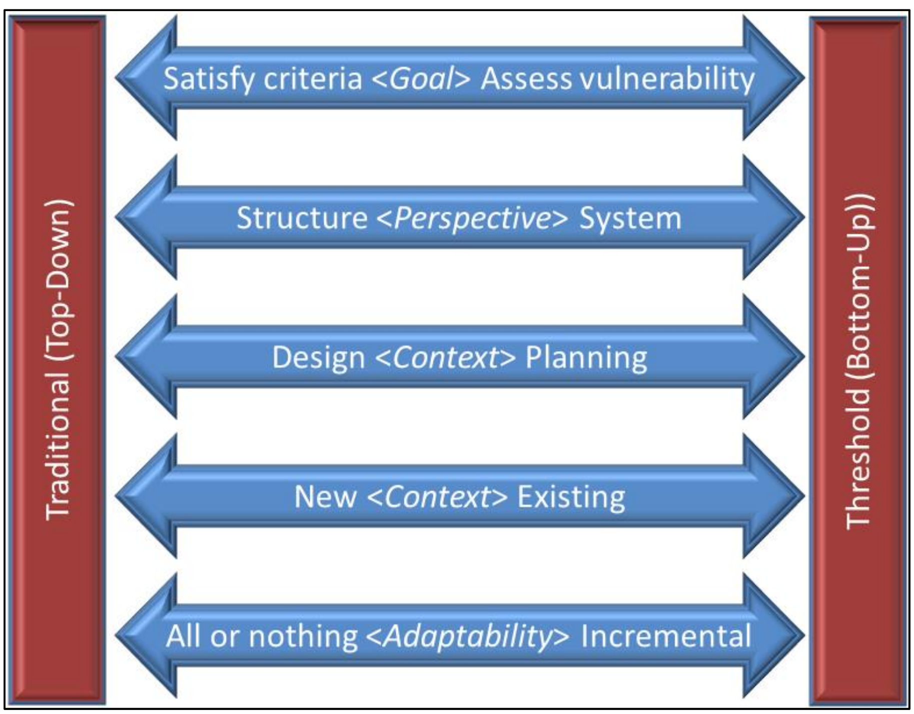

Figure 2.2. Considerations for choosing a decision-making framework.

If the objective of a project is to design a new individual structure with fixed design criteria, traditional (top-down) decision making is often the preferred choice. However, if the objective is to plan possible options for enhancing an existing system of infrastructure by identifying its vulnerabilities, threshold decision making is likely to be a more valuable approach. Beyond these two extremes, the relative importance of each of the factors shown in Figure 2.2 will influence the choice of a decision-making framework.

Figure 2.2 also refers to the potential for project adaptability for selecting the decision-making framework. Can the project be implemented in an incremental manner over time as conditions change or is the project such that it must all be built at one time to serve its function? While many types of infrastructure may have adaptable features, such as building in additional bridge width to add lanes later, design choices are often fixed and are not easily incrementally expanded or modified. For example, a culvert installed in a roadway embankment, cannot easily be expanded to accommodate future increases in discharge.

To illustrate the differences in the two decision-making frameworks, consider a vulnerability pilot project performed by the Connecticut Department of Transportation (CTDOT) of its bridges and culverts in the northwest part of the state (Connecticut Department of Transportation 2014). Furthermore, consider one of the culverts included in the study, known as structure number 02423, that was built in 1950 over an unnamed waterway. This structure was designed using the traditional decision-making framework to satisfy applicable design criteria related to the 1% AEP and 0.2% AEP (100-year and 500-year return periods) including providing adequate freeboard and maintaining an allowable headwater to diameter ratio (HW/D). (Headwater is the depth of water at the upstream end of a culvert measured from the bottom of the culvert at that location.)

CTDOT computed the relationship between headwater and discharge for the culvert shown in Figure 2.3. As discharge increases, the headwater also increases. The figure shows that the headwater at both the 100-year and 500-year design discharges are lower than relevant thresholds including the HW/D and freeboard criteria. Therefore, the culvert design more than satisfied these criteria suggesting that other considerations led to the size and type of culvert built.

In the pilot study, CTDOT considered the vulnerability of this culvert to current (higher) estimates of design discharge as well as to potentially higher discharges in the future that might occur because of a changing climate. Continuing with the traditional decision-making framework, the next task would be to estimate a future design discharge or discharges and evaluate the culvert with those estimated discharge(s).

A threshold decision-making framework could also be applied for this purpose. Referring to Figure 2.3 one can determine that the HW/D and freeboard criteria are reached at discharges of 2,330 cubic feet per second (cfs) and 2,700 cfs, respectively. Water would begin to flow over the road (referred to as overtopping) at a discharge of 2,900 cfs.

As described in Section 2.2, the threshold decision-making framework begins by defining the vulnerabilities and then evaluating the possibilities of such conditions occurring. For the first step, the planning/design team evaluates whether violation of the criteria (in this case HW/D or freeboard) represents a problem. At these levels, is there flooding of property or are there threats to the public safety? Are velocities at the culvert exit a threat downstream or do they present an erosion threat that could cause failure of the roadway? Similarly, at the threshold of overtopping, what are the answers to these same types of questions?

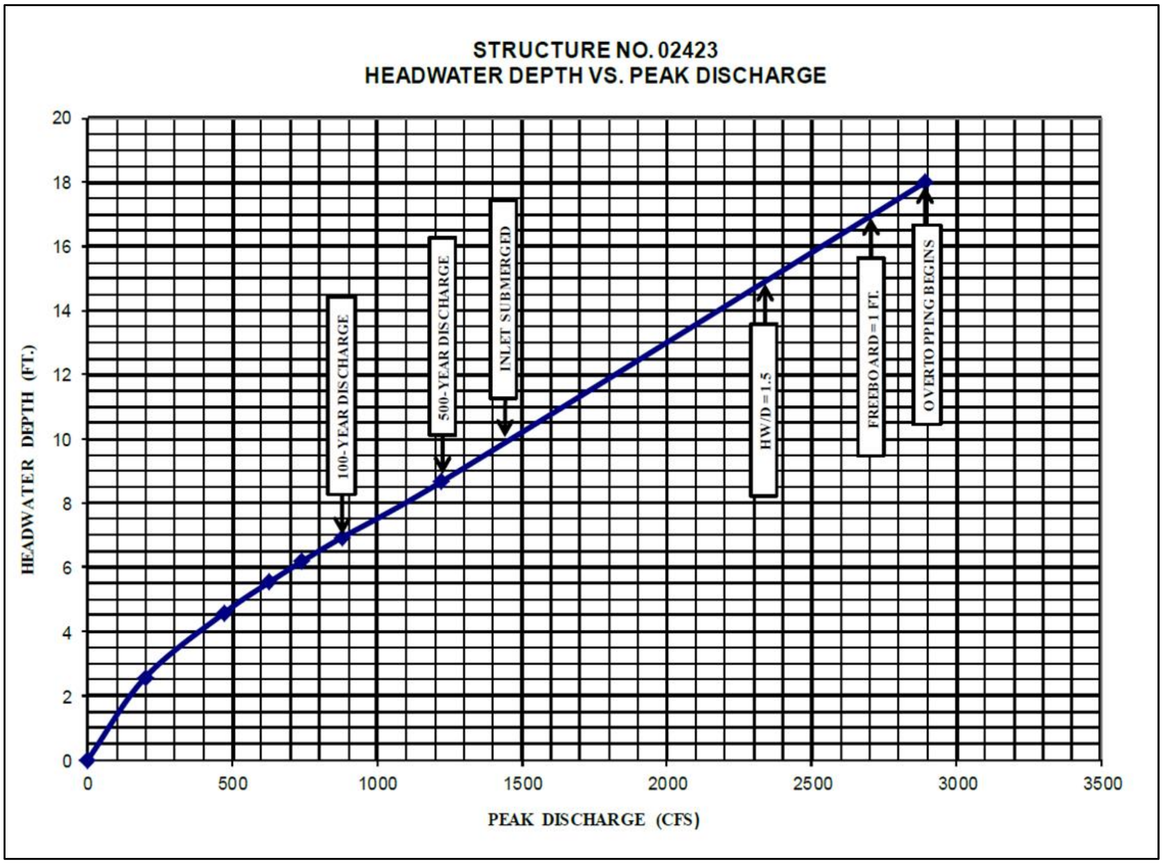

Figure 2.3. Relationship between headwater and discharge for structure 02423 (Connecticut Department of Transportation 2014).

Once the thresholds of concern are identified, then the possibility of such events occurring are evaluated. In the example, if it was determined that threshold of concern is overtopping, under what possible scenarios could a discharge of greater than 2900 cfs occur? For this culvert, a 2900 cfs discharge would be a very large increase over the existing design discharge suggesting that the vulnerability of this culvert to climate change may be low.

The threshold decision-making approach can be extended beyond the assessment of a particular structure to a larger system or collection of structures. In the pilot study, CTDOT evaluated numerous culverts in the state to identify those that were the most vulnerable. In this way, resources available to address vulnerabilities could be prioritized to those locations with the greatest threats. Referring to Figure 2.2, CTDOT approached their pilot study with the threshold approach because they were interested in assessing vulnerabilities, it was within a planning context to evaluate their resource allocation, and they were evaluating existing structures. Each of these point toward the threshold decision-making framework. Their study did not address responses to identified vulnerabilities which leads to the questions about whether corrective action would require an "all or nothing" type replacement or if there are incremental changes available to address vulnerabilities.

The tools provided in this *Guide* can be used to support either traditional or threshold decision making. As this example demonstrates, traditional and threshold decision-making frameworks should not be considered mutually exclusive. They can be blended so that the advantages of each are brought to the decision-making and design processes.

Part II: Inland Hydrology

Chapter 3. Selecting Downscaled Global Climate Model Precipitation for Hydrologic Analysis and Design

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§2.2.3 Factors affecting flood runoff/meteorological characteristics

§2.3.2 Data sources/sources of hydrologic data

§14.3 Factors influencing service life.

This chapter provides methods and guidance for selecting precipitation projections for hydrologic analyses and design. As the climate changes, historical weather records are becoming less representative of future conditions over the lifetime of many structures. To account for the influence of a changing climate on precipitation averages and extreme events, hydrologic analyses can combine information from historical observations with future climate projections. This chapter provides guidance for the appropriate selection of high-resolution climate projections for hydrologic analysis and design of transportation infrastructure.

Section 3.1 provides guidance for selecting one or more future ***scenarios***. Scenarios are sets of assumptions used to help understand potential future conditions such as population growth, land use, and sea level rise. Scenarios are neither predictions nor forecasts (USGCRP 2018). Future climate projections are based on a range of plausible scenarios reflecting human choices that determine the effect of human activities on climate in terms of greenhouse gas emissions. Scenarios are used as input to global climate models (GCMs), which simulate the physical processes of the climate system and calculate resulting changes in temperature, precipitation, and other relevant climate variables.

Section 3.2 provides guidance on selecting a high-resolution dataset of climate projections. The spatial resolution of a typical GCM is relatively coarse compared to the spatial scale required by most hydrologic applications. For that reason, GCM outputs are typically ***downscaled*** to higher spatial and/or temporal resolutions using a regional climate model (RCM), an empirical-statistical downscaling model (ESDM), or both. (Downscaling is a procedure to develop higher-resolution information from lower-resolution information that can include spatial disaggregation, temporal disaggregation, adjustment for systematic error through bias correction, modeling by higher-resolution deterministic physical process-based models, or some combination of the above.)

Section 3.3 provides guidance for selecting GCMs. GCMs are physically based models that simulate the internal natural variability and the response of global climate systems to external forces, both natural and human. There are currently more than 40 GCMs that are developed and maintained by climate modeling groups around the world. Because it is not possible to identify a single "best" GCM or "most likely" scenario, working with climate projections requires the selection of one or more scenarios and multiple GCMs.

Chapter 2 introduced the concept of levels of analysis, because not all projects require the same investment in estimating future conditions. The guidance in this chapter is applicable to projects where the more rigorous Level 3 or 4 analyses are justified. The next chapter (Section 4.1) provides guidance on selecting an appropriate level of analysis for projects.

3.1. Selecting Climate Scenarios

This section provides guidance for selecting one or more future scenarios. Most climate models and datasets provide projections that quantify future change and the corresponding effects on climate variability and extremes under multiple future scenarios that reflect a range of possibilities over a future period.

Climate projections cover a broad range of possible futures, from scenarios where carbon emissions continue to grow (e.g., Representative Concentration Pathway [RCP] with a radiative forcing of 8.5W/m^2 by 2100 [RCP8.5], Special Report on Emission Scenarios [SRES] A1FI and A2), to scenarios where emissions peak, then begin to fall (e.g., RCP6.0 and RCP4.5 or SRES B2 and B1), and even scenarios where carbon emissions are eliminated before the end of the century (RCP2.6). GCMs that contribute to the Coupled Model Intercomparison Project (CMIP) use these future scenarios as input to future model runs. The Fourth National Climate Assessment (NCA4) classifies the scenarios as “Higher,” “Mid-High,” “Lower,” or “Even Lower,” as summarized in Table 3.1 (USGCRP 2017, 2018). (See Kilgore et al. 2019, Section 4.3.3.1 for more detail on scenarios.)

Table 3.1. Climate scenario classification from both the CMIP3 and CMIP5 archives.

CMIP	Higher	Mid-High	Lower	Even Lower
CMIP3	SRES A1FI	SRES A2	SRES B1	N/A
CMIP5	RCP8.5	RCP6.0	RCP4.5	RCP2.6

The CMIP periodically coordinates GCM simulations from the latest generation of models that are developed and maintained by climate modeling groups around the world to conduct a series of specific experiments aimed at improving scientific understanding of both past and future climate. The CMIP then archives their output and maintains an archive of the GCM simulation output. The previous archive was CMIP3; the most recent archive is CMIP5. Simulations for the CMIP6 archive are in progress, and output is expected to be available by 2020 or shortly thereafter.

If the project service lifetime is approximately 30 years or less, scenario selection is not critical because there is no substantial difference among the changes that result from a higher versus a lower scenario over shorter time horizons. For such analyses, any or all of the scenarios in Table 3.1 can be used, with a focus on obtaining as many individual GCMs (see Section 3.3) as possible to capture the range of natural variability. In some cases, historical climate information over recent decades, rather than the complete historical record, can be used to inform decision making for shorter project service lifetimes (Meyer et al. 2014).

If the project service lifetime is longer than 30 years, scenarios are an important consideration. Unless there is a specific reason not to consider one end of the scenario range or the other, at a minimum, one higher and one lower scenario should be considered in the analysis and design. When assessing multiple scenarios more than 30 years into the future, do not average across the scenarios. Scenarios are entirely independent and should be treated as such.

Exception 1: If an asset is a critical part of the infrastructure system and its loss would cause unacceptable disruption or danger, a higher scenario should be used to ensure the design can withstand the effects associated with the more extreme conditions expected under a higher scenario.

Exception 2: If an asset is of lesser criticality and the difference in cost between designing for a lower or higher scenario is significant, in some cases it may suffice to design for a lower scenario and accept the risk.

Most existing high-resolution climate projection datasets discussed in the following section typically provide projections for selected higher and lower scenarios. When customized projections are being used, there may be a broader choice of scenarios.

A higher scenario generally leads to higher global temperatures, but may not always correspond to increases in flood risks. In addition, within a scenario flood risks may increase in the short term and then decrease. This possibility provides additional rationale for considering multiple scenarios whenever feasible.

BOTTOM LINE: When assessing multiple scenarios more than 30 years into the future, do not average across the scenarios. Scenarios are entirely independent and should be treated as such.

3.2. Selecting High-Resolution Climate Projections

This section provides guidance for selecting a high-resolution datasets of climate projections. As with scenarios and global climate models, there is no one-size-fits-all "best" choice of projections or downscaling methods or models for all applications. The scope of the hydrologic assessment defines what the most appropriate source of information may look like.

There are two types of high-resolution datasets: those generated by an ESDM and those generated by an RCM. If the project only requires site-specific precipitation and/or temperature, then a dataset generated by an ESDM is appropriate. For projects requiring multiple climate variables and/or for a region with sparse historical weather station observations, an RCM is recommended.

Selecting an ESDM Dataset. Eight high-resolution gridded datasets of climate projections generated by ESDMs are currently available: Asynchronous Regional Regression Model (ARRM), Bias-Correction Constructed Analogs (BCCA), Bias-Correction Spatial Disaggregation (BCSD), Localized Constructed Analogs (LOCA), two different Multivariate Adaptive Constructed Analogs products trained with different observed gridded products (MACAv2-METDATA, MACAv2-Livneh), NASA Earth Exchange Downscaled Climate Product (NEX-DCP30), NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP), and WorldClim. (See Kilgore et al. (2019) Section 4.2.9.2 for information on these datasets).

For the purposes of hydrologic design and analysis of transportation infrastructure, engineers are discouraged from using BCCA, MACAv2-METDATA, MACAv2-Livneh, and WorldClim. These approaches either do not produce daily outputs, do not use statistical methods that resolve the shape of the distribution of daily variables, or both.

The remaining five datasets can be used to design transportation infrastructure for specific types of applications. Of these five datasets, the ARRM and the LOCA datasets are recommended because they use methods that resolve extreme precipitation. ARRM only includes simulations from the older generation of CMIP3 GCMs. LOCA uses the more recent CMIP5 GCMs. Both methods provide 24-hour precipitation. Internal analysis has shown that near the coastline and in areas of very complex topography the ARRM product has a bias in extreme high temperatures. However, this caveat should be extended to all downscaling approaches (and in fact to all observational datasets, as well) for regions of very complex topography.

The BCSD and NEX-DCP30 datasets are recommended when long average daily precipitation is needed. For example, monthly precipitation values may be adequate as input to a groundwater model or for a wetlands assessment. These methods are not recommended if daily or shorter duration precipitation extremes are required.

If information outside the U.S. is required, the NEX-GDDP dataset should be used.

Selecting an RCM Dataset. Currently, there are two datasets of dynamically downscaled climate projections from RCMs: the North American Regional Climate Change Assessment Program (NARCCAP) and the North American component of the international Coordinated Regional Downscaling Experiment (NA-CORDEX). The NA-CORDEX dataset is recommended because it includes a higher and a lower scenario, its RCM simulations are driven by updated CMIP5 GCMs, and it includes outputs for a broad range of surface and upper-air variables at daily and even sub-daily temporal resolution. However, its resolution is still coarser than many of the ESDM datasets. The NARCCAP dataset is deprecated because it only includes one scenario, has a limited time period of output, and has a relatively coarse spatial resolution.

Table 3.2 summarizes the recommended datasets including the GCM generation, future scenarios, spatial resolution (grid cell size), and other characteristics of these datasets. All four of these datasets provide information for the continental United States. NARCCAP and NA-CORDEX include the southern portion of Alaska; ARRM includes all of Alaska. None of the gridded datasets in this table include Hawaii. However, NEX-GDDP may be used for Hawaii.

BOTTOM LINE: At this time, most applications requiring quantitative precipitation estimates should prioritize the LOCA dataset. It is important to note, however, that this choice may not be appropriate for all applications.

3.3. Selecting Climate Models

This section provides guidance for selecting climate models. GCMs simulate the response of global climate to interactions between land-surface processes, ocean and atmospheric circulation, biogeochemical processes, and human influences such as the release of greenhouse gasses into the atmosphere, land use changes, and more.

CMIP Selection. When selecting which GCMs to use, simulations from newer models in the most recent CMIP should be prioritized over simulations from older GCMs used in previous CMIPs. Newer CMIPs generally have a larger selection of GCMs, including newer generations of older GCMs along with newer GCMs that increasingly include other aspects of the climate system, such as the biosphere, cryosphere, and an interactive carbon cycle. However, if resources are available to use simulations from a large number of GCMs, simulations from multiple CMIPs can be pooled because projected changes in extreme precipitation from CMIP3 and CMIP5 simulations are broadly comparable (e.g., Knutti and Sedláček 2013, Kumar et al. 2014, Sheffield et al. 2013 and 2014). A limitation of CMIP3 is that some of the models did not save temporally continuous outputs, though most did.

Table 3.2. Four recommended high-resolution datasets of temperature and precipitation.

Characteristic	ESDM Datasets		RCM Datasets	
	ARRM	**LOCA**	**NARCCAP**	**NA-CORDEX**
CMIP Generation	CMIP3	CMIP5	CMIP3	CMIP5
Future Scenarios	A1FI, A2, A1B, B1	RCP4.5, RCP8.5	A2	RCP4.5, RCP8.5
Time Period of Output	1960-2099	1950-2100	1968-2000, 2038-2070	1950-2100
Time Frequency	Daily	Daily	3-hourly	Daily
Spatial Resolution	1/8th degree (~12 km)	1/16th degree (~6 km)	50 km	25-50 km
Obs. Training Dataset	Maurer[1]	Livneh[2]	not applicable	not applicable
Number of GCMs	16	30	4	6
Number of Group 1 GCMs	13	14	3	0
Number of RCMs	not applicable	not applicable	8	6

[1] USBR. (2013).
[2] Livneh et al. (2013).

GCM Selection. To ensure a robust design, all engineering analyses should use multiple GCMs. GCMs are extensively evaluated for their ability to reproduce observed large-scale physical characteristics and patterns of natural and human-forced variability in the climate system. A number of studies have found that using the average of multiple GCMs, for a given scenario, tends to provide a more accurate representation of observed climate than simulations from any single model (Kotamarthi et al. 2016, Hosseinzadehtalaei et al. 2017).

This *Guide* recommends prioritizing the use of "***Group 1 GCMs***" listed in Table 3.3. There are 15 CMIP3 and 21 CMIP5 GCMs in Group 1. Group 1 GCMs are defined as multi-generational versions (typically third to fifth) of long-established GCMs from modeling groups with decades of experience, whose performance is well documented in the literature. Other GCMs exist and may be available from data repositories, but are not recommended unless a larger ensemble of GCMs is desired to encompass a broader range of natural variability.

Engineers should use output from GCMs from all three sensitivity categories (high, medium, and low). As shown in Table 3.3, Group 1 GCMs are grouped by high, medium, and low climate sensitivity as defined by the response of global temperature to increasing levels of carbon dioxide in the atmosphere. Using a range of sensitivity values ensures the resulting projections encompass the basic range of scientific uncertainty in terms of the response of the climate system to human forcing.

A project should use as many GCMs as logistics permit. However, the minimum number of GCMs depends on the analysis objectives. For example, to compute a screening indicator, such as the climate change indicator (CCI) described in Section 4.4, at least three Group 1 GCMs should be selected, one from each category of climate sensitivity (high, medium, and low). For example, in Table 3.3, three CMIP5 Group 1 models that encompass the range of climate sensitivity are MRI-CGCM3, CCSM4, and GFDL-CM3.

Table 3.3. Climate sensitivity of Group 1 models from both the CMIP3 and CMIP5 archives (Randall et al. 2007; Flato et al. 2013).

CMIP	Low		Medium		High	
CMIP3	CCSM3	2.7°C	CGCM3.1 (T47)	3.4°C	IPSL-CM4	4.4°C
	GISS-EH	2.7°C	CGCM3.1 (T63)	3.4°C	MIROC3.2(hires)	4.3°C
	GISS-ER	2.7°C	CSIRO-Mk3.0	3.1°C	MIROC3.2(medres)	4.0°C
	INM-CM3.0	2.1°C	ECHAM5-MPI-OM	3.4°C	UKMO-HadGEM1	4.4°C
			GFDL-CM2.1	3.4°C		
			MRI-CGCM2.3.2	3.2°C		
			UKMO-HadCM3	3.3°C		
CMIP5	GISS-E2-H*	2.3°C	BCC-CSM1.1	2.8°C	CSIRO-Mk3.6.0*	4.1°C
	GISS-E2-H-CC	2.3°C	BCC-CSM1.1-m*	2.9°C	GFDL-CM3*	4.0°C
	GISS-E2-R*	2.1°C	CCSM4*	2.9°C	HadGEM2-A	4.6°C
	GISS-E2-R-CC	2.1°C	CNRM-CM5*	3.3°C	HadGEM2-CC*	4.6°C
	INM-CM4	2.1°C	CNRM-CM5-2	3.3°C	HadGEM2-AO*	4.6°C
	IPSL-CM5B-LR	2.6°C	GFDL-CM2.1	3.4°C	IPSL-CM5A-LR*	4.1°C
	MRI-CGCM3*	2.6°C	HadCM3	3.3°C		
			MIROC5*	2.7°C		

*Model simulation available from the Localized Constructed Analogs (LOCA) statistically downscaled dataset.

When using the LOCA dataset, it is recommended that the design team download the needed output from the 14 Group 1 models for both the lower (RCP4.5) and higher (RCP8.5) scenarios. Twelve of the 14 Group 1 models available in the LOCA dataset are listed in Table 3.3. The two omitted models (FGOALS-g2 and IPSL-CM5A-MR) do not have their climate sensitivity ranked (Flato et al. 2013). If a smaller subset of Group 1 models is used rather than all 14 Group 1 models, to ensure the entire range of sensitivity is evenly represented, the two unranked models are not recommended.

If a design team requires or prefers a smaller number of more regionally-appropriate GCMs because the project is in a region characterized by one or more regional-scale weather phenomena associated with extreme rainfall, GCM selection should be based on expert opinion from a climate scientist familiar with a GCM's ability to simulate regional climate dynamics and reflect the consensus of the peer-reviewed literature with respect to the project's objectives and context. Examples of such phenomena could include atmospheric rivers on the West Coast, the North American monsoon for the southwestern United States, night-time thunderstorm systems in the Midwest, jet stream blocking in the central and eastern United States, and convective rainfall and hurricanes along the Gulf and East Coasts.

DO NOT limit the GCMs or future scenarios to be considered by trying to identify the "most likely scenario" or "best models" (e.g., through calculating model biases compared to observations or historical events). Attempts to identify a "best" subset of models that are not based on an analysis of climate dynamics are more likely to generate false confidence in future performance, which cannot be guaranteed through historical analysis alone, than provide useful information. There is no one "most likely scenario," nor is there one single "best" climate model or (except in rare circumstances related to a specific phenomenon as described above) a small sub-set of "best models."

3.4. Additional Guidance

Future condition design flows using rainfall/runoff modeling should be based on the mean of the appropriate design precipitation values estimated separately for each scenario and tested based on precipitation values from each scenario. Future scenarios are not assigned a probability because they involve human choices rather than physical systems. Each scenario can be considered to be one plausible outcome with multiple scenarios capturing a range of plausible outcomes. See Section 6.1 for a detailed description of the recommended analysis procedure for estimating precipitation from multiple models and scenarios.

In the future, these recommendations may be updated as more resources become available. For example, the Seasonal Trends and Analysis of Residuals (STAR-ESDM) dataset, which is scheduled for release in Spring 2019, will provide gridded and downscaled CMIP5 temperature and precipitation at a 1/16th (~6 km) degree spatial resolution across the United States, 1/12th degree resolution across Canada, and point information for several thousand individual weather stations across North and Central America (Hayhoe and Stoner, personal communication). In addition, although NA-CORDEX does not yet include a sufficient number of simulations for recommended use, more will be added over time and it is anticipated that it will become the most comprehensive and up-to-date dataset of RCM output available for use in North America.

Finally, as an alternative to retrieving data from a specific dataset on a project-by-project basis, states or organizations may contract with universities or consultants to develop information that engineers may consult in the same way that NOAA Atlas 14 (e.g., Perica et al. 2013) is used for historical precipitation estimates. Recommended methodologies for implementing this approach are discussed in Section 6.2.4.

Incorporating climate change into hydrologic design of transportation infrastructure does not necessarily require changes in the evaluation tools used to compute design discharges or in existing practice for when and how those tools should be used. This chapter provides guidance for several aspects of the process for incorporating climate change into hydrologic design. Section 4.1 provides guidance for design and planning teams to select an appropriate level of analysis for a given project. Section 4.2 provides an overview of the design methods presented in detail in later chapters. Section 4.3 provides brief commentary on issues related to precipitation as snow versus rain, while Section 4.4 describes a simple tool that can be used to compare projected precipitation changes to historical precipitation variability – the climate change indicator (CCI). Finally, regional variations in the assessment of climate change are provided in Section 4.5.

4.1. Selecting the Appropriate Level of Analysis

Current analysis and design practices for the hydrologic design of transportation infrastructure vary by project and context. Key considerations include the criticality of the project, expected service life, functional classification of the roadway, regulatory requirements, type of project, and resources available for the project. Depending on these factors, some projects warrant more extensive evaluation and analysis than others.

The same is true when considering these same projects under future climate. The only difference is that, in addition to the previously listed considerations, the project team must consider the vulnerability to – and and risks associated with – potential climate change. To this end, four levels of analysis for inland hydrology were identified in Section 2.1.1; they range from the most basic level of analysis (Level 1) to the most comprehensive (Level 4).

The selection of the appropriate level of analysis can be informed by this *Guide,* a State DOT, or some other authoritative governmental entity. Useful information for this selection may include information or tools that are provided by an entity that has considered a set of issues or provided computational tools for use by a larger set of planners and designers so that project teams do not need to reevaluate the same topics on a project-by-project basis. State DOT hydraulic design manuals are examples of information specifying what project teams should do, or tools that they should use, under a given set of circumstances. States or others can further develop resources to define and guide what their jurisdictions should do to address climate change.

The following subsections provide guidance for selecting the appropriate level of analysis and describe resources that may be employed as part of that analysis. The planning or design team is ultimately responsible for selecting the appropriate level of analysis based on the full range of factors discussed previously. It is anticipated that most projects will be adequately addressed at Levels 1 and 2, and very few projects will justify a Level 4 analysis.

4.1.1 Level 1 Analysis – Design Discharge Based on Historical Data

Level 1 represents the exercise of techniques and protocols without explicitly incorporating the potential for climate change. For a Level 1 analysis, the design team applies traditional hydrologic design techniques for estimating a design discharge based on historical climate and watershed data. In addition, the design team qualitatively considers changes in the estimated design discharge based on possible future changes in land use and climate (e.g., precipitation).

The design team selects techniques and protocols according to applicable state or local guidance based on the type of project, its criticality, drainage area, and other factors. The design team chooses the appropriate rainfall/runoff model, statistical analysis, or other hydrologic technique appropriate for the project site.

One addition to traditional techniques and protocols is the use of readily available information for assessing the potential for climate change for that location. National, state, regional, or local organizations may have prepared information that has addressed projected precipitation or discharge trends or other guidance pertinent to the project location. The design team can use this information to determine if a Level 2 analysis might be appropriate. Generally, a Level 1 analysis will suffice for projects with low risks of damage or loss. For example, projects could be considered low risk if they would incur minor damage consequences as a result of flooding in excess of design conditions and/or had a shorter hydrologic service life.

If the qualitative assessment of future discharges suggests increasing discharges over the lifetime of the project, then the design team should conduct sensitivity analyses with higher discharges to explore the potential consequences of that possible outcome. Evaluating discharges higher than the design discharge does not change the design team's responsibility to satisfy applicable design criteria at the design discharge, but it does provide additional information regarding the exposure consequences of larger events. Using a culvert design project as an example, a Level 1 assessment could be as simple as evaluating the costs and benefits of increasing the culvert size by one standard size over the size required by applicable minimum design criteria.

Information supporting a qualitative assessment of future conditions as part of a Level 1 analysis could include maps and other information from the most recent U.S. National Climate Assessment (currently, NCA4; see Vol. 1 Chapter 7, Easterling et al. 2017) and, where relevant, the most recent assessment report from the Intergovernmental Panel on Climate Change (currently, IPCC AR5). Figure 2.1 is a sample resource that provides projected changes for two future scenarios to the 20-year return period for daily precipitation. The design team could use this information to assess the potential effects of higher precipitation on the project. If the assessment concludes that the effects may be important for the project, a Level 2 analysis should be conducted.

Another potential tool is the use of a "per degree" of global mean temperature increase approach, which is consistent with international targets such as the Paris Agreement that focus on global temperature goals. Though originally derived from scenario-based climate model simulations, projections per degree of warming are independent of a particular future scenario or time frame. This approach allows an estimate of future precipitation to be generated for a particular temperature increase or increases, with smaller increases likely over a few decades (e.g., +1^{o}C over 30 years; NCA4 Vol. 1 Chapter 4, Hayhoe et al. 2017) and larger increases (up to +5^{o}C; Hayhoe et al. 2017) more likely over longer time frames through the end of the century.

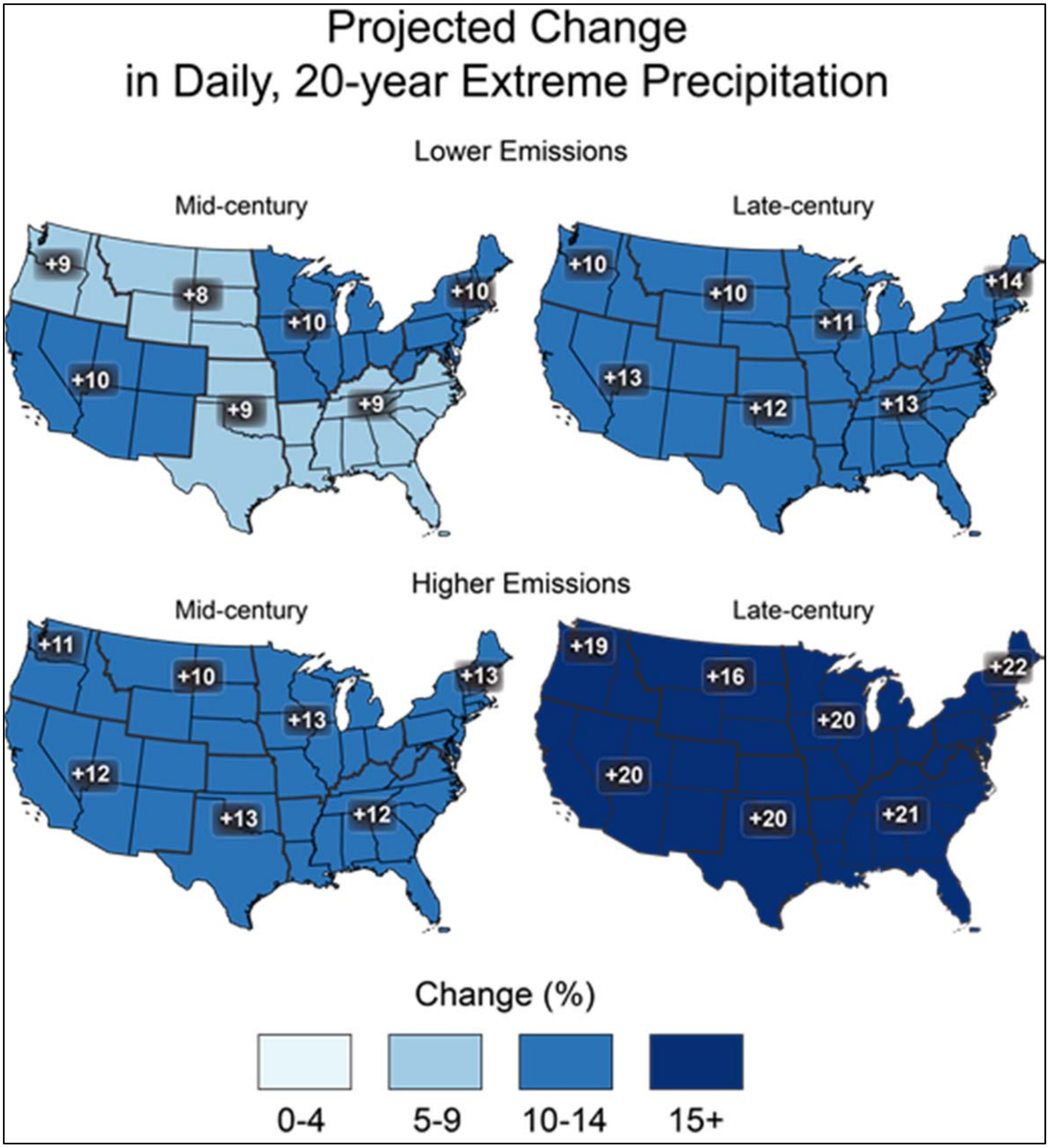

Figure 4.1. Projected change in the 20-year return period amount for daily precipitation for the mid- and late 21st century for a lower scenario (top, RCP4.5) and a higher scenario (bottom, RCP8.5), calculated from the LOCA dataset (Source: NCA4, Easterling et al. 2017).

Another example of useful information is publicly available precipitation/runoff modeling results, for example from the Variable Infiltration Capacity (VIC) model or the daily time step Precipitation-Runoff Modeling System (PRMS) National Hydrologic Model outputs from the U.S. Geological Survey (USGS) (Liang et al. 1994, Regan et al. 2018). Livneh et al. (2013)

produced a historical 1/16th-degree resolution dataset covering the continental United States with output from the VIC model. It is free to download and has daily and monthly output for variables such as precipitation, surface runoff, and evaporation. This dataset is also available at a 3-hourly temporal resolution upon request, and it has been used as the basis of daily and monthly streamflow projections using the BCSD empirical-statistical downscaling approach, combined with VIC simulations for CMIP3 GCM inputs.

The USGS has developed a National Climate Change Viewer that may be useful for assessing the potential climate changes at a project location. This web-based tool (available at https://www2.usgs.gov/climate_landuse/clu_rd/nccv.asp) provides projected changes in precipitation, snowfall, and runoff from a 1981-to-2010 baseline to three future time periods. The projections are based on two future scenarios (RCP4.5 and RCP8.5) and an ensemble of CMIP5 GCMs. While annual or monthly averages do not necessarily inform precipitation extremes, this tool can suggest whether overall changes at the location are expected to be significant or minor and also indicate whether the snow/rain mix may change in the future.

4.1.2 Level 2 Analysis – Design Discharge Based on Historic Data/Confidence Limits

For a Level 2 analysis, the design team performs all Level 1 analyses (qualitative and quantitative). In addition, the design team quantitatively estimates a range of discharges (confidence limits) based on historical data to evaluate plan/project performance.

By computing a range of discharges as determined from confidence limits, the design team explicitly considers the data uncertainty present in the historical record and uses that information to identify an appropriate range of conditions over which to evaluate the resilience of the proposed plan or project. Depending on the appropriate hydrologic design method, these confidence limits may apply to precipitation, land use, or flow data. The design team should consider the hydrologic model and input data uncertainty where such information is available. HEC-17 describes the development of confidence limits based on these uncertainties (Kilgore et al. 2016).

4.1.3 Level 3 Analysis – Design Discharge Based on Projected Information/Confidence Limits

A Level 3 analysis represents a transition from Levels 1 and 2, which focus on historical data, to Levels 3 and 4, which quantitatively incorporate projections of future climate into the project evaluation. A Level 3 analysis may start with computing the CCI as a measure of the potential change in magnitude of extreme precipitation. Described in detail in Section 4.4, the CCI can inform the design team regarding the potential importance of changing climate relative to the variability in the historical record.

In a Level 3 analysis, the design team computes quantitative estimates of projected discharge for the project. Depending on the specifics of the project and the applicable guidance, the design team will select the appropriate analytical tools to estimate projected design discharges and their associated confidence limits. Broad guidance for selecting appropriate tools, provided in Section 4.2, is based on whether the watershed is gauged or ungauged and whether event-based analysis or continuous simulation is most appropriate for the project objectives.

Some analyses will employ rainfall/runoff modeling or other techniques requiring future precipitation estimates for estimating future discharges. In those parts of the country that currently, or might in the future, experience precipitation in the form of both rain and snow, the engineer should consider future estimates of temperature to evaluate if a changing rain/snow mix may affect flood discharge estimates. (See Section 4.3 for additional information on the rain/snow mix.) Other Level 3 analyses will rely on techniques for analyzing future discharges that do not require estimates of future precipitation. These techniques are also outlined in Section 4.2.

When feasible, the design team should consider land use projections or other watershed characteristics that may affect future design flow conditions as part of a Level 3 analysis. Projections of land use are frequently available from local and regional planning agencies and are often presented as a series of scenarios and/or ranges. The U.S. Environmental Protection Agency's (EPA) Integrated Climate and Land Use Scenarios (ICLUS) database (U.S. EPA 2017) is a national source of future land use scenarios and impervious area projections. However, the EPA does not assign probabilities to these land use scenarios because they are predicated on human behavior and policy decisions that cannot be predicted with certainty, especially over longer time horizons.

With a Level 3 analysis, upper and lower confidence limits are developed and evaluated for projected conditions. The design team should consider both historical and projected confidence limits for developing a resilient plan/project.

4.1.4 Level 4 Analysis – Design Discharge Based on Projected Information/Confidence Limits/Custom Evaluation

For a Level 4 analysis, the design team performs the equivalent of the Level 3 analysis but customizes the analysis, because Level 3 analyses are not considered sufficient for the project. Customization may include using advanced modeling tools or developing project-specific data. Customization may also include expanding the design team to include personnel with appropriate expertise in climate science, advanced hydrologic modeling, and/or land use planning to secure more advanced and targeted analyses and information.

As with all levels of analysis, the design team should choose the most appropriate models and tools for the situation. The rationale for moving to a Level 4 analysis might include a response to one or more of the following needs:

- Insure the resilience of a critical and/or high-cost plan or project.
- Better understand the magnitude of climate change under various future scenarios for plans or projects with a long service life.
- Identify a subset of GCMs and scenarios appropriate for a given project and location.
- Explore alternative high-resolution climate datasets, other than those readily available, as described in Section 3.2.
- Evaluate new high-resolution climate datasets.
- Apply Regional Climate Models (RCM) or Convection-Permitting Models (CPMs).
- Customize land use or other watershed characteristic projections.

- Apply advanced hydrologic models or customized/experimental modeling tools.

Regardless of the data or tools used, the objective of a Level 4 analysis is to produce a range of conditions over which the design team can evaluate the resilience of the plan or project.

BOTTOM LINE: Since the needs and characteristics of each project are unique, the decision about the appropriate level of analysis rests with the design team. Most projects will be adequately addressed at Levels 1 and 2, and very few projects will justify Level 4 analysis.

4.2. Selecting Appropriate Hydrologic Methodologies

The intent of this *Guide* is to augment state DOT guidance and procedures so that planners and engineers can assess the effects of potential climate change on transportation infrastructure. Therefore, this *Guide* focuses on how planners and engineers can adapt methodologies currently used for deriving hydrologic estimates for design. Engineers currently select an appropriate methodology based on the watershed characteristics, the availability of data, and the applicable guidance (e.g., from the state DOT). Assessing for climate change does not necessarily alter this selection process, though some methods may not be as easily adapted to future conditions as others. As engineers become more experienced in assessing the effects of climate change, climate projections improve, or new tools are developed, the use of some existing hydrologic tools may evolve or fall out of use.

Table 4.1 lists the hydrologic methods explicitly discussed in this *Guide*. For each method, the table notes its applicability to gauged or ungauged watersheds. The table also notes whether the method is based on modeling the conversion of rainfall to runoff, that is, a rainfall/runoff model. Rainfall/runoff models – and some other methods – require precipitation as an input.

In addition, some methods require temperature as an input, as shown in Table 4.1. For methods that require precipitation and temperature, future projections of these parameters are required to use the method to assess the effects of climate change. Many advanced rainfall/runoff and continuous simulation models allow the analysis of precipitation as both rain and snow, which is useful for those regions and projects where that is important.

This *Guide* does not provide detailed descriptions of the hydrologic methods in Table 4.1, but many excellent references do, including the Federal Highway Administration's *Highway Hydrology* (McCuen et al. 2002). Interested readers who are not familiar with a given methodology, or would like to refresh their knowledge, are referred to this or other references.

Engineers use many methods not listed in Table 4.1, but the most commonly used methods are listed. A brief overview of each method follows the table, along with references to the relevant chapters in this *Guide*. Experienced engineers and designers may identify similarities between methods listed here and other methods with which they are familiar. Information in this *Guide* may be adapted to less-common methods after proper consideration of the differences and similarities of the methods.

Table 4.1. Summary of hydrologic methods in this Guide.

Methodology	Chapter in this *Guide*	Gauged or Ungauged Watershed?	Rainfall/ Runoff Model?	Precipitation Required?	Temperature Required?
Trend Projections	5	Gauged	No	-*	-*
Rational Method	6	Ungauged	Yes	Required	No
NRCS Graphical Peak	6	Ungauged	Yes	Required	No
Unit Hydrograph	6	Ungauged	Yes	Required	No
Advanced Rainfall/Runoff Models	6	Ungauged	Yes	Required	Depends on model
USGS Regression Equations	7	Ungauged	No	Depends on equation	Depends on equation
Other Regression Methods	7	Ungauged	No	Depends on method	Depends on method
Flood Index Methods	8	Gauged or Ungauged	Depends on method	Depends on method	Generally no
Continuous Simulation	9	Gauged or Ungauged	Yes	Required	Generally yes

*Precipitation and temperature will likely be required to properly attribute the cause of a trend.

4.2.1 Gauged Watersheds

Engineers use the methods of Bulletin 17C (England et al. 2018) for analyzing flow gauge records. When sufficient data exist, a gauge record is generally considered to be an excellent resource for estimating design flows. However, that fact that these analyses assume that the data are stationary limits their use for estimating future flows with a changing climate.

Chapter 5 provides information and guidance on how gauged records can be used to identify and project trends. The chapter also describes the limits of this method, as well as the need to properly attribute any trend to a cause that can also be projected.

4.2.2 Ungauged Watersheds

Engineers designing transportation infrastructure frequently work in ungauged watersheds. The primary methods in these situations fall into two major categories: 1) rainfall/runoff models and 2) regression methods.

Rainfall/runoff models can range from the most basic, such as the Rational Method, to advanced, customized models. Other commonly used techniques include the Natural Resources Conservation Service (NRCS) graphical peak discharge method and several variations on the unit hydrograph method. A common feature for all of these is the requirement for precipitation estimates as an input. Chapter 6 provides guidance for creating 24-hour-duration precipitation estimates, as well as techniques for estimating shorter duration (sub-daily) estimates.

USGS regression equations are the most commonly applied regression method for estimating design flows. While not all USGS equations can be used for estimating future design flows, Chapter 7 provides guidance and limitations for the use of these equations. Chapter 7 also provides information and guidance on other regression methods that may be of interest to state DOTs.

4.2.3 Index Flood Methods

The index flood approach is useful for estimating design flows in the future based on the existing flood frequency curve (FFC) and an estimate of a future "*index flood*." As shown in Table 4.1, the index flood method can be applied to gauged or ungauged watersheds. If a rainfall/runoff model is used as part of the method, then precipitation inputs are required as discussed in Chapter 6, but other approaches can be used when applying the Index Flood method. Chapter 8 describes the application and limitations of these methods when adapted for future climate.

4.2.4 Continuous Simulation

The methods discussed in previous sections – gauged watersheds, ungauged watersheds, and index flood methods – usually result in design discharges for required AEPs. Continuous simulation models produce a time series of flows over a period of days, months, or years, based on a time series of precipitation and, generally, temperature inputs. While these models can be used to estimate design flows under some circumstances, they are more commonly used for low flow analyses, water quality assessment, or development of water balances for wetland analysis. Chapter 9 describes the application and limitations of continuous simulation modeling adapted for future climate.

4.3. Rain/Snow Mix with Future Temperature Changes

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§2.2.3 Meteorological Characteristics

Many areas of the United States experience precipitation in the form of snow, as well as rain. In a subset of those areas where snow accumulates into a snow pack, flood events can be caused not only by direct runoff from rainfall, but also from snowmelt when temperatures warm, with or without additional rainfall. An event that includes rain falling on snow, which accelerates the snowmelt, is known as a "rain-on-snow" event. Since temperature is a dominant factor determining whether precipitation falls as rain or snow, how much snow accumulates, and how fast snow melts, a changing climate may change these interactions.

When preparing the National Oceanic and Atmospheric Administration (NOAA) Atlas 14 series of reports, NOAA analyzed the rain/snow mix in areas such as the Midwestern states, where both types of precipitation are possible (Perica et al. 2013). For those gauge locations where NOAA defined the snow precipitation as significant, the analysts determined that, at least in these Midwestern states, the differences between precipitation (rain and snow water equivalent) depth and rain depth alone were "non trivial" for common events, but there was little distinction for precipitation events equal to and above the 0.01 AEP event. Engineers should consult the applicable volume of NOAA Atlas 14 or other resources to determine if snowfall has historically influenced precipitation events of interest.

How precipitation falls addresses only a part of the complex interaction between precipitation, temperature, and snowpack that creates snowmelt or rain-on-snow flood events. A close examination of the record of large flood events cross-referenced with the time of year and snowpack data in the watershed can provide an engineer with insight into the historical role of these types of events and whether they influence the magnitude of floods with AEPs of interest for design. In some areas, these may be quite large floods that contribute to defining a 0.01 AEP flood, and in others they may only influence the magnitude of more frequent flooding events.

Among the methodologies discussed in Section 4.2, the analysis of flow gauge records using Bulletin 17C (England et al. 2018) considers flood events from all flood mechanisms, because the computations are based on the measured streamflow data, regardless of the mechanism(s) that influence the watershed. Many advanced rainfall/runoff models include the ability to represent snowfall and snowmelt. The U.S. Army Corps of Engineers (USACE) Hydrologic Engineering Center – Hydrologic Modeling System (HEC-HMS) model can be used for this purpose, as can some continuous simulation models.

Climate change may influence estimates of design flood events in areas affected by snowmelt, not only because the precipitation patterns change, but also because the temperatures may change. State DOTs infrequently model snowmelt or rain-on-snow events to support design activities. Superimposing the uncertainties of climate change and the interaction between precipitation and temperature increases the challenge of estimating the future occurrence of these events. However, there are a few basic points to remember.

First, to understand whether climate change has the potential for altering the governing mechanisms creating flood events, the engineer should first establish whether or not those mechanisms created floods of the magnitude of interest under historical climate conditions. If snowmelt or rain-on-snow events are important in creating these flood events, then changes in climate may be important.

Second, if snowmelt or rain-on-snow events are historically important, it is recommended that the engineer consider projections of seasonal temperatures. If this examination indicates that changes may be anticipated that would affect the performance of the transportation infrastructure, further analysis may be warranted.

Third, the engineer should apply an appropriate hydrologic model, such as HEC-HMS or a continuous simulation model, to assess the effects on discharge resulting from changes in temperature and precipitation form (rain versus snow). The engineer should develop scenarios representing existing conditions and a suite of future scenarios to estimate appropriate design conditions considering climate change.

4.4. The Climate Change Indicator

Section 4.1 describes four levels of analysis for considering climate change in project planning and design. The lower levels of analysis (1 and 2) employ qualitative information, while the upper levels of analysis require more involved quantitative analyses. The CCI can be used as a tool to inform a decision on whether a higher level of analysis is appropriate for a given project (Kilgore et al. 2016). The CCI provides a measure of the projected change in 24-hour precipitation for a given AEP from historical conditions, relative to the uncertainty within the estimates of historical precipitation. That is, the CCI provides a measure of whether projected future changes in precipitation are large, compared to the historical variability in precipitation. The CCI is defined in the following equation:

$$CCI = \frac{P_{24,T,P} - P_{24,T,O}}{P_{24,T,O,U} - P_{24,T,O}} \tag{4.1}$$

where:

CCI	=	*Climate change indicator.*
$P_{24,T,P}$	=	*Projected T-year 24-hour precipitation.*
$P_{24,T,O}$	=	*Observed T-year 24-hour precipitation.*
$P_{24,T,O,U}$	=	*Upper 90% confidence limit T-year 24-hour precipitation for the observed data.*

T represents the return period of interest. For example, if the design standard for the project is the 50-year return period (0.02 AEP) event, then *T* equals 50. Figure 4.2 describes the CCI conceptually. The observed *T*-year 24-hour precipitation is the mean (expected) value estimated from the historic data. There is some probability that the actual value is less or more, as indicated by the probability curve shown in the figure. The upper 90 percent confidence limit of the *T*-year 24-hour precipitation is also shown. The difference between these two values is represented as *B*. The projected *T*-year 24-hour precipitation is indicated in the figure as being larger than the historical value. The difference between these two values is represented as *A*. The CCI is simply the ratio of *A* to *B*.

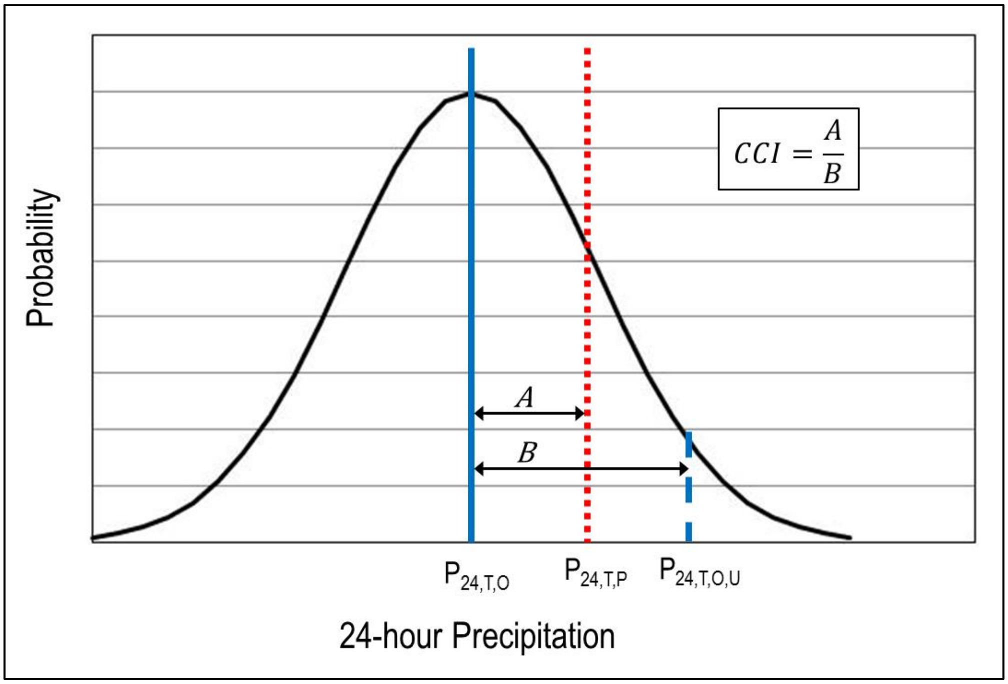

Figure 4.2. Definition of the CCI.

For the purpose of computing this indicator, the design team determines the observed *T*-year 24-hour precipitation and the corresponding upper 90 percent confidence limit from NOAA Atlas 14 or from any locally accepted source for historical precipitation. The 90 percent confidence limit is chosen because this value is easily available from NOAA Atlas 14. The *T*-year 24-hour estimate should be selected based on the annual series, rather than the partial duration series, both of which are available in NOAA Atlas 14.

The CCI should be calculated based on the guidance in Section 6.1 for estimating projected *T*-year 24-hour precipitation using an ensemble of high-resolution climate datasets. Chapter 3 discusses the selection of GCMs and future scenarios.

Changes in the *T*-year 24-hour precipitation do not necessarily translate to proportional changes in the *T*-year design discharge. However, the indicator provides a measure of how much change in precipitation the designer might expect, relative to variability in the observed data. If this indicator is large, then the climate change effects on design flow might be large; if this indicator is small, the effects on design flow might be small. As a broad guideline, CCI values less than 0.4 suggest that evaluating a project based on the historical confidence limits in Level 2 will provide a reasonable basis for evaluating project performance. Conversely, a CCI value of more than 0.8 suggests further analysis of projected conditions might be appropriate. For situations between these values, the design team should carefully weigh project specifics to determine whether additional analysis is advisable.

The purpose of the indicator is to inform a decision by the project team on whether to perform more detailed analyses of projected conditions. Since the needs and characteristics of each project are unique, the decision about moving to a higher level of analysis rests with the design team.

BOTTOM LINE: Since the needs and characteristics of each project are unique, the decision about moving to a higher level of analysis rests with the design team.

4.5. Regional Variations

Climatic and topographic variations across the country lead to the selection of different technical approaches, hydrologic models, and climatic inputs for hydrologic design. State DOT manuals and other hydraulic design manuals describe approved methods for application within their jurisdiction. Comparing these documents throughout the country reveals regional differences, not only related to watershed and meteorological characteristics, but also to the unique history in different regions of the country. As previously discussed, this *Guide* does not advocate changes to existing design guidance except that, in moving to higher levels of analysis, the design team may select alternative procedures (within the range of those already approved). Unless otherwise stated, this *Guide* applies to all 50 states.

With respect to the identification and use of projected climate information, particularly precipitation and temperature, the information discussed to support Level 1 analyses includes differing results by region. For quantitative analyses of a projected climate in using analysis Levels 3 and 4, the recommended high-resolution climate datasets provide site-specific projections, but the recommended procedures are consistent nationwide. However, as discussed earlier, a Level 4 analysis may include customization of the selection of high-resolution climate datasets to include a subset of more regionally appropriate GCM projections as determined by a qualified climate scientist. (See Section 3.2 for selecting high-resolution climate datasets.)

Another important regional variation pertaining to the assessment of the effects of climate change is distinguishing regions where changing temperatures will result in a change in the mix of snow versus rain, as discussed in Section 4.3. Such changes may have a significant effect on the estimates of future floods.

Other regional variations might include factors that have long-term effects on watersheds and result in changes to runoff characteristics. These might include factors such as land use changes and wildfire frequency and extent.

Chapter 5. Projections Based on Trends in Historical Discharges in Gauged Watersheds

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§2.3.2 Sources of Hydrologic Data

§2.6.1 Concepts of Probability and Frequency Analysis

§2.7.1 Individual Station Flood Frequency Analysis

A gauged record of flood flows in a watershed is an important hydrologic resource for estimating design flows. In these cases, engineers often estimate design flows from a flow gauge record using a frequency distribution, such as the Pearson Type III, applied to the logarithms of the annual maximum series of discharges following the procedures in Bulletin 17C (England et al. 2018). These analyses assume that the parameters of the distribution – such as the mean and standard deviation – are constant and do not vary with time. With a changing climate this may not be an appropriate assumption.

One approach for estimating design discharges when trends are present in the historical record is to estimate time-varying distribution parameters and use these to estimate design discharges. In this chapter, an approach for estimating trends in one of those parameters – the mean – is described, followed by a sample application.

5.1. Identifying and Estimating a Historical Time-Varying Mean

Frequency distribution parameters, such as the location (mean), scale (standard deviation), and shape (skew), of a distribution such as the Pearson Type III, may change over time as a result of changing land use, climate, or other factors. Bulletin 17C (England et al. 2018) recommends employing time-varying parameters or other appropriate techniques to account for changing land use and/or climate, but does not provide specific guidance.

With a three-parameter distribution such as the Pearson Type III, the values of one, two, or all three parameters are subject to variation if a trend in the annual maximum series (AMS) exists. The procedure presented here is applicable only for statistically significant trends in the mean that are greater than 0.25 percent per year, but less than 1 percent per year (Yu and Stedinger 2018). See Section 5.4 for information on the source of this procedure from the literature. The procedure includes the following steps:

1. Estimate a time-varying mean of the logarithms of the AMS over the period of record and determine if a statistically significant trend exists.
2. Develop a hypothesis regarding the cause of the trend. Evaluate the hypothesis for explaining the historical trend and its continuation in the future.
3. Based on the trend in Step 1 explained by attribution in Step 2, compute the appropriate statistics to develop an equation for estimating design flows.
4. Compute the design flow quantiles.

Step 1. Assessing a trend in the AMS is initiated by plotting the data versus time for a visual inspection of the period of record. The record can be taken in its entirety or a subset of the more recent part of the record can be used. Once the appropriate period of record is determined, the trend is estimated through a linear regression analysis of the logarithms of the AMS data fitting the following equation:

$$\log_{10}(Q) = \mathrm{Y} = LQ_0 + B\ t \quad (5.1)$$

where:

Q = *Annual peak flow, ft^3/s.*

B = *Slope (trend).*

t = *Time since the beginning of the record, years.*

LQ_0 = *Logarithmic intercept value at the beginning of the record.*

The slope, B, represents the magnitude of change in the time-varying mean and should be evaluated for statistical significance. A gradual increase in annual peak flows is commonly evaluated using the Mann-Kendall test (Helsel and Hirsch 1992, McCuen 2003) at a significance level of 5 percent. The Mann-Kendall test is now included in the USGS PeakFQ program and described in Appendix 4 of Bulletin 17C (England et al. 2018). If a statistically significant trend does not exist, a trend analysis cannot be used and further steps are unnecessary.

Step 2. Use of trend analyses can only be justified if a verifiable hypothesis explaining the trend can be validated. In this step, the engineer reviews the historical record for changes in land use, climate, or other potential factors to develop a hypothesis of why a trend in the AMS may be occurring. The time variable in Equation 5.1 is a surrogate for factors such as land use or climate change that may be driving the trend.

Validation of the hypothesis could include correlation analyses, but must go beyond simple correlation to describe a cause-and-effect relation. If the engineer is considering extrapolating a trend beyond the historical period, the hypothesis must include a rationale for the extrapolation and define realistic limits for how far the extrapolation can reasonably be extended.

Step 3. Based on the results of Step 1 and the trend attribution of Step 2, the engineer computes the appropriate statistics considering the trend to develop the equation incorporating the time-varying mean. The following equation is used to estimate the design quantiles (Serago and Vogel 2018):

$$\log_{10}(Q_x) = \overline{LQ} + B\ \left(t - \frac{(n+1)}{2}\right) + K_x(S_Y^2 - B^2 * S_t^2)^{0.5} \quad (5.2)$$

where:

$\overline{LQ}$ = *Mean of the logarithms of the historical AMS.*

Q_x = *Flow quantile associated with the x AEP.*

B = *Slope of the regression trend line.*

S_Y = *Standard deviation of the logarithms of the historical AMS.*

S_t = *Standard deviation of the time variable t.*

K_x = *Pearson Type III frequency factor that is a function of the x AEP and skew (G_Y) for the logarithms of the historical AMS.*

t = *Time since the beginning of the record, years.*

n = *Number of years in the record.*

The *x* AEP may be the 0.1 (10-year), 0.01 (100-year), or any other quantile needed for design. The quantity $(S_Y^2 - B^2 * S_t^2)^{0.5}$ is the standard deviation of the logarithmic residuals about Equation 5.1.

If there is no statistically significant trend, *B* is considered to not be significantly different from zero and Equation 5.2 reduces to the stationary form of the design quantile equation. When *B* is statistically different from zero, two general cases may be considered.

For Case 1, the engineer is confident that the historical trend is unlikely to reverse over the service life of the project under design, but is less confident about projecting the trend beyond the historical period of record. In this case, *t* is chosen to be equal to *n* in Equation 5.2. Using Equation 5.2 then yields estimates of flow quantiles based on the time-varying mean at the end of the historical record. For example, if the historical record covered the period from 1950 through 2016, this case represents the flow quantiles as of 2016.

For Case 2, the engineer's evaluation of the cause of the trend in Step 2 results in the determination that the engineer expects the trend to continue, or at least wishes to consider the consequences if the trend continues. In this case a value of *t* greater than n is used in Equation 5.2. Case 2 should only be used with high confidence in the continuity of the trend. More information on trend attribution is provided in Section 5.3.

Step 4. The design quantiles are computed for the selected case from Step 3. It may be informative to compute the quantiles for not only the selected case, but also for the case where there is no trend (*B approximately equal to 0*) for comparison.

> *BOTTOM LINE: The time-varying mean method is appropriate when the annual peak discharges at a gauging station are nonstationary or varying with time because of changes in land use or climate. The resulting estimated flood discharges are more indicative of current land use or climate conditions and are, therefore, more appropriate for design of structures. The trend in the mean can be projected into the future only if the trend can be attributed to some hydrologically meaningful covariate like land use change.*

5.2. Example: The Time-Varying Mean

The methodology for estimating and applying a time-varying mean is demonstrated on the Northeast Branch of the Anacostia River watershed draining to Riverdale located in Prince George's County, Maryland. As measured to the gauging station (01649500) at Riverdale Road (East Riverdale) and shown in Figure 5.1, the watershed has a drainage area of 73.35 square miles. The upper part of the watershed is in the Piedmont Region (17 percent) and the lower part in the Western Coastal Plain Region (83 percent) of Maryland.

There are several major highways within the watershed indicative of extensive development. The western and southern portion of the watershed is more heavily urbanized including the cities of

Calverton, Beltsville, College Park and the University of Maryland, Greenbelt, and East Riverdale. Major Federal installations within the watershed include the U.S. Department of Agriculture Beltsville Agricultural Research Center (BARC) (approximately 6,500 acres) and the National Aeronautical and Space Administration (NASA) (approximately 300 acres).

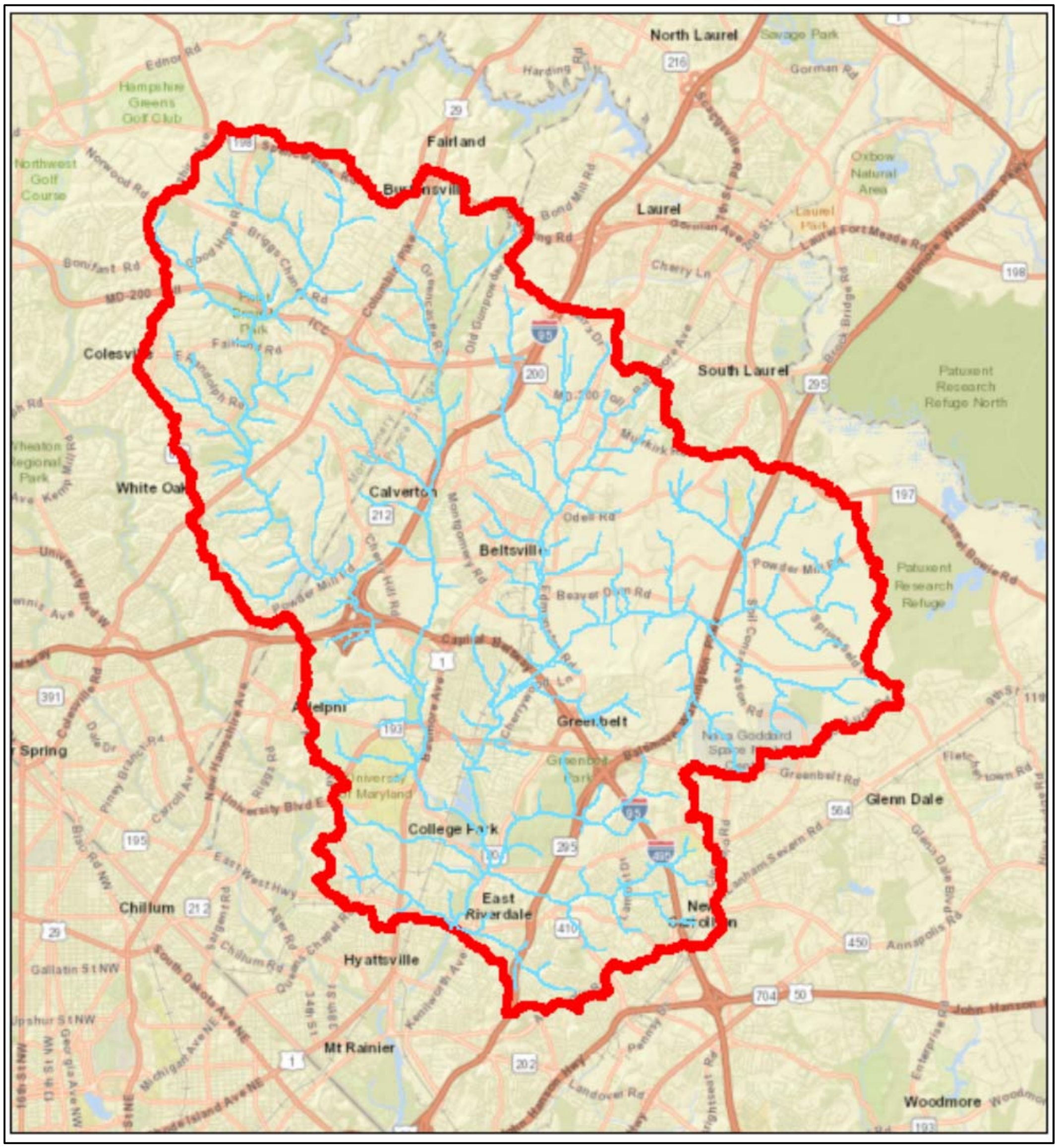

Figure 5.1. Watershed map for the Northeast Branch Anacostia River upstream of East Riverdale, Maryland.

Step 1. The AMS for the Northeast Branch Anacostia River at Riverdale is based on the systematic record from 1939 to 2016. Figure 5.2 shows the AMS plotted versus time in years since 1939 indicating an increasing trend with time. Lower annual peaks are evident in the 1950s and higher annual peaks in the 1970s. These variations from the trend line reflect the long-term persistence of wet and dry periods in climatic systems discussed by Cohn and Lins (2005) that can complicate the detection of a trend related to land use or climate change.

The linear trend line shown Figure 5.2 is fit to the form of Equation 5.1 with the result of LQ_0 equal to 3.299 and B equal to 0.00717. The variable, t, spans from 1 (year 1939) to 78 (year 2016). The relation is as follows:

$$\log_{10}(Q) = 3.299 + 0.00717\, t$$

Kendall's τ for the Northeast Branch of the Anacostia River at East Riverdale is 0.483 for the period 1939 to 2016 and the significance level is less than 0.01 percent indicating a significant upward trend (much less than 5 percent). Therefore, the slope of the trend line is statistically significant and represents a 0.717 percent annual increase in the logarithms of peak flows. This is within the bounds of 0.25 and 1 percent recommended by Yu and Stedinger (2018).

Step 2. The analysis for this step is to develop and evaluate a hypothesis for the trend identified in Step 1. For peak discharges, trends may be attributable to urbanization, climate, other factors, or a combination of several factors. For this example, the potential roles of urbanization and precipitation are examined.

This watershed has experienced significant urbanization during the period of record from 1939 to 2016. Estimates of impervious area in the Northeast Branch Anacostia River watershed are available for 1985, 1990, 1997, 2002, and 2010 and plotted versus time since 1939 in Figure 5.3. In 2010, the estimate of percent imperviousness for the watershed was 28.4 percent. It is assumed that the watershed was essentially rural in 1939 (percent imperviousness of 1 percent). This assumption agrees well with the near linear trend in impervious area since 1985. The historical impervious areas were estimated as the average percentage of each land use category covered with impervious area using land use data available from the Maryland Department of Planning (Moglen and Kim 2007). Comparing the trend in percent imperviousness (Figure 5.3) with the trend in AMS (Figure 5.2), correlation between the two is evident.

The possible contribution to the trend in the AMS from climate is considered, however, identifying the potential contribution of climate variables such as precipitation is challenging. First, there are many precipitation parameters to consider, for example, mean annual precipitation or particular AEP values for different durations. Second, there are other factors, such as antecedent moisture, that influence the link between rainfall and runoff.

For this example, the 24-hour annual maximum precipitation was retrieved and plotted in Figure 5.4. These data are from a rainfall station within the watershed (Beltsville) for the period 1941 to 2016. The precipitation trend line is slightly downward and visual inspection clearly shows no increase in the 24-hour annual maximum precipitation with time, suggesting that this parameter does not correlate with the increasing AMS.

A further complication for seeking a correlation is even though the rainfall station is located near the center of the watershed, the annual maximum precipitation does not always occur at the same time as the annual maximum peak discharge. An extreme example is the 9.43 inches of rainfall that occurred in August 1955 (Hurricane Connie), while the annual maximum peak discharge occurred in January 1955. While data for one rainfall station (point values) do not adequately reflect the basin-wide precipitation for a 73.35 square mile watershed, the point precipitation data at the Beltsville rain gauge suggest that the increasing annual peak discharges are not related to the 24-hour annual maximum precipitation. Other precipitation statistics could be evaluated to seek a correlation between rainfall and peak flow.

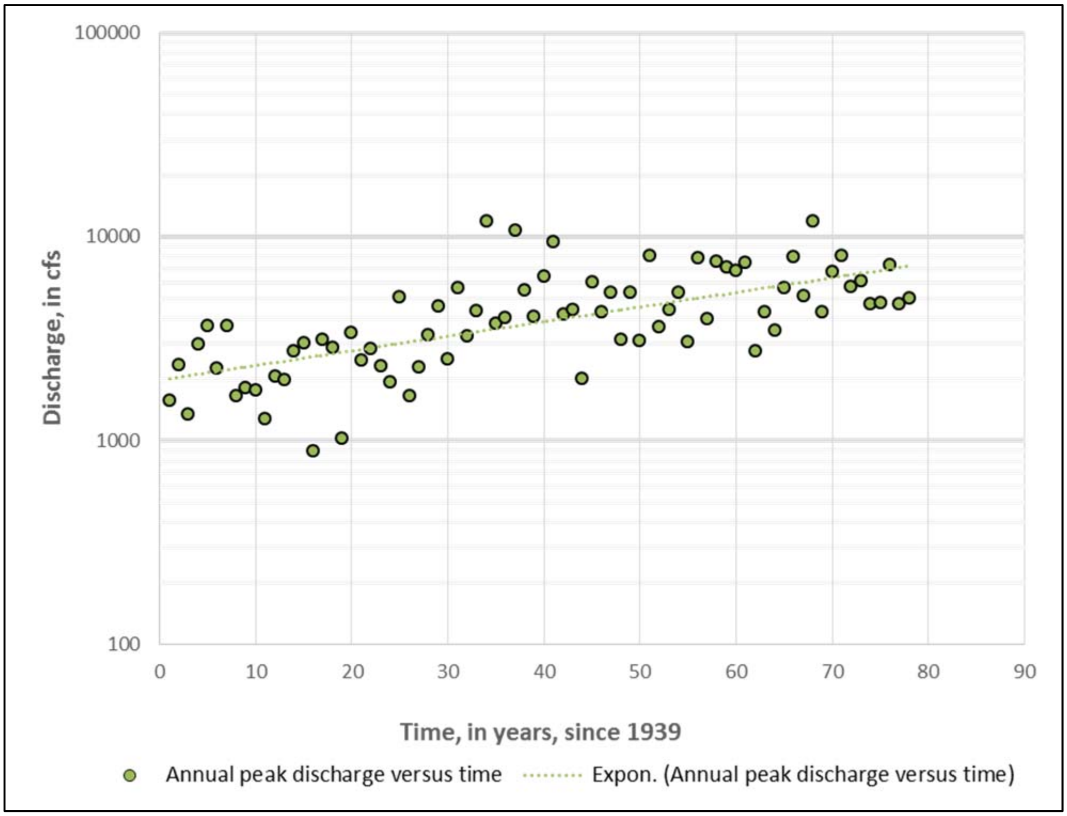

Figure 5.2. Annual maximum peak discharges for the Northeast Branch of the Anacostia River at Riverdale, Maryland for the period 1939 to 2016.

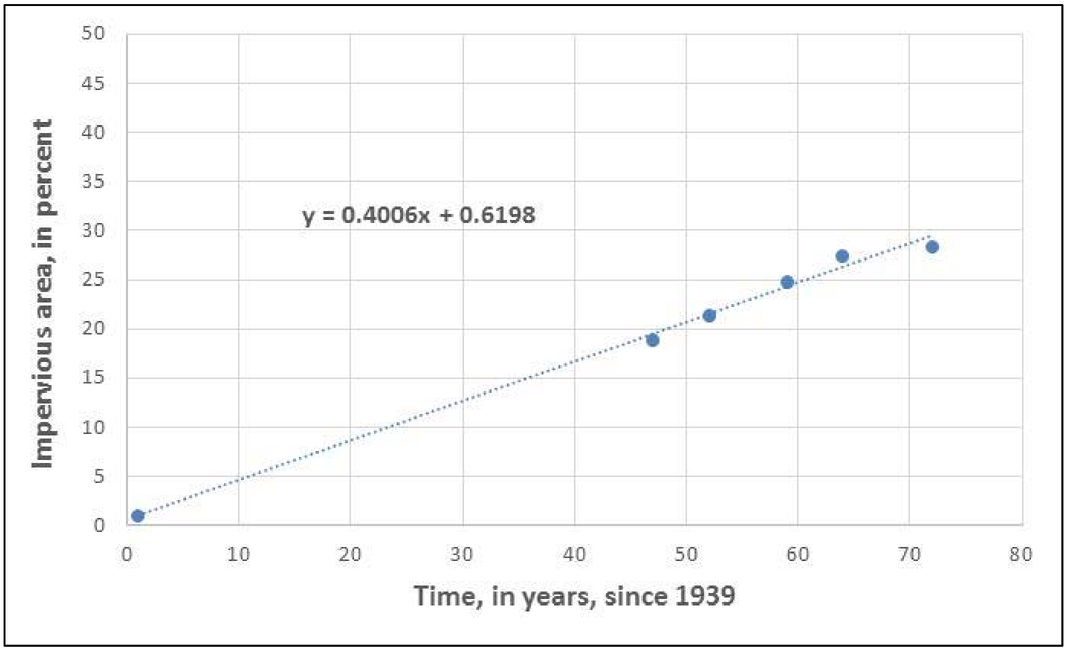

Figure 5.3. Impervious area since 1939 for the Northeast Branch Anacostia River at Riverdale, Maryland.

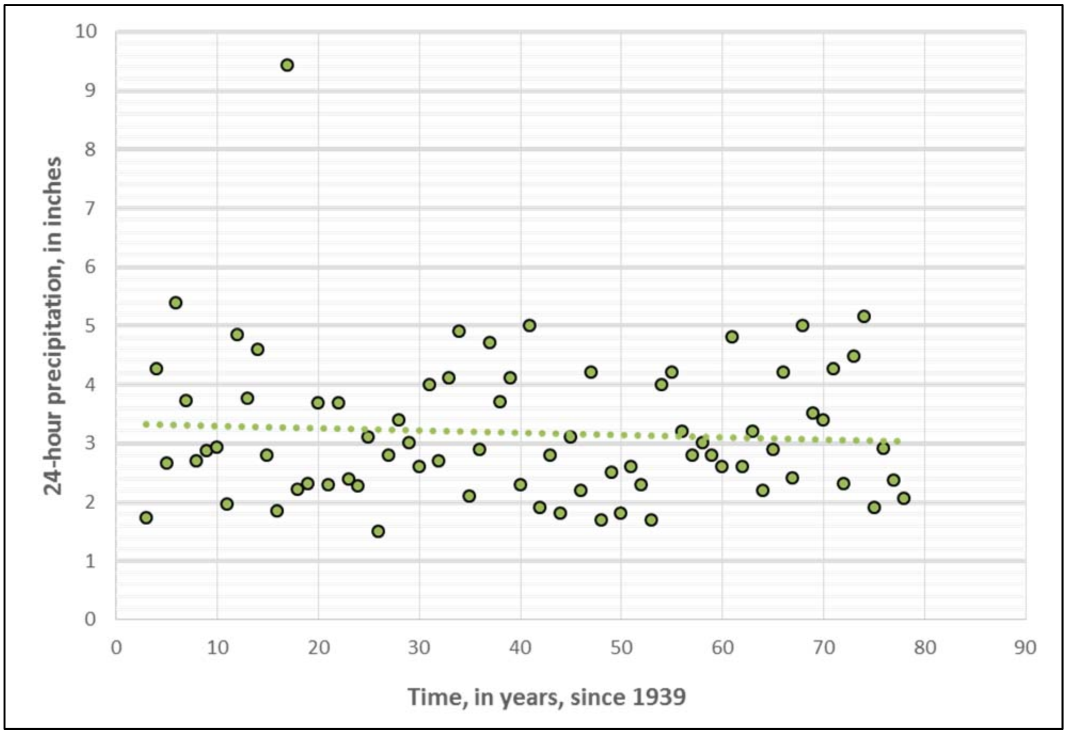

Figure 5.4. The 24-hour annual maximum precipitation at Beltsville, Maryland from 1941 to 2016.

Continuing with the role of land use in the trend in AMS, the next question is whether the increasing trend in percent imperviousness and, potentially, the AMS will continue. In the Northeast Branch of the Anacostia River watershed, it is likely that urbanization will continue to increase in the near future. Therefore, it is appropriate to consider future (ultimate) development conditions in the watershed. Using comprehensive planning maps available for the watershed, an impervious area for ultimate development conditions was estimated at 34.9 percent for the watershed. If the trend line in Figure 5.3 is extended to 34.9 percent, this will occur in 2024 (year 86). As noted above, the BARC occupies about 6,500 acres of the watershed (approximately 14 percent of the watershed) and most of the research center is agricultural with no plans to develop. Most of the remaining watershed is already fully developed, therefore, reaching ultimate development conditions in the watershed by 2024 is a reasonable assumption. The trend in increasing imperviousness, however, is not expected to continue beyond this time.

Step 3. A trend in the AMS was quantified in Step 1 and the role of watershed development as measured by percent imperviousness was identified as the likely cause in Step 2. Changes in climate during the period of record were discounted as a potential cause. The engineer now computes the remaining statistics required for estimating the design quantiles. The parameter values for estimating Q_x are summarized in Table 5.1.

Substituting the values for this example into Equation 5.2 results in the following:

$$\log_{10}(Q_x) = 3.582 + 0.00717\left(t - \frac{(78+1)}{2}\right) + K_x(0.1830)$$

Recall that K_x is the Pearson Type III frequency factor that is a function of the desired quantile (x AEP) and the skew of the annual peak discharges, G_Y.

Table 5.1. Parameters needed for estimating Q_x with Equation 5.2.

Parameter	Symbol	Value
Mean	$\overline{LQ}$	3.582
Number of Years of Record	n	78
Slope of Trend Line	B	0.00717
Standard Deviation of Y	S_Y	0.2447
Standard Deviation of Time	S_t	22.66
Standard Deviation of the Residuals	$(S_Y^2 - B^2 * S_t^2)^{0.5}$	0.1830
Skew of Y	G_Y	-0.270

Step 4. The values for the 0.50, 0.10 and 0.01 AEP quantile floods are computed using the equation derived in Step 3. To fully illustrate the procedure, the computations are made for the case where *B* equals zero and for the two cases where *B* is nonzero.

Assuming stationarity (*B*=0), the quantile estimates for the 0.5, 0.10, and 0.01 AEP quantiles are summarized in Table 5.2. Because the data in Figure 5.2 clearly illustrate an upward trend in annual peak discharges, these estimates are likely to underestimate the design discharges for a structure intended to serve today or in the future.

Acknowledging the identified trend, quantile estimates for 2016 conditions are estimated by using $t = 78$ in the equation from Step 3 and summarized in Table 5.2. These discharge estimates are significantly larger than when assuming stationarity, particularly for the more frequent 0.50 and 0.10 AEP events.

Since the analysis in Step 2 indicates that the trend could be projected to continue through 2024 an additional set of estimates can be estimated by using $t = 86$. These are also summarized in Table 5.2.

Table 5.2. Estimated discharges for the Northeast Branch of the Anacostia River at Riverdale.

AEP	Assuming Stationarity (*B = 0*) (cfs)	Time-varying mean (*t* = 78) (cfs)	Time-varying mean (*t* = 86) (cfs)
0.50	3,930	7,350	8,380
0.10	7,800	12,200	13,900
0.01	12,900	17,700	20,200

The discharges estimated using the time-varying mean and 2016 land use conditions ($t = 78$) are more appropriate for design of new hydraulic structures because they incorporate the upward trend in peak discharges resulting from increasing urbanization. Estimates from projecting the trend beyond the historical record (e.g., $t = 86$ in this example) are more speculative. They most likely can be used to inform design, but should not be used for design. This example is based on changing land use, but is also applicable to changing climate if the trend can be properly attributed as illustrated in this example and described in Section 5.3.

5.3. Applicability and Limitations

Estimating a time-varying mean from historical discharges and using it to estimate discharges for current conditions, or in some cases future conditions, is applicable when:

- There is a statistically significant trend in the mean of the logarithms of the AMS of discharges based on at least 30 years of record.
- The trend can be attributed to some hydrologically meaningful covariate like land use change that explains the trend and can, potentially, be projected into the future.
- The trend in the logarithms of the annual maximum discharges exceeds about +/-0.25 percent, but less than 1 percent, per year (Yu and Stedinger 2018).

Identification of a trend does not, by itself, reveal the cause of the trend. If the trend continues and the hydraulic structure has a long service life, the time-varying mean estimate of design flow might prove to be an underestimate if the source of the trend is accelerating. Conversely, projecting further into the future without knowledge that the underlying causes of the trend will continue could result in an overestimate of the design discharge. Therefore, it is critical to identify the underlying causes of a trend if that trend is to be projected into the future.

Read and Vogel (2015) and Salas et al. (2018) have stressed that the trend in the mean should only be extrapolated if there is some physically meaningful covariate (like land use change) that defines the trend into the future. However, there are no standardized protocols for drawing quantitative conclusions. Salas et al. (2018) note it may be reasonable to use the historical trends resulting from urbanization to simply update a flood frequency analysis to reflect current urbanization conditions, which may remain roughly constant for a short time into the future.

The procedures described in Sections 5.1 and 5.2 are applicable to climate change, but estimating a future trend in climate is uncertain. If the watershed has not undergone any land use or channel changes, then climate might be a causative factor for increasing flood discharges. Any procedures for estimating a future climate trend for the purposes of projecting historical discharges should be well documented and defensible.

With respect to the limits on the magnitude of the trend in mean and the value of considering trends in the standard deviation and skew, Yu and Stedinger (2018) concluded that depending on the magnitude of the trend, there is diminishing benefit to consider variation in parameters other than the mean. They recommend that when evaluating the logarithms of the annual maximum discharges:

- For trends less than 0.25 percent change per year, the stationary moment estimator is best regardless of the skew coefficient, that is, ignore the trend when estimating design discharges.
- For trends larger than 0.25 percent per year, but less than 1 percent per year, the best approach is to incorporate a trend in the mean.
- For trends larger than 1 percent per year, it is advantageous to estimate trends in both the mean and variance.

A 1 percent change per year (up or down) is likely to be an infrequent occurrence in the historical record of gauged watersheds. This is fortunate because simultaneous adjustment for the mean and variance is complicated and difficult to apply.

5.4. Discussion and Other Resources

Other procedures for estimating time-varying means and standard deviations are provided in the literature and are being further evaluated. Obeysekera and Salas (2014) describe an approach for adjusting both the mean and standard deviation of the flood series. Read and Vogel (2015) show that the coefficient of variation (standard deviation divided by the mean) is relatively constant for most real space flood data (no transformation to logarithms) with significant trends. This implies that the standard deviation and mean of the untransformed data are increasing together. However, for logarithmic transformed data only the mean is increasing, so a single nonstationary model for the logarithmic mean is sufficient for most applications.

Serago and Vogel (2018) describe the advantages of varying the distribution parameters with a single time-varying parameter for the logarithmic mean versus the development of other more complicated models. Equation 5.2 uses base 10 logarithms and different notation, but is equivalent to Equation 14 in Serago and Vogel (2018). The standard deviation S is the residual error about the trend line (Equation 5.1) and reflects the accuracy of the regression trend line. Serago and Vogel (2018) refer to this as the conditional standard deviation because it is conditional on the explanatory variable time (t). The skew coefficient G_Y is based on the logarithms of the annual peak discharges ($\log_{10}(Q)$) and is the conditional skew. As explained by Serago and Vogel (2018), the conditional skew is equal to the unconditional skew when the skew of the explanatory variable is equal to zero, which is the case when time is used as the explanatory variable. Equation 5.2 is appropriate for skews between -1.0 and +1.0 and that will accommodate most applications. For skews outside this range, consult Serago and Vogel (2018) for a more detailed equation.

Yu and Stedinger (2018) performed a Monte Carlo study based on the Pearson Type III distribution applied to the logarithms of the annual maximum discharges with assumed values of the skew coefficient ranging from -1 to +1. Yu and Stedinger (2018) considered five different cases with positive and negative trends in the mean, equal positive and negative trends in mean and variance, and positive trend in the mean and negative trend in the variance using a sample size of 40 and a 25-year projection.

Other approaches for analyzing data with trends and nonstationarity in flood data are discussed in Kilgore et al. (2016) and Salas et al. (2018). Two such approaches are:

- Adjustment of annual maximum discharges to current land use conditions (McCuen et al. 2002, Over et al. 2016a, Hejazi and Markus 2009, Beighley and Moglen 2003, Moglen and Shivers 2006). These procedures are reasonable, but are more time consuming than applying the time-varying mean approach.
- Use of a homogeneous subperiod of the historical record. This is the simplest approach for adjusting for nonstationarity, but one drawback is that the homogeneous subperiod may not include major floods that have occurred on the watershed.

Chapter 6. Discharge Projections Based on Future Precipitation and Rainfall/Runoff Models in Ungauged Watersheds

This chapter provides methods and guidance for projecting future design discharges in ungauged watersheds for situations when the design team has determined that rainfall/runoff models are an appropriate tool. The chapter focuses on estimating future precipitation as an input to rainfall/runoff models. However, the design team should also consider other non-climatic inputs, such as land use/land cover, required by the rainfall/runoff models. Because these aspects are not included in this *Guide*, the design team should use existing methods and guidance as applicable to the project type and location.

Section 6.1 addresses methods and guidance for estimating future precipitation quantiles for a 24-hour duration. The quantiles of interest typically range from 0.5 to 0.01 AEP, with the 0.002 quantile required for some scour and floodplain management applications. For rainfall/runoff modeling applications where a 24-hour duration is sufficient, such as many applications of the NRCS graphical peak discharge method or the unit hydrograph methods, this section guides the design team to these future design quantile estimates.

For applications that require durations shorter than 24 hours or complete Intensity Duration Frequency (IDF) curves, Section 6.2 provides methods and guidance for estimating future sub-daily precipitation estimates. Potential applications for sub-daily estimates include the Rational Method and some unit hydrograph methods.

Section 6.3 addresses the spatial scale of projected precipitation and how it is adjusted to be compatible with watershed scale analyses. The need for adjustment depends on both the source of the precipitation information and the size of the watershed of interest.

Many projects do not require quantitative estimates of future precipitation, including projects determined by the design team to be Level 1 or Level 2 projects (see Chapter 4). However, projects determined to be Level 3 or Level 4 projects do require quantitative estimates of future precipitation if a rainfall/runoff model is the tool of choice for the design team. The methods and guidance in this chapter are useful for these purposes.

6.1. Projected 24-Hour Precipitation

This section describes a recommended method for estimating projected 24-hour precipitation depths for analysis and design, including—but not limited to—the 0.5, 0.1, 0.04, and 0.01 AEP quantiles. This method is appropriate for projects requiring a Level 3 analysis and for some Level 4 analyses (see Chapter 4) to estimate a 24-hour duration precipitation depth as an input to rainfall/runoff modeling or for applying the CCI (see Chapter 4). The recommended procedure results in projected 24-hour precipitation quantiles and their corresponding confidence limits for each future scenario evaluated. As recommended in Chapter 3, the design team should evaluate multiple future climate scenarios, when feasible, to provide a more comprehensive understanding of possible future precipitation estimates and their effect on design discharges and, ultimately, project design.

6.1.1 Method for 24-Hour Precipitation

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§2.2.3.1 Factors Affecting Runoff/Meteorological Characteristics/Rainfall

§2.3.2.2 Data Sources/Sources of Hydrologic Data/Rainfall Data

§2.7.3 Methods for Estimating Flood Peaks, Durations, and Volumes/Empirical Hydrologic Models

§2.7.4 Methods for Estimating Flood Peaks, Durations, and Volumes/Unit Hydrograph Methods

§2.7.6 Methods for Estimating Flood Peaks, Durations, and Volumes/Mathematical Models

A 10-step method is recommended for estimating a future 24-hour duration rainfall frequency curve (RFC) with a range of AEP quantiles or for estimating a single future 24-hour duration AEP quantile. The method adjusts the historical AEP quantiles taken from established sources of observed precipitation data to future conditions based on information from high-resolution climate modeling datasets. To create these high-resolution climate modeling datasets (also referred to in this *Guide* as downscaled GCM output), climate scientists use scenarios as input to GCMs and then downscale the GCM outputs to create more temporally and spatially detailed datasets that include precipitation information (see Chapter 3).

Figure 6.1 summarizes a 10-step procedure for estimating future 24-hour-duration precipitation quantiles. The procedure includes two loops, repeated at the discretion of the design team, based on the number of future scenarios and the number of downscaled GCM outputs determined to be appropriate for the project. As shown in Figure 6.1, steps 5 through 9 are repeated for each future scenario and steps 5 and 6 are repeated for each GCM evaluated within a scenario. The following list summarizes each step, with more detail provided after the summary:

1. Determine the historical observed 24-hour precipitation RFC (or single AEP quantile, if only one quantile is required) for the site.
2. Select baseline and future periods for analysis, as appropriate for the plan or project.
3. Identify the future scenarios and downscaled GCM outputs of interest from the most appropriate database of high-resolution climate projections, using the recommendations in Chapter 3.
4. Determine the number of grid cells required to adequately cover the watershed of interest.
5. Acquire the daily precipitation values, and extract an annual maximum series (AMS) for each grid cell for the selected future scenario and downscaled GCM output dataset. Adjust the AMS to unconstrained point values with an areal reduction factor and an unconstrained 24-hour correction factor appropriate for the location.
6. For each grid cell, compute the 24-hour precipitation RFC (or single AEP quantile) for the baseline period and for the future period from the AMS from Step 5, using an appropriate statistical distribution.
7. Repeat steps 5 and 6 for each individual downscaled GCM output identified in Step 3. The result of this step is a set of estimates for a 24-hour RFC (or single AEP quantile)

for each grid cell and each downscaled GCM output for both the baseline and future periods for the selected scenario.

8. Compute the ratios of the modeled (downscaled GCM output) future 24-hour precipitation RFC (or single AEP quantile) to the modeled baseline 24-hour precipitation RFC (or single AEP quantile) for all grid cells and simulations.
9. Estimate the projected 24-hour precipitation RFC (or single AEP quantile) from the historical observed 24-hour precipitation RFC (or single AEP quantile) from Step 1 and the ratio(s) from Step 8.
10. Repeat steps 5 through 9 for each future scenario identified in Step 3.

In **Step 1**, the engineer determines the appropriate source for the historical observed quantile estimates, based on established state DOT or other guidance and datasets. Examples of such a datasets include NOAA Atlas 14 or a precipitation gauge at the site with a long record. Based on the appropriate source, the engineer estimates the 24-hour quantiles (the RFC) or a single AEP quantile based on the historical record. This step is accomplished the same way the engineer would estimate the RFC or single AEP, without consideration of climate change.

The engineer should also note the period of record for the source data for use in Step 2. Most volumes of NOAA Atlas 14 include data from 1948 to about 2005. As with most historical precipitation data sources, the historical record is based on gauging records of different lengths.

For large watersheds, the engineer may choose to estimate projected precipitation quantiles for multiple locations in the watershed. The engineer should base this decision on the level of disaggregation appropriate for the watershed when performing a hydrologic analysis without consideration of climate change. That is, the level of disaggregation required for an appropriate hydrologic analysis is generally not affected by potential changes in precipitation resulting from climate change.

> *BOTTOM LINE: In Step 1, the engineer uses the same rainfall data sources the engineer would use for an analysis if a changing climate was not a concern.*

In ***Step 2***, the engineer selects appropriate baseline and future periods for analysis. The baseline period should overlap as closely as possible the period of record used to develop the historical dataset selected in Step 1. For example, if the observed data from Step 1 covered a period from 1965 through 2010, the appropriate baseline period should be that entire period or a subset, but not less than 30 years.

The engineer defines the future period considering the expected service life of the project. For example, the engineer might define the future period to begin as early as the end of the baseline period and extend through 2100. The entire projected record could be defined as the future period or a subset, but it should not be less than 30 years. A minimum of 30 years is recommended for both the baseline and future periods because the climate science community generally uses 30 years for defining a climatological period. Climate scientists define a climatological period as the length of time within which the statistical characteristics of a given climate are considered representative for that period.

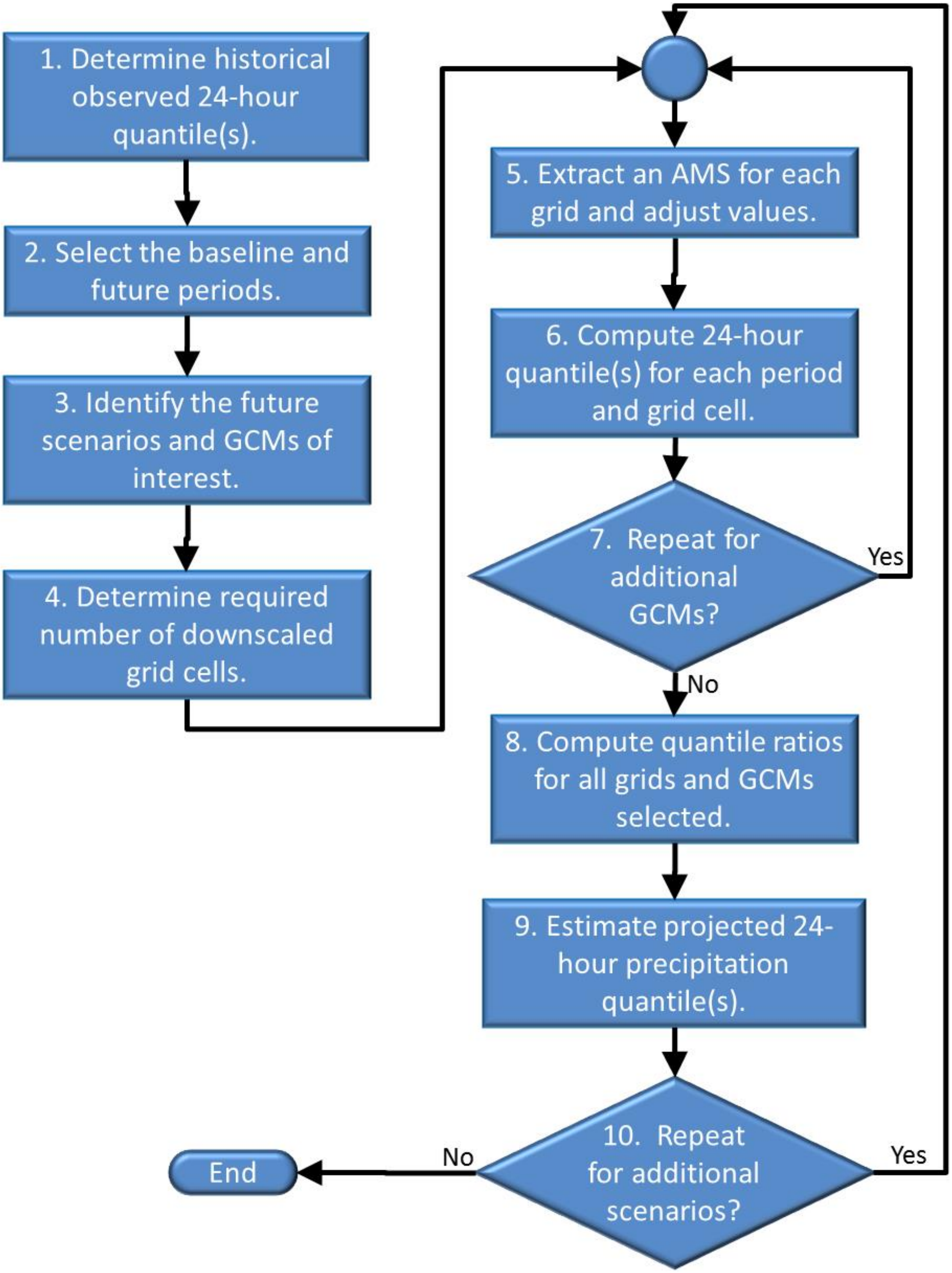

Figure 6.1. Recommended procedure for projecting 24-hour precipitation quantiles.

When selecting a future period, the engineer should consider the possibility that later periods may not always result in more extreme annual peak precipitation estimates than earlier periods. Therefore, it is recommended that the engineer inspect the behavior of the AMS developed in Step 5 before finalizing the selection of the future period. A visual inspection of a graphical representation of the AMS is appropriate for this purpose.

In ***Step 3,*** the engineer or design team selects the future scenarios and GCMs to support the analysis. The use of multiple GCMs for each scenario allows analysis of scientific uncertainty as expressed by the variability of estimates among the downscaled GCM outputs. Evaluation of multiple future scenarios permits assessment of the effects of alternative futures on the design or plan. Chapter 3 provides guidance for selecting an appropriate high-resolution climate dataset, as well as future scenarios and GCMs.

In ***Step 4,*** the engineer determines the high-resolution climate dataset grid cells required to cover the watershed of interest. This is necessary because the high-resolution climate datasets recommended for this procedure are organized in a grid format, with each grid defined by fractions of degrees latitude and longitude (see Chapter 3). The engineer identifies the required grid cells by overlaying the climate projection grid on the watershed. For smaller watersheds, a single grid cell may be larger than the watershed and fully cover it. For larger watersheds, multiple grid cells may be required. If the number of grid cells required to cover the watershed is less than three, it is recommended that three grid cells covering or adjacent to the watershed be identified. Using this minimum of three grid cells, the engineer is more likely to identify any anomalies in the data associated with a single grid cell.

In ***Step 5***, the engineer acquires the daily precipitation values from one of the selected high-resolution climate projection datasets for the first of the selected scenarios and the first of the selected downscaled GCM outputs for each grid cell. For example, data from the Localized Constructed Analogs (LOCA) dataset recommended in Chapter 3 may be downloaded from the Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections (DCHP) website (see https://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#Welcome). The LOCA dataset includes daily precipitation values from 1950 through 2100.

From the downloaded daily precipitation values, the engineer creates the ***unadjusted*** AMS for each grid cell for the entire downloaded period (historical and future) by taking the largest daily value from each year and discarding the other daily values. The engineer creates the ***adjusted*** AMS by making two corrections to each value in the unadjusted AMS: 1) conversion from constrained daily values to unconstrained 24-hour values; and 2) conversion from spatially averaged values to point values. The conversion from a spatial average to a point value can be accomplished using an areal reduction factor (ARF), as described in Section 6.3. HEC-17 (Section 7.4.4.1.1) describes both of these adjustments in more detail (Kilgore et al. 2016).

In ***Step 6***, the engineer separately estimates the 24-hour precipitation RFC (or single AEP quantile) from the AMS for the baseline and future periods for each grid cell. Estimating the 24-hour quantile(s) requires the use of an appropriate statistical distribution. HEC-17 (Section 7.4.3.1) provides guidance for selecting an appropriate distribution (Kilgore et al. 2016).

In ***Step 7***, the engineer repeats steps 5 and 6 for each simulation (GCM/scenario combination). In general, a larger ensemble of GCMs provides a greater opportunity to capture variability in the projections and generate more representative confidence limits for the quantile estimates for the selected future scenario. (See Chapter 3 for more information about GCM ensembles.)

In ***Step 8***, the engineer computes the ratio of the future and baseline modeled 24-hour quantiles for each grid cell and each simulation as described in Equation 6.1.

$$RFB_{q,n,m} = \frac{PF_{q,n,m}}{PB_{q,n,m}} \tag{6.1}$$

where:

$RFB_{q,n,m}$ = *Ratio of the future to baseline 24-hour precipitation quantile (q) for grid (n), model (m).*

$PF_{q,n,m}$ = *Future 24-hour precipitation quantile (q) for grid (n), model (m).*

$PB_{q,n,m}$ = *Baseline 24-hour precipitation quantile (q) for grid (n), model (m).*

The subscripts in the equation indicate the following:

- The subscript (*n*) indicates the grid cell and ranges from 1 to the number of grid cells (N).
- The subscript (*m*) indicates the downscaled GCM model output from which the estimate is derived and ranges from 1 to the number of models (M).
- The subscript (*q*) indicates the quantile, e.g., 0.5, 0.1, 0.04, and 0.01 AEP.

The computations for Step 8 generate a total of N x M ratios for a single AEP, as illustrated in Table 6.1. These ratios represent estimates of the change in the future 24-hour precipitation quantile, compared with the baseline 24-hour precipitation quantile for each grid cell, based on each GCM. The information for each grid cell should be analyzed to estimate useful statistics such as the mean ratio (assuming that each model output is equally likely) and upper and lower confidence limits of the ratios (assuming a normal distribution) for a given grid cell, as shown in Table 6.1

Table 6.1. Example matrix of future/baseline ratios, by grid cell and model, for a future scenario.

	Model (m = 1, 2,…, M)						
Grid Cell (n = 1, 2,…, N)	**1**	**2**	**…**	**M**	**Mean**	**Lower Confidence Limit (LCL)**	**Upper Confidence Limit (UCL)**
1	$RFB_{q,1,1}$	$RFB_{q,1,2}$	…	$RFB_{q,1,M}$	$\overline{RFB}_{q,1}$	$RFB_{q,1}^{LCL}$	$RFB_{q,1}^{UCL}$
2	$RFB_{q,2,1}$	$RFB_{q,2,2}$	…	$RFB_{q,2,M}$	$\overline{RFB}_{q,2}$	$RFB_{q,2}^{LCL}$	$RFB_{q,2}^{UCL}$
…	…	…	…	…	…	…	…
N	$RFB_{q,N,1}$	$RFB_{q,N,2}$	…	$RFB_{q,N,M}$	$\overline{RFB}_{q,N}$	$RFB_{q,N}^{LCL}$	$RFB_{q,N}^{UCL}$

The engineer should evaluate the information in the table to confirm consistency among the means, lower confidence limits, and upper confidence limits between the grid cells. For example, if the grid cell mean ratios typically range from 1.2 to 1.5 except for a single grid cell that has a significantly different ratio of 2.5, then the engineer should examine the outlier grid cell to assess whether there is a reasonable explanation for the departure from the other grid cells.

If a single estimate of precipitation is considered appropriate to represent the watershed in Step 1, then a single estimate of the mean ratio from Table 6.1 is usually sufficient for assessing potential effects of climate change. However, the level of spatial disaggregation of precipitation determined in Step 1 may be modified if large variations in the ratios are observed as a function of location in the watershed. Depending on this evaluation, the selected *RFB* value for each quantile may represent a watershed average of the ratios computed in Table 6.1 or may spatially vary.

In most cases, the engineer will select the mean estimate of the ratio for each quantile for use in Step 9. The engineer should also use the ratios from the lower and upper confidence limits to consider design sensitivity to the variation in downscaled GCM outputs for that future scenario.

In ***Step 9***, the engineer estimates the projected 24-hour precipitation quantile(s) by multiplying the historical precipitation quantile from Step 1 by the ratio of future to baseline model estimates from Step 8 as shown in Equation 6.2.

$$P_{q,p} = P_{q,h}\left(RFB_q\right) \tag{6.2}$$

where:

$P_{q,p}$ = *Projected 24-hour precipitation quantile (q).*

$P_{q,h}$ = *Historical 24-hour precipitation quantile (q).*

RFB_q = *Ratio of the model future to model baseline 24-hour precipitation for quantile (q).*

Equation 6.2 is not recommended for quantiles more extreme than the 0.1 AEP quantile, because the current ability of high-resolution climate datasets to represent precipitation extremes (in the engineering hydrology sense) is limited. Therefore, Equation 6.3 is recommended for more extreme quantiles, including the 0.04 and 0.01 AEP quantiles. In this equation, the ratio associated with the 0.1 AEP quantile is substituted for the ratios estimated for the more extreme quantiles.

$$P_{q,p} = P_{q,h}(RFB_{0.1}) \tag{6.3}$$

where:

$RFB_{0.1}$ = *Ratio of the model future to model baseline for the 24-hour precipitation 0.1 AEP quantile.*

The engineer should consider the uncertainty in the estimate(s) of the projected 24-hour precipitation quantile(s) by using the upper and lower confidence limits of the ratios. This will provide insight into the potential variation in these estimates resulting from scientific uncertainty based on the ensemble of GCMs.

In ***Step 10***, the engineer repeats steps 5 through 9 for each additional future scenario selected in Step 3. Analysis of multiple scenarios provides further insight into potential future precipitation and the resultant vulnerabilities of the infrastructure. In general, the longer the relevant service life, the more important it is to consider multiple scenarios, as differences between scenarios become most apparent after the mid-century.

BOTTOM LINE: *It is the responsibility of the design team to determine the number of scenarios and GCMs to be analyzed using this 10-step process. The decision should be based on the resources available and the risks associated with the project.*

6.1.2 Sample Application of the 10-Step Procedure

This example illustrates application of the 10-step procedure for estimating future 24-hour duration precipitation quantiles. The site is a small watershed in the Denver, Colorado region (latitude = 39.6875 degrees, longitude = -104.8125 degrees).

Step 1. Determine the historical observed 24-hour precipitation RFC (or single AEP quantile, if only one is required) for the site.

NOAA Atlas 14 is used to determine the historical 24-hour precipitation quantiles for the site. Table 4.1 summarizes the results for four AEPs from the existing RFC. The table also shows the corresponding lower (5 percent) and upper (95 percent) confidence limits from NOAA Atlas 14 for each quantile.

Table 6.2. NOAA Atlas 14 24-hour precipitation quantiles for Denver, Colorado example.

AEP	P (in)	5% Confidence Limit (in)	95% Confidence Limit (in)
0.5	1.84	1.52	2.22
0.1	3.00	2.56	3.65
0.04	3.72	2.96	4.69
0.01	4.89	3.67	6.37

Step 2. Select baseline and future periods for analysis, as appropriate for the plan or project.

The engineer selects a baseline period of 1950 through 1999, which roughly corresponds to the period of record for NOAA Atlas 14. The engineer also selects two future periods to compare potential variation introduced by future period selection. The two future periods are: 1) the first half of the 21st century (2000 through 2049); and 2) the second half of the 21st century (2050 through 2099). As described in the description of the method, baseline and future periods should be at least 30 years.

Step 3. Identify the future scenarios and downscaled GCM outputs of interest from the most appropriate database of high-resolution climate projections, using the recommendations in Chapter 3.

The RCP6.0 scenario is selected for illustrating the method (see Chapter 3). The engineer should also consider a second scenario to evaluate sensitivity of results between scenarios. For the RCP6.0 scenario, an ensemble of 12 GCMs from the CMIP5 archive will be used. (Downscaled BCCA information was used for this analysis. Results from LOCA or other downscaled datasets will differ, but the methodology is the same.)

Step 4. Determine the number of grid cells required to adequately cover the watershed of interest.

Since the watershed is small, one grid cell is sufficient to cover the watershed. Two additional cells should also be analyzed, per the recommendation, to ensure that the analyzed cell is not an outlier; however, only the computations for the single cell will be illustrated in this example.

Step 5. Acquire the daily precipitation values, and extract an annual maximum series (AMS) for each grid cell for the selected future scenario and downscaled GCM output dataset. Adjust the AMS to unconstrained point values with an areal reduction factor and an unconstrained 24-hour correction factor appropriate for the location.

The engineer downloads the data from the DCHP website described earlier and extracts the AMS for each GCM. The engineer adjusts the AMS values to unconstrained point values by multiplying the unadjusted values by an areal reduction factor (1.04) and an unconstrained 24-hour correction factor (1.13). See Section 6.3 for determining an areal reduction factor and HEC-17 (7.4.4.1.1) for information about the unconstrained correction factor (Kilgore et al. 2016).

Step 6. For each grid cell, compute the 24-hour precipitation RFC (or single AEP quantile) for the baseline period and for the future period from the AMS from Step 5, using an appropriate statistical distribution.

The engineer estimates the RFC, represented by the 0.5, 0.1, 0.04, and 0.01 AEP quantiles, from the AMS from each high-resolution dataset (model) and summarizes the results in Table 6.3, Table 6.4, and Table 6.5 for the baseline period, the first future period, and the second future period, respectively. These tables also summarize the mean, standard deviation, and skew estimated for each model and period.

Because of the variation in moments across models, most notably the skew, the estimated quantiles also vary across models. However, all models underestimate the quantiles for the baseline period (Table 6.3) compared with the NOAA Atlas 14 values (Table 4.1). GCMs tend to underestimate extreme quantiles, which is one reason that high-resolution climate datasets are never used directly, but always as differences or ratios between future and baseline periods. This methodology uses ratios, as is discussed in Step 8.

Step 7. Repeat steps 5 and 6 for each individual GCM output identified in Step 3. The result of this step is a set of estimates for a 24-hour RFC (or single AEP quantile) for each grid cell and each downscaled GCM output for both the baseline and future periods for the selected scenario.

The tables referenced in Step 6 show the results for each of the 12 downscaled GCM (model) outputs. Only one cell is used for this example, but a minimum of three is recommended in the procedure.

Step 8. Compute the ratios of the modeled (GCM-based) future 24-hour precipitation RFC (or single AEP quantile) to the modeled baseline 24-hour precipitation RFC (or single AEP quantile) for all grid cells and simulations.

Table 6.6 and Table 6.7 summarize the computed ratios for the 2000-2049 and 2050-2099 periods, respectively. By considering an ensemble of GCMs, the engineer can evaluate the varied outcomes from different models. Referencing the ratios from the first future period to the baseline period (Table 6.6), the following outcomes are notable in this example from Denver:

Table 6.3. Estimated moments and quantiles for the baseline period (1950-1999).

Quantity	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Mean	0.0291	-0.0051	0.0077	0.0160	-0.0286	0.0034	0.0013	0.0001	-0.0089	0.0044	-0.0001	0.0442
Standard Deviation	0.1381	0.1504	0.1437	0.1606	0.1387	0.1497	0.1501	0.1507	0.1404	0.1500	0.1517	0.1586
Skew	0.6	0.4	-0.1	0.3	-0.7	-0.1	0.2	0.6	0.6	0.1	0.7	-0.4
AEP=0.5 Precip. (in)	1.04	0.97	1.02	1.02	0.97	1.01	0.99	0.97	0.95	1.00	0.96	1.13
AEP=0.1 Precip. (in)	1.63	1.56	1.55	1.68	1.37	1.56	1.57	1.59	1.51	1.58	1.59	1.74
AEP=0.04 Precip. (in)	1.98	1.90	1.80	2.06	1.51	1.82	1.88	1.96	1.83	1.87	1.99	1.99
AEP=0.01 Precip. (in)	2.57	2.44	2.15	2.66	1.67	2.19	2.36	2.60	2.39	2.31	2.68	2.32

Table 6.4. Estimated moments and quantiles for the future period (2000-2049).

Quantity	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Mean	0.0995	-0.0152	0.0102	0.0121	0.0245	0.0063	0.0432	0.0301	0.0177	0.0196	-0.0094	0.0281
Standard Deviation	0.1412	0.1330	0.1332	0.1650	0.1594	0.1502	0.1375	0.1393	0.1425	0.1406	0.1171	0.1766
Skew	0.1	-0.1	0.2	0.4	-0.2	0.5	0.2	0.1	-0.1	0.1	-0.1	0.6
AEP=0.5 Precip. (in)	1.25	0.97	1.01	1.00	1.07	0.99	1.09	1.07	1.05	1.04	0.98	1.02
AEP=0.1 Precip. (in)	1.91	1.42	1.53	1.70	1.68	1.60	1.67	1.62	1.58	1.59	1.38	1.83
AEP=0.04 Precip. (in)	2.25	1.63	1.79	2.10	1.96	1.96	1.96	1.90	1.83	1.86	1.55	2.35
AEP=0.01 Precip. (in)	2.74	1.92	2.19	2.78	2.35	2.57	2.42	2.31	2.18	2.27	1.80	3.27

Table 6.5. Estimated moments and quantiles for the future period (2050-2099).

Quantity	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Mean	0.0604	-0.0059	0.0327	0.0264	0.0624	-0.0045	0.0019	0.0780	0.0612	-0.0251	0.0334	0.0425
Standard Deviation	0.1662	0.1490	0.1418	0.1390	0.1377	0.1547	0.1566	0.1440	0.1356	0.1646	0.1147	0.1728
Skew	0.0	-0.4	0.3	0.2	-0.1	0.0	0.8	0.0	0.3	-0.4	0.1	0.0
AEP=0.5 Precip. (in)	1.15	1.01	1.06	1.05	1.16	0.99	0.96	1.20	1.13	0.97	1.08	1.10
AEP=0.1 Precip. (in)	1.88	1.50	1.65	1.61	1.73	1.56	1.63	1.83	1.73	1.51	1.52	1.84
AEP=0.04 Precip. (in)	2.25	1.71	1.97	1.90	1.99	1.85	2.06	2.14	2.05	1.73	1.73	2.21
AEP=0.01 Precip. (in)	2.57	2.44	2.15	2.66	1.67	2.19	2.36	2.60	2.39	2.31	2.68	2.32

Table 6.6. Estimated quantile ratios for future period (2000-2049) to baseline.

AEP	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
0.5	1.21	1.00	0.99	0.98	1.10	0.97	1.10	1.10	1.10	1.04	1.02	0.90
0.1	1.17	0.91	0.98	1.01	1.23	1.03	1.06	1.02	1.05	1.01	0.87	1.05
0.04	1.13	0.86	1.00	1.02	1.30	1.08	1.04	0.97	1.00	1.00	0.78	1.18
0.01	1.07	0.79	1.02	1.04	1.41	1.17	1.03	0.89	0.91	0.98	0.67	1.41

Table 6.7. Estimated quantile ratios for future period (2050-2099) to baseline.

AEP	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
0.5	1.11	1.04	1.04	1.03	1.19	0.98	0.97	1.24	1.19	0.96	1.12	0.97
0.1	1.15	0.97	1.07	0.96	1.26	1.00	1.03	1.15	1.15	0.95	0.95	1.06
0.04	1.13	0.90	1.10	0.92	1.32	1.01	1.10	1.09	1.12	0.93	0.87	1.11
0.01	1.09	0.81	1.15	0.88	1.41	1.03	1.21	0.99	1.07	0.88	0.76	1.20

- The Model 1 ratios show a ***decline*** in the ratios, from 1.21 for the 0.5 AEP to 1.07 for the 0.01 AEP. This result suggests that the RFC will ***flatten*** in the future, compared with the historical RFC.
- The Model 5 ratios show an ***increase*** in the ratios, from 1.10 for the 0.5 AEP to 1.41 for the 0.01 AEP. This downscaled GCM output suggests that the RFC will become ***steeper,*** compared with the historical RFC.
- Models 3 and 4 show ***relatively constant*** ratios across the range of AEPs. These ratios are also close to unity, suggesting that the future RFC will be ***nearly the same*** as the historical RFC.
- Model 2 provides an example of ***declining*** ratios, as was noted for Model 1, but also exhibits ratios that are ***less than 1***. Model 2 projects that the more extreme precipitation events (e.g., AEP = 0.01) will be less than the historical precipitation amount for that AEP.

Comparing the ratios for the later future period (Table 6.7) with those for the earlier future period (Table 6.6), one would expect to see higher ratios for the later period, as global mean temperatures are projected to increase under the RCP6.0 scenario. In most cases, the ratios support this hypothesis. However, in a few cases, such as for Model 4 and Model 6, the opposite trend is indicated.

An important part of Step 8 is to assess these ratios for patterns and anomalies. Table 6.8 and Table 6.9 summarize the mean, standard deviation, and the confidence limits for the ensemble of ratios for 2000-2049 and 2050-2099, respectively. In both tables, the mean values of the ratios are roughly constant across the AEPs ranging from 1.03 to 1.04 for the early future period and from 1.04 to 1.07 for the later future period. In this example, the models with higher and lower ratios offset each other, though this may not occur at all locations and for all model ensembles.

Examination of the 90-percent confidence interval – bounded by the 5-percent and 95-percent confidence limits – shows that in both tables, the confidence interval widens as the AEP becomes more extreme. That is, the confidence interval is much wider for the 0.01 AEP, compared with the 0.5 AEP. Not surprisingly, this suggests greater uncertainty in the estimates of more extreme AEPs.

Table 6.8. Ensemble summary of ratios and projections for 2000-2049.

AEP	Number of Models	Mean of Ratios	Std Dev. of Ratios	5% CL of Ratios	95% CL of Ratios	NOAA 14 Precip. (in)	Projected Precip. (In)
0.5	12	1.04	0.082	1.01	1.08	1.84	1.92
0.1	12	1.03	0.098	0.99	1.08	3.00	3.10
0.04	12	1.03*	0.137	0.97	1.10	3.72	3.84
0.01	12	1.03*	0.220	0.93	1.14	4.89	5.05

*Ratio of 1.03 for the 0.1 AEP is used for the more extreme AEPs. In this case, this represents no change to the estimated ratios for these AEPs.

Table 6.9. Ensemble summary of ratios and projections for 2050-2099.

AEP	Number of Models	Mean of Ratios	Std Dev. of Ratios	5% CL of Ratios	95% CL of Ratios	NOAA 14 Precip. (in)	Projected Precip. (In)
0.5	12	1.07	0.099	1.02	1.12	1.84	1.97
0.1	12	1.06	0.101	1.01	1.11	3.00	3.18
0.04	12	1.05*	0.128	0.99	1.11	3.72	3.94
0.01	12	1.04*	0.189	0.95	1.13	4.89	5.18

*Ratio of 1.06 for the 0.1 AEP is used for the more extreme AEPs. In this case, 1.06 is greater than the estimated ratios for these AEPs.

Based on an assessment of the ratios, the engineer may discard models or grid cells that exhibit anomalous behavior. This assessment requires engineering judgement, and the engineer should document the rationale for any discarded models or grids. For this example, none of the models were discarded.

Step 9. Estimate the projected 24-hour precipitation RFC (or single AEP quantile) from the historical observed 24-hour precipitation RFC (or single AEP quantile) from Step 1 and the ratio(s) from Step 8.

The engineer obtains the projected 24-hour precipitation quantiles from the mean values or confidence limit values of the ratios multiplied by the estimate of the existing quantiles. In this example, the existing quantiles were taken from NOAA Atlas 14 in Step 1 and are reproduced in Table 6.8 and Table 6.9. These tables also summarize estimates of the projected future quantiles, using Equation 6.2 for the 0.5 and 0.1 AEP quantiles and Equation 6.3 for the 0.04 and 0.01 AEP quantiles. To illustrate a computation, the projected 0.01 AEP precipitation estimate in Table 6.9 is 1.06 x 4.89 inches = 5.18 inches.

Figure 6.2 displays the projected precipitation quantiles, along with the NOAA Atlas 14 historical AEP precipitation estimates. For this example, the projected change in 24-hour precipitation using the RCP6.0 scenario is not significant. In the context of the confidence limits for the NOAA Atlas 14 estimates in Table 4.1, the projected change in the 0.01 AEP precipitation is well within the 90-percent confidence interval based on the historical record (3.67 to 6.37 inches). Therefore, it may be advisable for the engineer in this example to evaluate project sensitivity to the variability in the historical record using the NOAA Atlas 14 confidence limits, rather than focusing on the projections of future precipitation under climate change scenarios. Alternatively, further analysis in this example of this future scenario could be conducted using the 95-percent confidence limit ratios to estimate alternative projected estimates.

BOTTOM LINE: Variability in the historical record of precipitation is quantified by confidence limits. The engineer should be aware of this variability and evaluate potential changes in precipitation resulting from a changing climate in the context of the historical confidence limits. Projected changes in precipitation may or may not be significant, compared with historical variability.

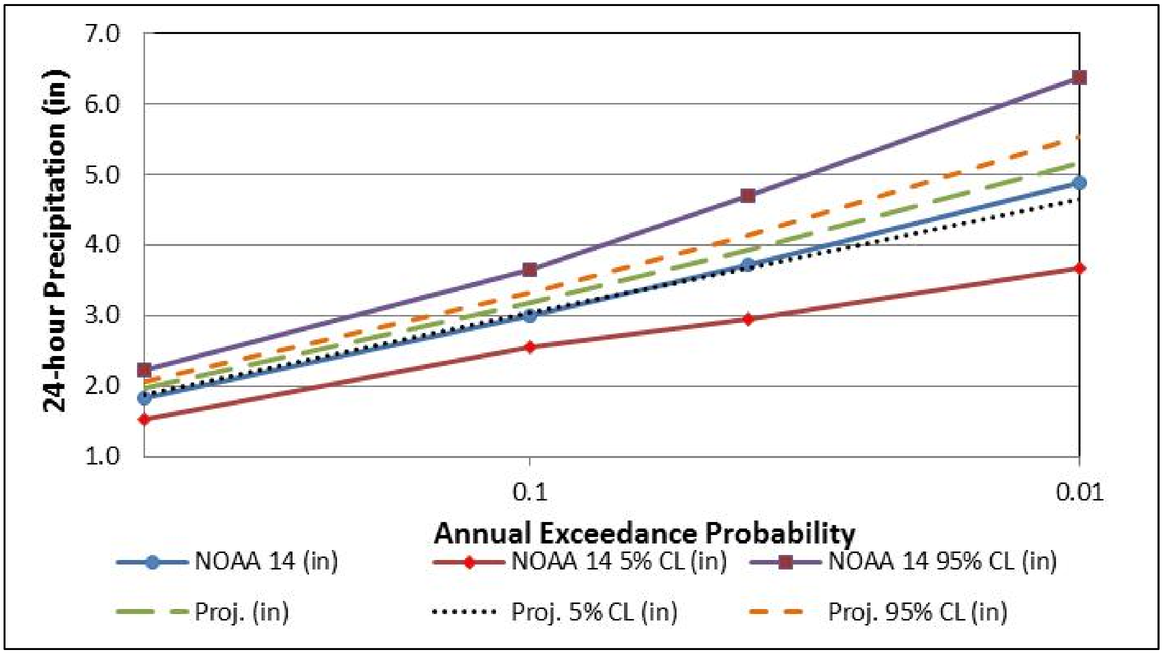

Figure 6.2. Projected (2050-2099) estimates of the 24-hour precipitation for Denver, Colorado.

Step 10. Repeat steps 5 through 9 for each future scenario identified in Step 3.

In the Denver example, the initial analysis was conducted using RCP6.0. It is recommended that more than one scenario be evaluated when the project and resources justify further analysis. In this case, the first scenario did not result in significant changes in the estimates of the 24-hour precipitation quantiles.

6.1.3 Applicability and Limitations

Section 6.1 describes a method for estimating projected 24-hour precipitation design depths including, but not limited to, the 0.5, 0.1, 0.04, and 0.01 AEP quantiles. The method is applicable to projects requiring a Level 3 analysis and some Level 4 analyses (see Chapter 4) requiring a 24-hour duration precipitation depth as an input to rainfall/runoff modeling or for applying the CCI (see Chapter 4). The rainfall/runoff modeling tools in which the projected 24-hour duration precipitation estimates can be applied include the NRCS graphical peak discharge method and many unit hydrograph procedures.

As recommended in Chapter 3, the design team should evaluate multiple future climate scenarios, when feasible, to provide a more comprehensive understanding of possible future precipitation estimates. Results will be more informative when a larger ensemble of GCMs are considered, giving a larger potential range of outcomes.

This procedure is limited by the ability of high-resolution climate datasets to represent historical and future extreme precipitation, particularly those extremes greater than the 0.1 AEP quantiles. As described in the introduction of the method and illustrated in the sample application, current high-resolution climate datasets tend to underestimate extremes. The procedure mitigates this limitation by using the 0.1 AEP ratio for estimating projected precipitation values for the more extreme quantiles, including the 0.04 and 0.01 AEPs.

6.1.4 Discussion and Other Resources

The projected changes in precipitation illustrated in this example, as shown in Figure 6.2, are not notable. However, application of this methodology using different scenarios, GCMs, and future periods might result in larger changes. In addition, application of the methodology in other parts of the country could exhibit different results.

The example demonstrates that engineers should consider confidence limits based on the historical data in the design process more often than is typical today. Recall that the confidence limits, such as those shown in Figure 6.2, are derived from historical data. The range in the confidence limits tells engineers that precipitation estimates are far from certain and should be considered in design for some projects, even without considering a changing climate.

The simplified procedure described in this section is intended to be used by hydrologic engineers without special training in climate change modeling or technology. The procedure uses existing hydrologic analysis tools and assumes that some relationships in the observed record will remain constant, even though projected estimates will increase (or decrease) relative to historical estimates.

More complex approaches are described in Kilgore et al. (2019). However, these require specialized skills and resources to implement. In some cases, regional or state organizations may collaborate to develop tools for projected conditions, such as a NOAA Atlas 14 – type resource, that design engineers could use in the same way they do the tools for existing conditions.

This 10-step procedure introduces innovations for estimating projected 24-hour precipitation quantiles. Components of this procedure where further research might improve the methodology include answering the following questions:

- How sensitive are projected precipitation quantiles to the selection of baseline and future periods?
- Is the analysis of a minimum of three grid cells for small watersheds necessary?
- What difference does the use of a ratio rather than a difference (delta) make in the estimate of the projected 24-hour precipitation quantiles?
- Does projecting the more extreme AEP quantiles (e.g., the 0.04 and 0.01 AEP) using the model ratio for the 0.1 AEP quantile provide a more accurate projection of the extreme AEP quantiles?

A challenge for further research is that because what may happen in the future is being considered, there is no objective reference with which to compare. However, by applying these procedures to examples, one can compare the results from the recommended procedure and other approaches to assess whether there are major differences and, if so, which procedure appears to provide more reasonable results.

6.2. Projected Sub-Daily Precipitation/IDF Curve

For many types of transportation infrastructure, such as roadways, storm drains, and stormwater management facilities, sub-daily rainfall information is required for rainfall/runoff modeling as part of a Level 3 or Level 4 analysis. The primary tool presented in this *Guide* for application at the project level is based on ***linear scaling***. Linear scaling requires establishing the 24-hour duration quantile projection (as in Section 6.1) and uses historical relationships between the 24-hour duration and shorter durations for the same AEP. This approach is recommended because the high-resolution climate datasets described in Chapter 3 do not include sub-daily precipitation outputs that can be used for design. As the models and methods used in climate science improve, reliable sub-daily information may become available, resulting in a need to revise the recommended procedures in this *Guide*.

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§2.2.3.1 Factors Affecting Runoff/Meteorological Characteristics/Rainfall

§2.3.2.2 Data Sources/Sources of Hydrologic Data/Rainfall Data

§2.7.3 Methods for Estimating Flood Peaks, Durations, and Volumes/Empirical Hydrologic Models

§2.7.6 Methods for Estimating Flood Peaks, Durations, and Volumes/Mathematical Models

Two linear scaling methods, the Kilgore method (Kilgore et al. 2016) and NRCS regional temporal distributions, are described in Section 6.2.1. These methods are based on scaling historical precipitation data from NOAA Atlas 14 or other precipitation sources. An application of these methods is provided in Section 6.2.2, and applicability and limitations are described in Section 6.2.3.

Other resources for projected sub-daily information have been developed, but they are not widely available. Examples of recent and relevant efforts include:

- Application of the Simonovic approach (Simonovic et al. 2016) on a state or regional level.
- Locally developed IDF curves for future conditions (e.g., New York City) (New York City 2017).

The Simonovic approach, described in Section 6.2.4, is likely too complex to consider for all but a very few project applications. Therefore, it is recommended that a state, or group of states, consider applying this approach, or others, on a regional level as a resource for a broader range of projects. A state or regional government would design and fund such a tool.

6.2.1 Linear Scaling

As described in this *Guide*, linear scaling assumes that historical relations between the 24-hour duration and shorter (sub-daily) durations can be assumed to hold in the future and can be combined with projected 24-hour precipitation values to estimate future sub-daily precipitation for a particular AEP or for a complete IDF relation. The general procedure for linear scaling is summarized in the following steps:

1. Determine the historical 24-hour and sub-daily precipitation estimates for a selected AEP from an accepted source, and calculate the ratio of each sub-daily value to the 24-hour value.
2. Estimate the future 24-hour precipitation depth for the selected AEP, using the 10-step procedure in Section 6.1 or other suitable approach.
3. Apply the sub-daily ratios computed in Step 1 to the future 24-hour precipitation estimated in Step 2 to compute the future sub-daily values for the selected AEP.
4. Repeat Steps 1 through 3 for each AEP of interest.

For **Step 1**, the engineer draws on the standard resources for determining historical sub-daily values (for a required duration and AEP) or a complete IDF relation. NOAA Atlas 14 is an example of such a resource, but many other region- or state-specific resources are available for this purpose. From these data, the ratio of each sub-daily value to the 24-hour value is computed.

For the Kilgore linear scaling method (Kilgore et al. 2016), the sub-daily ratios are site-specific because they are based on resources such as NOAA Atlas 14. The NRCS regional temporal distribution scaling method, as its name implies, relies on regional temporal distributions to estimate the sub-daily data. NRCS has developed regional temporal distributions using data from all volumes of NOAA Atlas 14.

For **Step 2**, the engineer applies the procedure described in Section 6.1 to estimate a future 24-hour duration precipitation depth for a given AEP. As discussed in Section 6.1, the engineer should evaluate multiple scenarios and use multiple GCMs to the extent that project resources allow. Approaches other than the 10-step procedure may be used for estimating the future 24-hour duration precipitation.

In **Step 3**, the engineer combines the information from Steps 1 and 2 to estimate the future sub-daily values for the given AEP. Application of the historical ratios in Step 1 to the computation in Step 3 assumes that these ratios from the historical record are valid in the future. That is, the computation assumes stationarity in these relations. This is a pragmatic assumption that permits rational estimates of sub-daily precipitation based on projected 24-hour precipitation estimates. As described earlier, as the high-resolution datasets discussed in Chapter 3 evolve to include reliable sub-daily precipitation, the recommended procedures in this *Guide* should be updated.

Finally, in **Step 4**, the engineer repeats the previous steps for each AEP of interest. In some applications, a single AEP may be sufficient to meet the project needs; in others, a range of AEPs or comprehensive IDF relation may be required. An example of linear scaling using the Kilgore method and the NRCS regional temporal distributions is provided in the following section.

6.2.2 Linear Scaling Example

Linear scaling is demonstrated using information for the Philadelphia, Pennsylvania area using both linear scaling methods. NOAA Atlas 14 is used for historical rainfall information, and a Pennsylvania Department of Transportation (PennDOT) study is used for projected precipitation information (PennDOT 2017).

6.2.2.1 Kilgore Method

For the Kilgore scaling method (Kilgore et al. 2016), site-specific sub-daily estimates are determined from the NOAA Atlas 14 historical ratio of the d-hour duration to the 24-hour duration, applying that ratio to the projected 24-hour duration value. (d in d-hour duration can be less than 1. For example, d could be 0.25 hours (15 minutes).) Each step is described as follows.

Step 1. Determine the historical 24-hour and sub-daily precipitation estimates for a selected AEP from an accepted source, and calculate the ratio of each sub-daily value to the 24-hour value.

The Kilgore scaling method uses the historical 24-hour and sub-daily data from NOAA Atlas 14 or another accepted source. The observed 24-hour and sub-daily data from NOAA Atlas 14, Volume 2 (Ohio Valley and neighboring states) are summarized in Table 6.10 for selected durations and AEPs for Philadelphia, Pennsylvania. Table 6.11 summarizes the ratio of each duration value to the corresponding 24-hour value in the historical record.

Table 6.10. Observed sub-daily precipitation depths or selected durations and AEPs from NOAA Atlas 14 for Philadelphia, PA.

Duration	AEP (0.50) (inches)	AEP (0.10) (inches)	AEP (0.04) (inches)	AEP (0.01) (inches)	AEP (0.002) (inches)
5-minute	0.38	0.53	0.60	0.68	0.76
15-minute	0.77	1.08	1.21	1.37	1.52
60-minute	1.33	2.03	2.38	2.89	3.47
6-hour	2.16	3.37	4.05	5.15	6.58
24-hour	2.99	4.76	5.83	7.67	10.20

Table 6.11. Quantile ratios for each AEP, based on NOAA Atlas 14 for Philadelphia, PA.

Duration	AEP (0.50) (inches)	AEP (0.10) (inches)	AEP (0.04) (inches)	AEP (0.01) (inches)	AEP (0.002) (inches)
5-minute	0.1271	0.1113	0.1029	0.0887	0.0745
15-minute	0.2575	0.2269	0.2075	0.1786	0.1490
60-minute	0.4448	0.4265	0.4082	0.3768	0.3402
6-hour	0.7224	0.7080	0.6947	0.6714	0.6451
24-hour	1.0000	1.0000	1.0000	1.0000	1.0000

Step 2. Estimate the future 24-hour precipitation depth for the selected AEP using the 10-step procedure in Section 6.1 or other suitable approach.

Because this example is based on a study performed for PennDOT (PennDOT 2017), the option to use another suitable approach, rather than the 10-step procedure, was adopted. However, many elements of the 10-step procedure are also used in the PennDOT study.

In the PennDOT study, downscaled GCM output daily data for a single grid cell in the Philadelphia area were obtained, as described in Step 5 of the 10-step procedure in Section 6.1. Because each grid cell is approximately 12 km by 12 km, or 56 square miles, the gridded (56-square-mile) daily data were also converted to point data by multiplying by 1.04 (Hershfield 1961) and converted to 24-hour data using the conversion factor 1.13 (NOAA Atlas 14, Volume 2), as described in Step 5 of the 10-step procedure.

The CSIRO-Mk3.6.0 (CSIRO) model output for the RCP8.5 future scenario was one of three GCMs used to estimate future precipitation in the PennDOT study. The CSIRO model results for the 2000-2049 period (RCP8.5 scenario) were chosen for this example because this scenario projected an increase in the extreme AEP events, such as the 0.01 AEP (100-year) event, from the historical period. Multiple models and scenarios should be used to provide the engineer with a more complete picture of possible future outcomes, as described in Chapter 3.

As described in Step 6 of the 10-step procedure, the PennDOT analysts computed the 24-hour quantiles for the historical period (1950-1999) and a future period (2000-2049, RCP8.5). The 24-

hour precipitation depths for selected AEPs for the historical period (1950-1999) and the future period (2000-2049) are given in Table 6.12. The future quantiles range from 12 to 15 percent higher than those of the historical period.

Table 6.12. 24-hour quantiles derived from downscaled GCM output for the baseline and future periods for the example.

AEP	Model Precipitation for the Baseline Period (1950-1999) (inches)	Model Precipitation for the Future Period (2000-2049) (inches)	Quantile Ratio (Future to Baseline)	Projected 24-Hour Precipitation (inches)
0.50	2.737	3.079	1.125	3.36
0.10	4.217	4.788	1.135	5.40
0.04	5.011	5.709	1.139	6.64
0.01	6.259	7.159	1.144	8.77
0.002	7.835	8.994	1.148	11.71

The projected 24-hour precipitation quantiles were computed from the historical quantiles in Table 6.10 and the model ratio in Table 6.12, using Equation 6.2. For the 0.01 AEP quantile, this becomes:

$$P_{0.01,p} = P_{0.01,h}(RFB_{0.01}) = 7.67(1.144) = 8.77\ inches$$

Results for the 0.01 AEP and other quantiles are shown in Table 6.12.

Step 3. Apply the sub-daily ratios computed in Step 1 to the future 24-hour precipitation estimated in Step 2 to compute the future sub-daily values for the selected AEP.

Using the 0.01 AEP as an example, the ratios and corresponding d-hour duration data for the Kilgore method are given in Table 6.13. The first column displays the historical ratios for the 0.01 AEP taken from Table 6.11. The last column in the table contains the estimated future sub-daily precipitation depths calculated by multiplying the ratio for each duration by the 24-hour 0.01 AEP estimate of 8.77 inches. These values are the sub-daily estimates for future conditions. By using other downscaled GCM output and alternative future scenarios, the engineer can evaluate the sensitivity of these results to alternative information.

Step 4. Repeat steps 1 through 3 for each AEP of interest.

The process summarized in the previous three steps can be repeated for alternative AEPs. In this example, taking the ratios for other AEPs from Table 6.11 and multiplying them by the projected 24-hour precipitation estimates from Table 6.12 yields projected sub-daily values for these AEPs.

Table 6.13. Summary of sub-daily precipitation from the Kilgore et al. (2016) scaling method.

Duration	Ratio of Atlas 14 Sub-Daily to 24-hour	Projected Sub-Daily Estimate (Ratio * 8.77) (inches)
5 minutes	0.0889	0.78
15 minutes	0.1786	1.57
60 minutes	0.3768	3.31
6 hours	0.6714	5.89
24 hours	1.0000	8.77

6.2.2.2 NRCS Regional Temporal Distribution Method

The NRCS regional temporal distribution scaling method also relies on scaling the 24-hour quantile from NOAA Atlas 14 and is similar to the Kilgore method. However, a regional temporal distribution, rather than specific at-site data, is used to estimate the sub-daily data. The following describes the steps using the same site in Philadelphia, Pennsylvania.

Step 1. Determine the historical 24-hour and sub-daily precipitation estimates for a selected AEP from an accepted source and calculate the ratio of each sub-daily value to the 24-hour value.

In the NRCS regional temporal distribution method, the ratios are embedded in the regional curves. NRCS has developed regional temporal distributions using data for all volumes of NOAA Atlas 14. A map of regional rainfall distributions for the site in Philadelphia, using data from Volume 2 of NOAA Atlas 14 (Ohio Valley and neighboring states), is shown in Figure 6.3 (Merkel et al. 2015).

The NRCS temporal distribution for the Philadelphia, PA area, identified as NOAA_C, is shown in Figure 6.4. Using the ordinates of the NOAA_C temporal distribution (available within the WinTR20 computer program), the fraction of precipitation within a given duration can be estimated. The computations for the NRCS regional distribution are summarized in the first column of Table 6.14.

Step 2. Estimate the future 24-hour precipitation depth for the selected AEP using the 10-step procedure in Section 6.1 or another suitable approach.

The process for estimating future 24-hour precipitation depths is identical to that used for the Kilgore method. Therefore, the results shown in Table 6.12 also apply to the NRCS method.

Step 3. Apply the sub-daily ratios computed in Step 1 to the future 24-hour precipitation estimated in Step 2 to compute the future sub-daily values for the selected AEP.

Like the Kilgore method, NRCS regional temporal distribution scaling method uses the ratios summarized in Table 6.14 and the projected 24-hour precipitation estimates from Table 6.12 to calculate the projected sub-daily precipitation estimates. Using the 0.01 AEP as an example, the results are shown in Table 6.14. These values are the sub-daily estimates for future conditions. By using other downscaled GCM output and alternative future scenarios, the engineer can evaluate the sensitivity of these results to alternative information.

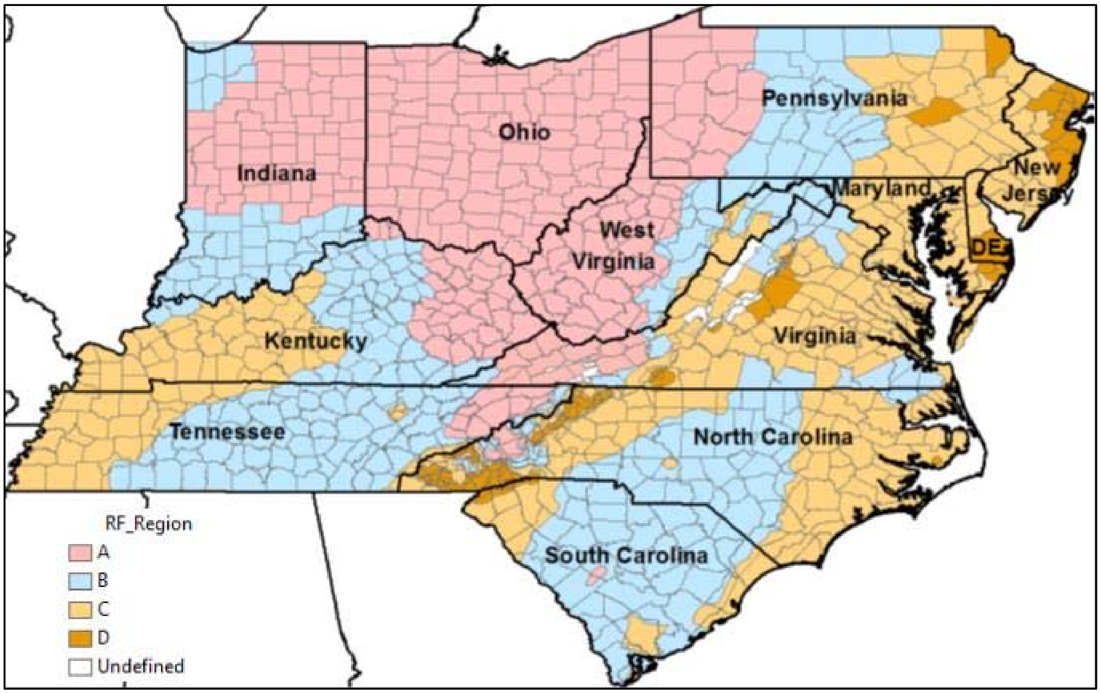

Figure 6.3. Map of NRCS regional rainfall distributions using data from Volume 2 of NOAA Atlas 14 (Merkel et al. 2015).

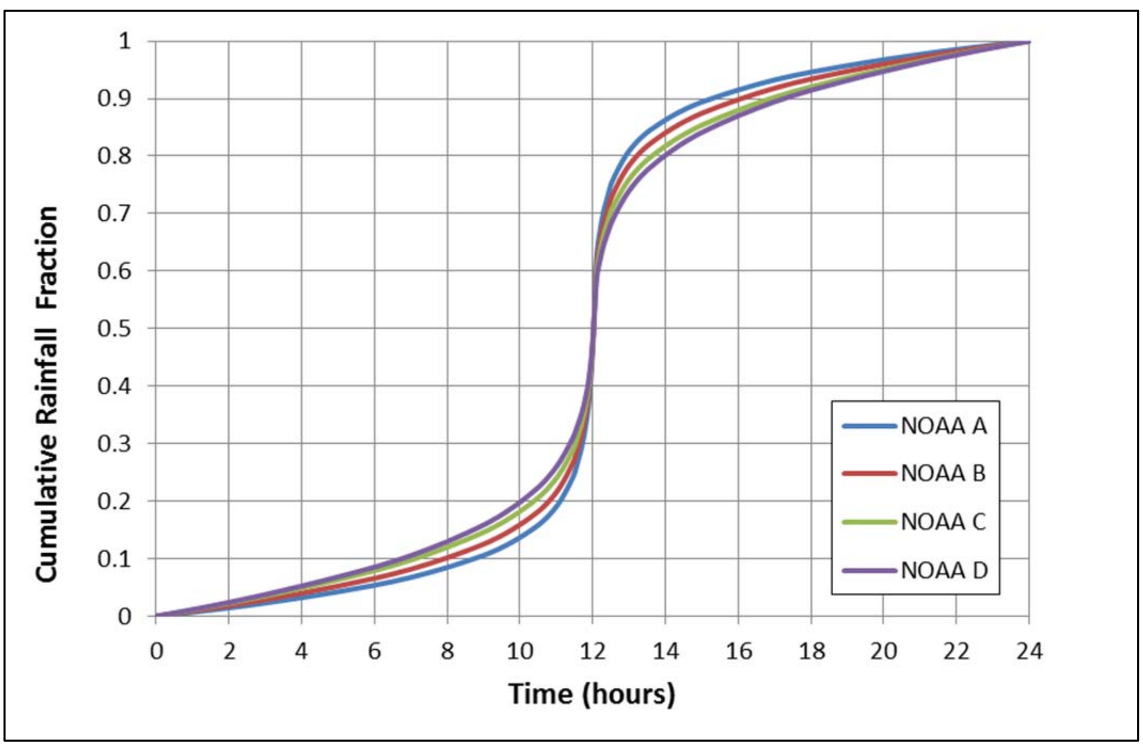

Figure 6.4. Four NRCS regional 24-hour rainfall distributions using data from Volume 2 of NOAA Atlas 14 (Ohio Valley and neighboring states).

Table 6.14. Example of sub-daily precipitation for the NRCS regional distribution scaling method using the NOAA_C temporal distribution.

Duration	Ratio of Precipitation for Given Duration	Projected Sub-Daily Estimate (Ratio * 8.77) (inches)
5 minutes	0.09726	0.85
15 minutes	0.20688	1.82
60 minutes	0.40940	3.59
6 hours	0.70790	6.21
24 hours	1.00000	8.77

Step 4. Repeat steps 1 through 3 for each AEP of interest.

The process summarized in the previous three steps can be repeated for alternative AEPs. With the NRCS methodology, the ratios in Table 6.14 are used for all AEPs. Therefore, the only difference in the sub-daily values for each AEP is the projected 24-hour precipitation from Step 2.

6.2.2.3 Comparison of Results for the Sample Application

Two linear scaling methods were applied to data for the Philadelphia, Pennsylvania area. In each case, the depth-frequency curves for the 0.01 AEP were estimated. Table 6.15 summarizes the results for using these methods for this site, along with those of a third method, referred to as the Simonovic method (Simonovic et al. 2016). The Simonovic method, more rigorous in many respects, is described Section 6.2.4. However, all three methods result in comparable increases from the NOAA Atlas 14 (historical) sub-daily values, also shown in the table.

Table 6.15. Summary of the depth-frequency curves the 0.01 AEP for estimating future precipitation in Philadelphia.

Duration	NOAA Atlas 14 (Historical) (inches)	Kilgore Method (inches)	NRCS Regional Distribution Method (inches)	Simonovic Method (inches)
5 minutes	0.68	0.78	0.85	0.74
15 minutes	1.37	1.57	1.82	1.48
60 minutes	2.89	3.31	3.59	3.25
6 hours	5.15	5.89	6.21	5.94
24 hours	7.67	8.77	8.77	9.00

For this example, the Kilgore and the Simonovic methods result in similar estimates, presumably because they are based on at-site data. The NRCS regional distribution method uses a regional temporal distribution. However, all three methods give similar results for this example, based on one GCM, one future scenario, and one future period. The NRCS method is easiest to apply, because the temporal distributions developed by NRCS are available and can be used directly in watershed modeling programs such as HEC-HMS and Win TR-20. The Simonovic method is the most time consuming and data intensive.

In the PennDOT analysis (PennDOT 2017), limited frequency analyses were performed for grids in the Baltimore, Maryland and Pittsburgh, Pennsylvania areas, in addition to Philadelphia, Pennsylvania, using simulations from three GCMs (CSIRO, CCSM4, and MIROC5). Estimates of the 0.01 AEP daily events both increased and decreased from historical to future periods. However, the mean of the annual maximum daily precipitation values always increased with time, suggesting that more frequent quantiles may consistently increase, even if more extreme quantiles might not. As with any dataset, the absence or presence of extreme events will likely affect the computed standard deviation and skew more than the mean. This absence or presence of extreme events in a particular modeling sequence may be random or may reflect the fact that some modeling approaches do not model the extremes of the AEP distribution very well.

6.2.3 Applicability and Limitations

The Kilgore and NRCS linear scaling methods are based on estimating a 24-hour projected quantile and then estimating the sub-daily precipitation based on historical sub-daily data distribution (Kilgore) or a predetermined temporal distribution (NRCS). A 24-hour storm was chosen to illustrate the methods, because future precipitation data are generally available for a daily time step. The methods could be extended to longer duration storms, such as a 48-hour duration, using the same approach described for the 24-hour storm. The 24-hour storm duration is appropriate for watersheds where the time of concentration is less than 24 hours.

The limitation of these methods is the assumption that the relation between the 24-hour duration and the sub-daily durations will be the same in the future as it is in the historical data. Until reliable sub-daily precipitation information is available from high-resolution climate datasets, this pragmatic assumption is valuable for estimating sub-daily precipitation.

6.2.4 Discussion and Other Resources

Kilgore et al. (2019) reviewed several approaches in the literature for estimating sub-daily precipitation for future periods, both on a site-specific basis and for a region. The development of tools that could provide estimates of future precipitation in the same way that NOAA Atlas 14 is used for historical precipitation is a goal of many of those efforts.

One method applied nationwide in Canada holds promise for application in the United States and elsewhere (Simonovic et al. 2016). This approach provides estimates of future sub-daily precipitation quantiles through a process that includes three primary statistical investigations:

- Determination of relations between sub-daily quantiles and the 24-hour quantile for historical data.
- Determination of relations between projected and baseline 24-hour quantiles, based on downscaled GCM output.
- Integration of the above statistical relations to define projected sub-daily quantiles of precipitation.

The Simonovic approach is recommended from among several alternatives because it has a relatively straightforward approach that can be applied to multiple rain gauges for a project-specific study, as well as to a larger area to develop a regional or national tool. The Simonovic approach is likely too complex to consider for all but a very few project applications. Therefore, it is recommended that a state, or group of states, consider applying this approach on a regional level as a resource for a broader range of projects. The steps in the application of the Simonovic approach, adapted for U.S. application, are:

1. Obtain the sub-daily observed (historical) quantiles from NOAA Atlas 14 for several sub-daily durations, such as 5, 10, 15, 30 and 60 minutes and 2, 3, 6, 12 and 24 hours.
2. Extract the daily annual maximums for each downscaled GCM output and future scenario for the baseline (historical) period for each grid cell, convert the gridded daily data to 24-hour point data, and estimate the quantiles using an appropriate three-parameter frequency distribution, assuming a stationary time series.
3. Extract the daily annual maximums for each downscaled GCM output and future scenario for each future period, convert the gridded daily data to 24-hour point data, and estimate the quantiles as described in Step 2.
4. Establish statistical relations between the GCM baseline 24-hour quantiles (Step 2) and the sub-daily observed (historical) quantiles obtained from NOAA Atlas 14 (Step 1). Need sufficient durations to represent adequately the IDF curves.
5. Establish a statistical relation between the GCM 24-hour quantiles for the baseline period (Step 2) and for the future period (Step 3) (One relation for each future period, GCM model, and future scenario).
6. Use the statistical relations from Steps 4 and 5 and future downscaled GCM output 24-hour quantiles to estimate future sub-daily precipitation for development of IDF curves for a given future time period and future scenario.

These steps are repeated for multiple GCMs and scenarios to provide an understanding of the variability in the projected information. To illustrate the procedure, the steps are applied to Philadelphia.

For Step 1, the observed 24-hour and sub-daily AEP quantiles for selected durations were extracted from NOAA Atlas 14 Volume 2. This information was summarized previously in Table 6.10. Five durations were chosen, to illustrate the technique and to simplify the computations.

To estimate the quantiles for Steps 2 and 3 of the procedure, the logarithms of the annual maximum series of daily GCM output were fit to the Pearson Type III distribution, assuming a stationary time series to determine the daily quantiles for the historical period (1950-1999) and the future period (2000-2049, RCP8.5). The precipitation depths for selected AEPs for the two periods were given in Table 6.12. Again, to illustrate the procedure and simplify the computations, a single GCM and future scenario were used.

In Step 4, a series (one for each duration) of statistical relations between the observed (historical) sub-daily quantiles and the GCM daily quantiles estimated for the 1950-99 historical period were developed. Each row in Table 6.10 (representing a duration) was regressed against the historical GCM daily quantiles in Table 6.12, pairing the data by AEP. These data are plotted in Figure 6.5. The resulting linear regression of the logarithms is defined as follows:

$$P_{1,\mathrm{h}} = 0.5375\left(PB_{24,m}\right)^{0.9144} \tag{6.4}$$

where:

$P_{1,h}$ = *Historical precipitation for a 1-hour duration.*

$PB_{24,m}$ = *Baseline period 24-hour precipitation from the downscaled GCM model (m) output.*

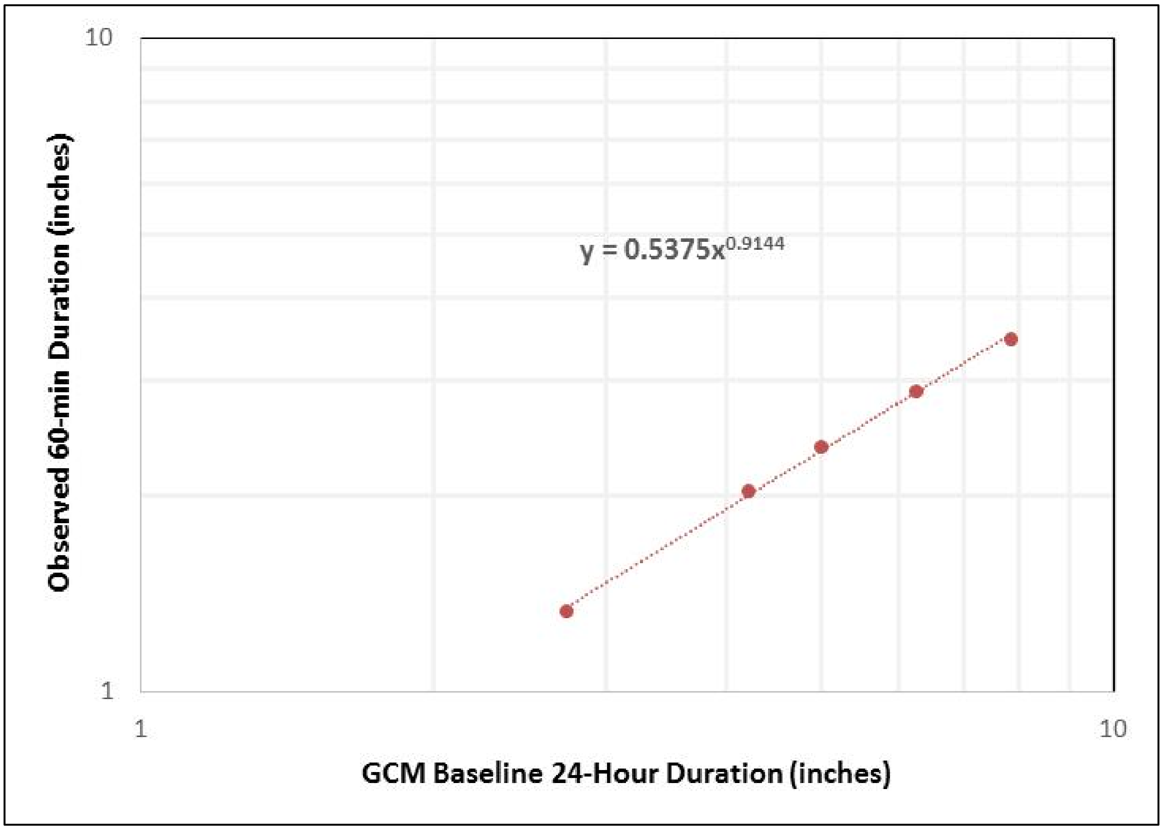

Figure 6.5. Relation between observed 60-minute duration quantiles and GCM baseline daily (24-hour) quantiles for the sample application to Philadelphia, PA.

In Step 5, a single statistical relation between future GCM quantiles and the historical GCM quantiles was developed for each GCM model, scenario, and future time period. For this example, both of these sets of quantiles are shown in Table 6.12 and plotted in Figure 6.6. With linear regression of the logarithms, the relation shown in the figure is defined as follows:

$$PF_{24,\mathrm{m}} = 1.1038\left(PB_{24,\mathrm{m}}\right)^{1.0193} \tag{6.5}$$

where:

$PF_{24,m}$ = *Future period 24-hour precipitation from the downscaled GCM model (m) output.*

$PB_{24,m}$ = *Baseline period 24-hour precipitation from the downscaled GCM model (m) output.*

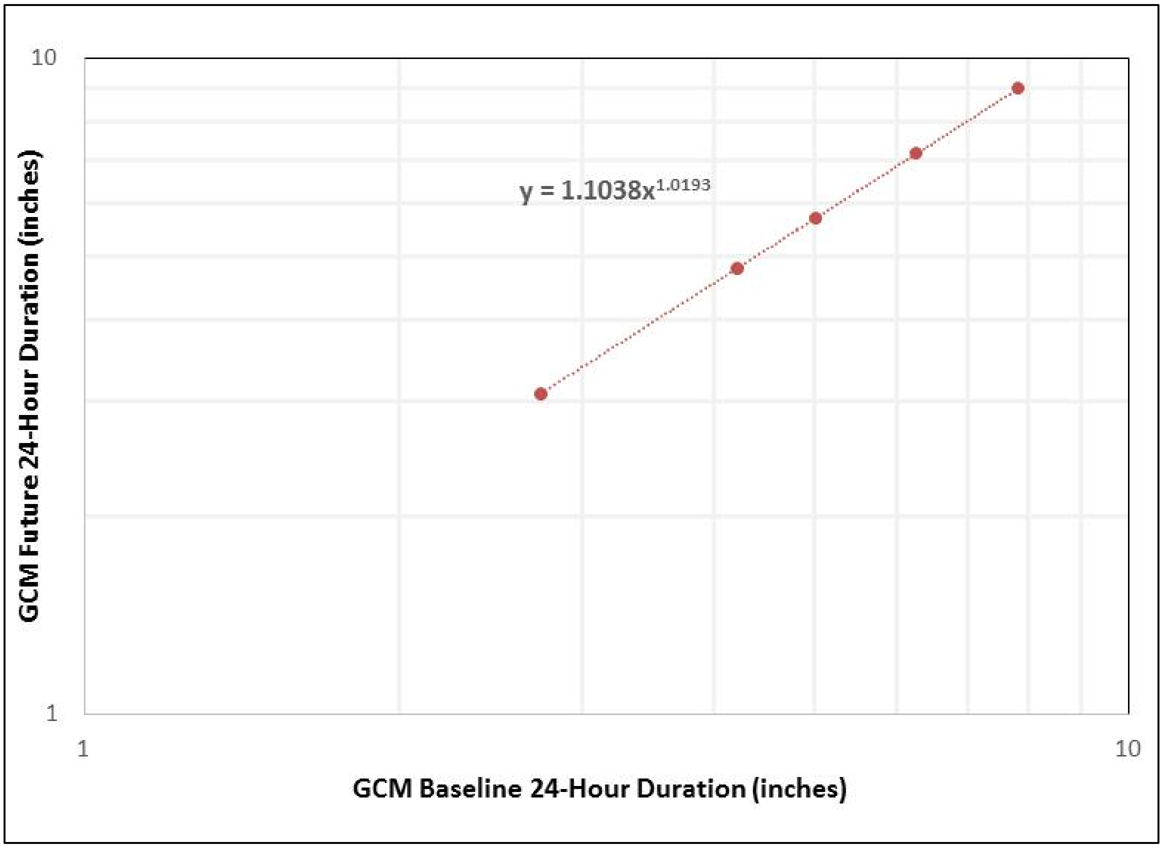

Figure 6.6. Relation between the GCM future and baseline daily (24-hour) quantiles for the sample application to Philadelphia, PA.

For Step 6, the previous two equations were transformed to generate projected sub-daily quantiles. First, Equation 6.4 was redefined for a future, rather than historical, period by assuming the future 60-minute quantiles and the future daily quantiles will have the same relation as in Equation 6.5. Then, Equation 6.5 was substituted into Equation 6.4 to yield:

$$P_{1,\mathrm{p}} = 0.588\left(PB_{24,,m}\right)^{0.932} \qquad (6.6)$$

where:

$P_{1,p}$ = *Projected precipitation for a 1-hour duration.*

While it appears from Equation 6.6 that the projected 24-hour precipitation information is no longer needed to compute the future sub-daily information, it is actually incorporated (in a smoothed form) within the equation. Also, in Equation 6.6, the AEP for the future 60-minute quantile is the same as the AEP for the 24-hour historical GCM daily quantile.

The historical and resulting future quantiles for the 60-minute duration are given in Table 6.16. The increase in the 60-minute quantile from historical to future for the given GCM and future scenario conditions ranges from 11 to 13 percent. That is consistent with the 12- to 15-percent increase in the daily quantiles in Table 6.12, because the observed 60-minute values are being scaled by the increase (or decrease) in the historical daily quantiles.

Table 6.16. Summary of historical and future 60-minute quantiles for Philadelphia, PA.

Exceedance Probability	Historical 60-minute precipitation depth (inches)	Future (2000-2049) 60-minute precipitation depth (inches)	Ratio of Future to Historical
0.50	1.33	1.50	1.13
0.10	2.03	2.25	1.11
0.04	2.38	2.64	1.11
0.01	2.89	3.25	1.12
0.002	3.47	4.00	1.13

Following the same procedure, future quantiles for the 5- and 15-minute durations, and the 6- and 24-hour durations were computed; they are summarized in Table 6.17. The quantiles for the 5- and 15-minute durations increased 6 to 13 percent from historical to future conditions, while the quantiles for the 6- and 24-hour durations increased 12 to 18 percent.

Table 6.17. Summary of historical and future (2000-2049, RCP8.5) quantiles for the 5- and 15-minute and 6- and 24-hour durations for Philadelphia, PA.

AEP	5-min historical (inches)	5-min future (inches)	15-min historical (inches)	15-min future (inches)	6-hour historical (inches	6-hour future (inches)	24-hour historical (inches)	24-hour future (inches)
0.50	0.381	0.422	0.766	0.854	2.16	2.43	2.99	3.36
0.10	0.532	0.566	1.06	1.14	3.37	3.88	4.76	5.62
0.04	0.598	0.636	1.21	1.28	4.05	4.67	5.83	6.90
0.01	0.682	0.739	1.37	1.48	5.15	5.94	7.67	9.00
0.002	0.762	0.860	1.52	1.72	6.58	7.57	10.2	11.75

IDF curves for existing conditions can be constructed from data in Table 6.10, while IDF curves for future conditions can be constructed from data in Table 6.16 and Table 6.17. For example, the historical and future depth-frequency curves for the 0.01 AEP are summarized in Table 6.18. The increases for the 0.01 AEP precipitation vary from 8 percent for the 5-minute duration to 17 percent for the 24-hour duration. This example illustrates that the shorter duration events do not necessarily change in the same proportion as the 24-hour events. In addition, the future IDF curve would vary according to the GCM and future scenario.

The 0.01 AEP curves are shown in Figure 6.7, with the ordinate converted to intensity in inches per hour illustrating the increase in precipitation intensity for the 0.01 AEP event from historical to future (2000-2049) conditions for Philadelphia. These results use data for one GCM (CSIRO), one future scenario (RCP8.5), and for the time period 2000-2049. Application of the method should use multiple GCMs and future scenarios. The mean IDF curve from all GCMs is chosen as the final curve for a given future scenario.

Table 6.18. Summary of historical and future (2000-2049) precipitation depths for the 0.01 AEP for Philadelphia, PA for the CSIRO model and the RCP8.5 emission scenario.

Duration (hours)	Historical (Atlas 14) precipitation depth (inches)	Future (2000-2049) precipitation depth (inches)	Ratio of Future to Historical
0.083	0.68	0.74	1.08
0.25	1.37	1.48	1.08
1	2.89	3.25	1.12
6	5.15	5.94	1.15
24	7.67	9.00	1.17

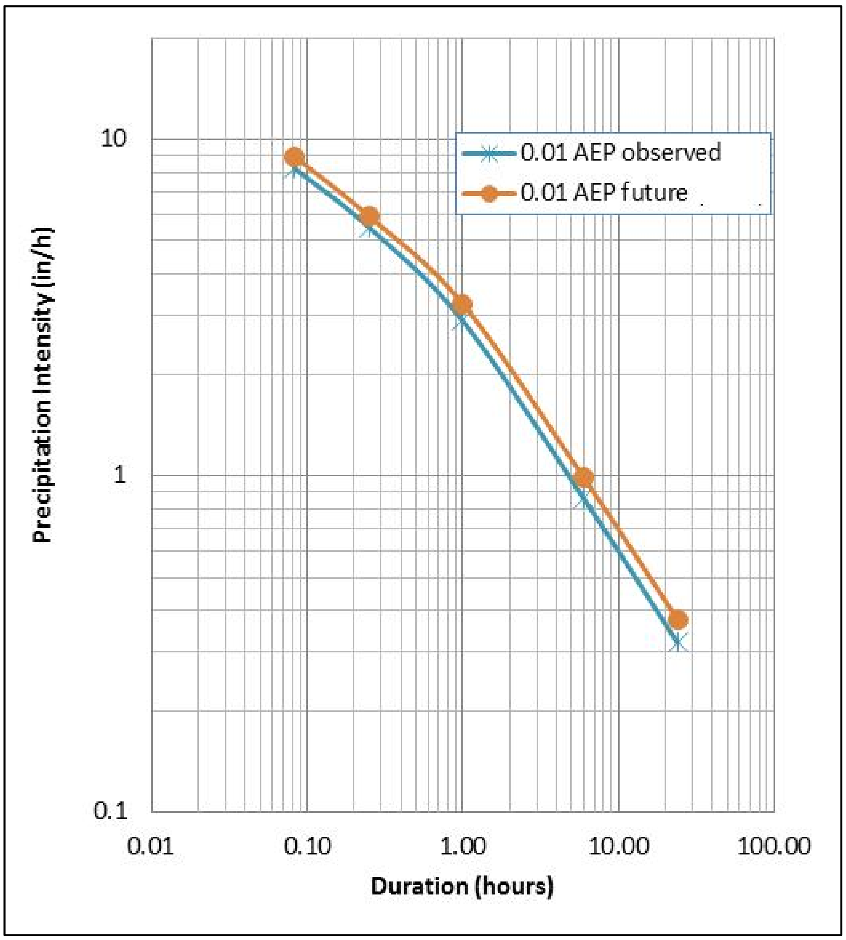

Figure 6.7. IDF curves for historical and future conditions for the 0.01 AEP for Philadelphia, PA.

The Simonovic approach is computationally intense; a web-based tool (IDF_CC) was developed to download data from the appropriate climate website and perform the computations in Canada. A similar computational package is needed for applying this technique in the United States.

6.3. Adapting Projected Climate Data Spatial Scale to Watershed Scale

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§2.2.3.1 Factors Affecting Runoff/Meteorological Characteristics/Rainfall

§2.3.2.2 Data Sources/Sources of Hydrologic Data/Rainfall Data

Many drainage design problems are associated with watersheds with a drainage area less than the size of the grid cell from even high-resolution climate datasets. For these cases, it is appropriate to adjust the precipitation values from the high-resolution climate dataset to an appropriate watershed average estimate or point design precipitation estimate, because precipitation depth decreases with the size of the rainfall field. Until higher resolution climate datasets are widely available, an Areal Reduction Factor (ARF) is a useful tool for engineers who require design precipitation depth at areal scales less than the averaging grid cell size of current high-resolution climate datasets.

6.3.1 Areal Reduction Factor Methodology

When using point rainfall estimates for large watersheds, engineers should adjust the point estimates to provide an appropriate rainfall depth averaged over the watershed. The ARF is one tool for accomplishing this adjustment by using the following equation:

$$P_{\mathrm{A,W}} = P_{Point}\ x\ ARF_W \tag{6.7}$$

where:

$P_{A,W}$ = *Spatially averaged precipitation for the watershed, inches.*

P_{Point} = *Point precipitation (from a rain gauge, NOAA Atlas 14, or equivalent), inches.*

ARF_W = *Areal reduction factor for the watershed, dimensionless.*

When applying the same concept to gridded precipitation estimates from high-resolution climate datasets, the relation is written as follows:

$$P_{\mathrm{Point}} = P_{A,G}\ x\ \frac{1}{ARF_G} \tag{6.8}$$

where:

$P_{A,G}$ = *Spatially averaged precipitation from the high-resolution climate dataset grid cell, inches.*

ARF_G = *Areal reduction factor for the high-resolution climate dataset grid cell, dimensionless.*

Precipitation estimates from high-resolution climate datasets, represented by $P_{A,G}$, are typically average values over a finite area, though some datasets provide point estimates. (See Chapter 3 for more information.) This highlights an important distinction between point estimates (from tools such as NOAA Atlas 14) and areal estimates (from high-resolution climate datasets). (Equation 6.8 can be used for the areal adjustment described in Step 5 of the 10-step procedure, detailed in Section 6.1.)

Converting a gridded precipitation from a high-resolution climate dataset to an appropriate areal average for the watershed of interest is accomplished by substituting Equation 6.8 into Equation 6.7, resulting in the following:

$$P_{A,W} = P_{A,G} \ x \ (ARF_W / ARF_G) \quad (6.9)$$

ARFs are commonly available in chart form, as presented in Figure 6.8. This chart was taken from National Weather Service Technical Report 24 (NWS-24) (U.S. Department of Commerce 1980) and is used as an example. The designer should use the recommended ARF from the applicable jurisdiction or agency or one developed from local/regional data. If locally applicable ARFs are not available, the designer should consult the applicable volume of NOAA Atlas 14 (e.g., Bonin et al. 2005, Perica et al. 2013). While NOAA Atlas 14 does not provide new ARFs, each provides references to appropriate documents containing ARFs for the location.

The general procedure for areal adjustment of gridded high-resolution climate dataset precipitation is summarized in the following steps for the required AEP and duration:

1. Determine the watershed size and the corresponding ARF for the watershed.
2. Determine the grid size and average precipitation for the grid, along with the ARF for the gridded high-resolution climate dataset precipitation.
3. Calculate the adjustment using Equation 6.9.

Step 1 represents the standard adjustment that engineers make for converting point precipitation to an appropriate area's average for large watersheds. The watershed area is determined, and the corresponding value of ARF_W is estimated from a tool such as that shown in Figure 6.8. For many smaller watersheds, the value is 1, which indicates that no areal adjustment from point values is necessary.

For **Step 2**, the engineer determines the grid size and average precipitation for the grid. Based on the grid size, the engineer determines the ARF to adjust the gridded precipitation value to a point value. The value of ARF_G is estimated using the same tool used in Step 1.

Finally, in **Step 3**, the engineer uses Equation 6.9 to compute the adjusted precipitation value for the watershed, given the information developed in Steps 1 and 2. If more than one AEP or duration is required, the steps are repeated with the new information.

BOTTOM LINE: Areal reduction factors, such as those used to reduce point estimates of precipitation depth from tools such as NOAA Atlas 14 to the watershed drainage area scale, can be used as a method for estimating a point precipitation from spatially averaged precipitation, such as those generated by downscaling GCM estimates of precipitation.

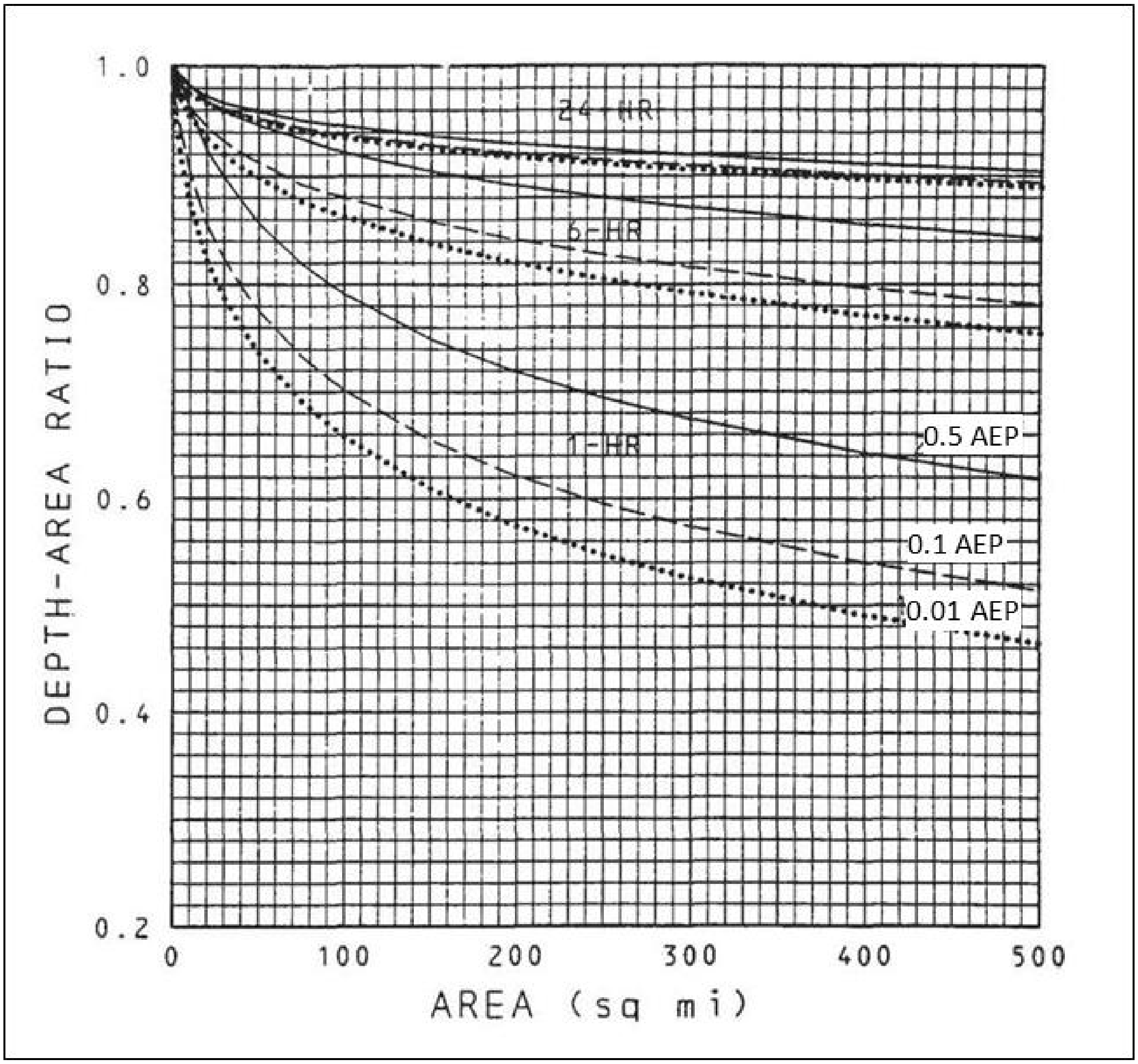

Figure 6.8. Areal reduction factor for 0.5, 0.1, and 0.01 AEP and 1-, 6-, and 24-hour storm durations (NWS-24).

6.3.2 Areal Reduction Factor Examples

Three examples are provided to show variations in watershed size, AEP, and duration. In each example, the ARFs are derived from Figure 6.8. However, a similar process can be used with a different ARF chart, if that is either appropriate or mandated for the jurisdiction or agency within which the designer is working.

Example 1: Suppose the precipitation from a 1-square-mile watershed is required for a 10-year, 24-hour event. Based on the method described in Section 6.1 or another appropriate method, the 10-year, 24-hour precipitation depth developed from a high-resolution climate dataset was estimated to be 4.52 inches. The grid cell size from the high-resolution climate dataset is 56 square miles (12-km x 12-km grid resolution).

Step 1. Determine the watershed size and the corresponding ARF for the watershed.

The watershed area is given as 1 square mile. With respect to ARFs, this is a small watershed. The ARF for this area is determined from Figure 6.8, using the curve in the figure for the 0.1 AEP and 24-hour duration. In this case, ARF_W equals approximately 1.0.

Step 2. Determine the grid size and average precipitation for the grid, along with the ARF for the gridded high-resolution climate dataset precipitation.

The grid cell average precipitation is given as 4.52 inches, which is the average over the 56-square-mile grid cell. The ARF was determined from the same curve on Figure 6.8 (0.1 AEP and 24-hour duration) for an area of 56 square miles. ARF_G equals approximately 0.96.

Step 3. Calculate the adjustment using Equation 6.9.

The adjusted precipitation for the watershed, using Equation 6.9, is:

$$P_{\mathrm{A,W}} = 4.52\ x\ (1.0/0.96) = 4.71\ inches$$

Therefore, the 10-year, 24-hour rainfall for the watershed is 4.71 inches. Because the sample watershed is small, the watershed estimate is approximately the same as the point estimate.

Example 2: Suppose that runoff from a 4-square-mile watershed is required for the 100-year, 1-hour event. Based on the linear scaling method described in Section 6.2 or another appropriate method, the 100-year, 1-hour precipitation depth developed from a high-resolution climate dataset was estimated to be 1.75 inches. The grid cell size from the high-resolution climate dataset is 56 square miles (12-km x 12-km grid resolution).

Step 1. Determine the watershed size and the corresponding ARF for the watershed.

The watershed area is given as 4 square miles. The ARF for this area is determined from Figure 6.8, using the curve in the figure for the 0.01 AEP and 1-hour duration. In this case, ARF_W equals approximately 0.92.

Step 2. Determine the grid size and average precipitation for the grid, along with the ARF for the gridded high-resolution climate dataset precipitation.

The grid cell's average precipitation is given as 1.75 inches, which is the average over the 56-square-mile grid cell. The ARF was determined from the same curve on Figure 6.8 (0.01 AEP and 1-hour duration) for an area of 56 square miles. ARF_G equals approximately 0.72.

Step 3. Calculate the adjustment using Equation 6.9.

The adjusted precipitation for the watershed, using Equation 6.9, is:

$$P_{\mathrm{A,W}} = 1.75\ x\ (0.92/0.72) = 2.24\ inches$$

Therefore, the 100-year, 1-hour rainfall for the watershed is 2.24 inches.

Example 3: Suppose that runoff from a large 500-square-mile watershed is required for the 100-year, 24-hour event. The cell size of the high-resolution climate dataset is 56 square miles. Therefore, the watershed will require at least nine grid cells to fully cover the watershed. Based on the method described in Section 6.1 or another appropriate method, the 100-year, 24-hour precipitation depth developed from a high-resolution climate dataset differs for each grid cell but averages 4.4 inches.

Step 1. Determine the watershed size and the corresponding ARF for the watershed.

The watershed area is given as 500 square miles. The ARF for this area was determined from Figure 6.8, using the curve in the figure for the 0.01 AEP and 24-hour duration. In this case, ARF_W equals approximately 0.88.

Step 2. Determine the grid size and average precipitation for the grid, along with the ARF for the gridded high-resolution climate dataset precipitation.

The average precipitation varies among the grid cells necessary to cover the watershed but averages 4.4 inches. The ARF was determined from the same curve on Figure 6.8 (0.01 AEP and 24-hour duration) for an area of 56 square miles. ARF_G equals approximately 0.945.

Step 3. Calculate the adjustment using Equation 6.9.

The adjusted precipitation for the watershed using Equation 6.9 is:

$$P_{\mathrm{A,W}} = P_{A,G} x\ (0.88/0.945) = P_{A,G} x\ (0.93)$$

Depending on how the engineer models the watershed, the engineer could multiply each individual grid cell precipitation by 0.93 or apply that adjustment to the average value for a uniform precipitation depth over the entire watershed. If the latter is chosen, the 100-year, 24-hour rainfall for the watershed is 4.4 x 0.93 = 4.1 inches.

Chapter 7. Projections Based on Regression Approaches in Ungauged Watersheds

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§2.7.2.2.1 Regional Flood Frequency Analysis/Multiple Regression Analysis/USGS-FHWA Urban Method

§2.7.2.2.2 Regional Flood Frequency Analysis/Multiple Regression Analysis/USGS Regional or Local Rural Methods

This chapter provides methods and guidance for projecting future design discharges in ungauged watersheds, when the design team has determined that regression approaches are an appropriate tool. These approaches may include multiple linear regression equations or panel regression equations, but the emphasis is on the use of USGS regional regression equations for estimating the effects of climate change on flood discharges.

The chapter begins in Section 7.1 with a description of USGS regional regression equations and a procedure for using these tools for estimating the effects of future precipitation on flood discharge. Next, Section 7.2 provides an example of the procedure illustrating the steps and details. Section 7.3 summarizes the applicability and limitations of the procedure. Finally, Section 7.4 provides a brief overview of two additional procedures that may be useful to engineers in the future: 1) statewide or multi-state regression tools and 2) panel regression.

7.1. Use of USGS Regional Regression Equations for Climate Change

Though many types exist, a common form of the USGS regional regression equations uses the power model as follows (McCuen et al. 2002):

$$Q_T = aX_1^{b_1}X_2^{b_2} \dots X_n^{b_n} \tag{7.1}$$

where,

Q_T = *Discharge for the T-year return period.*

X_i = *Independent variables where i=1 to the number of variables (n).*

a = *The intercept coefficient.*

b_i = *Variable exponents where i=1 to the number of variables (n).*

The independent variables describe aspects of watershed or meteorological characteristics at the watershed. The number of independent variables in each equation depends on how many statistically significant relationships between those variables and the dependent variable, Q_T, the USGS identifies in the region covered by the equation. The "region" refers to a hydrologic region, usually geographically based, where the relationship between discharge magnitude is consistently correlated to a subset of watershed and/or meteorological characteristics.

At least half the U.S. states have at least one region where the equations for rural applications include a precipitation variable, such as the mean annual precipitation (MAP) or the 2-year 24-hour precipitation. For the urban equations, there are few states where a precipitation variable and an urbanization variable are both included in the equations. For states and regions where the existing USGS regional regression equations include at least one precipitation variable, these equations may be useful for quantifying projected changes in peak discharges resulting from climate change.

The procedure for using USGS regional regression equations to assess the effects of climate change follows the same process used for traditional applications, with the added requirement of determining projected precipitation estimates. The following list summarizes each step in the procedure, with more detail provided after the summary:

1. Identify the applicable USGS regional regression equation with an appropriate precipitation variable.
2. Confirm the variable range for each independent variable used in the development of the equation.
3. Estimate the projected values of all independent variables, and confirm that the values fall within the range from Step 2.
4. Compute the projected discharge using the variable values computed in Step 3.

In **Step 1**, the engineer identifies the appropriate USGS regional regression equation for the project. This includes identifying the appropriate region and AEP for the project. If the appropriate equation does not include a precipitation variable, then the existing USGS regional regression equations cannot be used for the project. If it does have a precipitation variable, such as MAP or the 2-year 24-hour precipitation, then the engineer proceeds to Step 2.

In **Step 2**, the engineer confirms the variable range for the independent variables in the equation. USGS uses watershed and meteorological characteristics from gauged locations in the region to develop each equation. This range must be identified for each variable, because they serve as limits for application of the equation. For example, if an equation included two independent variables – drainage area and MAP – each has a range of values used to develop the equation that generally should not be exceeded when applying the equation.

In **Step 3**, the engineer estimates the values of all independent variables for the watershed of interest and confirms that each falls within the ranges identified in Step 2. Using the example where two independent variables are present (drainage area and MAP), the drainage area is estimated using accepted methods. Variables such as MAP (as well as various measures of urbanization) may change over time. In the traditional application of these equations, a value representing historical conditions is determined for the location.

For application to possible future conditions, the engineer must determine a projected equivalent. For a statistic such as the 2-year 24-hour precipitation, the method described in Section 6.1 is recommended unless another equivalent or better source of information is available. For a statistic such as the MAP, a process similar to that described in Section 6.1 may also be used unless an equivalent or better source is available. The following equation summarizes the basic process:

$$MAP_p = \frac{MAP_{f,m}}{MAP_{b,m}} MAP_h \qquad (7.2)$$

where:

MAP_p = *Projected mean annual precipitation.*

MAP_h = *Historical mean annual precipitation.*

$MAP_{b,m}$ = *Baseline mean annual precipitation estimated from high-resolution climate datasets derived from GCM model simulations.*

$MAP_{f,m}$ = *Future mean annual precipitation estimated from high-resolution climate datasets derived from GCM model simulations.*

The historical mean annual precipitation, MAP_h, is the value the engineer uses in a traditional application or the regression equations for historical conditions. The two GCM model-based parameters in Equation 7.2 are derived considering the appropriate baseline and future periods, future scenarios, and GCM models, following the guidance in Section 6.1. The projected MAP, MAP_P, then is simply the historical MAP adjusted by the ratio of future-to-baseline values from the downscaled GCM output.

Regardless of how the precipitation variables or any other independent variables are calculated, the engineer must confirm that all values are within the range of the data from which the equation was derived. This is true for projected precipitation, drainage area, and any other variables included in the USGS regional regression equation.

Finally, in **Step 4**, the engineer computes the design discharge from the regional regression equation using the independent variable values estimate in Step 3. For evaluating the potential effects of climate change, it is recommended that the engineer compute design discharges using both historical and projected precipitation values, so that the potential changes are quantified and can be compared. The next section provides an example of this procedure. Section 7.3 discusses the applicability and limitation of the procedure.

7.2. Sample Application with a USGS Regional Regression Equation

The procedure for using an existing USGS regional regression equation is illustrated using a hypothetical watershed in Southwestern New York. Climate projections suggest increasing precipitation in the future, and the engineer seeks to evaluate the potential effects of those changes on an existing structure that was recently constructed for a 100-year service life based on a 0.02 AEP (50-year) design event.

Step 1. Identify the applicable USGS regional regression equation with an appropriate precipitation variable.

The applicable regression equations for Southwestern (Region 5) New York are provided by the USGS and include the mean annual precipitation (MAP) as one of the independent variables (Lumia et al. 2006). The equation for the 0.02 AEP discharge is:

$$Q_{0.02} = 1.46A^{0.976}SL^{0.610}MAP^{0.651} \tag{7.3}$$

where:

A = *Drainage area, mi*^{2}.

SL = *Channel slope, ft/mi.*

MAP = *Mean annual precipitation, inches*

The USGS derived Equation 7.3 based on MAP estimates from the historical period of 1951-80.

Step 2. Confirm the variable range for each independent variable in the equation.

The applicable equation has three independent variables: 1) drainage area, 2) channel slope, and 3) MAP. The ranges for each of the variables are: drainage area (1.7 – 4770 square miles), channel slope (2.76 – 223 feet/mile), and MAP (31.6 – 49.8 inches) (Lumia et al. 2006).

Step 3. Estimate the projected values of all independent variables, and confirm that the values fall within the range from Step 2.

The watershed has a drainage area of 100 square miles, and the channel slope is 30 feet per mile. The historical MAP for the site is 36 inches. For a given future scenario, the ratio of the modeled MAP for the future, compared to the baseline for an ensemble of downscaled GCM outputs, is estimated to be 1.25. Applying Equation 7.2 yields an estimate of the projected MAP as equal to 1.25 x 36 inches, or 45 inches. Comparing the values of all three variables with the ranges provided in Step 2, all variable estimates are within the acceptable ranges.

Step 4. Compute projected discharge using the variable values computed in Step 3.

Applying the independent variable values from Step 3 in the equation for the 0.02 AEP in Step 1 results in a discharge of 10,700 ft^3/s using the historical MAP and 12,400 ft^3/s using the projected MAP. The 25-percent increase in MAP results in an estimated 16-percent increase in the 0.02 AEP (50-year) discharge.

Table 7.1 summarizes the discharge estimates for the 0.02 AEP, as well as other AEPs. The other AEP estimates were developed from the USGS regional regression equations from Lumia et al. (2006) for those AEPs.

Table 7.1. Increases in AEP discharges for a hypothetical increase in mean annual precipitation.

Annual Exceedance Probability	0.5	0.2	0.1	0.04	0.02	0.01
Flow with Historical MAP (ft^3/s)	3,290	5,060	6,800	8,920	10,700	12,600
Flow with Projected MAP (ft^3/s)	4,400	6,320	8,220	10,500	12,400	14,300

The existing structure was designed and constructed based on the historical MAP and an 0.02 AEP, resulting in a design flow of 10,700 ft^3/s. Under projected conditions, one can determine from Table 7.1 that a flow of that magnitude is associated with a 25-year (AEP = 0.04) return period. Consideration of climate change, therefore, suggests that a 10,700 ft^3/s (or 10,500 ft^3/s, which is essentially the same) event will be exceeded on average twice as frequently as intended in the traditional design. Rather than the design value being experienced once every 50 years on average, it is now expected once every 25 years. The existing USGS regional regression equation is useful for revealing this potential shift in design discharge.

7.3. Applicability and Limitations

USGS regional regression equations are among the most commonly used and useful tools for estimating design discharges for transportation infrastructure. They are broadly applicable throughout the United States, as long as the values of the independent variables are within the ranges of the data used when the USGS developed the equations.

Their primary limitations are that they rely on a statistical correlation between computed discharge quantiles and the corresponding independent variables from gauged watersheds and that they are limited by the form of the equation chosen. These two factors combine such that the equations do not fully explain variations in the discharge quantiles computed from gauged records. Therefore, uncertainty remains in the estimates for ungauged watersheds derived from these equations. Each USGS regional regression equation has a ***standard error of estimate*** that is a measure of the reliability of the equation. The larger the standard error of estimate, the less reliable the equation is for estimating the discharge. (See McCuen et al. 2002 for more information on the standard error of estimate.)

These limitations apply to all applications of USGS regression equations. When applying USGS regional regression equations for projected precipitation, as described in the previous sections of this chapter, additional caution is appropriate.

First, if the applicable equation(s) for the project location do not have an independent variable for precipitation, the equation is not equipped to estimate future conditions. As noted previously, many states and regions do not currently have equations with precipitation as an independent variable.

Second, as with traditional applications of USGS regression equations, the values of projected precipitation should remain within the range of the precipitation values the USGS used to generate the equation. Furthermore, this *Guide* recommends that projected precipitation values should be estimated by adjusting the historical values, by multiplying them by the ratio of modeled (GCM) future and modeled (GCM) baseline conditions. This process was illustrated in the previous sections.

Third, because the USGS develops these equations using information from the historical record, they implicitly assume that the relationships between the independent variables and discharge will remain the same; that is, the relationships are stationary. Because this procedure is accommodating a future precipitation that may differ from the historical precipitation, this assumption is not strictly true. In the future, the relationship between the independent variables and discharge may change: new variables may become more important and enter the equation, and other variables in the current equation may become less important and drop out.

Recall that USGS regional regression equations do not fully explain variations in discharge, even considering only historical information. This degree of reliability is measured by the standard error of estimate described previously. Use of future precipitation may reduce the reliability of the equation to an unknown degree, because changes in precipitation may be accompanied by changes in related physical phenomena, such as soil moisture, vegetation, evapotranspiration, etc., that are presumed to be encapsulated in the correlated behavior of the precipitation variable.

Urbanization may also alter the interrelationships within watersheds that contribute to discharges, but engineers frequently use regression equations with independent variables like impervious area to assess the effects of future urbanization on discharges. While the large-scale effects of climate change may alter watershed processes more fundamentally than urbanization, applying USGS regression equations to evaluate the effects of climate is a useful tool when used within prudent limits. For this *Guide*, prudent limits means that the values of the projected precipitation must remain within the range of the precipitation values used when developing the equation.

BOTTOM LINE: When USGS regional regression equations include a precipitation variable, they can be used for estimating the effects on design discharge, as long as the value for the precipitation variable is within the range of values for that variable used in the development of the equation.

7.4. Discussion and Other Resources

USGS regional regression equations are typically developed for multiple regions within an individual state, which limits the range of the climatic variables. This limited range often results in a determination that they are not statistically significant and, therefore, do not appear as an independent variable in the regression equation. A recent trend within the USGS is to perform regional regression analyses that cover whole or multiple states, which should enhance the possibility of climatic variables being included in future USGS regional regression equations.

In addition to the regional regression equations, other regression-based alternatives may be useful for state DOTs and others responsible for transportation infrastructure in the future, even though they are not broadly available today. These alternatives include: 1) developing regression equations for whole or multiple states to increase variability in the climatic variables and land use conditions, as described previously, and 2) to use panel regression techniques. Examples of these approaches are discussed in the following sections.

7.4.1 Regression Equations for Pennsylvania

Regression equations for whole or multiple states provide an opportunity for developing tools specifically intended to incorporate climate change. PennDOT provided an example of this approach by developing regression equations to project future 0.01 AEP discharges resulting from climate and land use changes for evaluating potential future flooding of roadways and bridges (PennDOT 2017).

Data for the 0.01 AEP discharges and watershed characteristics for gauging stations were obtained from USGS published reports and databases. The precipitation data were obtained from the Downscaled Climate and Hydrology Projections (DCHP) website. (See http://gdo-dcp.uclinl.org/downscaled_cmip_projections.) A regression equation for the 0.01 AEP discharge ($Q_{0.01}$) was developed using data from 230 gauging stations in and near Pennsylvania:

$$Q_{0.01} = 4.442 DA^{0.898} SL^{0.307} (ST + 1)^{-0.580} (IA + 1)^{0.217} P^{0.809} \quad (7.4)$$

where:

DA = *Drainage area, square miles.*

SL = *Main channel slope, feet per mile.*

ST = *Percent of the watershed area covered by lakes and ponds.*

IA = *Percent of the watershed covered by impervious surfaces.*

P = *Mean of the annual maximum daily precipitation for the historic period 1950-1999 from the DCHP website, millimeters.*

The intention in developing the regression equations was to use the precipitation variable for which projected values were available from the DCHP website. All of the independent variables in the equation were statistically significant at the 5-percent level, with all coefficients positive except *ST*. In addition, there were no multicollinearity issues with the regression analysis.

Data for gauging stations in New York, New Jersey, Delaware, and Maryland were used in the analysis to increase the variability in the time-varying parameters *IA* and *P*. Pennsylvania has a limited number of urban gauging stations (impervious area greater than 10 percent) with a sufficient record for frequency analysis; the majority of the urban gauging stations are in southeast Pennsylvania. Urban gauging stations from New Jersey, Maryland, and Delaware were used in the analysis to increase the variability in *IA*.

The highest annual maximum precipitation in Pennsylvania occurs in the southeast corner of the state, near Philadelphia, and the lowest annual maximum precipitation occurs in the southwest corner of the state, near Pittsburgh. Precipitation decreases from east to west across the state. Annual maximum precipitation is greater in New Jersey, Delaware, and Maryland; therefore, adding gauging stations from those states also increased the variability in the annual maximum precipitation.

Equation 7.4 was used to estimate 0.01 AEP discharges for two future time periods (2000-2049 and 2050-2099), based on changing land use conditions (*IA*) and changes in the mean of the annual maximum precipitation (*P*). Future land use projections were obtained from the Integrated Climate and Land-Use Scenarios (ICLUS) database developed by the U.S. Environmental Protection Agency (U.S. EPA 2009).

Projected precipitation data was obtained from the DCHP website for three downscaled GCM outputs. The three GCMs chosen were reasonably independent using criteria on the ICNet website (http://theicnet.org/?page_id=50). Because the objective of the study was to perform a conservative assessment of potential future effects on PennDOT infrastructure, the higher RCP8.5 scenario was used.

Equation 7.4 was used to estimate discharges for future and existing conditions from each downscaled GCM output. Future-to-existing ratios were computed for each downscaled GCM output and were averaged for the three GCMs for each period. The average ratio was multiplied by the historical estimate of the 0.01 AEP discharge to obtain estimates for future periods.

7.4.2 Panel Regression Analyses

Another potential tool for incorporating climate change is panel regression. In the types of multiple linear regression discussed in the previous sections, the data regressed varies in one dimension: spatially. That is, each gauge has a different location. In panel regression, the data varies in two or more dimensions. Incorporating a temporal dimension in the regression allows for the explicit capture of trends over time.

As defined by Steinschneider et al. (2013), panel regression is a statistical technique that pools multidimensional data recorded across several watersheds and through time (panel data) to identify response characteristics unique to each watershed and those common across watersheds. The panel regression procedure essentially combines the strengths of multiple linear regression and time series analysis into a single statistical framework.

The time series approach considers individual watersheds that are known to have undergone some level of land use change over the analysis period and may also be experiencing changes in precipitation. The analyst seeks to determine whether land use change trends in the watershed can be used to explain any trends in flow statistics for that watershed. However, climatic variability can mask the detection of any relation between land use and streamflow. By examining only one watershed at a time, it is difficult to separate the effects of trending climate and land use variables on streamflow. Panel regression allows for the simultaneous analysis of the impact of climatic and land use change across several watersheds.

The dependent variable in a panel regression is a single flow variable, such as the annual maximum peak discharge or the annual runoff, and there is an observation for each year of record for each gaging station in the panel regression analysis. In addition, the **predictor variables can vary in time,** which is a key difference from multiple linear regression analysis.

Panel regression is a complex statistical tool, and describing it is beyond the scope of this *Guide*. However, engineers and planners should be aware of this approach as it may, in the near future, yield benefits for analyzing future land use and climate change. See Kilgore et al. 2019 for more information on the technique, including a description of applying the technique for adjusting flood discharges for land use change in the Chicago, Illinois metropolitan area (Over et al, 2016a, 2016b).

Chapter 8. Projections Based on Index Approaches for Gauged and Ungauged Watersheds

This chapter provides methods and guidance for projecting future design discharges using index approaches in gauged and ungauged watersheds. The index flood approach is useful for estimating the flood frequency curve (FFC) or particular quantiles of the FFC based on the index flood, regardless of the methodology used to estimate the index flood. (See Chapter 6 of Kilgore et al. (2019) for more details on the index flood approach.)

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§2.6.1 Concepts of Probability and Frequency Analysis

§2.6.3 Design Flood Frequency

§2.6.3.4 Sensitivity to Increased Flood Magnitude

§2.7.1.1 Development of Flood-Frequency Curves

§2.7.1.3 Transfer of Data

§2.7.2.1 Index-Flood Method

The FFC for each watershed can be considered unique to that watershed, but similar to other FFCs in many ways. In the context of changing climate, the fundamental assumption of uniqueness may be exploited on a given watershed for different projected climate characteristics. The FFC for a given watershed under historical conditions can be developed by traditional methods, and flood ratios can be computed and then applied to future conditions.

The fundamental assumption behind the index flood method is that the shape (change in discharge from one probability value to another) of a flood frequency curve is relatively invariant within reasonable bounds of geography and watershed characteristics. The shape of an FFC is captured by selecting a base value from the FFC – the index flood discharge – and dividing all of the calculated discharges at desired probability quantiles by that value. The resulting set of flood ratios amount to multipliers of the index flood that represent the shape of the FFC. The multiplier of the index flood itself is unity.

Since FFCs are monotonically increasing with a decreasing probability of exceedance, quantile values with a greater probability of exceedance than the index flood result in smaller discharges with flood ratios between 0 and 1. Quantile values with a smaller probability of exceedance than the index flood result in discharges larger than the index flood and flood ratios greater than 1.

8.1. General Procedure

Traditionally, the index flood method has been used with the mean annual flood as the index flood. However, the principle behind the index flood method has no connection to any particular point on the FFC; any convenient value on the curve can be chosen. This *Guide* focuses on the 0.1 AEP (10-year) event as the index event. The 0.1 AEP value lies near the middle of the set of quantiles normally associated with highway drainage design and thus distributes the leverage of any error more evenly than using the smaller, more frequent, mean annual flood.

Applying the index flood method follows a straightforward process that allows the hydrologic engineer to choose from a variety of methodologies within that process. The general steps are:

1. Calculate an FFC for the watershed using traditional, historically based methods.

2. Calculate the historical flood ratios using the 10-year flood as the index value.
3. Estimate the projected 10-year flood for the site.
4. Calculate the projected FFC for the site using the flood ratios from Step 2 and the projected 10-year discharge from Step 3.

For **Step 1**, the existing FFC for the site is estimated by any method appropriate for the site. This may include rainfall/runoff modeling, regression equations, statistical analysis of gauged data, or any other method. FFCs resulting from a statistical analysis of data from several nearby and similar watersheds (if available) may provide further insight into, or validation of, the FFC shape, and may also be used to provide flood indices.

For **Step 2**, the discharge associated with each individual AEP quantile is divided by the 10-year discharge to create a series of dimensionless ratios representing the relation of each quantile to the 10-year flood discharge. By definition, the ratio for the 0.1 AEP is 1.0.

BOTTOM LINE: The shape and relative growth of FFCs are particular to each watershed; the reasons for variation among watersheds are not well understood. The index flood method allows the shape and relative growth to be preserved, while adjusting magnitudes of discharges for future climate conditions.

In **Step 3**, the projected 10-year discharge for the site is estimated. Chapters 5, 6, and 7 provide guidance for estimating projected discharges using trend analysis, rainfall/runoff modeling, and regression analyses, respectively. The engineer chooses the method or methods appropriate for the site. If it is adaptable to future conditions, the methodology used in Step 1 is likely to be appropriate. For example, if rainfall/runoff modeling is used in Step 1, rainfall/runoff modeling would also be appropriate in this step. If a different procedure than applied in Step 1 is used, then both the baseline and projected 10-year discharge is estimated and the projected/baseline ratio is computed. The projected 10-year discharge is then estimated by multiplying the historical 10-year discharge from Step 1 by the projected/baseline ratio so that the projected estimate is consistent with the historical estimate.

Finally, in **Step 4**, the ratios for the historical FFC (Step 2) are multiplied by the projected 10-year flood (Step 3) to create a projected FFC. These steps are illustrated using an example in Section 8.2.

8.2. Sample Application of the Flood Index Method

Consider a situation where an FFC appropriate for a future period is required, including an estimate of the projected 100-year discharge. The site is Pajarito Creek in Newkirk, New Mexico.

Step 1. Calculate an FFC for the watershed using traditional, historically based methods.

The first step is to estimate the historical FFC for the project site using an appropriate technique for the location. Table 8.1 summarizes the historical FFC for AEPs ranging from 0.5 to 0.01 for Pajarito Creek at Newkirk, New Mexico (USGS gauge 07225000). This FFC was developed by analyzing the gauge data documented in the ancillary materials (Appendix 1) of Asquith and Roussel (2009). This watershed has a contributing drainage area of 55 square miles and a historical mean annual precipitation of 14.1 inches.

Table 8.1. Flood ratio calculation for Pajarito Creek in Newkirk, NM.

AEP	ARI (yr)	Historical FFC (cfs)	Flood Ratio	Projected FFC (cfs)
0.5	2	940	0.38	1,040
0.2	5	1,840	0.74	2,030
0.1	10	2,490	1.00	2,750
0.04	25	3,330	1.34	3,680
0.02	50	3,990	1.60	4,410
0.01	100	4,650	1.87	5,140

Step 2. Calculate the historical flood ratios using the 10-year flood as the index value.

The second step is to compute the flood ratios using the 0.1 AEP flood (10-year ARI) as the index flood. As shown in the table, the historical FFC for the 0.1 AEP flood is 2,490 cfs. Each discharge in the historical FFC column is divided by that value to obtain the flood ratio, which is also shown in Table 8.1. For example, the flood ratio for the 0.01 AEP is 4,650/2,490 = 1.87.

Step 3. Estimate the projected 10-year flood for the site.

In Step 3, a projected discharge for the index flood (10-year flood) is estimated using one of the techniques described in this *Guide* in Chapters 5, 6, or 7. In this example, the projected 0.1 AEP discharge was estimated using USGS regional regression equations, as described in Chapter 7. The equation for the 0.1 AEP from Asquith and Thompson (2008) is as follows:

$$Q_{0.1} = 111A^{0.5311}MAP^{0.5469} \quad (8.1)$$

where:

$Q_{0.1}$ = *Discharge for the 0.1 AEP, ft^3/s.*

A = *Drainage area, mi^2.*

MAP = *Mean annual precipitation, inches.*

Evaluating the regression equation for the historical watershed characteristics of Pajarito Creek resulted in an estimated 0.1 AEP discharge of 3,964 ft^3/s. Evaluating the same regression equation for a projected 20-percent increase in MAP resulted in an estimated discharge (after the increase) of 4,380 ft^3/s.

Because the regression equations are used only to estimate the projected 0.1 AEP flood value, the ratio of the projected to historical regression value is multiplied by the historical 0.1 AEP flood from the gauge analysis. That is, the estimated projected 0.1 AEP flood is 2,490 x (4,380/3,964) = 2,750 ft^3/s, as shown in Table 8.1. (See Chapter 7 for more detailed guidance on using regression equations.)

Alternatively, the projected 10-year discharge could be estimated using a rainfall/runoff model. (This would be a logical choice if a rainfall-runoff model was used to determine the historical FFC in Step 1.) The procedures in Chapter 6 are used to estimate the projected 10-year precipitation for the model. The resulting discharge is an estimate of the AEP peak discharge considering future changes.

Step 4. Calculate the projected FFC for the site using the flood ratios from Step 2 and the projected 10-year discharge from Step 3.

In Step 4, the projected 10-year discharge is multiplied by each of the flood ratios to obtain a projected discharge for each AEP. In this manner, the entire FFC is adjusted for future conditions by applying the change to one value – the index flood. Whatever unknown factors exist that influence the shape of the original FFC are assumed to be sufficiently stable that they still govern the shape. Flood discharges for any AEP on the FFC, as listed in Table 8.1, can then be used as design or validation values. For the example, the 0.01 AEP flood is estimated to be 5,140 ft^3/s under future conditions.

In the case used for illustration, an FFC for the gauge in question was available from past analysis. This will not be the case for ungauged watersheds; however, FFCs for nearby gauges can be used to develop flood indices, and those indices can be applied to 0.1 AEP discharges for ungauged watersheds, estimated by any preferred method.

8.3. Applicability and Limitations

The axiom exploited by the index flood approach is that whatever unknown or little-understood watershed conditions exist that contribute to the unique shape of the FFC for each watershed retain their influence within that watershed, despite changes in rainfall of the magnitude anticipated by current projections. Changes in watershed conditions (land use, vegetative cover, transport efficiency, etc.) could result in changes to the shape of the FFC, but those could be addressed separately, in a similar manner.

The applicability of the index flood method has been extensively discussed in published literature, beginning with Kinnison and Colby (1945) of the USGS. It was described and documented by Dalrymple (1960) and has been the source of continued discussion into recent times (Dawdy et. al. 2012).

The phenomenological source of the wide variation in FFC shape, as compared to rainfall frequency curve shape by similar ratios, is not well understood. Changes in FFC characteristics because of human-made changes in the watershed, such as urbanization or regulation by dams, has been known and subject to hydrologic analysis for many decades. Well-documented and widely accepted procedures exist for these analyses, and the above-referenced procedures should continue to provide utility in the context of watershed change, regardless of changes in rainfall expectation.

8.4. Discussion and Other Resources

Rainfall/runoff modeling, transposition from gauged watersheds, or other methods can be substituted for regression equations to estimate the 0.1 AEP discharge in the example above. The procedures outlined above can reasonably be applied to any FFC developed using methods traditionally deemed appropriate for the development of design discharges. The underlying assumptions regarding the shape of the FFC are independent of the method for its development.

Flood ratios for an FFC developed by any method can be assessed for reasonability by comparing them to flood ratios for similar, nearby gauged sites, or those for watersheds with similar characteristics. Comparison among regression equation results and ratios from several appropriate gauge analyses may yield insight into local or regional tendencies in the shape of

FFCs for similar watersheds. The result might be the selection of a surrogate FFC to provide ratios, or an average among a number of FFCs that might be considered representative. Flood ratios from regression equation-derived discharges tend to be similar to a regional average value; comparison to average flood ratios from several nearby, similar watersheds should provide information on the influence of various characteristics on the shape of the FFC.

The results of gauge analysis in regions thought to be homogeneous and used in the development of regression equations are frequently available in the documentation accompanying the regression equations themselves. Flood ratios for all of the suitable gauges in a region can easily be calculated, tabulated, and made generally available for future reference, for use in comparison, validation, or transposition of FFC shape within a region. Summary statistics of the distribution of flood ratios for each quantile provide guidance information for the identification of anomalous or pathological watershed behavior.

Chapter 9. Estimating Continuous Simulation Information Under Projected Climate Conditions

This chapter provides methods and guidance for projecting future runoff for situations when the design team has determined that continuous simulation modeling is an appropriate tool. Design teams generally use continuous simulation modeling for stormwater quality and quantity analyses for lower return period high flows and for low flow statistics. It is also used to analyze and design wetland sites because continuous simulation can provide year-round estimates of flow and pollutants. Continuous simulation can be used to evaluate the effects of snowmelt, temperature changes, and rain on snow. It is rarely used for higher return period design.

A significant challenge for continuous simulation modeling is a lack of historical data that can be used for calibration/verification of model behavior. In addition, there are several parameters that are frequently correlated that must be estimated for the models to produce reasonable results.

Continuous simulation models require precipitation time series. In addition, they usually require temperature, evapotranspiration, and estimates of infiltration. Evapotranspiration is either computed outside the model and provided as an input or computed within the model from other time series data. Section 9.1 focuses on the use of change factors for representing climate change in continuous simulation models. Section 9.2 provides examples of the use of continuous simulation models for assessing the effects of climate change. Section 9.3 discusses the applicability and limitations of these methods for climate change and Section 9.4 provides additional discussion and other resources.

9.1. Use of Change Factors

The change factor methodology is one approach for incorporating projected future climate conditions into continuous simulation models such as the Stormwater Management Model (SWMM). Change Factors (CF) are defined as adjustments to historical values that result in projected or future values of particular model input parameters. CFs for assessing climate change are determined from downscaled GCM information for a given climatic variable for future and historical conditions. CFs are then used to adjust historical climate data by adding a difference in variable (additive CF) or multiplying by a factor (multiplicative CF) to obtain the future climate variable. Both additive and multiplicative CFs are known in the climate science community as the "delta" method.

> AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:
>
> §2.2.3 Factors Affecting Runoff/Meteorological Characteristics/Rainfall/Snow/temperature, Wind, Evaporation, and Transpiration
>
> §2.3.2.2 Data Sources/Sources of Hydrologic Data/Rainfall Data
>
> §2.7.6.4 Methods for Estimating Flood Peaks, Durations, and Volumes/Mathematical Models/The Stormwater Management Model (SWMM)
>
> §2.8 Characteristics and Analysis of Low Flows
>
> §2.9 Storage and Flood Routing for Stormwater Management

CFs may be categorized by how they address temporal scale and domain, their mathematical formulation, or the number of change factors. Temporal scale refers to the timescale (e.g. daily, monthly, seasonal, and annual) of the change factors used in the analysis. Temporal domain refers to both the time of year (e.g. monthly, seasonal, or annual) and the beginning and ending dates of the historical observed, historical modeled, and future modeled values to be included in the analysis (e.g., 1981–2000 compared to 2046–2065). (See Kilgore et al. (2019) Chapter 7 for additional information on change factors.)

The basic steps for using continuous simulation modeling to evaluate the effects of climate change using CFs are as follows:

1. Calibrate and run the continuous simulation model using historical precipitation data.
2. Obtain high-resolution climate data for both baseline conditions and future conditions from one or more future scenarios.
3. Determine the appropriate type of CF for the analysis.
4. Calculate the appropriate precipitation depth statistics for both the baseline conditions and future scenarios to determine the CF.
5. Compute the change factor based on the type of CF needed from Step 3 and the precipitation statistics from Step 4.
6. Adjust the historical (observed) precipitation time series used in Step 1 with the CFs from Step 5 to create a projected (future) time series of precipitation.
7. Rerun the continuous simulation model using the projected precipitation time series.
8. Evaluate the differences between historical and projected continuous simulation results to consider the implications for future climate change on the transportation infrastructure.

In **Step 1**, the design team performs the continuous simulations analysis using historical precipitation data as they would without consideration of climate change. This model run provides a reference point for evaluating climate change.

In **Step 2**, the design team acquires the high-resolution climate information for the scenarios of interest in the study. Chapter 3 provides guidance on the selection of scenarios and GCMs.

The team must also determine the temporal domain for both baseline (past) and future periods for the analysis. These should both be no less than 30 years as described in Section 6.1.1. For example, the baseline period could be 30 years (e.g. 1971-2000) and the future time domain could also be 30 years (e.g. 2071-2100) or longer.

In **Step 3**, the design team determines the type of CF appropriate for the analysis. As described in Kilgore et al. (2019), a single or multiple CF can be employed. A single CF means that one CF is applied to the entire time series. Multiple CFs can come in many forms including by month, by season, or by magnitude of the precipitation value. The choice depends on the objectives of the analysis and the detail in the supporting data.

The design team also chooses whether to use a multiplicative or additive CF. A multiplicative CF estimates a projected value of a parameter by multiplying the historical value by the CF. Similarly, an additive CF estimates the projected value by adding the CF to the historical value. This *Guide* recommends the use of multiplicative CFs for precipitation and additive CFs for temperature as used by the U. S. EPA in its Climate Resilience Evaluation and Analysis Tool (CREAT) (U.S. EPA 2016).

In **Step 4**, the design team computes the appropriate precipitation values for computing the CFs. For precipitation, the change factor analysis is typically performed on daily precipitation because of its availability. If projected temperature and evaporation data are needed in the continuous simulation, the same approach can be used as shown above for precipitation data except that an additive CF is used for temperature.

If a single CF is used then all the data are grouped together for the computations. If multiple CFs are used the data are grouped according to the number and type of CFs desired.

In **Step 5**, the CFs are computed for the desired CFs determined in Step 3 and the information in Step 4. The following equation is an example of the computation of a multiplicative CF:

$$CF_{mul,j} = \left(\frac{\bar{P}_{GCM,f,j}}{\bar{P}_{GCM,\mathrm{b},\mathrm{j}}}\right) \tag{9.1}$$

where:

$CF_{mul,j}$ = *Multiplicative CF for precipitation for domain j.*

$\bar{P}_{GCM,f,j}$ = *Average future period 24-hour precipitation from high-resolution climate data for domain j.*

$\bar{P}_{GCM,b,j}$ = *Average baseline 24-hour precipitation from high-resolution climate data for domain j.*

The CF domain describes the number of CFs required. For example, if a unique CF is needed for each month, then *j* varies from 1 to 12. For a single CF, *j* equals 1.

In **Step 6**, the design team applies the CFs computed in Step 6 to the historical time series used in the Step 1 modeling according to the following equation:

$$P_{p,i} = P_{h,i} \times CF_{mul,j} \tag{9.2}$$

where:

$P_{p,i}$ = *The projected precipitation value for the ith value in the time series.*

$P_{h,i}$ = *The historical (observed) precipitation value for the ith value in the time series.*

If the time series is composed of daily values, the CF is applied to each daily value. If multiple CFs are used, the CF from the appropriate domain is applied to the appropriate daily values. For example, if monthly change factors are used, the July CF is applied to the daily values that occur in July.

In **Step 7**, the design team runs a new modeling run using the adjusted time series from Step 6.

In **Step 8**, the design team compares the results from the historical conditions (Step 1) and the projected conditions (Step 8). If multiple scenarios are used, as recommended in Chapter 3, the process is repeated beginning at Step 2 for another scenario.

For some analyses, CFs computed by others may be sufficient to serve the purposes of a given study or analysis. The U.S. EPA has developed the CREAT database that includes computed CFs that may be used for some projects. CREAT is described briefly in Section 6.4.1.

BOTTOM LINE: Change factors (CFs) are determined from high-resolution climate datasets for a given climatic variable for future and baseline conditions. CFs are used to adjust historic climate data to maintain the variability and temporal correlation of the historic time series and spatial correlation among watersheds if more than one watershed is being modeled. Multiplicative CFs are generally used for precipitation and additive CFs for other climatic data such as temperature.

9.2. Examples of Applying Continuous Simulation Models for Advanced Analyses

Two examples illustrating the incorporation of climate change in continuous simulation modeling are described. In the nationwide EPA study, the continuous simulation modeling was conducted using the Hydrologic Simulation Program – FORTRAN (HSPF) and the Soil and Water Assessment Tool (SWAT) and monthly CFs were applied. In the study for the Iowa Department of Transportation a more specialized continuous simulation model was applied effectively using daily CFs. Both examples are more involved than the typical state DOT analysis, but both illustrate the primary processes in evaluating climate change using continuous simulation modeling.

9.2.1 EPA Study of 20 Watersheds Nationwide

U.S. EPA (2013) conducted watershed modeling in 20 large (6,000 to 27,000 square miles) watersheds shown in Figure 9.1 with the objective to assess the sensitivity of streamflow, total nitrogen, total phosphorous, and total suspended loads to a range of plausible mid-21st century climate change and urban development scenarios.

Urban and residential development scenarios were based on EPA's national-scale Integrated Climate and Land Use Scenarios (ICLUS) project (U.S. EPA 2009). Continuous simulation modeling was conducted using the Hydrologic Simulation Program – FORTRAN (HSPF) and the Soil and Water Assessment Tool (SWAT) watershed models.

The climate projections were from NARCCAP (Mearns 2009) and the bias-corrected and statistically downscaled (BCSD) dataset described by USBR (2013). The EPA study selected a subset of six projections from the NARCCAP dataset for the historical period 1971-2000 and the future period 2041-2070 (All of the NARCCAP projections are based on the A2 emissions scenario.). The BCSD projections were based on the same GCMs also using the A2 emission scenario but were just applied to five pilot watersheds to evaluate the accuracy of downscaling procedures.

The climatic time series input for the two watershed models were created using monthly multiplicative CFs for precipitation and additive CFs for temperature based on the GCM-derived outputs for baseline (1971-2000) and future (2041-2070) climate conditions. A time series of baseline historical climate input data was selected for each study area and the data series adjusted using the CFs.

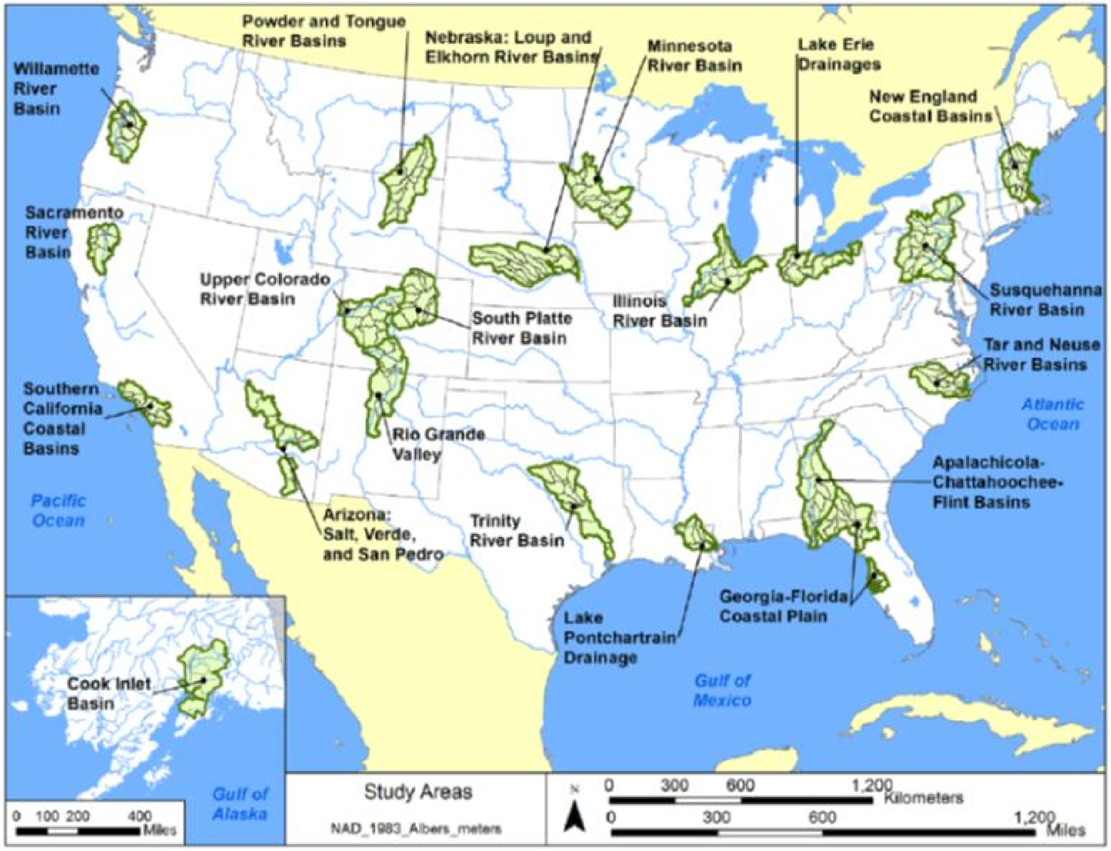

Figure 9.1. Watershed locations for the U.S. EPA (2013) study.

The continuous simulation models were re-run with the adjusted time series and the changes in streamflow and water quality constituents were reported for the 20 watersheds for just the SWAT model. The SWAT model was considered to have a technical advantage because it can account for the influence of changes in atmospheric CO_2 concentrations and other feedback responses of plant growth to climate change. In addition, there were practical advantages to the choice of SWAT, as the model is somewhat easier to set up and calibrate than HSPF. The projected change in three streamflow characteristics based on changes in the NARCCAP climatic data from the baseline period (1971-2000) to the future period (2041-2070) for the six projections for the 20 watersheds were as follows:

- Total average annual streamflow volume: median ratio ranged from 0.71 to 1.54 times the baseline values.
- Seven-day low flow: median ratio ranged from 0.67 to 2.80 times the baseline values.
- Hundred-year peak flow: median ratio ranged from 0.83 to 1.36 times the baseline values.

The changes in streamflow characteristics attributed to land use change were also evaluated, but were small because all 20 watersheds exceeded 6,000 square miles in drainage area. Similar results were reported for the water quality constituents. The study results indicate larger potential future increases in average flows or low flows as compared to flood flows. This is consistent with other studies. The study illustrates the benefits of the CF approach including its simplicity, elimination of the need for bias correction, and the ability to create spatially variable future climate scenarios that maintain the observed historical spatial correlation among the different watersheds.

9.2.2 Iowa Department of Transportation Study

The Iowa Department of Transportation conducted a pilot study of six bridges in two Iowa river basins – the Cedar River Basin (7,753 square miles) and the South Skunk River Basin (813 square miles) – to develop a methodology to evaluate their vulnerability to climate change and extreme weather (Anderson et al. 2015). The six bridges had been either closed or severely stressed by record flooding within the past seven years.

The data used in these analyses included daily precipitation data from 19 climate projections from nine GCMs for three emissions scenarios (seven A1B, three A1F1, and nine A2) downscaled to a one-eighth-degree grid using the asynchronous regional model (ARRM) (Stoner et al. 2013). Accuracy of downscaled precipitation data was evaluated by comparing the annual maximum precipitation statistics for the baseline period of 1960 to 1999 and a future period 2000 to 2013 from the GCM-derived precipitation time series to the statistics from the observed record for that period. This comparison was made to demonstrate the plausibility of using the continuous daily precipitation series from the GCMs as the climatic driver for the modeling analysis.

The distributed continuous simulation watershed model CUENCAS (Mantilla and Gupta 2005) was used to obtain estimates of flood discharges for the six bridges for the period 1960 to 2099 for each projection. Because the projected time series of climate inputs was computed on a daily basis, this study essentially implemented daily CFs.

Flood frequency curves were developed for the Cedar River and South Skunk River basins for two periods 1960-2009 and 1960-2059 using the median of the 19 climate projections. Figure 9.2 shows flood frequency curves for one location in each watershed for the two periods. The frequency curve for the period 1960-2059 is the blue solid line with the upper and lower 95 percent confidence limits based on the median of the 19 climate projections represented by the dotted lines. The shaded area in the figure represents the upper and lower 95-percent confidence limits for the baseline period 1960-2009.

Anderson et al. (2015) concluded that, with climate change, all six critical interstate and highway locations would be exposed to streamflow that exceeds current design. Bridge and highway resilience would need to be improved in four of the six bridge locations to withstand the projected increase in the frequency of extreme streamflow.

This effort is considered an example of a Level 4 analysis as described in Section 4.1. Specific climate science expertise was secured to select the GCMs, emissions scenarios, and downscaling appropriate for the study. In addition, a custom rainfall/runoff model was applied to each of the watersheds.

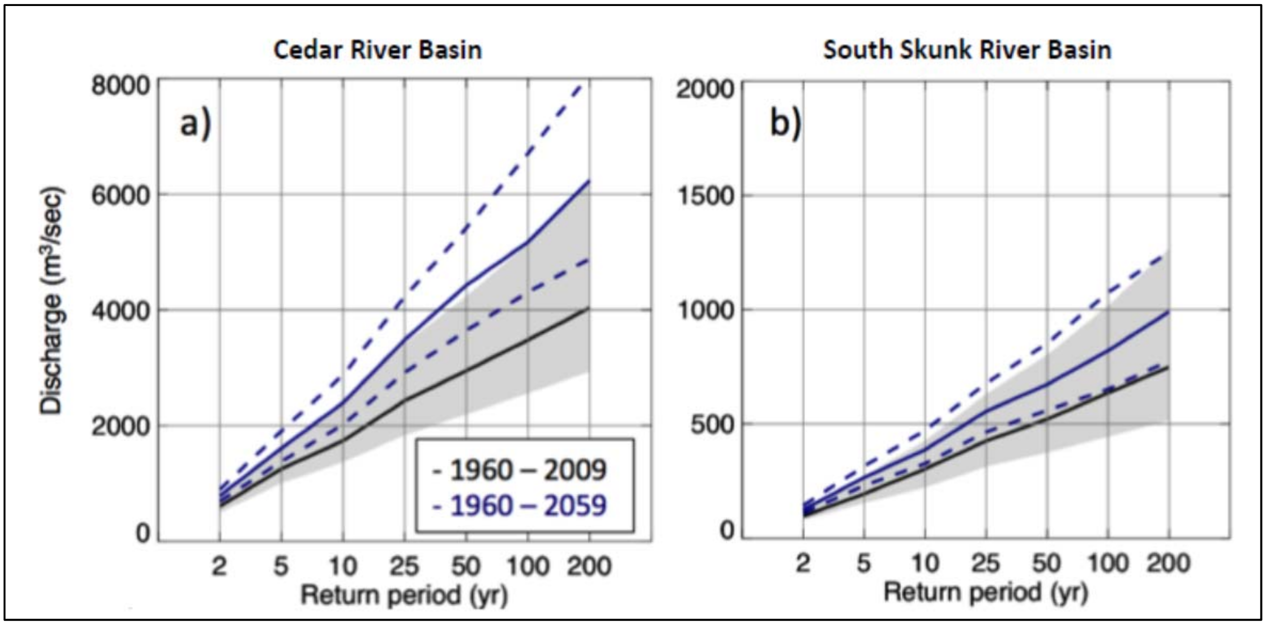

Figure 9.2. Frequency curves for the Cedar River and South Skunk River basins.

9.3. Applicability and Limitations

Continuous simulation models are more applicable for larger watersheds (greater than a few hundred square miles) as shown in the two examples in Section 9.2 where historical streamflow data and historical precipitation, temperature, evapotranspiration, and other climatic data are available for model calibration. However, continuous simulations can be, and are, applied to smaller watersheds, especially for stormwater management applications.

The continuous models are often better suited to larger watersheds because a daily time step is typically used to accommodate the many climatic variables in the analysis (precipitation, temperature, evapotranspiration, etc.) that may not be available at a more detailed temporal resolution and because in larger watersheds storage, antecedent moisture, and baseflow are more critical to the hydrologic analysis. In addition, continuous simulation models do not rely on the same assumptions of uniform spatial and temporal distribution of precipitation used in the design storm approach that are more likely to be unreasonable assumptions for larger watersheds.

Continuous simulation models are typically used for stormwater quality and quantity analyses for the more frequent floods and for low flow statistics. The U.S. EPA (2013) study discussed in Section 9.2.1 is an example application for water quality and low flow statistics. Continuous simulation models are infrequently used for extreme floods although the Iowa DOT study discussed in Section 9.2.2 is a good example.

A limitation of these models for assessing the effects of climate change is that several interrelated parameters need to be estimated to produce reasonable results and that requires long-term historical streamflow and climatic data for model calibration. In addition, the models are more complex and require a higher level of expertise and resources to apply.

9.4. Discussion and Other Resources

Continuous simulation models require several different types of climatic data and require calibration to historic data to ensure reasonable results. Obtaining the needed climatic data used in continuous simulation modeling can be challenging.

There are several continuous simulation models used in practice in addition to the SWMM model discussed in this section. Kilgore et al. (2019) describes other continuous simulation models such as HSPF and SWAT that were used in the EPA nationwide study discussed previously. AASHTO (2007) provides a brief description of other continuous simulation models for which user's manuals are available. The HSPF model has been incorporated into U.S. EPA's BASINS system (U.S. EPA 2015), which is widely used for water quality modeling.

Section 9.4.1 provides information on a U.S. EPA resource for CFs and Section 9.4.2 discusses situations where a state DOT may wish to secure additional expertise and resources to effectively apply continuous simulation modeling in specialized situations.

9.4.1 Climate Resilience Evaluation and Analysis Tool (CREAT)

The EPA Climate Resilience Evaluation and Analysis Tool (CREAT) database (U.S. EPA 2016) includes historical climate data and climate projections across the U.S. downscaled using a CF approach to a grid of ½ degree latitude and longitude (about 48 km square) that has data that may be useful for state DOTs. Projected information in CREAT is based on 38 CMIP5 GCMs for the higher RCP8.5 scenario. The projections cover two 20-year time domains: 2025 to 2045 and 2050 to 2070. By including only the higher RCP8.5 scenario and limited time domains, the CREAT database may be inappropriate for some applications.

The CREAT database also includes information on the projected changes to the magnitude and frequency of extreme precipitation events. The historical Generalized Extreme Value (GEV) curve for the 5-year, 10-year, 15-year, 30-year, 50-year, and 100-year return intervals were developed for precipitation stations that have data during 1981 through 2010, using the annual maxima time series for 24-hour precipitation. The changes in precipitation per degree of warming (global), for each quantile were determined for each GCM model from a subset (22 out of 38) of GCMs. The models were ranked based on the sensitivity of the 5-year return interval quantile to each degree of warming. The five models having the highest sensitivity were averaged to describe a "Stormy Future" while the five models with the lowest sensitivity were averaged to describe a "Not as Stormy Future." The historical GEVs were then adjusted using the ensemble averaged groups of GCMs and the estimated change in global mean temperature from the same model, thus creating a new GEV curve for each of the future time periods. These projected statistics may be useful to state DOTs for estimating changes in precipitation in their state. This tool essentially provides CFs for precipitation quantiles.

9.4.2 Considerations for Advanced Analysis

For an advanced analysis, such as a Level 4 analysis described in Section 4.1, the design team recognizes that it needs to include appropriate expertise in climate science to secure site-specific custom projections or to include more advanced watershed modeling expertise. The potential tasks for a climate scientist on the design team include the following:

1. **Guidance on GCM selection**: The most reliable, tested and documented GCMs were described in Chapter 3 as belonging to Group 1. Although there is good guidance on the Infrastructure and Climate Network (ICNet) website on model selection, a climate scientist can provide guidance on which models and how many of the Group 1 GCMs should be used in an analysis.
2. **Guidance on source of high-resolution climate datasets**: There are several websites with downscaled GCM output for CMIP3 and CMIP5 using various downscaling techniques. Several websites have data from the same GCMs and the climate scientist could provide guidance on what is the best source of downscaled GCM output.
3. **Guidance on scenario selection**: There are several choices of future scenarios including SRES and RCP scenarios. A climate scientist can advise the design team on the number and best scenarios to use.
4. **Guidance on obtaining climate data other than precipitation**: If temperature, relative humidity, evaporation, solar radiation or wind speed are needed in the hydrologic modeling, the climate scientist could provide guidance on obtaining these data.
5. **Guidance on assessing the uncertainty**: The results from an ensemble of GCMs will provide an estimate of the uncertainty in future projections and the climate scientist can provide guidance on assessing this uncertainty.
6. **Incorporating high-resolution climate projections**: In the future, there will be new datasets of high-resolution climate projections with more refined temporal and spatial scales that may use existing or new downscaling methods. The climate scientist can advise the design team how to incorporate these new data sources.

Part III: Coastal Applications

Chapter 10. General Guidance for Coastal Applications

This chapter of the *Guide*, along with Chapters 11 and 12, discuss coastal applications. Chapter 11 provides guidance on selecting sea level rise scenarios for design, while Chapter 12 gives guidance for evaluating coastal hazards, including water levels and waves. This chapter provides general guidance for incorporating climate change information into coastal design and analysis applications. It begins by outlining an overall framework for analysis and then describes common applications for using climate change information in the coastal environment.

10.1. Overall Approach

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§11.2 Data Collection

§11.3 Shoreline Topography

§11.4 Characteristics of Waves and Currents

§11.7 Planning for Shoreline Change

§15.6 Qualifications for Consultant Hydraulics Engineers

The most common elements of an assessment of the potential effects of the future climate on transportation infrastructure in the coastal environment are selecting appropriate sea level rise estimates and estimating the potential hazards associated with that rise, combined with the projected wave environment. The details will vary with the required levels of analysis, which were introduced in Section 2.1.2 and are described in subsequent sections of this chapter, but the general steps for these assessments are as follows:

1. Determine critical infrastructure elevations, performance/safety thresholds, or structure capacity.
2. Estimate the relative sea level rise (RSLR) at the project site.
3. Estimate the hazards associated with the water level and wave environment at the projected sea level from Step 2.
4. Compare the engineering demand (loads, scour, etc.) determined in Step 3 to the structure capacity (i.e., resistance) as defined in Step 1.

The following sections outline these steps as they apply to three distinct levels of analysis. In general, the level of analysis selected will be a function of the application or intended purpose, as well as the criticality of the infrastructure. Suggestions for selecting an appropriate level of analysis, as a function of these two metrics, are provided in the following sections. Additional information regarding these levels of analysis is available in Douglass et al. (2014).

10.1.1 Level 1 Analysis – Use of Existing Data and Resources

A Level 1 analysis provides meaningful information about the level and coverage of exposure to damaging storm parameters without performing complex modeling or calculations. This lowest level of analysis is simpler to perform and relies on the use of established maps and tools to determine the degree to which a particular asset or area is exposed to the effects of extreme events and climate change. This level of analysis may be appropriate for planning studies and vulnerability assessments for assets with low criticality.

Because a Level 1 analysis is relatively simple, the design team can consider a number of future climate scenarios, specifically sea level rise scenarios. Accordingly, the goal of a Level 1 study might be to capture the exposure of a particular asset or area to the effects of RSLR, rather than to predict an accurate value of flooding depth or wave height. In this manner, the design team uses a Level 1 analysis as a screening tool to identify areas or infrastructure assets that are exposed to the effects of sea level rise. These specific areas can be evaluated in more detail through additional refinements of a Level 1 analysis or by including them in assessments with higher levels of analysis.

The uncertainty in the results obtained in a Level 1 assessment will be relatively high. The results will include the assumptions and uncertainties inherent in existing inundation or flood hazard maps (or other existing tools used). The most commonly available existing data are typically the FEMA Flood Insurance Rate Maps (FIRMs) and the corresponding Flood Insurance Studies (FISs). Those studies focused on quantifying rare flood events, including the 100-year flood and 500-year flood levels. In some cases, other agency flood maps and studies may be available. It should be noted that modifying existing FEMA FIRM data to account for RSLR will not capture the expanded floodplain without additional mapping. Combining the modified flood hazard elevations with a digital elevation model (DEM) overcomes this issue, which is particularly important when a Level 1 analysis is applied to a large area, as opposed to an individual asset or location.

At the most basic level of analysis, the four-step procedure identified above is conducted with specific guidance on Step 2 and Step 3. The RSLR at the project site (Step 2) can be determined by the procedure below, with more detailed information provided in Chapter 11:

(a) Use existing data and resources – including inundation or tsunami hazard maps – to determine the exposure of infrastructure under selected sea (lake) level change scenarios, and sensitivity to depth-limited wave or wave runup processes.

(b) Use the recommended minimum Global Mean Sea Level Rise (GMSLR) projections in Section 11.1.1 (GMSLR based on RCP4.5/6.0) for design sea level increases. Assess the robustness of the design in response to higher GMSLR projections, such as those mentioned in Section 11.1. For critical infrastructure projects with low risk tolerance, consider the high range of scientifically plausible GMSLR. See Chapter 11 for guidance.

(c) Use recommendations from Chapter 11 for computing the RSLR at the project site. This includes the local and regional effects on RSLR (e.g., vertical land movement [VLM] and other regional effects).

Data and resources for a Level 1 analysis, with the understanding that they must be modified to account for the potential effects of RSLR, include the following:

- FEMA FIRMs and the corresponding FISs.
- The U.S. Army's Engineer Research and Development Center (ERDC) Coastal Hazards System (for return period water level data, as well as wave characteristics) (USACE 2017c).
- Coastal Emergency Risks Assessment (CERA) – Storm Surge and Wave Guidance (https://cera.coastalrisk.live/).

- NOAA IOOS Coastal & Ocean Model Testbed (https://ioos.noaa.gov/project/comt/).

The ERDC Coastal Hazards System is an example of storm hindcast data that can be used to support a Level 1 analysis. However, these data do not include RSLR. To incorporate RSLR in a Level 1 analysis, the engineer must add the RSLR to these database values using procedures described in Chapter 12.

Like the ERDC Coastal Hazards System, the CERA online tool contains storm hindcast model data, with new data being added frequently. One could extract these data and use the tools summarized in Chapter 12 to derive estimates of RSLR effects on surge and waves from historical events.

Similar to both the ERDC database and the CERA system, the NOAA IOOS database contains numerous storm hindcasts for notable storm events (extreme events). As in the other databases, these data would need to be modified using tools summarized in Chapter 12 to estimate the effects of RSLR on coastal hazards.

General data and resources for developing estimates of RSLR at the project site may include the following:

- Historical RSLR data and trends from NOAA tide gauges, such as those shown in Figure 10.1. The use of historical RSLR data for projecting future sea level rise is only advisable in the short term.
- Sweet et al. (2017a) GMSLR scenarios and RSLR scenarios for specific geographical locations.

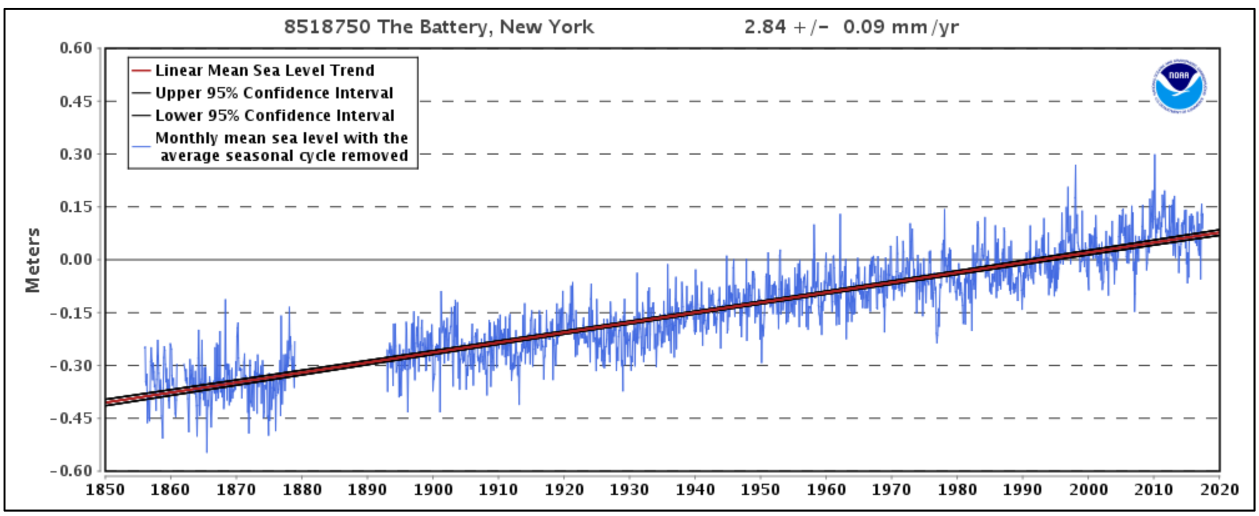

Figure 10.1. Relative sea level rise trend for New York City based on tide gauge data (downloaded from www.tidesandcurrents.noaa.gov/sltrends Sept. 30, 2017).

Project-based quantitative tools for a Level 1 analysis may include the following:

- Depth-limited wave calculations developed using tools from HEC-25 (Douglass and Krolak 2008).
- Simple methods for wave and surge hazard modification that accounts for RSLR (for example, the methods described in Chapter 12).

10.1.2 Level 2 Analysis – Original Modeling of Storm Surge and Waves

A Level 2 analysis provides detailed information about exposure under extreme events with climate change. One or more climate scenarios are explicitly incorporated into model simulations, so their effects on the critical coastal infrastructure can be determined. A Level 2 study requires the use of sophisticated hydrodynamic models that simulate storm surge and waves, or tsunamis, tides, freshwater inputs, wave runup, and any other relevant process that contributes to the total water level during an extreme event. The development and application of these models, as well as interpretation of their results, should be performed by a trained coastal engineer with expertise in hydrodynamic modeling.

A requirement of the Level 2 study is to thoughtfully select and model extreme events of interest (i.e., event-based modeling). These could be events of record for a region (e.g., a specific hurricane), a storm that caused a notable effect on a specific piece of infrastructure (e.g., bridge failure), or perhaps even an event that has not yet occurred (e.g., hurricane with a shifted track, tsunami). A goal of the Level 2 study could be to demonstrate the degree to which climate change might modify the exposure of an asset or area relative to a present-day (baseline) scenario. Incorporating climate change data into the hydrodynamic modeling is important for capturing any non-linear effects that result from RSLR or storm intensification. Addressing these non-linear responses is a strength of this approach, compared to the simpler Level 1 analysis.

An example of a Level 2 analysis for storm surge and wave sensitivity to RSLR is the work performed as part of the Gulf Coast 2 study (Choate et al. 2012). In that study, coastal hydrodynamic models were used to determine the effects of RSLR and future storm intensification on hurricane storm surge and waves in coastal Alabama. Two prior hurricanes, three RSLR scenarios, and one storm intensification scenario were chosen for the study. RSLR and storm intensification data were integrated into the hydrodynamic modeling such that the results captured any non-linear hydrodynamic response to the climate change scenarios. Those model results were subsequently used to assess vulnerability and evaluate the sensitivity of critical transportation infrastructure to future RSLR and storm scenarios.

The results of a Level 2 study may not be fully probabilistic, though it may be possible to assign a return period to a scenario if a historical storm or event is selected for analysis. It may be helpful to consider possible events and climate change scenarios that range from more frequent, lower intensity events to infrequent, higher intensity events. For a given storm event or return period scenario, these simulations may also selectively assess sensitivity to changes in storm parameters, such as forward speed, landfall location, landfall approach angle, radius to maximum winds, wind speed, and central pressure. This type of extended analysis may be most appropriate for the Level 3 analysis described next.

While each Level 2 study will be unique, an underlying methodology will be common to all studies and include the following elements:

- Selection of extreme event and climate scenarios appropriate for the region.
- Quantification of critical thresholds.
- Development of suitable hydrodynamic modeling tools.
- Validation of the hydrodynamic model(s) using hindcast simulations and observations; simulation of the extreme event and climate scenarios.

- Mapping of the hazards (e.g., inundation, waves, and wave runup).
- Assessments of exposure under each scenario.

While a Level 1 study uses inundation or flood hazard maps developed by others, new maps will be developed for each specific storm (or tsunami) and climate scenario evaluated as part of a Level 2 study. Such mapping constitutes a significant amount of work and serves purposes beyond the exposure assessment, like communication and public outreach. Maps generated in a Level 2 analysis will be event-based maps, perhaps augmented by changes in hazards resulting from the sea level rise or climate scenario modeled. Even if a return period scenario was used in the simulation, the subsequent results, maps, and products will not be fully probabilistic. For public outreach, it is crucial that maps and products for public consumption are prepared so that they are readily understood by lay persons.

The time, effort, and cost required to complete a Level 2 study are greater than those for a Level 1 study. However, this type of modeling is common in coastal engineering practice. With an increase in time, effort, and cost comes a reduction in uncertainty and a narrower range of possible answers. The reduction in uncertainty is mostly attributed to use of the hydrodynamic models that provide site-specific estimates of the critical regional coastal processes, such as water levels, wave heights and periods, velocities, etc. The improved quality and utility of these estimates does not suggest the values are necessarily "larger" values than those obtained in the Level 1 study, but that the outcomes are more accurate and the uncertainty is better understood.

A Level 2 analysis follows the general four-step procedure described previously. However, in Level 2, Step 3 and Step 4 are addressed through site-specific modeling of storm surge and waves. Project-based quantitative tools for a Level 2 analysis may include the use of ADCIRC or similar high-fidelity coastal hydrodynamics models with SWAN or STWAVE or similar wave models. See Douglass et al. (2014) for an introduction to some of these models.

10.1.3 Level 3 Analysis – Modeling in a Probabilistic Risk Framework

A Level 3 analysis characterizes coastal hazard exposure in terms of probability and risk. A probabilistic risk framework is one in which the joint probabilities of an event (e.g., hurricane) and its response (e.g., storm surge) are determined, and those results are used to make risk-based decisions.

> *BOTTOM LINE: A risk-based decision is one where a practitioner considers the likelihood of an event occurring during the life of a project, as well as its potential consequences.*

While the general methodology of a Level 3 analysis is similar to that of a Level 2 study, this higher level of assessment requires substantially more model simulations to consider the probability of events and to characterize the resulting risks in terms of exceedance probabilities. While a Level 2 study might be based on perhaps tens of unique event scenarios, a Level 3 study might require hundreds, or even thousands, of simulations to evaluate how the coastal hazards change with selected sea level rise scenarios. This probabilistic approach, based on joint probability methods, is essentially the approach FEMA uses for developing modern flood hazard maps (FEMA 2003). Additional information about the methods used to generate coastal hazard probabilities is provided in Douglas et al. (2016a).

An important distinction is that FEMA analyses do not consider either climate scenarios or the joint flood hazard probabilities between the riverine and coastal flood studies. However, they do consider a range of likely storm parameter values (e.g., land falling angle, forward speed, radius to maximum winds, wind speed, central pressure), all with assigned probabilities, in an effort to account for different storms that produce similar hazards. Since these types of approaches generally ignore the potential joint probabilities of storm surge and freshwater input to the coast, additional model simulations may be warranted. This level of analysis is appropriate for the design of critical infrastructure.

A Level 3 study requires a significant investment, exceeding a Level 2 study in time, effort, and cost. However, this highest level of analysis also provides the greatest understanding of the uncertainty in descriptions of the coastal hazards by explicitly accounting for probability in an objective manner. The number of simulations required in this analysis must be sufficient to allow the consideration of a range of return period events, providing results that may be applicable over a much larger geographic area. For example, a Level 2 study might focus on storm events that lead to failure or damage of a specific asset, such as a bridge. These results are valuable, but only near that bridge. The event probabilities derived from a Level 3 assessment may apply to more than one area, when multiple storm tracks or tsunami events are modeled. Also, the number of simulations required will grow proportionally to the number of sea level rise scenarios selected for the study.

A Level 3 study requires expertise in coastal engineering, numerical modeling, hazard analysis, probability, and risk. Accordingly, such studies should be performed by accomplished engineers with demonstrated expertise in modeling extreme events, as well as an understanding of the appropriate regional climate scenarios. A recent example of a Level 3 analysis is provided by Dompe et al. (2015). In this case, coastal hydrodynamic models were used to assess the vulnerability of coastal bridges for the Louisiana Department of Transportation and the North Carolina Department of Transportation.

A Level 3 analysis follows the general four-step procedure described previously. However, in Level 3, Step 3 and Step 4 are addressed through site-specific modeling of storm surge and waves placed in a probabilistic framework by estimating confidence limits on the range of likely outcomes. The results of those simulations reflect the present-day probabilities of coastal hazards and describe how they might change over time with future sea level rise.

However, the results will lack a full probabilistic characterization in the sense of incorporating future climate change, as those specific probabilities are ill-defined. This approach still has value, however, as the results provide estimates of the design conditions, at some specified future date, for the sea level rise scenario chosen for the project. In that sense, an appropriate suite of design conditions can be developed for an asset such that it continues to meet design criteria at the end of its projected life, under the assumed sea level rise scenario, for the return period event of interest. An added benefit, perhaps, is that the asset possesses some enhanced resilience to the design event over the life of the project.

In some cases, a Level 3 analysis might be informed by using the hundreds of event outputs, or at least a significant proportion of them, that constitute the 100-year and 500-year floodplains, that are part of the data underlying FEMA's FIRMs. (Data are available upon request through FEMA's Engineering Library, https://www.fema.gov/engineering-library.)

The storm events that define the relevant flood hazard can then be re-simulated with relevant climate effects incorporated into the numerical modeling (see Section 12.4). Project-based quantitative tools for a Level 3 analysis may include the following:

- ADCIRC or a similar high-fidelity coastal hydrodynamics models, with SWAN or STWAVE or a similar wave model. See Douglass et al. (2014) for an introduction to some of these models.
- Tools that support quantification of the probability, or joint probability, of each scenario to determine the resulting 100-year and 500-year coastal floods.
- Tools that support statistical analyses of storm event probabilities or statistical analyses of the response (for Great Lakes and Pacific coasts).
- Software that can generate randomly selected simulations and multi-processing capabilities.

10.2. Applications

This *Guide* provides specific recommendations for incorporating relevant climate change effects into the assessment of coastal design conditions. Guidance provided in the following two chapters focuses on selecting and applying future sea level rise projections for the purpose of planning and design (Chapter 11) and how to evaluate changes in coastal hazards with sea level rise (Chapter 12). The scope of these topics is introduced in Sections 10.2.1 and 10.2.2.

Other topics influencing coastal analysis and design include the effects of watershed contributions to coastal water levels and the effects of sea level rise on coastal geomorphology. This *Guide* does not currently provide recommendations for considering either of these phenomena, but the topics are addressed briefly in Sections 10.2.3 and 10.2.4.

10.2.1 Sea Level Rise

The planning and design of coastal transportation infrastructure should account for sea level rise. Sea level rise is currently affecting coastal roads and bridges, making them more vulnerable to flooding, waves, and erosion in both magnitude and frequency. Future sea levels are expected to rise at higher rates globally. However, most locations throughout the United States will experience site-specific rates of future relative sea level rise resulting from a combination of global sea level rise and the contributions of local and regional processes that add to, or subtract from, that value.

Chapter 11 of this *Guide* provides recommendations for selecting sea level rise scenarios for the purpose of planning and design. With respect to transportation design, the chapter recommends establishing a minimum GMSLR value of approximately 2 feet (0.6 meters) by the year 2100. This is a science-based recommendation for a future value of GMSLR that is likely to occur. The guidance also recognizes that higher GMSLR values are possible. Selecting a higher value may be appropriate for critical infrastructure or when risk tolerance is low. In the planning phase, the engineer may consider the full range of scientifically plausible GMSLR outcomes by 2100 or beyond, for the purpose of assessing vulnerability, performance, function, and connectivity to other transportation systems. These issues are also addressed in Chapter 11.

10.2.2 Coastal Hazards

Coastal hazards relevant to the design of transportation infrastructure include coastal water levels (e.g., storm surge), waves, and velocities. Each of these coastal hazards is sensitive to water depth, which increases with (relative) sea level rise. However, the sources of coastal hazard data mentioned previously do not account for future sea level rise: they describe coastal hazards under present sea level conditions. The effects of sea level rise on coastal hazards can be determined numerically using coastal hydrodynamic models in a manner consistent with the recommendations provided in Section 10.1.2 (Level 2) and Section 10.1.3 (Level 3). These levels of analysis, while robust, may not be appropriate for smaller projects, non-critical transportation infrastructure, or infrastructure that may not be particularly vulnerable to the effects of future sea level rise. In those cases, or for planning-level assessments, applying adjustments to existing coastal hazard data in a manner that explicitly accounts for higher future sea levels may prove useful.

Chapter 12 provides recommendations for combining coastal hazard data and climate change information. Specifically, a series of simple equations are provided that allow a practitioner to estimate the effects of future sea level rise on existing coastal hazard data. Methods for modifying coastal storm water levels, wave heights, wave periods, and velocities are provided, along with an example. Specific recommendations for incorporating climate change information into hydrodynamic modeling are also provided. For critical infrastructure, the effects of sea level rise on coastal hazards should be determined through the use of appropriate numerical modeling, not by the simple deterministic equations provided in this *Guide*.

10.2.3 Watershed Contributions to the Coast

The combination of coastal storm surge and heavy upland rainfall can cause an increased potential for flooding that poses a threat to coastal transportation infrastructure. Several climate change effects, including rising sea levels, will exacerbate this effect.

The combined streamflow and storm surge hydrograph related to a coastal storm can show greatly increased flow volume and magnitude. Combined hydraulic and hydrodynamic simulations of flow and water levels reveal that rainfall/runoff can significantly affect coastal water levels and that the presence of storm surge generally results in higher flood levels upstream. Important to these results is the locale: the topography of the watershed and an associated time lag between the rainfall event and the storm surge require careful consideration (Blumberg et al. 2015, Klerk et al. 2015, McGuigan et al. 2015, Torres et al. 2015).

When considered individually or as components, the peak flow resulting from storm surge tends be much higher than that from rainfall/runoff, owing to the intense flood and ebb of storm surge during a short-duration storm event. However, the total flood volume draining toward the coast tends to be dominated by rainfall/runoff (Torres et al. 2015).

Hydraulic design associated with peak flow (e.g., bridge foundation, culvert, drain, etc.) would likely be sensitive to the increased flows associated with the rushing flood or ebb of storm surge. Design that is most concerned with flow volumes (e.g., detention basins, routing reservoirs, stormwater wetlands, etc.) would be more sensitive to long-lasting or delayed drainage resulting from combined rainfall/runoff and storm surge.

Because this compound flooding is dependent on location-specific characteristics, the joint probability of rainfall/runoff and storm surge requires consideration. This effect is more likely on the Atlantic and Gulf coasts than on the Pacific Coast, for instance. The frequency of such events has increased in the last century. Sea level rise is one major cause of increased coastal flooding, but climate change effects will likely increase the probability of compound events (surge and heavy precipitation), which augment the flooding potential in some areas (Wahl et al. 2015).

10.2.4 Sea Level Rise and Coastal Geomorphology

Sea level is a critical component of coastal geology, and rising sea levels will impact bluff erosion, intertidal marsh locations, barrier island behavior, and shoreline positions. As sea levels rise, waves will affect shorelines at higher elevations, causing increased erosion and retreat of bluffs, with the side effect of adding sediment to coastal systems. Some intertidal marshes will be able to keep pace with local sea level rise by increasing in elevation or migrating. Unprotected wetlands with sediment shortages can become inundated and transition to shallow-water habitat, as in coastal Louisiana.

Most barrier islands will likely be able to adjust to rising sea levels through storm-induced overwash processes that cause island elevations to increase. The U.S. barrier islands have existed, but moved and changed shape, throughout the past 6,000 years in response to sea level fluctuations, wave-driven longshore sand transport, cross-shore sand transport including storm tide overwash, inlet formation and closure, and winds blowing sand into dunes. The barrier overwash or rollover process is a typical response of all barrier islands as they migrate toward the mainland across the shallow continental shelf. These barrier island migration processes will be affected by accelerated sea level rise rates (Fitzgerald et al. 2008).

Shorelines will respond in different ways to sea level rise, though in general they are anticipated to be recessional. Local considerations, such as weather effects and anthropogenic activities, can affect this response. The most common method to describe changes to beaches and barrier island positions has been the Bruun rule, which states that the wave conditions under a higher water level adjusts the beach profile by shifting subaerial material offshore, thereby causing the shoreline to recede (Bruun 1988). However, the Bruun rule can be considered overly simplistic, limited, and inaccurate in many cases (Cooper and Pilkey 2004). Beach nourishment as an adaptation strategy may be able to offset the recessional effects of sea level rise for most sea level rise projections this century (Houston 2017).

A number of coastal geomorphology models have been developed to address changes in response to sea level rise. The Probabilistic Coastline Recession (PCR) model provides probabilistic estimates of shoreline recession induced by sea level rise (Ranasinghe et al. 2012). The model is relatively simple to develop, easy to apply, and appropriate for use with any coastline. Use of the model entails the implementation of a storm time-series with long-term measurements of tides and waves. Such measurements are available for the U.S. coastline from NOAA and other agencies. The Coastal Storm Modeling System (CoSMoS) was developed by the USGS (2017) to predict coastal flooding caused by future sea level rise and storms integrated with long-term coastal evolution (e.g., beach changes and cliff/bluff retreat). Lentz et al. (2015) developed a coastal geomorphology model that predicts landform change with sea level rise, with particular emphasis on inundation. Nearly 70 percent of the coastal landscape has some capacity to respond dynamically to sea level rise, and inundation models overpredict land likely to be submerged (Lentz et al. 2016).

Climate change may also affect coastal morphology through fluvial processes. Precipitation and runoff are the main drivers of the movement of sediment to the coast, and augmentations to the sediment supply can have a pronounced effect on shoreline positions (Blum and Törnqvist 2000). The degree to which these processes change and what effects those changes have may be an area of study in the future.

Chapter 11. Selecting Sea Level Rise for Design

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§11.2 Data Collection

Rising mean sea level can have significant effects on the long-term functionality and vulnerability of transportation infrastructure near the coast. Therefore, sea level rise projections should be included in the planning and design of transportation assets near the coast. Sea level rise is a well-understood physical process that is a component of the coastal design environment (along with tide range, storm surge, waves, winds, soils, etc.) that is specific to every site. This chapter provides recommendations concerning sea level rise for engineers tasked with designing coastal transportation infrastructure. This *Guide* has three primary recommendations:

1. Future sea level rise should be included in coastal asset planning and design.
2. Minimum projections of sea level throughout the remainder of this century should be used in many situations.
3. More conservative (higher) estimates of future sea level rise should be used when overall project performance is very sensitive to design sea levels and/or when designing critical transportation infrastructure.

Many governmental organizations (including federal agencies, state governments and DOTs, and local governments) have implemented guidance regarding appropriate sea level rise assumptions for planning and design. This *Guide* recognizes that many choices are possible. Therefore, nothing in this *Guide* should be interpreted as countervailing existing guidance.

Selecting appropriate sea level rise projections for engineering assessment and design requires consideration of the following decision criteria:

- Risk tolerance, system sensitivity and redundancy (if little or no redundancy exists, or if the system is highly sensitive, then the risk tolerance is low and the design requires a higher projection)
- Policy choices (e.g., protection or versus retreat).
- Timeframe (e.g., short term preparedness versus long term planning)

There are often trade-offs in design decisions, and some engineering projects near the coast will not be particularly sensitive to the specific assumed design value of sea level rise. Also, the available projections of sea level rise do not have significant variations until past mid-century. Thus, GMSLR projections from many possible sources may be adequate for design if the existing local and/or regional processes, such as Vertical Land Movement (VLM), are appropriately included. (See Chapter 8 of Kilgore et al. (2019) for a description of GMSLR projections.)

Depending on the project evaluation with respect to the various trade-offs, planning and design efforts for some types of projects and contexts should consider a range of sea level rise scenarios to properly account for uncertainties and risk. For some projects, decisions are best informed by an estimate of an appropriate minimum design value with an understanding of the distribution of possibilities about that value. A simple procedure is recommended in this chapter for estimating a minimum design value and, when appropriate, a range of values for sea level rise. However, this approach is not intended to limit designers who, depending on the needs of the project, may opt for other approaches, as discussed in Section 11.1.3.

11.1. Projected Sea Level Rise for a Range of Situations

Developing an estimate of the recommended minimum and possible design range of RSLR for the planning or design horizon is the first step in assessing the potential consequences of future climate change. Considerations of uncertainty in that estimate for design can then be evaluated as needed by the design engineer.

At least four strategies exist for developing an appropriate estimate of RSLR. First, regional assessments of RSLR are available in the published literature, and the design engineer should determine if a suitable study exists for the project location (see Kilgore et al. [2019] for some recommendations). Second, one can use the gridded RSLR data developed by Sweet et al. (2017a) and published in a supplemental data file. Third, the practitioner can develop estimates of RSLR using the USACE Sea Level Change Curve Calculator. Fourth, a simple procedure is outlined below for developing estimates of RSLR at or near specific tide stations.

The following simple procedure is recommended for developing estimates of RSLR at specific tide stations:

1. Estimate the existing, historical RSLR rate using the available analyses for a nearby NOAA tide station.
2. Adjust that value to develop an estimate of the local component by subtracting the longer term historical GMSLR rate (1.7 mm/year) from the historical RSLR rate. Convert the result to an elevation change by the end of the desired time period (e.g., middle or end of the planning horizon).
3. Estimate the total GMSLR.
4. Combine the two elevation components, Step 2 and Step 3, to estimate the total RSLR for the planning horizon.
5. If needed for design, adjust that RSLR value to the North American Vertical Datum of 1988 (NAVD 88).
6. If appropriate, repeat Steps 3 to 5 using a higher GMSLR value to develop a possible design range.

The remainder of this chapter provides guidance for implementing this procedure, particularly the estimation of the total GMSLR (Step 3). A potential weakness of this procedure is that it only accounts for the historical local effects on GMSLR (Step 2). The practitioner should exercise caution when applying this simple procedure: it may not be appropriate for northern latitudes or Pacific islands, where future local contributions to GMSLR may overwhelm the historical signal.

BOTTOM LINE: The benefit of this simple procedure is that it allows the user to consider any suitable GMSLR estimate in Step 3. Existing studies, reports, and tools, like those mentioned above, often provide RSLR information only for the GMSLR scenarios considered therein.

11.1.1 Recommended Minimum

The values provided in Table 11.1 are recommended for estimating the minimum GMSLR for use in planning and design, if no other information is available to the design team (Step 3 above). However, any appropriate future projection of GMSLR or guidance (excluding extrapolation of the historical linear rate) may be used in this general procedure, with proper justification.

Table 11.1. Recommended minimum GMSLR estimates for use in planning and design.

	Unit	2020	2030	2040	2050	2060	2070	2080	2090	2100
GMSLR (relative to MSL of 2000: mid-point of 1991-2009)	m	0.08	0.12	0.18	0.23	0.29	0.36	0.43	0.51	0.59
	ft	0.26	0.41	0.58	0.76	0.96	1.18	1.42	1.67	1.94

Table 11.1 provides estimates of GMSLR, by decade, for the remainder of this century. These are estimates for the 19-year averages centered on the decade relative to that of 2000. They must be adjusted to account for local historical contributions (e.g., VLM and other processes) in order to obtain an RSLR estimate. The values shown in Table 11.1 were developed using a second-order polynomial equation (following NRC 1987 and USACE 2014) to model the GMSLR rate throughout the century to reach the target GMSLR by 2100 using the following equation:

$$GMSLR(\mathrm{t}) = \mathrm{a}(\mathrm{t} - 2000) + \mathrm{b}(\mathrm{t} - 2000)^2 \tag{11.1}$$

where:

a = 0.0034 m/yr or 0.011155 ft/yr.

b = 0.000025 m/yr^2 or 0.000082 ft/yr^2.

t = Time in years (≥ 2000).

A GMSLR of 0.59 m (1.94 ft) is the median (50th percentile exceedance probability estimate) for RCP4.5/6.0 from Kopp et al. (2014). Although Kopp et al. did not estimate exceedance probabilities specifically for RCP6.0, they stated that RCP4.5 and RCP6.0 are virtually equivalent in terms of GMSLR through the end of this century.

The initial linear rate of rise in the equation is set to 3.4 mm/yr. This initial rate corresponds to an estimate of the rate of GMSLR for the past two decades. Therefore, it is the most reasonable way to represent GMSLR from approximately the year 2000 to the present. The values in Table 11.1 are within 0.02 m of the median projections of Kopp et al. (2014) for RCP4.5/6.0 throughout the century (and exactly equal in 2100). A projection of this median value and its corresponding 90-percent confidence interval are shown, along with the planning scenarios of Sweet et al. (2017a), in Figure 11.1. The recommended minimum GMSLR projection is mostly equal to or greater than the Intermediate-Low scenario of Sweet et al. (2017a), and the 95th percentile values closely follow the Intermediate scenario of Sweet et al. (2017a).

BOTTOM LINE: This minimum recommendation is not a "conservative" projection, as it is the median (50th percentile) value of the RCP4.5/6.0 scenarios and thus does not explicitly include any consideration of upper bound possibilities for this or other possible scenarios. It is essentially one reasonable answer to the question "What is likely to occur?"

Equation 11.1 and the values in Table 11.1 are proposed as a simple, reasonable estimate of the recommended minimum projection of GMSLR for the design of some transportation facilities in the coastal environment. Projects for which this minimum approach are appropriate may include establishing design tailwater elevations for stormwater management infrastructure, parking lots, and roadways or embankments for which the consequences of failure are low or moderate, as determined by the design team (see Section 11.1.3).

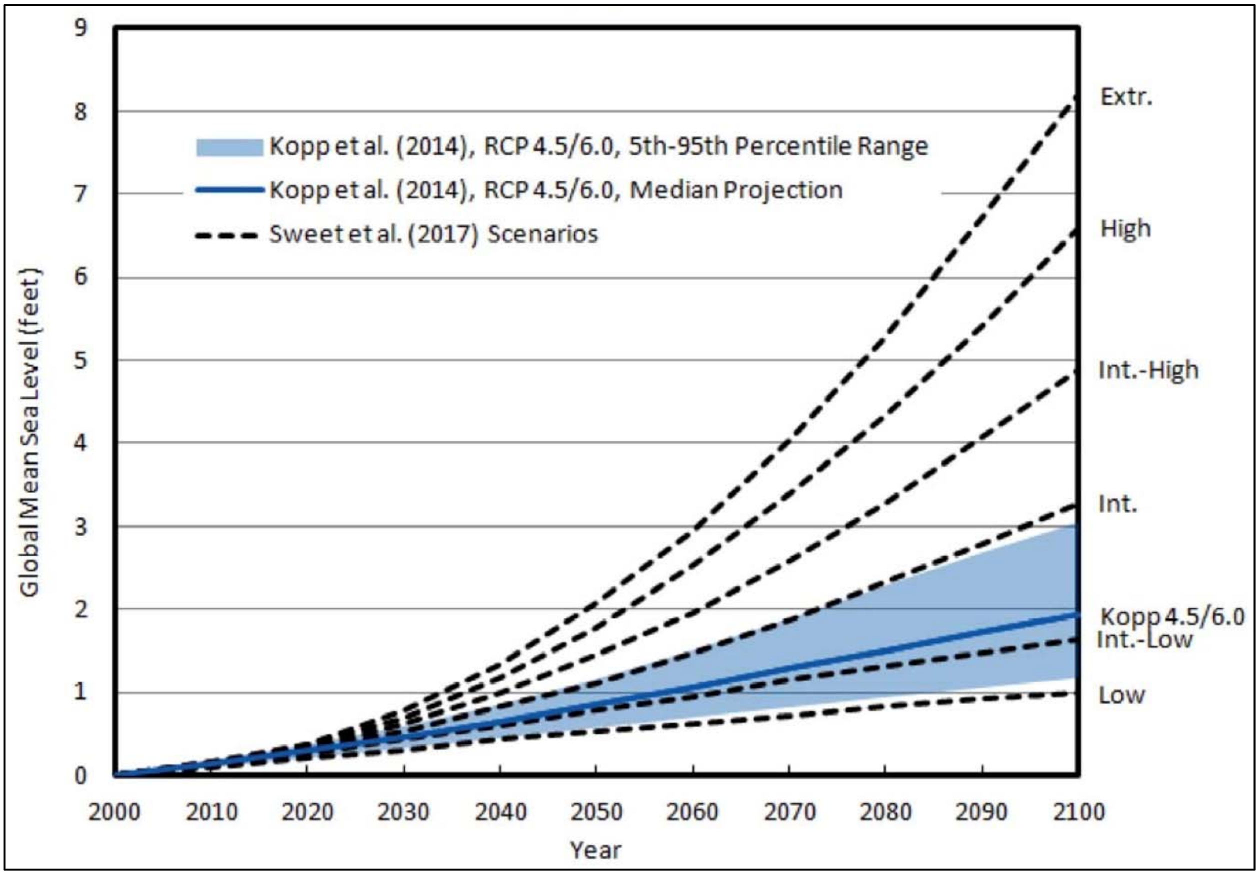

Figure 11.1. Recommended minimum (blue line) and RCP4.5/6.0 5th to 95th percentile (blue shading) GMSLR projections relative to the scenarios presented in Sweet et al. (2017a).

11.1.2 Possible Design Range

Evaluating the performance and vulnerability of transportation infrastructure against a range of GMSLR estimates is recommended. Consideration of a range, rather than simply a minimum, is particularly beneficial for the design of more vulnerable infrastructure, or when risk tolerance is low. Projects for which a range of estimates is more appropriate may include roadways, embankments, revetments, or other coastal infrastructure for which the consequences of failure are moderate to high, as determined by the design team (see Section 11.1.3).

The lower end of a practical design range should be no lower than the values provided in Table 11.1. The upper end of the range could reflect an estimate of what is generally considered a reasonable increment above the recommended minimum, based on scientific analysis, while also meeting the demands of engineering practicality. As described in many places, including Kilgore et al. (2019), estimates of future GMSLR vary greatly. However, for engineering purposes, a value of 1.21 m (3.96 ft) is a reasonable higher estimate. This value corresponds to the 95th-percentile GMSLR estimates for the RCP8.5 scenario as estimated by Kopp et al. (2014).

To put this higher recommended GMSLR value into perspective, it is shown in Figure 11.2, relative to the incremental GMSLR scenarios of Sweet et al. (2017a). The recommended alternative GMSLR projection for design (upper end of blue shading) is greater than the Intermediate scenario of Sweet et al. (2017a).

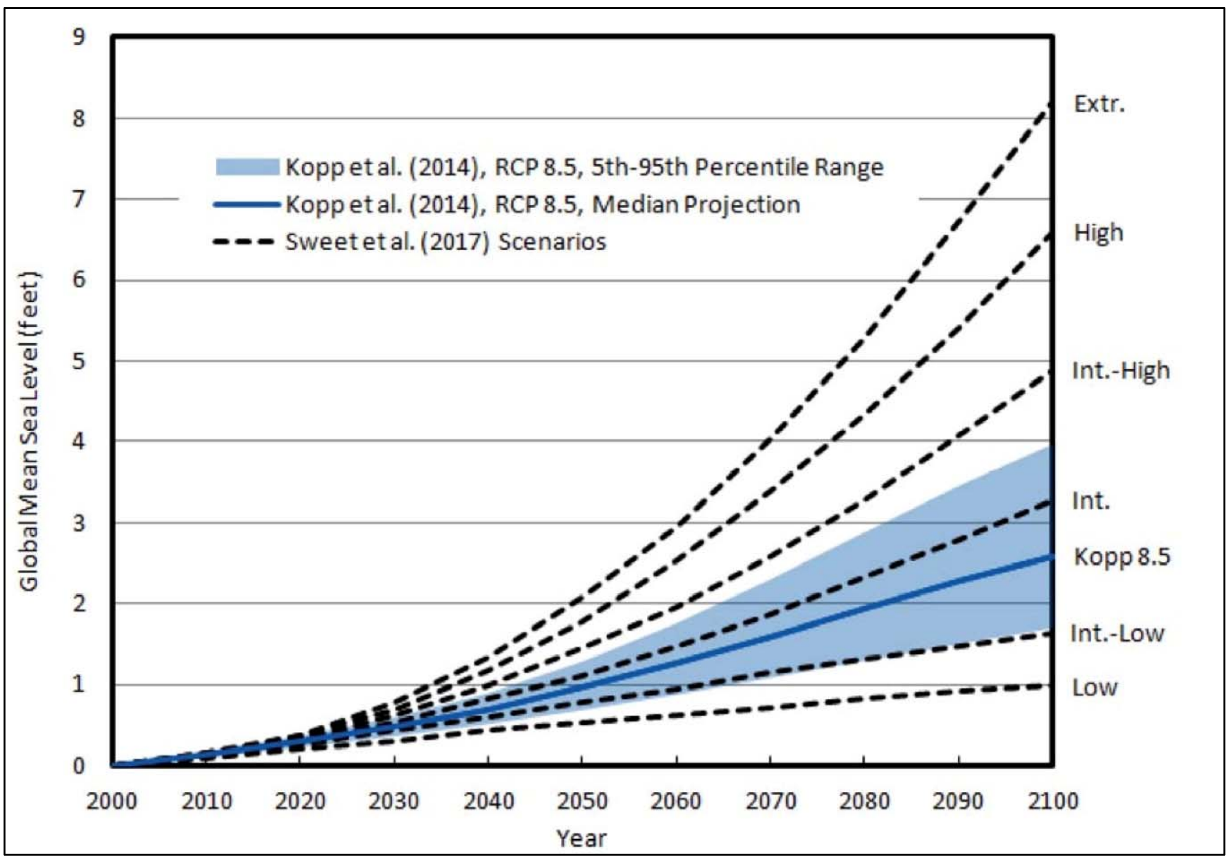

Figure 11.2. Recommended alternative RCP8.5 projection showing the median (blue line) and 5th to 95th percentile (blue shading) GMSLR projections, relative to the scenarios presented in Sweet et al. (2017a).

11.1.3 Recommendations for Critical Infrastructure

Where critical infrastructure is the subject of the investigation, such as for some Level 2 and Level 3 analyses, either a greater level of conservativism or the use of a probabilistic analysis may be more appropriate than the recommendations in sections 11.1 and 11.2. In fact, planners and designers should always consider the specifics of their project and may choose to go beyond the simplified recommendations presented in the previous sections for any project. Examples of coastal transportation assets that may be extremely sensitive to design elevation decisions are a major bridge over water or the entrance to a major tunnel (as in the example provided in Section 11.4 for the Boston tunnels). In those situations, increased design elevation decisions can provide for both future sea levels and a lower risk of damage during extreme events.

For these purposes, many of the primary GMSLR projection methods available can be used in the planning and design of coastal transportation assets (except for linear extrapolation of historical rates). Preference should be given to the most recent scientific information, as it typically accounts for improved understanding of the physical processes and dynamic results. These are discussed in Kilgore et al. (2019), and sea level rise expertise may be required to select the approach or approaches most suited for a given project.

Selecting a design stillwater level is a part of many coastal engineering analysis efforts, and sea level rise should be included in that analysis, as recommended above. For major projects and projects that have long planning horizons, particularly those with severe consequences of exceedance, the full range of potential RSLR projections should be evaluated. For those types of projects, an important question beyond "what is likely to occur?" is "how bad can things get?" Design decisions should be made with a probabilistic justification, and the specifics of the decision will include conservative engineering judgment and existing policy guidance.

11.1.4 Selecting a Scenario

This section provides a general decision-making framework for selecting an appropriate GMSLR scenario. The two previous sections provide recommendations for a minimum and a higher alternative GMSLR scenario for engineering design. These two GMSLR scenarios bracket a reasonable range of outcomes by the year 2100, with the understanding that higher GMSLR values can always be substituted when appropriate. But when is it appropriate to do so? And what are the circumstances that lead to a practitioner selecting from the lower or higher bounds of such a range? That decision, which should ultimately be made by the entire design team in consultation with the owner of the infrastructure, depends on the sensitivity of the system to GMSLR, system redundancy, and the consequence of failure. In other words, it is a decision based on tolerance to risk, but one in which the probability of the outcome is not well defined.

A suggested framework for considering GMSLR scenarios is shown graphically in Figure 11.3. The intent of the figure is to guide the selection or decision-making process; practitioners may substitute their own justifications as appropriate. The figure guides the practitioner to a reasonable GMSLR scenario as a function of sensitivity, redundancy, and consequences of failure. The recommendations are tied to the range outlined above: the minimum scenario is defined by Table 11.1 (0.59 m by 2100); the alternative scenario is the RCP8.5 95th percentile value (1.21 m by 2100) from Kopp et al. (2014); and a higher scenario might be any higher, scientifically plausible projection.

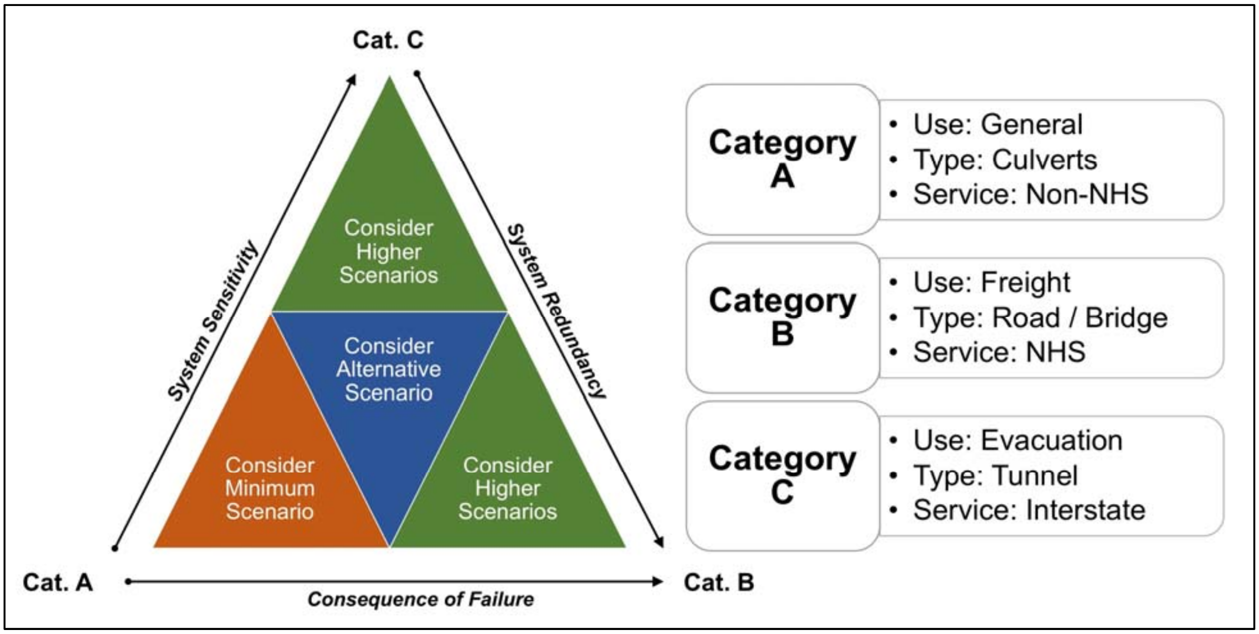

Figure 11.3. A suggested framework for considering GMSLR scenarios for design or planning. Arrows point in the direction of increasing sensitivity, redundancy, or consequence of failure.

The framework shown in Figure 11.3 is based on a simple principle: as risk tolerance decreases, a more conservative estimate should be considered. Therefore, if the consequence of failure is low, if sensitivity of the system to GMSLR is low, and/or if the system redundancy is high, then using the minimum GMSLR recommendation in this guide may be appropriate. These types of transportation infrastructure may fall into a category (Category A) that includes general use roads and bridges outside of the National Highway System (NHS), culverts, or stormwater infrastructure. Regardless of sensitivity or redundancy, if the consequence of failure is very high, one might consider a higher GMSLR scenario that is unlikely to be exceeded. Examples of infrastructure in this category (Category B) might include freight infrastructure, major roads and bridges within the NHS. A third category (Category C) of infrastructure may include evacuation routes, tunnels, and major Interstate highway infrastructure that, because of their sensitivity to GMSLR or lack of redundancy, may warrant additional consideration and the use of higher GMSLR scenarios.

11.2. Sample Computation of Sea Level Rise

Using the six-step procedure described in Section 11.1, develop a recommended minimum estimate of GMSLR and possible design range for a project near Hampton Roads, Virginia with a 50-year service life, and express the answer relative to the NAVD88 vertical datum. Assume that the project starts in 2020 and ends in 2070.

Step 1. Develop an estimate of the existing, historical RSLR rate using the available analyses for a nearby NOAA tide station.

The nearest NOAA tide station is Sewells Point, Virginia. The historical RSLR trend at that location is reported as 4.62 mm/yr on the NOAA Tides and Currents website:

https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8638610).

Step 2. Adjust that value to develop an estimate of the local component by subtracting the longer-term historical GMSLR rate from the historical RSLR rate, and convert the result to an elevation change by the end of the desired time period.

The longer-term historical GMSLR rate is 1.7 mm/year, and the historical RSLR rate is 4.62 mm/year. Recall that GMSLR values are referenced to the year 2000; therefore, 70 years of local effects (LE) should be incorporated.

LE rate = 4.62 mm/yr – 1.7 mm/yr = 2.92 mm/yr

Total LE (2070) = (2.92 mm/yr)(70 years) = **0.204 m**

Step 3. Estimate the total GMSLR.

Develop an estimate of the total GMSLR in year 2070 using the recommended minimum values shown in Table 11.1. Recommended minimum GMSLR (2070) = **0.36 m**

Step 4. Combine the two elevation components, Step 2 and Step 3, to estimate the total RSLR for the planning horizon.

Combine the total local SLR effects (LE) and the minimum recommended GMSLR to estimate the total RSLR for the planning horizon:

RSLR (2070) = 0.204 m + 0.36 m = **0.564 m**

Step 5. Adjust that RSLR value to the NAVD88 datum.

The Sewells Point tide gauge datums show that the NAVD88 datum is 0.079 m above the MSL datum of 1983-2001 (from NOAA's Tides and Currents website: https://tidesandcurrents.noaa.gov/datums.html?units=1&epoch=0&id=8638610&name=Sewells+Point&state=VA). Using an average of the monthly sea level trends from the website identified in Step 1, the average MSL for the period 1991-2009 was determined to be 0.043 m higher than the MSL datum for the 1983-2001 tidal epoch. Therefore, the NAVD88 datum is only 0.036 m above the MSL for the year 2000. The resulting RSLR value in 2070 is then 0.528 m above the NAVD88 datum.

NAVD88 = +0.079 m MSL of 1983-2001

MSL of 1991-2009 = +0.043 m MSL of 1983-2001

NAVD88 = 0.079 – 0.043 = +0.036 m MSL of 1991-2009

RSLR (2070) = 0.564 m – 0.036 m = 0.528 m = **+0.53 m NAVD88**

Step 6. If appropriate, repeat Steps 3-5 using a higher GMSLR value to develop a possible design range.

Substitute the 95th percentile RCP8.5 GMSLR value of 2070 (0.712 m) for the recommended minimum value used previously (0.36 m). Make the appropriate substitutions in Step 4 and Step 5 as well.

[Step 3 revised] Recommended alternative GMSLR (2070) = **0.712 m**

[Step 4 revised] Combine components for RSLR (2070) = 0.204 m + 0.712 m = **0.916 m**

[Step 5 revised] Adjust to NAVD88 for RSLR (2070) = 0.916 m – 0.036 m = **+0.88 m NAVD88**

11.3. Applicability and Limitations

The simple six-step procedure outlined above neglects some of the future changes in the regional/local non-GMSLR rate components of RSLR, including regional differences in thermal expansion, long-term changes in meteorological conditions (wind and atmospheric pressure), changes in ocean circulation, and changes in the regional gravity field resulting from the redistribution of ice melting from continental-scale ice sheets. It only accounts for the existing, historical processes, such as VLM, as measured at the tide gauges. It has been shown that these other processes will have a significant effect on relative sea level at the northern latitudes and along the north Atlantic, particularly later in the century, as discussed in the Kilgore et al. (2019) and also in Kopp et al. (2014). Thus, this simple approach is recommended only as an approximation that can be improved with the use of the methodology of Kopp et al. (2014) and/or the tables in Sweet et al. (2017a).

According to the Climate Science Special Report (CSSR) (USGCRP 2017), the GMSLR by 2100 is very likely to fall within the range of 0.5 to 1.30 m (1.6 to 4.3 ft) for the RCP8.5 scenario. The recommended minimum GMSLR of 0.59 m (1.94 ft) in Table 11.1 falls within this range. The upper value of 1.30 m (4.3 ft) corresponds to the 95th-percentile GMSLR estimates for the RCP8.5 scenario, as estimated by Kopp et al. (2016) and approximates the 95th-percentile estimates for the same scenario of Kopp et al. (2014) at 1.21 m (3.96 ft) and Mengel et al. (2016) at 1.31 (4.3 ft). All three sources provide support for the findings of the CSSR. To provide for consistency in the methodologies for the recommended minimum (Section 11.1.1) and possible design range (Section 11.1.2), the year 2100 means and confidence limits, as well as intermediate decadal values from Kopp et al. (2014), are used.

The USACE Sea Level Change Calculator is a useful tool for estimating RSLR. The tool is updated as new science-based projections become available (USACE 2017a). This web-based calculator also provides the added benefits of performing epoch and/or datum adjustments. It also contains the Sweet et al. (2017a) data at 1-degree intervals along the coastline, which may provide useful data for locations between tide gauge locations.

11.4. Discussion and Other Resources

Engineering and planning studies have generally selected a range of low and high estimates to test the robustness of assessments and design parameters within this range. Sensitivity analysis using extreme or upper bound estimates are also recommended to highlight the limitation of current policies or thresholds for new actions (for example, when to consider switching from protection strategies to accommodation or retreat strategies) (Nicholls et al. 2014). Selecting projections that represent multiple timeframes can also be informative when policy or design changes need to be considered.

> *BOTTOM LINE: When applying GMSLR scenarios, look for major constraints that may render the infrastructure useless or impractical. Developing plans for abandonment may be an appropriate non-structural solution in such cases.*

The vulnerability assessment of the Central Artery/Tunnel (CA/T) system in Boston, Massachusetts (Bosma et al. 2015, Douglas et al. 2016a) is an example where GMSLR scenarios were examined in an attempt to identify constraints in the system. The initial possibilities they selected to examine were several points along the highest GMSLR curve presented by Parris et al. (2012), which also coincided with later times along a lower curve. In Figure 11.4, point 2 represents the sea level rise height by 2030 under the highest emissions scenario. The same height at point 2a represents sea level rise by 2070 under the intermediate low emissions scenario (based on Parris et al. 2012). Therefore, when making design engineering decisions for projects that will have very long lives, some sea levels will be experienced under many scenarios; the only difference is when a particular level will occur. In the assessment of the CA/T, three GMSLR estimates were used to simulate six scenarios, offering a sensitivity analysis of both risk and timeframe.

The more recent work of Kopp et al. (2014) presents a probabilistic approach that accounts for all the physical processes of importance in RSLR, informed by state-of-the-art process modeling, expert assessment, and expert elicitation. This method was used in Douglas et al. (2016b) to produce a continuum of location-specific probability distributions based on the tide gauge at Boston Harbor. These RSLR projections aggregate the components of sea level rise, including thermal expansion, regional ocean dynamics, changes in alpine glacier and ice sheet mass, land-water storage, and land subsidence. The exceedance probabilities of future RSLR (converted from the cumulative probabilities output by the method) can be linked to the analysis of specific threats, such as storm surge, and the time-evolving flood protection appropriate for specific assets. Kopp et al. (2017) updates this method with ice mass loss estimates from newly validated ice sheet dynamic models.

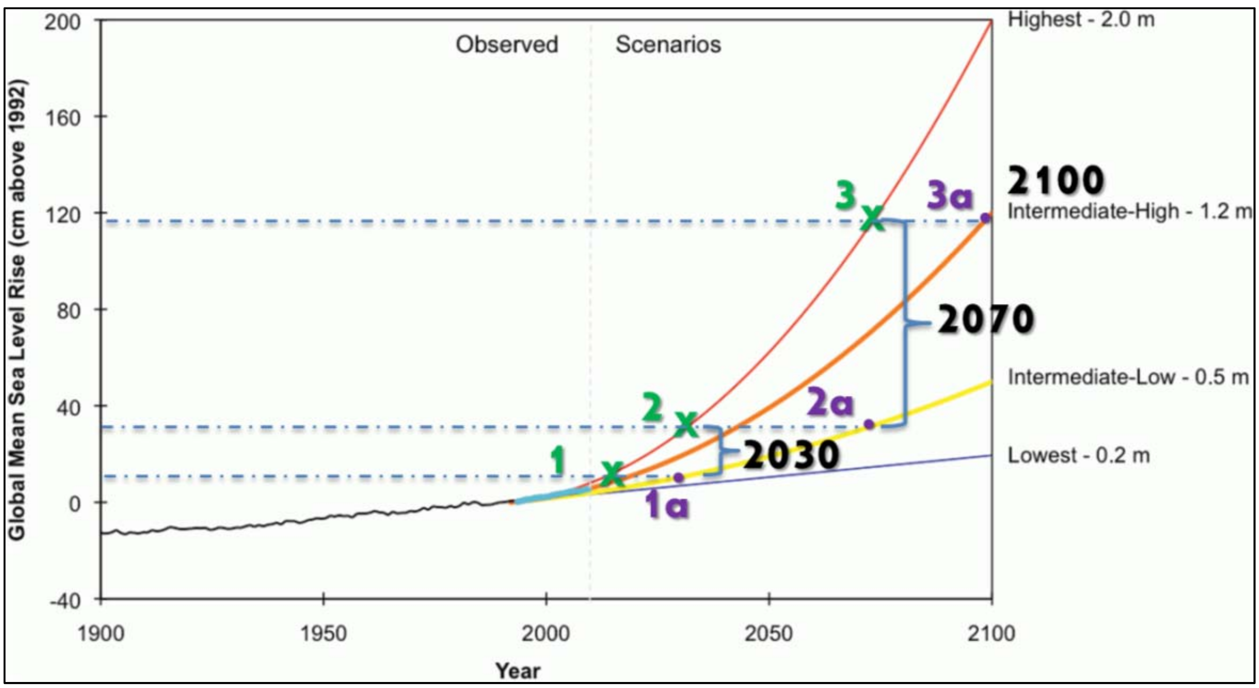

Figure 11.4. Selection of GMSLR projections for vulnerability assessment and adaptation strategies for the Central Artery/Tunnel system in Boston, MA (Source; Bosma et al. (2015); Douglas et al. (2016a). Used with permission.)

The Massachusetts Department of Transportation's (MassDOT) CA/T vulnerability analysis is currently being expanded to evaluate the vulnerability of transportation infrastructure along the entire coastline of Massachusetts. For this expanded work, the probabilistic methodology of

Kopp et al. (2014) has been used to select RSLR projections for 2030, 2050, 2070, and 2100. Figure 11.5 compares the RSLR projections for this expanded project with those selected for the CA/T system analysis and with the range of other applicable projections. At this point, the project is still using single RSLR projections at the specified timeframes (2030, 2050, 2070, 2100), but the DOT is considering a way to incorporate the probability of the RSLR projection within a Monte Carlo analysis.

Most projects will not require the extensive analysis and modeling evident in the MassDOT CA/T study. However, given the high consequences of failure and the expected longevity of the project, considering the range of vulnerabilities to future GMSLR is appropriate.

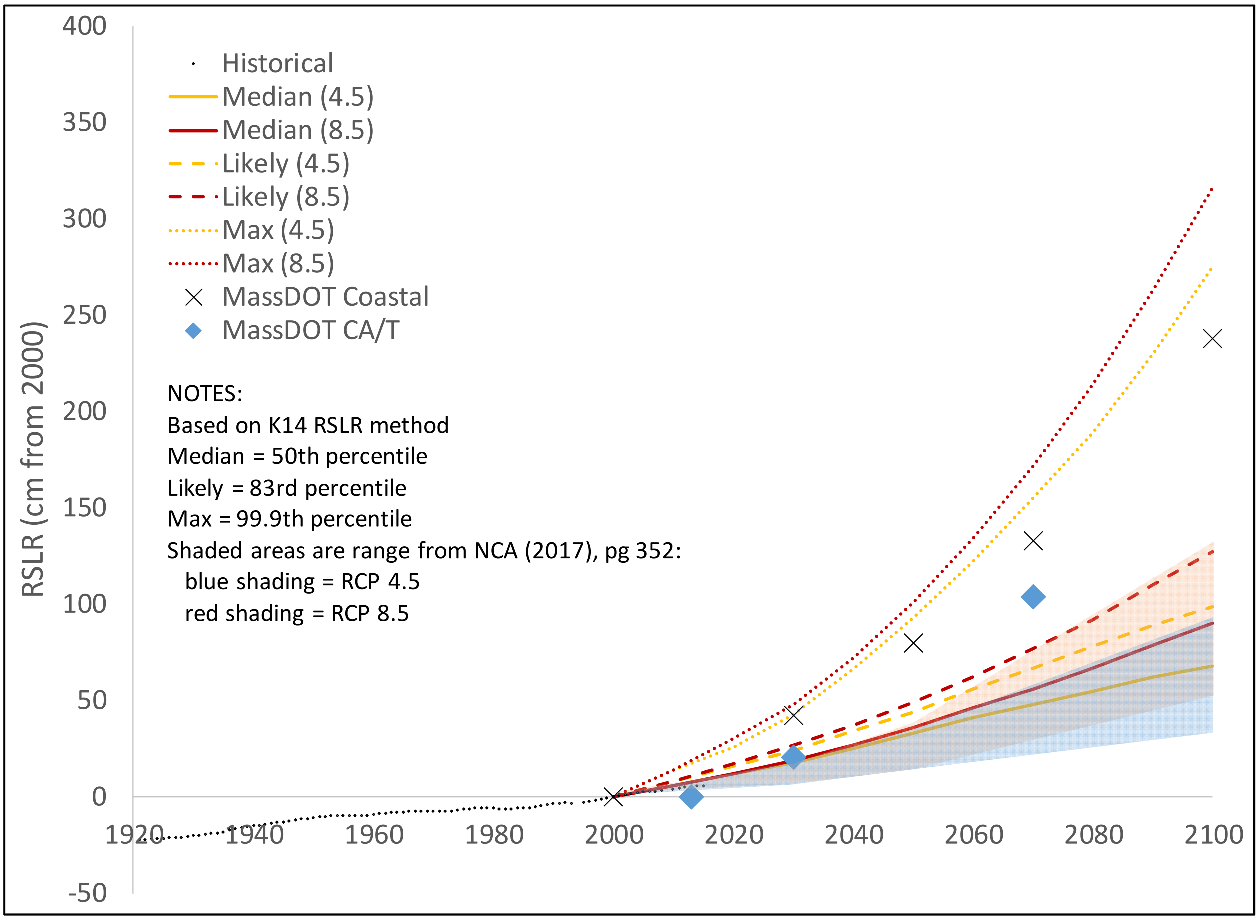

Figure 11.5. Comparison of RSLR projections used by MassDOT in the CA/T vulnerability analysis (blue diamonds; Bosma et al. 2015; Douglas et al. 2016a) and the vulnerability analysis along the entire Massachusetts coastline (X's; project in process). Also shown are observations (black dotted line); selected probabilities from Douglas et al. (2016b) using the Kopp et al. (2014; K14) methodology (colored dashed and dotted lines); and ranges presented in Sweet et al. (2017b) as shaded areas.

Chapter 12. Combining Coastal Hazard and Climate Change Information

AASHTO Link - This topic relates to AASHTO "Hydraulic Design Guidelines" sections:

§11.2 Data Collection

§11.4 Characteristics of Waves and Currents

§11.5.2 Design Considerations/Design Waves

§11.5.5 Design Considerations/Scour

This chapter summarizes recommended guidance for combining coastal hazard and climate information. Coastal hazards relevant to the design of transportation infrastructure include coastal water levels (e.g., storm surge), waves, and velocities. Each of these coastal hazards is sensitive to water depth, which increases with (relative) sea level rise. The effects of sea level rise on coastal hazards can be determined numerically using coastal hydrodynamic models in a manner consistent with the recommendations provided in Section 10.1.2 (Level 2) and Section 10.1.3 (Level 3). For many projects, these levels of analysis may not be appropriate for smaller projects, non-critical transportation infrastructure, or infrastructure that may not be particularly vulnerable to the effects of future sea level rise. In those cases, a Level 1 analysis (as described in Section 10.1.1) in which adjustments to existing coastal hazard data are applied in a manner that explicitly accounts for higher future sea levels may prove useful.

This chapter provides a series of simple equations that allow a practitioner to estimate the effects of future sea level rise on existing coastal hazard data. Methods for modifying coastal storm water levels, wave heights, wave periods, and velocities are provided along with an example. More detailed information about sources of coastal hazard data and development of the recommended equations is provided in Chapter 8 of Kilgore et al. (2019).

12.1. Modification of Existing Hazard Data to Estimate Climate Effects

Hydrodynamic modeling with climate effects may not be warranted for Level 1 analyses focused on minor projects, or when used in planning-level studies or vulnerability assessments. In those cases, existing coastal hazard data can be modified to estimate the effects of climate change on coastal processes. The simplified procedures summarized below do not account for all of the possible non-linear hydrodynamic responses resulting from changes in sea level: they should be applied with caution.

BOTTOM LINE: This simplified approach is not recommended for critical infrastructure or when performing engineering design for projects with a low risk tolerance.

The following equations for estimating the effects of RSLR on water levels, wave heights, wave periods, and water velocities were determined through hydrodynamic model simulations of hurricane storm surge and waves that describe the non-linear behavior of those parameters with RSLR. More information about the equations and their development is available in Chapter 8 of Kilgore et al. (2019).

Modifying existing flood elevations to account for RSLR, including their potential non-linear interaction, is performed using Equation 12.1. This equation provides an estimate of a future flood elevation, or flood depth, based on a specified RSLR increment as well as the estimated amount of non-linearity through specification of an amplification ratio (*AR*).

$$\eta_2 = \eta_1 + (AR)(SLR) \tag{12.1}$$

where:

η_2 = *Flood elevation of interest in the future.*

η_1 = *Flood elevation of interest today.*

SLR = *(relative) Sea level rise increment for a given scenario.*

AR = *Amplification ratio value (0.7 ≤ AR ≤ 1.5).*

The *AR* value represents the ratio of the increase in flood elevation (or depth) to the RSLR increment considered. An *AR* value of one represents a linear combination with no amplification. An analysis of the hydrodynamic model simulation results revealed that 99 percent of all *AR* values were greater than 0.7 and less than 1.5. To further constrain selection of an *AR* value, consider the location being studied. Locations on the coastal floodplain exhibit higher degrees of non-linearity so larger values of *AR* should be chosen. Locations in open water exhibit lower degrees of non-linearity so *AR* values closer to one may be appropriate. When used as part of a Level 1 analysis, an *AR* value less than one should only be used with appropriate justification.

A simple method for modifying wave heights to account for RSLR and non-linearity is given by Equation 12.2. This equation predicts a change in wave height based on the water depth at the location of interest and the results of Equation 12.1. Any potential error attributed to the selection of an *AR* value in Equation 12.1 will propagate to the results of Equation 12.2. The result of this equation is that wave heights will increase with RSLR.

$$H_2 = H_1\left(\frac{d+\eta_2}{d+\eta_1}\right) \tag{12.2}$$

where:

H_2 = *Future zero moment wave height.*

H_1 = *Present zero moment wave height.*

d = *Present water depth.*

In addition to estimating RSLR effects on wave heights, potential modifications to wave periods may also be needed for some coastal engineering calculations. Equation 12.3 can be used to estimate the change in wave period as a function of the change in wave height resulting from RSLR and non-linear effects. As in Equation 12.2, the expected change in wave period is an increase with RSLR. Error associated with the selection of an *AR* value will similarly propagate through Equation 12.2 to impact the results of Equation 12.3. Errors associated with Equation 12.3 are largest when wave periods are less than five seconds and greater than 15 seconds.

$$T_2 = T_1\sqrt{\frac{H_2}{H_1}} \tag{12.3}$$

where:

T_2 = *Future peak wave period.*

T_1 = Present peak wave period.

Unlike water levels, wave heights, and wave periods that all exhibit increases with future RSLR, water velocity exhibits a decrease in magnitude with RSLR. Equation 12.4 provides a simple means of modifying existing water velocity values to account for RSLR and non-linear interactions. The equation is similar to the one given for wave heights, except the ratio of the total depths is inverted. The errors attributed to this simple equation were generally 10 percent or less. Additional errors may be introduced in the results depending on the value of *AR* selected in Equation 12.1.

$$V_2 = V_1 \left(\frac{d+\eta_1}{d+\eta_2}\right) \tag{12.4}$$

where:

V_2 = Water velocity magnitude under future sea levels.

V_1 = Water velocity magnitude under present sea levels.

12.2. Sample Adjustments of Existing Hazard Information

Determine the change in the 100-year return period (1-percent-annual-chance event) water level and wave height for Hampton Roads, Virginia (the same location used in the example in Section 11.2).

12.2.1 Example: Water Level

For the water level, use the USACE ERDC Coastal Hazards System database (https://chswebtool.erdc.dren.mil) to determine the current 100-year return period water level at a location in Hampton Roads, east of the I-64 bridges. Express the water level relative to the NAVD88 datum.

Step 1. Go to https://chswebtool.erdc.dren.mil and select the USACE NACCS v1 study data (Base Conditions), as shown in Figure 12.1. Navigate to the study region and select the save point labeled 15603, located just east of the I-64 bridges in Hampton Roads. Download the annual exceedance probability (AEP) data for that point (by first using the pencil tool to draw a polygon around the point of interest, and then clicking the Submit icon), or simply read it from the plot that appears after clicking on the point. The value of the 100-year stillwater level at this location, in open water, is approximately +2.5 m above the MSL tidal datum of 1983-2001, as shown in Figure 12.2.

Step 2. Convert the 100-year stillwater level from the MSL datum to the NAVD88 datum using the datum relationships at the Sewells Point tide gauge. The Sewells Point tide gauge datums show that the NAVD88 datum is 0.079 m above the MSL datum of 1983-2001 from NOAA's Tides and Currents website:

https://tidesandcurrents.noaa.gov/datums.html?units=1&epoch=0&id=8638610&name=Sewells+Point&state=VA

NAVD88 = +0.079 m MSL of 1983-2001

SWL_{100} = +2.5 m – 0.079 m = **+2.42 m NAVD88**

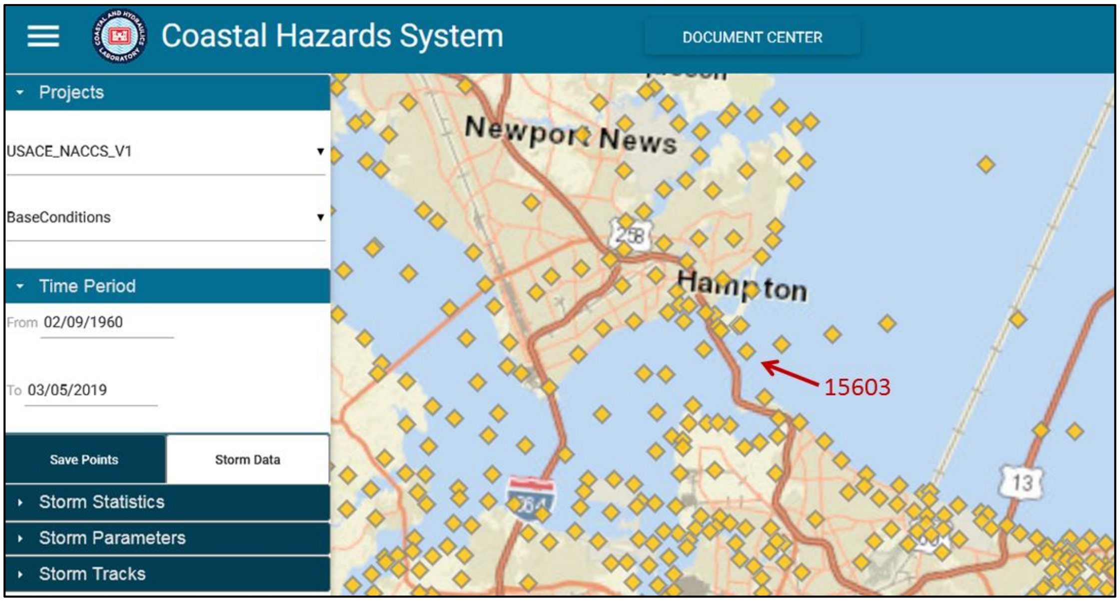

Figure 12.1. Screenshot from the web tool highlighting selections for the example.

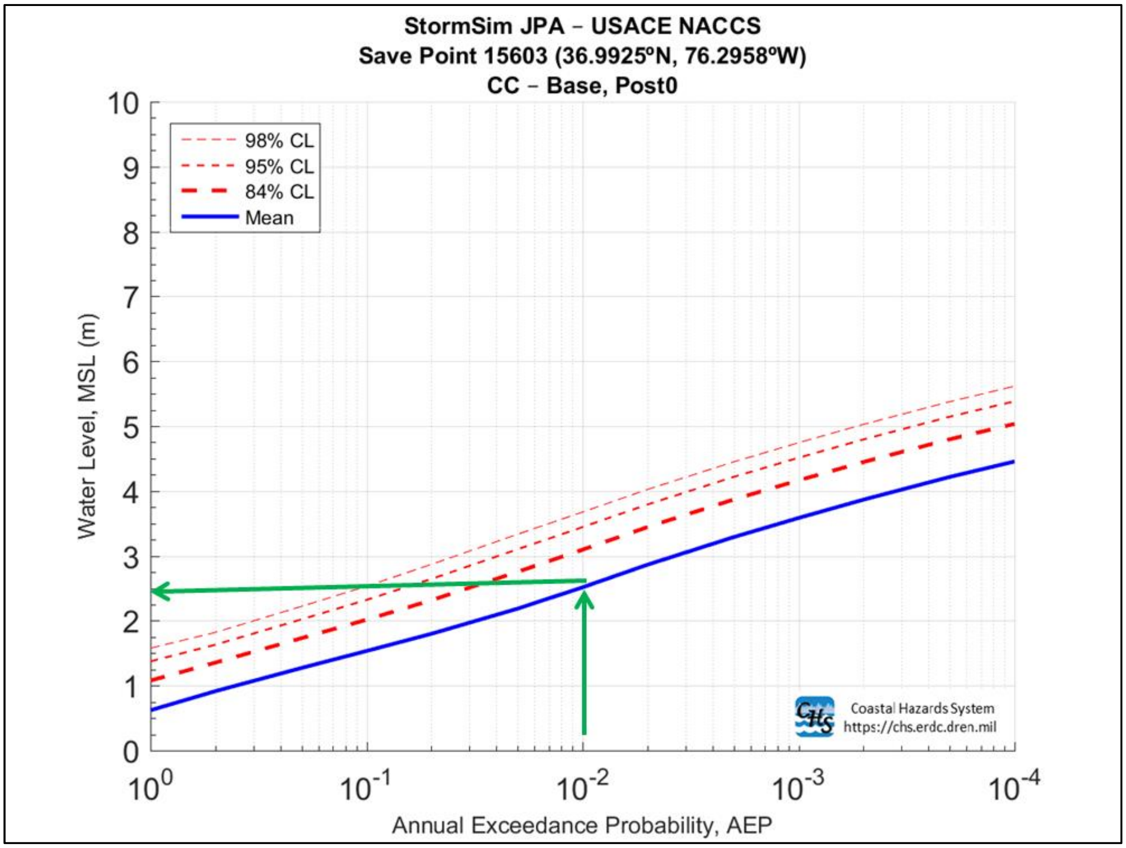

Figure 12.2. Annual exceedance probability plot for water level for point 15603

Step 3. Use Equation 12.1 to determine the modified stillwater level associated with the recommended minimum GMSLR scenario in the year 2070, which was estimated previously in the example in Section 11.2 to be +0.53 m NAVD88. Since this point is in open water, use a lower value of *AR* to minimize the non-linear effects (*AR* = 1.1).

η_1 = SWL$_{100}$ = +2.42 m NAVD88

η_2 = 2.42 m + (1.1)(0.53 m) = 3.0 m = **+3.0 m NAVD88**

The resulting answer is that the 100-year stillwater level at this location, presently +2.42 m NAVD88, changes to +3.0 m NAVD88 by the year 2070. This increased value is equivalent to the present-day 300-year return period event.

12.2.2 Example: Wave Height

To compute the wave height, use the USACE ERDC Coastal Hazards System database to determine the present-day return period wave height.

Step 1. Go to https://chswebtool.erdc.dren.mil and select the USACE NACCS v1 study data (Base Conditions+1Tide). Navigate to the study region and select the save point labeled 15603, located just east of the I-64 bridges in Hampton Roads. Download the annual exceedance probability (AEP) wave height (H_s) data for that point, or simply read it from the plot that appears after clicking on the point as shown in Figure 12.3. The value of the 100-year significant wave height at this location, in a water depth of approximately 12 m (NOAA chart for Hampton Roads, VA) is 2.5 m.

Step 2. Apply Equation 12.2 using the results of Equation 12.1, the water depth of 12 m, and the present-day wave height value of 2.5 m.

$$H_2 = H_1\left(\frac{d+\eta_2}{d+\eta_1}\right) = 2.5\,m\left(\frac{12\,m+3.0\,m}{12\,m+2.42\,m}\right) = \underline{\mathbf{2.6\ m}}$$

The modification results in a 4-percent increase in the 100-year return period significant wave height by the year 2070 for the recommended minimum GMSLR scenario.

12.3. Applicability and Limitations

These simple methods are presented only as reasonable means for estimating the effect of GMSLR and RSLR on coastal hazards. The simple equations assume that only changes in sea level rise lead to changes in the coastal hazard values. That is a limiting assumption, because there are many other factors that will affect those values. Sea level rise will lead to changes in frictional characteristics and geomorphological features across scales ranging from small to large, all of which will influence coastal hazards in unique ways. The increase in ocean temperature will allow for more efficient energy exchange between the atmosphere and ocean, leading to potentially larger wave heights and different wave periods. Changes in storm conditions (e.g., wind speed, duration, trajectory, precipitation, etc.) will also have direct effects on coastal hazards. While none of these additional factors are accounted for in the simple procedures outlined above, most can be easily captured in numerical modeling.

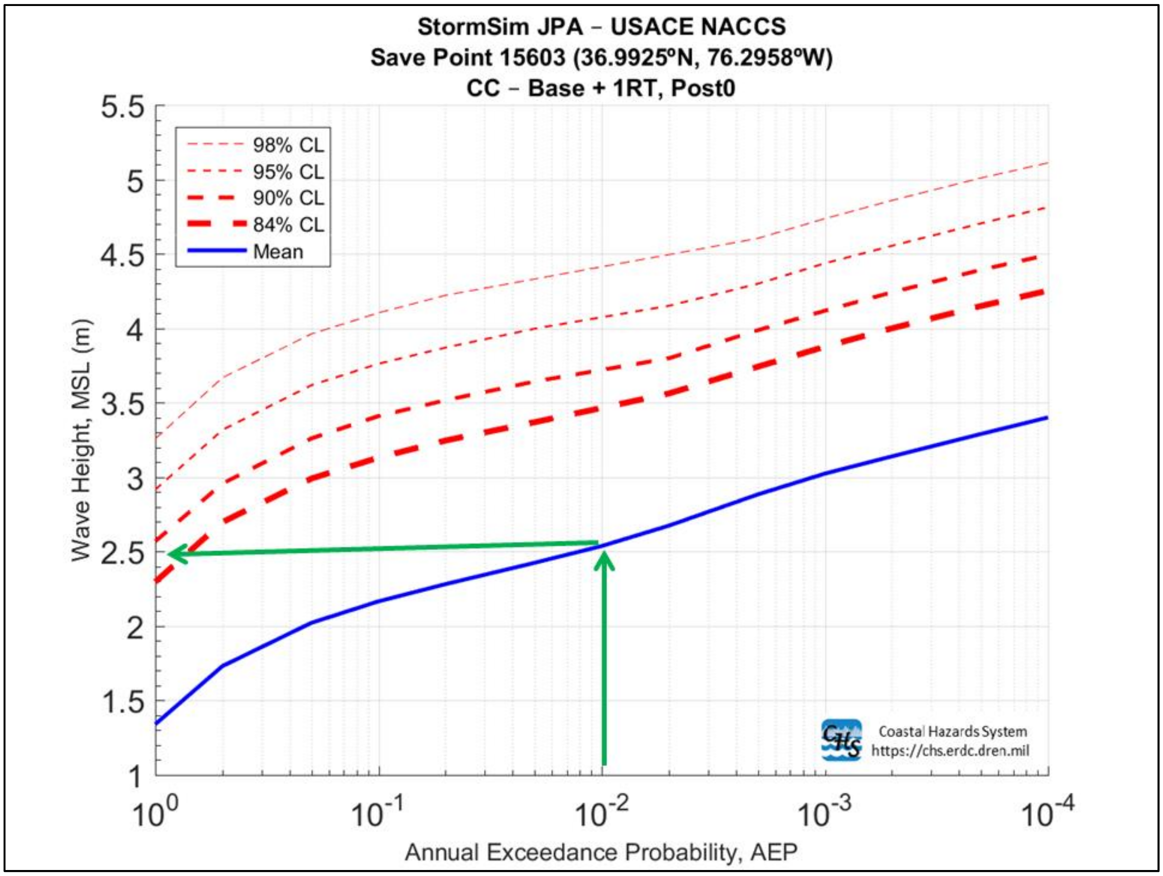

Figure 12.3. Annual exceedance probability plot for wave height for point 15603

These simple methods are not intended to serve as a substitute for the appropriate numerical modeling discussed in Section 12.4. Such modeling captures many of the potential non-linear and landscape interactions that more appropriately describe the effects of changing sea levels on coastal water levels, waves, and currents. Application of these simple equations is reserved for Level 1 analyses or when the application of sophisticated models is not warranted. For example, use of these equations in design may be appropriate for Category A in Figure 11.3, but it would not be advised for Category B or C.

12.4. Incorporating Climate Change Data into Hydrodynamic Modeling

The most informative way to simulate the potential effects of climate change on relevant coastal hazards is by incorporating them into hydrodynamic simulation models used in Level 2 and Level 3 analyses. Any potential non-linear effects that arise from climate change effects are better captured by a hydrodynamic model that provides the type of site-specific information needed for the engineering design of a highway, bridge, or tunnel.

Coastal hydrodynamic modeling is essentially "event-based" on the Gulf and Atlantic coasts, while a "response-based" approach is more appropriate for the Great Lakes and Pacific coasts. In the response-based approach, the event/scenario probability is determined through extremal analysis, as opposed to joint probability methods.

BOTTOM LINE: For most major transportation planning or design projects, original hydrodynamic modeling is justifiable, and it is preferable to the simple methods outlined in Section 12.1.

Most hydrodynamic models can be adapted to simulate the effects of a relative sea level change. A relative sea level rise is incorporated into a hydrodynamic model by raising the water surface or lowering the land elevations, with an increment equal to the relative sea level rise of interest. A relative sea level decrease is incorporated by lowering the water surface or increasing the land elevations, with an increment equal to the relative sea level decrease of interest.

There are some limitations to these methods. When incrementally adjusting the water surface up or down relative to land, it must be done uniformly across the entire model domain. If the modeling domain covers a broad geographic region with significant variability in regional sea level change, this method may not capture all of the potential effects of future sea level change on a process of interest. While the regional variability can be incorporated by accounting for it in terms of land elevation changes in the model grid, doing so would be quite tedious. The potential benefits of using such a method may only be realized if the hydrodynamic model is being used to develop regional information (i.e., across multiple states).

The change in bottom friction should be addressed when incorporating a relative sea level change into a hydrodynamic model. Many models that simulate coastal flooding do so through a Manning's-type formulation of frictional resistance. The frictional resistance of the coastal floodplain today is potentially much higher than it will be under a future sea level rise scenario, as macro roughness features on the upland terrain are eliminated or changed through conversion of the upland to open water. Conversely, as relative sea level falls in some places (e.g., Alaska and the Great Lakes), the present frictional resistance of the shallow water environment is lower than it may be under a future stand of lower sea level. Future changes in land use and land cover will also drive frictional changes that could be captured in the hydrodynamic modeling. These changes in frictional resistance can be incorporated into hydrodynamic model simulations by appropriately adjusting the friction coefficients, like Manning's *n* values, wherever necessary. The degree to which modifying the frictional resistance affects simulation results is not presently known, but there are published studies that account for the effect in sea level rise simulations (Smith et al. 2010, Bilskie et al. 2014, Bosma et al. 2015).

Some potential climate change effects can also be incorporated into hydrodynamic models as boundary conditions. For study regions that reside in a coastal setting where water levels and circulation are overwhelmed by inputs from the coastal watershed, specifying inflow boundary conditions may be necessary (Webb and Marr 2016). This is typically achieved by specifying a time-series of stage and/or discharge values on an open boundary of a model that is coincident with a stream or river cross-section. If the potential effects of a climate change scenario on stream flows or watershed inputs can be described, then these changes can be incorporated into the hydrodynamic model boundary conditions. The results of hydrodynamic simulations may also be used as downstream boundary conditions for hydraulic or hydrologic models applied within the coastal watersheds. Some information about the potential importance of watershed contributions to coastal areas is provided in Section 10.2.3.

If they can be properly described, the future effects of climate change on storm characteristics (e.g., wind speed, pressure, track, forward speed, etc.) can be incorporated into hydrodynamic model simulations. This was done in a limited fashion in the Gulf Coast 2 Study (Choate et al.

2012). The anticipated changes to hurricane wind speed and central pressure for the year 2100, as described by Knutson and Tuleya (2004), were incorporated into the characteristic storm parameters used to define the meteorological forcing in a hydrodynamic simulation of storm surge and waves on a projected 2100 sea level.

Expected changes in future morphologic conditions have not typically been accounted for *a priori* in hydrodynamic simulations of future scenarios. Where known, local rates of shoreline retreat can be incorporated into a future sea level rise scenario by accounting for the horizontal change in shoreline position, and lateral translation of the resulting shoreline profile, that would occur over the period of time in question. Modifying other large-scale morphologic features, like ebb or flood tidal shoals, would require site-specific knowledge about the potential effects of sea level rise on those features, but could similarly be accounted for in the bathymetry of the hydrodynamic models (see Anarde et al. 2017). Additional comments on sea level rise effects on geomorphology are provided in Section 10.2.4.

References

American Association of State Highway and Transportation Officials (AASHTO). 2007. "Highway Drainage Guidelines." Washington, D.C.

Anarde, K.A., S. Kameshwar, J.N. Irza, J.A. Nittrouer, J. Lorenzo-Trueba, J.E. Padgett, A. Sebastian, and P.B. Bedient. 2017. "Impacts of Hurricane Storm Surge on Infrastructure Vulnerability for an Evolving Coastal Landscape." *Natural Hazards Review,* Vol. 19, No. 1, 14 pp.

Anderson, C., D. Claman, and R. Mantilla. 2015. *Iowa's Bridge and Highway Climate Change and Extreme Weather Vulnerability Assessment Pilot*. Final Report HEPN-707, Institute for Transportation, Iowa State University, Ames, IA.

Asquith, W.H. and D.B. Thompson. 2008. *Alternative Regression Equations for Estimation of Annual Peak-Streamflow Frequency for Undeveloped Basins in Texas Using PRESS-Minimization*. U.S. Geological Survey Scientific Investigations Report 2008-5084, U.S. Geological Survey, Reston, VA.

Asquith, W. H. and M.C. Roussel. 2009. *Regression Equations for Estimation of Annual Peak-Streamflow Frequency for Undeveloped Basins in Texas Using an L-Moment-Based, PRESS-Minimized, Residual-Adjusted Approach*, U.S. Geological Survey Scientific Investigations Report 2009-5087, U.S. Geological Survey, Reston, VA.

Beighley, R.E. and G.E. Moglen. 2003. "Adjusting Measured Peak Discharge from an Urbanizing Watershed to Reflect a Stationary Land Use Signal." *Water Resources Research*, Vol. 39, No. 4, p. 1093.

Bilskie, M.V., S.C. Hagen, S.C. Medeiros, and D.L. Passeri. 2014. "Dynamics of Sea Level Rise and Coastal Flooding on a Changing Landscape." *Geophysical Research Letters*., Vol. 41, doi: 10.1002/2013GL058759.

Blum, M.D., and T.E. Törnqvist. 2000. "Fluvial Responses to Climate and Sea-level Change: A Review and Look Forward." *Sedimentology*, Vol. 47, No. s1, pp. 2–48.

Blumberg, A.F., N. Georgas, L. Yin, T.O. Herrington, and P.M. Orton. 2015. "Street-Scale Modeling of Storm Surge Inundation along the New Jersey Hudson River Waterfront." *Journal of Atmospheric and Oceanic Technology*, Vol. 32, No. 8), pp. 1486–1497.

Bosma, K., E. Douglas, P. Kirshen, S. Miller, K. McArthur, and C. Watson. 2015. MassDOT-FHWA Pilot Project Report: Climate Change and Extreme Weather Vulnerability and Adaptation Options for the Central Artery/Tunnel System in Boston, MA.

Bruun, P. 1988. "The Bruun Rule of Erosion by Sea Level Rise: A Discussion on Large-scale Two- and Three-dimensional Usages." *Journal of Coastal Research*, Vol. 4, pp. 627–648.

Choate, A., W. Jaglom, R. Miller, B. Rodehorst, P. Schultz, P. and C. Snow. 2012. "Impacts of Climate Change and Variability on Transportation Systems and Infrastructure: The Gulf Coast Study, Phase 2: Climate Variability and Change in Mobile, Alabama: Final Report, Task 2." FHWA-HEP-12-053, 228pp.

Cohn, T.A. and H.F. Lins. 2005. "Nature's Style: Naturally Trendy." *Geophysical Research Letters*, Vol. 32, L23402, doi: 10.1029/2005GL024476.

Connecticut Department of Transportation. 2014. "Climate Change and Extreme Weather Vulnerability Pilot Project." Final Report, December.

Cooper, J.A.G., and O.H. Pilkey. 2004. "Sea-level Rise and Shoreline Retreat: Time to Abandon the Bruun Rule." *Global and Planetary Change*, Vol. 43, No. 3-4, pp. 157–171.

Dalrymple, T. 1960. "Flood-Frequency Analyses." *Manual of Hydrology: Part 3. Flood-Flow Techniques*, Geological Survey Water-Supply Paper 1543-A, U.S. Geological Survey, Reston, VA.

Dawdy, D.R., V.W. Griffis, and V.K. Gupta. 2012. "Regional Flood Frequency Analysis: How We Got Here, and Where We Are Going." *Journal of Hydrological Engineering,* 10.1064(ASCE) HE, 1943-5584.0000584, pp. 953–959.

Dompe, P.E., J.M. McBee, and H. Demir. 2015. "Storm Surge and Wave Vulnerability Assessment of Coastal Bridges." *Proceedings of the World Environmental and Water Resources Congress: Floods, Droughts, and Ecosystems*. ASCE, Reston, VA: pp. 1256–1263.

Douglas, E.M., P. Kirshen, K. Bosma, C. Watson, S. Miller, and K. McArthur. 2016a. "Simulating the Impacts and Assessing the Vulnerability of Boston's Central Artery/Tunnel System to Sea Level Rise and Increased Coastal Flooding." *Journal of Extreme Events*, Vol 3, No. 4, 1650013, https://doi.org/10.1142/S2345737616500135.

Douglas, E., P. Kirshen, R. Hannigan, R. Herst, and A. Palardy. 2016b. *Climate Change and Sea Level Rise Projections for Boston*. Boston Research Advisory Group for Climate Ready Boston.

Douglass, S. L., and J. Krolak 2008. *Highways in the Coastal Environment*. Hydraulic Engineering Circular No. 25, Vol. 1, FHWA-NHI-07-096.

Douglass, S.L., B.M. Webb, and R. Kilgore 2014. *Highways in the Coastal Environment: Assessing Extreme Events.* Hydraulic Engineering Circular No. 25 (Vol. 2), Federal Highway Administration, FHWA-NHI-14-006.

Easterling, D. R., K.E. Kunkel, J.R. Arnold, T. Knutson, A.N. LeGrande, L.R. Leung, R.S . Vose, D.E. Waliser, and M.F. Wehner. 2017. "Precipitation Change in the United States." In *Climate Science Special Report: Fourth National Climate Assessment*, Vol. I [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (Eds.)]. U.S. Global Change Research Program, Washington, DC, pp. 207–230, doi: 10.7930/J0H993CC.

England, J.F., Jr., T.A. Cohn, B.A. Faber, J.R. Stedinger, W.O. Thomas, Jr., A.G. Veilleux, J.E. Kiang, and R.R. Mason 2018. "*Guidelines for Determining Flood Flow Frequency – Bulletin 17C*." U.S. Geological Survey Techniques and Methods 4-B5, Reston, VA, 164 pp.

Fitzgerald, D.M., M.S. Fenster, B.A. Argow, and I.V. Buynevich. 2008. "Coastal Impacts due to Sea Level Rise." *Annual Review of Earth and Planetary Sciences*, Vol. 36, pp. 601–647.

Flato, G., J. Marotzke, B. Abiodun, P. Braconnot, S.C. Chou, W. Collins, P. Cox, F. Driouech, S. Emori, V. Eyring, C. Forest, P. Gleckler, E. Guilyardi, C. Jakob, V. Kattsov, C. Reason, and M. Rummukainen. 2013. "Evaluation of Climate Models." In *Climate Change 2013: The Physical Science Basis*. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G. K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (Eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Hayhoe, K., J. Edmonds, R.E. Kopp, A.N. LeGrande, B.M. Sanderson, M.F. Wehner, and D.J. Wuebbles. 2017. "Climate Models, Scenarios, and Projections." In *Climate Science Special Report: Fourth National Climate Assessment, Volume I* [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (Eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 133–160, doi: 10.7930/J0WH2N54.

Hejazi, M.I. and M. Markus 2009. "Impacts of Urbanization and Climate Variability on Floods in Northeastern Illinois." *Journal of Hydrologic Engineering*, Vol. 14, No. 6, pp. 606–616.

Helsel, D.R. and R.M. Hirsch. 1992. "Statistical Methods in Water Resources." Elsevier, New York, 55 pp.

Hershfield, D.M. 1961. *Rainfall Frequency Atlas of the United States for Durations of 30 Minutes to 24 Hours and Return Periods from 1 to 100 Years*, Technical Paper 40, U.S. Department of Commerce, Weather Bureau, Washington, D.C.

Hosseinzadehtalaei, P., H. Tabari and P. Willems. 2017. “Uncertainty Assessment for Climate Change Impact on Intense Precipitation: How Many Model Runs Do We Need?” *International Journal of Climatology*, Vol. 37, pp. 1105–1117, doi: 10.1002/joc.5069.

Houston, J. 2017. “Shoreline Change in Response to Sea-Level Rise on Florida's West Coast.” *Journal of Coastal Research*, http://www.jcronline.org/doi/abs/10.2112/JCOASTRES-D-17-00024.1.

IPCC. 2012. “Glossary of Terms.” In *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (Eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, United Kingdom, and New York, NY, USA, pp. 555—564.

IPCC. 2013. *Climate Change 2013: The Physical Science Basis*. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (Eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.

Kilgore, R., G.R. Herrmann, W.O. Thomas, Jr., and D.B. Thompson. 2016. *Highways in the River Environment – Floodplains, Extreme Events, Risk, and Resilience*. Hydraulic Engineering Circular No. 17 (HEC-17), Federal Highway Administration, FHWA-HIF-16-018.

Kilgore, R.C. Anderson, J.M. Jacobs, K. Hayhoe, G.R. Herrmann, A.Stoner, W.O. Thomas, Jr., and D.B. Thompson. 2019. *Applying Climate Change Information to Hydrologic and Hydraulic Design of Transportation Infrastructure*. Project NCHRP 15-61 Final Report, Transportation Research Board, NAS-NRC.

Kinnison, H.B. and B.R. Colby. 1945. “Flood Formulas Based on Drainage-Basin Characteristics.” ASCE Trans. 100, pp. 849–904.

Klerk, W.J., H.C. Winsemius, W.J. van Verseveld, A.M.R. Bakker, and F.L.M. Diermanse. 2015. “The Co-incidence of Storm Surges and Extreme Discharges within the Rhine–Meuse Delta.” *Environmental Research Letters*, Vol. 10, No. 3, 035005.

Knutti, R., and J. Sedláček. 2013. “Robustness and Uncertainties in the New CMIP5 Climate Model Projections.” *Nature Climate Change*, Vol. 3, pp. 369–373, doi: 10.1038/nclimate1716.

Knutson, T.R. and R.E. Tuleya. 2004. “Impact of CO2-induced Warming on Simulated Hurricane Intensity and Precipitation: Sensitivity to the Choice of Climate Model and Convective Parameterization.” *Journal of Climate,* Vol. 17, No. 18, p. 3477.

Kopp, R.E., R.M. Horton, C.M. Little, J.X. Mitrovica, M. Oppenheimer, D. Rasmussen, and C. Tebaldi. 2014. Probabilistic 21st and 22nd Century Sea-level Projections at a Global Network of Tide-Gauge Sites. *Earth’s Future*, Vol. 2 No. 8, pp. 383–406.

Kopp, R.E., A.C. Kemp, K. Bittermann, B.P. Horton, J.P. Donnelly, W.R. Gehrels, C.C. Hay, J.X. Mitrovica, E.D. Morrow, and S. Rahmstorf. 2016. “Temperature-driven Global Sea-level Variability in the Common Era.” *Proceedings of the National Academy of Sciences*, Vol. 113, pp. E1434–E1441, http://dx.doi.org/10.1073/pnas.1517056113.

Kopp, R.E., R.M. DeConto, D.A. Bader, C.C. Hay, R.M. Horton, S. Kulp, M. Oppenheimer, D. Pollard, and B.H. Strauss. 2017. “Evolving Understanding of Antarctic Ice-sheet Physics and Ambiguity in Probabilistic Sea-level Projections. *Earth’s Future*, Vol. 5, No. 12, pp. 1217–1233, doi:10.1002/2017EF000663.

Kotamarthi, R., C. Castro, K. Hayhoe, L. Mearns, and D. Wuebbles. 2016. *Use of Climate Information for Decision-Making and Impacts Research: State of our Understanding*, U.S. Department of Defense Strategic Environmental Research and Development Program.

Kumar, D., E. Kodra, and A.R. Ganguly. 2014. "Regional and Seasonal Intercomparison of CMIP3 and CMIP5 Climate Model Ensembles for Temperature and Precipitation." *Climate Dynamics*, Vol. 43, 2491–2518, doi: 10.1007/s00382-014-2070-3.

Lentz, E.E., Stippa, S.R., Thieler, E.R., Plant, N.G., Gesch, D.B., and Horton, R.M. 2015. Evaluating Coastal Landscape Response to Sea-level Rise in the Northeastern United States—Approach and Methods (ver. 2.0, December 2015): U.S. Geological Survey Open-File Report 2014–1252, 27 pp., http://dx.doi.org/10.3133/ofr20141252

Lentz, E.E., E.R. Thieler, N.G. Plant, S.R. Stippa, R.M. Horton, and D. B. Gesch. 2016. "Evaluation of Dynamic Coastal Response to Sea-level Rise Modifies Inundation Likelihood." *Nature Climate Change*, Vol. 6, pp. 696–700, doi:10.1038/nclimate2957.

Liang, X., D.P. Lettenmaier, E.F. Wood, and S.J. Burges. 1994. "A Simple Hydrologically Based Model of Land Surface Water and Energy Fluxes for GSMs," *Journal of Geophysical. Research*, Vol. 99, No. D7, pp. 14,415–14,428.

Livneh, B., E.A. Rosenberg, C.Y. Lin, B. Nijssen, V. Mishra, K.M. Andreadis, E.P. Maurer, and D.P. Lettenmaier. 2013. "A Long-Term Hydrologically Based Dataset of Land Surface Fluxes and States for the Conterminous United States: Update and Extensions," *Journal of Climate*, Vol. 26, No. 23, pp. 9384–9392. (available at https://www.esrl.noaa.gov/psd/data/gridded/data.livneh.html)

Lumia, R., D.A. Freehafer, and M.J. Smith. 2006. "Magnitude and Frequency of Floods in New York." *U.S. Geological Survey Scientific Investigations Report 2006-5112*, 153 pp.

Mantilla, R. and V.K. Gupta. 2005. "A GIS Numerical Framework to Study the Process Basis of Scaling Statistics in River Networks." *IEEE Geoscience and Remote Sensing Letters*, Vol. 2, No. 4, pp. 404–408.

McCuen, R.H., P.A. Johnson, and R.M. Ragan. 2002. *Highway Hydrology*. Hydraulic Design Series 2 (HDS 2), Second Edition, FHWA-NHI-02-001.

McCuen, R.H. 2003. "Modeling Hydrologic Change – Statistical Methods." Lewis Publishers, A CRC Press Company, 433 pp.

McGuigan, K.,T. Webster, and K. Collins. 2015. "A Flood Risk Assessment of the LaHave River Watershed, Canada Using GIS Techniques and an Unstructured Grid Combined River-Coastal Hydrodynamic Model." *Journal of Marine Science and Engineering*, Vol. 3, No. 3), pp. 1093–1116.

Mearns, L. O. 2009. "The North American Regional Climate Change Assessment Program (NARCCAP): Overview of Phase II Results." *Earth and Environmental Science Transactions,* Vol. 6,p. 022007.

Mengel, M., A. Levermann, K. Frieler, A. Robinson, B. Marzeion, and R. Winkelmann. 2016. "Future Sea Level Rise Constrained by Observations and Long-term Commitment." *Proceedings of the National Academy of Sciences*, Vol. 113, pp. 2597–2602. http://dx.doi.org/10.1073/pnas.1500515113.

Merkel, W.H., H.F. Moody, and Q.D. Quan. 2015. *Design Rainfall Distributions Based on NOAA Atlas 14 Rainfall Depths and Durations*. Proceedings of the 2015 Federal Interagency Hydrologic Modeling Conference in Reno, NV, April 19–23, 2015.

Meyer, M., M. Flood, J. Keller, J. Lennon, G. McVoy, C. Dorney, K. Leonard, R. Hyman, and J. Smith. 2014. "Volume 2: Climate Change, Extreme Weather Events, and the Highway System: Practitioner's Guide and Research Report." NCHRP Report 750.

Moglen, G.E. and D.E. Shivers 2006. "Methods for Adjusting USGS Rural Peak Discharges in an Urban Setting." *U.S. Geological Survey Scientific Investigations Report*, 2006-5270, 65 pp.

Moglen, G.E. and S.Kim. 2007. "Limiting Imperviousness." *Journal of the American Planning Association*, Vol. 73, No. 2, pp. 161–171.

New York City. 2017. "Preliminary Climate Resiliency Design Guidelines." NYC Mayor's Office of Recovery and Resiliency, April 21, 2017, Version 1.0.

Nicholls, R.J., S.E. Hanson, J.A. Lowe, R.A. Warrick, X. Lu and A.J. Long. 2014. “Sea-level Scenarios for Evaluating Coastal Impacts.” *WIREs Climate Change*, Vol. 5, pp. 129–150, doi:10.1002/wcc.253.

NRC. 1987. *Responding to Changes in Sea Level: Engineering Implications*. National Research Council, The National Academies Press, Washington, DC, 160 pp. (http://www.nap.edu/catalog/1006.html).

Obeysekera, J. and J.D. Salas. 2014. “Quantifying the Uncertainty of Design Floods under Nonstationary Conditions.” *Journal of Hydrologic Engineering*, Vol. 19, No. 7, pp. 1438–1446.

Over, T.M., R.J. Saito, and D.T. Soong. 2016a. “Adjusting Annual Maximum Peak Discharges at Selected Stations in Northeastern Illinois for Changes in Land-Use Conditions.” *U.S. Geological Survey Scientific Investigations Report 2016-5049*, 33 pp.

Over, T.M, R.J. Saito, A.G. Veilleux, J. Sharpe, D.T. Song, and A. Ishii. 2016b. “Estimation of Peak Discharge Quantiles for Selected Annual Exceedance Probabilities in Northeastern Illinois.” *U.S. Geological Survey Scientific Investigations Report 2016-5050*, 50 pp.

Parris, A., P. Bromirski, V. Burkett, D. Cayan, M. Culver, J. Hall, R. Horton, K. Knuuti, R. Moss, J. Obeysekera, A. Sallenger, and J. Weiss. 2012. “Global Sea Level Rise Scenarios for the US National Climate Assessment.” NOAA Tech Memo OAR CPO-1, 37 pp.

Pennsylvania DOT (PennDOT). 2017. *PennDOT Extreme Weather Vulnerability Study, Phase I,* Appendix D Methodology for Forecasting Flooding Vulnerabilities, April.

Perica, S., D. Martin, S. Pavlovic, I. Roy, M. St. Laurent, C. Trypaluk, D. Unruh, M. Yekta, and G. Bonnin. 2013. “Precipitation-Frequency Atlas of the United States.” *NOAA Atlas 14*, Volume 8 Version 2.0: Midwestern States, National Weather Service, Silver Spring, MD.

Ranasinghe, R., D. Callaghan, and M.J.F. Stive. 2012. “Estimating Coastal Recession due to Sea Level Rise: Beyond the Bruun Rule.” *Climatic Change*, Vol. 110, No. 3-4, pp. 561–574.

Read, L.K. and R.M. Vogel. 2015. “Reliability, Return Periods, and Risk under Uncertainty.” *Water Resources Research*, Vol. 51. doi: 10.1002/2015WR017089.

Regan, R.S., S.L. Markstrom, L.E. Hay, R.J. Viger, P.A. Norton, J.M. Driscoll, and J.H. LaFontaine. 2018. Description of the National Hydrologic Model for use with the Precipitation-Runoff Modeling System (PRMS): U.S. Geological Survey Techniques and Methods, Book 6, Chapter B9, 38 pp., https://doi.org/10.3133/tm6B9.

Salas, J.D., J. Obeysekera, and R.M. Vogel. 2018. “Techniques for Assessing Water Infrastructure for Nonstationary Extreme Events.” *Hydrological Sciences Journal*, International Association of Hydrological Sciences, pp. 1–28.

Serago, J.M. and R.M. Vogel. 2018. “Parsimonious Nonstationary Flood Frequency Analysis.” *Advances in Water Resources,* Vol. 112, Elsevier, pp. 1–16.

Sheffield, J., A.P. Barrett, B. Colle, D.N. Fernando, R. Fu, K. L. Geil, Q. Hu, J. Kinter, S. Kumar, B. Langenbrunner, K. Lombardo, L.N. Long, E. Maloney, A. Mariotti, J.E. Meyerson, K.C. Mo, J.D. Neelin, S. Nigam, Z. Pan, T. Ren, A. Ruiz-Barradas, Y.L. Serra, A. Seth, J.M. Thibeault, J.C. Stroeve, Z. Yang, and L. Yin. 2013. “North American Climate in CMIP5 Experiments. Part I: Evaluation of Historical Simulations of Continental and Regional Climatology.” *Journal of Climate,* Vol. 26, pp. 9209–9245. http://dx.doi.org/10.1175/jcli-d-12-00592.1.

Sheffield, J., et al. 2014. *Regional Climate Processes and Projections for North America: CMIP3/CMIP5 Differences, Attribution and Outstanding Issues*. NOAA Climate Program Office, 47pp.

Simonovic, S., A. Schardong, D. Sandink, and R. Srivastav. 2016. “A Web-Based Tool for the Development of Intensity Duration Frequency Curves under Climate Change.” *Environmental Modelling & Software,* Vol. 81, pp. 136–153.

Smith, J.M., M.A. Cialone, T.V. Wamsley, and T.O. McAlpin. 2010. “Potential Impact of Sea Level Rise on Coastal Surges in Southeast Louisiana. *Ocean Engineering*, Vol. 37, pp. 37–47.

Steinschneider, S., Y.E. Yang, and C. Brown. 2013. "Panel Regression Techniques for Identifying Impacts of Anthropogenic Landscape Change on Hydrologic Response." *Water Resources Research*, Vol. 49, pp. 7874–7886.

Stoner, A., K. Hayhoe, X. Yang, and D.J. Wuebbles 2013. "An Asynchronous Regional Regression Model for Statistical Downscaling of Daily Climate Variables." *International Journal of Climatology,* Vol. 33, No. 11, pp. 2473–2494.

Sweet, W., R. Kopp, C. Weaver, J. Obeysekera, R. Horton, R. Thieler, and C. Zervas. 2017a. "Global and Regional Sea Level Rise Scenarios for the United States." *NOAA Technical Report NOS CO-OPS 083*.

Sweet, W., R. Horton, R.E. Kopp, A.N. LeGrande, and A. Romanou. 2017b. "Sea Level Rise." In *Climate Science Special Report: Fourth National Climate Assessment, Volume I* [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (Eds.)]. U.S. Global Change Research Program, Washington, DC, USA, pp. 333–363, doi: 10.7930/J0VM49F2.

Torres, J.M., B. Bass, N. Irza, Z. Fang, J. Proft, C. Dawson, M. Kiani, and P. Bedient. 2015. "Characterizing the Hydraulic Interactions of Hurricane Storm Surge and Rainfall–Runoff for the Houston–Galveston Region." *Coastal Engineering*, Vol. 106, pp. 7–19.

USACE. 2014. *Procedures to Evaluate Sea Level Change: Impacts, Responses, and Adaptation*. U.S. Army Corps of Engineers, ETL 1100-2-1, June 30, 2014, 254 pp.

USACE. 2017a. Sea Level Change Curve Calculator, version 2017.55, (see http://corpsclimate.us/ccaceslcurves.cfm)

USACE. 2017b. Wave Information Studies website (see http://wis.usace.army.mil/)

USACE. 2017c. Coastal Hazards System website (see https://chs.erdc.dren.mil)

USBR. 2013. *Downscaled CMIP3 and CMIP5 Climate Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with Preceding Information, and Summary of User Needs,* U.S. Department of the Interior, Bureau of Reclamation, Technical Service Center, Denver, CO, 116 pp.

USGCRP. 2017. *Climate Science Special Report: Fourth National Climate Assessment, Volume I* [Wuebbles, D.J., D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C. Stewart, and T.K. Maycock (Eds.)]. U.S. Global Change Research Program, Washington, DC, USA, 470 pp, doi: 10.7930/J0J964J6.

USGCRP. 2018. *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II* [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (Eds.)]. U.S. Global Change Research Program, Washington, DC, USA, 1515 pp. doi: 10.7930/NCA4.2018.

USGS. 2017. Coastal Storm Modeling System: CoSMoS, (see https://walrus.wr.usgs.gov/coastal_processes/cosmos/)

U.S. Department of Commerce. 1980. "A Methodology for Point-to-Area Rainfall Frequency Ratios," NOAA Technical Report NWS 24, Washington, D.C.

U.S. EPA. 2009. "Land-Use Scenarios: National-Scale Housing-Density Scenarios Consistent with Climate Change Storylines," Global Change Research Program, National Center for Environmental Assessment, EPA/600/R-80/076F, Washington, DC.

U.S. EPA. 2013. *Watershed Modeling to Assess the Sensitivity of Streamflow, Nutrient and Sediment Loads to Potential Climate Change and Urban Development in 20 U.S. Watersheds*, National Center for Environmental Assessment, Washington, DC, EPA/600/R-12/058F.

U.S. EPA. 2015. *BASINS 4.1 (Better Assessment Science Integrating Point and Non-point Sources) Modeling Framework,* National Exposure Research Laboratory, Research Triangle Park, North Carolina.

U.S. EPA. 2016. Climate Resilience Evaluation and Awareness Tool, Version 3.0 Methodology Guide. https://www.epa.gov/sites/production/files/2016-05/documents/creat_3_0_methodology_guide_may_2016.pdf

U.S. EPA. 2017. *Updates to the Demographic and Spatial Allocation Models to Produce Integrated Climate and Land Use Scenarios (ICLUS)* (Final Report, Version 2), Washington, DC, EPA/600/R-16/366F, (https://cfpub.epa.gov/ncea/iclus/recordisplay.cfm?deid=322479)

Wahl, T., S. Jain, J. Bender, S.D. Meyers, and M.E. Luther. 2015. "Increasing Risk of Compound Flooding from Storm Surge and Rainfall for Major U.S. Cities." *Nature Climate Change*, Vol. 5, No. 12, pp. 1093–1097.

Webb, B.M. and C.D. Marr. 2016. "Spatial Variability of Hydrodynamic Timescales in a Broad and Shallow Estuary: Mobile Bay, Alabama." *Journal of Coastal Research*, Vol. 32, pp. 1374–1388.

Wehner, M. 2013. "Very Extreme Seasonal Precipitation in the NARCCAP Ensemble: Model Performance and Projections." *Climate Dynamics*, Vol. 40, No 1, pp. 59–80.

Yu, X., and J.R. Stedinger. 2018. "LP3 Flood Frequency Analysis Including Climate Change." Proceedings of the World Environmental and Water Resources Congress, ASCE, pp. 459–467.

Abbreviations

AASHTO	American Association of State Highway and Transportation Officials
AEP	Annual Exceedance Probability
AMS	Annual Maximum Series
AR4	Fourth Assessment Report (IPCC)
AR5	Fifth Assessment Report (IPCC)
ARF	Areal Reduction Factor
ARRM	Asynchronous Regional Regression Model
ASCE	American Society of Civil Engineers
BCCA	Bias-Correction Constructed Analogues
BCSD	Bias-Correction Spatial Disaggregation
CCI	Climate Change Indicator
CF	Change Factor
CMIP	Coupled Model Intercomparison Project
CO_2	Carbon Dioxide
CREAT	Climate Resilience Evaluation and Analysis Tool
DCHP	Downscaled Climate and Hydrology Projections
ENSO	El Niño Southern Oscillation
ESDM	Empirical-Statistical Downscaling Model
FEMA	Federal Emergency Management Agency
FFC	Flood Frequency Curve
FHWA	Federal Highway Administration
FIRM	Flood Insurance Rate Map
GC2	Gulf Coast Study, Phase 2
GEV	Generalized Extreme Value
GIS	Geographic Information System
GCM	Global Climate Model (or General Circulation Model)
GHG	Greenhouse Gases
GMSLR	Global Mean Sea Level Rise
GrIS	Greenland Ice Sheet
H&H	Hydrologic and Hydraulic
HCDN	Hydro-Climatic Data Network

HDG	Highway Drainage Guidelines
HDS	Hydraulic Design Series
HEC	Hydraulic Engineering Circular
HEC-HMS	Hydrologic Engineering Center – Hydrologic Modeling System
HWM	High Water Mark
ICLUS	Integrated Climate and Land Use Scenarios
ICNet	Infrastructure and Climate Network
IDF	Intensity-Duration-Frequency
IPCC	Intergovernmental Panel on Climate Change
LOCA	Localized Constructed Analogs
LULC	Land Use/Land Cover
MACA	Multivariate Adaptive Constructed Analogs
MSL	Mean Sea Level
NA-CORDEX	North American Coordinated Regional Downscaling Experiment
NARCCAP	North American Regional Climate Change Assessment Program
NAVD	North American Vertical Datum
NCA	National Climate Assessment
NCHRP	National Cooperative Highway Research Program
NEX-DCP30	NASA Earth Exchange Downscaled Climate Projections (30 arcsec resolution)
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
NFIP	National Flood Insurance Program
NHC	National Hurricane Center
NOAA	National Oceanic and Atmospheric Administration
NOS	National Ocean Service
NRC	National Research Council
NRCS	Natural Resources Conservation Service
NWS	National Weather Service
PDO	Pacific Decadal Oscillation
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RFC	Rainfall Frequency Curve
RSL	Relative Sea Level
RSLR	Relative Sea Level Rise

SCS	Soil Conservation Service (now the NRCS)
SERDP	Strategic Environmental Research and Development Program
SLR	Sea Level Rise
SRES	Special Report on Emission Scenarios
SSIM	Storm Surge Inundation Map
SWL	Still Water Level
SWMM	Stormwater Management Model
USACE	U.S. Army Corps of Engineers
USGCRP	U.S. Global Change Research Program
USGS	United States Geological Survey
VLM	Vertical Land Movement
WAIS	Western Antarctic Ice Sheet

Glossary

Abrupt or rapid climate change. The non-linearity of the climate system may lead to rapid climate change, sometimes called abrupt events or even surprises. These are defined as large-scale changes in the climate system that take place over a few decades or less, persist for at least a few decades, and cause substantial disruptions in human and natural systems (IPCC 2013). Some abrupt future events may be imaginable, such as a dramatic reorganization of the thermohaline circulation, rapid deglaciation, or massive melting of permafrost leading to fast changes in the carbon cycle. Others may be truly unexpected, a consequence of a strong, rapidly changing, forcing of a non-linear system.

Accuracy. How close measurements are to the actual or true value. Climate model accuracy can be evaluated for weather aggregated over time periods (climate accuracy) and decadal forecasts for near-term climate (forecast accuracy). In the context of climate model projections, accuracy refers to model ability to reproduce the aggregate statistical properties of real-world weather and climate patterns, not specific historical events. Most model simulations develop their own pattern of internal natural variability, making them accurate at climatological time scales of 20 to 30 years, but not at weather-relevant time scales of days to years.

Adaptation. Preparing for the effects of extreme events and climate change on transportation infrastructure and systems. Adaptation refers to the planning, designing, constructing, operating, or maintaining transportation infrastructure while incorporating consideration of extreme events and climate change.

Adaptive capacity. The degree to which the system containing the asset (road, bridge, etc.) can adjust or mitigate the potential for damage or service interruption resulting from climatic hazards.

Annual exceedance probability. The probability that the magnitude of the random variable (for example annual maximum flood peak) will be equaled or exceeded in a single year.

Bankfull. Water level in a stream corresponding to where water is flowing within the banks just before it spills out into the floodplain.

Beach. The zone of unconsolidated material, typically sand, that extends landward from closure depths, where sand is moved by waves, to the place where there is marked change in material or physiographic form, or to the line of permanent vegetation (usually the effective limit of storm waves).

Boundary conditions. Environmental conditions, e.g., water levels, waves, currents, drifts, etc. used as input for numerical models.

Bottom-up analysis. A process where the vulnerabilities of existing infrastructure or draft designs of new infrastructure are identified so that potential conditions that expose the infrastructure to these vulnerabilities can be quantified.

Climate. The characteristic weather of a region, particularly temperature and precipitation, averaged over some significant interval of time (20 to 30 years or longer). A specific event is weather; the risk of such a weather event occurring during a significant time interval is climate.

Climate change. 1) A significant and lasting shift in the statistical distribution of weather patterns around the average conditions (e.g., more or fewer extreme weather events) over periods ranging from decades to millions of years. 2) Any significant shift in the measures of climate lasting for an extended period of time, including major alterations in temperature, precipitation, coastal storms, or wind patterns, among others, that occur over several decades or longer. 3) A non-random shift in climate that is measured over several decades or longer. The change may result from natural or human causes.

Climate change detection and attribution. Detection builds the statistical evidence for a change in climate without providing a reason for that change. Attribution establishes the most likely causes for the detected change and assigns a level of confidence or certainty to those causes.

Climate projections. Output from global climate model simulations that attempts to estimate the future evolution of the climate system, given a specific set of plausible external forcings that can include both natural (e.g., changes in solar energy, volcanic eruptions) and human (greenhouse gas emissions, soot and dust) factors. Simulations from multiple models are typically combined into a probabilistic multi-model ensemble of future projections.

Climate sensitivity. The change in global mean temperature from a doubling of atmospheric carbon dioxide levels relative to a pre-industrial base. The current estimate of this value is 3^{o}C, with a range from 2.0 to 4.5^{o}C.

Climatological standard normal. A climatological standard normal is a consecutive 30-year period of observations.

Coastal engineering. The planning, design, construction, and operation of infrastructure in the wave, tide, and sand environment that is unique to the coast. A well-established specialty area of civil engineering that focuses on the coastal zone and coastal processes.

Coastal environment. The sum of all external conditions (e.g. tides, waves, sediments) affecting built infrastructure near the coast.

Coastal processes. Collective term covering the action of natural forces on the shoreline and nearshore seabed.

Confidence interval. An interval estimated from data that has a stated probability of including the true value of a statistic. The limits of the interval are called **confidence limits**.

Confidence limits. Limits that define an interval in which the true value of a statistic is expected to lie with the stated probability.

Conservative estimate. To a climate scientist, this refers to a "best-case scenario," which in the context of climate projections would be the lowest estimate of future emissions or climate change. To an engineer, this refers to a "worst case scenario," which in the context of climate projections would be a higher estimate of future emissions or change.

Datum. Any permanent line, plane, or surface used as a reference point for elevations.

Design flood. The peak discharge, volume (if appropriate), stage, or wave crest elevation of the flood associated with the annual exceedance probability (AEP) selected for the design of a transportation asset.

Design storm (coastal). Hypothetical extreme storm that coastal protection structures may be designed to withstand. The severity of the storm (i.e. return period) is chosen given an acceptable level of risk of damage or failure. A design storm consists of a design wave condition, design water level, and duration. In coastal flood analysis, the design storm frequently refers to water level elevation.

Deterministic. A prediction or projection where each state develops in a predictable manner from the previous state, according to known principles or processes. For example, climate models are based on physical equations that produce one and only one output sequence for a given set of input and boundary conditions.

Discharge. Volume of water passing a given point per unit time. Also known as flow.

Downscaling. A procedure to develop higher-resolution information from lower-resolution information.

El Niño. Phenomenon characterized by a large-scale weakening of the trade winds and warming of the surface layers in the eastern and central equatorial Pacific Ocean. El Niño events occur irregularly at intervals of 2 to 7 years, although the average is about once every 3 to 4 years. They typically last 12 to 18 months and are accompanied by swings in the Southern Oscillation, an interannual see-saw in tropical sea level pressure between the eastern and western hemispheres. During El Niño, unusually high atmospheric sea level pressures develop in the western tropical Pacific and Indian Ocean regions, and unusually low sea level pressures develop in the southeastern tropical Pacific. Southern Oscillation tendencies for unusually low pressures west of the date line and high pressures east of the date line have also been linked to periods of anomalously cold equatorial Pacific sea surface temperatures, sometimes referred to as La Niña.

El Niño Southern Oscillation (ENSO). The atmospheric component of El Niño.

Epoch. 1) Tidal epoch is a time related to astronomical cycles of the earth-moon-sun system lasting about 19 years. 2) Geological epoch is a subdivision of the geologic timescale that is longer than an age and shorter than an era.

Eustatic sea level change. Change in sea level resulting from change in the volume of the world's ocean basins and the total amount of ocean water. Vertical land movement is not included. See Global Sea Level Rise.

Exposure. The frequency, nature, and degree to which a transportation asset (road, bridge, etc.) will experience a climatic hazard.

Extratropical. A term used in advisories and tropical summaries to indicate that a cyclone has lost its "tropical" characteristics. The term implies both poleward displacement of the cyclone and the conversion of the cyclone's primary energy source from the release of latent heat of condensation to baroclinic (the temperature contrast between warm and cold air masses) processes. Cyclones can become extratropical and still retain winds of hurricane or tropical storm force.

Extreme event. Severe and rare natural occurrence that may pose significant risks of damage, destruction, or loss of life.

Extreme flood event. Specific type of extreme weather event that is manifested as flooding.

Extreme weather event. Significant anomalies in temperature, precipitation, and winds that may manifest as heavy precipitation and flooding, heatwaves, drought, wildfires, or windstorms (including tornados and tropical storms). They are rare, weather-induced events that usually cause damage, destruction, or severe economic loss.

Flood. A general and temporary condition of partial or complete inundation of normally dry land areas resulting from the overflow of inland or tidal waters.

Flood frequency curve. A curve relating a range of flood flows to their respective annual exceedance probabilities (frequencies).

Floodplain. The land area susceptible to being inundated by flood waters.

Flow. Volume of water passing a given point per unit time. Also known as discharge.

Forcing. Factors that affect the Earth's climate. For example, natural factors such as volcanoes and human factors such as the emission of heat-trapping gases and particles through fossil fuel combustion.

Freeboard. Vertical distance above a design water-surface elevation that provides a safety factor for waves, surges, drift, uncertainty in hydrologic estimates, and other contingencies.

Geomorphology. 1) The branch of physical geography that deals with the form of the Earth, the general configuration of its surface, the distribution of the land, water, etc. 2) The investigation of the history of geologic changes through the interpretation of topographic forms.

Global sea level rise. The sea level rise averaged across the world's oceans. This is the average change in sea level resulting from a change in the volume of the world's ocean basins and the total amount of ocean water. Vertical land movement is not included. See Eustatic Sea Level Change.

Hazard. Something that is potentially dangerous or harmful, often the root cause of an unwanted outcome.

High-resolution. Climate information on a spatial and/or temporal scale that is finer than standard GCM output. At present, spatial grids at or less than 25 km and daily time increments or less are considered high resolution.

Hindcasting. Application of a numerical model to simulate a past event. Often used in model validation to see how well the output matches known events or historical statistics.

Hurricane. An intense tropical cyclone in which winds tend to spiral inward toward a core of low pressure, with maximum sustained (1-minute average) surface wind velocities that equal or exceed 75 mph or 65 knots (120 km/h). Term is used in the Atlantic, Gulf of Mexico, and eastern Pacific.

Hydrodynamic. Having to do with the science of moving water.

Hydrograph. 1) Time series of flow (discharge) or stage at a particular location in a watershed. 2) The graph of the variation of stillwater level with time (coastal).

Hyetograph. Time series of rainfall, which can be expressed as intensity (rate), depth per incremental time unit, or total (accumulated) rainfall from the beginning of the storm (mass hyetograph).

Hydrology. The earth science that considers the occurrence, distribution, and movement of water in the atmosphere, between the atmosphere and the Earth's surface, and on the Earth.

Hydraulics. The applied science and engineering of the mechanical properties of water.

Likelihood. A probabilistic estimate of the occurrence of a single event or of an outcome - for example, a climate parameter, observed trend, or projected change - lying within a given range. Likelihood may be based on statistical or modeling analyses, elicitation of expert views, or other quantitative analyses. The engineer will tend to use the term "likelihood" to refer to general, or non-numeric, matters and use the term probability to refer to computed, or numerical, values. The climate scientist may rely more on the statistical definitions of likelihood and probability, where the terms may be used interchangeably.

Mean sea level. The average height of the surface of the sea for all stages of the tide over a 19-year period, usually determined from hourly height readings. Not necessarily equal to mean tide level.

Monte Carlo. A class of computational algorithms that use repeated random sampling to obtain risk estimates.

Morphology. The form and structure, and the changes of form and structure, of the Earth's surface.

Nonstationarity. A characteristic of time series data where statistical parameters of the series, such as trend, variability, or temporal dependence change over time. Such changes over time complicate the use of historical data for estimating future conditions.

Pacific Decadal Oscillation. A long-lived El Niño-like pattern of Pacific climate variability.

Perfect model approach. A method for evaluating the stationarity of downscaling approaches against future projections from a high-resolution global climate model. This approach assumes the high-resolution projections from the global model represent "truth," relative to which projections that have been downscaled from a coarser global climate model grid can be compared and their biases quantified.

Precipitation. Water in the form of rain, hail, sleet, or snow that forms in the atmosphere and falls to the Earth's surface.

Projection. A potential future evolution of a quantity or set of quantities, often computed with the aid of a model. Unlike predictions, projections are conditional on assumptions concerning, for example, future socio-economic and technological developments that may or may not be realized.

Quantile. Value in a distribution of a random variable representing a certain probability threshold. For example, the 0.1 AEP discharge quantile is the discharge that is equaled or exceeded in a given year with a probability of 0.1.

Relative sea level change. Sea level change at a coastal location relative to the land. This includes both the eustatic sea level rise component and local components such as the vertical land movement. This is the sea level change measured by long-term tide gauges.

Resilience. The ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions.

Resilient. Capable of maintaining or rapidly recovering functionality in response to changing conditions or disruptions.

Return period. The average length of time, *T,* between occurrences in which the value of a random variable (e.g., flood magnitude) is equaled or exceeded. Actual times between occurrences may be longer or shorter, but the return period represents the average interval. The return period is the inverse of the AEP. For example, if the AEP equals 0.01 (or 1 percent), the return period, T, is 100 years.

Risk. The consequences associated with hazards (including climatic) considering the probabilities of those hazards. More specifically for this document, risks are the consequences associated with the probability of flooding attributable to an encroachment. It shall include the potential for property loss and hazard to life during the service life of the highway (23 CFR 650 A).

Runoff. The portion of a rainfall event discharged from a watershed into the stream network during and immediately following the rainfall.

Runup. The upper level reached by a wave on a beach or coastal structure relative to the stillwater level.

Scenarios. Sets of assumptions used to help understand potential future conditions such as population growth, land use, and sea level rise. Scenarios are neither predictions nor forecasts. Scenarios are commonly used for planning purposes.

Sea level rise. A rising long-term trend in mean sea level.

Sensitivity. The degree to which an asset is damaged or service is interrupted by a climatic hazard.

Shoreline. The intersection of a specified plane of water with the shore or beach (e.g., the high-water shoreline would be the intersection of the plane of mean high water with the shore or beach). The line delineating the shoreline on National Ocean Service nautical charts and surveys approximates the mean high-water line.

Standard error. A measure of the sampling variation of a statistic.

Stationarity. A characteristic of time series data where the statistical properties of the series do not change over time. There are no trends or other changes that would prevent historical data from being used to estimate future conditions.

Stillwater level. The elevation of the water surface if all wave and wind action were to cease.

Stochastic. A climate process or its functional representation that contains unpredictable components. In climate projections, weather sequences are considered stochastic; climate statistics are a combination of stochastic and deterministic processes. In hydrology, a stochastic process is a phenomenon (e.g., rainfall, streamflow) whose variation in time or space includes a random component.

Storm surge. A rise in average (typically over several minutes) water level above the normal astronomical tide level caused by the action of a storm. Storm surge results from wind stress, atmospheric pressure differences, and wave setup.

Storm surge hydrograph. Graph of the variation in the rise and fall of the stillwater level with time during a storm.

Submarine. The surface of the Earth under the ocean.

Tidal epoch. A 19-year cycle in the astronomical (sun and moon) producing tide forces that are averaged to obtain a tidal datum.

Tide. The periodic rising and falling of water that results from the gravitational attraction of the moon, sun, and other astronomical bodies acting upon the rotating Earth. Although the accompanying horizontal movement of the water resulting from the same cause is also sometimes called the tide, it is preferable to designate the latter as “tidal current,” reserving the name “tide” for the vertical movement.

Top-down analysis. A process where a defined set of information, design procedures, and design criteria is applied to a project to determine the resulting solution or to evaluate an existing solution.

Tropical storm. A tropical cyclone with maximum winds less than 75 mph (119 km/h) and greater than 39 mph (63 km/h). Tropical storms are characterized by less strength than hurricanes or typhoons.

Tsunami. A long-period wave caused by an underwater disturbance such as a volcanic eruption or earthquake. Commonly (non-technical usage) called "tidal wave."

Uncertainty. A state of incomplete knowledge that can result from a lack of information or from disagreement about what is known or even knowable. It may have many types of sources, such as imprecision in the data, ambiguously defined concepts or terminology, or uncertain projections of human behavior (IPCC 2013). Uncertainty can be represented by quantitative measures, such as a probability-density function, or by qualitative statements.

Validation. The process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model.

Verification. A term used in reference to the accuracy of forecast values.

Vulnerability. The extent to which a transportation asset is susceptible to sustaining damage from hazards (including climatic). Vulnerability is a function of exposure, sensitivity, and adaptive capacity.

Water year. The 12-month period from October 1 for any given year through September 30 of the following year, according to the USGS. The water year is designated by the calendar year in which it ends and which includes 9 of the 12 months.

Weather. Meteorological conditions (including, but not limited to, temperature, moisture, precipitation, and wind) and the resulting events at a particular place over a short period of time.