Faisal Hossain
Editor

Resilience of Large Water Management Infrastructure

Solutions from Modern Atmospheric Science

Springer

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With advisory support from The Task Committee
on Infrastructure Impacts of Landscape-driven
Weather Change under the ASCE Watershed
Management Technical Committee and the
ASCE Hydroclimate Technical Committee

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Preface

Infrastructure that manages our water resources (such as dams and reservoirs, irrigation systems, channels, navigation waterways, water and wastewater treatment facilities, storm drainage systems, levees, urban water distribution, and sanitation systems) are critical to all sectors of an economy. Yet, they are aging beyond their design lifespan in many parts of the world. In addition, these infrastructures are subjected to excessive “wear and tear” from factors such as (but not limited to) rising water demand, increasing frequency of flooding from urbanization or human encroachment of water bodies. Such water management infrastructures, by virtue of their service to society, are also directly or indirectly responsible for changes to the surrounding landscape. For example, a newly built water supply distribution system favors a faster growth rate of urban development which then leads to landscape transforming to one that is more impervious. Similarly, a large flood control and irrigation dam can increase downstream urbanization and convert barren or forested land to irrigated landscape. Inversely, by changing a river’s or lake’s edge through levees and seawalls can cause naturally irrigated areas to become barren. The body of knowledge accumulated by the atmospheric science community since the early 1970s informs us that changes in extreme weather and climate can be a direct product of such landscape modification. Thus, the issue of infrastructure resilience becomes directly relevant as large infrastructures are usually designed to handle “worst-case” or extreme weather and climate scenarios in mind.

Realizing the importance of large water infrastructures, efforts have already begun on understanding the sustainability and resilience of such systems under changing conditions expected in the future. These changing conditions can be due to a variety of factors such as global warming, land-cover/land-use change, industrialization/urbanization, and demographic forces (increasing population). In early 2014, an American Society of Civil Engineers (ASCE) Task Committee (TC) was set up titled “Committee Infrastructure Impacts of Landscape-driven Weather Change” under the ASCE Watershed Management Technical Committee and the ASCE Hydroclimate Technical Committee. The TC was tasked with providing the engineering community additional “scenarios” (from modern atmospheric and climate science) for improving infrastructure resilience for securing water supply and protection against water hazards.

Development of the Book

The following key arguments can be made for the timeliness of such a book:

1. Infrastructure that manages water resources (dams, irrigation systems, channels, storm management systems, levees, etc.), while being critical to vital sectors of the economy, are aging in the USA and the rest of the world.
2. Large-scale water infrastructures are directly, indirectly responsible for and/or simply experience, through aging, climate/weather-sensitive changes to the surrounding landscape. These landscape changes consequently interact with local, regional, and even planetary scale forcings (such as greenhouse gas-driven global warming) and can alter the future behavior of extreme events to an amplitude or phase space not recorded before.
3. It is believed that the civil engineering community is not yet harnessing very effectively the vast body of knowledge that has accumulated in this field of local-to-regional drivers of extreme weather/climate beyond the more well-known greenhouse gas drivers. This is despite the fact that the first field campaign to study the impact of urbanization of weather kicked off in 1970s in St. Louis (MO) called METROMEX. There are numerous such findings that have accumulated over the past decades by the land-use/land-cover community, although most are not as directly investigated for the immediate benefit of engineering design/operations.

With these motivations in mind, the Task Committee was formed with four key objectives (each being a unique task):

(1) Define “Infrastructure Resilience” for water infrastructure at the intersection of weather and climate;
(2) Identify knowledge gaps on the role of local-to-regional landscape drivers of weather and climate of relevance to engineering;
(3) Identify effective and complementary approaches to assimilate knowledge discovery on local (mesoscale)-to-regional landscape drivers to improve practices on design, operations, and preservation of large water infrastructure systems;
(4) Identify an effective approach to start a conversation with the larger civil engineering education community on the ASCE Body of Knowledge (BOK) with particular focus on identifying ways to understand the engineering implications of prognostic uncertainty of climate/weather models.

The ASCE Task Committee Members in Advisory Role

The Task Committee members were:
Faisal Hossain, University of Washington—Chair
Ed Beighley, Northeastern University—Co-Chair
Casey Brown, University of Massachusetts—Secretary
Steve Burian, University of Utah
Dev Niyogi, Purdue University
Vincent Tidwell, Sandia Laboratories
Anindita Mitra, CREA Affiliates
Roger A. Pielke Sr., University of Colorado
Jie Chen, Hong Kong University
Jeffrey Arnold, US Army Corps of Engineers
Shahrbanou Madadgar, University of California, Irvine
Dave Wegner, Senior Staff, US House of Representatives—retired

During 2014–2017, the TC met mostly via teleconference meetings or group email exchanges to have discussions for each task, usually at one meeting per 2 months. In addition, the TC chair (Faisal Hossain) or Co-Chair, Ed Beighley, reported updates regularly to ASCE EWRI Technical Council for Watershed Management each month.

As the committee went about completing each task, some of the tasks were prepared in an end-to-end report and submitted to a journal (typically an ASCE venue). For example, the very first task of defining resilience and identifying the landscape-change drivers has appeared as a forum paper in ASCE's Journal of Hydrologic Engineering. Forum papers are meant to be thought-provoking and timely opinion pieces that are not original research to get the civil engineering community engaged in a discussion. The second task on the identification of knowledge gaps was pursued in the form of surveying water managers with a lot of experience in the practice of water resources decision making for large management infrastructures. This survey appeared in PLOS One (an open-access journal). The third task of identifying methods for resilience assessment is currently being pursued as a forum paper in ASCE's Journal of Infrastructure Systems. For remaining tasks, the TC pulled from literature relevant work on the application of numerical models for the atmosphere for simulation of extreme storms and their probable maximum precipitation.

What follows in the rest of the book is essentially a packaged version of the published work listed above in various forums, rewritten in a wholesale manner for a more multi-disciplinary audience. Chapters 1–6 consolidate all relevant material produced by the TC on water infrastructure to make it easier for the practitioner to find the material in one place. In addition, two guest writers (Chaps. 7 and 8) who are experts in the field were also sought for timely commentary or review of the state of the art. Each chapter was proofread and then re-edited by a professional writer to make the entire book more readable as one single reference manual.

Lastly, this book compilation could not have been possible without the active and tireless support from all the TC members, editorial assistant, Li-Chien Wang, at University of Washington and a highly skilled professional editor—Dallas Staley. It is because of their dedication that we are now able to put all the things together in the form of a book and make it relevant for practitioners engaged in water management. The book is certainly not without its fair share of flaws and typos for which the editor (Faisal Hossain) takes full responsibility. We will make an attempt to correct these errors in a future edition or through adding a list of errata. We hope engineers and practitioners who routinely deal with large water management infrastructure will find this book worthwhile for improving the state of the art on infrastructures for water management.

Seattle, USA Faisal Hossain

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Resilience of Water Management Infrastructure

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Ji Chen, Dave Wegner, Anindita Mitra, Steve Burian,
Shahrbanou Madadgar, Ed Beighley, Casey Brown
and Vincent Tidwell

Introduction

This chapter presents a compilation of work conducted by the ASCE Task Committee 'Infrastructure Impacts of Landscape-driven Weather Change' under the ASCE Watershed Management Technical Committee and the ASCE Hydroclimate Technical Committee. The chapter argues for explicitly considering the well-established feedbacks triggered by infrastructure systems to the land-atmosphere system via landscape change. A definition for Infrastructure Resilience (IR) at the intersection of extreme weather and climate is provided for the engineering community. The broader range of views and issues than what is currently in the front view of engineering practice is expected to ensure more robust approaches for resilience assessment by the engineering community by affording a greater number of

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‘scenarios’ in its decision-making. The engineering community needs to understand the predictive uncertainty of changes to extreme weather and climate and how it can be addressed to improve infrastructure design and operations.

Why Water Management Infrastructure?

Today, water infrastructure of the nation is critical to vital sectors of the economy such as energy, transportation, food, and health. These infrastructures comprise dams, levees, irrigation systems, city drainage systems, water supply and hydropower generation systems, nuclear power plants, and flood control structures, among many. Unfortunately, of all the different types of infrastructures the civil engineering profession deals with, the water management infrastructure facilities share a consistently poor rating of grade ‘D’ or lower according to the ASCE Infrastructure report card (ASCE 2013). For example, most US dams will be at least 50 years or older by 2020 (Fig. 1.1) and yet they provide major cities with vital water supply during dry periods (see Hossain and Kalyanapu 2012 in ‘Civil Engineering’ Magazine). This aging infrastructure problem has prompted reexamination of critical infrastructure assumptions by the engineers who design and manage these structures (Hossain et al. 2012). In the USA, dams provide about 60% of total renewable energy (6% of total energy) and 60% of water for irrigation.

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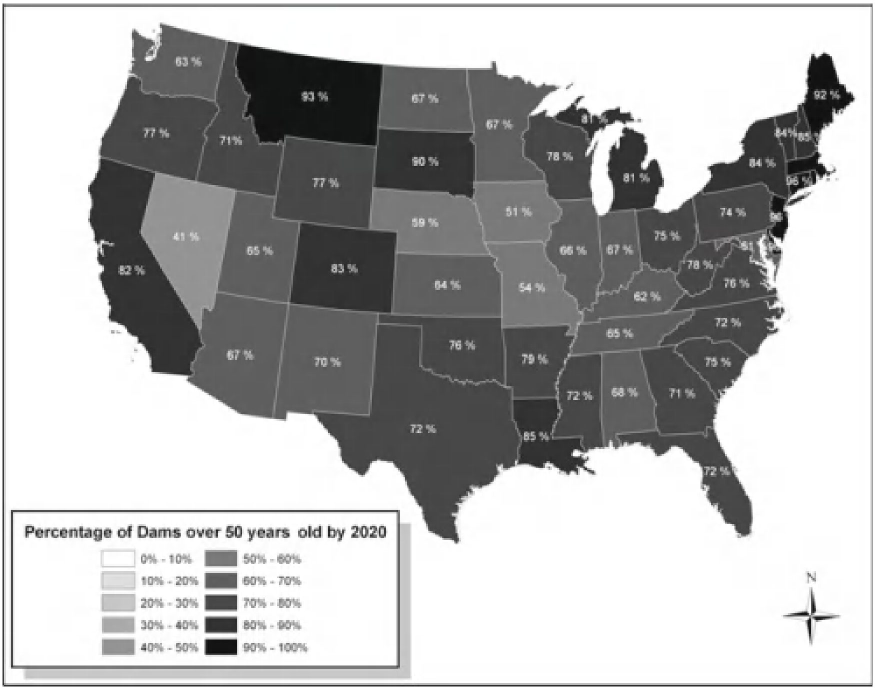

Fig. 1.1 The percentage of dams per state that will be over 50 years old in 2020 (reproduced from USACE report and Hossain et al. 2009)

Globally, about 20% of world food production (40% of the world's irrigated water) and 7% of world energy demand is met with large water infrastructures such as dams, levees, and irrigation systems (Vorosmarty et al. 2010; Biemans et al. 2011).

According to the Environmental Protection Agency (EPA), the USA has 14,780 wastewater treatment facilities and 19,739 wastewater pipe systems. Although access to centralized treatment systems is widespread, the ASCE Infrastructure report card (ASCE 2013) states that the condition of many of these systems is also poor, with aging pipes and inadequate capacity leading to annual discharges of 900 billion gallons of untreated sewage. Emerging challenges are likely to increase water treatment costs. For example, in 2009, the EPA reported to Congress that the states had assessed 16% of America's stream miles and found that 36% of those miles were unfit for use by fish and wildlife, 28% were unfit for human recreation, 18% were unfit for use as a public water supply, and 10% were unfit for agricultural use (source: www.epa.gov). Thus, there is now a critical need to reexamine water management infrastructure from the standpoint of resilience.

From the standpoint of resilience, two factors make a reassessment necessary. First, we are living in a changing climate where downstream effects of greenhouse gas emissions are expected to significantly alter surface water availability by the end of the twenty-first century (IPCC 2007). Second, climate change, water budgets, and socioeconomic population data models clearly indicate that water stress is projected to worsen by 2025 in the USA (Sun et al. 2008) and globally (Vorosmarty et al. 2005, 2010). Even if the expected impact of climate change is ignored, rising water demands due to population growth will heavily dictate the future state of water systems (Gleick 2002).

Broadening the Focus on Drivers of Change for Resilience Assessment

Realizing the importance of water management infrastructures, efforts have already begun on understanding the resilience of water infrastructure systems under drivers of change, such as climate. Such efforts could now benefit the engineering community from leveraging the scientific community's understanding of additional contributing factors of climate change. These factors comprise the local-regional human drivers of landscape change. These additional contributing factors provide a complementary view to the more well-known greenhouse gas (GHG)-based planetary warming as they focus more on mesoscale-to-regional changes (radiative and non-radiative) to weather/climate. Despite the three decades of research by the land-use community that has accumulated on the human impact of landscape change on weather and climate, the engineering infrastructure community appears less aware of these additional drivers of change. Such drivers do not have a uni-directional impact on weather and climate but can be modeled at the infrastructure scale (100 m–1 km) with useful accuracy. In this chapter, knowledge gaps are identified that currently prevents the engineering community from formulating practical solutions to more resilient water infrastructure building.

Local-to-Regional Landscape Driver of Extreme Weather and Climate

[Adapted from Hossain et al. (2015).]

> With many calculations, one can win; with few one cannot. How much less chance of victory has one who makes none at all!—Sun Tzu in 'The Art of War'

The above statement made by Sun Tzu in his seminal book 'The Art of War' more than two thousand years ago summarizes best the mission statement of the ASCE Task Committee (TC) on the topic of this chapter. In early 2014, the TC was tasked with providing the engineering community additional 'calculations' for improving infrastructure resilience for securing water supply and protection against water hazards. It was set up in follow-up to a forum article that appeared in 2012 in ASCE Journal of Hydrologic Engineering (Hossain et al. 2012) and in Civil

Engineering Magazine (Dec 2012 issue). These articles encouraged engineers to explore the well-established feedbacks triggered by large infrastructures on the land-atmosphere system for decision-making related to water management, better design and operations. The goal of this introductory chapter is to shed light on the findings of the initial round of dialogue within the TC to understand the role of landscape change for improving resilience of our water infrastructure.

Infrastructure that manages our water resources (such as dams and reservoirs, irrigation systems, channels, navigation waterways, water and wastewater treatment facilities, storm drainage systems, levees, urban water distribution, and sanitation systems) is critical to all sectors of an economy. Yet they are aging beyond their lifespan and design in many parts of the world. In addition, these infrastructures are subjected to excessive 'wear and tear' from rising water demand, increasing frequency of flooding from urbanization or human encroachment of water bodies. Such water infrastructures, by virtue of their service to society, are also directly or indirectly responsible for changes to the surrounding landscape. For example, a newly built water supply distribution system favors a faster growth rate of urban development which then leads to landscape transforming to one that is more impervious. The body of knowledge accumulated by the atmospheric science community since the early 1970s informs us that changes in extreme weather and climate can be a direct product of such landscape modification. Thus, the issue of infrastructure resilience becomes directly relevant as large infrastructures are usually designed to handle 'worst-case' or extreme weather and climate scenarios in mind. For a sample of the cumulative body of work on effects of landscape change on extreme weather and climate, the reader is referred to Cotton and Pielke (2007) and Pielke et al. (2011).

The commonly observed landscape changes around water infrastructures also interact with other local, regional, hemispheric, and global-scale atmospheric forcings and can often alter the future behavior of extreme events to an amplitude or phase-space not recorded before or during the design phase of the infrastructure. According to the Clausius–Clapeyron relationship, the water holding capacity of air increases approximately 7% per 1 °C warming (at 288 K). In the USA, the increase in water holding capacity is already evident from recorded increases in dew point temperatures over the last 40 years (Robinson 2000). If such a trend continues, then it implies that future extreme storms would occur under conditions of increased available moisture, which can result in potentially higher intensities and higher frequency of occurrence of extreme precipitation events (Kunkel et al. 2013; Trenberth 2011). It should be noted, however, that observational studies of water vapor do not yet indicate a consistent trend on water vapor (Wang et al. 2008; Vonder Haar et al. 2012).

Future resilience of water infrastructure is dictated by the future behavior of extreme patterns of weather and climate, and because wear and tear are a constant stressor magnified by the increasing demand for or damage from water. It is therefore important for the engineering community to recognize these local-to-regional drivers of landscape change for a more robust assessment of resilience. While there is a broader and complex impact of such landscape change,

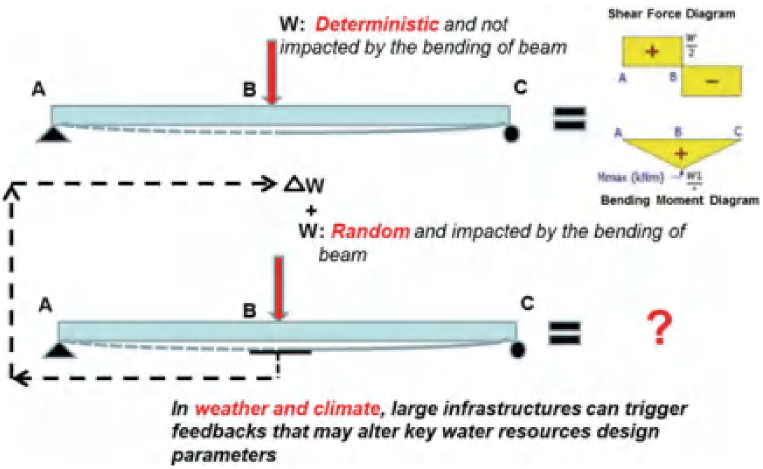

Fig. 1.2 Beam loading example to demonstrate the potential impact of a local random perturbation to a deterministic load in which the perturbation is triggered by the bending of the beam; the upper panel shows the conventional situation where it is assumed that W is a deterministic variable, whereas the lower panel shows that W is now a random (stochastic or deterministic) variable due to ΔW load added through a feedback mechanism triggered when a certain amount of bending has occurred

it is the local effect (or local perturbation) that is important for understanding vulnerability or resilience of water infrastructure. Many such local effects may warrant a 'relook' of parameters and factors of safety for which an infrastructure is designed or operated. In this report, the local effects are referred to as a 'delta x' type perturbation and a random function. The important question to ask the engineering community now is whether this delta x is large enough to require a wholesale reassessment of infrastructure resilience.

This concept can be demonstrated through a classic beam loading scenario, where the standard shear force and bending moment diagram need to be derived for a known deterministic load W (Fig. 1.2). If the load is perturbed randomly by ΔW due to the bending of the beam itself, then the derivation of the shear force and bending moment diagrams become a non-trivial process. The ΔW variable could also be represented as a chaotic variable due to the nonlinearity of the land-atmosphere feedbacks, as demonstrated in Zeng et al. (1993). Thus, ΔW may not be a random (stochastic) effect but a result of deterministic chaos (i.e., deterministic random variable), which consequentially may make the problem of deriving the shear force and bending moment diagrams with the ΔW feedback all the more tractable. Today, in conventional engineering practice, future design or operations changing impacts directly triggered by the infrastructure itself are not addressed proactively to estimate such local perturbations. Thus, it is now imperative to understand the importance (or the lack of) of such local perturbations triggered by local-regional landscape change on the land-atmosphere system.

This chapter does not strive to seek consensus on any particular view or recommend a universal design/operations strategy for improving resilience. It does not claim to present the most comprehensive and up-to-date synopsis of knowledge on the topic available today. Rather, the key goal is to lay out the diverse perspectives and findings on the impact of landscape change that have potential implications for our current and future water infrastructure. Hereafter, we will use the term 'climate' as the statistics of weather events over historical (i.e., already occurred) multi-decadal time periods, wherein the actual weather event in the future will dictate resilience.

Why Is Landscape Change Important?

Pielke et al. (2011) summarize where the world currently appears to stand (as of 2011) in giving landscape drivers its due recognition for climate as follows:

> A great deal of attention is devoted to changes in atmospheric composition and the associated regional responses. Less attention is given to the direct influence by human activity on regional climate caused by modification of the atmosphere's lower boundary—the Earth's surface.

This perspective has not changed as of 2013 (Mahmood et al. 2013). According to Forster et al. (2007), the direct radiative impact of global landscape change since the industrial revolution has been a reduction in the amount 0.2 ± 0.2 W m^{-2}. Being a relatively smaller number (compared to the radiative forcing from greenhouse gas emissions which is an order higher), Pielke et al. (2011) and many others (such as Narisma and Pitman 2006; Pitman 2003) have suggested that this is why landscape change is mostly omitted from the climate models used in previous Intergovernmental Panel on Climate Change (IPCC) reports up until the fourth Assessment Report (AR4). Yet this omission is a mistake as weather events that are hydrologically important result from regional and local atmospheric circulation features and are little, if at all, affected by global average forcings. More importantly, there is a local perturbation of significance to the infrastructure (as will be elaborated next from published literature). An unexpected casualty of this historical omission has been that the engineering profession was deprived of additional 'calculations' as more reliable alternatives to highly uncertain and model-based climate change impacts that are predicted from global climate models (GCMs). As an example of the current limitations of the GCMs, Stephens et al. (2010) concluded that 'models produce precipitation approximately twice as often as that observed and make rainfall far too lightly…. The differences in the character of model precipitation are systemic and have a number of important implications for modeling the coupled Earth system…little skill in precipitation [is] calculated at individual grid points, and thus applications involving downscaling of grid point precipitation to yet even finer-scale resolution has little foundation and relevance to the real Earth system.'

The interactions between local-to-regional drivers of climate (such as landscape change) with hemispheric or planetary forcings (such as rising greenhouse gas emissions and other changes in atmospheric composition) have also not received the attention they should have. Another reason often cited for this is that the impact of planetary-scale greenhouse gas emissions is consistently unidirectional (i.e., an increase in positive radiative forcing) while the role of landscape change can result in both cooling and warming depending on other ambient conditions of the region. For example, Narisma and Pitman (2006) explored the relative role of land-cover change in the context of increasing greenhouse gas concentrations and warming for the Australian climate. Their study clearly showed the interaction of the unidirectional warming with bidirectional landscape change wherein reforestation resulted in a 40% reduction in temperature increases while deforestation had the effect of amplifying warming. These interactions were found to be highly localized. There appears to have been little research reported until 2011 on local-regional landscape interactions with global forcings with a view to guiding the engineering community for improving infrastructure resilience against future change in extreme weather.

The more localized and variable sensitivity of landscape change to extreme weather should be a strong reason why engineers need to be aware this landscape change is an additional driver. Engineering practice concerning design and operations is never geographically universal. One size does not fit all. Infrastructure has variable factors of safety that are driven by the ambient environmental risks, which are spatially variable. A perfect example of this can be found in reservoir sizing. The dust bowl of the 1930s and the ensuing high rates of soil erosion led to a necessary oversizing of reservoirs built in the 1940s in the Great Plains and Midwestern United States. Another appropriate example of how engineering practice has inadvertently accepted the variable response of landscape to extreme weather is ‘Probable Maximum Precipitation’ (or PMP). According to the American Meteorological Society (AMS 1959), PMP, which is a design parameter for storm and flood drainage infrastructure, is defined as, ‘the theoretically greatest depth of precipitation for a given duration that is physically possible over a particular drainage area.’ [Note: PMP is visited in Chaps. 5 and 6 of this book].

In the USA, the currently practiced PMP values reported in Hydrometeorological Reports (HMRs) are derived from maximum persisting humidity records for storms east of the 105th meridian or from sea surface temperature (SST) for storms west of the 105th meridian (Stratz and Hossain 2014). The argument for this differential approach has been that storms on the west coast are due to large synoptic-scale moisture originating in the Pacific Ocean and thus they are not as sensitive to landscape change effects as heavy storms in the Southeast or Eastern seaboard. Overall, the TC suggests that the impacts of landscape change on extreme weather should be considered with other issues that are currently in front of the engineering profession. The civil engineering community is not yet effectively harnessing the vast body of knowledge that has accumulated in the field of local-to-regional drivers of extreme weather and climate. This is despite the fact that the first field campaign to study the impact of urbanization on weather occurred in the 1970s in St. Louis (MO) called METROMEX (Chagnon 1979). A rich history of observational and modeling studies that followed METROMEX over the last three decades have reported a wide array of attributable impacts of land-use change, such as increasing precipitation intensity (e.g., Barnston and Schickedanz 1984; Shepherd et al. 2002, 2010), frequency of convective storms (e.g., Pielke and Avissar 1990; Taylor 2010), and tornado activity around urban areas (Kellner and Niyogi 2013).

For example, recent research using mesoscale numerical models has shown that PMP, which is a legally mandated design parameter in the USA for high hazard dams (those upstream of a population center), can vary in the range of 2–7% due to post-dam changes to landscape such as irrigation and urbanization (Woldemichael et al. 2012). Such studies also report that the nature of change is dependent on the surrounding terrain and underlying moisture convergence conditions (leeward or windward side of orographic mountains) and geographic location (Woldemichael et al. 2014). Beauchamp et al. (2013) hypothesized a 6% increase in PMP values by 2070 from projected increases in atmospheric humidity based on simulations by a GCM for a local watershed in Canada. Several global climate models (GCMs) forecast a 20–30% increase by 2100 A.D. in maximum precipitable water due to greenhouse gas emissions (Kunkel et al. 2013).

Landscape changes have also been known to alter Probable Maximum Flood (PMF) not just through increased runoff due to reduced infiltration, but also via the atmospheric pathway of PMP changes. In the ‘Design of Small Dam’ manual produced by the U.S. Bureau of Reclamation (USBR), the case of a Texas reservoir that experienced eight times the design PMF inflow due to rapid urbanization effects is a well-known example to engineers of the non-atmospheric effects of landscape change on water infrastructure resilience (USBR 1987). Recent research now indicates that the terrestrial hydrologic effects can be compounded by PMP modifications through land-atmosphere feedbacks. A recent study on the American River in California and Folsom Dam by Yigzaw et al. (2013) reports the need to estimate and perhaps account for future land-cover changes upfront during the dam design and operation formulation phase by considering the gradual climatic effects on PMF via PMP modification. This compounding effect can also manifest in sedimentation rates. Soil erosion, which is usually dictated by rainfall intensity as well as landscape change, results in reservoir sedimentation through inflow and a gradual loss of reservoir storage. With changing patterns of extreme precipitation through landscape change, the engineering community needs to understand how reservoir storage would be impacted to address the multiple objectives (such as flood control, water supply, and hydropower).

Another implication for infrastructure resilience is on land-use zoning for placement of critical infrastructure. Many, if not all, of the most critical infrastructures (such as large schools, hospitals, waste treatment facilities, nuclear power plants) for society are often placed outside the PMF floodplain. The PMF floodplain has historically been treated as an ‘absolute’ boundary in land-use planning (Fig. 1.3). If this PMF floodplain is deemed no longer absolute and can potentially encroach on the previously designated safe zone for critical infrastructures, then the quantification of future risks associated with a changing PMF via PMP and landscape change becomes urgent.

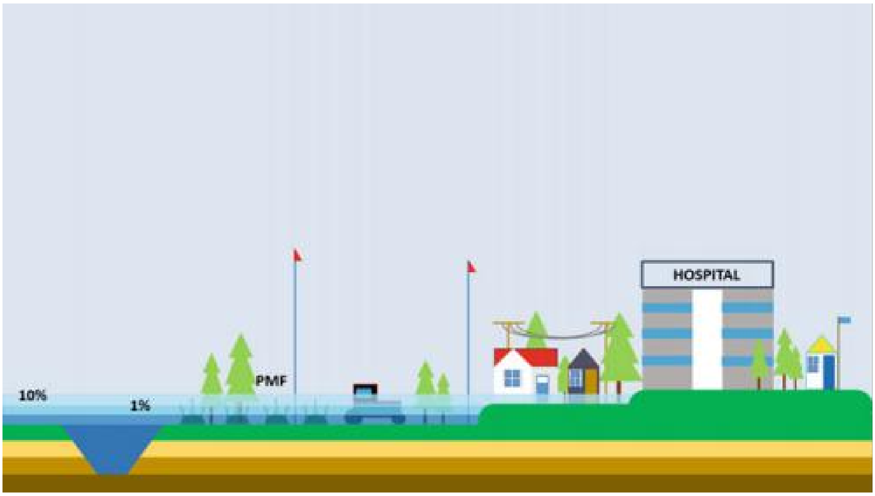

Fig. 1.3 Floodplain zone for a 10-year flood, 100-year flood, and PMF; critical infrastructure is usually placed outside the boundaries of the PMF floodplain (recreated from Queensland Government Australia 2011, courtesy of WMAwater)

Engineers need to recognize that there has been massive but gradual redistribution of water through artificial reservoirs, numerous irrigation schemes, land-cover change and urbanization since the early 1900s. Such redistribution has altered the regional and global water cycle with local and regional implications of the change. For example, numerous irrigation schemes have contributed to increased moisture availability and altered atmospheric convergence patterns over land in the USA (Puma and Cook 2010; DeAngelis et al. 2010). The United States Geological Survey (USGS) records (Kenny et al. 2009) indicate an increase in irrigation acreage from 35 million acres (1950) to 65 million acres (in 2005)—enabled through water infrastructure. Similarly, there are about 75,000 artificial reservoirs built in the USA during the last century with a total capacity almost equaling one year's mean runoff (Graf 1999, 2006; GWSP 2008). The cumulative effect of this extensive impoundment has been to triple the average residence time of surface water from 0.1 years (in 1900) to 0.3 years in 2000 (Vorosmarty and Sahagian 2000), an aspect that clearly has not received the attention of the global change community. Additionally, what do these local perturbations to extremes mean for engineers who design and operate infrastructure?

The research findings summarized above clearly exemplify infrastructure-sensitive impacts of landscape change on extreme weather via land-atmosphere feedbacks. A more relevant question for the engineering community now is whether the sensitivity (i.e., the local perturbations or 'delta x' in Fig. 1.2) observed in the landscape's impact on extremes and whether the associated uncertainty is within the margins of safety practiced in the conservative engineering design of very large and high hazard infrastructure.

Definition of Water Infrastructure Resilience

It is important, given the mounting body of research, to propose a definition for 'Infrastructure Resilience' (IR) at the intersection of weather and climate for the engineering community. The definition proposed here is as follows:

> A Weather-Climate Resilient Water Infrastructure is defined as an infrastructure that can to a degree anticipate or adapt and recover from external disruptions due to severe weather and climate and carry on providing the essential services the infrastructure is designed for with managed interruption to non-essential services, while balancing tradeoffs among social (e.g., security), environmental, and economic factors.

The term 'anticipate' in the above definition requires elaboration as it may appear counterintuitive to the engineering community. With the complex land-atmosphere modeling capability that is now available, it is now possible to model the future impact of landscape change on extreme weather likely to be triggered by an infrastructure change. For example, the proposed Grand Renaissance Dam on the Blue Nile in Ethiopia, that is expected to be completed in 2020, will irrigate vast areas of land for agricultural production. Clearly, the expected impact of this irrigation on the local-regional climate can be modeled to consider whether the anticipated local perturbations to extreme weather (during post-dam phase) need to be explicitly addressed in infrastructure design as the dam is being built and later in operations. Such an exercise is akin to a 'life cycle' assessment and, if performed, may make the infrastructure 'anticipate' better the possible future changes to extreme weather.

Herein, a point to keep in mind is the trade-off between the three bottom lines that are currently practiced for sustainability—social, environmental, and economic factors. In the USA, the ongoing failure to adequately address the state of the nation's existing infrastructure makes infrastructure resilience all the more critical for the engineering community. For example, between 1889 and 2006, a total of 1133 US dams were overtopped, according to a database maintained by Stanford University's National Performance of Dams Program. Of the structures that were overtopped, 625 dams, or roughly 55 percent, experienced a hydrologic performance failure triggered by extreme weather events that the dam spillways or downstream levees could not handle. A challenge now is to find smart ways to address the trillions of dollar needed to rehabilitate infrastructure across the nation. One smart, cost-effective approach entails understanding the future resilience of infrastructure and developing procedures for adapting infrastructure so as to manage expected risks. In other words, the traditional notion of demolishing existing infrastructure and rebuilding it as necessary is not an option. For example, this approach relies on uninterrupted economic growth and abundant resources, an outcome that cannot always be counted on. Meanwhile, cement production's global contribution to greenhouse gas emissions cannot be ignored.

While making the present infrastructure stronger and bigger may be appropriate in some cases, there will be situations where it may mean abandoning existing solutions and considering others that are less expensive with similar results.

Infrastructure resilience must weigh affordability in selecting infrastructure solutions against structural resilience. It may be that in order to build infrastructure that is financially feasible and create neighborhoods that are affordable, engineers may have to design infrastructure that can fail safely rather than to expend a greater amount of funds to withstand the changing patterns of extreme weather. Engineers may also find that 'natural' solutions are more affordable over solutions that demand excessive construction interventions, for instance by exploring natural water storage systems over manmade reservoirs, etc.

Key Landscape Drivers of Importance

It is worthwhile at this stage to itemize the various landscape drivers referred to earlier that have implications for infrastructure resilience. The list provided below is by no means exhaustive but highlights the landscape changes most commonly known to impact extreme weather and climate.

(1) Irrigation and crop production resulting in altered surface temperature and humidity, moisture flux, and precipitation patterns.
(2) Urbanization and urban heat islands (concretization, upward expansion, and densification leading to change in albedo, turbulence, and convergence patterns) resulting in precipitation anomalies over and downwind regions of cities.
(3) Urban Archipelago (note—this is a newer concept that has emerged from the concept of large cities joining through corridors to alter the regional dynamics of extreme weather and climate).
(4) Deforestation and forest fire impacts (which also impact soil erosion, landslides, and infiltration rates).
(5) Afforestation resulting in altered infiltration and moisture fluxes.
(6) Overgrazing and desertification resulting in drought and altered local climate.
(7) Dryland farming.
(8) Industrialization (aerosols/air quality impacting cloud condensation nuclei) resulting often in altered precipitation rates and the ability of clouds to precipitate.
(9) Reservoir creation (upstream of dams) resulting in lake effect rain, snow and fog, and altered evaporation and precipitation rates in adjacent lands.
(10) Wetland shrinkage (downstream or upstream of dams; tragedy of commons or urban encroachment).
(11) Emissions (carbon dioxide, nitrogen deposition impacts water quality for water infrastructure systems).

As noted earlier, the above landscape drivers are compounded by the hemispheric or planetary forcings of climate and weather. At this stage, it appears that much less is known about the compounding factors due to the historical focus mostly on global atmospheric composition changes and the effect on the global average temperatures. The list below itemizes a few potentially compounding factors that the engineering community would benefit from knowing, particularly for water management.

(1) Salinity of stream flow reaching the ocean. Due to increasing withdrawal, diversion, and redistribution of water in infrastructure systems from the natural pathways, freshwater flux to the ocean is likely to become increasingly saline. This trend can have significant impact on ocean circulation which in turn impacts climate.
(2) Location/terrain (Woldemichael et al. 2014; Kunstmann and Knoche 2011; Mahmood et al. 2010).
(3) Large-scale regulation, inter-basin transfers and redistribution (replumbing) of watersheds through inter-connected water infrastructure systems (e.g., this topic is recently coined as 'hydromorphology' by Vogel 2011).
(4) Season/climate type (Mahmood et al. 2010; Pielke et al. 2011).
(5) Synoptic-scale moisture convergence pattern (e.g., the Asian Monsoon has been reported to mask any local-to-regional-scale impact of Three Gorges Dam on heavy precipitation patterns—see Zhao and Shepherd 2011).

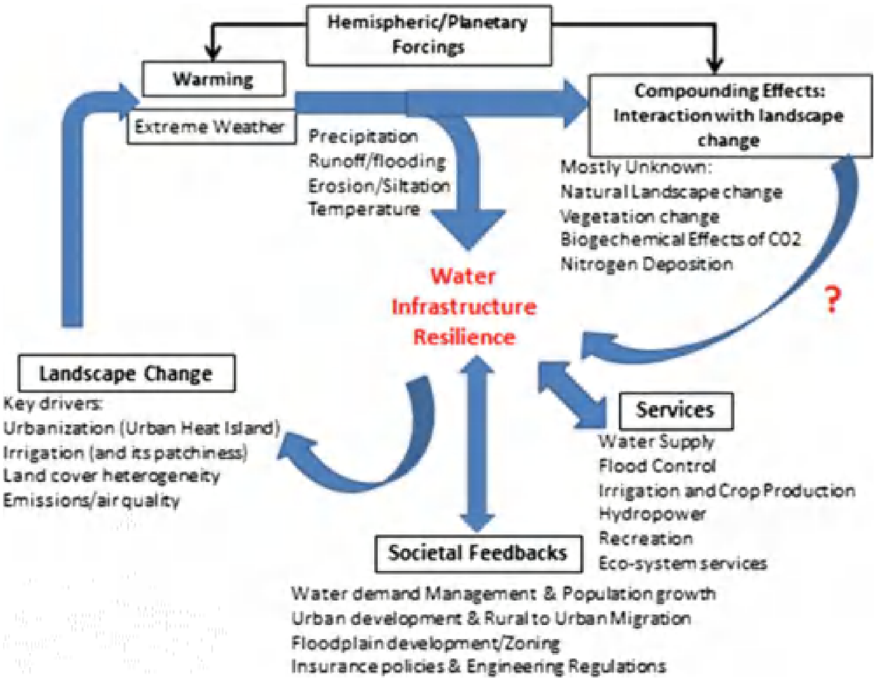

Fig. 1.4 Schematic of landscape change drivers on extreme weather and climate and their compounding effect in the context of societal feedbacks and services

(6) Dew point temperature trends (e.g., a study by Robinson (2000) indicate average dew point has risen 1 degree over the last 40 years in most parts of the USA) and some, or even all of this, could be due to landscape conversion (e.g., see Fall et al. 2009).
(7) The biogeochemical effects of added CO_2 (as well as its radiative forcing) and nitrogen deposition (Galloway et al. 2004).

To put the landscape drivers and their potential compounding effect in the context of infrastructure resilience, societal feedbacks, and essential services, the TC proposes the following schematic (Fig. 1.4) as a platform for considering the ‘additional calculations’ for the engineering community.

Integrating Landscape Change in Current Engineering Practice

The engineering profession can still benefit from a few suggestions on how the ‘additional calculations’ from landscape drivers might be addressed in current engineering practice for improving infrastructure resilience.

The first suggestion pertains to an extensive use of historical observations on weather events and extreme climate spanning the pre- and post-construction phase of large water infrastructure projects. In the developed world such as the USA and Europe, such data is available. Therefore, engineers are uniquely positioned to perform data-based observational studies (or hypothesis testing) of the statistical difference in extreme weather and climate processes due to infrastructure-triggered changes in landscape. Examples of such observational studies may be found for the case of large dams of the world in Hossain (2010) and Hossain et al. (2010). Degu et al. (2011) and Degu and Hossain (2012) provide an observational study of 92 large dams in the USA by observing the statistical difference in atmospheric proxies for heavy storms (e.g., Convective Available Potential Energy (CAPE), precipitation intensity and frequency downwind and upwind of reservoirs). Pizarro et al. (2012) reported that the inland water bodies of Chile may have intensified precipitation at higher elevations. For sedimentation effects, Graf et al. (2010) provide a comprehensive synopsis of how the large dams in the Western United States have lost storage.

The use of satellite remote sensing appears to have considerable potential in regions lacking in situ measurements as demonstrated by a recent study by Taylor (2010) over the Niger Delta. Although not directly related to infrastructure issues, Taylor (2010) reported that the 24 years of cloud imagery from satellites indicates the favoring of convection when the inner delta is inundated (which has implications to regional water supply and upstream dam operations for the riparian nations of Senegal, Nigeria, and Mali). It should be noted that most current methods today focus on using historical data to define design criteria. The focus on trend detection or discrete shifts is not new but needs more attention by the engineering community.

The next suggestion for the engineering community is to explicitly embrace high-resolution numerical models that can model land-atmosphere processes and feedbacks due to landscape changes down to the mesoscale (* 500 m, hourly). Models widely used today such as the Weather Research and Forecasting (WRF) model and the Regional Atmospheric Modeling System (RAMS; Pielke 1992) are some examples that have seen use in this regard. For example, Georgescu et al. (2014) have looked into the effect of albedo changes (through artificial whitening of the urban canopy) on the heat signature in major cities of the USA using WRF. Burian (2006) reported on how urbanization impacts of rainfall can impact a city's storm drainage infrastructure. Kunstmann and Knoche (2011) applied a numerical model to track the precipitation recycling effects for Lake Volta Dam in Ghana. A series of studies reported in Woldemichael et al. (2012, 2014), Ohara et al. (2011), Tan (2010), and Yigzaw et al. (2012, 2013) provide examples on the use of atmospheric models for estimation of PMP and a hydrologic model (Variable Infiltration Capacity—VIC; Liang et al. 1994) for deriving the consequential PMFs for modeling the resilience of large dams in the Western United States.

Another suggestion is to partially modify standard engineering practice that allows a 'swapping' with more recent climate-driven data or methods (Rakhecha et al. 1999). A good example of this is the HMR approach to estimating PMP (Schreiner and Riedel 1978). The HMR approach is a relatively straightforward and linear method based on using a historical storm and maximizing it according to the ratio of historical maximum precipitable water to the storm precipitable water (Rakhecha and Singh 2009). The engineering assumptions behind this HMR approach are: (1) the precipitation is linearly related to the precipitable water; (2) the precipitation efficiency of the storm does not change as the moisture available to the storm increases; and (3) terrain modulates the distribution of the precipitation but does not affect the synoptic-scale dynamics of the storm. Abbs (1999) has investigated the validity of these assumptions and has identified possible reasons why certain accepted PMP values have been exceeded by recently observed extreme storm events (such as the 1996 flood in Sydney, Australia). Thus, such standard procedures can be easily modified where the precipitable water data can be extracted from more climate-informed approaches (based on newer observations or models). Stratz and Hossain (2014) have demonstrated this approach in two ways: (1) using RAMS-derived humidity profiles to 'update' HMR PMP, and (2) using Robinson (2000) data on dew point temperature trends over the last 40 years to project future HMR PMP. In both cases, considerable changes to PMP were found. In Chap. 6, we revisit these issues and provide more concrete examples of updating numeric design parameters for improving resilience.

Currently, engineering risk assessment is already practiced from a multi-criteria decision-making approach that includes sustainability metrics. This approach, known as the triple bottom line (TBL), usually includes socioeconomic, social, and environmental components, and is standardized by the U.S. Army Corps of Engineers (USACE) and USBR (Kalyanapu et al. 2011), to identify balanced alternatives. The TBL is therefore an ideal framework to add the impact of ‘additional calculations’ (such as from landscape change). Applying the TBL framework that also includes the local perturbations expected from land-atmosphere feedback effects should yield more resilient alternatives (as an adaptation policy) for water infrastructures in terms of not only the economic benefits (e.g., damage reduction), but also societal benefits (e.g., realistic perception of flood risk, increase in land value, and improved health) and environmental benefits (e.g., minimal disruption of riparian ecology, water quality, and natural conditions).

The Road Ahead

This chapter explored the importance of the well-established feedbacks triggered by infrastructure systems to the land-atmosphere system. Such feedbacks and the consequential implications serve as ‘additional calculations’ for water management decision-making related to infrastructure management, design, and operations. The chapter has shed light on the findings of the initial round of dialogue initiated to understand various issues in its first year. A definition for Infrastructure Resilience (IR) at the intersection of extreme weather and climate has been proposed for the engineering community. By providing a broader range of views and issues than what is currently in the front view mirror of engineering practice, a higher level of empowerment can be achieved by the engineering community by affording a greater number of ‘calculations’ in its decision-making.

Although the chapter hasn’t striven to seek consensus on any particular view or recommend a particular design/operations strategy for improving resilience, there are several open issues that require work in the near future. For example, it is not entirely clear how best to impact engineering practice directly through the research that appears well established on land-atmosphere feedbacks triggered by infrastructure systems. Some examples related to adjusting PMP and PMF as wholly new (model-based) or modified current practices have appeared in recent literature. Although many of the issues are addressed in greater detail in Chaps. 5 and 6, more work is required in this area and for exploring acceptance as the field of engineering practice for design/operations/risk assessment is much broader (e.g., Intensity Duration Frequency—IDF, curves; return periods, flood frequency, design storm, envelope curves, etc.).

On the curricular side, one specific suggestion is that the civil engineering profession represented by the American Society of Civil Engineers (ASCE) and ABET include adequate provisions during the freshman and sophomore years for prerequisite courses on climate, atmospheric science, and the role played by human activity such as infrastructure building. Currently, most four-year civil engineering programs require a certain number of credit hours on general education and humanities. A discussion is now needed as to how much of that requirement can be modified to include climate feedback-based provisions so that a civil engineer is aware of the climate implications of the infrastructure that he/she will be involved with. To maximize the success of such a curriculum change, it is perhaps equally important to ensure that new courses are taught in a way where the science of climate and the atmosphere can be related directly to the real-world infrastructure activities that students will be engaged in later as professional engineers.

Another precursor to devising effective ways to impact current engineering practice is to first identify knowledge gaps on landscape change that currently prevent the engineering community from formulating practical solutions to more resilient water infrastructure building or management. For example, the interaction at regional to global scales with atmospheric composition (a planetary forcing) is not sufficiently well known. Also, GCMs do not provide the skill required at the spatial scale that impacts engineering practices at the infrastructure scale. Thus, such gaps need to be identified and recommended as new research areas. A key focus should be to understand the predictive uncertainty of changes to weather and climate, and the implications of this uncertainty on infrastructure design and operations. This first chapter hopes to work on these important issues and provide further reports as updates in the coming years for the engineering community.

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Chapter 2
Survey of Water Managers for Twenty-First Century Challenges

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Introduction

This chapter presents the survey results from a cross section of experienced water managers using a set of carefully crafted questions. These questions covered water resources management, infrastructure resiliency, and recommendations for inclusion in education and curriculum. The chapter describes the specifics of the survey and the results obtained in the form of statistical averages on the 'perception' of these managers. Finally, these 'perception' averages may help focus the ASCE community on issues required for stewardship of the civil engineering profession. The survey and the responses gathered are not exhaustive nor do they represent the

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ASCE-endorsed viewpoint. However, the survey provides a critical first step in developing the framework of a research and education plan for ASCE. Given the Water Resources Reform and Development Act passed in 2014, the engineering community should now take into account the perceived concerns of the water management community (Hossain et al. 2015).

The Need to Survey Water Managers

In an effort to further the upkeep of water infrastructure for more robust management, a key aspect that often gets ignored is 'what do experienced water managers think of changing water resource patterns?' We have already witnessed many scientific studies at local-regional-global scales on recorded and predicted patterns of water resources in the last and current century. For example, studies by Vorosmarty and Sahagian (2000) have quantified the impact of water regulation on surface water residence time in impounded river basins. Vorosmarty et al. (2010) have also explored how water resources availability during current and future scenarios may evolve under the pressures of population growth when juxtaposed with projected climate change. Their studies make a profound conclusion, which is '(When) climate change is superimposed on the complex hydrologic landscape, its signal is difficult to isolate and its influence felt throughout the water supply, demand, and buffering system' (Vorosmarty et al. 2010).

Zarfl et al. (2014) documented plans that many nations have undertaken in building hydropower dams while others like Grill et al. (2015) explored the impact of current and future water regulation on ecosystem function. These studies provide

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little insight on the perceptions of experienced managers at water installations regarding the state of current and future water resources. It is important here into stress the keyword ‘perception’—which is a qualitative yet insightful measure if used judiciously. A qualitative measure does not provide the quantitative rigor needed for the foundations of an engineering design or practice. However, understanding the ‘perception’ of experienced water managers and practitioners with decades of water infrastructure management experience can expose issues that need prioritizing. This is especially important given the ‘Water Resources Reform and Development Act’ (WRRDA) that was passed in 2014 by the United States Congress. While the 2014 Act is quite comprehensive, WRRDA has several aspects that are worth addressing for the engineering community. For example, regarding ‘River Basins and Coasts areas,’ a section of WRRDA reads:

> (Sec. 4002) Directs the Secretary of the Army, in consultation with specified federal officials, to improve forecasting on the Mississippi River by: (1) updating forecasting techno logy deployed on the Mississippi River and its tributaries, (2) constructing additional sedimentation ranges on the River, and (3) deploying additional automatic identification system base stations at river gage sites. Requires the Secretary to report to Congress on activities to improve forecasting and make such report publicly available.

Similarly on the topic of ‘Water Resources Infrastructure’ of WRRDA, the following is stated:

> (Sec. 7002) Authorizes the Secretary to carry out final feasibility studies with respect to: (1) navigation in Louisiana, Florida, Georgia, Massachusetts, and Texas; (2) flood risk management in California, Kansas, Kentucky, Iowa, Minnesota, Missouri, Nevada, and North Dakota; (3) hurricane and storm damage risk reduction in California, Florida, Louisiana, and North Carolina; (4) hurricane and storm damage risk reduction and environmental restoration in Mississippi; and (5) environmental restoration in Florida, Louisiana, Maryland, Minnesota, North Carolina, Oregon, and Virginia.

In this chapter, results of the ASCE TC’s survey of a cross section of experienced water managers are presented using a set of carefully crafted questions. These questions covered water resources management, infrastructure resiliency, and recommendations for inclusion in education and curriculum. The survey plan was reviewed and approved by an institutional review board of the American Society of Civil Engineers (ASCE) before the study began. This chapter describes the specifics of the survey and the results obtained in the form of statistical averages on the ‘perception’ of these managers.

Methodology Used for the Survey

Thirteen key questions were crafted through iterative discussions by the ASCE TC (see Chap. 1 for details of the TC). It was felt that a short survey would be appropriate and encourage a quick response. Most of the questions were designed as multiple choice with the exception of a few that allowed respondents to provide their feedback. Below we outline the questions with multiple choices. Appendix at the end of this chapter provides the detailed results of each of these 13 questions. The survey was conducted on www.surveymonkey.com using an ASCE account under the Water Management Technical Council (WMTC). When respondents were sent the link for the survey, they were greeted with an introductory note that explained how the survey results would be used for providing stewardship for the civil engineering profession. This accompanying preamble read as follows:

> This survey is being carried out under the auspices of the American Society of Civil Engineers (ASCE) by the ASCE Task Committee titled "Infrastructure Impacts of Landscape-Driven Weather Change" under the Watershed Management Technical Council (WMTC). The goal of this survey is to poll practitioners and water managers who have been responsible for the management of water resources and infrastructure over a considerable period of time. The survey aims to elicit input on the key issues of observed change in and perception of the distribution of water as a resource due to its management that need to be addressed for future policy and planning in the 21st century. The data gathered from this survey will initiate a dialogue among various stakeholders (academia, legislative bodies, practitioners and public) that is needed to ensure alignment of goals and ensure a more sustainable and resilient water management infrastructure. The data gathered will also guide the ASCE Task Committee on the future work that needs to be carried out to further the understanding of water infrastructure impacts of landscape-driven weather change. This issue has traditionally not been at the forefront of engineering practice. Thus, completion of the survey will provide strategic guidance to help the committee produce publications, reports, webinars and guiding documents for positively impacting the engineering practice for future generations.

Question 1: Over the last few decades, what would you rate as the most significant change in the distribution of water resources (surface or ground) in the area in which you have managed or worked?

(a) Change in magnitude of extremes (low flows or high flows)?
(b) Change in frequency of extremes (low flows or high flows)?
(c) Temporal trend in extremes (declining or rising trend)?
(d) Change in variability (compared to mean flow)?
(e) Other (elaborate in a few words below)

Upload your document (optional).

Question 2: In your opinion, what are the likely external drivers of change in the distribution of water resources that you indicated in Question 1? [Note: You may select more than one.]

(a) None. It's all within the natural range of variability
(b) Terrestrial—Land-use/land-cover (landscape) change resulting in change in infiltration patterns (e.g., increasing imperviousness)
(c) Terrestrial—land-atmosphere feedbacks [landscape driven changes in weather and climate]
(d) Atmospheric—Changing weather patterns from natural and/or human effects

(e) Engineering—Human management and redistribution of water resources (e.g., diversions, impoundments, irrigation projects; inter-basin transfer; inadequate storm water management)
(f) Other—please name it below

Upload your document (optional).

Question 3: If you selected more than one answer in Question 1, please rank your responses from most significant to least significant (for example, b, d, e).

Question 4: Do you feel the water quality of water resources (e.g., both surface and ground) has experienced any significant change over the last few decades due to landscape change?

(a) Yes
(b) No

Question 5: If you answered yes to Question 4, what do you believe could be the key reason for the change in water quality?

(a) Non-point source pollution (e.g., fertilizer application; agricultural practice; industrial waste)
(b) Urbanization
(c) Atmospheric processes (e.g., acidification; aerosol)
(d) Other—please name it below

Upload your document (optional).

Question 6: What are the most concerning implications and impacts of the aforementioned changes on water management and associated infrastructure?
Question 7: Do you feel the conventional techniques and management practices used for managing water resources by large water infrastructures are currently adequate for the twenty-first century?

(a) Yes
(b) No
(c) N/A

Upload your document (optional).

Question 8: If you had to prioritize areas of research required for improving water management using infrastructure for the twenty-first century, what would they be?

(a) Understanding engineering implications on distribution of water resources;
(b) Developing flexible operational procedures for water management;
(c) Conducting risk management and vulnerability assessments for water infrastructure;
(d) Understanding the uncertainty of the role of external drivers (such as climate change);

(e) Other—please elaborate briefly

Upload your document (optional).

Question 9: Please outline briefly any knowledge gaps in external drivers (landscape or weather) that you feel currently prevents the engineering community from formulating practical solutions for more resilient water infrastructure (Note: These gaps may be considered as ‘recommended research areas’).
Question 10: In follow up to Question 9, what specific type of information or assessment do you think is most useful in immediately and positively impacting engineering practices? (Please limit your response to 250 characters).
Question 11: Do you feel the current curriculum in environmental engineering or in the sciences is adequate to inform a graduate (B.S. degree) of the challenges facing water resource management this century?

(a) Yes
(b) No
(c) No opinion

Question 12: If you answered No to Question 11 above, please elaborate briefly on the type of curriculum changes needed (e.g., an undergraduate course on the human impacts of weather/climate, surface hydrology; water management; hydrometeorology; land management).
Question 13 (Last Question!): Please provide some information about your profession:

(a) State or region with which you are most concerned
(b) Affiliation (academia; think tank, federal/state agency, non-profit).

Profile of Respondents

The survey was sent out to 90 potential respondents who met the following qualifiers: (1) operational involvement with water management and/or water infrastructure facility/installation, (2) two or more decades of experience in water management and decision making, (3) practitioner, researcher or academician, or think-tank member. Those surveyed included numerous water facility managers of federally owned facilities as well as city (metro) facilities, state climatologists, and private consulting (for-profit) firms in the water sector. Anonymity was guaranteed. The survey was released on February 5, 2015, and closed after a four-month period punctuated with periodic reminders. After several repeated reminders, 44 respondents provided their responses, which the TC considered adequate as a fair representation of this group. Figure 2.1 summarizes the relative distribution of respondent type by sector, with the majority from federal/state agencies.

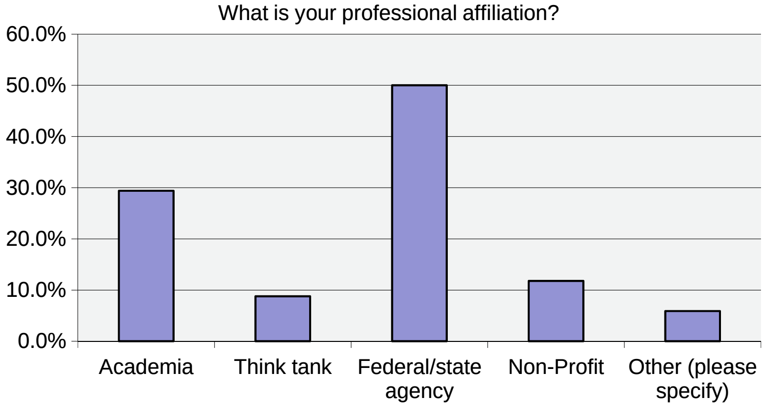

Fig. 2.1 Profile distribution of respondents for the ASCE TC survey on perceptions of water resources

Discussion of Survey Results

On the first question, most respondents opined that change in frequency of low or high flows was becoming more noticeable than the change in flow values per se. Thus, it seems that water managers are feeling the extremely high or low flow values as becoming either more frequent or less frequent than before. One can argue that this may potentially be an effect of increasing regulation, or damming and diversion/withdrawal of freshwater where outflow systems are often operated episodically based on societal demand. The majority of respondents felt the changes are driven by atmospheric drivers (natural and human-modified weather patterns). However, the interesting nuance to this issue (Question 2) is that respondents also believe that landscape change that results in changing infiltration patterns (due to altered perviousness) is another likely driver of the change in water resources patterns. An overwhelming 70% believe that water quality has been impacted over the last few decades just as much as water quantity. This change in water quality is attributed to two dominant drivers—non-point source pollution (41%) and urbanization (27.6%). What is clear from this particular response is that future assessment of water availability should encompass both quality and quantity (flux and volume) metrics in a coordinated manner that is mostly absent today. Without one, the value of the other is harder to define.

There was a broad perspective of the most concerning implications and impacts of the changes on water management and associated infrastructure discussed above. Some of the most unique or common responses are listed below:

1. If more extreme events (major floods our droughts) are becoming more common, our assumptions of stationarity must be replaced with something else that can be easily used/understood by practitioners in the *fi*eld.

2. Lack of regulation on nonpoint source pollution.
3. In the West, land use has a direct impact on water availability.
4. Historical distributions may not be representative of evolving distribution of extreme events.
5. Uncertainty associated with links between urbanization and its impacts.
6. Reduced reliability (due to less certainty @ underlying distribution) of water supplies.
7. Future increases in population will accelerate decrease in quality.
8. Application of nutrients, particularly animal waste on agricultural lands.
9. Rural water (small town) availability from confined aquifers over appropriation of irrigation wells within Natural Resource Districts.
10. First most urban infrastructure is not currently built to treat for all of these contaminants and that coupled with salinity increases will drive the need to build new enhanced treatment facilities that will be very expensive. These newer facilities will in all likelihood also drive an increase in power consumption. Hence urban water rates are going to experience significant increases.
11. Too much emphasis is placed upon short-term (few decades) history, longer-term data (100–150 years) shows wide range of extremes/short-term trends that many scientists seem to be unaware of and have become too dependent upon personal short-term perception and less from the full suite of historical data available.
12. Recognizing the mix between urban and rural pollution sources with the role that urbanization has in these processes.

The key concerns of most water managers appear to be

(a) reduced reliability of water delivery systems;
(b) role of rural systems in relation to ever-expanding and resource-hungry urban systems; and
(c) rising costs for addressing emerging contaminants in water that will make water systems more expensive.

Given these concerns, an overwhelming number (71%) of respondents do not feel that conventional techniques and management practices used for managing water resources are adequate for the twenty-first century (Question 7). As a potential solution, most respondents feel that it is worthwhile to make current operational protocols more flexible (62%) while accounting for the uncertainty in the drivers of change in water resources (41%).

In terms of knowledge gaps that need to be addressed for better management of our water resources and infrastructure (Question 9), key responses included the following:

1. Understanding the range of uncertainty in hydrologic climate change impacts
2. Helping decision makers understand the implications of various solutions, including the do nothing approach.

3. Feedback between land-use changes and atmospheric reactions.
4. The role of land drainage modifications (such as tile drains) on streamflow.
5. Development of improved historical environmental data bases for precipitation, temperature, streamflow, snow cover, etc. Also much better understanding (through field trials, not modeling) of the hydrologic implications of land-use practices (tillage methods, crop types, soil erosion, drainage practices, etc.
6. Impacts from droughts, wildfires, climate change. For example, I′ve seen knowledge gaps in drinking water infrastructure and have become more visible during drought.
7. Need to learn how to take the systems approach better.
8. I think the gaps are in political consensus and political will. The water management community should formulate workable solutions and communicate to increase their practical implement ability.
9. Lack of knowledge about implications of climate change on variability of local-to-regional scale precipitation patterns.

On the question of required changes to undergraduate curriculum for training the future generation, a general sense of ambivalence was noted. More than half of the respondents responded ‘No Opinion’ indicating that most water managers have probably not given much thought to how the higher education model for engineers may need to be adjusted to suit the emerging needs of water management. This perhaps points to the need for greater collaboration between academics and practicing water managers in designing a use-inspired curriculum that addresses new challenges. Finally, when asked about the region within the USA that respondents were most concerned about for water management, an overwhelming majority cited the Western United States. This endorses the viewpoint that the Western United States is in greater need of adaptive and creative solutions to manage its increasingly scarce water resources than the rest of the country.

Conclusion

It is important to stress that the survey results do not necessarily reflect a view that is endorsed by ASCE or any particular agency. However, the survey of the perceptions of experienced water managers revealed several insights that the engineering community should take heed of as it formulates better management strategies for the twenty-first century. The wide ranging viewpoints provide a catalyst for discussions on stimulating changes. For example, it is clear that little thought has been given on the required academic-practitioner collaboration in developing more use-inspired curriculum for our future engineers who will manage our water infrastructure of tomorrow. Similarly, water quality issues can no longer be treated separately from water resources management issues that focus mostly on quantity. The very essence of a resource implies both quality and quantity; without one the other is quite hard to define. In this regard, the emergence of new contaminants or changes to quality due to varying quantity brought by climate variability such as drought or flood will likely add to the cost of water delivery systems—an issue that is not yet in the limelight. Lastly, engineers concede that understanding the uncertainty brought about by future climate variability on water is a critical knowledge gap hampering effective adaptive practices. Engineers have never avoided uncertainty and have always found a durable way to address it in design and operations. As we try to discover how engineering practices should adapt to make our water infrastructure more resilient, quantification of this future uncertainty will be important.

The survey and the responses gathered are not exhaustive. They provide a critical first step to developing the framework of a research and education plan for ASCE. Given the Water Resources Reform and Development Act passed in 2014, we must now take into account the perceived concerns of the water management community.

Appendix: Survey Results

See Figs. 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, and 2.9.

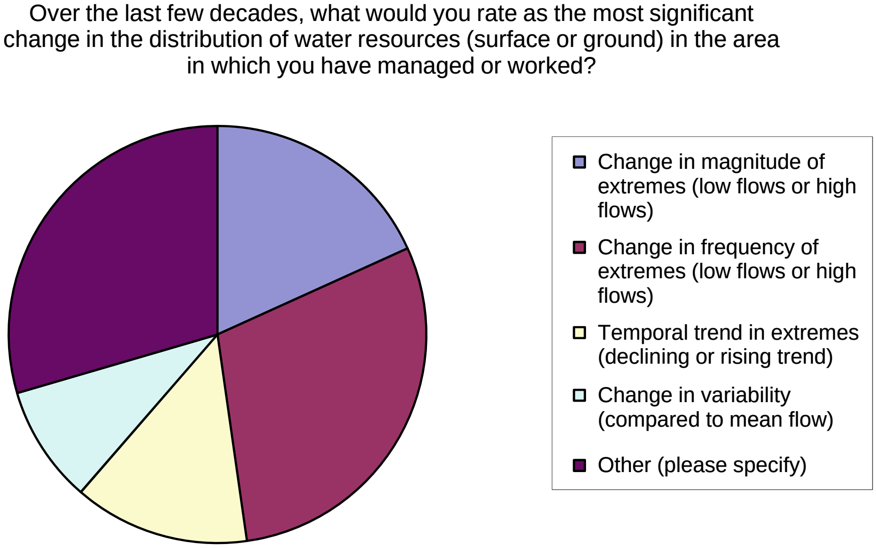

Fig. 2.2 Response to Question 1

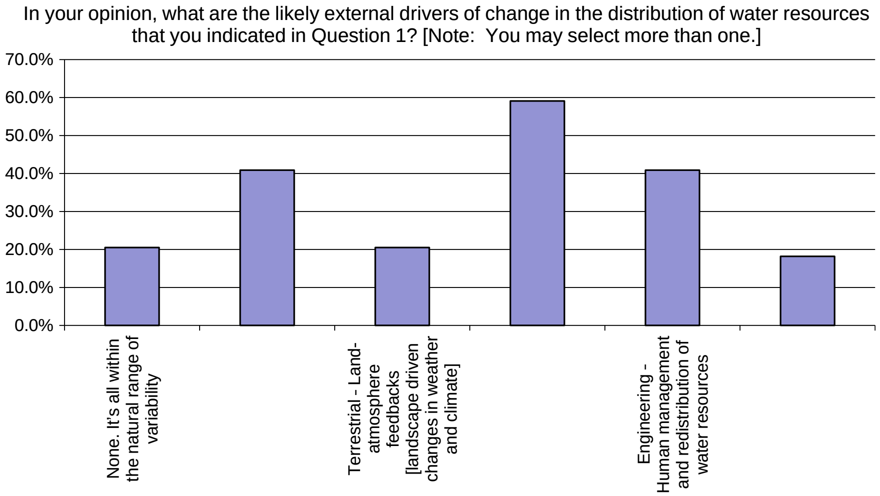

Fig. 2.3 Response to Question 2

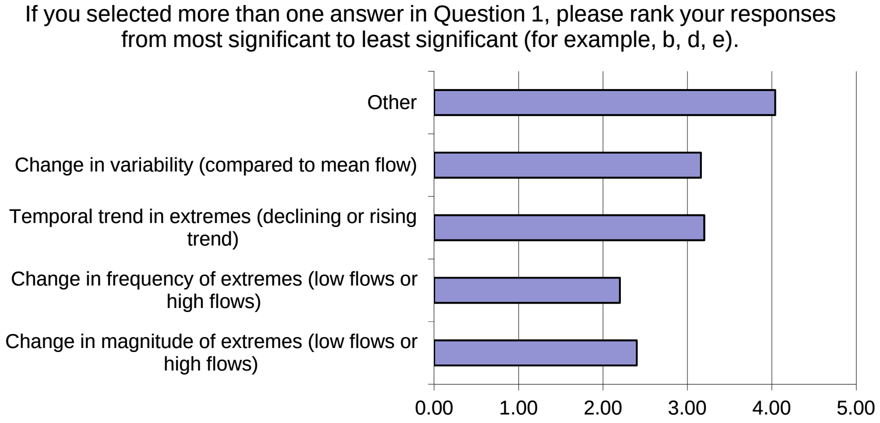

Fig. 2.4 Response to Question 3

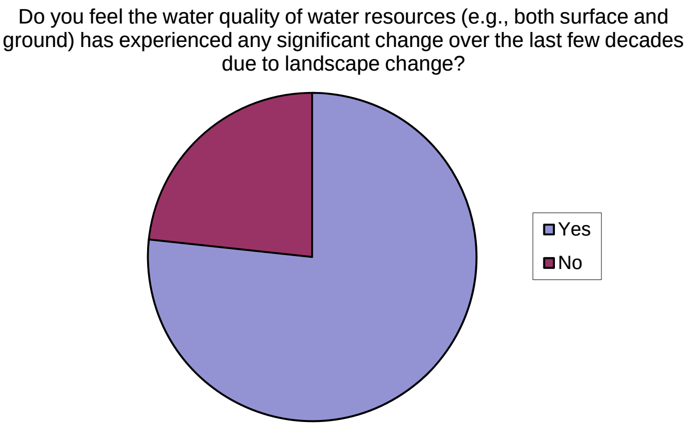

Fig. 2.5 Response to Question 4

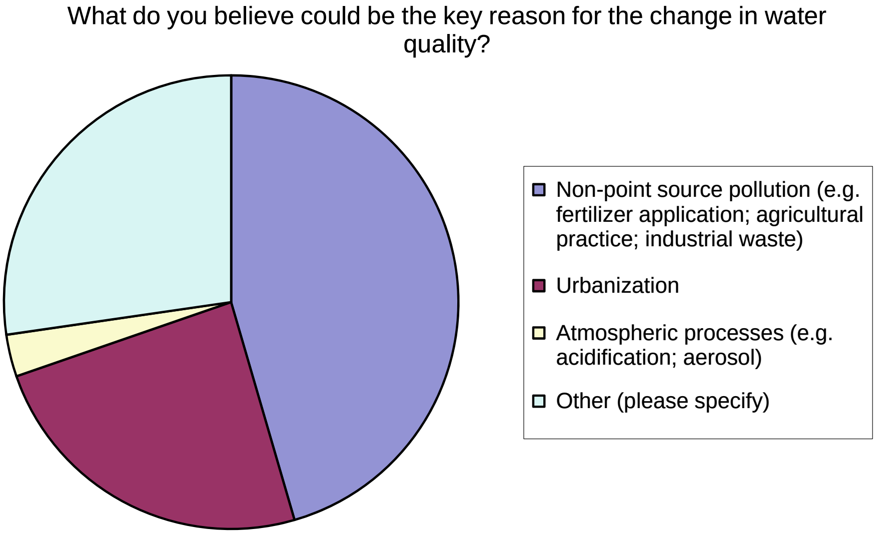

Fig. 2.6 Response to Question 5

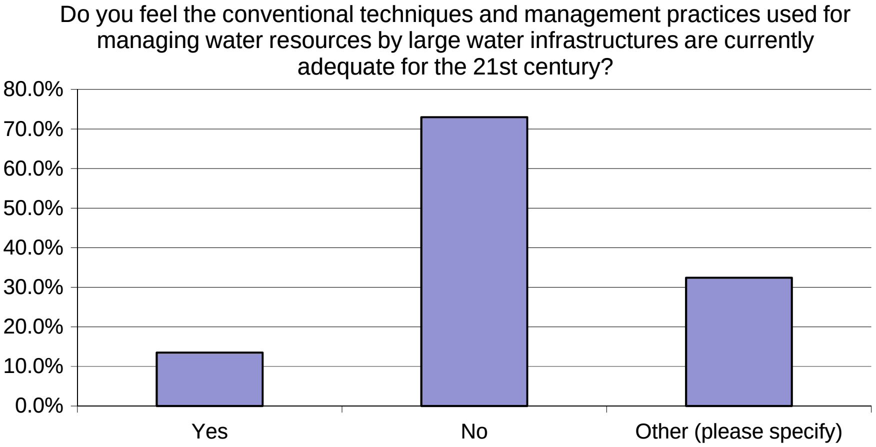

Fig. 2.7 Response to Question 7

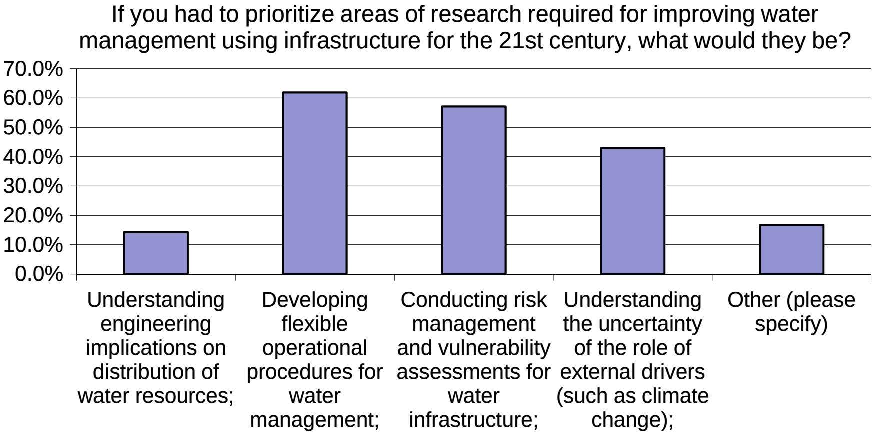

Fig. 2.8 Response to Question 8

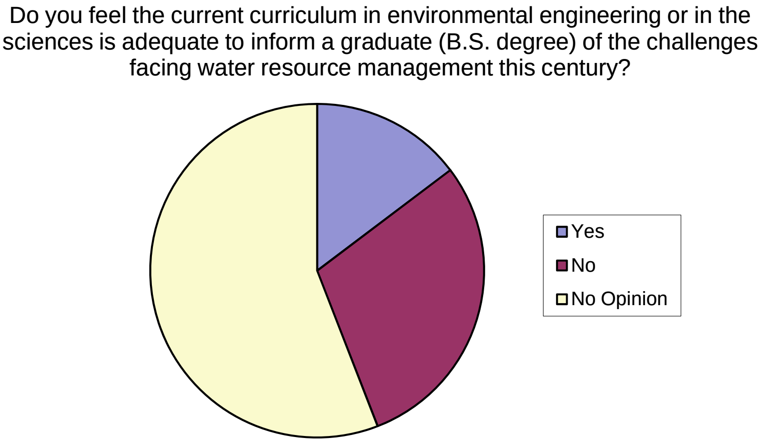

Fig. 2.9 Response to Question 11

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Chapter 3

Current Approaches for Resilience Assessment

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Introduction

This chapter provides a brief overview of some of the more established approaches to resilience and risk assessment as practiced in other fields of engineering that may be pertinent to water management infrastructures. It also traces ASCE's historical role in addressing risks to large infrastructure for water management. Finally, the chapter makes some recommendations as a way forward for improving resilience assessment involving greater use of numerical models Hossain et al. (2017).

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Reviewing Resilience Assessment Methods

When the Task Committee (TC) on ‘Infrastructure Impacts of Landscape Driven Weather Change’ was being proposed to American Society of Civil Engineers (ASCE) during the 2012–2013 timeframe, several news events related to improving infrastructure resilience for water management happened across the nation. In 2009–2010, the Tennessee Valley Authority (TVA) reported that the height of four of their dams would be raised by four feet (Hydroworld 2009).

Although the scientific reasoning behind the height increase was not clearly known, media reports suggested that it was the projected increased risk of greater flooding from global climate models (GCMs) that may have driven this decision. It should be noted here that there exist significant uncertainty, inadequate skill, and considerable debate, despite its wide use for adaptation policies, of GCM projections at the infrastructure scale for water management (e.g., Hossain et al. 2012; Kundzewicz and Stakhiv 2010; Anagnostopoulos et al. 2010; Stephens et al. 2010; van Haren et al. 2012). Nevertheless, media reports suggested that TVA was anticipating an order of magnitude increase in flood risk later this century. Some other studies, such those on storm water infrastructure, also show that the use of GCMs may lead to a design mismatch (Moglen and Vidal 2014).

The survey introduced in Chap. 2 was part of the second in the series of reports produced by the ASCE Task Committee. It revealed that the engineering profession may need greater academic-practitioner collaboration to develop more use-inspired curriculum for our future engineers who will have to solve inter-disciplinary problems not experienced before (Hossain et al. 2015b). For example, water management implicitly means that both quality and quantity will be managed. However, historical management practices focused one over the other. For example, the eutrophication of water bodies near agricultural land is traditionally treated as a non-point pollution runoff problem rather than also a water management issue. Practitioners now recognize that both need to be addressed jointly in management

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practices to address emerging challenges. Many practitioners also felt that the emergence of new contaminants or changes to water quality due to varying quantity brought by a drought or a flood will likely add to the cost of water delivery systems–an issue that is not yet in the limelight of water management.

More recently, during the recent October 2015 flooding of South Carolina, a record amount of rainfall caused mass disruption of daily life for the entire state. However, the biggest casualty was not really life or property, but rather the freshwater supply and wastewater treatment system that got knocked out in the immediate aftermath of the flooding (Good 2015). This resulted in a shortage of safe drinking water for large sections of the state. The next big casualty was the increased vulnerability of 36 large dams in the state that were all overtopped during the flooding (Good 2015). These dams, according to the American Society of Dam Safety Officials (ASDSO), were already in need of repair and posed a high risk downstream. What seems evident from all this is that trying to make one entity of an infrastructure system more resilient (e.g., power distribution, transportation, or flood control) is not going to be sufficient. The entire infrastructure system providing us with reliable transportation of goods, supply of energy and water, and a cleaner and safer environment will need to be made smart as a whole. Thus, it is worthwhile for engineers engaged with water management to explore what other engineering communities have already addressed for improving resilience. In this chapter, a review of approaches on resilience assessment from various communities is provided. This review is expected to initiate a discussion on how they may be relevant for water management infrastructure.

History of ASCE on Addressing Resilience

A review of the literature reveals that the ASCE has been at the forefront of addressing water infrastructure resilience longer than we might think. As early as 1956, a task force on Spillway Design Floods was established by the ASCE that concluded that ‘for large major structures that would be subject to possible failure if the selected capacity were exceeded, there would be few instances, if any, where anything less than provision for the probable maximum flood can be justified’ (Snyder 1964). Later, ASCE set up a Task Committee on the ‘Reevaluation of the Adequacy of Spillways of Existing Dams’ and produced a paper, ‘Reevaluating Spillway Adequacy of Existing Dams’ (ASCE 1973). During the 1970s, the key issue of contention was the ‘probable maximum flood’ (PMF) that currently serves as the mandatory design standard for many high hazard US dams. Because many thousands of dams in the USA would be overtopped and possibly fail using the calculated PMF at each dam site, the focus then was on prioritizing the dams that needed spillway upgrade more urgently than others. Many researchers had already suggested that modifying dams to accommodate the PMF could be wasteful (see, e.g., Dawdy and Lettenmaier 1987). Graham (2000) provides an excellent historical overview of this issue and the heritage of ASCE on addressing water infrastructure resilience that readers should explore.

Graham (2000) also proposed an approach of assessing if any structural retrofitting or upgrade to a dam was sound from an economic and loss of life perspective. This approach is designed to avoid costly overdesign in the name of a false sense of improved resilience. The approach is quoted below.

"For each proposed modification designed to reduce or eliminate dam failure, compute:

1. Annualized Cost of the modification, C_M, (dollars).
2. Annualized Economic loss caused by flooding, E_M, (dollars).
3. Annualized Life loss caused by flooding, L_M, (number of lives).
4. Life loss from Construction spending (0.14 lives per $100 million expended) and convert to annualized value, L_C, (number of lives).
5. Economic Benefits derived from modification, E_B, where $E_B = E_S - E_M$ (dollars).
6. Life Benefits derived from modification, L_B, where $L_B = L_S - L_M - L_C$ (number of lives saved).
7. Use Table 2 of Graham (2000) to reject or accept the infrastructure modification."

The above approach outlined by Graham (2000) would be relevant today for this TC and the broader community to reevaluate resilience issues impacted by changing extreme events and climate. For example, physical model-based PMP and PMF that are becoming increasingly common (Tofiq and Guven 2015; Yigzaw and Hossain 2015; Yigzaw et al. 2013), provide a framework for testing sensitivity of large water infrastructures to anticipated changes in extreme events. The estimated changes in PMP and PMF can consequently be translated into required modifications in spillway design and assessed of their urgency using the seven steps outlined above by Graham (2000).

In relatively more recent times, the National Research Council (NRC 1994) set up a committee to understand the bounds of extreme weather events of relevance to large water management infrastructure. Many of such historical extreme weather events have been 'maximized' by engineers as 'probable maximum precipitation' (PMP) using adhoc approaches. Since engineers design large infrastructure for the upper bound of an extreme event, this NRC study was a timely effort for civil engineers. The NRC (1994) recommended that while there was no immediate need to drastically change current engineering practices for designing water infrastructure, more research was recommended using atmospheric numerical models to understand the sensitivity of extreme events and PMP estimation to changing boundary conditions.

The NRC (1994) followed by the Abbs (1999) model-based study on PMPs ushered the engineering community to the twenty-first century with more frequent use of numerical models to understand sensitivity to design-relevant extreme events for water management infrastructure. Examples include Chen and Bradley (2006), Tan (2010), Ohara et al. (2011), Beauchamp et al. (2013), to name a few. While it is not yet clear how many of these model-based studies examining extreme events directly addressed improving resilience of water management infrastructure, such a body of work is timely and a good omen for the engineering profession.

As mentioned earlier, before the dawn of computers (1960s) and the complex modeling capability they provide, the engineering community had to depend on procedures that were very ad hoc and linear. However, such ad hoc procedures do not allow one to address the important question facing the engineering community, which is—Will the current engineering methods for storm management infrastructure planning and design remain adequate to protect society from flooding hazards in the coming decades? For example, the standard engineering practice for estimation of PMP today is based on a linear and regression-based forcing of atmospheric conditions associated with past observed extreme precipitation events (Rakhecha and Singh 2009). Such an approach is often criticized as being insufficiently physical as it assumes a linear relationship between precipitation and water holding capacity of the atmosphere leading to a discrepancy between conventional PMP estimates and what would be consistent using modern physically-based climate and weather modeling methods. While a discrepancy on the side of caution for ad hoc approaches (i.e., overdesign for high hazard infrastructure; Micovic et al. 2015) is acceptable as long as the economics are justifiable, there is currently no fundamental reason for engineers not to take advantage of numerical model capabilities and the science on atmosphere to address various external changes facing water management today.

According to recent news in the ASCE Civil Engineering Magazine November-2015 issue, it appears that water managers are now paying attention to the fledging body of work on the use of numerical models for PMP reassessment and for short-term (7–10 days) weather forecasts. At the time of writing this manuscript, a bill to Congress was being formulated titled 'Fixing Operations of Reservoirs to Encompass Climatic and Atmospheric Trends Act' (or FORECAST ACT H.R. 813 for short). Essentially, this bill is meant to make the rule curves for large dams more adaptive through the use of numerical models for weather forecast. Such models can reduce waste of impounded water for dam managers and allow more water storage during periods of big drought when floods are not likely in the weekly forecasts (ASCE 2015).

Approaches for Resilience Assessment

For a network of infrastructure systems, Cavarallo et al. (2014) provide a methodology for the assessment of urban resilience to catastrophic events. The catastrophic events for the case of water infrastructure could be a hurricane or a major drought. This approach aims to bridge the gap between the engineering and ecosystem approaches to resilience. The approach of Cavarallo et al. (2014) involves the social component to resilience and demonstrates an application to simulated earthquakes in the city of Acerra, Italy. For the TC, such an approach could be beneficial for addressing the collective improvement of resilience of networked water management infrastructures (i.e., a series of dams along a river, or a large storm water and water supply infrastructure of a city). There appears to be a considerable amount of work on resilience assessment and improvement of networked infrastructure (such as Reed et al. 2009) focusing on the interdependency of components.

Upadhaya et al. (2014) provide recent insights on water infrastructure systems in Canada that this TC can leverage for U.S. infrastructure. Although water management infrastructure is quite similar in design (with the exception of colder ambient conditions), Canadian engineering professionals rate their nation's infrastructure as 'good but headed towards fair' unlike the USA Upadhaya et al. (2014) use storm water infrastructure as an example to examine current sustainability assessment methods. They report that most methods of assessing infrastructure address functional aspects and resource use reduction; however, they do not consider long-term sustainability issues to maintaining resilience. In addition to climate, their resilience assessment is divided into categories of economics, health and safety, population growth, ecological, and institutional. On the issue of climate, they correctly quote:

> Climate change science and modeling currently is not at a level of detail suitable for storm water management where knowledge of the intensity, duration, frequency of storms and their locations and timing is required. However the economic, health and environmental risks dictate a need to be proactive in the management of storm water.

Upadhaya et al. (2014) further quotes—'These uncertainties require a process for continuously assessing the adapted measures, as well as assessing the physical facilities or infrastructures affected by these adaptations.' A recent work by Micovic et al. (2015) reports a methodology for estimating the uncertainty in conventional estimates of PMP. Given such uncertainty and the general lack of consideration of sustainability in infrastructure resilience assessment, Upadhaya et al. (2014) presented a protocol relevant to this TC on extreme events. This protocol is called the Public Infrastructure Engineering Vulnerability Committee (PIEVC) protocol to 'assess the vulnerability of buildings, roads and associated structures, stormwater and wastewater systems, and water resources.' The PIEVC identifies the following five steps:

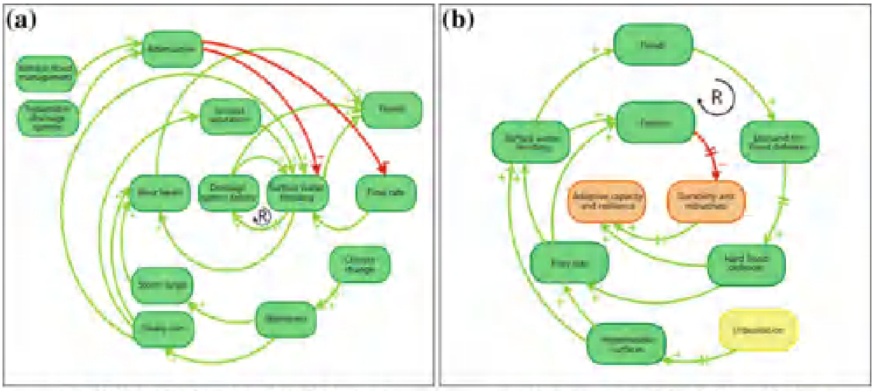
Step I—Project definition; Step II—Data gathering and sufficiency; Step III—Risk assessment; Step IV—Engineering analysis; Step V—Conclusions and recommendations.

The PIEVC approach can be explained by quoting Upadhaya et al. (2014) as follows:

> In the project definition stage, the infrastructure to be assessed, time period of study, and required climate parameters (note: this is where the TC can recommend extreme weather related parameters such as PMP and PMF) are established. Next, relevant data are gathered and then in the risk assessment phase, the relationship between climate loads and the

> infrastructure capacity are determined. Vulnerability will exist if the load exceeds the capacity of the infrastructure. In the risk assessment stage, the following formula is applied: $R = P \times S$, where, R is the risk, P is the probability of extreme climate event, and S is the severity of the infrastructure component response. Generally, the risk assessment process is undertaken in a workshop setting involving multiple experts, employing a number of assumptions, and using a consensus decision process. A risk matrix is developed and the vulnerability of the infrastructure is based upon the experience of the operators and managers. An engineering analysis is required where potential vulnerability exists and data quality is also undertaken. Medium risk items are evaluated, high-risk items move directly to recommendations, and low risk items are eliminated. Recommendations on remedial action, management action, no action or additional study requirements are made for the vulnerable infrastructure components.

In the UK, a similar approach for improving infrastructure resilience has been promoted after the UK floods of 2007 and the cold snap of 2011–2012. Essentially this approach recognizes the need for infrastructure resilience for business continuity. The methodology consists of a database of causal interactions which, when combined with a process, allows users to produce causal loop diagrams that identify unanticipated systemic behavior, communicate risks, share knowledge, and identify systemic intervention points that minimize negative consequences and add value in a project context (Montgomery et al. 2012). The causal loop diagram proposed in this methodology is something that is of relevance to this TC for improving infrastructure resilience for water management. Below, two causal loop diagrams (Fig. 3.1) for flooding impact on infrastructure are directly reprinted. The first TC report (Hossain et al. 2015a) had a similar causal loop on the role of land-atmosphere feedbacks on extreme events, although at that time, the TC was not aware of such insightful work done in the UK by Montgomery et al. (2012).



Causal loop diagram showing some physical causes of flooding – the cyclical cause and effect acting on parts of the physical causes of flooding results in indirect and cumulative effects

Causal loop diagram showing the effect of some flooding interventions – action to prevent flooding has had the unintended consequence of reducing the long-term resilience of flood defence measures

Fig. 3.1 A causal loop diagram approach proposed by Montgomery et al. (2012) for infrastructure resilience improvement. The examples for the causal loop are for flooding impact on infrastructure

Conclusion

A review of literature was conducted to identify published methodologies on improving infrastructure resilience for water management for the ASCE Task Committee on ‘Infrastructure Impacts for Landscape-driven Weather Change.’ Review revealed that several new practices currently available for resilience assessment have found wide acceptance by civil engineers in fields of geotechnical, transportation,and structural engineering. The review also revealed a much longer heritage by ASCE (since the 1950s) of addressing infrastructure resilience issues dictated by extreme events. Lastly, the review identified four approaches used in allied disciplines of civil engineering that can be leveraged for improving resilience of water management infrastructure.

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Chapter 4
Application of Numerical Atmospheric Models

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Introduction

Intense storms, or extreme rainfall events as they shall be called in this chapter hereafter, pose challenges to infrastructure management and design, and trigger other catastrophic events such as floods, landslides, and dam failures. They are also the cornerstone of engineering design and risk assessment of large infrastructures such as dams, levees, and power plants (Stratz and Hossain 2014). Therefore, it is of great societal interest to physically predict and understand the occurrence and magnitude of such extreme events for both design and operation of engineering infrastructures, and testing their resilience.

In current engineering practice, safety of hazardous infrastructure (where lives are at stake with infrastructure failure) is achieved through designs based on Probable Maximum Precipitation (PMP). It depicts the precipitation potential of an already intense storm that is "maximized" to an upper bound using some basic engineering assumptions (Kunkel et al. 2013; Stratz and Hossain 2014). The National Oceanic and Atmospheric Administration (NOAA) has created a database of such intense storms in the USA from about 1900–1990 that were maximized to PMPs and publicly released as Hydrometeorological Reports (HMRs) for the engineering infrastructure community.

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PMP is expressed mathematically as: P × wp (maximum)/wp (storm), where P is the observed rainfall accumulation, wp(maximum) is the highest observed precipitable water from historical records, and wp(storm) is the storm precipitable water. The above approach is often criticized as being insufficiently physical as it assumes a linear relationship between precipitation and water holding capacity of the atmosphere (Abbs 1999; Kunkel et al. 2013). It also heavily relies on historical observation data. For very early extreme events used in PMP analysis (such as Storm Elba of 1929), it is difficult to obtain a physically consistent picture due to limitations of record keeping and the linearity assumption (Abbs 1999). In this context, numerical simulation of extreme storms and their consequent physical maximization to a "PMP" is gaining much more traction among science and engineering communities than before (Kunkel et al. 2013; Stratz and Hossain 2014).

A numerical modeling approach has several key advantages over a traditional approach and is able to produce finer details on the spatial–temporal structure of storms using fewer assumptions and experience-based estimation. It is more tailored to a region that has little or no long-term rainfall record or is rapidly undergoing changes in weather patterns due to land-cover change or global warming. More importantly, a well-established numerical modeling framework is often able to handle various extreme events within the model domain spanning decades.

Previous studies suggest that the performance of storm simulation heavily depends on the parameterization schemes, which is the mathematical identification of physical processes in numerical models (Stensrud 2007). Though a wise choice of parameterization schemes results in improved simulations of big storms, often times it has to be achieved by trial and error. For example, several numerical studies for the Mumbai July 2005 storm (Chang et al. 2009; Kumar et al. 2008; Rao et al. 2007; Vaidya and Kulkarni 2007) show steady progress in reconstructing the high precipitation values in the various modeling platforms with different parameterization schemes. Rajeevan et al. (2010) revealed that the optimal combinations of parameterization schemes and IC/BC in the model can be quite different for the southeast Indian thunderstorms. Similarly, Carvalho et al. (2012) showed that for other engineering purposes, the WRF modeling framework can be established using carefully chosen model options. These high heterogeneities within optimal model configurations make it difficult for engineering communities to set up and operate these models.

Given that the engineering community is relatively new to the setup/operation of numerical models, as well as the use of models for maximization of extreme storms in PMP estimation, a framework here in this book to explore the role of various parametrizations and IC/BC on extreme storm simulation accuracy can provide a baseline for optimal criteria for PMP simulation. Such a comprehensive study, as provided in this chapter, will also illustrate ways to identify optimal model configurations for extreme storm simulations, and help the engineering infrastructure community that engage in hydrologic analyses for design and operations embrace numerical models for PMP estimation further advancing the methodology.

Taking the Nashville, TN 2010 storm as a test case that extensively flooded infrastructure and was partially due to reservoir operations, this chapter illustrates procedures required to achieve a good storm reconstruction using the WRF model (Chen et al. 2016). Three questions are explored for the engineering community engaged with water management infrastructures:

1. What combinations of model options in WRF are most skillful for extreme storm event simulation?
2. What are the strengths and weaknesses of each model option in reference to simulation accuracy of extreme precipitation?
3. What are the optimal model configurations for engineering operations and infrastructure implications?

Methodology for WRF Model Application

Nashville, TN 2010 Extreme Storm

On 1–2 May 2010, the west and middle Tennessee region of the USA experienced a record-breaking storm. This two-day rainfall event brought huge amounts of water to western Tennessee, with 48-h cumulative rainfall exceeding historical records at

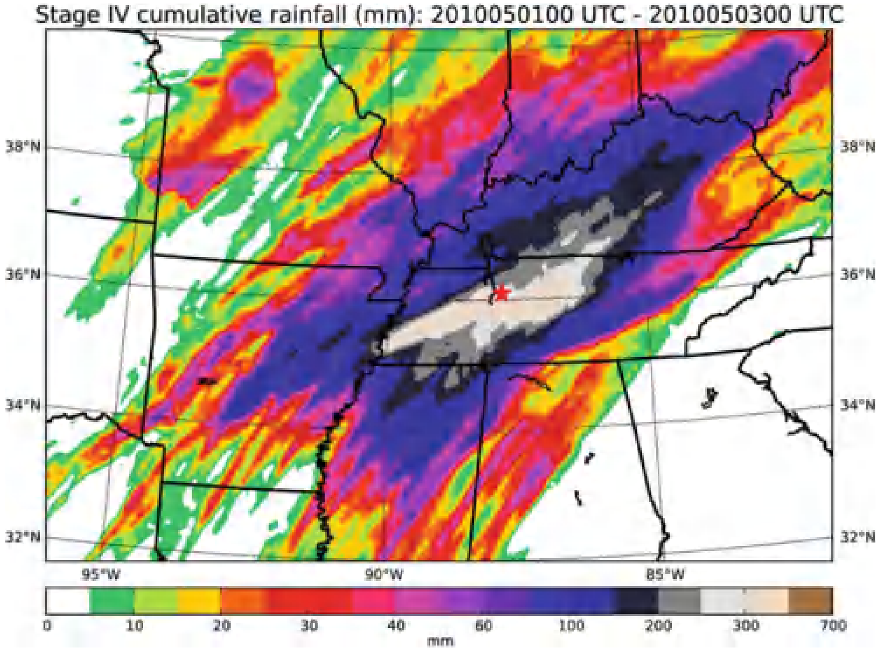


Fig. 4.1 48-h (0000 UTC 1 May—0000 UTC 3 May, 2010) total rainfall from Stage IV data

several gauge stations (such as the Nashville and Camden station in Tennessee). Figure 4.1 shows the 48-h cumulative rainfall from this storm as observed from the NEXRAD network, which shows a southwest–northeast pattern.

This storm, hereafter referred to as the “Nashville 2010 storm,” led to a flood in the following days that NOAA categorized as a 1000-year return period flood event (NOAA National Weather Service and Weather Forecast Office, NWSWF, 2010). The maximum 48-h total precipitation observed was 493 mm (19.41 inches) at the Camden COOP station (36.05° N, 88.08° W, Fig. 4.1). This value is quite close to the 5000 mi^2 48-h design PMP (495 mm, or 19.5 inches) for west Tennessee (an area in the HMR 1951 report; we will call it as HMR51 region hereafter). Nashville international airport recorded its 1st and 3rd highest 24-h total rainfall in history on 1 and 2 May (NWSWF 2010). These statistics qualify this rainfall event as a reference extreme storm for PMP design for the HMR 51 region. During the ensuing flood event, 21 deaths were reported, and over 30 counties were declared as major disaster areas by the government. This unique rainfall record and infrastructure-damaging impact make this event worth revisiting with numerical simulation (Durkee et al. 2012). There have not been many numerical simulation efforts on this storm; thus, a successful model reconstruction of this event would provide an important baseline for studying other local events or events in similar environmental conditions for engineering infrastructure applications.

Previous studies have identified several key atmospheric factors such as the superposition of the polar/subtropical jet (Winters and Martin 2014) and the atmospheric river (Durkee et al. 2012; Moore et al. 2012). Because some elements present in the Nashville 2010 event are common ingredients in other extreme storms, reconstructing this extreme event may serve as an important test case for evaluating the ability of the WRF model for simulating other storms.

The Numerical Atmospheric Model—WRF

WRF is an atmospheric modeling system (Skamarock et al. 2005) that features two non-hydrostatic solvers including the Advanced Research WRF (ARW) core for atmospheric research and the Non-hydrostatic Mesoscale Model (NMM) core for operational forecasts. It is designed for mesoscale simulation with spatial resolution ranging from 1 to 100 km. In this study we adopted WRF-ARW v3.6.1 for the storm simulation. WRF-ARW has been employed in various big storms studies and demonstrated to be capable of simulating several large storms across the world (Kumar et al. 2008; Rajeevan et al. 2010; Tan 2010).

WRF is built on the Arakawa-C grid and resolves atmosphere state in terrain-following hydrostatic-pressure coordinate vertically. ARW incorporates the recent advances in atmospheric science, while providing a flexible framework that is compatible with different parameterization schemes. Many options for physics parameterizations have been implemented to support various applications for simulations across a wide range of temporal and spatial scales.

Experiment Design of WRF Recommended for Engineers

Previous studies suggest that the performance of numerical atmospheric models is mostly affected by cloud physics parameterization, model resolution, initial and boundary conditions in the model, as well as the simulation period. Steps below illustrate the workflow needed by engineers to establish the optimal modeling framework based on WRF. A schematic is shown in Fig. 4.2, and the details for each step for practitioners are explained with an example for the Nashville 2010 storm simulation.

(1) Study previous modeling efforts to understand the background of the study domain;
(2) Determine the atmospheric numerical model(s) of interest;
(3) Determine the study domain and simulation period. Prioritize the main physical factors in the model that affect the simulation quality. This can be gained from step 1. Outline the model options (i.e., combination of parameterizations) to be tested;
(4) Collect the input data, set up the model and make model runs;
(5) Determine the main purpose of the modeling framework and the evaluation criteria. As shown below in the Nashville 2010 case, different purposes of the

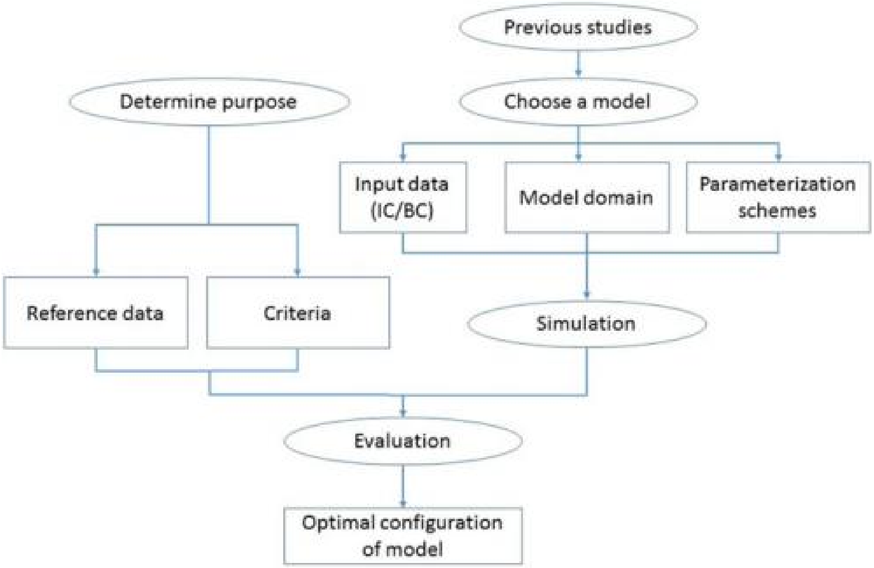


Fig. 4.2 Generic framework for exploring optimal model configuration for reconstruction of extreme storms recommended by the water management community

modeling framework require different criteria and lead to different configurations in the optimal atmospheric model. Collect the reference data;

(6) Evaluate the simulation results using the metric(s) that best serve the purpose.

The Nashville 2010 storm period is 1–2 May 2010, and previous studies conclude that long spin-up would result in less rainfall during the event. Thus, the simulation period is chosen as 0000 UTC 1–3 May 2010. Here we tested three configurations of nested domains to test model performance at 15, 5, and 1.6 km (the latter is referred to as "2 km" for convenience) grid sizes. Figure 4.3 shows the nested domains that were tested, and all three nested domains were centered over western TN. In the first configuration (g15, Fig. 4.3a), the domain covers the contiguous USA at 15-km grid spacing. In the second configuration (g5, Fig. 4.3b), a d02 domain at 5 km resolution (white box in the panel) is nested inside the larger 15 km domain. The third configuration (g2, Fig. 4.3c) further includes a d03 domain of 1.6 km spatial resolution (red box in the panel) to better resolve convection at 1.6-km grid spacing. When there is more than one domain involved in the simulation, WRF runs in a two-way nesting mode, which means the coarse grid results are updated using results in finer grids where available. This experiment design allows us to evaluate the impacts of higher resolution achieved through nesting, with the same placement of the outermost lateral boundaries for all simulations. Nominal

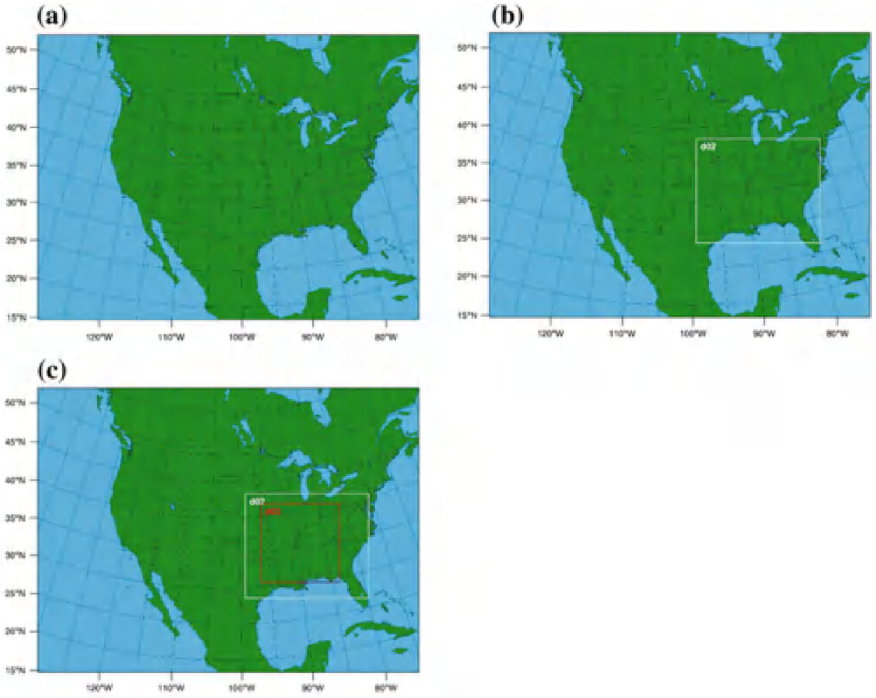


Fig. 4.3 Spatial domain in the modeling framework for the Nashville 2010 storm

time steps of 60, 20, and 6.7 s were used for the 15, 5, and 1.6 km grids, respectively. Model outputs are archived hourly between 0000 UTC 1 May 2010 and 0000 UTC 3 May 2010, similar to Moore et al. (2012).

Three sources of data were used to generate IC/BCs: (1) NCEP/DOE reanalysis product (NCEP2) at 2.5 degree resolution; (2) NCEP/NCAR reanalysis product (NNRP) at T62 (209 km) resolution; and (3) North America Mesoscale (NAM) forecast output at T221 (32 km) resolution. For this study the NAM forecast initialized at 0000 UTC 1 May 2010 was used.

Previous studies suggest that precipitation simulation is more sensitive to microphysics and cumulus parameterization schemes than parameterizations for other processes in the model. Here three microphysics parameterization schemes were tested for mixed phase clouds including the (1) Morrison double moment scheme (coded as "Morrison" here); (2) New Thompson scheme ("Thompson"); and (3) WSM-5 scheme ("WSM5"). Three cumulus parameterization schemes were tested including the (1) Kain-Fritsch scheme (coded as "KF" here); (2) Grell-Devenyi scheme ("GD"); and (3) Grell-Freitas scheme ("GF"). Other schemes are fixed in all the experiments, and they are the RRTM longwave radiation scheme, Dudhia shortwave radiation scheme, revised MM5 surface layer scheme, Yonsei University (YSU) planetary boundary layer scheme, and Noah land-surface scheme. The total number of combinations of the different options in grid sizes (3), IC/BCs (3), microphysics schemes (3), and cumulus schemes (3 in the g15 runs, 2 in the g5 and g2 runs) amounts to 63 WRF runs designed and conducted for this study.

Identifying the Optimal WRF Setup

Independent precipitation observation data is required for the assessment of the storm simulations. One option is gauge data, since they provide the most accurate estimate of rainfall amount and duration. In some cases gauge data may not be available, due to either the age of the storm or nonfunctioning gauges (such as the Nashville international airport station in the Nashville 2010 storm event); therefore, spatial gridded data can be used to validate model results. Here the NEXRAD Stage IV precipitation dataset (Fig. 4.1) is used as the reference, given its high accuracy and good spatial coverage. Cumulative 48-h rainfall is evaluated by the spatial correlation coefficient between the simulated and Stage IV 48-h total rainfall. This reveals how the model performs in capturing the rainy area and the spatial heterogeneity of total rainfall. For extreme rainfall events used in engineering analysis, it is important that the numerical model captures the core precipitating areas as accurately as possible.

Additional metrics we employed include: probability of detection (POD), false alert ratio (FAR), frequency bias (Bias), Heidke skill score (HSS), critical success index (CSI or TS), and Gilbert skill score (GSS or ETS). They are defined as statistics of the binary result indices in Table 4.1. Table 4.2 shows the definitions of

Table 4.1 Binary results indices for evaluation metrics

Simulated	Observed		
	Yes	No	Sum
Yes	Hits (YY)	False alarms (YN)	YY + YN
No	Misses (NY)	Correct rejections (NN)	NY + NN
Sum	YY + NY	YN + NN	Total = YY + YN + NY + NN

Table 4.2 Definition of evaluation metrics[a]

Metric	Definition	Valid range
POD	$\frac{\mathrm{Hits}}{\mathrm{Hits}+\mathrm{Misses}}=\frac{\mathrm{YY}}{\mathrm{YY}+\mathrm{NY}}$	[0,1]
FAR	$\frac{\mathrm{False\ alarms}}{\mathrm{Hits}+\mathrm{False\ alarms}}=\frac{\mathrm{YN}}{\mathrm{YY}+\mathrm{YN}}$	[0,1]
Bias	$\frac{\mathrm{Hits}+\mathrm{False\ alarms}}{\mathrm{Hits}+\mathrm{Misses}}=\frac{\mathrm{YY}+\mathrm{YN}}{\mathrm{YY}+\mathrm{NY}}$	[0, +∞)
HSS	$\frac{2\times(\mathrm{YY}\cdot\mathrm{NN}-\mathrm{YN}\cdot\mathrm{NY})}{(\mathrm{YY}+\mathrm{NY})+(\mathrm{NY}+\mathrm{NN})+(\mathrm{YY}+\mathrm{YN})(\mathrm{YN}+\mathrm{NN})}$	(−∞,1]
TS	$\frac{\mathrm{Hits}}{\mathrm{Hits}+\mathrm{Misses}+\mathrm{False\ alarms}}=\frac{\mathrm{YY}}{\mathrm{YY}+\mathrm{NY}+\mathrm{YN}}$	[0,1]
ETS	$\frac{\mathrm{YY}-\mathrm{YY}_{\mathrm{rand}}}{\mathrm{YY}+\mathrm{NY}+\mathrm{YN}-\mathrm{YY}_{\mathrm{rand}}}$, where $\mathrm{YY}_{\mathrm{rand}}=\frac{(\mathrm{YY}+\mathrm{YN})(\mathrm{YY}-\mathrm{NY})}{\mathrm{Total}}$	[−1/3,1]

[a] Note YY (Hits) means both simulation and observation indicate rainfall at the grid/station; YN (False alarm) means only simulation indicates rainfall at the grid/station; NY (Misses) means only observation indicates rainfall at the grid/station; NN (Correct rejection) means neither observation nor simulation indicates rainfall at the grid/station. More details are in Table 4.1

these metrics, as well as the ranges of their values. These metrics only measure the accuracy in the coverage of rainy/non-rainy areas. Therefore, when the magnitude of precipitated water is vital, it would be better to use the correlation or root mean square error (RMSE) between observed rainfall and simulated rainfall for the period of interest (e.g., 6, 24, 48, and 72 h in PMP design). This can be done using either station data or gridded data. Other terms worth considering are the storm duration (start time and end time) and peak rainfall (to classify the storm severity). These metrics quantitatively evaluate the model performance; thus, the recommendations given by these metrics can be applied to engineering practice with confidence (Bennett et al. 2013).

These metrics measure different aspects of model performance and provide different recommendations for the "best" combination of parameterizations to support different applications. The POD metric as well as storm duration is more useful if the successful forecast of rainy area is more important, such as in the search of possible shelter areas. The FAR metric should be weighted more if the cost of emergency relocation is high, in which case we would like to avoid unnecessary effort from areas that are actually not rainy. In the infrastructure design practice, the total amount of rainfall and peak rainfall would be more important. If simulated rainfall data is being used as input to other models (such as hydrological models for streamflow forecasting), then a high spatial correlation between simulated and observed rainfall would be more desirable.

We take into consideration multiple metrics as a “set” when assessing model performance as no single metric captures all the pertinent performance features. For example, a good numerical model configuration should produce high probability of detection for rain as well as high critical success index. We combine several metrics and create a unified score (US). The US is defined by Eq. (4.1), in which $\mathrm{POD_n}$, $\mathrm{FAR_n}$, and $\mathrm{CSI_n}$ are normalized metrics defined by Eqs. (4.2), (4.3) and (4.4). By combining different aspects of model performance into the score, the unified score is used to identify the best combinations for the overall performance reflected by the multi-dimensional metrics that appeal to the engineering infrastructure community.

$$\mathrm{US} = \mathrm{POD_n^2} - \mathrm{FAR_n^2} + \mathrm{CSI_n^2} \tag{4.1}$$

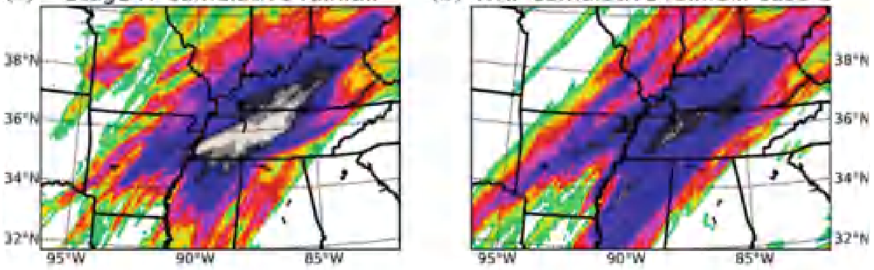
$$\mathrm{POD_n} = \frac{\mathrm{POD} - \min(\mathrm{POD})}{\max(\mathrm{POD}) - \min(\mathrm{POD})} \tag{4.2}$$

$$\mathrm{FAR_n} = \frac{\mathrm{FAR} - \min(\mathrm{FAR})}{\max(\mathrm{FAR}) - \min(\mathrm{FAR})} \tag{4.3}$$

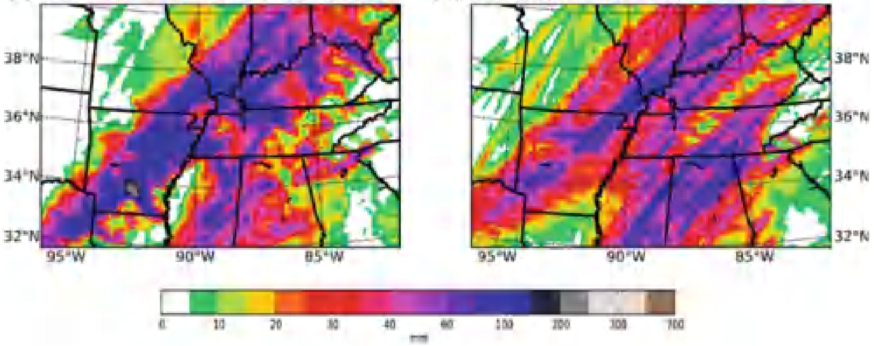
$$\mathrm{CSI_n} = \frac{\mathrm{CSI} - \min(\mathrm{CSI})}{\max(\mathrm{CSI}) - \min(\mathrm{CSI})} \tag{4.4}$$

Figure 4.4 shows the observed and simulated 48-h total rainfall. Panel of Fig. 4.4a is the NEXRAD observation, and panel of Fig. 4.4b is from the WRF simulation using the g5 grids (15–5 km nested grids), NAM IC/BC, Morrison microphysics, and KF cumulus parameterization schemes. This is one of the best simulations suggested by the evaluation. Comparison of panel of Fig. 4.4b with panel of Fig. 4.4a indicates that this model configuration is able to reconstruct the heavy rainfall area in midwestern Tennessee. The rainfall amount gradient is properly described by this model setup and the large southwest-northeast pattern of 48-h total rainfall is clearly captured. Panel of Fig. 4.4c shows a simulation with moderate scores under evaluation, and panel of Fig. 4.4d shows one of the worst simulations. The simulated rainfall distribution from various model configurations differs significantly; thus, evaluation based on the modeling framework is necessary and shown in Fig. 4.4 as an example of the different metrics used to establish the extreme storm events modeling framework in the HMR 51 region.

Sixty-three WRF model combination results were evaluated as proposed in Section “Experiment Design of WRF Recommended for Engineers”, using NEXRAD Stage IV precipitation data as reference. All simulations captured the northeast–southwest-oriented rainband comparable to the NEXRAD data while some of the model configurations were able to present the peak 48-h total rainfall amount up to 303 mm, which is close to the observed peak in western Tennessee (330 mm).


(a) Stage IV cumulative rainfall

(b) WRF cumulative rainfall: case 1


(c) WRF cumulative rainfall: case 2

(d) WRF cumulative rainfall: case 3

Fig. 4.4 Stage IV observed and WRF simulated 48-h (0000 UTC 1 May—0000 UTC 3 May 2010 total rainfall during Nashville 2010 storm event

All of these combinations tend to underestimate total rainfall in the evaluation area. However, the best results (such as g15-NCEP2-Thompson-KF and g5-NAM-Thompson-KF) are fairly close to the observed amount, with a difference within 10%. Also, NCEP2 performance is comparable to NAM IC/BC, both of which are significantly better than NNRP IC/BC. Simulated total rainfall amounts are sensitive to the cumulus scheme, as the difference in KF results from NCEP2 and NAM IC/BC is less than 7%, while differences due to cumulus schemes are larger than 10%. It is also worth noting that the best results come from coarser resolution. Thus for total rainfall estimation, the optimal framework would go up to only 5 km resolution.

At 5- and 2-km grid scale, all the combinations produce stronger correlations. As we can see in the following analysis, NAM often produces the best quantitative evaluation values in the finer grids. The top combinations for the 5 and 2 km grids are similar. The difference among the best correlation results at the three different grid scales is not significant. In general, higher resolution simulations are able to capture finer-scale features, although the improvement from 5 to 2 km is marginal.

In certain types of engineering infrastructure analyses, it is important to know both the location and period of the storm event. A better picture of spatial–temporal

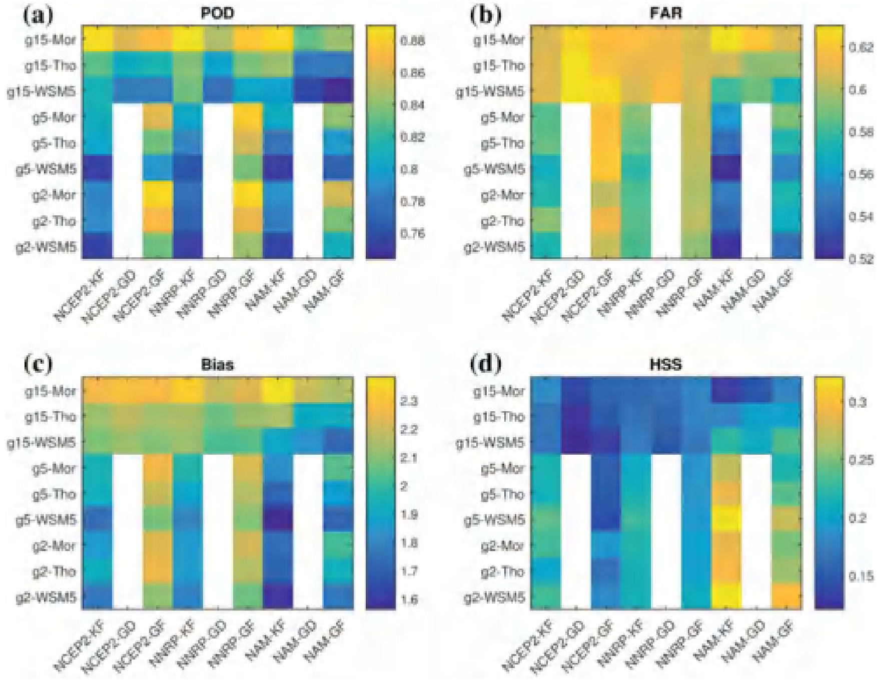


Fig. 4.5 Evaluation of storm reconstruction as simulated by WRF

storm would help improve operation plans for drainage systems, for example. To better evaluate the simulated spatial–temporal structures of the storm, quantitative scores were computed for the 63 simulations. Unlike the calculation of spatial correlation using rainfall total, the computation here used hourly rainfall data. Figure 4.5 depicts evaluation of the spatial coverage of hourly rainfall simulated by WRF. Blank panels means the corresponding combination was not tested (similar to the "–" in Table 4.3). Panel of Fig. 4.5a shows the POD, with greater values representing more skillful simulations. Similarly, panel of Fig. 4.5b shows the FAR (lower values are better). POD reflects the probability of rainfall gridpoints being successfully simulated as "rainy" by the numerical model. FAR evaluates the simulation accuracy of non-rainy regions, so combining it with POD can provide a better assessment of the simulation quality.

The general information from panel of Fig. 4.5a, b suggests that as the numerical model takes advantage of the finer grids, the simulation quality usually improves. The g15 grid shows somewhat better POD than some of the g5 and g2 results, which is possible because POD only measures how complete the observed rainfall area is covered by the simulation. Panel of Fig. 4.5a suggests that the Morrison microphysics scheme tends to overestimate rainfall coverage, and this is supported by the higher FAR values in panel of Fig. 4.5b. Compared with the g15 grid, finer-grid simulations are able to reduce the likelihood of false alert: The range of

Table 4.3 48-h total simulated rainfall (normalized using observed total)[a]

MP	NCEP2			NNRP			NAM		
	KF	GD	GF	KF	GD	GF	KF	GD	GF
15 km grids									
Morrison	0.857	0.727	0.708	0.745	0.662	0.661	0.855	0.678	0.684
Thompson	0.921	0.774	0.744	0.797	0.711	0.707	0.879	0.719	0.719
WSM-5	0.866	0.754	0.740	0.753	0.705	0.698	0.855	0.712	0.718
5 km grids									
Morrison	0.874	–	0.766	0.695	–	0.680	0.890	–	0.759
Thompson	0.856	–	0.766	0.676	–	0.707	0.905	–	0.766
WSM-5	0.892	–	0.787	0.707	–	0.706	0.899	–	0.793
2 km grids									
Morrison	0.827	–	0.780	0.692	–	0.663	0.882	–	0.816
Thompson	0.773	–	0.723	0.636	–	0.603	0.855	–	0.781
WSM-5	0.841	–	0.794	0.683	–	0.648	0.898	–	0.829

[a] Note Bold numbers are the top 3 scores with the best performance within each grid resolution

the best three FAR scores in the g15 grid is 0.571, 0.588 which is less skillful than the g5 results of 0.520, 0.551. Similar to the findings from the spatial correlation and total rainfall analyses, the biggest difference in the FAR comes from the choice of IC/BCs: NAM outperforms others at both coarser and finer grids. Also, the WSM-5 scheme tends to produce less spatial distribution of rainfall, so it performs better for the FAR score.

Panel of Fig. 4.5c shows the frequency bias scores. A bias score larger than 1 means the model overestimates the rainfall coverage, and a score less than 1 suggests an underestimation. As WRF is applied in the finer grids, the bias scores steadily converge to 1. All microphysics schemes benefit from the use of the finer grids. All of the bias scores are larger than 1, which indicates that all the models overestimate the rainfall area. Since the total rainfall amount analysis suggests that all models underestimated the total rainfall amount, the simulated picture is most likely to be an expanded rainy area with rain rates less than observed. This is confirmed by comparing Fig. 4.4b to a. Panel of Fig. 4.5d presents the HSS, with higher scores indicating better simulations. For a simulation with nonzero capability in forecasting/simulation, the HSS must be greater than 0. Panel of Fig. 4.5d shows that all 63 simulations have some capability for forecasting. Similar to the FAR scores, NAM IC/BC performs best at both coarser and finer grids. The improvement from the g15 to g5 grids is significant (about 20% increase), but the even finer g2 grid does not provide further improvement. Thus the 5 km grid is an acceptable compromise for PMP simulation as it does not compromise simulation quality at the expense of reduced computational burden. In terms of microphysics schemes, WSM-5 is best for both the finer and coarse grids. In the coarse grid, the KF cumulus scheme is also a good choice when combined with the Morrison or new Thompson cumulus schemes.

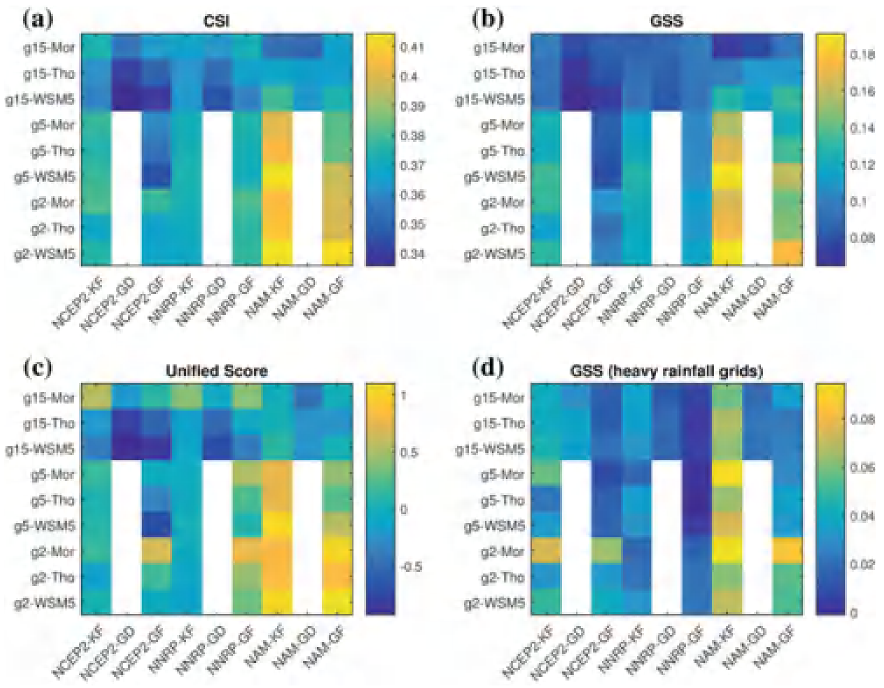


Fig. 4.6 Evaluation involving multiple aspects of rainfall simulation quality

Figure 4.6 shows the evaluation based on metrics that considers multiple aspects of rainfall simulation quality. Panel of Fig. 4.6a shows the CSI grades (the higher the better). Any skillful forecast/simulation should have greater than 0 grades. Panel of Fig. 4.6c shows the GSS grades (the higher the better). GSS improves CSI grades by taking into account the randomness of the observation, and it also requires a positive grade for the simulation to be considered skillful. The largest differences come from the choice of the IC/BC data source, and it is obvious that WSM-5 is the most accurate microphysics scheme at various grids.

Key Recommendations for Applying WRF

As shown in the figures above, different metrics usually yield differing recommendations. They are helpful for a specific purpose, but a better metric would be desired to evaluate multiple aspects of the modeling framework. For this purpose, the unified scores (US, see Eq. 4.1) were calculated and shown in panel of Fig. 4.6c. It is clear that at coarser grids (15 km), the Morrison microphysics scheme provides the best results. With the NCEP2 IC/BC, the KF scheme yields the highest scores in the g15 domain setup (Fig. 4.2a) group. As the model is applied at the finer grids, the NCEP2 results show lower and even negative scores. With finer grids (5 and 2 km), however, NAM is able to yield the most accurate estimates of rainfall. NNRP gives the worst results in both coarse and fine grids, and the scores degrade further in the finer grids. With NAM providing IC/BC, the 2 km simulations are more skillful than at 5 km and are less sensitive to the parameterizations used, although the extra improvement is marginal. It is also noted that the GF cumulus scheme produces the best US score in g5 and g2 domain setup. This implies the GF scheme is scale aware, and it does not double count the deep convection along with rainfall that is resolved by the microphysics process.

In summary, NAM is better for simulations at finer grids, while NCEP2 is also a good choice at coarse grids for extreme storms. At finer grids, WSM-5 outperforms the other two microphysics schemes. On a coarse gridscale, the results from different microphysics and cumulus schemes are mixed. Combinations that better resolve the spatial–temporal structure of the storm are: g15-NCEP2-Thompson-GF, g5-NAM-WSM5 (without a cumulus parameterization or with the GF scheme). The improvement from g5-NAM-WSM5 to g2-NAM-WSM5 is insignificant (e.g., CSI changed from 0.40 to 0.41), so given the larger computing requirements, the g2 option is not recommended here.

Conclusion

In this chapter, we provided an approach to establish an optimal numerical-model (WRF)-based framework for extreme storm event simulation. Our goal was to introduce an increased physically based methodology to the engineering design and analyses community currently engaged in large water management infrastructure issues of today and tomorrow. This framework takes into consideration the uncertainties coming from various IC/BC data sources, grid resolutions, cloud microphysics, and cumulus parameterization schemes. These are the major contributors to the final model performance. Following the same methodology outlined in Section "Methodology used for the Survey", more factors (such as land-surface processes, planetary boundary layers physics, and land-use conditions) can be added into this evaluation framework to achieve even better simulation quality, if desired by the engineering community. Overall, our proposed approach is to establish an optimal model framework that can be applied over any given area and storm for engineering applications.

The steps required by practitioners in implementing the optimal modeling framework can be summarized as follows:

(1) Study the previous modeling effort to understand the background of the study domain;
(2) Determine the atmospheric numerical models of interest and the main application of the modeling framework;

(3) Determine the study domain and simulation period. Choose the main model factors that affect simulation quality. Outline the model options to be tested;
(4) Collect the input data and reference data, and make model runs;
(5) Evaluate the simulation results using the metric(s) that best serve the engineering application.

In the demonstration, we established a WRF-based modeling framework for extreme storm events in the HMR51 region and validated it using the Nashville 2010 storm. Based on the engineering intent, the best model configuration can be different. In general, WRF was able to reconstruct the 48-h total rainfall map reasonably well, which would prove useful in estimating PMP for engineering design. It was able to produce good estimates of total rainfall amount and spatial coverage of rainy areas, each with a slightly different model configuration.

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Chapter 5
Infrastructure-Relevant Storms of the Last Century

Xiaodong Chen and Faisal Hossain

Introduction

Over the past 100 years, numerous water management infrastructures have been constructed to serve the water-related needs of people worldwide (Mitchell 1990). The larger ones are typically reservoirs with a dam and are often built for multiple purposes (e.g., water supply, disaster control, energy production, recreation, and navigation). These large water management infrastructures are the center of local and regional water resources management (Grigg 1996; Asmal et al. 2000). With the projected increase of water usage in the coming decades due to population growth and economic development, dams and reservoirs will remain one of the most ubiquitous and centralized solutions to satisfy water demands (Graf et al. 2010; Schlosser et al. 2014).

In the past decades, modeling efforts to reconstruct big storm events have mostly focused on recent events (those after the 1980s) (Hu et al. 1983; Kato 1998; Jansa et al. 2000; Kumar et al. 2008). On the other hand, a large part of big storms used in PMP estimation occurred long before the 1980s. It is necessary for engineers to check the current state of the art of atmospheric science to reconstruct the Hydrometeorological Report (HMR) storms of different types in various regions, as

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Table 5.1 Duration and characteristics of the 10 big storms of relevance to water management infrastructure

Storm ID	Dates	HMR region	Representative location	Duration (h)	Maximum point rainfall (mm)
1997-CA	Jan 1–3, 1997	59	(38.60° N, 121.50° W)	24	284
1982-CA	Jan 3–5, 1982	59	(37.08° N, 122.02° W)	24	525
1980-PNW	Dec 24–26, 1980	57	(44.92° N, 123.73° W)	24	234
1973-OK	Oct 10–11, 1973	53	(36.42° N, 97.87° W)	24	472
1970-UT	Sep 5, 1970	49	(37.63° N, 109.92° W)	Event	165
1964-PNW	Jun 6–8, 1964	57	(48.58° N, 113.38° W)	24	364
1943-CA	Jan 20–24, 1943	59	(34.20° N, 118.05° W)	24	581
1939-CA	Sep 24, 1939	49	(33.72° N, 116.23° W)	6	310
1930-NM	Oct 10, 1930	49	(35.22° N, 103.28° W)	24	566
1929-AL	Mar 11–16, 1929	53	(31.42° N, 86.07° W)	6	355

they lay the platform for PMP analyses (see Chap. 6) for future safety of our infrastructures such as dams.

In this chapter, the engineering community is provided with a synopsis of current model ability to reconstruct 10 big rainstorms of the last century over the contiguous U.S. (CONUS) from 1920 to 2000 (Table 5.1). We test the performance of atmospheric numerical models with different microphysics and cumulus parameterization schemes (Chen and Hossain 2016). The best model configuration is determined with evaluation involving ground-based observations. Building on the methodology for use of numerical models shown in the preceding chapter, two questions are answered for practitioners to assess infrastructure resilience:

1. What is the best combination(s) for extreme PMP-class storms with different types and locations across CONUS?
2. Are we ready to reconstruct the big storms in the past 100 years for engineering purpose using numerical models?

Answers to the questions above form a recommendation for best practices for numerical model setup over the USA.

The Infrastructure-Relevant Storms of the Last Century

Figure 5.1 shows the distribution and key rainfall statistics for 10 large storms events from the last century that have been used in the HMR report. The HMR reports, published by NOAA, divide the CONUS into 9 regions, and they provide detailed instruction and historical extreme events data to help engineers make PMP estimations in the specific region. These 10 events are located in 4 HMR regions (i.e., regions that are defined by the HMRs), namely HMR49, HMR53, HMR57, and HMR59 regions. These regions cover most of CONUS. Table 5.1 shows the duration and main record of these 10 events. Hereafter, we use the storm IDs in Table 5.1 to refer to these 10 rainfall events in this study.

Each storm event was caused by varying meteorological phenomena and belongs to different classes of storm. The 1997-CA rainfall event was caused by an atmospheric river originating from the Hawaiian tropical region that penetrated the west coast (Tan 2010). The 1982-CA rainfall event was caused by an extratropical cyclone accompanied by an atmospheric river (Ellen and Wieczorek 1988). The 1973-OK rainfall event set the Oklahoma State record for daily rainfall. The tornado during this event led to the "Enid Flood" in the following days (Chang 1998). The 1970-UT rainfall event was caused by tropical storm "Norma", which developed off the coast of Mexico and moved all the way to California. The 1964-PNW rainfall event was caused by one of the greatest low-pressure systems in the Pacific Northwest recorded since 1950. The 1939-CA rainfall event was among the four tropical storms that affected southern California during September 1939, and it was

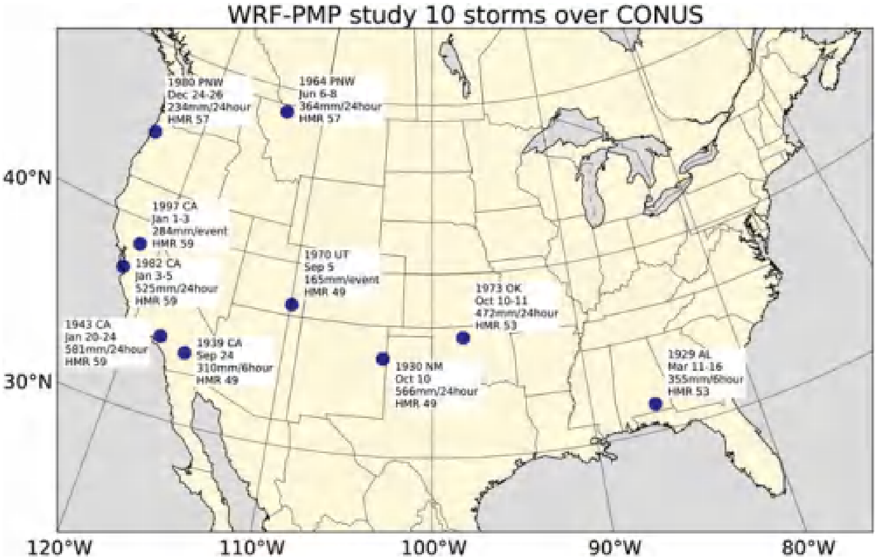

Fig. 5.1 Location of the 10 big storms in this study

one of very few events in the Pacific Ocean with the tropical storm that actually hit the coast. The 1929-AL rainfall event was amid a series of heavy rainfall events that occurred in February–March 1929, causing one of the worst flood events in Alabama's history at Elba (Bullard 2008).

Experimental Design

Previous studies suggest that WRF performance is mostly affected by the choice of cloud microphysics and cumulus parameterization schemes (Stensrud 2007; Kumar et al. 2008; Chang et al. 2009). Model resolution and initial/boundary conditions (IC/BC) also affect the simulation quality (Rajeevan et al. 2010; Liu et al. 2012). The model configurations are taken from a study by Chen et al. (2017). Specifically, we tested three different cloud microphysics schemes including the: (1) Morrison scheme, denoted as "M"; (2) new Thompson scheme, "T"; (3) WSM-5 scheme, "W". Three cumulus schemes were also tested and include the: (1) Kain-Fritsch (new Eta) scheme, "KF"; (2) Grell-Devenyi scheme, "GD"; (3) Grell-Freitas scheme, "GF". For the IC/BC in the simulation, the NCEP/DOE Reanalysis II product (NCEP2) is used for storms after 1979, the NCEP/NCAR reanalysis project (NNRP) is used for storms between 1948 and 1979, and the NOAA-CIRES Twentieth Century Reanalysis Product (20CR) is used in simulations before 1948. Previous studies (Chen et al. 2017) also suggest that for big storms, finer resolution does not always improve the simulation quality. Thus, for these 10 storms, two spatial resolutions were tested: (1) single 15 km domain; (2) two-way nested 15–5 km domain. Model configuration is coded as "gX-Y-Z", where X is the resolution, Y is the microphysics scheme, and Z is the cumulus scheme. For example, "g5-W-GF" means a 15–5 km nested run using WSM-5 microphysics and Grell-Freitas cumulus schemes. The simulation durations are chosen to include the storm duration until complete dissipation, with one extra day in the beginning to spin up the model. Simulation durations are summarized in Table 5.3.

The evaluation of WRF-simulated precipitation was done using Livneh the daily CONUS near-surface gridded meteorological dataset (Livneh et al. 2013). This precipitation data was generated from rain gauge records since 1915, and it is one of the very few long-term precipitation datasets available over CONUS. The evaluation consists of two parts: (1) evaluation of the spatial coverage of daily rainfall. This uses various metrics (Probability of Detection, POD; False Alert Ratio, FAR; Frequency Bias, Bias; Heidke Skill Score, HSS; Critical Score Index, CSI), and their definitions are shown in Chap. 4; (2) evaluation of storm statistical characteristics. Because PMP is defined as the maximum probable rainfall for a given duration, it is also useful to check the simulated temporal storm structure, as well as the maximum rainfall for some specified durations. This evaluation involves the correlation between the simulated rainfall and reference rainfall (Livneh data) as daily rainfall, maximum 1-day, 2-day, and 3-day rainfall.

Results

To make the WRF results comparable to the Livneh dataset, all the WRF results were first conservatively regridded to the 1/16° (* 8 km) grids, which is the native resolution of Livneh dataset.

Spatial Coverage of Rainy Area

The ability to reproduce correct rainy areas is useful in some engineering practice, such as preventive migration before the storm/flood events. Also, this shows the vulnerable areas under big storms from an infrastructure damage and flash flood perspective, where extra attention is sometimes required.

The spatial coverage evaluation is done using the simulated and observed daily rainfall data. Figure 5.2 illustrates the calculated POD, FAR, Bias, and HSS scores of these 10 storms using all 15 model configurations. In these panels, the x-axis shows 10 storms from the recent ones to older ones; the y-axis shows the different model configurations as coded in Section "Methodology Used for the Survey". Panel of Fig. 5.2a displays the POD scores, where higher scores indicate better coverage of rainy areas while Panel 5.2b shows the FAR scores, where lower scores indicate that the model yields less "rainy area" that is actually not rainy. A good model configuration should produce higher PODs with lower FARs. The general trend from these 2 panels is that model performance is mostly sensitive to the choice of IC/BCs: NCEP2 IC/BC generally produces the highest POD and lowest FAR, and differences in the three storms (1997-CA, 1982-CA, 1980-PNW) are very small (i.e., the POD range of 0.9038–0.9967, compared with 0.6773–0.9971 in NNRP group and 0.4538–0.9582 in 20CR group). As we examine storms that are a few decades old, the simulations become less accurate, and the simulation quality has an abrupt drop in 1940. The results are also more sensitive to the cumulus scheme choices than the microphysics scheme choices. This is in agreement with the study of Pei et al. (2014), where the cumulus process was identified as one of the controlling factors of precipitation patterns. For the 1982-CA storm, 1970-UT storm, and 1929-AL storm, POD is consistently lower when the KF cumulus scheme is used, despite the use of a microphysics scheme. This might suggest that the KF scheme tends to underestimate rainfall from cumulus cloud processes during the big storms.

Panel of Fig. 5.2c shows the frequency bias in the simulations. Perfect simulations should produce a frequency bias close to 1 (green band in the panel). It is obvious that simulations with NCEP2 IC/BC can reconstruct the rainy regions whose area is close to the observations. In the simulations with NNRP and 20CR IC/BC, however, the frequency biases have much larger variations (more biased underestimation or overestimation). Also simulations with NCEP2 IC/BC tend to overestimate the rainy area, while simulations with NNRP IC/BC tend to

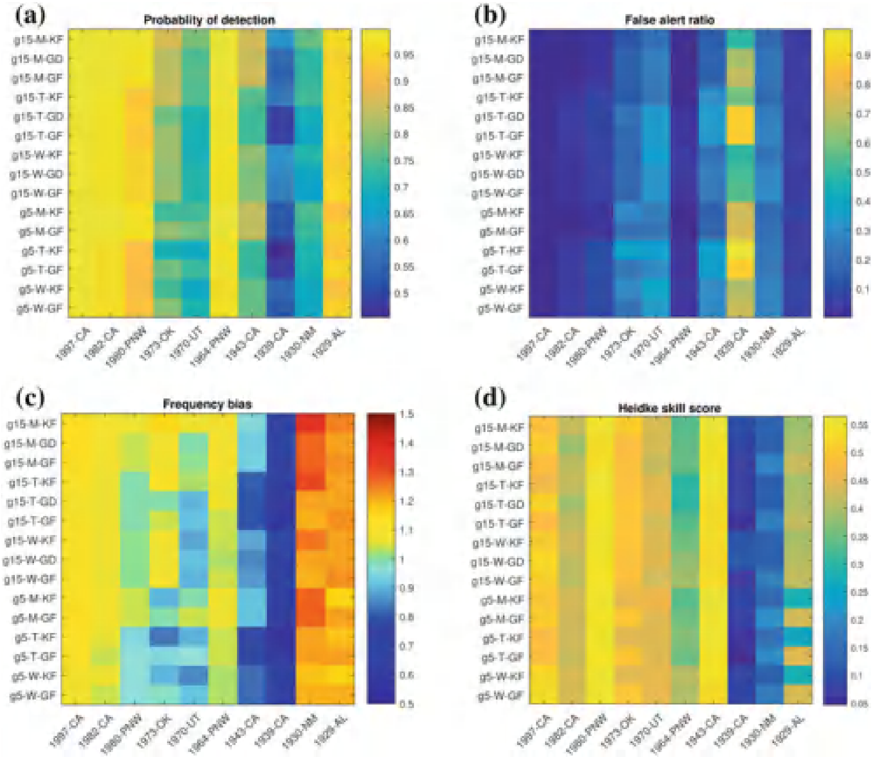

Fig. 5.2 Evaluation of reconstructed big storms: spatial coverages. Panels show a the probability of detection; b the false alert ratio; c the frequency bias; and d the Heidke skill score. The panels a, b, c were computed using 0 mm/day rainfall threshold (any rainy grids/days were counted as rainy), and panel d was computed using 5 mm/day threshold (grids/days with >5 mm/day were counted as rainy)

underestimate the rainy area. We will investigate this difference using histograms of daily rainfall amounts later. Panel of Fig. 5.2d shows the Heidke skill scores, which need to be larger than 0 for a model to be skillful. All four metrics indicate that for all these storms, the 1939-CA case produced the worst scores.

Maximum Daily and Multi-daily Rainfall

Here the analysis accounts for the actual daily rainfall combined with spatial information. This is to ensure that WRF-reconstructed precipitation is able to represent the storm centers and observed rainfall amounts. To make such comparisons, we calculated the correlation coefficients between simulated and observed

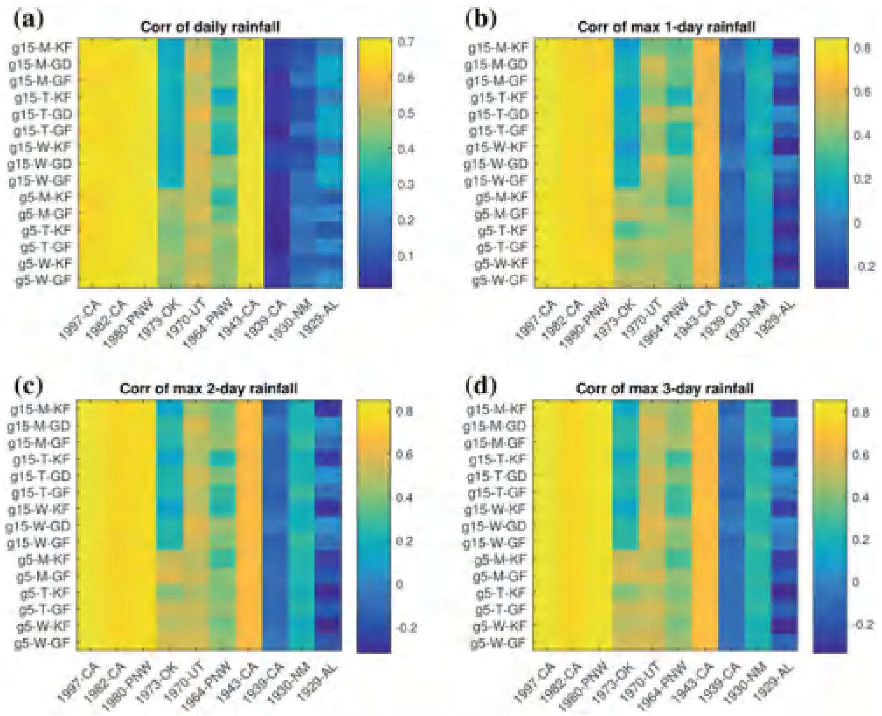

Fig. 5.3 Evaluation of reconstructed big storms: correlations with observed rainfall maps. Panels show a the correlation coefficient between simulated and observed daily rainfall; b the correlation between the simulated and observed maximum 1-day rainfall maps; c the correlation between the maximum 2-day rainfall maps; and d the correlation between the maximum 3-day rainfall maps

rainfall maps. Figure 5.3 shows the correlation coefficient between daily rainfall in the simulated duration (panel of Fig. 5.3a), between simulated and observed maximum 1-day rainfall (panel of Fig. 5.3b), maximum 2-day rainfall (panel of Fig. 5.3c), as well as maximum 3-day rainfall (panel of Fig. 5.3d). The scores are better when we focus more on overall storm characteristics (maximum rainfall of a given duration) rather than spatial-temporal structures (daily rainfall series), which is indicated by the largest correlations that exceed 0.8 in panels of Fig. 5.3b, c d. These four panels are quite similar, and the correlations can be classified into three categories according to the IC/BC inputs used. NCEP2 and NNRP IC/BC can produce sufficiently accurate rainfall estimates, while 20CR fails in the evaluation.

Figure 5.4 shows the daily rainfall correlations, max 1-day, 2-day, and 3-day rainfall correlations from these configurations shown in Table 5.2. It suggests that with a good choice of model configuration, WRF can achieve comparable reconstruction quality for all the storms after the 1940s. The correlation coefficients for these reconstructions are larger than 0.5. The reconstructions are better for more

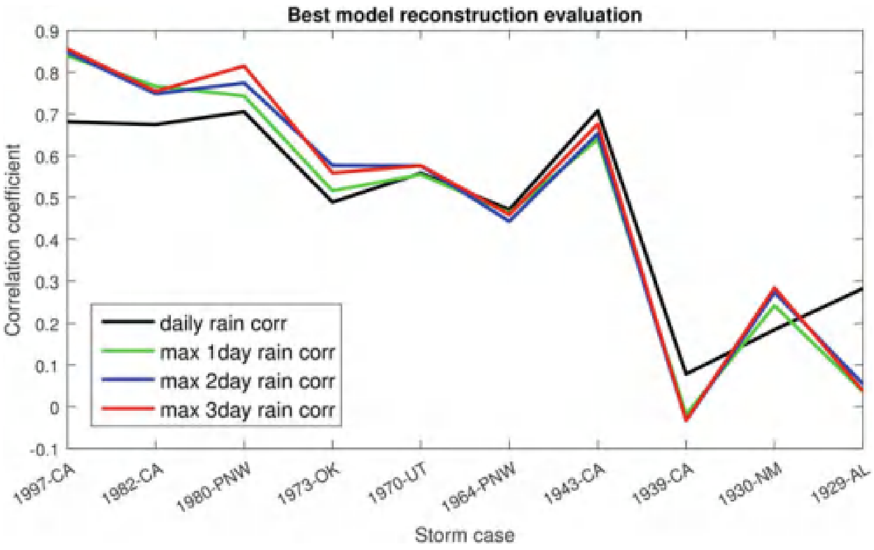

Fig. 5.4 Correlations between the best reconstructions and observations

recent storms. In order to make a case of convincing PMP estimates based on numerical models under LULC and temperature change, we may need to maximize storms after the 1980s for maximum skill.

Maximum Rainfall and Duration

Figure 5.5 shows the simulated and observed maximum 3-day rainfall for the three post-1979 storms. Figure 5.6 depicts the same comparison of 1948–1979 storms, and Fig. 5.7 shows the comparison of pre-1948 storms.

For storms after 1979, the simulated maximum 3-day rainfall maps share the same patterns as observations (Fig. 5.5). In the 1997-CA event, the most rainy area is within the American River basin, and the model gives the correct 3-day rainfall peak as 450–500 mm. In this event and the 1982-CA event, the rainbands are along the Sierra Nevada. In both events, the model tends to overestimate rainfall in the southern part of Sierra Nevada, as indicated by the blue area in panels of Fig. 5.3c, f. In the 1980-PNW event, the north–south rainbands are captured by the model, both along the Pacific coast and along the Cascades. The model underestimates rainfall in the coastal area, but overestimates in the Cascade region. Heavy rain areas (3-day rainfall >240 mm) are correctly captured in the Olympia peninsula and northern Washington.

Table 5.2 CSI scores for the 10 storms

Storm	1997-CA	1982-CA	1980-PNW	1973-OK	1970-UT	1964-PNW	1943-CA	1939-CA	1930-NM	1929-AL
g15-M-KF	0.879	0.891	0.904	0.672	0.610	0.918	0.798	0.555	0.480	0.744
g15-M-GD	0.877	0.893	0.903	0.661	0.601	0.919	0.790	0.500	0.461	0.746
g15-M-GF	0.877	0.892	0.903	0.666	0.602	0.920	0.791	0.489	0.462	0.745
g15-T-KF	0.879	0.883	0.877	0.671	0.588	0.908	0.721	0.520	0.471	0.751
g15-T-GD	0.873	0.881	0.879	0.631	0.584	0.909	0.703	0.440	0.448	0.751
g15-T-GF	0.877	0.881	0.875	0.649	0.573	0.908	0.706	0.436	0.442	0.748
g15-W-KF	0.878	0.883	0.881	0.636	0.577	0.902	0.741	0.540	0.459	0.739
g15-W-GD	0.879	0.883	0.882	0.625	0.595	0.904	0.726	0.532	0.432	0.737
g15-W-GF	0.880	0.882	0.883	0.635	0.592	0.911	0.732	0.521	0.426	0.740
g5-M-KF	0.879	0.891	0.905	0.638	0.590	0.916	0.788	0.473	0.491	0.730
g5-M-GF	0.879	0.892	0.904	0.668	0.605	0.920	0.784	0.462	0.471	0.742
g5-T-KF	0.879	0.879	0.865	0.610	0.563	0.903	0.702	0.413	0.470	0.740
g5-T-GF	0.878	0.877	0.865	0.658	0.587	0.913	0.695	0.428	0.461	0.752
g5-W-KF	0.878	0.876	0.867	0.633	0.570	0.902	0.723	0.493	0.450	0.734
g5-W-GF	0.877	0.877	0.870	0.660	0.586	0.912	0.721	0.472	0.438	0.744

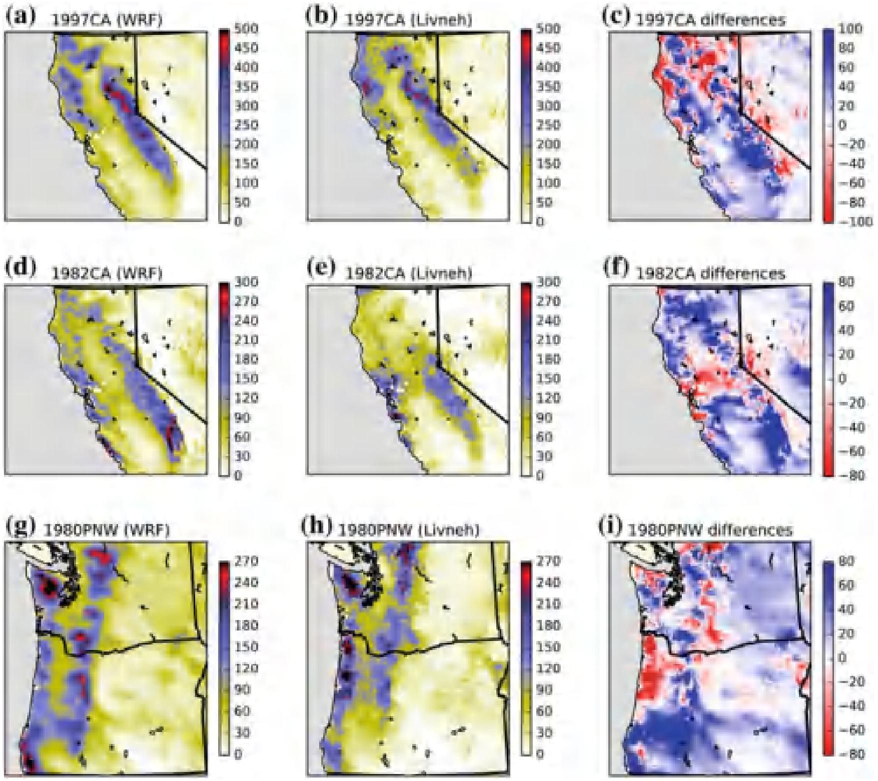

Fig. 5.5 Maximum 3-day rainfall from simulation and observation (post-1979). Panels a, d, g are the WRF simulation, and panels b, e, h are the gauge observation from Livneh dataset. Panels c, f, i are the difference (WRF—obs). All the units are mm

In the reconstruction of storms between 1948 and 1979 (Fig. 5.6), the storm patterns were not captured as precisely as was possible by WRF for the post-1979 storms. In the 1973-OK event, the heavy rainy area in northern Oklahoma and eastern Kansas are reflected in the simulation, although WRF produces an over-estimated continuous peak rainfall band in eastern Kansas. For 1970-UT, WRF simulations yield two separate rainy areas, one in central Arizona and one in southwest Colorado. This is in agreement with the observation. However, the model fails to reconstruct the heavy rainfall in central Colorado. In the 1964-PNW event reconstruction, WRF successfully estimates the rainfall amount in the storm center, which is located at the US-Canada border. The observed storm center is to the south of the simulated one, although their area is quite similar. Therefore, total rainfall and distribution of rainfall intensities are well captured.

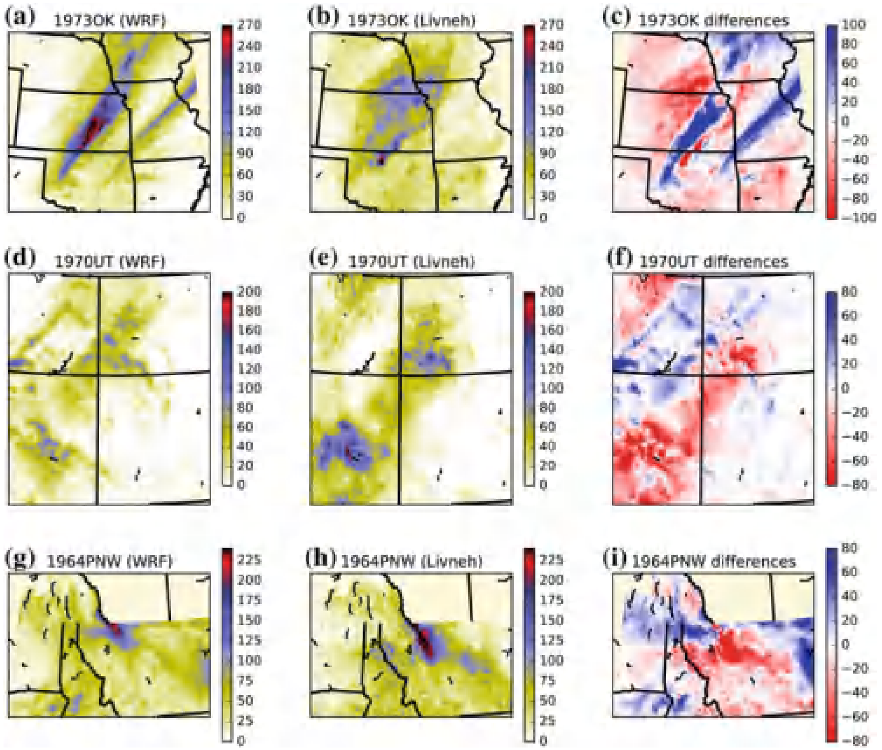

Fig. 5.6 Maximum 3-day rainfall from simulation and observation (1948–1979). Panels a, d, g are the WRF simulation, and panels b, e, h are the gauge observation from the Livneh dataset. Panels c, f, i are the difference (WRF—obs). All the units are mm

For the four storms before 1948, the quality of model reconstruction varies (Fig. 5.7). The 1943-CA event is one of the best-simulated cases of these 10 big storms. Two rainbands are well simulated by the model: the northeast one centered at Sierra Nevada and the southern rainband centered to the east of Los Angeles. Model overestimates the rain in the mountain area, but underestimates it in the southern plain. The 1939-CA simulation is the worst reconstruction among the 10 cases. WRF fails to capture the rainy area to the east of the city of Los Angeles (Fig. 5.7e), and the south–north rainfall gradient is not captured. The situation is similar for the 1930-NM storm, where the model underestimates the rainfall in the entire storm domain. In the 1929-AL event, however, the situation is a little different. The simulated storm is in central Tennessee, while the observation indicates the storm center in southern Alabama. The maximum 3-day rainfall from the simulation is barely over 200 mm, which is far less than the observed 280 mm peak.

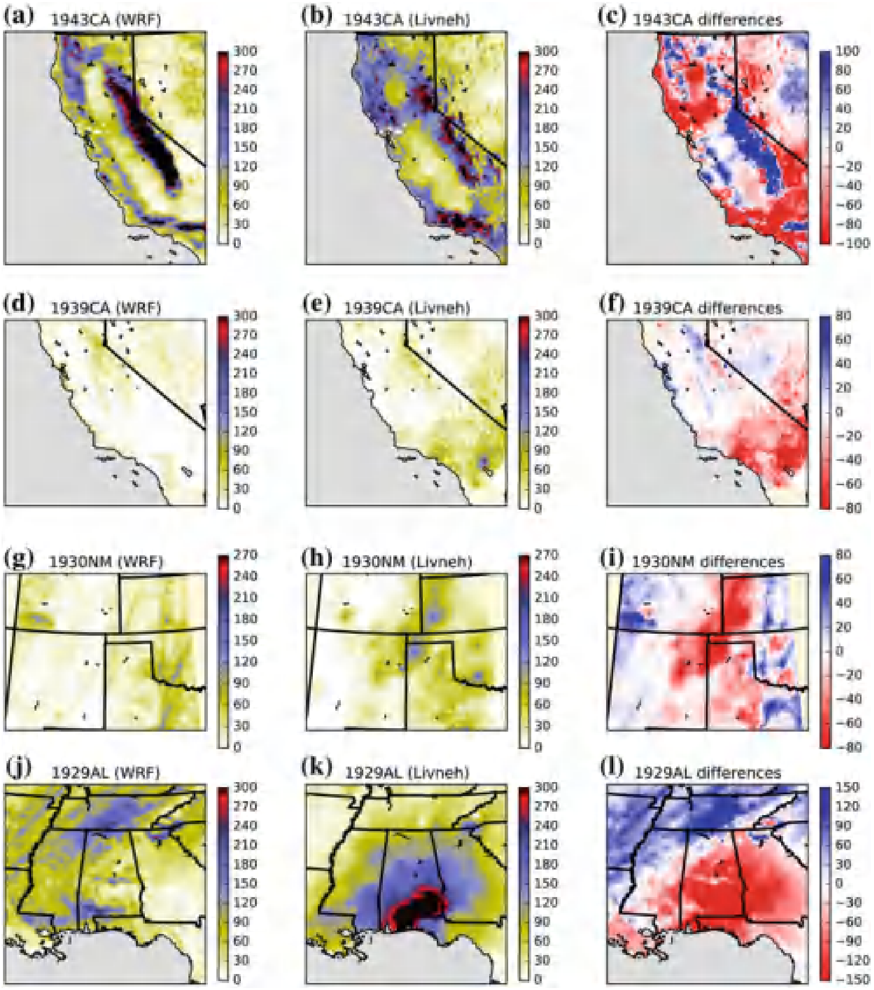

Fig. 5.7 Maximum 3-day rainfall from simulation and observation (pre-1948). Panels a, d, g, j are the WRF simulation, and panels b, e, h, k are the gauge observation from the Livneh dataset. Panels c, f, i, l are the difference (WRF—obs). All the units are mm

Conclusions

In this chapter, we evaluated the performance of a numerical atmospheric model in reconstructing 10 big storms over CONUS during 1920–2000. Our ability to reconstruct past extreme storms will dictate how well we can understand how such storms may evolve in the future for assessing water infrastructure safety. Using the gauge observation data as a reference, we evaluated the reconstruction qualities on the spatial coverage of rainy area and the correlations between simulated and observed maximum rainfall in different periods. The main results moving forward for the engineering community are:

(1) Model reconstruction is most sensitive to the choices of initial/boundary conditions. Therefore, reconstruction of historical big storms is restricted by the availability of the initial/boundary conditions;
(2) We are able to reconstruct the big storms after 1948, using carefully chosen initial/boundary conditions. The spatial patterns of these big storms are well captured by the model;
(3) The storm characteristics, presented by the maximum daily, 2-day, and 3-day rainfall, can be well captured by the numerical models. Models tend to slightly overestimate the heavy rainy area, and this puts the constructed rainfall maps on the safe side for engineering practices;
(4) The Twentieth Century Reanalysis (20CR) Product, one of the very few available choices of IC/BC to simulate storms before t 1948, is not yet ready for single extreme event studies.

As we look into the future of a sustainable supply of water and protection against hazards, we need to contend with the state of our extensive water management infrastructure that was built using historical records as well as approaches that do not provide future insights. To gain insight as to how design-class extreme storms may behave in the future given changes to land cover and a warming atmosphere, it is important that we understand how well past storms can be physically reconstructed. This chapter provided a platform for extreme PMP-class storm reconstruction of the last 100 years using a numerical modeling framework that can now be used for future design parameters under a future scenario of change.

Appendix: Details on Model Setup

See Appendix Tables 5.3 and 5.4.

Table 5.3 Model configuration codes used in the results and discussion sections

Configuration code	Model resolution (km)	Microphysics scheme	Cumulus scheme
g15-M-KF	15	Morrison	Kain-Fritsch
g15-M-GD	15	Morrison	Grell-Devenyi
g15-M-GF	15	Morrison	Grell-Freitas
g15-T-KF	15	New Thompson	Kain-Fritsch
g15-T-GD	15	New Thompson	Grell-Devenyi
g15-T-GF	15	New Thompson	Grell-Freitas
g15-W-KF	15	WSM-5	Kain-Fritsch
g15-W-GD	15	WSM-5	Grell-Devenyi

(continued)

Table 5.3 (continued)

Configuration code	Model resolution (km)	Microphysics scheme	Cumulus scheme
g15-W-GF	15	WSM-5	Grell-Freitas
g5-M-KF	15–5	Morrison	Kain-Fritsch
g5-M-GF	15–5	Morrison	Grell-Freitas
g5-T-KF	15–5	New Thompson	Kain-Fritsch
g5-T-GF	15–5	New Thompson	Grell-Freitas
g5-W-KF	15–5	WSM-5	Kain-Fritsch
g5-W-GF	15–5	WSM-5	Grell-Freitas

Table 5.4 WRF simulation duration of the 10 storms

Storm	Starting time (UTC)	End time (UTC)
1997-CA	1996-12-29 00:00	1997-01-05 00:00
1982-CA	1982-01-01 00:00	1982-01-07 00:00
1980-PNW	1980-12-22 00:00	1980-12-30 00:00
1973-OK	1973-10-08 00:00	1973-10-14 00:00
1970-UT	1970-09-03 00:00	1970-09-10 00:00
1964-PNW	1964-06-04 00:00	1964-06-11 00:00
1943-CA	1943-01-18 00:00	1943-01-27 00:00
1939-CA	1939-09-21 00:00	1939-09-29 00:00
1930-NM	1930-10-08 00:00	1930-10-18 00:00
1929-AL	1929-03-10 00:00	1929-03-19 00:00

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Chapter 6

Sensitivity of Probable Maximum Precipitation (PMP)

Steven Adam Stratz and Faisal Hossain

Introduction

The vital question that motivated this chapter is to what extent are universally accepted, stationary Probable Maximum Precipitation values as published in Hydrometeorological Reports, representative of current and future climate behavior given our current understanding of changes to climate? To the best of our knowledge, none have explored the extent to which PMP values are altered using a replication of the procedures outlined in the Hydrometeorological Reports coupled with future climate data from numerical modeling tools or observational analyses of climatic trends. These climate differences can be caused by both top-down phenomena such as heat entrapment from greenhouse gasses as well as bottom-up influences such as land-use/land-cover (LULC) change. Studies have recently looked at the effects of LULC changes in the post-dam construction era on climate (see, e.g., Yigzaw et al. 2013; Lo and Famiglietti 2013) as well as global effects of the changes in climatic statistics on air moisture content. A simple change in land use or land cover can significantly alter the hydrology of an area from changes in permeability, evapotranspiration rates, water loss through irrigation, and so on leading to changes in the local hydroclimate. A replication of the conventional procedures outlined in HMRs substituting non-stationary atmospheric variables for stationary values has not been performed. This chapter therefore aims to provide

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insights for practitioners into the extent to which HMR-PMP values in large dams may have been altered since their construction using both top-down and bottom-up modeling approaches (Stratz and Hossain 2014).

Moisture Maximization of Storms in HMR Studies

The concept of probable maximum precipitation, as mentioned previously, was developed in the 1940s with the first publication of a series of Hydrometeorological Reports (Foufoula-Georgiou 1989). These reports, primarily produced by the Weather Bureau (now the National Weather Service), contain procedures detailing the intricate processes and datasets used for the derivation of PMPs. Though region-specific variables contribute to specific modeling methods used in each report, the general approach used in all HMRs is moisture maximization. This method increases atmospheric moisture to the upper possible limit for the time and location of the rainfall event. The method of moisture maximization is demonstrated by the following equation (Rakhecha et al. 1999):

$$\mathrm{PMP_T} = \mathrm{P_{0;SL}} \times \left(\frac{\mathrm{W_p(max)_T}}{\mathrm{W_p(Observed)}}\right) \tag{6.1}$$

where $\mathrm{P_{0;SL}}$ is the maximum recorded depth of rainfall for a particular duration over a particular area of the storm location, $\mathrm{W_p(max)_T}$ is the maximum probable precipitable water of an air column in the transposed location based on seasonal 12-h maximum persisting 1000-h Pa dew point, and $\mathrm{W_p(Observed)}$ the actual precipitable water in the moisture column of the storm being maximized (in some circumstances along the west coast, particularly areas west of the 105th meridian, it is necessary to substitute maximum persisting 12-h sea surface temperatures in place of dew point) (U.S. Department of Commerce 1999). The observed precipitable water is found using HMR tables that relate 12-h maximum persisting 1000-h Pa dew point to the available precipitable water in an air column (U.S. Department of Commerce 1965), or if available, vertical soundings taken during the storm. Equation (6.1) yields a PMP value at the transposed location with the same spatial and temporal values as the location of the maximized storm.

In addition to moisture maximization, both duration and areal factors must be considered when following the HMR methodology. Duration and areal factors can be obtained from the depth-area-duration curve of the appropriate controlling storm. The desired PMP duration (usually 72 h in the design of large dams) and area of the watershed in question can be interpolated from these curves for use in the PMP calculation of the transposed location (U.S. Department of Commerce 1999).

In areas of significant orography, elevation influences and storm separation into orographic and convergent components must also be employed during moisture maximization (Rakhecha and Singh 2009). Splitting the storm rainfall into convergence-induced precipitation and orographic effects allows the storm to be transposed to locations with varying topographic features. The non-orographic component, or Free Atmospheric Forced Precipitation (FAFP), is the portion of rainfall caused solely by atmospheric conditions. This value can then be transposed to the desired location and multiplied by the orographic factor, or K factor, of that location. Equation (6.2) is used to calculate K factors.

$$K = M^2\left(1 - \frac{T}{C}\right) + \frac{T}{C} \tag{6.2}$$

where M is the storm intensification factor, T is the total 100-year precipitation, and C is the 100-year convergence component (U.S. Department of Commerce 1999). Values of T and C can be found in tables in HMR 59. M varies by rainfall event and can be considered the precipitation in the most intense period of the storm divided by the storm duration. Multiplying the K factor by the FAFP-PMP reveals the PMP of the transposed location in orographic regions. Figure 6.1 summarizes the overall procedure in the form of a flowchart.

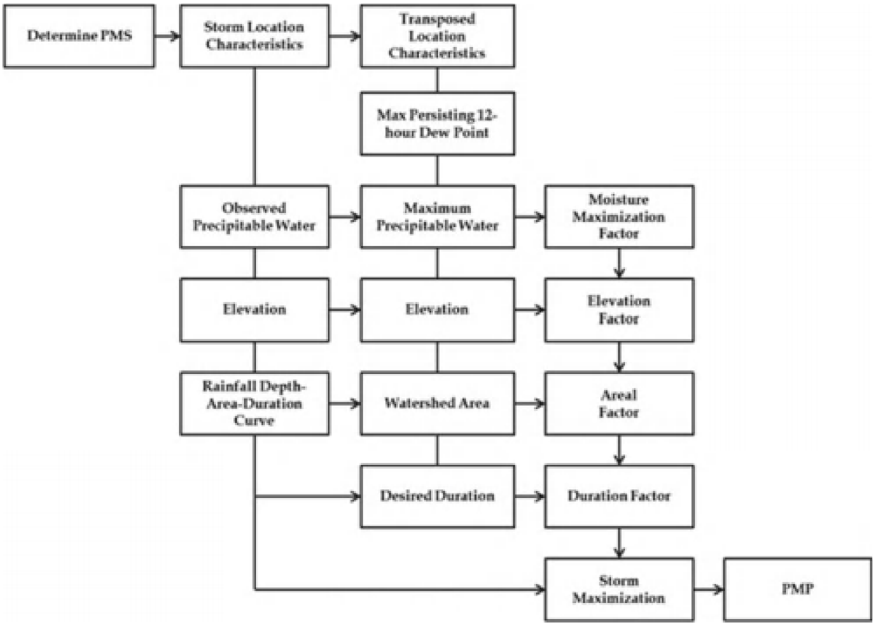

Fig. 6.1 The overall PMP estimation approach

Non-stationary Re-derivation of PMP Values

Three study regions were considered for the re-calculation of PMP values substituting non-stationary climate data in place of stationary data used in the HMR reports: the Upper American River Watershed in California (Folsom Dam), the Owyhee River Watershed extending across Idaho, Nevada, and Oregon (Owyhee Dam), and the Holston River Watershed spanning parts of Virginia, North Carolina, and Tennessee (South Holston Dam).

Folsom Dam is a multipurpose dam situated 23 miles northeast of Sacramento, California. Its major intended function is flood control, but it also provides hydropower and irrigation to the surrounding region. It was constructed in 1955 along the American River and currently impounds Folsom Lake (California Department of Parks and Recreation, 2013; Fig. 6.2.)

Further to the northeast of Folsom Dam is Owyhee Dam, situated in Oregon across the Idaho border from Boise (Fig. 6.2). The dam was constructed for use in irrigation projects. The Owyhee River drains into Owyhee Reservoir, which is fed by excess runoff from the Owyhee River Watershed (ORW). The watershed is about 11,588 square miles in surface area as shown in Fig. 6.2 (Oregon Environmental

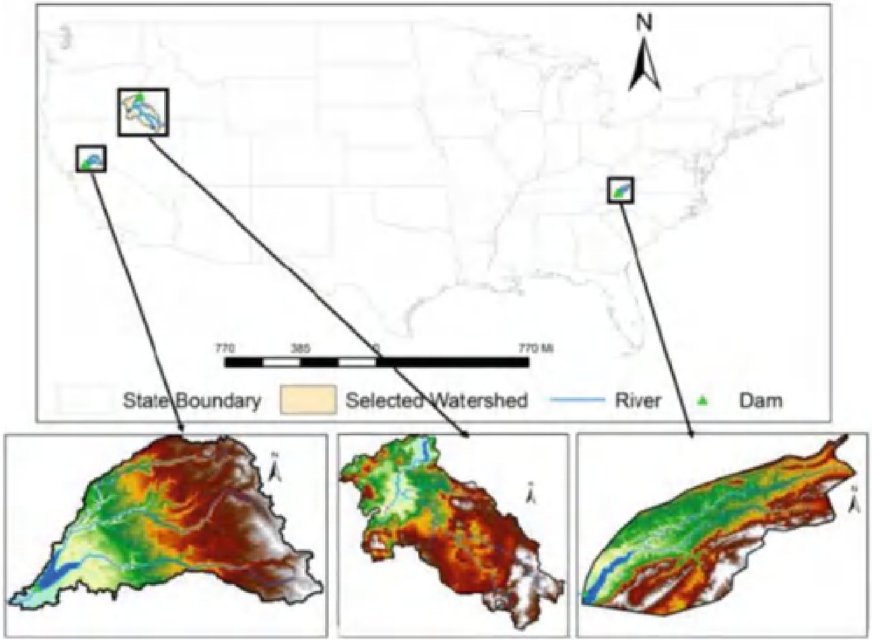

Fig. 6.2 Selected impounded river basin and dam sites for investigation of HMR-PMP with non-stationary climate forcings. Leftmost panel—American River (Folsom Dam); Middle panel—Owyhee River (Owyhee Dam); Rightmost panel—Holston River (South Holston Dam)

Council 2013). The dam was completed in 1932 and was, at the time, the tallest dam in the world (Bureau of Reclamation 2012).

The Holston River watershed feeds South Holston Reservoir, which is an impoundment by South Holston Dam near Bristol, Tennessee. The dam was opened in 1950 and was intended primarily for hydropower and flood control, but irrigation supplied by the reservoir now delivers water to numerous surrounding croplands (Tennessee Valley Authority 2013).

A bottom-up climate modeling approach using the Regional Atmospheric Modeling System (RAMS; Pielke et al. 1992) was applied to two of the study regions (UARW and ORW) in order to determine the impact of LULC change on future PMP values. RAMS is a numerical model similar to WRF used in Chaps. 4 and 5. Changes to land cover, as explained in Chap. 1, can have a significant effect on the water cycle due to drainage ability, evapotranspiration, irrigation, etc., and lead to a change in local climate. A storm of historical significance (January 1997; Dettinger et al. 2004) was numerically modeled over both watersheds using four different LULC scenarios to determine the difference in storm behavior between the scenarios. The dew point data (or more specifically, the 12-h maximum persisting dew point) from each scenario could then be extracted and used to directly simulate the HMR-PMP procedure. The LULC scenarios considered were: (a) Control (current land conditions of the watershed); (b) Reservoir-Double (an assumed land condition where the reservoir surface area is assumed to be doubled); (c) Non-Irrigation (a land condition where the irrigation surrounding the reservoir is assumed to be replaced with pre-dam land cover); and (d) Pre-Dam (representative of the land condition at the time of construction of the dam before the reservoir was impounded).

A point to note is that the Reservoir-Double scenario is more of a hypothetical scenario that was used to explore the sensitivity of open-water evaporation on extreme precipitation rates. On the other hand, the “Non-Irrigation” scenario was represented by replacing currently irrigated land surfaces with land-use information pertaining to the pre-dam period that was available from the HYDE database (available at http://themasites.pbl.nl/en/themasites/hyde/index.html) while keeping the reservoir intact. HYDE presents a gridded time series of land use for the last 12,000 years (Goldewijk et al. 2011). This land data is useful in reconstructing the early twentieth-century land-use scenario for an atmospheric modeling domain. The numerical modeling details using RAMS may be found in Woldemichael et al. (2012).

The next step after extracting the dew point data from the RAMS model for each of the two watersheds was the identification of the convergence component of the January 1997 storm, which excludes all orographic influences. The orographic influences of this storm were stripped from the total rainfall so that new orographic conditions in the transposed location (in this case, the UARW) could be inserted. This was done by use of the K factor (Eq. 6.2), which gives the total PMP when multiplied by the convergence component. However, this was later found redundant as the desired transposition location had similar orographic characteristics to the region of maximum rainfall that occurred at an elevation of 5200 ft (above mean sea level). Areal and temporal adjustments were then made followed by moisture maximization.

Based on the RAMS modeled surface dew points for the 12/15/1996–01/02/1997 period of the storm, the maximum persisting 12-h surface dew point for each of the four scenarios (Control, Reservoir-Double, Non-Irrigation, and Pre-Dam) was obtained and compared to the 12-h maximum persisting 1000 mb dew points for the month of December. Using the precipitable water tables reported in the HMRs, the values (of total precipitable water) corresponding to both stationary and non-stationary dew points were found. Using the moisture maximization equation and an areal reduction factor (and following the flowchart outlined in Fig. 6.2), the non-stationary PMP for each of the LULC scenarios was calculated for the Folsom and Owyhee Dams. For the methodological details, the interested reader is referred to Stratz (2013).

In contrast to the bottom-up methodology used for PMP re-calculations at the UARW and ORW, a top-down approach was used to re-calculate the PMP at the Holston River Watershed using observational dew point trends. Instead of looking at the sensitivity of PMPs to land-induced mesoscale climate change, an analysis of the sensitivity of PMPs to an increase in dew point alone was performed. Numerical modeling of the Elba storm for various LULC scenarios was not feasible given the absence of atmospheric forcing data dating back to 1929 needed to run the RAMS model. Thus, the PMP re-calculation was performed on the basis of a projected trend in dew points derived from a long observational record. A study by Robinson (2000) collected nearly 40 years of dew point data across the USA from 178 stations to establish dew point trends occurring over long periods of time in various regions of the USA. The vast amounts of data were analyzed and indicated an increase of slightly over 1 °C (1.8 °F) over 100 years in the spring and autumn seasons. This long-term study over a widespread area is used to re-calculate a non-stationary PMP for the Holston River Watershed. The maximum persisting 12-h dew point chart for March (the month of the controlling storm) was adjusted to accommodate the 1.8 °F average dew point increase over a 100-year period. For convenience, a 111-year period corresponding to a 2 °F increase in dew point was chosen for this calculation.

PMP Sensitivity

Upper American River Watershed

The re-calculated PMP values for the UARW using RAMS climate model data for each LULC change scenario are shown in Table 6.1. The increase in PMP values using mesoscale anthropogenic climate variability is substantial. A comparison between the Control scenario and Non-Irrigation scenario shows a 5.4% difference in PMP, signifying a significant PMP intensification due to an influx of irrigation

Table 6.1 Non-stationary 72-h PMP values for various LULC scenarios for the upper American River Watershed (using RAMS numerical modeling data)

Scenario	PMP (in)	% Increase	% Change from RAMS control
HMR 59 (stationary)	24.67	–	–
RAMS control	29.22	18.4	–
RAMS reservoir-double	29.53	19.7	1.1
RAMS non-irrigation	27.65	12.1	−5.4
RAMS pre-dam	28.44	15.3	−2.7

around the reservoir. The two highest non-stationary PMP values result from situations where both the reservoir and irrigation are in place (Control and Reservoir-Double scenarios). This shows the impact of impounded reservoirs and irrigation on the intensification of the water cycle, leading to potentially serious non-stationarity and a rising trend in extreme precipitation. It can be inferred from the other two scenarios (Non-Irrigation and Pre-Dam) that irrigation has a much larger impact on atmospheric intensification than reservoir size, but both contribute to a notable increase in overall PMP. Pro-active accounting for post-dam irrigation development appears essential for the development of more robust PMP variables for the design of large dams.

Owyhee River Watershed

The re-calculated non-stationary PMP values for the Owyhee River Watershed for various LULC change scenarios are shown in Table 6.2. The Control and Reservoir-Double scenarios dominate, while Non-Irrigation and Pre-Dam yield the lowest change to PMP values. However, unlike the Upper American River Watershed, the Non-Irrigation scenario produces a higher PMP value than the Pre-Dam scenario in the Owyhee River Watershed. It appears that the reservoir has a larger influence on atmospheric water cycle intensification than does the vegetation cover in the pre-dam era. This is a likely result of the leeward side of the

Table 6.2 Non-stationary 72-h PMP values for various LULC scenarios for the Owyhee River Watershed (using RAMS numerical modeling data)

Scenario	PMP (in)	% Increase	% Change from RAMS Control
HMR 57 (stationary)	5.38	–	–
RAMS control	14.38	167.3	–
RAMS reservoir-double	15.34	185.1	6.7
AMS non-irrigation	12.62	134.6	−12.2
RAMS pre-dam	11.84	120.1	−17.7

mountain on which the reservoir is located. The leeward side of the mountain is dominated by LULC changes due to the rain shadow effect, while the windward side experiences moisture contributions from the Pacific which may mask any localized impact of LULC changes. Previous research supports this conclusion (see Woldemichael et al. 2013a, b).

The difference between the non-stationary PMP values and HMR 57 PMP values (for the Owyhee River Watershed) is significant when compared to the Upper American River Watershed results (an increase of 167.3 and 185.1% for the Control and Reservoir-Double scenarios, respectively, compared to an 18.4 and 19.7% increase in Folsom Dam for the same scenarios). The discrepancy can be attributed to an upper computational limit employed for the In-Place Maximization Factor (IPMF) (the in situ moisture maximization value before transposition) in HMR 57 (U.S. Department of Commerce 1994). The maximization factor for the LULC change scenarios using the RAMS model was 6.57, while a limit of 1.7 is set in HMR 57. The difference in calculated dew point when compared to maximum dew point for the time of year of the storm’s occurrence in the RAMS model was substantial, leading to a large maximization factor. However, because the storm is reproduced over the ORW in the RAMS model, no transposition factor was introduced. While the IPMF has an upper limit in HMR 57, the transposition factor does not. Since the IPMF and transposition factors cannot be separated for an in situ scenario, a direct comparison between HMR-PMP and RAMS-PMP for the ORW (and only the ORW) is difficult. Nonetheless, wisdom can still be obtained from the impact of LULC change on this watershed.

Holston River Watershed

For the HRW, both HMR 41 and 51 contribute to PMP calculations due to the orography introduced by the Appalachian Mountains. The PMP values published in these reports are not concentric isohyets as found in HMR 57 or HMR 59. Rather, they are shown as isolines extending from the East Coast to the 105th meridian near the foothills of the Rocky Mountains. The re-calculated PMP values using a rise of 2 °F per 111 years are compared to the values in HMR 41 and 51 and are presented in Table 6.3. The values highlighted in red correspond to the approximate average latitude of the HRW. These values are reduced to the area of the HRW (3747 square miles) and shown in Table 6.4. Substituting projected trends of dew point rise into the HMR procedure produced an approximately 2.4-inch 72-h PMP increase for the Holston River Watershed. It is important to note that this estimation is directly tied to a 2 °F rise in average dew point rather than a concrete estimation for a 111-year period due to the intrinsic uncertainty in climate projections.

Table 6.3 Re-calculated PMP values for 10,000 square miles over the Eastern USA

Approximate latitude (east of Mississippi River)	24-h PMP (HMR)	24-h PMP (projected)	72-h PMP (HMR)	72-h PMP (projected)
39 N	9.89	11.48	13.85	16.07
38 N	11.48	12.69	16.07	17.77
37 N	12.69	14.00	17.77	19.60
35 N–37 N	13.33	14.69	18.66	20.57
34 N–35 N	14.00	15.43	19.60	21.60
33 N–34 N	14.69	16.20	20.57	22.68
33 N	15.43	17.00	21.60	23.81
32 N	16.20	17.86	22.68	25.01
31 N	17.00	18.76	23.81	26.26

Table 6.4 Non-stationary 72-h PMP values for the Holston River Watershed (using observed dew point trends)

Approximate latitude (east of Mississippi River)	10,000 mi^2 PMP (HMR)	10,000 mi^2 PMP (projected)	HRW PMP (HMR)	HRW PMP (projected)
39 N	14.5	16.1	19.3	21.4
38 N	16.1	17.8	21.4	23.7
37 N	17.8	19.6	23.7	26.1
35 N–37 N	18.7	20.6	24.9	27.4
34 N–35 N	19.6	21.6	26.1	28.8
33 N–34 N	20.6	22.7	27.4	30.2
33 N	21.6	23.8	28.8	31.7
32 N	22.7	25.0	30.2	33.3
31 N	23.8	26.3	31.7	35.0

Conclusion

The key findings of the hindsight investigation of HMR-PMP values with non-stationary climate forcings can be summarized for practitioners and water managers as follows:

(1) Irrigation has the largest LULC impact on PMP intensification. Removing irrigation from the control scenario lowered the HMR-PMP by 5.4% for the UARW and by 12.2% for the ORW.

(2) Using atmospheric model-derived persisting dew point indicates that PMPs for dams on the leeward side of mountains are more impacted by LULC change than those located on the windward side.

(3) Observed trends in dew point records point to a noteworthy rise in PMP values for watersheds east of the 105th meridian should current dew point trends continue. A 2.4-inch (10.1%) 72-h PMP increase may be expected for the HRW for a 2 °F rise in average dew point.

These findings have profound implications for the aging water resources infrastructure of the USA. The aging of existing hydraulic infrastructure designed under the assumption of PMP stationarity is now of significant concern. An additional compounding risk, for dams in particular, stems from natural aging and loss of storage through sedimentation, a topic that is relatively much better understood (Graf 1999, 2006; Graf et al. 2010), for the 85% of the dams in the USA that will be over 50 years old in 2020 (Hossain et al. 2009). Gradual loss of storage reduces the routing potential of a floodwave and makes the downstream flood risk posed by the Probable Maximum Flood, which is derived from PMP, more enhanced. Thus, the implications of the re-calculation of non-stationary PMP values should now trigger a discussion on how best to leverage this understanding for better risk assessment and adaptation.

It is highly recommended that a re-evaluation of existing and aging dams designed with static HMR-PMP values be performed, taking into account projected climate trends due to global warming and predicted LULC changes in the post-dam era, both of which are known to impact extreme rainfall processes. Also, prospective dams should be constructed with the assumption of a dynamic PMP variable derived from numerical models of the atmosphere. The purpose of the dam (hydropower, irrigation, recreation, etc.) gives a relatively accurate indication of the LULC changes that will take effect after completion, which can be taken into account proactively during design stages together with the impacts expected from global warming trends should they continue into the future.

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Chapter 7
A Recommended Paradigm Shift in the Approach to Risks to Large Water Infrastructure in the Coming Decades

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Abstract We propose the adoption of a bottom-up, resource-based vulnerability approach in evaluating the effect of climate and other environmental and societal threats to large water management infrastructure. To effectively reduce risk and increase resiliency requires as a prerequisite the determination of the major threats to local and regional water supplies and quality from weather including those from extreme flood and drought events, but also from other social and environmental issues. After these threats are identified, the relative risks can be compared in order to adopt optimal preferred mitigation/adaptation strategies. This is a more inclusive way of assessing risks, including from climate variability and human and natural climate change, than using the outcome vulnerability approach adopted by the Intergovernmental Panel on Climate Change (IPCC). This "contextual vulnerability" assessment using the bottom-up, resource-based framework is a more inclusive approach for policymakers dealing with water management infrastructure to adopt effective mitigation and adaptation methodologies to deal with the complexity of the spectrum of social and environmental events that will occur in the coming decades.

Introduction

This article discusses two different approaches to improve the resilience of large water management infrastructure in the coming decades to threats from weather including extreme floods and droughts. As discussed in more detail later, the two methods are called: "outcome vulnerability" and "contextual vulnerability."

The outcome vulnerability starts with global climate model projections and then downscales, by either interpolation or statistical and/or dynamic regional and local-scale models to water basin and smaller regions. Their projections are made

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by inputting different levels of CO_2 and other greenhouse gas and aerosol emissions into global climate models to produce scenarios. This is the approach used by IPCC WG1 (2013; Chap. 12 and Annex I) and the US National Assessment (2014). Thus, the current emphasis is to use multidecadal global climate model projections as a primary tool to assess risk to water infrastructure and to other societal and environmental concerns in the coming decades. An example of this limited focus is reported on in Lukas et al. (2014) where the IPCC scenarios are used as the primary approach to assess future climate risks.

However, as discussed in this article, this is a fundamentally flawed approach as it is based on model predictions which, which when tested in hindcast runs, fail to show significant regional skill at simulating observed changes in regional climate statistics. To base water infrastructure development on this approach is fraught with risk as costs may be spent that is not needed, or worse, money is not spent that would have the most benefit in promoting infrastructure resilience for water management.

In contrast, the contextual vulnerability approach assesses risks faced by large water management projects in the coming decades in a bottom-up framework. All known risks, including from possible changes in regional and local climate statistics are considered, but also other environmental and social risks are considered (Pielke and Bravi de Guenni 2004; Pielke et al. 2012).

To present this reasoning, this article is segmented into these topics

- What are weather and climate?
- What are weather and climate models? What do they do?
- How well do climate models perform with respect to multidecadal prediction?
- What is the spectrum of human climate forcings?
- What is a more inclusive approach to assess and reduce risks to water infrastructure.

What Are Weather and Climate?

To accurately define the terms weather and climate, it is necessary to start from the definition of the climate system. NRC (2005) presents a figure (Fig. 7.1) that schematically shows the different Earth system components. As shown in the following text, terminology is often contradictory in its use.

Climate is defined in that report (and by the American Meteorological Society) as

> The system consisting of the atmosphere, hydrosphere, lithosphere, and biosphere, determining the Earth's climate as the result of mutual interactions and responses to external influences (forcing). Physical, chemical, and biological processes are involved in interactions among the components of the climate system.

A climate feedback is defined as

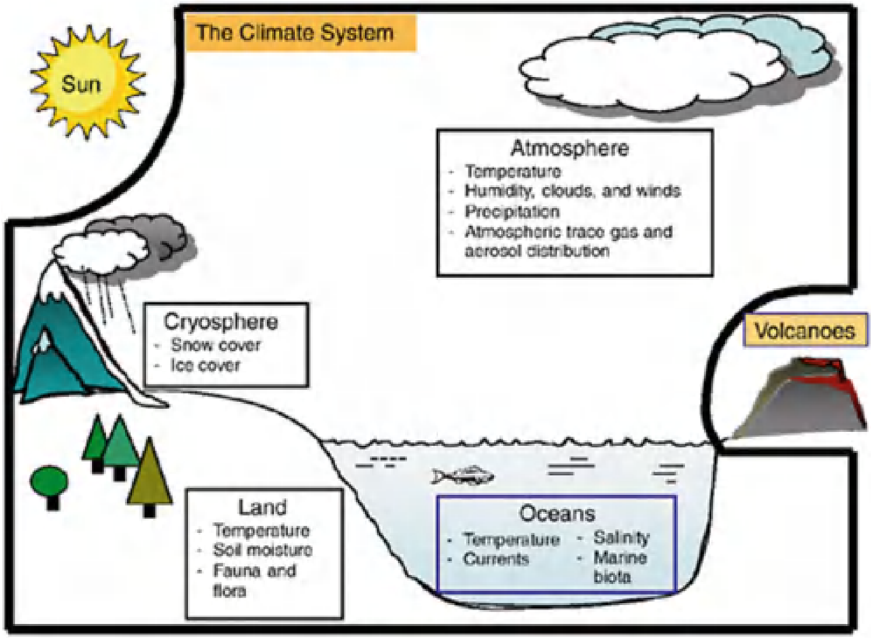

Fig. 7.1 The climate system, consisting of the atmosphere, oceans, land, and cryosphere. Important state variables for each sphere of the climate system are listed in the boxes. For the purposes of this report, the Sun, volcanic emissions, and human-caused emissions of greenhouse gases and changes to the land surface are considered external to the climate system. From NRC (2005)

> An amplification or dampening of the climate response to a specific forcing due to changes in the atmosphere, oceans, land, or continental glaciers.

While climate forcing is given as

> An energy imbalance imposed on the climate system either externally or by human activities.

However, a confusing separation is made between a “direct climate forcing” and an “indirect climate forcing”

They define “direct climate forcing” as

> Climate forcing that directly affects the radiative budget of the Earth’s climate system. For example, this perturbation may be due to a change in concentration of the radiatively active gases, a change in solar radiation reaching the Earth, or changes in surface albedo. Radiative forcing is reported in the climate change scientific literature as a change in energy flux at the tropopause, calculated in units of watts per square meter (W m^{-2}); model calculations typically report values in which the stratosphere was allowed to adjust thermally to the forcing under an assumption of fixed stratospheric dynamics.

An indirect climate forcing is defined as

> A climate forcing that creates a radiative imbalance by first altering climate system components (e.g., precipitation efficiency of clouds), which then almost immediately lead to changes in radiative fluxes. Examples include the effect of solar variability on stratospheric ozone and the modification of cloud properties by aerosols.

The reason that they (artificially) separate is a result of the conflict in goals between the UN Framework on Climate Change (UNFCC) and the Intergovernmental Panel on Climate Change (IPCC).

The UNFCC's mandate [https://unfccc.int/resource/docs/convkp/conveng.pdf] is

> "Climate change" means a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods.

The focus is on greenhouse gas emissions, including carbon dioxide.

This narrow definition, however, is not present in the IPCC mandate to Working Group (WG1) 1—The Physical Science Basis—http://www.ipcc.ch/report/ar5/wg1/docs/WG1AR5_Questions.pdf. The IPCC definition is

> to provide a comprehensive and robust assessment of the physical science basis of climate change

Thus, the IPCC mandate is not limited to just greenhouse gases.

Specifically, in the Glossary to the IPCC Report [http://www.ipcc.ch/pdf/assessment-report/ar5/wg1/WG1AR5_AnnexIII_FINAL.pdf], they define climate change as

> Climate change refers to a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes or external forcings such as modulations of the solar cycles, volcanic eruptions and persistent anthropogenic changes in the composition of the atmosphere or in land use. Note that the Framework Convention on Climate Change (UNFCCC), in its Article 1, defines climate change as: 'a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods'. The UNFCCC thus makes a distinction between climate change attributable to human activities altering the atmospheric composition, and climate variability attributable to natural causes.

The IPCC has a second definition for "climate" which complicates the subject even further. The IPCC defines this climate term as

> Climate in a narrow sense is usually defined as the average weather, or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. The classical period for averaging these variables is 30 years, as defined by the World Meteorological Organization (WMO). The relevant quantities are most often surface variables such as temperature, precipitation and wind. Climate in a wider sense is the state, including a statistical description, of the climate system.

Although not stated in this narrow definition, the only difference between this limited meaning for climate and what we refer to as weather is just the averaging time for the statistics. In weather, we use daily or weekly averages, for example. In this narrow definition of climate, 30-year averages are used by the WMO.

Clearly, it is more scientifically robust to use the NRC definition that climate is an integration of physical, biological, and chemical processes and state variables. Climate change involves alterations of these process and variables by humans or naturally. That will be the definition used in this paper. However, this confusion in terms has been part of the reason the climate issue has become so contentious.

Figure 7.1, therefore, accurately captures the climate system schematically. Within this figure, the atmospheric portion can be subset into weather when (i) short averaging time periods are considered; e.g., hours to weeks to a few months, and (ii) other components of the climate system are usually specified (e.g., sea surface temperatures, vegetation, soil moisture).

In contrast, the time periods that are focused on in the IPCC and UNFCC reports are multidecadal. Moreover, unlike weather, there is not the luxury of being able to prescribe components of the system; they all interact through interfacial fluxes between the atmosphere, oceans, land, and cryosphere. The narrow definition of “climate” defined by the IPCC is just the multidecadal statistics of the atmospheric portion of the climate system.

There is another issue with respect to how climate information is communicated to policymakers. The assumption of a stable climate system (e.g., the reason for the use of the terminology “climate stabilization”) in the absence of human intervention is made. This, however, is a mischaracterization of the behavior of the real climate system.

It is based on model runs with added atmospheric CO_2 and runs made without. The runs without added CO_2 show only small excursions over hundreds of model-simulated years. Thus, a model is used to define how the real-world climate system behaves and much of the climate policy is based on this claim. Yet the real world shows significant excursions even without significant human involvement (e.g., Rial et al. 2004; Sveinsson et al. 2003).

As concluded, for example, in Rial et al. (2004),

> The Earth’s climate system is highly nonlinear: inputs and outputs are not proportional, change is often episodic and abrupt, rather than slow and gradual, and multiple equilibria are the norm.

Humans are now adding to the complexity of forcings and feedbacks, but change has always been a part of the climate system. “Climate change” is and always has been occurring. The added word “change” is, therefore, redundant.

Moreover, there is yet an additional misunderstanding. “Global warming,” which is an increase in the global annual average heat content measured in Joules, is often incorrectly equated to mean “climate change.” Global warming, however, is just a subset of “climate change.” The term “climate change,” is also erroneously used to mean only “anthropogenic-caused changes in climate” from nearly “static” climatic conditions. Clearly, more precise terminology needs to be provided in order to better communicate to the impact community and to policy managers.

In summary, this section shows there are two definitions of “climate” that engineers and water managers should be aware of if they are to take advantage of scientific research for improving resilience of water infrastructure. The narrow definition is that climate is the multidecadally averaged statistics of weather. The inclusive (more robust) definition is that “climate” involves all physical, biological, and chemical aspects of the Earth. This dual set of definitions has contributed to confusion when communicating to policymakers and the impacts communities.

The focus of the UNFCC on just a subset of human climate forcings has also confused the issue. The IPCC and UNFCC have different emphases, with the UNFCC considering only a part of the subject. What is often overlooked is that hydrological processes are as much a part of climate as atmospheric dynamics and thermodynamics, as reported in NRC (2005) and Kabat et al. (2004).

In addition, the focus of a global average metric (i.e., the 1.5 °C or 2 °C threshold of the Paris Agreement) obscures the spatial and temporal scales that matter much more to large water infrastructure issues. Both natural and human-caused climate forcings cause changes in the statistics of extreme and long-term weather events. These events are regional and local in scale and occur from hours (e.g., flash flood) to seasons and longer (e.g., drought). Thus, the focus should be on regional and local climate as this is the spatial scale needed by water resource managers.

The next section presents an overview of weather and climate models which are being used to make both short-term and multidecadal predictions.

What Are Weather and Climate Models? What Do They Do?

Models include fundamental concepts and parameterizations of the physical, biological, and chemical components of the climate system. For climate, they need to include all important climate processes, while for weather only a subset is needed, as explained in the previous section. The models are expressed as mathematical formulations and then averaged over grid volumes [e.g., described in depth in Pielke (2013) for mesoscale models]. These formulations are then converted to a programming language so that they can be solved on a computer and integrated forward in discrete time steps over the chosen model domain. For multidecadal time periods, a global domain is used and then often statistically and/or dynamically downscaled to regions. With dynamic downscaling, a different (regional) model is typically used.

For short-term prediction (weather), both global and regional domains are used with the latter generally a different model, but using lateral boundary conditions from the global model. A global weather model is a subset of a climate model which focuses on the atmosphere on averaging times of days and weeks. An extremely important advantage of weather models (often referred to as numerical weather prediction) is that real-world observations are input into the model at frequent intervals so as to constrain the drift from reality in making their forecasts. Radiosondes, for example, are routinely launched at 12-h intervals and assimilated into the weather models. Satellite and other observations can be inserted more frequently. In contrast, multidecadal climate forecasts have no such constraint.

Also, weather models are run several times a day, thus building up a large database to evaluate their skill. Their skill is quantitatively tracked. Much of the world followed the forecasts of such models as Hurricane Irma moved across the Caribbean and made landfall in Florida in September 2017—http://www.nhc.noaa.gov/text/MIATWSAT.shtml. Their accuracy (landfall location) was followed on the news as events unfolded.

In contrast, there has been a limited assessment of multidecadal climate model skill since only a few realizations are possible in hindcast runs for the last few decades. As discussed later in this article, the hindcast runs that have been completed show very limited skill, at best.

There are three types of applications of climate and weather models.

Process studies: The application of the models to improve our understanding of how the system works. This is a valuable application of these tools. The term sensitivity study can be used to characterize a process study. In a sensitivity study, a subset of the forcings and/or feedback of the system may be perturbed to examine its response. For example, added CO_2 into a global climate model without inserting all of the other important human climate forcings is a process (sensitivity) study.

Diagnosis: With this application, observed data is assimilated after the fact into the model to produce an analysis that is consistent with our best understanding of the system. The fundamental concepts and parameterizations are represented but constrained (i.e., must agree with) real-world observations. These are called reanalyses. This marriage between real-world observations and models is assumed to produce the best estimate of the system at specified times. This can be accomplished, of course, only in hindcast.

Forecasting: For this use, models are used to predict the future state of the system. Forecasts can be made from a single realization, or from an ensemble of forecasts which are produced by slightly perturbing the initial conditions and/or other aspects of the model. Weather prediction does this several times each day. It has been a great success in terms of forecasts on daily and weekly timescales, as exemplified by the long lead time to warn citizens in southeast Texas of the risk of catastrophic floods from Hurricane Harvey and damaging winds from Hurricanes Irma and Maria in 2017. With these hurricanes, the ensemble of forecast tracks was presented to the public as “spaghetti plots” which illustrated the model uncertainty.

With these definitions, the question is where do the IPCC and US National Assessment Models fit? Since the models they use do not contain all of the important climate forcings and feedbacks (e.g., as given in NRC 2005), the models results should not be interpreted as forecasts (or even "what if" forecasts, which have been termed "projections"). Since they have been applied to project the decadal-averaged weather conditions in the next 50–100 years and more, they cannot be considered as diagnostic models since we do not yet have the observed data to insert into the models.

Therefore, the IPCC and US National Assessments appropriately should be communicated as process studies in the context that they are sensitivity studies only. The specification of periods of time in the future (e.g., 2050–2059), for example, and the communication in this format as a skillful "what if" prediction (projection) are providing an (incorrect) inferred level of skill to the users of this information. This skill does not yet exist.

This is a very important distinction which has been missed by policymakers and scientists who study climate impacts using the output from these models.

The summary for this section is that weather prediction on daily and weekly time periods has been rigorously evaluated based on millions of forecasts. These weather predictions use real-world initial conditions and assimilate real-world data during the model integration so that drift from reality is constrained. In contrast, multi-decadal climate model predictions can drift from reality. There are also only limited tests of their skill when run in hindcasts.

The next section documents the level of performance of the climate models when run in hindcast for decades and longer.

How Well Do Climate Models Perform with Respect to Multidecadal Prediction?

The excessive and myopic focus by policymakers on the emissions of CO_2 as the primary climate forcing on multidecadal time periods, raises the question as to whether knowledge of CO_2 levels alone is sufficient to generate accurate and meaningful forecasts on that time period?

Two hypotheses have emerged.

The first argues that the accuracy of climate forecasts emerges only at time periods beyond a decade, when greenhouse gas emissions dominate over other human forcings, natural variability, and influences of initial value conditions. The hypothesis assumes that changes in climate are dominated by atmospheric emissions of greenhouse gases, of which CO_2 is the most important. It represents the current stance of the IPCC (2013; Chap. 12 and Annex I) and was adopted as the basis of the Paris Agreement.

A second hypothesis is that multidecadal forecasts incorporating detailed initial value conditions set an upper bound on the accuracy of climate projections based primarily on greenhouse gas emissions. According to that view, successful models must account for all important human forcings—including land surface change and management—and accurately treat natural climate variations on multidecadal timescales. Those requirements significantly complicate the task of prediction. This is a subject of Chap. 11 in IPCC (2013).

The assumption in the first hypothesis is that the results of Chap. 11 of the IPCC report (which show little skill in regional decadal predictions) do not mean there is no skill in longer time period forecasts. The assumption is made that skill will emerge in time periods beyond a decade. Quite a remarkable assumption but this is the basis of the IPCC report and of plans being made with respect to water resource infrastructure development. The credibility of the IPCC claim can be tested by using "hindcast" simulations that attempt to reproduce past climate behavior over multidecadal time scales. The simulations must be assessed by their ability to predict not just globally averaged metrics but changes in atmospheric and ocean circulation patterns and other regional phenomena since it is these spatial scales that matter to large water infrastructure projects. These circulations determine droughts, floods, and hurricane tracks, as just three examples. We have provided below just a few examples that have implications for water management infrastructure, where such tests have been done with summary text extracted from these papers:

Dawson et al. (2012)

> We have shown that a low resolution atmospheric model, with horizontal resolution typical of CMIP5 models, is not capable of simulating the statistically significant regimes seen in reanalysis, …. It is therefore likely that the embedded regional model may represent an unrealistic realization of regional climate and variability.

Taylor (2012)

> …the erroneous sensitivity of convection schemes demonstrated here is likely to contribute to a tendency for large-scale models to 'lock-in' dry conditions, extending droughts unrealistically, and potentially exaggerating the role of soil moisture feedbacks in the climate system.

Stephens et al. (2010)

> …models produce precipitation approximately twice as often as that observed and make rainfall far too lightly…. The differences in the character of model precipitation are systemic and have a number of important implications for modeling the coupled Earth system … little skill in precipitation [is] calculated at individual grid points, and thus applications involving downscaling of grid point precipitation to yet even finer-scale resolution has little foundation and relevance to the real Earth system.

As reported in Kundzewicz and Stakhiv (2010)

> Simply put, the current suite of climate models were not developed to provide the level of accuracy required for adaptation-type analysis.

More examples are reported on in Pielke et al. (2012).

As these papers show, the tests so far document that the climate models do not have the skill necessary to make robust assessments of changes in infrastructure risk in coming decades. Providing predictions (i.e., projections/forecasts) to the impacts communities and policymakers involved with large water system infrastructure, in which they are claimed to be skillful, is not a robust scientific endeavor. Downscaling does not make the forecasts more skillful either as discussed in Pielke and Wilby (2011) or as summarized in Tables 7.1 and 7.2. As written in that paper

> There is also an assumption that although global climate models cannot predict future climate change as an initial value problem, they can predict future climate statistics as a boundary value problem (Palmer et al. 2008). However, for regional downscaling (and global) models to add value (beyond what is available to the impacts community via the historical, recent paleorecord and a worst case sequence of days), they must be able to skillfully predict changes in regional weather statistics in response to human climate forcings. This is a greater challenge than even skillfully simulating current weather statistics… It is therefore inappropriate to present [multidecadal climate predictions] results to the impacts community as reflecting more than a subset of possible future climate risks”

In summary, if global climate models are run in hindcast, they have little if any skill to predict changes in regional and local climate statistics on decadal and longer timescales. The claim that skill emerges on longer time periods is not supported by existing evidence of model performance over the last few decades. Indeed, the expectation that better regional and local skill occurs in multidecadal time period predictions is counter not only to the available evidence, but common sense. The climate is a nonlinear chaotic system, and to expect a signal to emerge requires tests of the models which demonstrate that.

The next section summarizes the human climate forcings.

Table 7.1 Contrast between a top-down versus bottom-up assessment of the vulnerability of resources to climate variability and change

Approach	Scenario	Vulnerability
Assumed dominant stress	Climate, recent greenhouse gas emissions to the atmosphere, ocean temperatures, aerosols, etc.	Multiple stresses: climate (historical climate variability, land use and water use, altered disturbance regimes invasive species, contaminants/pollutants, habitat loss, etc.
Usual timeframe of concern	Long-term, doubled CO_2 30–100 years in the future	Short-term (0–30 years) and long-term research
Usual scale of concern	Global, sometimes regional. Local scale needs downscaling techniques. However, there is little evidence to suggest that present models provide realistic, accurate, or precise climate scenarios at local or regional scales	Local, regional, national, and global scales
Major parameters of concern	Spatially averaged changes in mean temperatures and precipitation in fairly large grid cells with some regional scenarios for drought	Potential extreme values in multiple parameters (temperature, precipitations, frost-free days) and additional focus on extreme events (floods, fires, droughts, etc.) measures of uncertainty
Major limitations for developing coping strategies	Focus on single stress limits preparedness for other stresses Results often show gradual ramping of climate change-limiting preparedness for extreme events Results represent only a limited subset of all likely future outcomes—usually unidirectional trends Results are accepted by many scientists, the media, and the public as actual "predictions" Lost in the translation of results is that all models of the distant future have unstated (presently unknowable) levels of certainty or probability	Approach requires detailed data on multiple stresses and their interactions at local, regional, national, and global scales—and many areas lack adequate information Emphasis on short-term issues may limit preparedness for abrupt "threshold" changes in climate sometime in the short or long term Requires preparedness for a far greater variation of possible futures, including abrupt changes in any direction—this is probably more realistic, yet difficult

From Kabat et al. (2004) and Pielke and Wilby (2012)

Table 7.2 Two interpretations of vulnerability in climate change research

	End-point interpretation	Starting-point interpretation
Root problem	Climate change	Social vulnerability
Policy context	Climate change mitigation, compensation, technical adaptation	Social adaptation, sustainable development
Illustrative policy question	What are the benefits of climate change mitigation?	How can the vulnerability of societies to climatic hazards be reduced?
Illustrative research question	What are the expected net impacts of climate change indifferent regions?	Why are some groups more affected by climatic hazards than others?
Vulnerability and adaptive capacity	Adaptive capacity determines vulnerability	Vulnerability determines adaptive capacity
Reference for adaptive capacity	Adaptation to future climate change	Adaptation to current climate variability
Starting point of analysis	Scenarios of future climate hazards	Current vulnerability to climate stimuli
Analytical function	Descriptive, positivist	Explanatory, normative
Main discipline	Natural sciences	Social sciences
Meaning of "vulnerability"	Expected net damage for a given level of global climate change	Susceptibility to climate change and variability as determined by socioeconomic factors
Qualification according to the terminology from Sect. 2	Dynamic cross-scale integrated vulnerability [of a particular system] to a global climate change	Current internal socioeconomic vulnerability [of a particular social unit] to all climatic stressors
Vulnerability approach	Integrated, risk-hazard	Political economy
Reference	McCarthy et al. (2001)	Adger (1999)

From the work of Füssel (2007, 2009) and Pielke and Wilby (2012)

What Is the Spectrum of Human Climate Forcings

The sun and volcanic eruptions are well accepted as non-human climate forcings. The human climate forcings, of course, include the radiative effect of industrial, vehicular and other human emissions of CO_2, NH_3, and other greenhouse gases.

However, other first-order human climate forcings are important to understanding the future behavior of Earth's climate. These forcings are regionally and locally heterogeneous and include:

(i) The biogeochemical effect of added CO_2 on vegetation (e.g., Eastman et al. 2001; Pielke et al. 2002)

(ii) The effect of aerosols on clouds and associated precipitation (e.g., Rosenfeld et al. 2008),

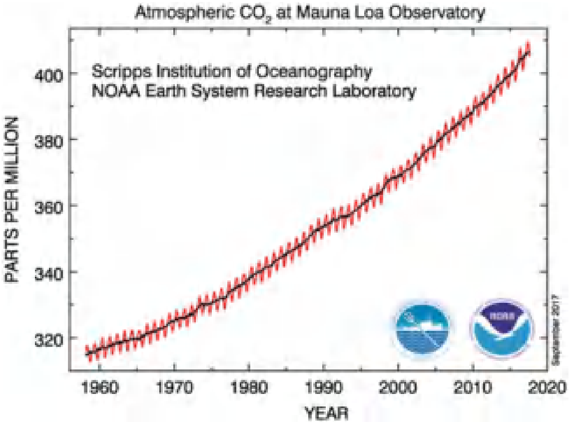

Fig. 7.2 Available at: https://www.esrl.noaa.gov/gmd/webdata/ccgg/trends/co2_data_mlo.png

(iii) The influence of aerosol deposition (e.g., black carbon (soot); Flanner et al. 2007 and reactive nitrogen; Galloway et al. 2004),

(iv) The role of changes in land use/land cover/land management (e.g., Takata et al. 2009; Mahmood et al. 2013).

Illustrations of several of these forcings, including added CO$_2$, are given in Figs. 7.2, 7.3, 7.4, 7.5, 7.6, and 7.7.

Fig. 7.3 A farm in Kukkal, Tamil Nadu, India, captured on April 25, 2009. Image Credit Vinod Sankar/flickr.com/CC BY SA2.0. Available at: https://lpdaac.usgs.gov/user_resources/data_in_action/irrigation_and_land_use_change_in_tamil_nadu

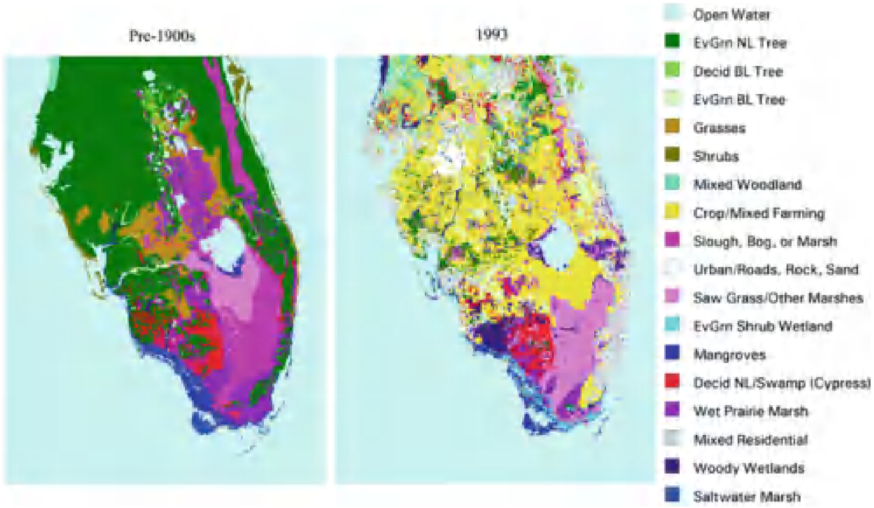

Fig. 7.4 USGS land-cover data for (left) pre-1900 natural land cover and (right) 1993 land use. From Marshall et al. (2004)

Fig. 7.5 Ground-level view of burning savanna grasslands in South Africa. Greenhouse gas carbon dioxide and solid carbon soot particulates are components of the emissions. When inhaled, the particulates lead to respiratory problems. From https://earthobservatory.nasa.gov/Features/BiomassBurning/

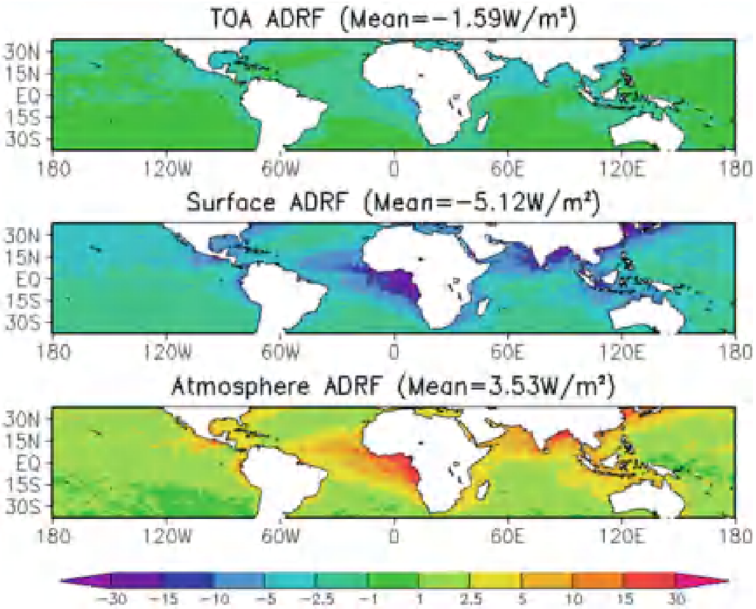

Fig. 7.6 Shortwave aerosol direct radiative forcing (ADRF) for top-of atmosphere (TOA), surface, and atmosphere. from Matsui and Pielke Sr. (2006)

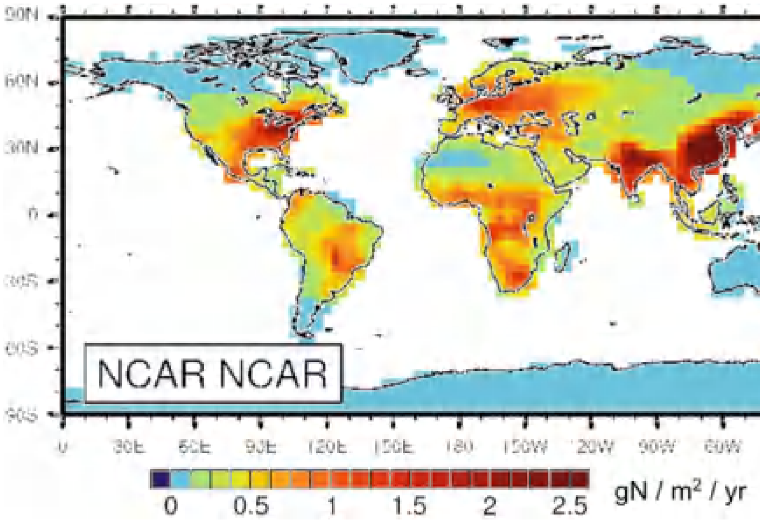

Fig. 7.7 Nitrogen deposition (teragrams per square meter) projected by NCAR's atmospheric chemistry model, coupled to the Community Atmosphere Model, for the year 2100, based on the IPCC's A2 emissions scenario. Areas in orange and red show the largest increases in deposition. These largely coincide with those land areas shown at left where plant growth is most strongly limited by nitrogen, such as eastern North America, Europe, and Southern Asia. Obtained from UCAR newsletter

Among their effects is their role in altering atmospheric and ocean circulation features away from what they would be in the natural climate system (NRC 2005). As with CO_2, the lengths of time that they affect the climate are estimated to be on multidecadal timescales and longer. There is evidence that land-use change associated with construction of large dams has altered extreme rainfall, particularly in semi-arid regions (Hossain et al. 2010) which will affect risks faced by large water infrastructures in the coming decades (Hossain et al. 2012).

The human climate forcings, therefore, involve a diverse range of first-order climate forcings, including, but not limited to, the human input of carbon dioxide (CO_2). Most, if not all, of these human influences on regional and global climate will continue to be of concern during the coming decades. Unfortunately, the IPCC and US National Assessments neglected to properly assess the role of these other forcings.

As a result, even if the climate models were otherwise accurate in terms of how they represent physics, chemistry, and biology, multidecadal climate predictions would still be unable to provide robust information to use for water resource infrastructure policy. They are missing key human climate forcings.

In summary, human climate forcings involve more than added CO_2 and other greenhouse gases. Neglecting them necessitates that predictions of changes in climate statistics of relevance to water infrastructure needs in the future will be flawed.

There is a way forward; however, this is the focus of the next section.

Is There an Alternative and More Robust Approach to Assess Risk to Large Infrastructure?

The current IPCC/US National Assessment approach to determine vulnerability in the coming decades with respect to climate is summarized in Fig. 7.8 and Tables 7.1 and 7.2 from Pielke et al. (2012). The drivers for the approach on the left side of Fig. 7.8 are the global climate model predictions. Using terminology introduced in O'Brien (2007), this top-down view is defined as "outcome vulnerability." It is fundamentally flawed if the global model has little or no skill at predicting multidecadal changes in regional climate statistics.

In contrast, the "contextual vulnerability" approach is a bottom-up view that does not require a global model to define the envelope of future climate risk. This inclusive bottom-up vulnerability concept also permits the determination of the major threats to these resources from climate, but also from other social and environmental issues.

After these threats are identified for each resource, the relative risk from natural- and human-caused climate change (estimated from global climate model (GCM) projections if one chooses and provides the caveat that there is essentially no skill in hindcast tests), as well as the historical, paleorecord, and worst-case sequences of events can be compared with other environmental and social risks in

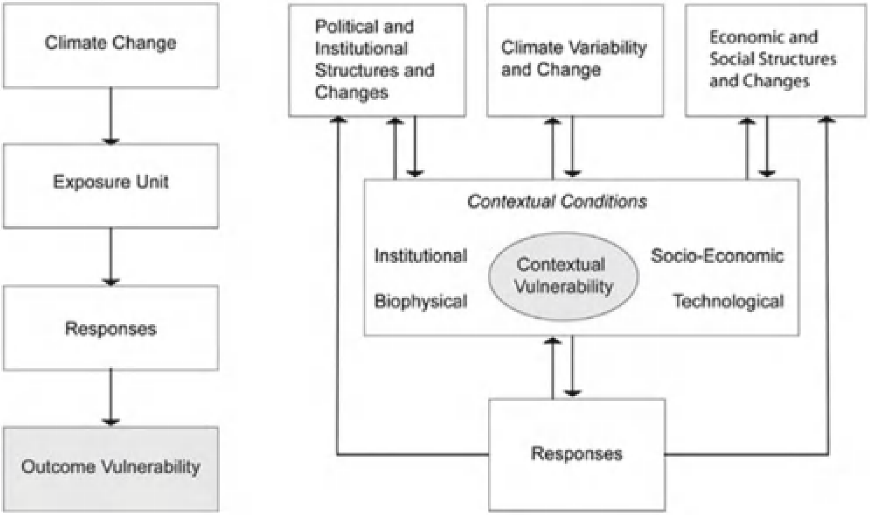

Fig. 7.8 Framework depicting two interpretations of vulnerability to climate change: (left) outcome vulnerability and (right) contextual vulnerability. Adapted by D. Staley from the works of Füssel (2009) and O'Brien et al. (2007). From Pielke and Wilby (2012)

order to adopt the optimal mitigation and adaptation strategies with respect to water infrastructure projects.

Moreover, even if climate were not to change in terms of regional statistics of weather patterns that threaten water resources, it is still essential to ascertain what are risks if past historical or recent paleorecord extreme events reoccurred. A worst-case selection of sequences of what occurred in the past would likely provide a better envelope of risk than relying on models with very little demonstrated skill at predicting changes in regional climate statistics.

For the climate component of risk, the outcome vulnerability (the top-down) approach relies on skillful weather predictions and analyzes with a regional and a local focus. For weather prediction on time periods of days to a week or two, excellent skillful predictions are available for use in outcome vulnerability assessments. On seasonal timescales, there is also some limited predictive skill to apply to outcome vulnerability assessments, particularly for such well-defined weather events such as an El Niño or La Niña (Castro et al. 2007). However, for decadal and multidecadal predictions, as shown earlier in this article, little, if any, predictive skill has been shown in hindcast climate model predictions of changes in regional weather statistics beyond what is available to the impacts community via the historical, recent paleorecord, and a worst-case sequence of weather events.

Since the top-down outcome vulnerability approach depends on skillful decadal and longer regional and local climate predictions, even though they have shown little if any skill, the application of the contextual vulnerability approach is needed.

The questions to address with respect to large water infrastructure projects to assess contextual vulnerability are:

(1) Why is this project important? How is it used? To what stakeholders is it valuable?
(2) What are the key environmental and social variables that influence the achievement of the goals of this project?
(3) What is the sensitivity of the project to changes in each of these key variables? This includes, but is not limited to, the sensitivity of the water resource to weather/climate variations and change on short (e.g., days), medium (e.g., seasons), and long (e.g., multidecadal) timescales.
(4) What changes (thresholds) in these key variables would have to occur to result in a negative (or positive) response to the water resource?
(5) What are the best estimates of the probabilities for these changes to occur? What tools are available to quantify the effect of these changes? Can these estimates be skillfully predicted?
(6) What actions (adaptation/mitigation) can be undertaken in order to minimize or eliminate the negative consequences of these changes (or to optimize a positive response)?

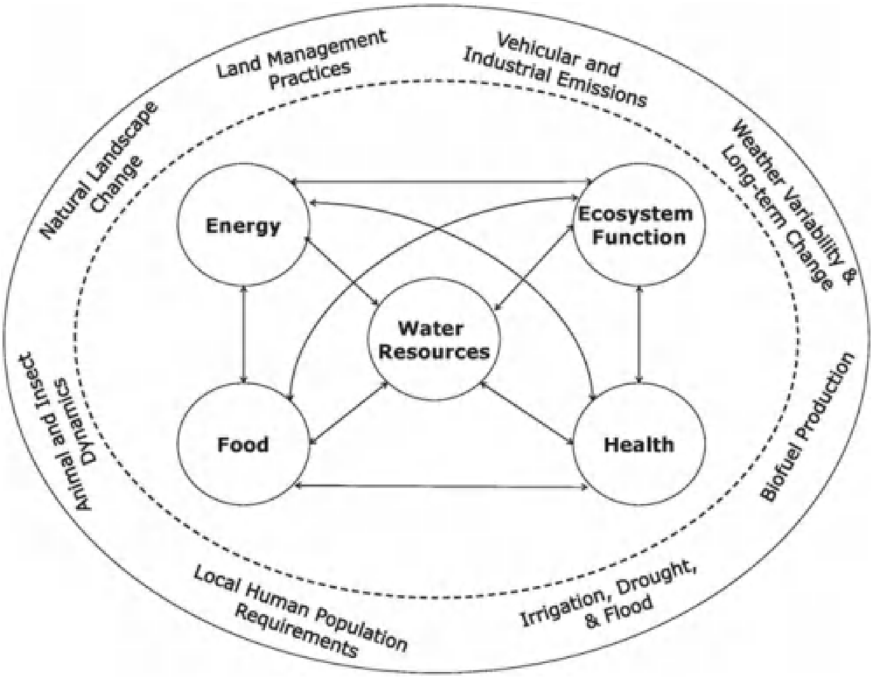

Fig. 7.9 Schematic of the spectrum of risks to water resources. Other key resources associated with food, energy, human health, and ecosystem function can replace water resources in the central circle. From the work of Hossain et al. (2011) and Pielke and Wilby (2012)

(7) What are specific recommendations for policymakers and other stakeholders?

With the answers to these questions, a much more inclusive framework can be achieved to reduce risk including surprises if (and when) real-world weather and climate in the coming decades fall outside of the results produced by the global climate prediction models.

Figure 7.9 illustrates schematically how the contextual vulnerability approach can be applied.

Conclusions

This article presented the confusing definitions used with the terms weather, climate, and climate change and presented more precise terminology. Weather and climate models were also described. Evidence was presented from peer reviewed papers that document a lack of the needed multi-decadal climate prediction skill for their use in accurate large water infrastructure planning. Indeed, their presentation as skillful predictions is misleading policymakers and the impacts communities of the actual spectrum of risks to water infrastructure in the future.

The spectrum of human climate forcings was briefly presented and reported that global models do not yet adequately represent these effects. Planning for large water projects without adequate consideration of their effect on rainfall and other weather statistics is not a robust approach.

Since we do not know how the regional and local climate will change in the coming decades, we propose a more inclusive approach to assess and reduce risks to water infrastructure. This is the adoption of a bottom-up, resource-based vulnerability approach in evaluating the effect of climate and other environmental and societal threats to large water management infrastructure. After these threats are identified, then the relative risks can be compared in order to adopt optimal preferred mitigation/adaptation strategies to reduce risks to large water infrastructures.

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Chapter 8

Safety Design of Water Infrastructures in a Modern Era

Xiaodong Chen

Infrastructure Safety Design: Probable Maximum Precipitation

Over the past century, numerous water infrastructures have been built to serve the water-related need of people worldwide (Mitchell 1990). Those larger ones often serve multiple purposes, such as agriculture, navigation, hydropower, and flooding control. Failure of such high-hazard dams, especially those with flooding control purposes, would bring catastrophic ecological and societal loss. For example, the failure of the South Fork dam in Pennsylvania, USA, in 1889 caused 2,209 deaths and an economic loss of 17 million dollars (Frank 1988; Van den Berge et al. 2011). The failure of a series of dams in China in 1975, including Banqiao Reservoir Dam, caused 26,000 deaths through flooding and 100,000 fatalities with the succeeding disease (Hu and Luo 1992). For these infrastructures, Probable Maximum Precipitation (PMP), or Probable Maximum Flood (PMF) which can be derived from PMP, has been widely used to ensure their safety under the extreme weather conditions (Hossain et al. 2012). PMP is also a widely used design criteria for other critical energy infrastructures, such as nuclear plants, since any possible failure of these sites/infrastructures is unacceptable (International Atomic Energy Agency 2003, 2009; Prasad et al. 2011; Hayes et al. 2015).

Probable Maximum Precipitation (PMP) follows the idea of creating an extreme scenario that covers all the possibilities. In engineering practice, the definition by the World Meteorological Organization (WMO) is often adopted, which is: "PMP is the theoretical maximum precipitation for a given duration under modern

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meteorological conditions. Such a precipitation is likely to happen over a design watershed, or a storm area of a given size, at a certain time of year." Besides this definition, WMO also provides detailed instructions on how to make PMP estimation using various approaches (World Meteorological Organization 2009). In general, they can be classified into local method (maximization of local storms), transposition method (storm transposition from same climatological regions), generalized method (based on some provided PMP distribution maps), as well as statistical method such as the one proposed in Hershfield (1965).

At the global scale, different countries adopt different methods for their PMP estimation. For example, PMP in India follows the generalized PMP approach (Rakhecha and Kennedy 1985; Rakhecha and Singh 2009), with the adjustment carried out for the impact of local topography. In the USA, moisture maximization method is chosen by NOAA as the standard approach, and NOAA has published a series of instructions for different climatological regions, now known as Hydrometeorological Reports (HMRs).

The moisture maximization approach estimates PMP as Eq. (8.1), where P is the observed precipitation, PW is the observed maximum 12-h persisting precipitable water in the storm duration, and $\mathrm{PW_m}$ is the climatological maximum 12-h persisting precipitable water at this location. In practice, PW and $\mathrm{PW_m}$ are estimated from ground measurement of dew point temperature, assuming a pseudo-adiabatic air condition (World Meteorological Organization 2009). From long-term ground observations, the most severe rainstorms in the history are maximized following this equation, and the maximum of these derived values are defined as the PMP of this site. At those HMR regions where surface topography plays a critical role in the storm processes (such as the watersheds along the west coast of USA), the topographic adjustment is applied as appropriate.

$$\mathrm{PMP} = \mathrm{P} \times \frac{\mathrm{PW_m}}{\mathrm{PW}} \tag{8.1}$$

Issues with Traditional PMP Estimation

Although the issues have been elaborated earlier in this book chapter (see preface, Chaps. 4, 5, and 6), it is worth repeating them here in the context of this chapter. Traditionally, PMP is treated as a static value, estimated using long-term precipitation and related meteorological data (such as humidity, temperature, winds). The static nature of PMP estimation has been questioned as global warming can lead to more intense precipitation. There have been numerous studies on the potential change of precipitation under climate change, and they mostly conclude that extreme precipitation has been and will continue to be more frequent and severe (Trenberth et al. 2003; Min et al. 2011; Kunkel et al. 2013). Various non-stationary statistical analyses of extreme precipitation also suggest that PMP, an upper bound of extreme precipitation, is likely to change in the future (Cheng and AghaKouchak

2014; Cheng et al. 2014; Gao et al. 2016; Wi et al. 2016). Therefore, concerns have been raised over whether the PMP that is derived from historical observations could be representative of the future extreme rainfall risk.

Because of this stationarity concern, moisture maximization approach has been revisited with high-quality observation and advanced atmospheric modeling. Several other flaws within the method have also been identified and discussed:

1. The assumptions in the maximization procedure. Abbs (1999) used an atmospheric model and checked the linear assumption between moisture and precipitation in Eq. (8.1). This study found that such linear assumption may introduce bias in the maximization procedure. Chen and Bradley (2006) analyzed observation data and concluded that surface dew point temperature plus pseudo-adiabatic assumption tend to overestimate PW of the air column.
2. Effect of inconsistent/incomplete observation data. From the data-based perspective, the observation network during historically old events was not dense enough to derive detailed precipitation map. Also, during the extreme precipitation events, the rain gauges might have stopped working, which may result in a loss of measurement. Such case can be found in, for instance, the study by Wang et al. (2008). These factors would lead to incomplete records or results that may not be very accurate in spatial details. This is especially a concern in the statistical method, as the parameters derived from a small collection of extreme storms (which happen very rarely by definition) may not be very stable. On the other hand, even if the record is complete, it may not be consistent in terms of techniques, operations, and methodology. This is especially the case on the scales of decades. For example, the National Weather Service (NWS) introduced the automated surface observation system (ASOS) at the ground dew point temperature measurement sites across the USA around 1992. This caused a gradual but significant departure from the previous practice, and the influence of such departure is still not clear even several years later (Heim and Guttman 1997).
3. Scientific rationale of moisture maximization. This can be summarized as “Is moisture maximization enough to maximize precipitation?” As Abbs (1999) found, the storm efficiency (which is defined as P/PW) during the observed extreme precipitation events is often between 80 and 100%. Thus, the moisture maximization does not fully realize the precipitation potential. Also, since the extreme events are not physically maximized, it is possible that this maximization process does not include some necessary adjustments depending on topography and seasons. These adjustments have been adopted as HMRs are revised, but further revisions may always be required as we have a better understanding of the extreme precipitation processes. For example, in the old HMR for California (HMR36, (US Weather Bureau 1961)), the topographic adjustment was not considered. As a consequence, there have been several events that produced greater short-duration precipitation than the PMP estimates since 1961 (Bergeron 1965; Hobbs 1989). This led to a revision of HMR in California, but the new instruction (HMR 59) then assumed that the topographic effect could

be treated separately from the non-topographic component. Such modifications improved the PMP estimation in the region (i.e., making the PMP estimation higher than any historical observations), but the whole framework is still empirical, and the risk of PMP being surpassed is still there. Aside from the topographic effect, similar separation approaches have been proposed for other effects such as typhoon and large-scale circulation (Liu et al. 2016). However, this type of study is not well recognized as they made lots of posterior adjustment on the estimated "PMP" value that made it harder to interpret the final results.

4. Interpretability of PMP estimations. Moisture maximization method suffers less from this concern, as it assumes a constant storm efficiency (which can be taken as its "physics"). However, it becomes more difficult to interpret storm transposition and separation procedures, as several assumptions (mainly to make these methods doable) are applied: Storms can be transferred from a location to another location, and total precipitation can be separated into various independent components. A statistical approach, though providing simple and quick PMP estimation, is the one most difficult to interpret. It often takes the form of Eq. (8.2), where the mean P_m and standard deviation P_{std} are derived from long-term rainfall observation (Hershfield 1965). However, the major parameter k is often chosen arbitrarily, and it is hard to interpret it. There have been some efforts to interpret this statistical method from the conventional perspective such as generalized extreme value distribution (National Research Council 1994; Koutsoyiannis 1999; Papalexiou and Koutsoyiannis 2006), but such frequency-based interpretation (i.e., finite return period) are then criticized as violating the "impossibility" nature of PMP.

$$PMP = P_m + k \times P_{std} \tag{8.2}$$

5. Uncertainty. Just like any statistic, PMP should be provided with its uncertainty. However, all of the traditional approaches are deterministic approaches, which cannot reveal the uncertainty in the final estimates. A significant part of the uncertainty comes from the PMP estimation procedures (Salas et al. 2014; Micovic et al. 2015). To reveal this uncertainty, we need to make "ensemble" calculations in each step (i.e., same method, but reasonably different input). However, the uniqueness of observation cannot satisfy such requirement.

Modernized PMP Estimation

Over the past decades, there have been two major types of efforts in improving the PMP estimation: mathematical approaches and physics-based approaches. Mathematical approaches are based on some sophisticated mathematics, and some good examples are those PMP studies involving multifractals (Douglas and Barros 2003; Sun and Barros 2010). Also, the non-stationary analysis over the extreme precipitation is likely to provide promising ways of non-stationary PMP estimation in the future. However, mathematical approaches heavily rely on the accuracy of mathematical models to depict precipitation. Thus, they still suffer from the assumptions that they take.

Physics-based approaches, on the other hand, rely on the advancement of atmospheric numerical models. The philosophy of physics-based approaches is to conduct "moisture maximization" in the numerical models, so it includes all the physical impacts of amplified moisture extent. As stated in Chapter five of this book, numerical models now allow us to reconstruct the extreme precipitation events since the 1940s. At the same time, various global/regional atmospheric reanalysis datasets have become available for the scientific and engineering communities, such as those produced by National Center of Atmospheric Research (NCAR), National Aeronautics and Space Administration (NASA), European Centre for Medium-Range Weather Forecasts (ECMWF), as well as the Japan Meteorological Agency (JMA). They essentially provide us a huge extreme event pool for PMP estimation in the numerical models. Also, the availability of various reanalysis products over the same period would allow us to make ensemble PMP estimations that also reveal uncertainty information.

In the meanwhile, the major climate datasets, such as those in the latest Coupled Model Intercomparison Project (CMIP5), have the climate constructions after the 1850s all the way into the next century. This allows us to not only reevaluate the PMP in the historical period but also make PMP prediction for the future. This provides us a better view of PMP in the changing climate, where non-stationary extreme events have been detected or projected.

Based on reliable constructions of extreme precipitation events, some ways to modify the model and make model-based PMP estimations have been proposed. As can be imagined, in the numerical models we have full access to various atmospheric driving variables, including air temperature, (3-D) wind fields, relative humidity, as well as geopotential height. Therefore, it is possible to explore other ways of storm maximization. The idea of such evolution follows the "maximization" in the traditional approach, but not limited from the "moisture" perspective. In general, these approaches can be classified into 3 categories: (1) disturbance of air moisture through changing air temperature/relative humidity and keeping the atmospheric columns throughout the simulation domain sufficiently moist during the storm events (Tan 2010; Ohara et al. 2011; Lee et al. 2017; Rastogi et al. 2017); (2) disturbance of moisture flux through changing wind speed or wind fields (Ishida et al. 2015); (3) combination of worst historical environmental conditions (Tan 2010). Compared with traditional approaches, the physics-based approaches are free of almost all the criticisms that traditional approaches receive:

1. Effect of inconsistent/incomplete observation data. Physics-based approaches take all the necessary information from reanalysis products or climate simulations. Therefore, they have comparable quality over time and are not biased by the measurement equipment or operations.

2. Stationarity in PMP. Climate simulations automatically produce non-stationary data. Thus, the extreme storm construction and the PMP estimation in the model will automatically reflect the climate information at that time.
3. Uncertainty. The benefit of using climate simulation is the availability of various climate models, which allows the ensemble PMP estimation to be made. Together with the stepwise analysis of uncertainty, such data availability addressed the concern on the uncertainty of PMPs.
4. The assumptions in the maximization procedure. Physics-based PMP estimation introduces the full atmospheric dynamics and thermodynamics during the precipitation process. Thus, it allows us to drop the linear storm efficiency assumption. We leave it to the model to resolve how the storm system will respond to the extra moisture.
5. Scientific Rationale of moisture maximization. We now add extra moisture to the model boundary and the initial fields. The model will resolve surface feedback to the precipitation system itself. Thus, the role of topography in the "moisture maximization" is automatically handled. By involving numerical models, we also allow all the other factors to be considered that are hard to quantify/simplify in the traditional approach.
6. Interpretability of PMP estimations. The results from model-based estimations are easier to interpret as they reflect the physical consequence of certain modified model input (initial or boundary conditions). Therefore, we do not need to establish a relationship between precipitation and any meteorological variables in order to interpret the results.

Given these benefits, the only question left is how we should run the model to obtain the maximum maximization scenario. Unlike in the conventional era when we only have surface dew point temperature observation, in the model era, we have control of all the basic atmospheric variables (i.e., air temperature, wind fields, relative humidity). Therefore, there is a possibility that the storm magnitude may be maximized most with modified temperature or wind fields or humidity. However, all these studies up to now are based on the "trial or trial," and the largest maximized precipitation amount is taken then as PMP value. Some intercomparison of different techniques is available in the studies of Ohara et al. (2011) and Tan (2010), and it can be seen there that different techniques produce quite different results even when they are based on the same historical event. Therefore, it is essential to pick up the most reasonable maximization technique in the model.

The most straightforward way is to check the sensitivity of extreme storm to other meteorological factors: If, for example, a given extreme storm is most sensitive to moisture availability in the storm duration, then moisture maximization is likely the best way to go. Alternatively, if the storm is most sensitive to wind convergence, then wind-based maximization would make more sense.

Therefore, a better understanding of the physics behind various extreme precipitation is required before we can choose the most reasonable maximization method in the model (before trying out all the possibilities). With the study done by Chen and Hossain (2018), we now have clearer ideas on how to proceed. In this study, the extreme storms across the contiguous U.S. between 1979 and 2015 are analyzed, and their relationship with meteorological factors is examined. This study reveals some useful patterns: extreme storms in the Western United States are closely related to moisture availability, while storms in the Eastern United States and the west coast are more closely related to vertical wind fields. With such information, we now know (before running the model) that model-based PMP in the Western United States needs to be done with moisture maximization, while in those regions where wind is important, wind maximization is required.

Transition to Modern PMP Estimates

As can be seen from above, the physics-based approach is quite different from the traditional approach in PMP estimation. Therefore, it is necessary to find a path that will lead the engineers to switch to the physics-based approaches summarized here with confidence. Figure 8.1 illustrates such a possible pathway, where the hybrid approach is involved.

The idea behind the hybrid approach is that we will switch from the observation-based estimation in the traditional approach to climate data-driven estimation. In the meanwhile, the traditional moisture maximization method is adopted. Such step can be called "data evolution." Later we will switch to the physics-based estimation, which can be called "method evolution."

The major challenge of using climate model data in a direct way is their coarse resolution, which cannot satisfactorily present the impact of surface topography and finer-scale convections. Therefore, they need to be downscaled, either statistically or dynamically, before they are suitable for PMP studies. Some of the examples based on the dynamically downscaled climate data are the studies by Beauchamp

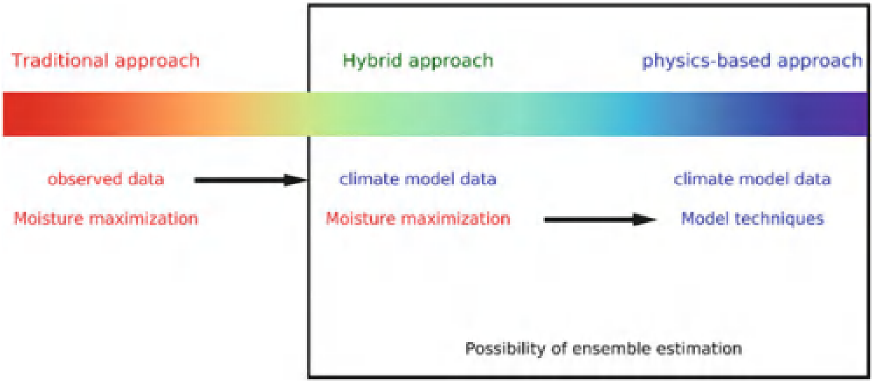

Fig. 8.1 A naturally intuitive transition from traditional PMP to physics-based PMP

et al. (2013), Rousseau et al. (2014), as well as Rouhani (Rouhani 2016). In these studies, regional climate models (RCMs) are first employed to downscale climate model data to a usable high resolution (e.g., * 10 km or even less). Then the traditional PMP estimation approaches are applied for PMP estimation.

At the same time, there have been efforts to use statistically downscaled data or even raw climate model data (which is often available at 1° resolution). An example is the study by Chen et al. (2017). This study estimates the PMP in the US Pacific Northwest region based on CMIP5 climate model data, and the raw data are preferred over any downscaled data. Therefore, only statistically downscaled precipitation is used, and all the other required information (3-D wind fields, sea surface temperature) are taken from the climate data. This study shows that with some advanced tools (such as the HYSPLIT back-trajectory program used), it is possible to generate reliable PMP estimation based on raw climate data. This conclusion holds for all those regions where extreme precipitation is triggered by large-scale weather systems such as atmospheric rivers. Compared with the studies based on dynamic downscaling, this approach saves lots of computation and is more appealing to the engineering community.

By following the moisture maximization procedures in the traditional approach but switching to climate model data, those studies indicate that climate data-based PMP estimates are similar to those traditional estimates. This is especially important when we estimate future PMPs. To illustrate the importance of such consistency, let's consider an example. Assume there is a dam that was designed and built against 700 mm 3-day PMP estimation. So the PMP based on the conventional approach is 700 mm. Now think of 3 situations: (1) A new approach now indicates that PMP is 600 mm for the historical period and 650 mm for the future period. It would be difficult to infer the safety of this existing dam: Whether the future risk would increase by 50 mm (650–600 mm), or it is still safe (as 650 mm is still lower than 700 mm)? (2) Another different approach indicates that the PMP is 800 mm for the historical and 900 mm for the future period. Does this mean we just need to fix the dam to handle the extra 100 mm (900–800 mm) storm risk increase, or we need to fix the dam to handle all the projected 900 mm total storm risk? (3) Now another new approach indicates that historical PMP is 700 mm and future PMP is 750 mm. This time we know that we can convey this 50 mm PMP increase to the engineering community, and they would correctly understand what this means. Through this example, it is clear that consistent estimation of historical PMP is vital for the safety re-assessment of those existing dams. In the long-term future, we will have a good understanding of the difference between traditional PMP and physics-based PMP, and we may develop techniques to translate these estimations. But for the near future, the hybrid approach will be the most acceptable way to assess the future risks of existing water infrastructures for practicing engineers.

Recommendations for the Future

Safety design of large water management infrastructures needs better approaches to estimating PMP in the changing climate. The proposed physics-based PMP estimation approach would best serve such purpose. However, there are still many works that we need to complete before it could be widely applied in the engineering practice with confidence:

1. A better understanding of the relationship between extreme precipitation and meteorological conditions. The study by Chen and Hossain (2018) has developed the statistical framework to analyze such relationship. Naturally, an interesting follow-up question is: how will extreme precipitation respond to the reasonable perturbations of meteorological conditions? A good example is available from Yang and Smith (2018), where an extreme storm event is enforced with several perturbations. The results show the response of storm magnitude and structure change as a function of "how much moisture perturbation is applied," and it would help to find the correct magnitude of perturbation that is required for more reasonable storm maximization, i.e., PMP estimation.
2. More validation of proposed physics-based PMP estimation methods. As proposed in Chen and Hossain (2018), several techniques can be considered at different geographic locations for PMP estimation: relative humidity (RH) maximization, wind maximization, temperature perturbation. To what extent they will maximize the storm magnitude remains to be checked. To be specific, in the RH-controlled region as shown in this study, we should examine a reasonable amount of extreme storm events and see how they respond to the increase RH level in the storm duration. This would confirm the findings in this study and provide necessary supplements to the conclusions. Such systematic check requires some serious computation, but once this check is done, the conclusions of the Chen and Hossain (2018) study will be verified, and for future PMP estimations, only the indicated approach specific to that region is needed.
3. More systematic guidance to the engineering community. For engineering practice, it is vital to have some robust and detailed instructions. On the other hand, as shown in some studies (e.g., Ohara et al. (2017)), even at the same location, it matters a lot how the maximization is conducted in the model. For extreme storm construction, the modeled spatial domain is often quite large. When the RH/wind perturbation is applied at the domain boundaries, it is sometimes offset or shielded by land surface topography, or the impact becomes negligible as the perturbation reaches the desired watershed. Therefore, there is still a lot of work left to determine how the perturbation should be applied. More numerical experiments are required to find some robust and systematic guidelines. Some examples are:

(1) Within the numerical models, how should we determine the boundary of the domain where the perturbation would be applied?

(2) When applying the perturbation, what is the critical period when the boundary condition data should be modified? Outside the precipitating period, how should the boundary condition in the spin-up period be handled to make a tangible transition from event construction to PMP simulation?

(3) How should we reasonably determine the maximum level of RH and wind fields (or other meteorological variables that need to be maximized)? For RH, 100% would be good (though we still have to handle the super-saturation conditions occasionally). For wind, what would the best way to determine the climatological maximum wind value?

    Aside from these questions, as we run the model in different climatological regions, we may still run into some region-specific questions. In those cases, we also need to develop systematic guidelines to handle these questions.

(4) A better connection of physics-based PMP to traditional PMP. For those new infrastructures to be built in the future, the physics-based PMP can be confidently applied in the design stage. However, for those existing infrastructures, they have already been designed with some traditional PMP. Therefore, when reassessing their future climate risks, it is critical to connect the historical PMP to any future PMP estimates that we are making. Hybrid PMP provides a naturally intuitive pathway to connect traditional PMPs to those PMPs computed from climate model data. From there, it would be easier to determine the impact of different PMP estimating techniques on the numbers we get.

It is also important to incorporate new technologies into the extreme precipitation study, as well as the PMP estimation. Figure 8.2 shows an example, where the storm classification is done using machine learning techniques. Here all of the storms are classified into two categories without any prescribed characteristics. It turns out that this more objective-based approach also generates similar results to those in Chen and Hossain (2018). This confirms that the conclusions in Chen and Hossain (2018), and such machine learning-based approach can also be applied to other regions of the world.

Lastly, physics-based PMP is more urgent in those remote regions where long-term ground observation is unavailable. For such cases, the framework for the extreme precipitation in the Chen and Hossain (2018) can be easily applied to other regions if global reanalysis products are available. An example of extended global analysis (based on ERA-Interim data) result is shown in Fig. 8.3. Following such analysis, we know how to physically maximize a given extreme storm event in the numerical models.

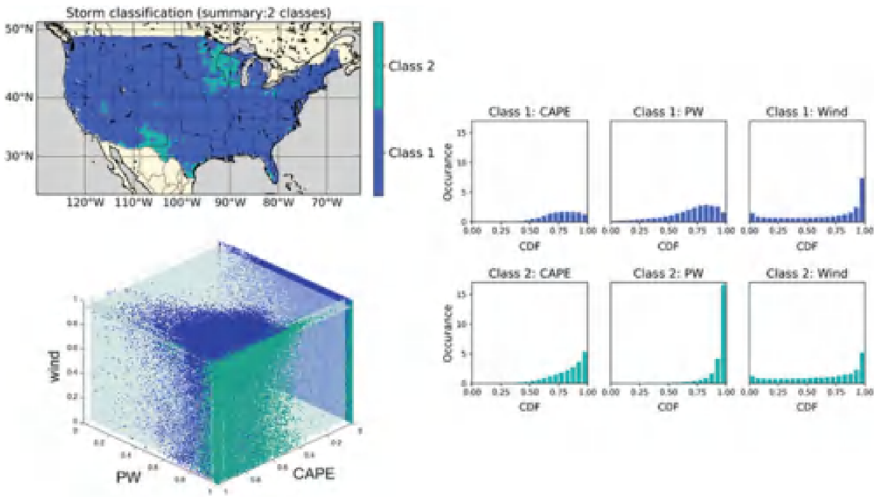

Fig. 8.2 Machine learning-based storm classification. Here the idea is similar to that in Chen and Hossain (2018), but some steps are automated using machine learning techniques. As a result, some artificial parameters are avoided, and the results would be more objective

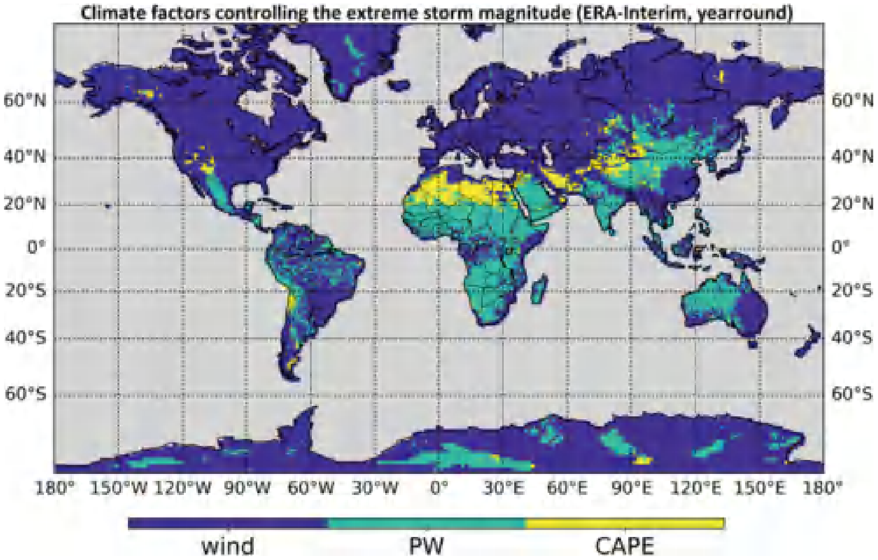

Fig. 8.3 Relationship between extreme precipitation and meteorological factors. The analysis is done over the ERA-Interim reanalysis product, following the methodology in Chen and Hossain (2018)

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