PAST, PRESENT, AND FUTURE IMPACTS OF CLIMATE ON INFRASTRUCTURE

EDITED BY: Abhishek Gaur and Ronita Bardhan
PUBLISHED IN: Frontiers in Water

frontiers Research Topics

ISSN 1664-8714
ISBN 978-2-88966-792-5
DOI 10.3389/978-2-88966-792-5

About Frontiers

Frontiers is more than just an open-access publisher of scholarly articles: it is a pioneering approach to the world of academia, radically improving the way scholarly research is managed. The grand vision of Frontiers is a world where all people have an equal opportunity to seek, share and generate knowledge. Frontiers provides immediate and permanent online open access to all its publications, but this alone is not enough to realize our grand goals.

Frontiers Journal Series

The Frontiers Journal Series is a multi-tier and interdisciplinary set of open-access, online journals, promising a paradigm shift from the current review, selection and dissemination processes in academic publishing. All Frontiers journals are driven by researchers for researchers; therefore, they constitute a service to the scholarly community. At the same time, the Frontiers Journal Series operates on a revolutionary invention, the tiered publishing system, initially addressing specific communities of scholars, and gradually climbing up to broader public understanding, thus serving the interests of the lay society, too.

Dedication to Quality

Each Frontiers article is a landmark of the highest quality, thanks to genuinely collaborative interactions between authors and review editors, who include some of the world's best academicians. Research must be certified by peers before entering a stream of knowledge that may eventually reach the public - and shape society; therefore, Frontiers only applies the most rigorous and unbiased reviews.
Frontiers revolutionizes research publishing by freely delivering the most outstanding research, evaluated with no bias from both the academic and social point of view. By applying the most advanced information technologies, Frontiers is catapulting scholarly publishing into a new generation.

What are Frontiers Research Topics?

Frontiers Research Topics are very popular trademarks of the Frontiers Journals Series: they are collections of at least ten articles, all centered on a particular subject. With their unique mix of varied contributions from Original Research to Review Articles, Frontiers Research Topics unify the most influential researchers, the latest key findings and historical advances in a hot research area! Find out more on how to host your own Frontiers Research Topic or contribute to one as an author by contacting the Frontiers Editorial Office: frontiersin.org/about/contact

PAST, PRESENT, AND FUTURE IMPACTS OF CLIMATE ON INFRASTRUCTURE

Topic Editors:
Abhishek Gaur, National Research Council Canada (NRC-CNRC), Canada
Ronita Bardhan, University of Cambridge, United Kingdom

Citation: Gaur, A., Bardhan, R., eds. (2021). Past, Present, and Future Impacts of Climate on Infrastructure. Lausanne: Frontiers Media SA.
doi: 10.3389/978-2-88966-792-5

Table of Contents

04 ***Editorial: Past, Present, and Future Impacts of Climate on Infrastructure***
Abhishek Gaur and Ronita Bardhan

06 ***Increasing Coastal Disaster Resilience Using Smart City Frameworks: Current State, Challenges, and Opportunities***
Fahim Nawroz Tonmoy, Samiul Hasan and Rodger Tomlinson

19 ***Relative Impacts of Projected Climate and Land Use Changes on Terrestrial Water Balance: A Case Study on Ganga River Basin***
Anamitra Saha and Subimal Ghosh

33 ***Infrastructure Interdependency Failures From Extreme Weather Events as a Complex Process***
Emily N. Bondank and Mikhail V. Chester

39 ***Next-Generation Intensity-Duration-Frequency Curves for Climate-Resilient Infrastructure Design: Advances and Opportunities***
Hongxiang Yan, Ning Sun, Xiaodong Chen and Mark S. Wigmosta

47 ***Evidence-Driven Approach for Assessing Social Vulnerability and Equality During Extreme Climatic Events***
Ram A. Barankin, Michelle E. Portman, Paul Kirshen and Robert E. Bowen

57 ***Opportunities and Challenges for Artificial Intelligence Applications in Infrastructure Management During the Anthropocene***
Samuel A. Markolf, Mikhail V. Chester and Braden Allenby

frontiers in Water

EDITORIAL
published: 30 March 2021
doi: 10.3389/frwa.2021.670950

Editorial: Past, Present, and Future Impacts of Climate on Infrastructure

Abhishek Gaur[1]* *and Ronita Bardhan*[2,3]

[1] National Research Council Canada, Ottawa, ON, Canada, [2] Department of Architecture, University of Cambridge, Cambridge, United Kingdom, [3] Centre for Urban Science and Engineering, Indian Institute of Technology Bombay, Mumbai, India

Keywords: climate change, infrastructures, resiliency, sustainability, natural disasters

Editorial on the Research Topic

Past, Present, and Future Impacts of Climate on Infrastructure

Climate change is one of the biggest challenges that the global community faces. The changing climate may lead to the infrastructure bring exposed to unprecedented climate with an increase in the frequency and intensity of extreme weather events, such as more intense rain events and flooding, extreme winds, landslides, and other hazards, that could result in infrastructure damage and failure (Stocker et al., 2013). The consequences of failure can be quite significant and cause fatalities, injuries, and illnesses, disruption or loss of service, increased costs to infrastructure owners, and unforeseen costs to infrastructure users, and considerable negative socioeconomic impacts to the governments.

Infrastructure systems are primarily located in urban areas. The urban climate is often different from the surrounding rural climate. It is generally warmer, rainier, less windy, and more polluted. This means that more drastic effects of changing climate will be experienced by the urban infrastructure systems than the surrounding areas (Krayenhoff et al., 2018). The cities and infrastructure systems will also be overburdened in the future due to ongoing rapid urbanization. It is predicted that by the 2050s, 66% of the world's population will live in urban areas, up from about 50% living in the urban areas in the year 2007, making the infrastructure systems increasingly strained in the future also due to increases in urban population (UN, 2014).

To design urban infrastructure systems considering the non-stationarity in climate, it is essential to assess the impacts of past, current, and future climate on the infrastructure systems. This will entail developing approaches to reliably model the extreme climate hazards and their interactions with the complex urban systems. The papers part of this Research Topic aims to provide new knowledge in these areas.

Saha and Ghosh study the relative impacts of future projected climate and land-use change on the hydrological response of the Ganga river basin in India. The complex chain of analysis performed included: generation of future climate projections following different global warming scenarios and socioeconomic pathways, preparation of future land-use scenarios using a land allocation model and performing hydrologic simulations using a semi-distributed hydrologic model, followed by application of Bodyko framework to understand the relative impacts of climate and land-use changes on the basin characteristics. The study found that as a consequence of global warming, the Ganga river basin will become more arid in the future. However, the basin's future hydrologic response will mostly be governed by projected changes in climate. Land-use changes will have minimal effect on its hydrologic response.

Yan et al. provided a review of a recently developed science-driven engineering product: next-generation Intensity-Duration-Frequency (NG-IDF) curve to establish a consistent IDF design methodology for both rain-dominated and snow-dominated regions. The NG-IDF captures multiple flood-generating mechanisms, including rainfall, snowmelt, and rain-on-snow

OPEN ACCESS

Edited and reviewed by:
Auroop Ratan Ganguly, Northeastern University, United States

***Correspondence:**
Abhishek Gaur
Abhishek.Gaur@nrc-cnrc.gc.ca

Specialty section:
This article was submitted to Water and Built Environment, a section of the journal Frontiers in Water

Received: *22 February 2021*
Accepted: *08 March 2021*
Published: *30 March 2021*

Citation:
Gaur A and Bardhan R (2021) Editorial: Past, Present, and Future Impacts of Climate on Infrastructure. Front. Water 3:670950. doi: 10.3389/frwa.2021.670950

as opposed to the typical precipitation-based IDF curves (PREC-IDF), which only captures flood occurrences due to extreme rainfall. NG-IDF is the outcome of a coordinated effort from climate scientists developing necessary climate information with global and regional scale climate models, hydrologists simulating snow processes and estimating water available for runoff using hydrologic models, the civil engineering community on integrating the snow processes into the IDF design process. Recent developments toward validating the NG-IDF curves on a larger spatiotemporal domain and incorporating future projected effects of climate change more accurately in them are discussed.

Bondank and Chester advocate that infrastructure systems and not merely complicated systems that contain many parts and there is uncertainty included in the system, they are complex systems characterized by "unpredictability and the presence of unknown unknowns," and so the common cause-and-effect approach of managing the uncertainty of the failure of infrastructure systems in the face of climate change hazards may not be best suited to model them. They recommend that best practices from complex system sciences such as Decision Making Under Deep Uncertainty and Safe-to-Fail frameworks should be used to improve the decision-making when managing the complex infrastructure systems. Besides, it is highlighted that the communication and coordination between managers of different infrastructure systems need to be enhanced to better implement strategies.

Data is central in the climate change debate. Especially data that is multidimensional and explores the societal impacts are crucial for informed decision making. Using information as evidence to derive social vulnerability is much needed. Barankin et al. describe this in their work on an evidence-driven approach for assessing social vulnerability during extreme events. A novel data-driven predictive approach is forwarded that overcomes over-generalization or aggregation in the indicator-based method. Using the case of Hurricane Sandy in the State of New Jersey, the authors demonstrate variability in the vulnerability among the Minorities" is substantial, with a low approval rate in the insurance claims. The study successfully showed that using the need-based, evidence-driven method provides a validation route for vulnerability assessments and is scalable across geographies. The universality of the process is worth reproducing. It can be considered the new direction of research on climate-related vulnerability measurements unbiased from the statistical inflation of indicators.

Markolf et al., while exploring the opportunities and challenges for artificial intelligence applications in infrastructure management to combat climate change, emphasizes that handling rapid technological transitions is the primary challenge. The magnanimity and the complexity of the problem make it incognisable for any individual or organization to handle. Artificial intelligence offers a seamless ability to manage complexity while providing insightful feedback. Although the authors underscore that while AI provides potential benefits which outweighs the drawbacks of over-reliance on reliable data, they are cautious in mentioning that an open dialogue is required.

A similar understanding is put forward by Nawroz Tonmoy et al., where the potential of utilizing smart city frameworks for disaster resilience in coastal cities is reviewed. The authors use a unique infrastructural lens to review the academic literature that focuses on smart systems' new development in coastal disaster management. The findings are interesting as they point out that while IoT and crisis informatics offer considerable potential for disaster resiliency, it remains understudied for coastal cities which need disaster resiliency that their inland counterparts.

The topic editorial team of this Research Topic on Past, Present, and Future Impacts of Climate on Infrastructure would like to thank all of the authors for considering this Research Topic for submitting their scholarly work. Thanks to the reviewers' hard work who provided their expert reviews under very tight schedules, the quality of the final papers presented in this Research Topic have dramatically improved. Without their contributions, this Research Topic would not have been so timely and successful.

AUTHOR CONTRIBUTIONS

AG and RB wrote sections of the manuscript. Both authors contributed equally to the manuscript revision, read, and approved the submitted version.

REFERENCES

Krayenhoff, E. S., Moustaoui, M., Broadbent, A. M., Gupta, V., and Georgescu, M. (2018). Diurnal interaction between urban expansion, climate change and adaptation in US cities. *Nat. Clim. Change* 8, 1097–1103. doi: 10.1038/s41558-018-0320-9

Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, S. K., Allen, J., Boschung, A., et al. (2013). *Climate Change 2013: The Physical Science Basis.Working Group 1 (WG1) Contribution to the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report (AR5)*. New York, NY; Cambridge.

UN (2014). *World Urbanization Prospects: The 2014 Revision, Highlights (ST/ESA/SER.A/352). Department of Economic and Social Affairs, Population Division.* New York, NY.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Water

REVIEW
published: 10 March 2020
doi: 10.3389/frwa.2020.00003

Increasing Coastal Disaster Resilience Using Smart City Frameworks: Current State, Challenges, and Opportunities

Fahim Nawroz Tonmoy[1,2,3]*, *Samiul Hasan*[4] and *Rodger Tomlinson*[5]

[1] Civil Engineering School, Griffith University, Southport, QLD, Australia, [2] School of Civil Engineering, University of Sydney, Sydney, NSW, Australia, [3] BMT, Brisbane, QLD, Australia, [4] Department of Civil, Environmental and Construction Engineering, University of Central Florida, Orlando, FL, United States, [5] Griffith Centre for Coastal Management, Griffith University, Southport, QLD, Australia

OPEN ACCESS

Edited by:
*Ronita Bardhan,
University of Cambridge,
United Kingdom*

Reviewed by:
*Subimal Ghosh,
Indian Institute of Technology
Bombay, India*
*Andre Schardong,
University of Western
Ontario, Canada*

***Correspondence:**
*Fahim Nawroz Tonmoy
fahim.tonmoy@hotmail.com*

Specialty section:
*This article was submitted to
Water and Built Environment,
a section of the journal
Frontiers in Water*

Received: 30 June 2019
Accepted: 17 February 2020
Published: 10 March 2020

Citation:
*Tonmoy FN, Hasan S and
Tomlinson R (2020) Increasing Coastal
Disaster Resilience Using Smart City
Frameworks: Current State,
Challenges, and Opportunities.
Front. Water 2:3.
doi: 10.3389/frwa.2020.00003*

Sea-level rise, storm surges, and floods in coastal cities have already threatened large population and infrastructure with potential to increase significantly in future as climate changes. Therefore, increasing disaster resilience has become a major priority for coastal cities. At the same time, recent development in information and communication technology, ubiquitous sensors, and advanced data science allow us to generate insights that were unimaginable before and can assist in better managing coastal disaster risks. In this paper, using an infrastructure resilience lens, we critically review a set of academic literature that focus on the new development of smart systems in coastal disaster management and a set of use cases that focus on their practical application in different coastal cities. We find that smart city technologies such as internet of things (IoT) and crisis informatics have significant potential and have been increasingly used in academic studies but their city-scale applications in coastal disaster management have been limited. We discuss the challenges and opportunities of using smart city frameworks for increasing disaster resilience of coastal communities.

Keywords: coastal disaster, smart city, resilience, vulnerability, internet of things, crisis informatics

INTRODUCTION

Natural hazard events have been an ongoing element in the coastal regions around the world. Flooding and erosion episodes in the coastal margins during storms, hurricanes or cyclones are putting a significant amount of assets, infrastructures, and communities at risk. Seventy-two percentage of the 63 most populated cities (with 5 million or more inhabitants in 2011) are located on or near the coast (United Nations, 2019). In one hand, population density in the hazard-prone coastal areas and megacities is expected to grow by 25% by 2050 (Hallegatte et al., 2013). On the other hand, a rise in sea level is likely to increase the frequency and impacts of these episodic coastal hazard events. In 2005, average global flood losses in the world's largest 131 coastal cities was approximately US$6 billion per year with the potential to increase to US$52 billion per year by 2050 due to sea level rise (Hallegatte et al., 2013). As a result, global investment and maintenance costs of protecting the coast from sea level rise estimated to be US$ 12–71 billion per year in 2100 (Hinkel et al., 2014). Therefore, increasing resilience of our coastal cities, their infrastructure systems and community in general to these episodic natural disasters is very critical.

Cities are inherently complex with interactions among multiple systems (e.g., supply chains and transportation networks, water and energy networks, housing and business infrastructures, social networks), agents (individuals, businesses etc.) and institutes that manage or influence these systems and agents (Tyler and Moench, 2012). The impacts of natural disasters in a coastal city therefore stems from complex interactions among a potentially damaging physical event (e.g., flood, erosion, storm) and the vulnerability of these systems, agents, and institutes (Birkmann, 2006; Tonmoy et al., 2014). Therefore, increasing disaster resilience of a coastal city needs an understanding of inherent stresses and vulnerabilities of these multiple systems. Specifically disruption in vulnerable critical infrastructure systems such as water supply network, transportation network, electricity production and distribution systems, health care facilities etc. that are located in the hazard prone areas of a coastal city can result in significant social and economic disruption. Therefore major coastal cities around the world are putting emphasis on increasing disaster resilience of their critical infrastructure systems (Aerts et al., 2014). Here critical infrastructure refers to any infrastructure that provides a service to the maintenance of the well-being of the population and something that if disrupted might cause serious harm to the well-being of the community (Attwood et al., 2011).

On the other hand, information and communications technology (ICT) has seen significant advancements in recent years with different types of smart and connected technologies capable to generate real-time information at an unprecedented scale. Alongside there has been significant improvement in computational power to manage and analyse big datasets. Specifically, rapid advancements in artificial intelligence, ubiquitous sensing technology, smart city/infrastructure, availability of big data sources such as social media, mobile devices, infrastructure management systems (e.g., SCADA) allow us to collect and analyse data with details and coverage unimaginable before (Kitchin, 2014; Gupta and Gupta, 2016; Murayama et al., 2017). These advancements offer opportunities to develop data-driven decision support tools for a better understanding and management of coastal disasters in cities with a substantial potential to increase the resilience of coastal communities. Deploying these advanced ICT infrastructures within a city context to improve citizen services is often referred as "smart city" and has become the latest trend in urbanization (Hollands, 2008; Batty et al., 2012; Kitchin, 2015; Wiig, 2015).

The definition of a "smart city" is diverse and so are its applications. Two distinct understandings of smart cities are prevalent in the literature. First, smart cities are viewed as urban places with ubiquitous computing and digitally instrumented devices built into the very fabric of urban environments. Examples include wireless telecom networks, digitally controlled utility services and transport infrastructure, sensor and camera networks, building management systems, smart phones producing data about resident's location, and activity etc. (Kitchin, 2014). These can make a city "knowable and controllable" and ultimately improve the performance and delivery of public services. A second view of smart cities is broader: this is seen as the development of knowledge economy within a city driven by ICT as a central platform. This notion of smart cities is based on the fact that embedding ICT in urban infrastructure on its own does not make a city smart; rather its entire ecosystem (economy, community, infrastructure, environment) should be managed having ICT as one of the central platform (Hollands, 2008). A similar view is presented by Batty et al. (2012) where authors sketched the fundamentals of what constitutes a smart city and argued that smart cities should include smart economy (competitiveness and entrepreneurship), smart people (social and human capital), smart governance (participation in decision making), smart mobility (transport and ICT), smart environment (sustainable resource management and smart living (quality of life). In both schools of thought, however, a common theme is the need to enhance the sustainability and resilience of the city as a whole. This paper adopts the former definition in order to investigate to what extent smart city frameworks have been used around the world toward increasing coastal disaster resilience of critical infrastructure systems.

Disaster resilience of a city is often characterized in three distinct stages of a hazard event namely preparedness of multiple systems of the city to reduce potential impact of the hazard, ability to manage and respond during the event to minimize loss, and finally the ability to manage recovery of the affected systems from the hazard impacts (i.e., bringing the system to its normal state). A review of the use of communications technology during disasters in recent years shows that while it has played a positive role, its full potential has not yet been realized (Diane and Meier, 2009; Dunaway et al., 2017). Different smart city features have been implemented around the world for better management of all these three phases of disasters. City specific case studies have been released highlighting how cities have implemented smart features in their urban margins [e.g., (Caragliu et al., 2011; Bakici et al., 2013; Scuotto et al., 2016)] but not all of them attempted to tackle coastal disasters. Furthermore, some of these case studies do not appear in the peer reviewed literature as they are often published as project reports. On the other hand, there has been a number of academic peer reviewed research publications reporting on the innovative development and implementation of smart city features for disaster management of cities from a range of natural and man-made hazards (e.g., Alazawi et al., 2011, 2012, 2014; Ancona et al., 2015; Choi and Bae, 2015; Kumar et al., 2015; Lo et al., 2015; Hernández-Nolasco et al., 2016; Shalini et al., 2016). This peer reviewed literature often reports a specific application or innovation of using smart features in disaster management. Therefore, it is difficult to understand from this body of literature to what extent new innovations are infiltrating in practical applications and what are the major challenges and opportunities of implementing smart city features for increasing coastal disaster resilience. There are several review papers that highlight the broader application of smart city features, but mainly focusing on different aspects of the discipline e.g., review of definitions and terminologies of smart cities used around the globe, review of smart city governance, review of enabling technologies, review of IBM smart city projects etc. (Caragliu et al., 2011; Cocchia, 2014; Anthopoulos, 2015; Yin et al., 2015; Meijer and Bolívar, 2016). However, to the best of our knowledge, none of the review papers investigated both gray literature application case studies and academic peer reviewed literature to analyse the variety of development and application of smart city features in coastal disaster management. This knowledge gap makes it difficult to anticipate future research directions and major development trends within the field of coastal disaster management.

To this end, the objectives of this study are: (1) to describe the broad characteristics of coastal disasters and their potential impacts on the resilience of city infrastructures; (2) to investigate a sample of case studies around the world to identify how coastal disaster resilience has been tackled using smart city features in those cities; (3) to analyse a sample of peer reviewed literature on disaster management and smart city to identify new innovation and development trends; (4) discuss current challenges, opportunities, and potential future research directions for this sector.

CHARACTERISTICS OF COASTAL DISASTER RESILIENCE IN CITIES

A number of coastal hazards can trigger a natural disaster in the coastal zone. Here it is important to make a distinction between "Coastal Hazards" and "Hazards in the coastal zone." Where the first one is about hazards that are introduced by the action of sea and its interaction with the coast, the second one includes all hazards that are relevant for the coastal zone regardless whether they are due to action of sea or not (e.g., heatwave, landslide etc.). The scope of his paper is limited to the former. Different coastal hazards such as coastal flooding, erosion, sea level rise etc. propagate and have impact on coastal systems at a different time scale. As an example, while coastal flooding during a storm or cyclone is a rapid event with immediate impacts (in the order of hours and days), sea level rise has a slow onset with longer-term impacts (in the order of decades to centuries). Similarly, coastal erosion can have a rapid onset when a coastal storm or cyclone swept away significant part of the sand of a beach (in the order of days), but erosion can also have a moderate-term onset as a result of long-shore sediment transport where sediments are transported by waves from one beach to the other resulting in sediment deficit and erosion (in the order of seasons) and a longer-term onset where erosion of the coast increases as sea level gradually rises (in the order of decades and century) (**Table 1**). These time scales of coastal hazard govern the hazard impacts on coastal infrastructure. On top of temporal variation, these hazards also vary spatially as intensity of these hazards are amplified with specific geographic and geomorphic formation of the coastal area (e.g., low lying areas, erodible shoreline etc.).

In order to make coastal infrastructure systems robust against hazards that vary temporally and spatially, the concept of "resilience" is becoming increasingly popular among disaster management professionals and researchers. The definitions of resilience emanate from multiple disciplines (e.g., ecology, disaster management, engineering) and therefore are quite diverse in the literature (Cimellaro et al., 2010). In general, resilience is defined as the ability of a system to resist and/or to recover from a shock. Scholars use other terminologies as a measure of resilience such as flexibility and the ability to maintain the status quo or to reorganize after stress or shock (Manyena, 2006; Bhamra et al., 2011). Resilience is also considered as an emergent property of a system to manage high variability and uncertainty in order to continuously pursue successful performance of a system (Cimellaro et al., 2010; Francis and Bekera, 2014; Kong and Simonovic, 2019; Kong et al., 2019). Tyler and Moench (2012) argued that the application of the concept of resilience to urban climate adaptation and hazard mitigation practice would help to address some of the "predict and prevent" approach and allow preparing infrastructure systems for climate change even under high uncertainty.

Disaster Risk Management (DRM) includes all activities, programmes, and measures which can be taken up before, during and after a disaster with the purpose to avoid a disaster, reduce its impact or recover from its losses (Khan et al., 2008). **Figure 1** shows the characteristics of a resilient infrastructure system in these three distinct phases of DRM. To better prepare for any future hazard, in the preparedness stage, several steps can be conducted such as understanding the characteristics of coastal hazards though modeling and engineering analysis, developing early warning systems, installing hazard mitigation measures, educating and informing communities about hazards etc. When a disaster is unfolding (e.g., crossing of a cyclone/hurricane over a coastal area) a resilient infrastructure system should be able to absorb physical stresses from the hazard and maintain serviceability even with reduced capacity and should have the capacity to restore the system to full operation mode once the stress from the hazard is over (e.g., providing backup, restore function etc.). Finally, a resilient system uses its learnings from an event, policies are implemented and capacity increased so that in the face to future disaster stress, the system can better cope and fight back quickly. For any critical infrastructure operator it is crucial to reduce the time the system spend between t_1 and t_2.

INCREASING COASTAL DISASTER RESILIENCE IN CITIES USING ICT

Due to technological advancements as well as increased trend in natural and man-made disasters, the importance and scope of information and communication technology (ICT) in increasing disaster resilience have increased in recent years. Different phases of disaster management of infrastructure systems that are discussed in the earlier section (**Figure 1**), are benefitting from the recent advancement of ICT. Examples can be drawn from the use of early warning systems (in the preparedness phase), collection and analysis of real-time hazard information for effective coordination of disaster management and recovery operation (during the disaster), setting up of long-term monitoring systems for understanding trend of the coastal or climatic variable that are responsible for creating the hazard (during the post disaster state). At a global, regional, and national scale advanced information and communication technologies have been implemented for the generation and distribution of disaster alerts and warnings (be it coastal or not) (see **Table 2**). Among these, Common Alerting Protocol (CAP) and Emergency Data Exchange Language (EDEL) messaging

TABLE 1 | Characteristics of coastal disasters in cities.

Coastal hazards	Potential cause	Time scale of the hazard	Potential impacts to coastal cities
Coastal flooding	Coastal storms, cyclones, king tide etc.	Short-term with fast onset	Destruction of assets, infrastructure, and lives. Disruption of business, supply chain, and have negative impact on economy.
Coastal erosion	Soft and erodible geomorphology sometimes coupled with destabilization of the shoreline due to human intervention.	It can be short, medium and long term	Damage to nearby private properties and public infrastructure. Loss of sand on beach can also have negative impact on beach tourism.
Concurrent effect of catchment and coastal flooding	Excessive rainfall in the upper catchment coincide with coastal storm and/or king tide	Short term with fast onset	Due to coincidence of both catchment and coastal flood events, upper catchment flood waters are unable to escape in the coast. This often extend the impact of coastal flood beyond the coastal zone causing disruption in lives and economic activities.
Sea level rise	Increase global average temperature as a result of climate change	Longer term with slow onset	Permanent inundation in low lying areas, frequent inundation during high and king tide events. These can lead to loss of coastal properties and assets, decrease in property values, conflict between affected city residents and city authorities in terms of deciding "who to pay" for the increased requirement of coastal protection measures.

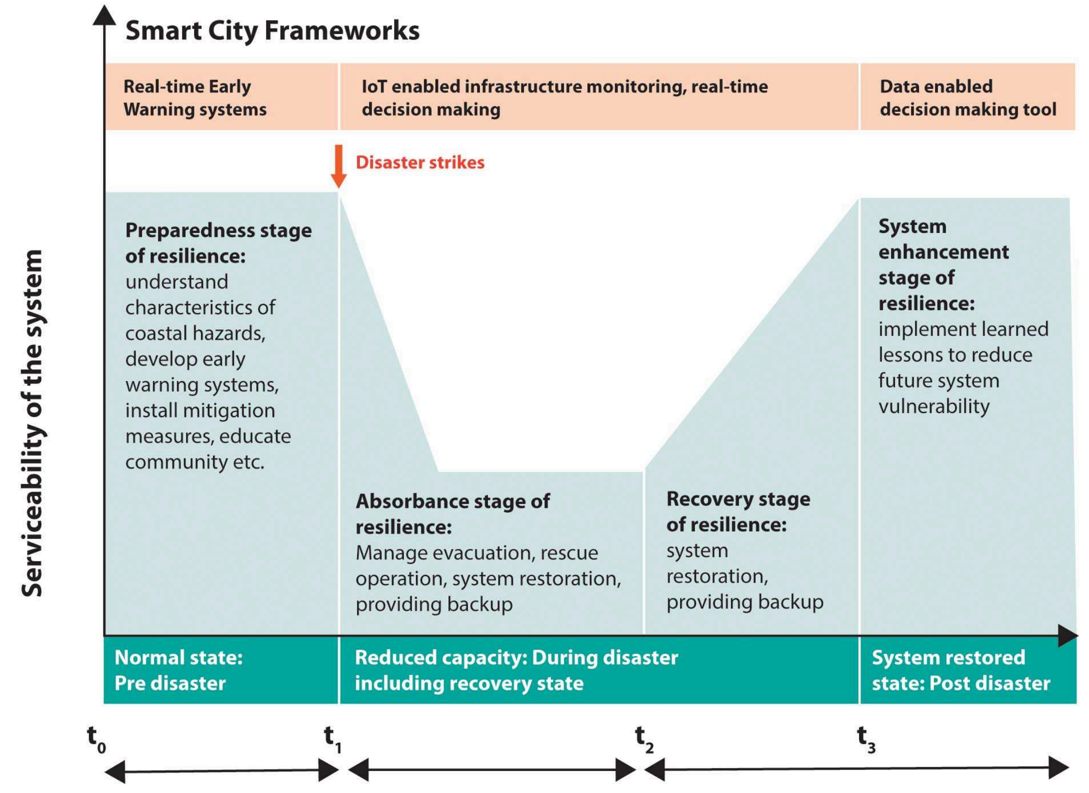

FIGURE 1 | Characteristics of a resilient infrastructure system in three distinct phases of disaster risk management.

standards have been adopted by developed nations such as in Canada, Australia, Japan and Taiwan etc. These systems allow these countries to facilitate automatic notification of certain natural hazards by sensor systems, analyse, and exchange results between emergency information systems and services. CAP and EDEL are international standards for exchanging emergency alerts in a digital format that allows a consistent alert message to be disseminated simultaneously over many different communications systems. These consistent formats allowed development of critical services such as Google Alert, European public warning systems etc.

These global and regional alert systems act as early warning systems for coastal disasters and assist national, regional authorities to communicate the risk of the cyclones, hurricanes, flooding etc. to coastal communities so that they can take necessary measures to reduce their loss from the disaster. Owner

TABLE 2 | Example of ICT based global and regional disaster alert systems.

Global and regional disaster alert systems	References
CAP: Common Alerting Protocol, V1.2	http://docs.oasis-open.org/emergency/cap/v1.2/CAP-v1.2-os.html
EDXL-DE: Emergency Data Exchange Language Distribution Element	http://www.oasisopen.org/committees/download.php/17227/EDXL-DE_Spec_v1.0.html
IPAWS-OPEN (Integrated Public Alert and Warning System—Open Platform for Emergency Networks used in the US)	http://www.fema.gov/integratedpublic-alert-warning-system
GDACS: Global Disaster Alert and Coordination System	https://www.gdacs.org/
European Public Warning System (EU-Alert) Using Cell Broadcast	https://ec.europa.eu/programmes/horizon2020/en/news/emergency-alert-system-europe
Google Public Alerts	https://support.google.com/publicalerts/?hl=en

and operators of critical infrastructure systems also use these early warning systems to inform their disaster management activities. However, these global and regional alerts alone are not sufficient for managing disaster risks of critical infrastructure systems within a city. These critical systems often have complex and interdependent networks and increasing disaster resilience of such networks requires finer scale real-time information that goes beyond just the disaster alert systems.

To this end, recent development of sensors, their web of networks with ability to communicate via internet (i.e., internet of things) provide a tremendous opportunity to make better and real-time disaster management decisions for critical interdependent infrastructure systems. Specific opportunities of using ICT at a local scale coastal disaster management includes:

- Supplementing early warning systems with near-real-time to real-time analysis of hazard information. This will allow more pro-active decision making due to any disruption and recovery effort of a critical infrastructure failure.
- Opportunity to know more about how different infrastructure systems perform under stress during disasters (e.g., maintain physical integrity, cope with increased demand, cope with reduced capacity as result of disruption of connected services etc.), so that system vulnerabilities can be identified and initiatives can be taken to make them more resilient.
- Opportunity to use of data enabled decision support systems to prepare, manage, and recover from coastal disasters. Visualization and analysis of near-real-time information from sensors about the extent of the hazard, performance of the infrastructure etc. provides an opportunity to make informed decision about where and how resources should be allocated to recover lost infrastructure services

EMERGENCE OF THE SMART CITY CONCEPT AND ITS USE IN COASTAL DISASTER MANAGEMENT AT A CITY SCALE

The term "smart cities" has gained significant attention in academia, businesses and government in the last decade, especially in cities where ICT has been embraced as a development strategy. Cities that are embedding digital infrastructure in the urban fabric for providing better service to its citizens through web access services, to better manage facilities and to promote entrepreneurship are often termed as "smart cities," "intelligent cities," "connected cities" etc. (Kitchin, 2014).

What Does a Smart City Framework Look Like?

There are four main layers in a smart city framework (**Figure 2**). A perception layer which includes range of sensors that can collect real-time or "near real time" data. This also includes a sensor or device management component to handle registration of new devices, assignment of unique identifiers, format data, etc. A network of sensors provides interfaces to interconnect heterogeneous information sources in a secure way and a data storage services to persistently store collected data. Finally this includes a layer which analyses and visualizes stored and real-time data stream. Visualization services include different formats like visual diagrams, reports, graphs, etc. Some of the specialized type of application also include analysis of georeferenced data and dissemination of alarms and notifications. This is beyond the scope of this paper to present detailed smart city frameworks and for more information readers are directed to following references (Alazawi et al., 2014; Sanchez et al., 2014; Scuotto et al., 2016). Rather, we investigate how this generic framework has been used for the coastal disaster management in cities.

Development Trend in Peer Reviewed Academic Literature

Selection of Peer Reviewed Academic Literature

In order to identify relevant academic papers we conducted an extensive search in the "Web of Science" database in early 2018. Initial search was conducted using key words "smart" AND "disaster management" within topics for the entire database and it yielded 223 papers (Type-1). This included papers related to disaster planning and management of all hazards which goes beyond the scope of the paper. We then refined the search by adding "coast" in the search term and it yielded only 6 papers. It was quite clear that these search terms are very narrow therefore we then expanded the scope of the search by making it "smart" AND "disaster management" AND "flood" which yielded 33 papers (type-2). Often flooding in the coastal city is a big issue

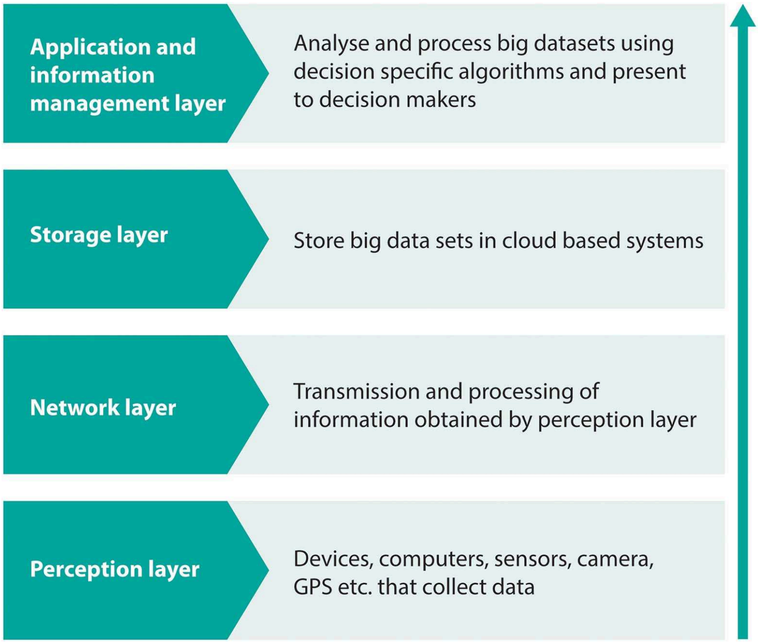

FIGURE 2 | Different layers of a smart city framework (a generic view).

and used as a topic in the academic papers. However, by reading through the abstracts of this list it was evident that this list includes studies that are non-coastal in nature. In order to get a representative sample of coastal studies we replaced "flood" with "coast OR flood" and also included "IoT" (internet of things) along with our initial search term "smart." Type 3 search criteria was "smart OR IoT" AND "disaster management" AND "coast OR flood" which yielded 18 papers. IoT has been one of the main driver of smart city developments and its inclusion in our search criteria allowed capturing technical papers that not necessarily use the term "smart" rather report their development using a more technical terms. A clear trend is visible in all these three sets that research on smart and innovative disaster management systems have been growing exponentially since 2010 (**Figure 3**). It is possible that we may have missed few papers, but our aim was not to find every paper that deals with smart city and coastal disaster, rather to find a representative sample of papers to understand major trend within this emerging body of work.

Analysis of Peer Reviewed Literature

Analysis of this final type-3 set of papers revealed two clear branches. First, a set of papers developed innovative IoT based smart systems for better identification and communication of hazard information (flooding, Tsunami etc.). **Table 3** shows key feature of these studies. **Table 3** maps seven studies from the type 3 sample (which specifically used IoT based smart systems) across their application, type of hazards they addressed, resilience stage which they aimed to cover and technologies used across four layers of smart city framework that are described in **Figure 2**. It shows that application of IoT based major innovations in our study samples mainly focused on managing two types of coastal hazards, flood and Tsunami. While investigating the technologies that are used across different layers the smart city framework, it was found that in the "perception layer" along with different types of sensors, CCTV camera and smart phones are used for collection of real-time information. Collected information of the perception layer is transmitted by various mediums e.g., Wi-Fi, cellular, internet. Studies which conducted further analysis to generate insights often stored the data either in cloud based systems of local servers. Choice of storage was primarily guided by the size of data generated by the perception layer and analysis method that were used by the authors.

The second group of papers, often categorized as "crisis informatics," reported use of different advanced analysis techniques (optimization, social media or crowd sourced information etc.) or advanced technologies such as virtual reality for better preparing and managing coastal disasters. As an example, Basu et al. (2016), collected situational information through interactive crowd-sourcing using SMS from the "crowd" present at the disaster site, and analyzed them to develop situational awareness to support appropriate decision-making regarding damage or need assessment during coastal disasters in India. Ai et al. (2016) combined a geographical information system and social media to develop a dynamic decision support system (GIS-SM-DDSS) that integrates geographical information with Twitter technology to enable self-organized information networks to support decision making and collective actions in emergency situations. Ogie et al. (2017) used network analysis to determine optimal sensor locations in developing countries, so that a low cost early warning system of coastal flooding can be implemented. Anbalagan and Valliyammai (2016) used real time social media contents such as micro blogs, tweets, posts

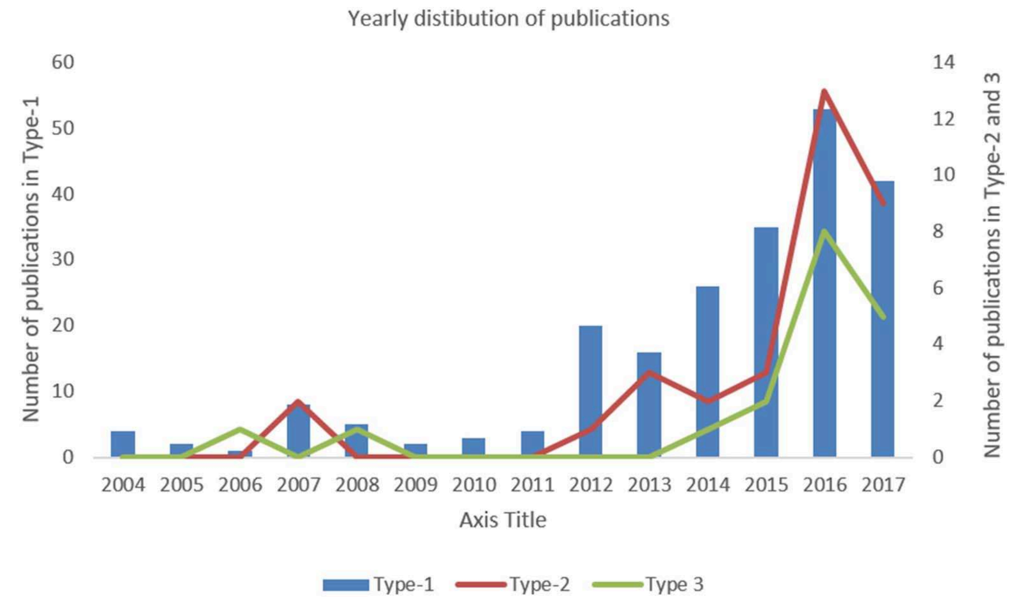

FIGURE 3 | Yearly distribution of publication that appeared in different search sets.

and multimedia content along with geographical location tags (geo-tags) to map the severity of the disaster. Kawai et al. (2015) developed a smart Tsunami drill system using virtual reality technologies to educate and increase awareness of Tsunami disaster among school children.

Implementation Trend at a City Scale

After investigating the development trends in the academic literature, we investigated, how cities are embracing some of these smart city features for managing their coastal disasters. Smart city projects are often reported as case studies to showcase city's progress in embracing new technology to serve its citizens. Among many other information, these case studies generally highlight key technical features of the implemented smart city projects. Analyzing a sample of such case studies can provide a sense about how new developments in the academic literature are translated into practical project implementation.

Selection of the Case Study Sample

A google search was conducted using key words "smart city" AND "Case study" to generate a sample of city specific case studies from the unpublished gray literature that document how city's smart city projects are implemented. Initial screening of the sample documents revealed that not all smart city case studies have disaster management related content. This is mainly due to the fact that some cities do not include disaster management as their focus while implementing their smart city, be it coastal or not, or the case study document that we selected may not have included the disaster management component of the city. Whichever is the case, our analysis discarded those case studies and retain only those that report any disaster management related features. In the next step some of the non-coastal city specific case studies were eliminated to ensure that our final sample only consists of case studies that include coastal disaster management.

Table 4 shows the final list of the sample case studies. It should be noted that this list is not exhaustive and it is likely to miss some. However, the aim of this paper is not to develop an exhaustive list of case studies rather analyzing a sample in order to understand major trends.

Analysis of Selected Case Studies

Six sample case studies were analyzed to identify what types of coastal disasters were tackled by cities using smart systems, at what stages of the disaster were they used (e.g., early warning, during disaster, disaster recovery etc.), and what smart city features and systems were implemented in the city (**Table 4**). Flooding (coastal and riverine), cyclone (typhoon, hurricane, tornado, and thunderstorm), tsunami, and landslide have been tacked by these cities. Early warning systems of these hazards were most benefited as information about these hazards were collected, analyzed and communicated to citizens for better preparation. As an example, Tokyo's smart disaster early warning system covers a range of hazards, not just coastal, including earthquake. Technology vendor NEC has developed Tokyo's disaster resilience solution which includes observation systems, information gathering capabilities, data analysis and decision-making aids, together with an intelligent warning system, all linked together in an interoperable manner.

Another example is from Rio De Janeiro, which has a central disaster coordination and operation center. Since opening, the Rio Operations Center has integrated information and processes from across 30 different city agencies into a single operations center that provides a holistic view of how the city is functioning on a 24 h basis. The Operations Center serves as the nerve center

TABLE 3 | Example of studies reporting IoT based coastal disaster management systems.

Example	Type of application	Type of hazard	Resilience stage	Perception layer	Network layer	Storage layer	Application and information management layer
Hernández-Nolasco et al. (2016)	Use sensors to measure water level in rivers, lakes, lagoons and streams.	Flood	Preparedness and management of hazard	Sensor	Wi-Fi	No storage	Netduino apps are written using C# language and suitable for mobile applications
Shalini et al. (2016)	Use sensors to measure water level and send SMS to alert	Flood	Management of hazard	Sensor	Cellular	Cloud	
Lo et al. (2015)	Use CCTV to collect imagery and process them via machine learning algorithms to automate real time flood monitoring	Flood	Management of hazard	Visual imagery collected using CCTV	Internet	Cloud	Image detection and processing using machine learning algorithms
Kumar et al. (2015)	Early flood detection SMS service	Flood	Management of hazard	Sensor	Cellular	Local storage	Machine to machine processing
Ancona et al. (2015)	Early detection of flood using low power consuming sensors	Flood	Management of hazard	Ultra-Low Power Micro Controller together with rain gauge sensors	Internet	Cloud	IoT platform Thingworx
Aimmanee et al. (2016)	Adaptable devices such as foldable flood barriers and hydrodynamically supported temporary banks	Flood and Tsunami	Mitigation of hazard	composite cylindrical shell structure embedded with piezoceramic sensor	Cellular	No storage	Bio-mimicking column structures capable of high-velocity water interception and velocity detection in the case of tsunami.
Kitada et al. (2017)	Dessiminate disaster information to smart phone users even after the failure of transmission systems	Flood, Tsunami	Management of hazard	Smart phones	Internet	Local storage	Disaster servers designed using Java and MySQL

for the city, applying analytical models developed by IBM to more effectively predict and coordinate disaster management.

DISCUSSION

Increased potential of natural disaster events as a result of climate change along with rapid development and population growth in coastal cities have created significant risks and challenges for disaster management authorities. Rapid improvement in IT systems has fuelled growing interest in designing and implementing disaster management systems which can predict climatic conditions based on near real-time information, analyse them and communicate with citizens so that disaster impacts can be minimized. To this end a range of innovative systems, tools etc. are developed by the research and academic sector and some of them are making their way to practical city scale implementation. Among these, "smart-city" concept or framework is growing in interest among disaster management professionals, specifically in developed countries. A "smart-city" concept uses embedded sensors, live camera, radar to collect near real-time information and further analyse them to generate valuable insights for disaster management professionals. In the earlier part of the paper, our analysis of a selected sample of peer reviewed academic papers as well as gray unpublished literature revealed some interesting facts about using ICT based smart city frameworks in disaster management and resilience.

Trends and Gaps

The present review highlights the lack of scalable smart city technologies for improving coastal disaster resilience, and as a result, the lack of at scale implementation of smart city frameworks from a coastal disaster resilience perspective. Our findings are summarized below:

- Various smart city technologies, platforms, analysis techniques and applications that are relevant to coastal disaster resilience have been identified. It is clear that the choice and appropriateness of the technology should be judged under the decision-making contexts for which it is developed (i.e., early warning or pre-disaster stage, disaster management when the disaster is unfolding or post disaster recovery etc.). Future applications and/or further development of a smart city tool for coastal disaster resilience depend on the specific decision-making context. Thus, the lens of decision-making contexts is absolutely necessary to assess the appropriateness of a smart city technology.
- While comparing the analysis findings of both peer reviewed literature and city scale case studies, it is clear that while peer reviewed literature is testing and trialing new approaches

TABLE 4 | Analysis of Smart city case studies for identifying key features of coastal disaster management.

City	Hazards	Stages of disaster addressed	Key smart city features
Tainan, Taiwan	Coastal and riverine flood	Early warning and disaster management	1. 48 remotely controlled pumping station to pump out flood water. They are controlled and monitor in real-time using 4G network. 2. 20 Wearable real time video monitoring sets for outdoor use during typhoon seasons. They provide real-time video stream to disaster coordination center. Image recognition algorithms are used for water level automatic recognition. 3. Water disaster management platform for coordination. 4. Mobile app for disaster information access to citizens.
Barcelona, Spain	Coastal and riverine flood	Early warning and disaster management	1. Flash flooding early warning system which composed on a high-tech radar, a city wide network of sensors for monitoring rainfall in the catchment. 2. Early warning system detect and forecast flooding and provide a series of reliable, understandable and timely warning messages to people at risk and to people in charge of managing that risk. 3. Smart platform for information dissemination such as COWAMA tool in coastal cities and iBeach App for smartphones. They include information on wave, wind, tide and temperature as well as weather forecasts for all beaches of Barcelona. This app also allows the public to proactively warn others about the presence of jellyfish, establishing a means of collaboration between the public and the city council.
Tokyo, Japan	All hazard (including tsunami, typhoon etc.)	Early warning, disaster management and recovery	1. Tsunami is a major coastal hazard in Tokyo and therefore it has smart Tsunami warning and management systems in place. 2. The Japan Meteorological Agency (JMA) and the central government are responsible for developing national emergency solution. On the other hand, when a coastal disaster strikes, cities such as Tokyo become the central coordination and response unis. 3. Key technical features of the coastal disaster management systems are: • nine Ocean Bottom Observation Systems that connect 5,000km of submarine cable, • 150 undersea seismometers, and seismometers in strategic locations in building foundations and other structures across the cities, • Rain and water level gauges are equipped with sensors and transmit real time data using telecom networks. • These data are analyzed and potential hazards are transmitted to cell phone users through cell broadcasting. • Mobile users can update their status i.e., whether affected or not, locations etc. in a central system so that if required they can be assisted in their recovery.
Songdo, Korea	Riverine flooding, land subsidence	Early warning and disaster management	Songdo U-disaster prevention system is in charge of spreading information when disaster occurs, monitoring for land subsidence, flooding, and corresponding to fires etc. Main functions include civil defense, spreading situation information to the National Disaster Management System, monitor weak lands for subsidence/flooding, monitor using CCTVs with high magnification during fires, and corresponding to fires. Because Songdo is built upon reclaimed land, monitoring for land subsidence and flooding is important. Key technical features of the disaster management systems are: • One satellite dish to receive and transmit data • 3 water level monitoring camera for flood monitoring • 3 flood sensors to detect changes in water level and to detect ground safety according to water pressure levels with in grounds.
Rio de Janeiro, Brazil	Coastal and riverine flooding and associated land slides	Early warning, disaster management and recovery	The automated alert system notifies city officials and emergency personnel in the disaster operation center when a flood is forecasted. As opposed to a previous system in which notifications were manually relayed, the new alert system is expected to drastically reduce the reaction times to emergency situations by using instantaneous mobile communications, including automated email notifications and instant messaging, to reach emergency personnel and citizens. This forecasting system pulls data from the river basin, topographic surveys, the municipality's historical rainfall logs, and radar feeds and process them using a unified mathematical model. This model then predicts rain and possible flash floods, and has also evaluate the effects of weather incidents on other city situations such as city traffic or power outages. Key smart infrastructure behind this system are: • 1 weather radar with operating range of 250 km • 164 rainfall stations that generate data automatically every 15 min, • 26 gauged stations • 164 audible alert stations with sirens • 200 points of support to high-risk.
Orlando, USA	Coastal flooding, hurricane, tornadoes, thunderstorms	Early warning, disaster management and recovery	OCAlert is an alert system with nearly 14,000 registered subscribers that allows Orange County Government to contact citizens during an emergency by immediately sending message to email account, cell phone and smartphone with real-time updates, instructions on where to go, what to do, or what not to do, who to contact, open shelters, water distribution centers, evacuation routes and other important information under emergency situation. Key smart features are: • Feeds from Doppler radar and satellite for weather data • Flood sensors in critical coastal locations • Live camera feeds from expressways • GIS based water management system fitted with sensors • Automatic Vehicle Location (AVL) function that enables the staffs to track the movement of police cars, fire trucks, emergency medical vehicles etc. during disasters.

and techniques, city scale applications are leaning toward more matured approaches and technologies. As an example, in our study sample of the academic literature an innovative CCTV enabled and machine learning based visual monitoring system was used for automating and process real time flood monitoring using image processing. Whereas, this approach did not proliferate in our city scale case studies as cities mostly used conventional sensors. While, conventional sensing networks can only offer one-dimensional physical parameters measured by gauge sensors, visual sensors can acquire dynamic image information of monitored sites and provide disaster prevention agencies with actual field information for decision-making to relieve flood hazards (Lo et al., 2015).

- At present, there is a scarcity of studies investigating and applying smart city technologies for managing coastal hazards at a local government scale. However, coastal local governments commonly face such issues related to the management and planning for potential coastal hazards. As sea-level rises, this issue is likely to become more critical for coastal local governments (Torabi et al., 2017; Tonmoy et al., 2018).
- In peer reviewed literature "Crisis informatics" has become an emerging smart city framework that develops analytics approaches to extract, analyze, and predict online activities (e.g., tweets and Facebook posts) to address challenges in disaster warning, response, and recovery operations (Palen and Anderson, 2016). For instance, during a disaster, disseminating information effectively and timely plays a critical role in spreading awareness in a community. It requires a range of delivery techniques to reach the target audience using different media and communication means. Online social media (such as Facebook, Twitter) can serve as alternative channels to disseminate information to a wider audience. Applications of such crisis informatics can be found in many recent studies using social media data during disasters (Kryvasheyeu et al., 2015; Thom et al., 2016; Sadri et al., 2018). Since crisis informatics is a relatively new field investigating the role of social media during disasters, most studies commonly focus on high-level correlations among the variables of interest when analyzing large-scale data sets (Palen and Anderson, 2016). However, many other questions (Gladwin et al., 2007; Murray-Tuite and Wolshon, 2013) about behavioral and social phenomena, critical to achieving disaster resilience, still remain open. These questions include: how to use social media communications to rapidly identify infrastructure disruption issues and monitor disaster responses and recovery efforts; or how to measure the effectiveness of the available information sources in warning message propagation using the topological properties of the social network observed?
- In city scale implementation case studies:

  a) different types of early warning systems are developed for communicating detected coastal hazard (e.g., flood, cyclone) warnings to public through variety of mechanisms such as SMS alerts, social media, sirens etc.

  b) different types of remote sensing technologies such as water sensors, radar imagery etc. are used to monitor water levels in flood, tide and rain gauges or to continuously measure the water level variation within a large area (e.g., flood monitoring systems). As an example, flash flood alarming systems require a dense network of rain gauges for monitoring intense local rain storms both to ensure its survival in case of extreme weather and to have a more accurate collection of data. However, those data have to be interpreted using empirical models by correlating in real time the river level and the flow intensity for early flood forecasting and consequent anticipated alarming (Ancona et al., 2015).

  c) application of other types of sensors such as temperature sensors, pressure sensors in this domain remain limited.

- One common theme emerged as IoT based software platforms are used in both academic literature and city specific case studies for deploying sensors, communicating collected near-real time data, their storage and analysis.

Lack of Use in Erosion Management

Although coastal erosion has been a major coastal hazard, but it did not appear neither in academic literature nor in city scale case studies. Long-term monitoring of shoreline changes is of significant importance for coastal erosion prediction and coastal planning. Using drones or fixed CCTV camera in combination with image analysis techniques can provide opportunity to implement coastal erosion monitoring of city's most erosion prone beaches (Turner et al., 2016). However, this lack of application of smart city frameworks in coastal erosion management brought up a critical point that *time scale* of coastal hazard governs the choice of ICT in disaster management. Coastal hazards not only vary in space (e.g., lower areas get inundated in coastal flooding) but also vary in time (e.g., while cyclones can cause inundation of coastal areas within days, increase in sea level rise may cause inundation gradually over decades). The time scale of coastal hazards often determines the choice and characteristics of the ICT feature that are to be used for risk management. As an example, for managing longer-term coastal hazards such as sea level rise, it is important to understand trends and therefore monitoring tides, sea levels, sediment transport etc. are critical with relevant ICT features such as implementation of monitoring systems with sensors being used (Harley et al., 2015). On the other hand, ICT features for managing coastal storms and cyclones require real-time information to feed early warning systems therefore relevant ICT features and sensors with capability to transmit real time information are used.

Not All Smart City Projects Include Smart Disaster Management

ICT have been used for providing early warning to coastal hazards at both global and local scale (Application of local scale mostly in developed countries). Analysis of a sample of smart city gray literature case studies suggest that not all smart city projects around the world have incorporated smart ICT features for managing coastal hazards. There is a chance that not all features get reported in case studies therefore this needs to be further investigated.

FUTURE DIRECTIONS AND CHALLENGES

Major Research Questions

Major Research Questions That Need to Be Addressed Include.

- How can we design and implement a smart city decision support system for coastal hazards which includes the vast range of stakeholder concerns and decision-making contexts related to disaster management?
- How can we develop models to better understand infrastructure interdependency at a local government or city scale and integrate them with smart city platforms?
- Will it be possible or effective to develop one smart city tool that can satisfactorily address all the key disaster management issues in coastal areas, or will it be more effective to create an ensemble of smart city platforms with properly designed interfaces allowing information and decision exchange among various platforms?
- How can we create a smart city platform with linked models and data interoperability for modeling coastal hazards and use them for the development of smart decision making under different types of disaster management contexts (pre disaster, during disaster, and post disaster) in coastal areas?

Opportunities for Implementing Smart City Framework for Coastal Disaster Management

Use of a smart city framework provides a basis for monitoring coastal activities and there are significant opportunities to integrate them with computational models of floods (coastal, riverine, Tsunami) and erosion. These models are developed and validated and used for identifying hazard prone areas. Combining these models with real-time information using smart city frameworks can provide opportunity to disaster managers' to dynamically characterize coastal hazards as they unfold. This is especially critical for cyclone or hurricane as their track changes dynamically and so does areas that are likely to get affected by the cyclone or hurricane. Combining validated numerical hydrodynamic model of coastal inundation with real-time information of cyclone track can assist disaster managers to prioritize evacuation dynamically as cyclone changes its track. Not only cyclones, flood models can also be integrated with smart systems to understand concurrent events of catchment flooding and coastal surge. All of this knowledge can then be integrated with socioeconomic and demographic information (i.e., location of vulnerable populations, critical infrastructure, old structure etc.) to better inform disaster management.

Challenges for Implementing Smart City Framework for Coastal Disaster Management

One of the main driving factors of this framework is power and communication systems which are vulnerable to any man-made or natural disasters including coastal ones. If we lose either we will lose the effectiveness of the whole system. Use of these smart systems will increase in future in managing different infrastructure layers and the connectivity will only increase. Smart city technologies will make different city functions more interdependent. Emergency services depending on data analytics or artificial intelligence will have to depend on the availability of the sensors. However, these interdependencies will be a major challenge in future as there are gaps in our understanding about infrastructure interdependency at a local scale that are arising from these smart infrastructures (Tonmoy and El-Zein, 2013; Hasan et al., 2015; Ersoy, 2017).

Although academic literature is developing innovative new smart systems and analysis techniques, they are often designed and tested in isolation. Integration of these systems to serve a common goal such as disaster management at a city scale across different city systems still remains an unresolved challenge. Transferring a newly developed prototype of smart technology for disaster management into a real-life city scale implementation to inform existing disaster management (DM) decision-making protocol is difficult. DM sector is often very hierarchical and often can be resistant toward getting information from different sources that might affect central command under emergency situation. At the same time, multi-asset integration of disaster management is challenged by data sharing although some progress has been made. As an example, safe data sharing initiative has been initiated and implemented across multiple infrastructure operators in Australia to support managing critical infrastructure during disaster events (Australian Government: Department of Infrastructure, 2018).

Because of the complexity of the disaster management issues in the coastal region and a diverse range of stakeholders and available smart systems, it will be a nearly impossible task to build a super-smart city platform to support a wide range of disaster management related decision-makers. Instead, a more pragmatic approach will be to build interfaces amongst different aspects of the problem linking models, platforms and their outputs. Such an interoperable approach of decision support system will be able to fit different smart technologies, analysis techniques in the decision support platform depending on the disaster management decision context. Also, there is a need for a consistent benchmark of relevant data sets to be able to integrate them within smart city compatible decision support systems.

CONCLUSIONS

A disaster resilience framework has been presented to assess current state of research and application of smart city frameworks in disaster management within coastal cities. A set of academic literature and city specific application case studies were reviewed. We find that smart city technologies such as internet of things (IoT) and crisis informatics have significant potential and have been increasingly used in academic studies but their city-scale applications in coastal disaster management have been limited. We have identified critical gaps, RandD needs and practical challenges to foster development of smart city oriented decision support systems for coastal disaster management.

AUTHOR CONTRIBUTIONS

FT research idea and manuscript preparation. SH and RT research idea enhancement and review of draft.

REFERENCES

Aerts, J. C., Botzen, W. W., Emanuel, K., Lin, N., de Moel, H., and Michel-Kerjan, E. O. (2014). Evaluating flood resilience strategies for coastal megacities. *Science* 344, 473–475. doi: 10.1126/science.1248222

Ai, F., Comfort, L. K., Dong, Y., and Znati, T. (2016). A dynamic decision support system based on geographical information and mobile social networks: a model for tsunami risk mitigation in Padang, Indonesia. *Safety Sci.* 90, 62–74. doi: 10.1016/j.ssci.2015.09.022

Aimmanee, S., Ekkawatpanit, C., and Asanuma, H. (2016). Smart disaster mitigation in Thailand. *Paper Presented at the Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*. doi: 10.1117/12.2219206

Alazawi, Z., Abdljabar, M. B., Altowaijri, S., Vegni, A. M., Mehmood, R. (2012). "ICDMS: an intelligent cloud based disaster management system for vehicular networks," in *Communication Technologies for Vehicles. Nets4Cars/Nets4Trains 2012. Lecture Notes in Computer Science*, Vol. 7266, eds A. Vinel, R. Mehmood, M. Berbineau, C. R. Garcia, C. M. Huang, and N. Chilamkurti (Berlin: Springer).

Alazawi, Z., Alani, O., Abdljabar, M. B., Altowaijri, S., and Mehmood, R. (2014). A smart disaster management system for future cities. *Paper Presented at the Proceedings of the 2014 ACM International Workshop on Wireless and Mobile Technologies for Smart Cities*. doi: 10.1145/2633661.2633670

Alazawi, Z., Altowaijri, S., Mehmood, R., and Abdljabar, M. B. (2011). Intelligent disaster management system based on cloud-enabled vehicular networks. *Paper Presented at the ITS Telecommunications (ITST), 2011 11th International Conference on*. doi: 10.1109/ITST.2011.6060083

Anbalagan, B., and Valliyammai, C. (2016). "ChennaiFloods: leveraging human and machine learning for crisis mapping during disasters using social media," in *2016 IEEE 23rd International Conference on High Performance Computing Workshops (HiPCW)* (Hyderabad), 50–59.

Ancona, M., Dellacasa, A., Delzanno, G., Camera, A., and Rellini, I. (2015). An "Internet of Things" vision of the flood monitoring problem. *Paper Presented at the Performance: The Fifth International Conference on Ambient Computing, Applications, Services and Technologies* (Nice).

Anthopoulos, L. (2015). "Understanding the smart city domain: a literature review," in *Transforming City Governments for Successful Smart Cities. Public Administration and Information Technology*, Vol. 8, ed M. Rodríguez-Bolívar (Cham: Springer).

Attwood, A., Merabti, M., Fergus, P., and Abuelmaatti, O. (2011). Sccir: Smart cities critical infrastructure response framework. *Paper Presented at the Developments in E-systems Engineering (DeSE)*. doi: 10.1109/DeSE.2011.112

Australian Government: Department of Infrastructure, R. D. a. C. (2018). *National Infrastructure Data Collection and Dissemination Plan*. Available online at: https://bitre.gov.au/data_dissemination/files/National_Infrastructure_Data_Collection_and_Dissemination_Plan.pdf (accessed January 11, 2019).

Bakici, T., Almirall, E., and Wareham, J. (2013). A smart city initiative: the case of Barcelona. *J. Knowl. Econ.* 4, 135–148. doi: 10.1007/s13132-012-0084-9

Basu, M., Bandyopadhyay, S., and Ghosh, S. (2016). Post disaster situation awareness and decision support through interactive crowdsourcing. *Proc. Eng.* 159, 167–173. doi: 10.1016/j.proeng.2016.08.151

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., et al. (2012). Smart cities of the future. *Eur. Phys. J. Spec. Top.* 214, 481–518. doi: 10.1140/epjst/e2012-01703-3

Bhamra, R., Dani, S., and Burnard, K. (2011). Resilience: the concept, a literature review and future directions. *Int. J. Prod. Res.* 49, 5375–5393. doi: 10.1080/00207543.2011.563826

Birkmann, J. (2006). "Measuring vulnerability to promote disaster-resilient societies: conceptual frameworks and definitions," in *Measuring Vulnerability to Natural Hazards: Towards Disaster Resilient Societies.* (Tokyo: United Nations university press) 1, 7–54.

Caragliu, A., Del Bo, C., and Nijkamp, P. (2011). Smart cities in Europe. *J Urban Technol.* 18, 65–82. doi: 10.1080/10630732.2011.601117

Choi, S., and Bae, B. (2015). "The real-time monitoring system of social big data for disaster management," in *Computer Science and its Applications* (Springer), 809–815. doi: 10.1007/978-3-662-45402-2_115

Cimellaro, G. P., Reinhorn, A. M., and Bruneau, M. (2010). Framework for analytical quantification of disaster resilience. *Eng. Struct.* 32, 3639–3649. doi: 10.1016/j.engstruct.2010.08.008

Cocchia, A. (2014). "Smart and digital city: a systematic literature review," in *Smart City* (Springer), 13–43. doi: 10.1007/978-3-319-06160-3_2

Diane, C., and Meier, P. (2009). *New Technologies in Emergencies and Conflicts: The Role of Information and Social Networks.* Washington, DC; London: UN Foundation-Vodafone Foundation Partnership.

Dunaway, M., Murphy, R., Venkatasubramanian, N., Palen, L., and Lopresti, D. (2017). Research agenda in intelligent infrastructure to enhance disaster management, community resilience and public safety. *arXiv [preprint] arXiv*:1705.01985.

Ersoy, A. (2017). Smart cities as a mechanism towards a broader understanding of infrastructure interdependencies. *Reg. Stud. Reg. Sci.* 4, 26–31. doi: 10.1080/21681376.2017.1281154

Francis, R., and Bekera, B. (2014). A metric and frameworks for resilience analysis of engineered and infrastructure systems. *Reliab. Eng. Syst. Safe.* 121(Suppl. C), 90–103. doi: 10.1016/j.ress.2013.07.004

Gladwin, H., Lazo, J. K., Morrow, B. H., Peacock, W. G., and Willoughby, H. E. (2007). Social science research needs for the hurricane forecast and warning system. *Nat. Hazards Rev.* 8, 87–95. doi: 10.1061/(ASCE)1527-6988(2007)8:3(87)

Gupta, R., and Gupta, R. (2016). ABC of Internet of Things: advancements, benefits, challenges, enablers and facilities of IoT. *Paper Presented at the Colossal Data Analysis and Networking (CDAN), Symposium.* doi: 10.1109/CDAN.2016.7570875

Hallegatte, S., Green, C., Nicholls, R. J., and Corfee-Morlot, J. (2013). Future flood losses in major coastal cities. *Nat. Clim. Change* 3, 802–806. doi: 10.1038/nclimate1979

Harley, M. D., Turner, I. L., Short, A. D., Bracs, M. A., Phillips, M. S., Simmons, J. A., et al. (2015). Four decades of coastal monitoring at Narrabeen-Collaroy Beach: the past, present and future of this unique dataset. *Paper presented at the Australasian Coasts & Ports Conference 2015: 22nd Australasian Coastal and Ocean Engineering Conference and the 15th Australasian Port and Harbour Conference.*

Hasan, S., Tonmoy, F., Foliente, G., and El-Zein, A. (2015). Modelling infrastructure interdependency at a local scale: value, methodologies and challenges. *Paper presented at the 21st International Congress on Modelling and Simulation* (Gold Coast, QLD).

Hernández-Nolasco, J. A., Ovando, M. A. W., Acosta, F. D., and Pancardo, P. (2016). Water level meter for alerting population about floods. *Paper presented at the Advanced Information Networking and Applications (AINA), 2016 IEEE 30th International Conference on.* doi: 10.1109/AINA.2016.76

Hinkel, J., Lincke, D., Vafeidis, A. T., Perrette, M., Nicholls, R. J., Tol, R. S., et al. (2014). Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proc. Natl. Acad. Sci. U.S.A.* 111, 3292–3297. doi: 10.1073/pnas.1222469111

Hollands, R. G. (2008). Will the real smart city please stand up? Intelligent, progressive or entrepreneurial? *City* 12, 303–320. doi: 10.1080/13604810802479126

Kawai, J., Mitsuhara, H., and Shishibori, M. (2015). Tsunami evacuation drill system using smart glasses. *Proc. Comput. Sci.* 72, 329–336. doi: 10.1016/j.procs.2015.12.147

Khan, H., Vasilescu, L. G., and Khan, A. (2008). Disaster management cycle-a theoretical approach. *J. Manag. Mark.* 6, 43–50.

Kitada, S., Sato, G., and Shibata, Y. (2017). "Performance evaluation of a DTN based multi-hop network for disaster information transmission by smart devices," in *International Conference on Broadband and Wireless Computing, Communication and Applications* (Cham: Springer). doi: 10.1016/B978-0-12-809859-2.00004-8

Kitchin, R. (2014). The real-time city? Big data and smart urbanism. *GeoJournal* 79, 1–14. doi: 10.1007/s10708-013-9516-8

Kitchin, R. (2015). Making sense of smart cities: addressing present shortcomings. *Camb. J. Regions, Econ. Soc.* 8, 131–136. doi: 10.1093/cjres/rsu027

Kong, J., and Simonovic, S. P. (2019). Probabilistic multiple hazard resilience model of an interdependent infrastructure system. *Risk Anal.* 39, 1843–1863. doi: 10.1111/risa.13305

Kong, J., Simonovic, S. P., and Zhang, C. (2019). Resilience assessment of interdependent infrastructure systems: a case study based on different response strategies. *Sustainability* 11:6552. doi: 10.3390/su11236552

Kryvasheyeu, Y., Chen, H., Moro, E., Van Hentenryck, P., and Cebrian, M. (2015). Performance of social network sensors during hurricane sandy. *PLoS ONE* 10:e0117288. doi: 10.1371/journal.pone.0117288

Kumar, A. V., Girish, B., and Rajesh, K. R. (2015). Integrated weather & flood alerting system. *Int. Adv. Res. J. Sci. Eng. Technol.* 2, 21–24.

Lo, S.-W., Wu, J.-H., Lin, F.-P., and Hsu, C.-H. (2015). Visual sensing for urban flood monitoring. *Sensors* 15, 20006–20029. doi: 10.3390/s150820006

Manyena, S. B. (2006). The concept of resilience revisited. *Disasters* 30, 434–450. doi: 10.1111/j.0361-3666.2006.00331.x

Meijer, A., and Bolívar, M. P. R. (2016). Governing the smart city: a review of the literature on smart urban governance. *Int. Rev. Admin. Sci.* 82, 392–408. doi: 10.1177/0020852314564308

Murayama, Y., Velev, D., Zlateva, P., and Gonzalez, J. J. (2017). *Information Technology in Disaster Risk Reduction: First IFIP TC 5 DCDRR International Conference, ITDRR 2016.* Sofia: Springer.

Murray-Tuite, P., and Wolshon, B. (2013). Evacuation transportation modeling: an overview of research, development, and practice. *Transp. Res. C* 27, 25–45. doi: 10.1016/j.trc.2012.11.005

Ogie, R. I., Shukla, N., Sedlar, F., and Holderness, T. (2017). Optimal placement of water-level sensors to facilitate data-driven management of hydrological infrastructure assets in coastal mega-cities of developing nations. *Sustain. Cities Soc.* 35, 385–395. doi: 10.1016/j.scs.2017.08.019

Palen, L., and Anderson, K. M. (2016). Crisis informatics—New data for extraordinary times. *Science* 353, 224–225. doi: 10.1126/science.aag2579

Sadri, A. M., Hasan, S., Ukkusuri, S. V., and Cebrian, M. (2018). Crisis communication patterns in social media during Hurricane Sandy. *Transp. Res. Rec.* 2672, 125–137. doi: 10.1177/0361198118773896

Sanchez, L., Muñoz, L., Galache, J. A., Sotres, P., Santana, J. R., Gutierrez, V., et al. (2014). SmartSantander: IoT experimentation over a smart city testbed. *Comput. Networks* 61, 217–238. doi: 10.1016/j.bjp.2013.12.020

Scuotto, V., Ferraris, A., and Bresciani, S. (2016). Internet of Things: applications and challenges in smart cities: a case study of IBM smart city projects. *Bus. Process Manag. J.* 22, 357–367. doi: 10.1108/BPMJ-05-2015-0074

Shalini, E., Surya, P., Thirumurugan, R., and Subbulakshmi, S. (2016). Cooperative flood detection using SMS through IoT. *Int. J. Adv. Res. Elect. Electron. Instrum. Eng.* 5, 3410–3414.

Thom, D., Krüger, R., and Ertl, T. (2016). Can Twitter save lives? A broad-scale study on visual social media analytics for public safety. *IEEE Trans. Vis. Comput. Graph.* 22, 1816–1829. doi: 10.1109/TVCG.2015.2511733

Tonmoy, F., and El-Zein, A. (2013). Vulnerability of infrastructure to Sea Level Rise: a combined outranking and system-dynamics approach. *Paper presented at the European Safety and Reliability (ESREL-2013)* (Amsterdam). doi: 10.1201/b15938-359

Tonmoy, F. N., El-Zein, A., and Hinkel, J. (2014). Assessment of vulnerability to climate change using indicators: a meta-analysis of the literature. *Wiley Interdiscip. Rev. Clim. Change* 5, 775–792. doi: 10.1002/wcc.314

Tonmoy, F. N., Wainwright, D., Verdon-Kidd, D. C., and Rissik, D. (2018). An investigation of coastal climate change risk assessment practice in Australia. *Environ. Sci. Policy,* 80, 9–20. doi: 10.1016/j.envsci.2017.11.003

Torabi, E., Dedekorkut-Howes, A., and Howes, M. (2017). Not waving, drowning: can local government policies on climate change adaptation and disaster resilience make a difference? *Urban Policy Res.* 35, 312–332. doi: 10.1080/08111146.2017.1294538

Turner, I. L., Harley, M. D., and Drummond, C. D. (2016). UAVs for coastal surveying. *Coast. Eng.* 114, 19–24. doi: 10.1016/j.coastaleng.2016.03.011

Tyler, S., and Moench, M. (2012). A framework for urban climate resilience. *Clim. Dev.* 4, 311–326. doi: 10.1080/17565529.2012.745389

United Nations, Department of Economic and Social Affairs, and Population Division (2019). *World Urbanization Prospects: The 2018 Revision (ST/ESA/SER.A/420).* New York, NY: United Nations.

Wiig, A. (2015). IBM's smart city as techno-utopian policy mobility. *City* 19, 258–273. doi: 10.1080/13604813.2015.1016275

Yin, C., Xiong, Z., Chen, H., Wang, J., Cooper, D., and David, B. (2015). A literature survey on smart cities. *Sci. China Inform. Sci.* 58, 1–18. doi: 10.1007/s11432-015-5397-4

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Water

ORIGINAL RESEARCH
published: 11 June 2020
doi: 10.3389/frwa.2020.00012

Relative Impacts of Projected Climate and Land Use Changes on Terrestrial Water Balance: A Case Study on Ganga River Basin

Anamitra Saha[1] *and Subimal Ghosh*[1,2]*

[1] *Department of Civil Engineering, Indian Institute of Technology Bombay, Mumbai, India,* [2] *Interdisciplinary Program in Climate Studies, Indian Institute of Technology Bombay, Mumbai, India*

OPEN ACCESS

Edited by:
Abhishek Gaur,
National Research Council Canada (NRC-CNRC), Canada

Reviewed by:
Hui Xu,
Argonne National Laboratory (DOE), United States
Mohit Prakash Mohanty,
University of Western Ontario, Canada

***Correspondence:**
Subimal Ghosh
subimal@civil.iitb.ac.in

Specialty section:
This article was submitted to Water and Built Environment, a section of the journal Frontiers in Water

Received: *19 November 2019*
Accepted: *13 May 2020*
Published: *11 June 2020*

Citation:
Saha A and Ghosh S (2020) Relative Impacts of Projected Climate and Land Use Changes on Terrestrial Water Balance: A Case Study on Ganga River Basin. Front. Water 2:12. doi: 10.3389/frwa.2020.00012

The Ganga river basin, being one of the largest river basins in South-East Asia, with area over 1 million Km^2 and population over 400 million, is highly vulnerable to water scarcity due to climate change and rapid growth in agriculture, industrialization, and urbanization. To understand the potential impact of climate and land use changes on regional terrestrial water balance has become crucial for ensuring appropriate water management strategies for adaptation and mitigation purposes. In this study we employ an RCP-SSP (Representative Concentration Pathways—Shared Socioeconomic Pathways) scenario framework (1.5 and 2°C warming scenarios and SSP1–5) to explore the relative impacts of projected twenty-first century climate and land use changes on the surface hydrology of the Ganga river basin. By statistically comparing the hydrological responses of each combination of socioeconomic and climate mitigation pathways against a control scenario, we distinguish between the impacts of each scenario. We also analyze our data in a conceptual framework to understand how climatic and land use factors impact the basin characteristics and which one among them is projected to be the dominant factor in our study region. Our results show that, in terms of hydrologic impact assessment, climate change mitigation pathways are the dominant factor and the land use changes associated with socio-economic pathways contribute little to the projected future changes.

Keywords: climate change, shared socioeconomic pathways, low-warming scenarios, Budyko framework, integrated assessment

INTRODUCTION

India has a population of more than 1.3 billion, which is around 17% of the world's population, but only 1,121 Km^3 of estimated utilizable water resources, about 4% of global freshwater resources [Central Water Commission (CWC), 2013; United Nations (UN), 2019]. In the last few decades the country has experienced a continuous rise in population along with economic growth and increased food, energy, and water consumption [Global Water Partnership (GWP), 2013]. Rapid growth in agriculture, industrialization, and urbanization has led to increasing demand for freshwater throughout the country. In terms of water usage, agriculture is the dominating sector, with about 80% share of the total water demand (Bhat, 2014). The water availability and the agricultural and economic productivity of India are heavily dependent on the south-west monsoon (Krishna Kumar et al., 2004; Gadgil and Gadgil, 2006). More than 80% of annual rainfall in India occurs during the monsoon months (June-September, JJAS), which totals to 904 mm on average, compared to 294 mm of rainfall during the rest of the year (Amarasinghe et al., 2005). However, climate changes associated with increased atmospheric carbon dioxide (CO_2) level are impacting water availability by changing the spatial and temporal distribution of monsoon rainfall, both globally and at regional level (Wang and Ding, 2006; Kundzewicz et al., 2008; Turner and Annamalai, 2012; Kim et al., 2016). The Ganga river basin, being one of the most populated river basins in the world, is highly vulnerable to water scarcity, due to the changing pattern of the Indian summer monsoon rainfall in a warmer climate (Misra, 2013). The water management practices in the Ganga basin are not sustainable and over-reliance on groundwater withdrawal for irrigation is leading to imminent water crisis (Briscoe and Malik, 2006). Hence reliable hydro-meteorological projections for the twenty-first century at a regional scale are important for water resources planning and policy making.

As the future greenhouse gas emissions and land uses are highly uncertain, typically they are represented by a group of plausible scenarios. The current state-of-the-art Earth System Models (ESM), from Coupled Model Intercomparison Project phase 5 (CMIP5) (Taylor et al., 2012), use emission based Representative Concentration Pathways (RCP) (Van Vuuren et al., 2011) as future scenarios to project the changing climate over the twenty-first century. However, in 2015, the Paris Agreement was signed at the twenty-first Conference of parties (COP21) of the United Nations Framework Convention on Climate Change (UNFCCC), and two new temperature based scenarios were introduced. The aim of this agreement was to limit the global mean air temperature increase, below 2°C above pre-industrial condition, by the end of the twenty-first century, and further attempt to limit it within 1.5°C (UNFCCC, 2015). To achieve the goal of 1.5°C scenario, we need a global emission rate reduction of 5%/year and a substantial effort to develop negative carbon emission technologies (Sanderson et al., 2017). Irrespective of the achievability of these goals, it is important to quantify their impacts on regional climate and hydrology, for future climate negotiations.

Apart from the climate scenarios, the Shared Socioeconomic Pathways (SSP), which represent a range of substantially different plausible socioeconomic conditions, are also important for impact assessment. Each SSP scenario describes the characteristics of societal development, such as population growth, economic development, energy and land use, technological development, environmental protection etc. At a fundamental level, each scenario depicts a narrative of challenges on adaptation and mitigation to climate change (O'Neill et al., 2017). In principle, SSPs can be combined with climate mitigation pathways to generate a scenario matrix. However, some SSP-RCP combinations can be unrealistic and are ignored in impact assessment analysis.

In this study, using an ensemble of model outcomes, we analyze the projected impacts for an SSP-RCP scenario matrix on the hydrometeorology of the Ganga River basin. There are several studies assessing the hydrologic responses of river basins under climate change (Nijssen et al., 2001; Raje et al., 2014) or land use changes (Cruise et al., 2010; Zheng et al., 2012). Multiple studies have been performed in order to distinguish between their impacts as well, using different approaches such as regression analysis (Wang et al., 2012), hydrologic simulations (Bao et al., 2012; Zhang et al., 2012), Budyko framework (Li et al., 2007; Wang and Hejazi, 2011), or a combined approach (Jiang et al., 2011; Ahn and Merwade, 2014). However, most of these studies either focus on the historical changes, or estimate the projected future changes using climate mitigation pathways only. By incorporating the projected changes in land use associated with SSPs, we explore the relative impacts of both climate and land use on the hydrologic variables, in future scenarios.

We also explore the relative contributions of climate and land use change on the basin characteristics parameter of Budyko framework (Budyko, 1974; Choudhury, 1999), a conceptual framework for modeling terrestrial water balance. In scientific literature, it is a common practice to assume that basin characteristics is independent of climate change and affected by other factors, such as land use, vegetation dynamics, soil, topography, and human water management (Donohue et al., 2006; Wang and Hejazi, 2011; Xu et al., 2013). However, impacts of climatic variables such as seasonality and intra-seasonal variability of rainfall, number of precipitation events and their intensity, phase shift between rainfall and evapotranspiration etc. on the basin characteristics parameter have also been documented (Milly, 1994; Potter et al., 2005; Padrón et al., 2017). Even though vegetation is considered one of the most important factors controlling the basin characteristics (Donohue et al., 2006), Padrón et al. (2017) and Abatzoglou and Ficklin (2017) didn't find any significant relation between Normalized Difference Vegetation Index (NDVI) and the variability of basin characteristics parameter. As there is not enough consensus on which factors dominate the basin characteristics, in this study we compare the relative impact of two factors, climate and land use change. Our analysis helps us gain a better understanding of the factors influencing river basin scale terrestrial hydrology, to better prepare us for adaptation and mitigation.

METHODS

In **Figure 1** we represent the overall methodological framework of our study. The hydrological projections are performed using the model Variation Infiltration Capacity (VIC) (Liang et al., 1994). Climate model simulations associated with various warming scenarios have gone through a statistical bias correction and downscaling methodology (Kannan and Ghosh, 2013) to provide meteorological forcing for VIC. Land use projections associated with various SSP-RCP combined scenarios, from the land allocation model Asia-Pacific Integrated Model/integration Platform for Land-Use and Environmental Modeling (AIM/PLUM) (Hasegawa et al., 2017), are used as vegetation input data in VIC.

Study Area

Our study is performed over the region of Ganga river basin, within the political boundary of India. The Ganga river basin is located within geographical coordinates of 73.5°E−89°E

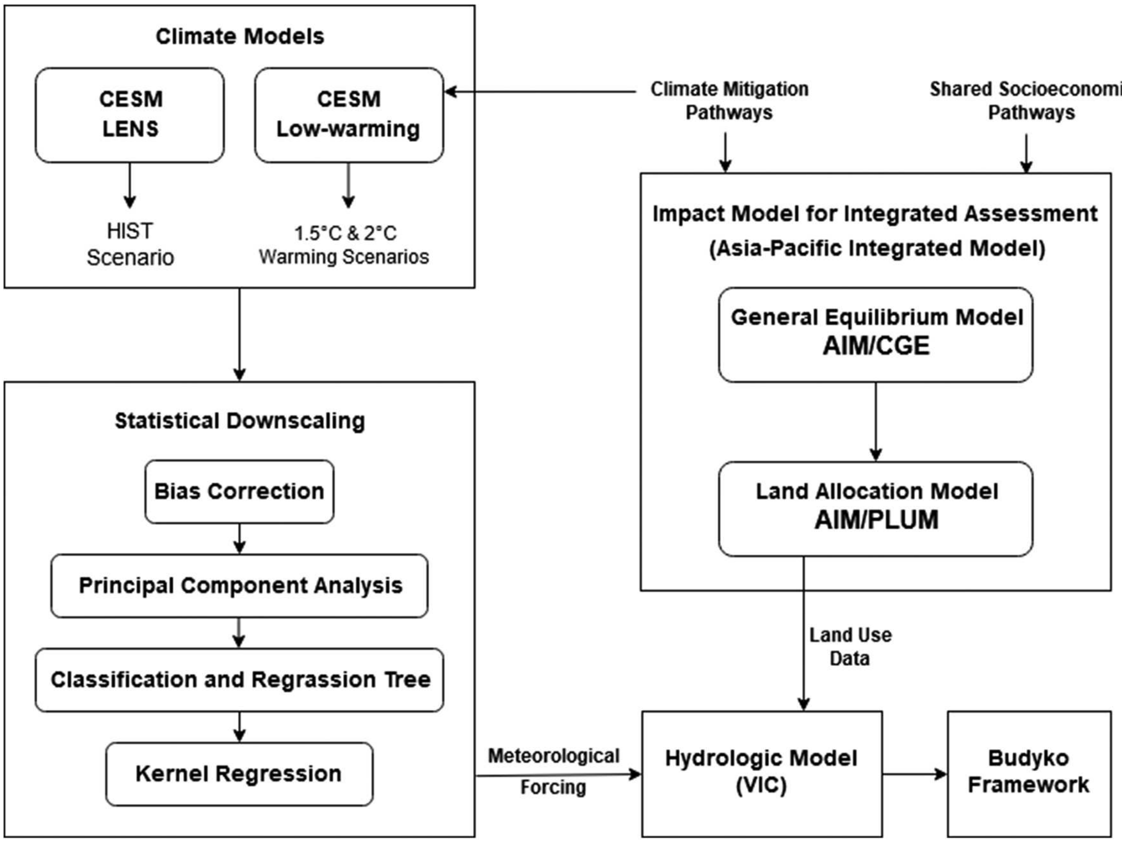

FIGURE 1 | Methodological framework of the study.

longitude and 22.5°N−31.5°N latitude. The basin consists of mountainous region at the northwest side, and the remaining area is plain encompassing northern and eastern India. The majority of the land in the Ganga basin plain is used for agriculture. The basin receives most of its rainfall over the summer monsoon season (June–September). Based on the Watershed Atlas of India, provided by the Central Ground Water Board (Ministry of Water Resources, Government of India), the basin is divided into 15 sub-basins, as shown in **Figure 2**.

Scenario Matrix

In our study, 1.5 and 2°C warming scenarios are considered as climate change mitigation pathways, and SSP1, SSP2, SSP3, SSP4, and SSP5 are considered as socio-economic pathways. SSP1 (sustainability) represents low challenges for adaptation and mitigation, with low population growth, higher growth in per capita income and high environmental awareness. On the other hand SSP3 (regional rivalry) represents high challenges for adaptation and mitigation, due to increasing regional conflicts, less international trade, low income growth among the general population and low effort for environmental protection. SSP2 (middle of the road) represents medium challenges for both adaptation and mitigation, with modest population and economic growth with a slow pace of trade liberalization. SSP4 (inequality) represents high challenges in adaptation, due to increasing disparities in economic development among population, coupled with low challenges in mitigation due to technological advancement. Lastly SSP5 (fossil-fueled development) pushes for overall economic and social growth of general population by exploiting fossil fuel resources, depicting high challenges in mitigation with low challenges in adaptation. Apart from the aforementioned scenarios, a climate scenario with historical emissions (HIST) and a control socio-economic scenario with land use classes kept constant at year 2005 level (CTL) are also considered with the purpose of comparison. The overall scenario matrix for our study is presented in the **Table 1**. Each combined scenario in this matrix is named after the socio-economic scenario and warming scenario it belongs to. For example, the CTL_HIST scenario represents the control (CTL) socio-economic scenario and historical (HIST) emission scenario.

Climate Model Simulations

The climate model projections are obtained from CESM low-warming runs, performed using Community Earth System Model version 1 (CESM1) with Community Atmosphere Model version 5.2 (CAM5.2) and the Greenhouse gas (GHG) emission associated with 1.5 and 2°C warming scenarios, obtained from

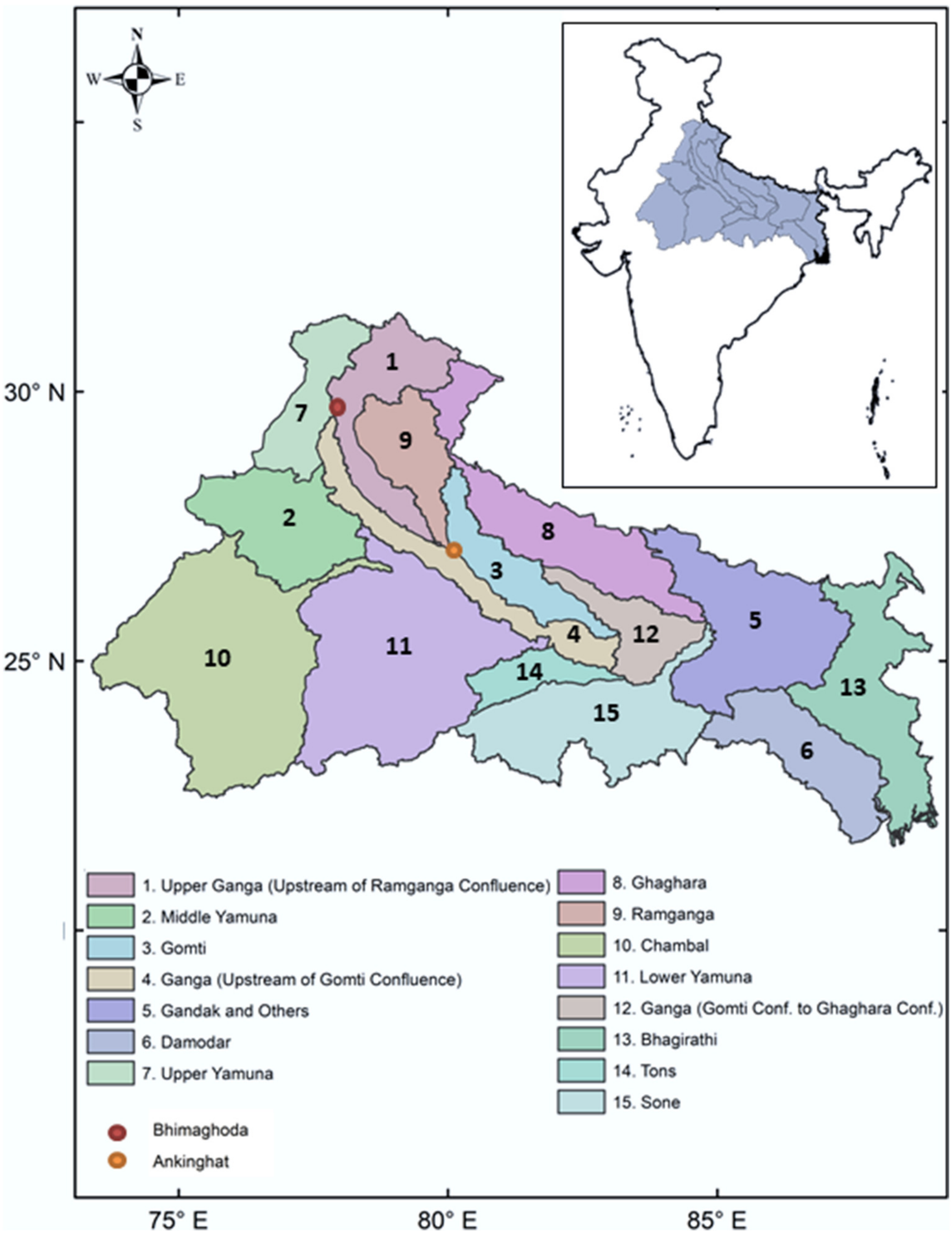

FIGURE 2 | Study area: Ganga river basin divided into 15 sub-basins. Inlet is representing location of the basin within India. Location of streamflow measurement stations, Bhimaghoda and Ankinghat are marked with dots.

Minimal Complexity Earth Simulator (MiCES) (Sanderson et al., 2017). The historical climate scenario outcomes are obtained from CESM Large Ensemble (LENS) simulation (Kay et al., 2015), which are performed with the same CESM version and model parameters as the low-warming runs. Five ensembles of each simulation: Historical (HIST) (1951–2005), 1.5°C (2006–2100), and 2°C (2006–2100) were chosen for our study and bias correction and statistical downscaling methodologies are applied on each of them independently.

Statistical Downscaling

The outputs of CESM LENS and low-warming simulations are of coarse resolution (1° horizontal resolution) and not suitable for regional hydrological modeling. To use the model outcomes as meteorological forcing in hydrological model, they need to go through a bias correction and downscaling procedure. In this study, we have used a non-parametric regression-based multisite statistical downscaling method (Kannan and Ghosh, 2013; Salvi et al., 2013), where a statistical relationship is

TABLE 1 | Scenario matrix used in the study.

Climate mitigation pathways	Socio-economic pathways					
	CTL	**SSP1**	**SSP2**	**SSP3**	**SSP4**	**SSP5**
HIST	CTL_HIST	X	X	X	X	X
1.5°C	CTL_1.5°C	SSP1_1.5°C	SSP2_1.5°C	X	X	X
2°C	CTL_2°C	SSP1_2°C	SSP2_2°C	SSP3_2°C	SSP4_2°C	SSP5_2°C

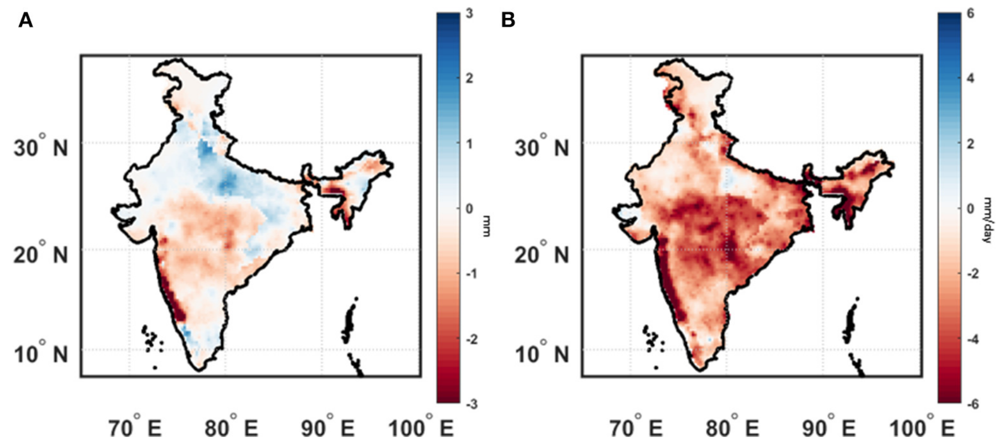

FIGURE 3 | Performance of statistical downscaling model. **(A)** Difference between mean projected JJAS rainfall and observed JJAS rainfall for validation period (1981–2005) **(B)** Difference between projected standard deviation of JJAS rainfall and observed standard deviation of JJAS rainfall for validation period (1981–2005).

established between observed coarse resolution predictors (1° horizontal resolution) and fine resolution observed rainfall (0.25° horizontal resolution); and the derived relation is applied on the bias-corrected model-simulated predictors to obtain a better projection of future rainfall. In this study, for the development of statistical relationship between the predictors and rainfall, we have used daily reanalysis data from National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) (Kalnay et al., 1996), as proxy for observed predictors; and observed daily rainfall data from APHRODITE, Monsoon Asia (Yatagai et al., 2009), both for the period 1951–2005. The data from 1951 to 1980 is used for training the statistical model and the rest of the data is used for validation. The following climate variables have been used as predictors: air temperature, zonal and meridional wind at surface level; mean sea level pressure; air temperature, zonal and meridional wind, specific humidity at 850 hPa pressure level; and air temperature and geopotential height at 500 hPa pressure level. The downscaling methodology is performed for the entire landmass of India, by applying it separately for 7 meteorological homogeneous zones, suggested by India Meteorological Department (IMD) (Parthasarathy et al., 1996) and four seasons: June–September (JJAS), October–November (ON), December–February (DJF), and March–May (MAM). For each homogeneous zone, we have used a separate zone of predictors, as suggested by Salvi et al. (2013).

TABLE 2 | Datasets used in hydrological modeling or validation.

Data	Time period	Resolution	Source
Meteorological forcing	1951–2100	Downscaled or Upscaled to 0.5°	CESM LENS and Low-warming simulations (processed by bias correction and statistical downscaling method)
Elevation map	N/A	0.5°	U.S. Geological Survey
Vegetation data (Land Use)	1951–2100	0.5°	AIM/PLUM Land allocation model
Vegetation parameters	N/A	N/A	Global Land Data Assimilation Systems (GLDAS)
Soil data	N/A	0.5°	Food and Agriculture Organization, USA
Streamflow data at Ganga river basin	1998–2009	N/A	Central Water Commission, India
Soil moisture	2000–2009	0.5°	European Space Agency Climate Change Initiative
Global Terrestrial Evapotranspiration	2000–2009	0.5°	Moderate Resolution Imaging Spectroradiometer (MODIS)

The downscaling methodology essentially involves four steps: bias correction, dimensionality reduction, rainfall state estimation, and rainfall value estimation through regression.

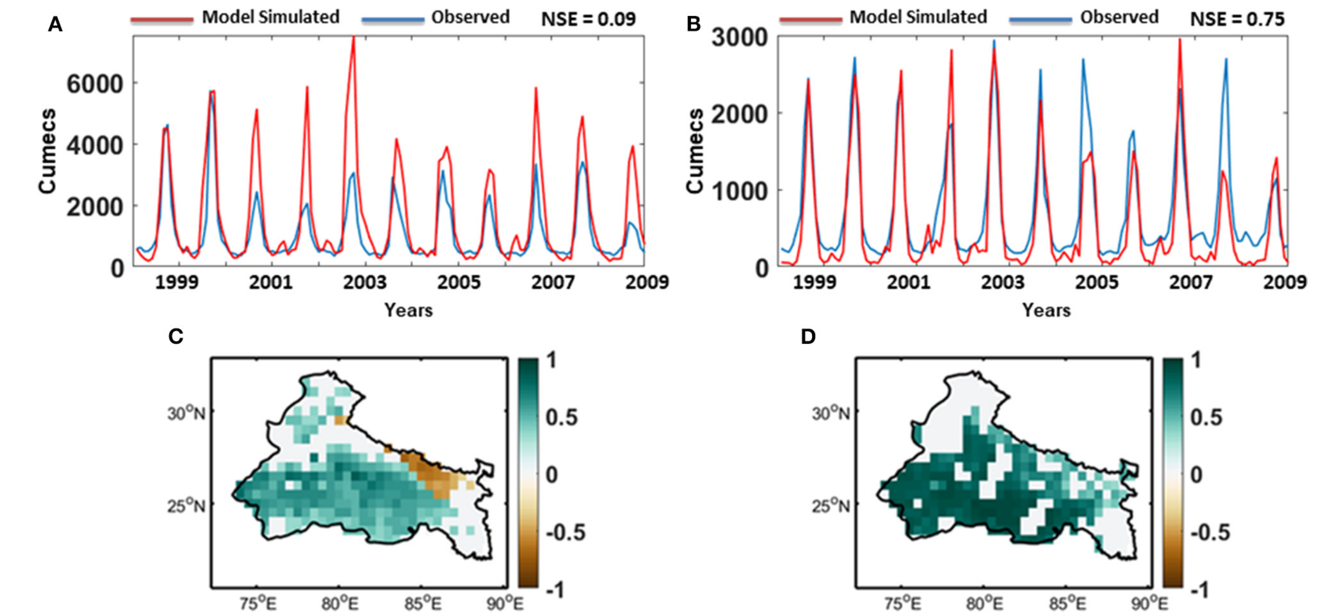

FIGURE 4 | Calibration and Validation of hydrologic model VIC. **(A)** Time series of monthly observed (blue) and model simulated (red) streamflow at Ankinghat station. **(B)** Time series of monthly observed (blue) and model simulated (red) streamflow at Bhimaghoda station. **(C)** Correlation of observed and model simulated evapotranspiration during JJAS season at 95% significance level. **(D)** Correlation of observed and model simulated soil moisture during JJAS season at 95% significance level.

First, we have bilinearly interpolated the model-simulated predictors to the same grids as reanalysis predictors and used a quantile mapping method proposed by Li et al. (2010), for correcting the bias in the model data. A distribution is fitted to all the grids separately for both reanalysis and model data. We have fitted Normal distribution for wind and specific humidity and Gamma distribution for rest of the predictors. Then, for the historical period (1951–2005), the Cumulative Distribution Function (CDF) of the reanalysis and the model-simulated data are compared and the biased model data at each grid and time step is replaced by the reanalysis data with same CDF. For future (2006–2100), additionally, the shift between model-simulated historical and future data with same CDF is added to the replacement value, to account for the climate change. Apart from the predictors used in the statistical downscaling of precipitation, we have also bias-corrected daily minimum and maximum temperature, which are later used as meteorological forcing in the hydrological model. Next, in order to get rid of the multidimensionality and multicollinearity of the predictors, we have used principal component analysis (PCA) on the reanalysis predictors. We have sorted the principal components in the descending order based on their explained variance and taken the first few of them till the sum of explained variance reached 80%. The same coefficients were used to transform the model simulated predictors also. We have classified the observed rainfall into 3 states using unsupervised K-means clustering and apply Classification and Regression Tree (CART) to establish a relationship between reanalysis predictor PCs and observed rainfall states. We have then applied the derived relation on Model predictor PCs to estimate the rainfall state. For each rainfall state, we have applied Kernel Regression on the predictor PCs to obtain the projected daily rainfall amounts. We have used the Nadaraya-Watson estimator for kernel density estimates (Nadaraya, 1964) and asymptotic mean integrated square error (AMISE) criteria for bandwidth selection (Wand and Jones, 1995; Scott, 2015). The final resolution of the downscaled rainfall is same as that of the observed rainfall, which is 0.25° in our case. After downscaling is performed, rainfall and other meteorlogical variables for the grids belonging to Ganga basin region are extracted to be used as an input to the hydrological model.

The performance of the downscaling model is presented in **Figure 3**. The difference between mean observed and projected JJAS rainfall for validation period (1981–2005) doesn't exceed 3 mm for majority (98%) of the grids. Standard deviation is underestimated in the projected rainfall. For more than 96% of the grids, difference between standard deviation of projected and observed JJAS rainfall is within 6 mm/day. Overall, we find the performance of the model satisfactory. More discussion on the performance of the model can be found on Salvi et al. (2013).

Land Allocation Model

The gridded land use projections are obtained from the impact model Asia-pacific Integrated Model (AIM). The computable general equilibrium (AIM/CGE) component is a recursive-dynamic general equilibrium model, which takes population, gross domestic product (GDP), consumption, technological progress, pollution level etc. associated with socio-economic pathways into account and provides regionally aggregated emission, energy, and land use information for each scenario in SSP-RCP scenario matrix (Fujimori et al., 2017). This aggregated

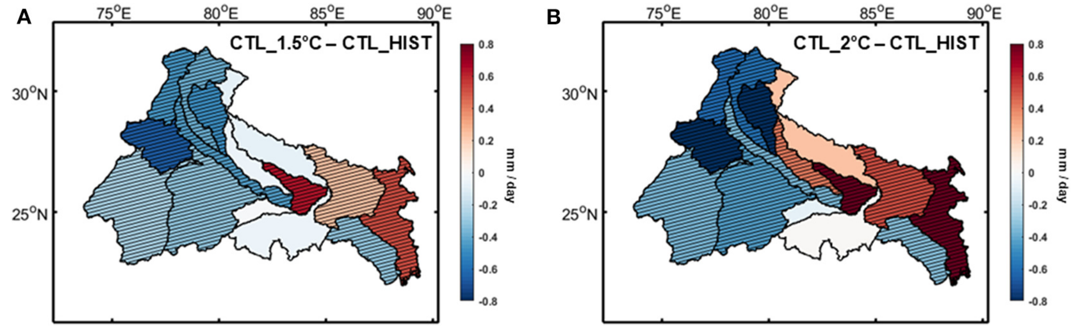

FIGURE 5 | Changes in downscaled precipitation from HIST to 1.5°C **(A)** and from HIST to 2°C **(B)** for CTL scenario over Ganga river basin for JJAS season. Hatched regions denote areas with statistically significant changes.

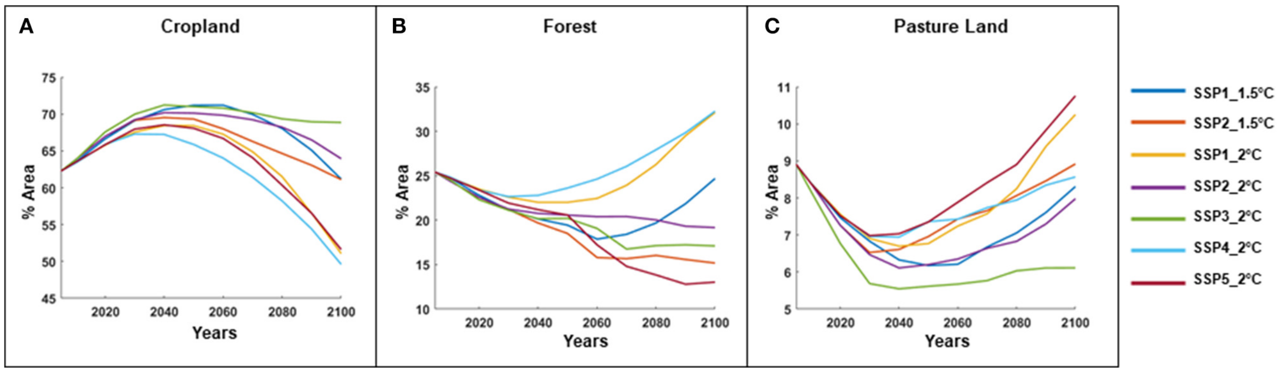

FIGURE 6 | Time evolution of percentage area of **(A)** cropland, **(B)** forest, and **(C)** pasture land at Ganga river basin, for each combination of RCP-SSP scenario over twenty-first century, as projected by AIM/PLUM model.

land use projections are then regionally disaggregated into 0.5° × 0.5° gridded land use data by the land allocation model AIM/PLUM. Land allocations are performed to maximize the economic efficiency for a given biophysical land productivity (Hasegawa et al., 2017). The outcomes of AIM/PLUM are available globally for the year 2005 and then every 10 years from 2010 onwards, which we have extracted for our study region. It should be noted that the outcomes of this model are available for emission based RCPs, not temperature based climate scenarios we are using in our study. However, RCP1.9 and RCP3.4 have been used among climate mitigation pathways for AIM; even though they are not part of the originally proposed pathways (Van Vuuren et al., 2011), today they are widely used as analogous to 1.5 and 2°C warming scenarios (Fujimori et al., 2018).

Hydrologic Simulation

The projected meteorological data and land use data are forced grid-wise into a semi-distributed mesoscale hydrological model (VIC), which balances water and surface energy budgets. The key characters of the VIC model includes representation of multiple land cover types on a single grid, spatial variability of soil moisture capacity, multiple soil layers, and interactions between them, non-linear base flow and clumped vegetation formulation with time-varying spacing between plants (Bohn and Vivoni, 2016). A list of datasets used as an input to the hydrological model is presented in **Table 2**. The elevation map for VIC is acquired from U.S. Geological Survey (USGS) HYDRO1K dataset (Raje et al., 2014). Vegetation parameters, such as leaf area index, are collected from Global Land Data Assimilation Systems (GLDAS) dataset (Rodell et al., 2004). Soil data is extracted from a global database from Food and Agriculture Organization (FAO) at 0.5° resolution. Certain soil parameters, such as soil depth, are obtained by calibrating the model at two stations, Ankinghat and Bhimaghoda. The observed streamflow for these two stations are collected from Central Water Commission (CWC), India at monthly scale (Chawla and Mujumdar, 2015; Joseph et al., 2018). After calibration, the comparison of observed and VIC simulated streamflow is presented in **Figures 4A,B**. We have also calculated Nash-Sutcliffe efficiency (NSE) of the model in each station. The model simulated streamflow matches the observed flow reasonably well at Bhimaghoda station (NSE = 0.75), but overestimated at the Ankinghat station (NSE = 0.09). It should be noted that the flow is highly regulated at downstream, which may have contributed to the relatively poor performance of the model at Ankinghat station. We have tried to minimize the impact of human water management in the streamflow data, by incorporating data from water diversion structures and canals. We have validated our

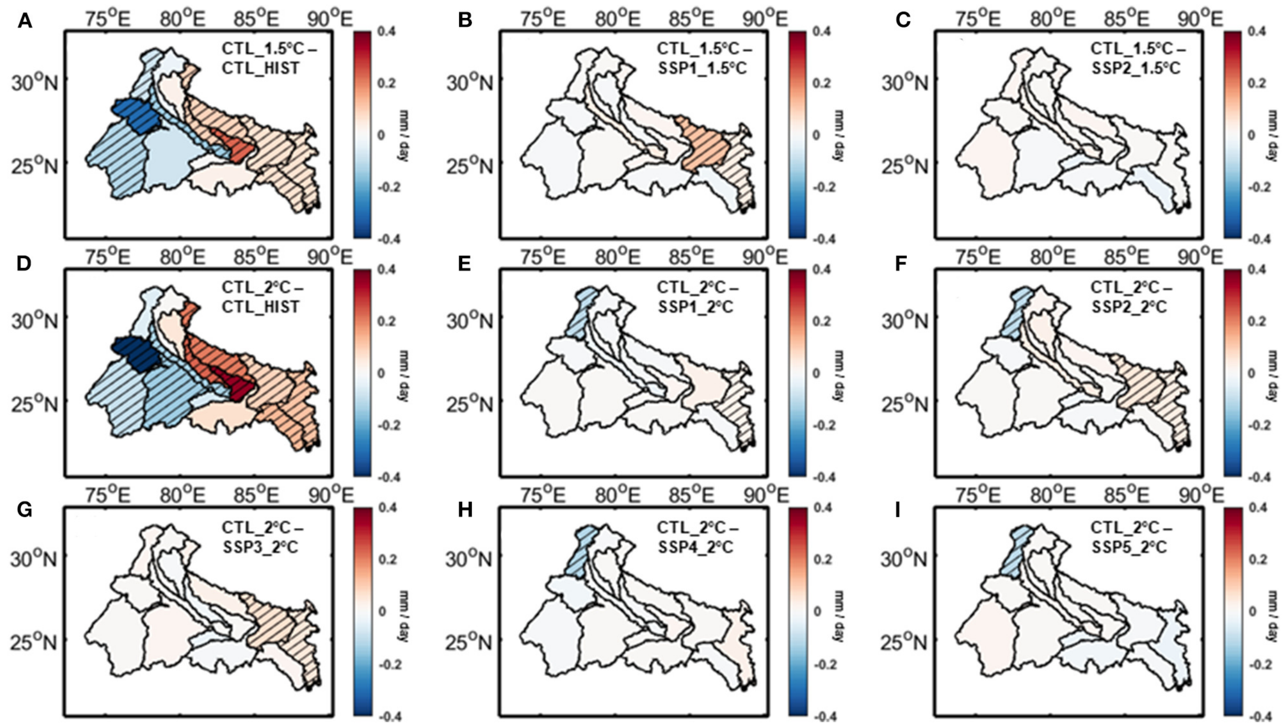

FIGURE 7 | Changes in VIC simulated evapotranspiration associate with climate change for **(A)** 1.5°C warming, **(D)** 2°C warming and land use change for **(B)** SSP1_1.5°C scenario, **(C)** SSP2_1.5°C scenario, **(E)** SSP1_2°C scenario, **(F)** SSP2_2°C scenario, **(G)** SSP3_2°C scenario, **(H)** SSP4_2°C scenario, **(I)** SSP5_2°C scenario over Ganga river basin. Hatched regions denote areas with statistically significant changes.

model against an observed evapotranspiration data collected from Moderate Resolution Imaging Spectroradiometer (MODIS) MOD16 Global Terrestrial Evapotranspiration Data Set and a satellite based soil moisture data from European Space Agency Climate Change Initiative, for the time period 2000–2009, results of which are presented in **Figures 4C,D**, respectively. Overall the simulated evapotranspiration and soil moisture show high positive correlation for majority of the grids in our study area.

Budyko Framework

Budyko (1974) proposed a deterministic non-parametric framework to model the long-term water budget constrained by atmospheric water supply and water demand limit. According to this framework, the evaporative fraction (ratio of evapotranspiration to precipitation) can be expressed as a function of aridity index (ratio of potential evapotranspiration to precipitation). However, the relationship between evaporative fraction and aridity changes among catchments and to account for that various functional forms of Budyko equation has been proposed in scientific literature (Fu, 1981; Choudhury, 1999). In these Budyko equations, basin characteristics parameter is introduced, which, by definition, explains the combined effect of all factors other than aridity on the terrestrial water balance. In this study we use the following functional form of the Budyko equation, known as the Mezentsev equation.

$$\frac{E}{P} = \left(1 + \left(\frac{E_0}{P}\right)^{-n}\right)^{\frac{-1}{n}} \tag{1}$$

Where P is the precipitation, E is the evapotranspiration, E_0 is potential evpotranspiration and n is the basin characteristics parameter.

One assumption of Budyko framework is that the long term change in mean water storage is negligible and the whole incoming precipitation either evaporates or contributes to runoff. However, our study focuses on the long term mean of seasonal (JJAS) rainfall, this assumption does not hold true. In order to apply the Budyko framework to long-term mean of seasonal rainfall, we have introduced the change in storage (ΔS) in the equation.

$$\frac{E}{P - \Delta S} = \left(1 + \left(\frac{E_0}{P - \Delta S}\right)^{-n}\right)^{\frac{-1}{n}} \tag{2}$$

In this study, we apply the Equation 2 on the hydrological outcomes obtained from VIC for each of the 15 sub-basins and each scenario to estimate the basin characteristics parameter, in order to understand the relative impacts of climate and land use changes on the basin characteristics.

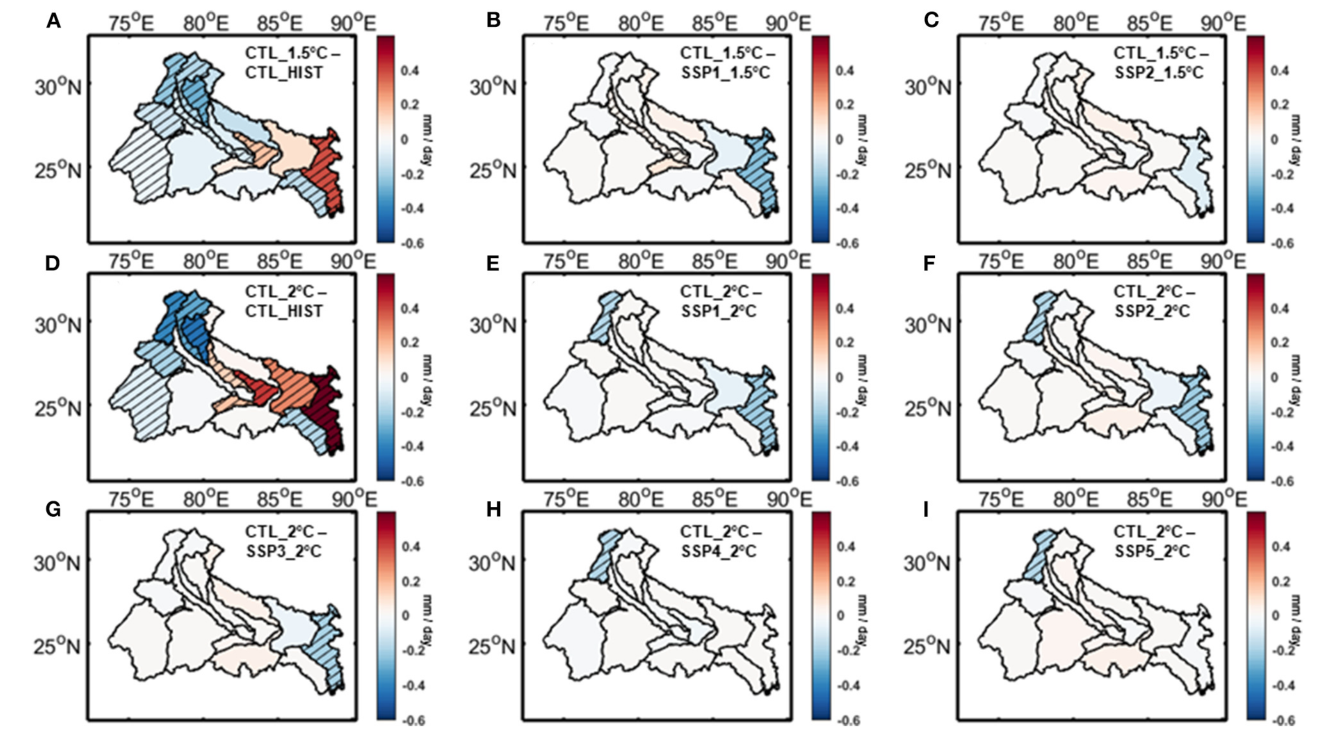

FIGURE 8 | Changes in VIC simulated total runoff associate with climate change for **(A)** 1.5°C warming, **(D)** 2°C warming and land use change for **(B)** SSP1_1.5°C scenario, **(C)** SSP2_1.5°C scenario, **(E)** SSP1_2°C scenario, **(F)** SSP2_2°C scenario, **(G)** SSP3_2°C scenario, **(H)** SSP4_2°C scenario, **(I)** SSP5_2°C scenario over Ganga river basin. Hatched regions denote areas with statistically significant changes.

RESULTS

In **Figure 5** we have presented the projected climate change at the Ganga river basin in terms of mean precipitation during monsoon (JJAS). The changes are calculated between last 25 years of each century (1976–2000 for HIST and 2076–2100 for future scenarios), which remains true throughout this study, unless otherwise mentioned. We have found an east–west asymmetry in the projected rainfall changes. The eastern part of the basin shows an increase in rainfall in the twenty-first century, where the western part, which is part of the core monsoon zone, is projected to have a declining trend in the warming scenario. The extent of this asymmetry is higher in the 2°C warming scenario comparatively. As a similar spatial pattern has been found in the present day observed rainfall trend (Das et al., 2014), this asymmetry can be considered a characteristic climatic response of the Ganga basin region to global warming.

In **Figure 6** we have shown the time evolution of various land use classes throughout the twenty-first century, as projected by AIM/PLUM model for the Ganga basin region. The outputs of the land allocation model are provided at $0.5^\circ \times 0.5^\circ$ grids, which are aggregated to prepare the projection for the whole basin. **Figure 6A** shows the changes in cropland, which covers the majority of the lands in our study area. In every scenario the cropland area increases during the first few decades and then starts declining throughout the century. The SSP3_2°C scenario, which is the least sustainable among all, doesn't feature this decline in cropland area and roughly maintain its peak throughout the century. **Figure 6B** depicts the projected area of unmanaged forests, which shows a decline at the beginning, but gets reversed into an increasing trend for some scenarios. For the scenarios associated with low challenges for mitigation (i.e., SSP1 and SSP4) we find this increasing trend in forest land in the latter part of the century; however the others scenarios continue to show decline throughout the century. In **Figure 6C** we have shown the projected changes associated with pasture lands, which are comparatively smaller than the previous two land classes. Overall, pasture land area is projected to increase after an initial decrease. In most cases the direction of changes are closely tied with and opposite to the changes in cropland for that specific scenario.

In **Figures 7–10**, we have compared the relative impacts of projected climate and land use changes on the hydrometeorological variables at Ganga river basin, as captured by the VIC simulations. Even though the impacts of these changes are not perfectly linearly additive, we can roughly estimate them by subtracting the outcomes of various VIC experiments from each other. For example, subtracting the outcomes of CTL_HIST experiment from CTL_1.5°C experiment will give us an estimate of the impact of 1.5°C warming scenario. On the other hand, the impacts of land use change associated with SSP1_1.5°C scenario can be estimated by subtracting the outcomes of CTL_1.5°C experiment from that of SSP1_1.5°C experiment. The statistical significance of these differences are estimated using t-test with

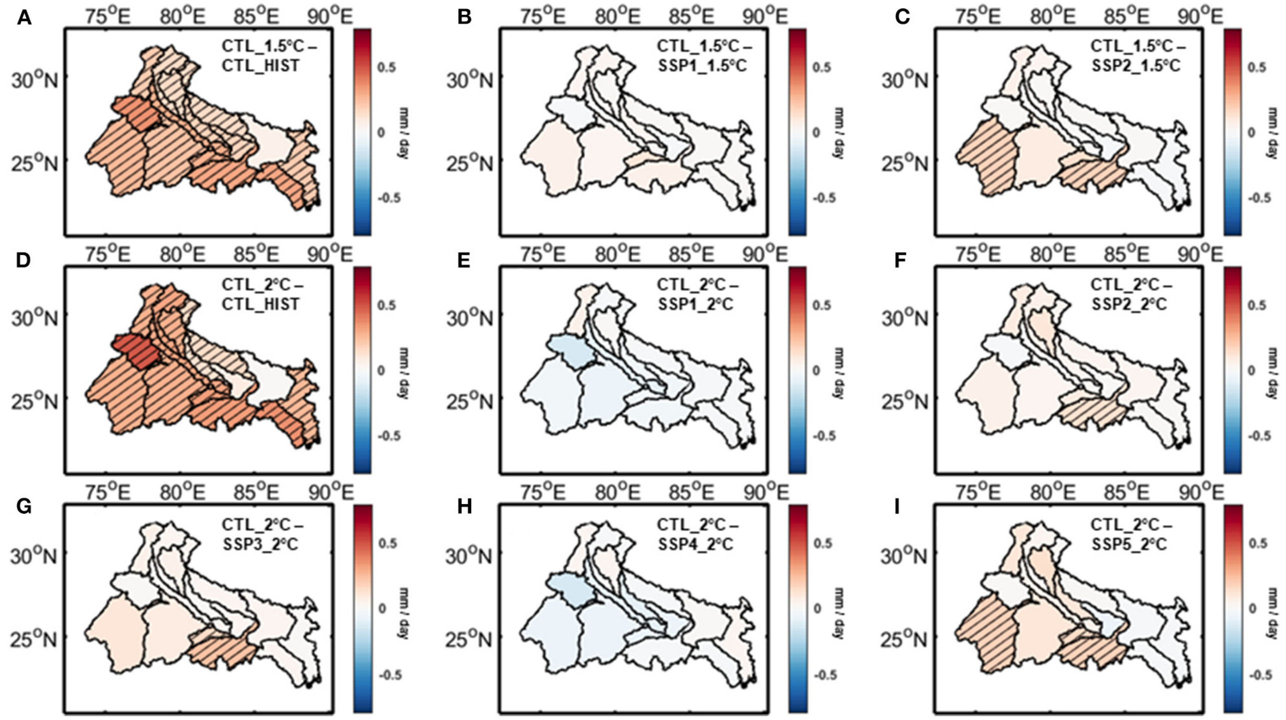

FIGURE 9 | Changes in VIC simulated potential evapotranspiration associate with climate change for **(A)** 1.5°C warming, **(D)** 2°C warming and land use change for **(B)** SSP1_1.5°C scenario, **(C)** SSP2_1.5°C scenario, **(E)** SSP1_2°C scenario, **(F)** SSP2_2°C scenario, **(G)** SSP3_2°C scenario, **(H)** SSP4_2°C scenario, **(I)** SSP5_2°C scenario over Ganga river basin. Hatched regions denote areas with statistically significant changes.

a 95% significance level and the sub-basins showing significant differences are highlighted in the figures. We have found a few notable patterns consistent across the hydrologic variables. In **Figures 7A,D**, **8A,D**, **9A,D**, **10A,D** we have shown the impacts of 1.5 and 2°C warming on evapotranspiration, total runoff (surface runoff and baseflow), potential evapotranspiration, and aridity index at the Ganga river basin, respectively. As evapotranspiration and runoff are correlated with precipitation, the spatial patterns of their changes closely resemble the projected precipitation trend. The east-west asymmetries are still present here. On the other hand potential evapotranspiration is correlated with temperature and projected to increase almost uniformly throughout the basin. In case of aridity of the basin, even though the asymmetry in changes can still be noticed, majority of the sub-basins show an increase in the warming scenario, implying increased water stress as a result of global warming. **Figures 7B,C**, **8B,C**, **9B,C**, **10B,C** show the impact of land use changes associated with SSP1-2 and 1.5°C warming and **Figures 7E–I**, **8E–I**, **9E–I**, **10E–I** represent the same for SSP1-5 and 2°C warming for evapotranspiration, total runoff, potential evapotranspiration, and aridity index, respectively. We have found that hardly any changes associated with land use are visible in the figures, which suggests that the impacts of projected land use changes are negligible compared to its climate change counterpart. Neither of these hydrologic variable changes shows any significant contribution from the projected land use changes for most of the basins. However, there are a few exceptions in some of the sub-basins. For example, the Bhagirathi sub-basin gets more arid in few SSP scenarios, but doesn't show any significant change when only climate change is considered. These exceptions are a result of potential evapotranspiration increasing proportionately with precipitation due to climate change, but not being impacted significantly because of land use change.

From the VIC simulated hydrologic variables, we have calculated the value of basin characteristics parameter (n) for each sub-basin using Budyko framework (Equation 2). The result is presented in **Table 3**. We have found two notable patterns in this data. Firstly, the basin characteristics is influenced by climate change. As the warming goes higher from HIST to 1.5–2°C, many sub-basins show a consistent increase or decrease in the projected basin characteristics parameter. Secondly, the impact of projected land use changes is not as prominent. For the majority of the sub-basins there is hardly any difference between SSP scenarios and their CTL counterpart for the same level of warming. However, there are a few exceptions to this pattern. In certain scenarios, the land use changes have been found to have some impact in Bhagirathi, Tons, Sone, Damodar, and Gandak and others sub-basins, although not as high as the climate impact in most cases. The reasons behind these exceptional cases are unclear, and require further examinations to be uncovered. Given that all of these sub-basins are located at the east side of the basin, it can be speculated to be related to the east-west asymmetry of climate change response.

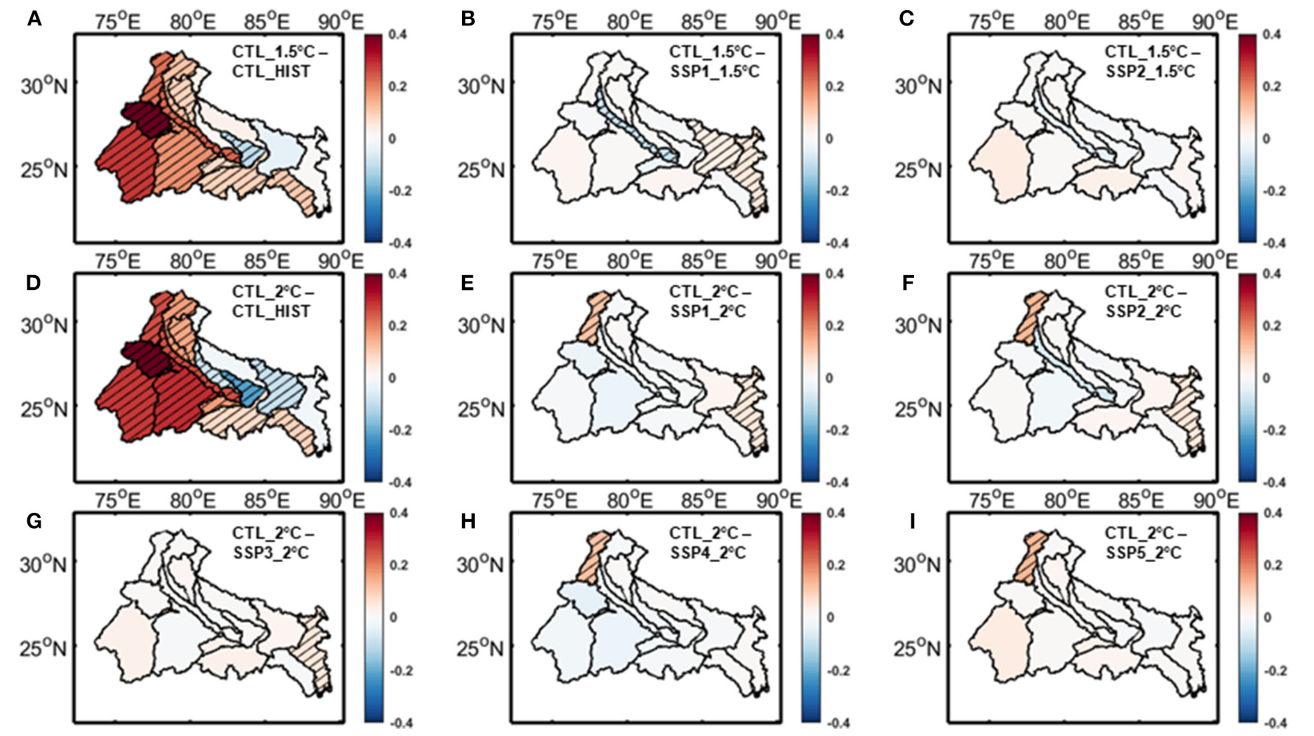

FIGURE 10 | Changes in VIC simulated aridity index associate with climate change for **(A)** 1.5°C warming, **(D)** 2°C warming and land use change for **(B)** SSP1_1.5°C scenario, **(C)** SSP2_1.5°C scenario, **(E)** SSP1_2°C scenario, **(F)** SSP2_2°C scenario, **(G)** SSP3_2°C scenario, **(H)** SSP4_2°C scenario, **(I)** SSP5_2°C scenario over Ganga river basin. Hatched regions denote areas with statistically significant changes.

DISCUSSIONS

There are multiple sources of uncertainty present in our modeling framework. Our choices of climate change mitigation pathways as well as parameterizations in climate model simulations and their internal climate variability (Knutti and Sedláček, 2013) are major sources of uncertainties, although it is partly mitigated by considering multi-ensemble mean of climate model outcomes. Our choices of socioeconomic pathways, the impact model (AIM) and the statistical downscaling methodology, all contribute substantially to the uncertainty of the climate and land use projections. The assumption of linear responses of land use and climate change to the hydrologic variables imposes some uncertainties as well. The parameter uncertainty in the hydrologic model is also responsible for a significant portion of the overall uncertainties (Chawla and Mujumdar, 2018), although they are relatively lower than the uncertainties resulting from climate models and downscaling methods (Joseph et al., 2018). However, we believe that the presence of these uncertainties in the projections do not affect the key findings of our study. The hydrologic changes associated with climate change are significantly higher than that of land use change, close to one magnitude of order in many cases. This pattern is also consistent across hydrologic variables, scenarios and sub-basins. Our finding is consistent with Chawla and Mujumdar (2015)'s analysis on Upper Ganga basin for historical climate and land use changes. Analyzing our data in the Budyko framework also shows that the climatic variables have a significant impact on the basin characteristics, while vegetation has lesser impact, which is contrary to the traditional assumption. This finding is consistent with Padrón et al. (2017) and Abatzoglou and Ficklin (2017)'s global analyses with observed datasets in historical time period. The methodology used in our study is generic and can be applied to other river basins as well. However, the conclusion of this analysis may vary depending on the climate and land use of the basin. Worldwide, there have been multiple attempts to distinguish between climate and land use change impacts on basin-scale hydrology, even though majority of the studies are for historical period and very few studies consider projections for future scenarios. The conclusions drawn in these studies are mixed; while some studies have found significant contributions from land use changes (Schilling et al., 2008; Wang and Hejazi, 2011), others have found it to be negligible (Gupta et al., 2015).

CONCLUDING REMARKS

In this study we have explored the impacts of projected climate change as well as land use changes on the terrestrial water balance at river basin scale. We have found that a major part of the Ganga river basin is projected to become significantly more arid in the warming scenarios. However, the projected land use changes hardly contributes to or counteracts climate change impacts. In

TABLE 3 | Calculated basin characteristics parameter for all sub-basins and scenarios.

	HIST	1.5°C			2°C					
	CTL	CTL	SSP1	SSP2	CTL	SSP1	SSP2	SSP3	SSP4	SSP5
Ganga (Above Ramganga Confluence)	1.42	1.46	1.46	1.46	1.53	1.52	1.53	1.53	1.53	1.52
Middle Yamuna	1.18	1.13	1.13	1.13	1.11	1.11	1.11	1.11	1.11	1.11
Gomti	1.43	1.48	1.47	1.48	1.45	1.45	1.45	1.44	1.46	1.43
Ganga (Upstream of Gomti Confluence)	1.51	1.48	1.47	1.47	1.43	1.43	1.42	1.43	1.44	1.42
Gandak and others	1.38	1.36	1.44	1.36	1.33	1.36	1.36	1.37	1.33	1.33
Damodar	1.36	1.40	1.37	1.37	1.44	1.43	1.43	1.44	1.43	1.43
Upper Yamuna	1.09	1.11	1.11	1.11	1.16	1.18	1.18	1.16	1.18	1.18
Ghaghara	1.32	1.37	1.36	1.36	1.37	1.37	1.36	1.36	1.37	1.36
Ramganga	1.48	1.60	1.59	1.60	1.68	1.67	1.67	1.67	1.67	1.65
Chambal	1.11	1.08	1.07	1.06	1.10	1.10	1.09	1.09	1.10	1.09
Lower Yamuna	1.16	1.13	1.12	1.12	1.09	1.09	1.09	1.08	1.10	1.08
Ganga (Gomti Confluence to Ghaghara Confluence)	1.48	1.47	1.48	1.48	1.44	1.46	1.44	1.44	1.46	1.46
Bhagirathi	1.11	1.06	1.11	1.07	1.02	1.05	1.05	1.06	1.02	1.01
Tons	1.30	1.25	1.22	1.22	1.18	1.19	1.16	1.15	1.19	1.14
Sone	1.43	1.43	1.42	1.39	1.41	1.42	1.37	1.36	1.41	1.36

contrast with the traditional assumption, climatic variables are found to have significantly more impacts on basin characteristics compared to land use and vegetation. Overall, our results show that, in terms of hydrologic impact assessment, climate change mitigation pathways are the dominant factor and the land use changes associated with socio-economic pathways contribute little to alleviate the impacts of climate change.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

SG designed the problem and reviewed the manuscript. AS performed the required computation, wrote the manuscript, and prepared the figures. SG and AS analyzed the results.

FUNDING

The CESM LENS and Low warming simulation data are collected from Earth System Grid (https://www.earthsystemgrid.org). The observed precipitation data is collected from APHRODITE (www.chikyu.ac.jp/precip/english/products.html) and NCEP/NCAR Reanalysis data are collected from Earth System Research Laboratory (https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.html). The elevation data is acquired from U.S. Geological Survey; Gridded land use projection data is acquired from AIM (http://www-iam.nies.go.jp/aim/data_tools/aimssp/aimssp.html); soil data is collected from Food and Agriculture Organization, USA; observed streamflow data is acquired from Central Water Commission, India; satellite based soil moisture data is collected from European Space Agency Climate Change Initiative; observed evapotranspiration data is acquired from MODIS MOD16 Global Terrestrial Evapotranspiration Data Set.

ACKNOWLEDGMENTS

The authors acknowledge the financial support from Ministry of Earth Sciences, Government of India through MoES-NERC Newton Bhaba funding (MoES/NERC/IA-SWR/ P2/09/2016-PC-II) and from Department of Science and Technology (SPLICE—Climate Change Programme), Government of India, Project reference number DST/CCP/CoE/140/2018, Grant Number: 00000000000010013072 (UC ID: 18192442).

REFERENCES

Abatzoglou, J. T., and Ficklin, D. L. (2017). Climatic and physiographic controls of spatial variability in surface water balance over the contiguous United States using the budyko relationship. *Water Resour. Res.* 53, 7630–7643. doi: 10.1002/2017WR020843

Ahn, K. H., and Merwade, V. (2014). Quantifying the relative impact of climate and human activities on streamflow. *J. Hydrol.* 515, 257–266.

Amarasinghe, U., Sharma, B. R., Aloysius, N., Scott, C., Smakhtin, V., and De Fraiture, C. (2005). *Spatial Variation in Water Supply and Demand Across River Basins of India, Vol. 83.* Colombo: International Water Management Institute.

Bao, Z., Zhang, J., Wang, G., Fu, G., He, R., Yan, X., et al. (2012). Attribution for decreasing streamflow of the haihe river basin, northern China: climate variability or human activities? *J. Hydrol.* 460, 117–129. doi: 10.1016/j.jhydrol.2012.06.054

Bhat, T. A. (2014). An analysis of demand and supply of water in India. *J. Environ. Earth Sci.* 4, 67–72.

Bohn, T. J., and Vivoni, E. R. (2016). Process-based characterization of evapotranspiration sources over the North American monsoon region. *Water Resour. Res.* 52, 358–384. doi: 10.1002/2015WR017934

Briscoe, J., and Malik, R. (2006). *India's Water Economy: Bracing for a Turbulent Future*. New Delhi: Oxford University Press.

Budyko, M. I. (1974). *Climate and Life, International Geophysical Series Vol. 18, Ist Edn.* New York, NY: Academic Press.

Central Water Commission (CWC) (2013). *Water and Related Statistics*. New Delhi: Water Planning and Projects Wing, Central Water Commission.

Chawla, I., and Mujumdar, P. P. (2015). Isolating the impacts of land use and climate change on streamflow. *Hydrol. Earth Syst. Sci.* 19, 3633–3651. doi: 10.5194/hess-19-3633-2015

Chawla, I., and Mujumdar, P. P. (2018). Partitioning uncertainty in streamflow projections under nonstationary model conditions. *Adv. Water Resour.* 112, 266–282. doi: 10.1016/j.advwatres.2017.10.013

Choudhury, B. (1999). Evaluation of an empirical equation for annual evaporation using field observations and results from a biophysical model. *J. Hydrol.* 216, 99–110. doi: 10.1016/S0022-1694(98)00293-5

Cruise, J. F., Laymon, C. A., and Al-Hamdan, O. Z. (2010). Impact of 20 years of land-cover change on the hydrology of streams in the southeastern United States 1. *J. Am. Water Resour. Assoc.* 46, 1159–1170. doi: 10.1111/j.1752-1688.2010.00483.x

Das, P. K., Chakraborty, A., and Seshasai, M. V. R. (2014). Spatial analysis of temporal trend of rainfall and rainy days during the Indian summer monsoon season using daily gridded (0.5× 0.5) rainfall data for the period of 1971-2005. *Meteorol. Appl.* 21, 481–493. doi: 10.1002/met.1361

Donohue, R. J., Roderick, M. L., and McVicar, T. R. (2006). On the importance of including vegetation dynamics in Budyko' s hydrological model. *Hydrol. Earth Syst. Sci. Discuss.* 3, 1517–1551. doi: 10.5194/hessd-3-1517-2006

Fu, B. P. (1981). On the calculation of the evaporation from land surface. *Sci. Atmos. Sin* 5, 23–31.

Fujimori, S., Hasegawa, T., Ito, A., Takahashi, K., and Masui, T. (2018). Gridded emissions and land-use data for 2005-2100 under diverse socioeconomic and climate mitigation scenarios. *Sci. Data* 5:180210. doi: 10.1038/sdata.2018.210

Fujimori, S., Hasegawa, T., and Masui, T. (2017). "AIM/CGE V2. 0: basic feature of the model," in *Post-2020 Climate Action: global and Asian perspectives*, eds S. Fujimori, M. Kainuma, and T. Masui (Singapore: Springer), 305–328.

Gadgil, S., and Gadgil, S. (2006). The Indian monsoon, GDP and agriculture. *Econ. Polit. Week.* 4887–4895.

Global Water Partnership (GWP) (2013). *Water and Food Security - Experiences in India and China. Technical Focus Paper*. Stockholm: Global Water Partnership Technical Committee.

Gupta, S. C., Kessler, A. C., Brown, M. K., and Zvomuya, F. (2015). Climate and agricultural land use change impacts on streamflow in the upper midwestern United States. *Water Resour. Res.* 51, 5301–5317. doi: 10.1002/2015WR017323

Hasegawa, T., Fujimori, S., Ito, A., Takahashi, K., and Masui, T. (2017). Global land-use allocation model linked to an integrated assessment model. *Sci. Total Environ.* 580, 787–796. doi: 10.1016/j.scitotenv.2016.12.025

Jiang, S., Ren, L., Yong, B., Singh, V. P., Yang, X., and Yuan, F. (2011). Quantifying the effects of climate variability and human activities on runoff from the Laohahe basin in northern China using three different methods. *Hydrol. Process.* 25, 2492–2505.

Joseph, J., Ghosh, S., Pathak, A., and Sahai, A. K. (2018). Hydrologic impacts of climate change: comparisons between hydrological parameter uncertainty and climate model uncertainty. *J. Hydrol.* 566, 1–22. doi: 10.1016/j.jhydrol.2018.08.080

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., et al. (1996). The NCEP/NCAR 40-year reanalysis project. *Bull. Am. Meteorol. Soc.* 77, 437–472. doi: 10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2

Kannan, S., and Ghosh, S. (2013). A nonparametric kernel regression model for downscaling multisite daily precipitation in the Mahanadi basin. *Water Resour. Res.* 49, 1360–1385. doi: 10.1002/wrcr.20118

Kay, J. E., Deser, C., Phillips, A., Mai, A., Hannay, C., Strand, G., et al. (2015). The Community Earth System Model (CESM) large ensemble project: a community resource for studying climate change in the presence of internal climate variability. *Bull. Am. Meteorol. Soc.* 96, 1333–1349. doi: 10.1175/BAMS-D-13-00255.1

Kim, S. H., Hejazi, M., Liu, L., Calvin, K., Clarke, L., Edmonds, J., et al. (2016). Balancing global water availability and use at basin scale in an integrated assessment model. *Clim. Change* 136, 217–231. doi: 10.1007/s10584-016-1604-6

Knutti, R., and Sedláček, J. (2013). Robustness and uncertainties in the new CMIP5 climate model projections. *Nat. Clim. Chang.* 3:369. doi: 10.1038/nclimate1716

Krishna Kumar, K., Rupa Kumar, K., Ashrit, R. G., Deshpande, N. R., and Hansen, J. W. (2004). Climate impacts on Indian agriculture. *Int. J. Climatol.* 24, 1375–1393. doi: 10.1002/joc.1081

Kundzewicz, Z. W., Mata, L. J., Arnell, N. W., Döll, P., Jimenez, B., Miller, K., et al. (2008). The implications of projected climate change for freshwater resources and their management. *Hydrol. Sci. J.* 53, 3–10. doi: 10.1623/hysj.53.1.3

Li, H., Sheffield, J., and Wood, E. F. (2010). Bias correction of monthly precipitation and temperature fields from intergovernmental panel on climate change AR4 models using equidistant quantile matching. *J. Geophys. Res.* 115:D10101. doi: 10.1029/2009JD012882

Li, L. J., Zhang, L., Wang, H., Wang, J., Yang, J. W., Jiang, D. J., et al. (2007). Assessing the impact of climate variability and human activities on streamflow from the Wuding River basin in China. *Hydrol. Process. Int. J.* 21, 3485–3491. doi: 10.1002/hyp.6485

Liang, X., Lettenmaier, D. P., Wood, E. F., and Burges, S. J. (1994). A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *J. Geophys. Res.* 99, 14415–14428. doi: 10.1029/94JD00483

Milly, P. C. D. (1994). Climate, soil water storage, and the average annual water balance. *Water Resour. Res.* 30, 2143–2156. doi: 10.1029/94WR00586

Misra, A. K. (2013). Climate change impact, mitigation and adaptation strategies for agricultural and water resources, in Ganga Plain (India). *Mitigat. Adaptat. Strat. Glob. Change* 18, 673–689. doi: 10.1007/s11027-012-9381-7

Nadaraya, E. A. (1964). On estimating regression. *Theor. Prob. Appl.* 9, 141–142. doi: 10.1137/1109020

Nijssen, B., O'Donnell, G. M., Hamlet, A. F., and Lettenmaier, D. P. (2001). Hydrologic sensitivity of global rivers to climate change. *Clim. Change* 50, 143–175. doi: 10.1023/A:1010616428763

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., et al. (2017). The roads ahead: narratives for shared socioeconomic pathways describing world futures in the 21st century. *Glob. Environ. Chang.* 42, 169–180. doi: 10.1016/j.gloenvcha.2015.01.004

Padrón, R. S., Gudmundsson, L., Greve, P., and Seneviratne, S. I. (2017). Large-scale controls of the surface water balance over land: insights from a systematic review and meta-analysis. *Water Resour. Res.* 53, 9659–9678. doi: 10.1002/2017WR021215

Parthasarathy, B., Rupa Kumar, K., and Munot, A. A. (1996). *Homogeneous Regional Summer Monsoon Rainfall Over India: Interannual Variability And Teleconnections*. Pune: Indian Institute of Tropical Meteorology.

Potter, N. J., Zhang, L., Milly, P. C. D., McMahon, T. A., and Jakeman, A. J. (2005). Effects of rainfall seasonality and soil moisture capacity on mean annual water balance for Australian catchments. *Water Resour. Res.* 41:W06007. doi: 10.1029/2004WR003697

Raje, D., Priya, P., and Krishnan, R. (2014). Macroscale hydrological modelling approach for study of large scale hydrologic impacts under climate change in Indian river basins. *Hydrol. Process.* 28, 1874–1889. doi: 10.1002/hyp.9731

Rodell, M., Houser, P. R., Jambor, U. E. A., Gottschalck, J., Mitchell, K., Meng, C. J., et al. (2004). The global land data assimilation system. *Bull. Am. Meteorol. Soc.* 85, 381–394. doi: 10.1175/BAMS-85-3-381

Salvi, K., Kannan, S., and Ghosh, S. (2013). High-resolution multisite daily rainfall projections in India with statistical downscaling for climate change impacts assessment. *J. Geophys. Res.* 118, 3557–3578. doi: 10.1002/jgrd.50280

Sanderson, B. M., Xu, Y., Tebaldi, C., Wehner, M., O'Neill, B. C., Jahn, A., et al. (2017). Community climate simulations to assess avoided impacts in 1.5 and 2 C futures. *Earth Syst. Dyn.* 8, 827–847. doi: 10.5194/esd-8-827-2017

Schilling, K. E., Jha, M. K., Zhang, Y. K., Gassman, P. W., and Wolter, C. F. (2008). Impact of land use and land cover change on the water balance of a large agricultural watershed: historical effects and future directions. *Water Resour. Res.* 44:W00A09. doi: 10.1029/2007WR006644

Scott, D. W. (2015). *Multivariate Density Estimation: Theory, Practice, and Visualization.* Hoboken, NJ: John Wiley & Sons, Inc.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* 93, 485–498. doi: 10.1175/BAMS-D-11-00094.1

Turner, A. G., and Annamalai, H. (2012). Climate change and the South Asian summer monsoon. *Nat. Clim. Chang.* 2:587. doi: 10.1038/nclimate1495

UNFCCC (2015). *Adoption of the Paris Agreement*. Geneva: United Nations Office at Geneva.

United Nations (UN) (2019). *World Population Prospects, Population Division, United Nations*. Available online at: https://population.un.org/wpp/ (accessed April 20, 2020).

Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., et al. (2011). The representative concentration pathways: an overview. *Clim. Change* 109:5. doi: 10.1007/s10584-011-0148-z

Wand, M. P., and Jones, M. C. (1995). *Kernel Smoothing. Number 60 in Monographs on Statistics and Applied Probability*. London: Chapman & Hall/CRC, 1:6.

Wang, B., and Ding, Q. (2006). Changes in global monsoon precipitation over the past 56 years. *Geophys. Res. Lett.* 33:L0671. doi: 10.1029/2005GL025347

Wang, D., and Hejazi, M. (2011). Quantifying the relative contribution of the climate and direct human impacts on mean annual streamflow in the contiguous United States. *Water Resour. Res.* 47:W00J12. doi: 10.1029/2010WR010283

Wang, S., Yan, Y., Yan, M., and Zhao, X. (2012). Quantitative estimation of the impact of precipitation and human activities on runoff change of the huangfuchuan river basin. *J. Geogr. Sci.* 22, 906–918. doi: 10.1007/s11442-012-0972-8

Xu, X., Liu, W., Scanlon, B. R., Zhang, L., and Pan, M. (2013). Local and global factors controlling water-energy balances within the Budyko framework. *Geophys. Res. Lett*. 40. 6123–6129. doi: 10.1002/2013GL058324

Yatagai, A., Arakawa, O., Kamiguchi, K., Kawamoto, H., Nodzu, M. I., and Hamada, A. (2009). A 44-year daily gridded precipitation dataset for Asia based on a dense network of rain gauges. *Sola* 5, 137–140. doi: 10.2151/sola.2009-035

Zhang, A., Zhang, C., Fu, G., Wang, B., Bao, Z., and Zheng, H. (2012). Assessments of impacts of climate change and human activities on runoff with SWAT for the huifa river basin, northeast China. *Water Resour. Manag.* 26, 2199–2217. doi: 10.1007/s11269-012-0010-8

Zheng, J., Yu, X., Deng, W., Wang, H., and Wang, Y. (2012). Sensitivity of land-use change to streamflow in Chaobai river basin. *J. Hydrol. Eng.* 18, 457–464. doi: 10.1061/(ASCE)HE.1943-5584.0000669

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Water

PERSPECTIVE
published: 18 August 2020
doi: 10.3389/frwa.2020.00021

Check for updates

Infrastructure Interdependency Failures From Extreme Weather Events as a Complex Process

Emily N. Bondank and Mikhail V. Chester*

Department of Civil, Environmental, and Sustainable Engineering, Arizona State University, Tempe, AZ, United States

The loss of infrastructure services under extreme weather events from climate change emerges from complex interactions between the social, environmental, and technological system variables which drive the behavior of infrastructure systems. The complexity of interactions causes failures to cascade in unpredictable ways, often between different infrastructure systems. A common approach to managing this unpredictability is to attempt to characterize the cause-and-effect relationships of infrastructure interdependencies, whether it be related to the resource flows, geographic proximity, logical connections, or the common use of cyber infrastructure. We posit that though a reductive approach toward characterization of interdependencies produces useful insights, it is an insufficient strategy by itself due to the complexity and unpredictability involved in the occurrence and magnitude of cascades of failure across systems. We present historical case studies which demonstrate that cascades from interdependencies display essential tenets of complexity—namely non-linearities, path dependence, and emergence. The Cynefin decision-making framework suggests that management of systems that are in the complex domain include strategies such as Decision Making Under Uncertainty and Safe-to-Fail, which address uncertainty by probing, testing, collecting and analyzing data, and lastly deploying solutions with a commitment to reassessing the systems as conditions change. We therefore recommend that in order to mitigate the surprise from cascades of failure across systems from extreme weather events, infrastructure managers supplement their planning efforts with these types of strategies.

Keywords: interdependencies, complexity, management strategies, historical case studies, climate—impact of

OPEN ACCESS

Edited by:
Abhishek Gaur,
National Research Council Canada (NRC-CNRC), Canada

Reviewed by:
Lance W. Vail,
Independent Researcher, Sequim, United States
Dan D. Koo,
Indiana University, Purdue University Indianapolis, United States

****Correspondence:***
Emily N. Bondank
ebondank2@gmail.com

Specialty section:
This article was submitted to Water and Built Environment, a section of the journal Frontiers in Water

Received: *10 April 2020*
Accepted: *30 June 2020*
Published: *18 August 2020*

Citation:
Bondank EN and Chester MV (2020) Infrastructure Interdependency Failures From Extreme Weather Events as a Complex Process. Front. Water 2:21. doi: 10.3389/frwa.2020.00021

INTRODUCTION

Extreme weather events caused by climate change often exceed infrastructure capacities and design standards and initiate infrastructure hardware and institutional failures which can cascade to service outages (Pederson et al., 2006). Cascades of failures are the result of the many interactions between social, environmental, and technological system variables (Leveson, 2002; Grabowski and Miller, 2017; Markolf et al., 2018; Oughton et al., 2018; Chester and Allenby, 2019). These interactions are part of the *complexity* of infrastructure systems, a domain of systems characterized by unpredictable behaviors when perturbed (Snowden and Boone, 2007). An example of an emergent cascade of failures initiated by a climate event is the 2003 Northeast blackout. An outage of power to around 50 million people resulted from the confluence of several critical variables including an abnormally hot summer day (environmental), high demand (social/technological), ineffective management of vegetation (environmental/social), limited redundancy (technological), and ineffective operational communication (social) (North American Electric Reliability Council, 2004). During the event, the cascade of failure was surprising to managers and it was only until a task force retrospectively studied the event that causes of failure were identified and understood (North American Electric Reliability Council, 2004).

A significant variable that contributes to failures is the connection between infrastructure systems, or infrastructure interdependencies (Rinaldi et al., 2001; Wilbanks et al., 2015). As described by Rinaldi et al. (2001), interdependencies can exist in many different forms, including the exchange of material outputs (physical), the influence of spatially proximal hardware failures (geographic), the shared dependency on communications systems for operation (cyber), and the influence of institutional decisions (logical). In the 2003 Northeast Blackout example, failures cascaded through physical interdependencies between different power systems and between power and water systems, resulting in a greater extent of power outages and the occurrence of water outages, respectively (Bella et al., 2004). Through the increase in frequency of similar events spurred by climate change, infrastructure mangers are recognizing the effect that interdependencies can have on reliability and they are developing strategies to mitigate these effects (Bella et al., 2004). Since the existence of interactions has been recognized and defined for interdependencies, a reductive approach to understanding them is attractive, and many studies suggest characterizing and modeling interdependencies to anticipate how cascades might occur in the future. Though this strategy can provide useful and necessary insights, we posit that it must be accompanied by other strategies which directly address the inherent complexity of modern infrastructure. Through review of historical cases of failures from interdependencies, we find that there is complexity inherent in the dynamics of cascades of failure across systems which is not conducive to purely reductionist approaches. We therefore recommend that managers augment their methods of planning with strategies which are appropriate in the complex domain of the Cynefin framework including decision making under uncertainty, and safe-to-fail (Leavitt et al., 2006; Snowden and Boone, 2007; Ilic, 2014; Derrible, 2017; Kim et al., 2017; Chester and Allenby, 2019). Without including strategies such as these, the surprise from the emergent cascading failures from climate change and other hazards will continue to strain institutions managing infrastructure systems and the customers they serve.

COMPLEX SYSTEMS DIFFER FROM COMPLICATED SYSTEMS

Complex systems share characteristics with complicated systems, but there are important differences which are critical for managers to recognize. Complicated systems contain many parts and there is uncertainty included in the system, however, cause-and-effect relationships can be understood by characterizing the uncertainty via methods such as statistical distributions (Chester and Allenby, 2019). In contrast, complex systems are characterized by "unpredictability and the presence of unknown unknowns," or uncharacterizable uncertainty, making it impossible to establish cause and effect relationships (Snowden and Boone, 2007). An example of a complicated system is the process of water treatment. Though there are many interacting parts including sedimentation rate, concentrations of chemicals and organics in the water, and the communities of microbes treating the water, the interactions are well-characterized and the outcomes, the pathogens removed, is predictable (Reynolds and Richards, 1982). Conversely, infrastructure systems which form networks and span across cities have unknown interactions with other aspects of cities, society, and the environment and thus become unpredictable. The essential tenets of complex systems, according to the overview provided by Turner and Baker, are *path dependence* where outcomes are sensitive to initial conditions, *system history* where past events influence future outcomes, *non-linearity* where changes to the system produce disproportionate outcomes, *emergence* where "the interactions from the system components tend to lead to new states, contributing to the system's unpredictability," and *irreducibility* where "higher-order states cannot be reduced to their original lower-level states" (Turner and Baker, 2019).

Literature outlining the needs for future design and management of infrastructure systems recommends applying different management approaches for complex systems vs. complicated systems. Knowledge management researchers and consultants, Snowden and Boone, developed the Cynefin framework to help leaders choose strategies which align with their specific context. Through reviewing their experience with consulting they "sorted the issues facing leaders into five contexts defined by the nature of the relationship between cause and effect"—simple, complicated, complex, chaotic, and disorder (Snowden and Boone, 2007). Chester and Allenby adapt the Cynefin framework to infrastructure, and state that "knowing whether you are working in the complicated vs. complex domain when it comes to infrastructure is critical because each domain requires fundamentally different approaches" (Chester and Allenby, 2019). For complicated systems, it is appropriate to primarily use data collection and analysis techniques because experts have the ability to identify the majority of cause-and-effect relationships in the system (Chester and Allenby, 2019). For complex systems, however, analysis techniques are by themselves insufficient (Chester and Allenby, 2019) because hidden or unknown factors contribute significantly to the cause-and-effect dynamics (Park et al., 2013). Therefore, it is recommended that modeling and analysis is only one of a suite of approaches necessary for managing complex systems. Given the unpredictability of complex systems, navigating through their dynamics requires approaches primarily focused on probing and testing, then collecting and analyzing data, and lastly deploying solutions, with a commitment to reassessing the systems as conditions change.

LIMITATIONS OF CHARACTERIZING INTERDEPENDENCIES

In an effort to manage the complexity of interdependent infrastructure systems, the predominant approach has been to employ modeling and analysis to elucidate the interdependencies between systems. Many studies cite modeling as the most appropriate approach (Haimes and Jiang, 2001; Ghorbani and Bagheri, 2008; Lauge et al., 2015), or dive into a modeling approach without justification (Rinaldi et al., 2001; Smith, 2002; Barton et al., 2004; Visarraga, 2005; Pederson et al., 2006). The assumption present in these studies is that though interdependencies are responsible for contributing to complexity in systems, the dynamics of how they impact systems through cascades can reasonably be understood through modeling, and thus are only *complicated* in nature. The basic tenets of complexity are not well-represented in the studies. Many studies have modeled the physical resource flow connections between different infrastructure systems and the exchange of resources across systems (Lall and Mays, 1981; Haimes and Jiang, 2001; Veselka et al., 2001; Barrett et al., 2003; Panzieri et al., 2003; Barton et al., 2004; Eidson and Ehlen, 2005; Zhang et al., 2005; Pederson et al., 2006; Bagheri et al., 2007; Donzelli and Setola, 2007; Pate et al., 2007; Johansson and Hassel, 2010; Pye and Warren, 2011; Rübbelke and Vögele, 2011; Birol and Olerjarnik, 2012; Rheinheimer et al., 2012; Shahid, 2012; Wang et al., 2012, 2013; Bartos and Chester, 2014; Carter, 2014; Lubega and Farid, 2014a; Moini and Asce, 2014; Hwang and Lansey, 2015; Loggins and Wallace, 2015; Berardy and Chester, 2017; Clark et al., 2018). This information can be useful for long-term resource planning, where utilities can plan for the generation of enough resources to support the connected infrastructure system. When interpreting these studies for understanding vulnerability to cascading failures across systems, however, the assumption is often that cascades are linearly related to the amount of resources exchanged between systems. Other studies identify specific places in the infrastructure networks where resources might be exchanged and evaluate how flows of resources might be disrupted if the point of exchange were to be disrupted (Panzieri et al., 2003; Visarraga, 2005; Pederson et al., 2006; Wang et al., 2013; Lubega and Farid, 2014b; Lauge et al., 2015). This information is useful for identifying the impacts of cascades. However, these studies assume that the existence of a potential connection between components determines the occurrence of a cascade. Moreover, while each types of interdependency study contributes particular insights about connected systems, no studies include all of the socio-eco-technical interactions and dynamics between time and space that would be necessary to fully predict the occurrence and magnitude of cascades from interdependencies.

COMPLEXITY OF CASCADES OF FAILURE FROM INTERDEPENDENCIES

Historical events of cascades of failure across infrastructure systems reveal that interdependencies are *complex* in nature instead of complicated—where the occurrence of cascades emerges from the confluence of many contextual factors in addition to possible connections through interdependencies (Bella et al., 2004; Chang et al., 2007; Rong et al., 2010; Markolf et al., 2018). The following review of select historical events shows that the dynamics of cascading failure from interdependencies display essential tenets of complexity including non-linearity, emergence, and path dependence.

There are *non-linearities* in the outcomes from cascades due to interdependencies. The occurrence and magnitude of cascades are not directly related to only the magnitude of resource flows between systems (in the case of physical interdependencies) or the existence of a connection (for geographic, cyber, and logical types of interdependencies). Other factors contribute significantly to the cascade outcomes. For example, in the 2003 Northeast Blackout, the amount of power resources each of the connected water systems required for their pumping stations did not dictate the number of water outages which occurred. All systems required power and are similar in size, but the water outages seemed to occur more for systems which had less backup water storage or backup power generation (Bella et al., 2004). Clifton, New Jersey was able to avoid having any outages because they had 3 days-worth of water storage (Bella et al., 2004). Thus, the characterization of interdependency connections in terms of the magnitude of resource exchanged, or existence of a connection, provides limited capability for understanding the potential of cascades across systems. The non-linearity of occurrences and magnitudes of cascades is consistent with the vaguely defined "tightness or looseness" aspect of interdependencies described in Rinaldi et al. (2001).

Interactions of social, ecological, and technological systems over time contribute to the *path dependency* of the occurrence of cascades from interdependencies. It is known that these interactions create path dependencies in infrastructure systems operations (Leveson, 2002; Grabowski and Miller, 2017; Markolf et al., 2018; Oughton et al., 2018; Chester and Allenby, 2019), but the occurrence of path dependencies which affects the behavior of cascades across systems is less well-recognized. A historical example is that Clifton, New Jersey evolved to be more prepared for power outages than surrounding cities during the 2003 Northeast Blackout because they prepared for the possible fallout of Y2K ahead of time by installing dual electric feeds and making agreements with their public electric company that they would "run three peaking generators in order to sustain their main treatment plants" (Bella et al., 2004). An additional example presented by Markolf et al. (2018) regards Miami's approach to managing their "sunny-day floods," which are initiated by sea level rise and extreme precipitation events, and result in service losses of transportation infrastructure through the transportation system's interdependency with the deteriorating stormwater infrastructure. They posit that the resulting failures may cause additional interdependency-related failures in the future because the City of Miami may end up encouraging development into the area to raise taxes for the roadway pumps they are installing to mitigate the stormwater vulnerability, which may outpace the pump development and in turn increase the number of people vulnerable to flooding in the future (Markolf et al., 2018). In a general sense, because infrastructure systems are designed to last decades, the historical design of infrastructure systems will always be a factor in the behavior of current systems, and therefore also in the occurrence of cascades from interdependencies from extreme weather events. Thus, characterizations of interdependencies that omit the effects of historical interactions of social, ecological, and technical systems provide a limited understanding of the potential for cascades across systems.

Interdependent infrastructure systems in different locations vary in characteristics which determine cascades, leading to unpredictability of outcomes, or the *emergence* of outcomes for different cases. For example, two studies which look empirically at the impacts of power outages from similar extreme ice storms in two different cases—in Canada in 1998 (Chang et al., 2007) and China in 2008 (Rong et al., 2010)—show that even though both power systems were connected to the same set of infrastructure, the connected systems that had the greatest extent of cascades and impact from cascades differed. Chang et al. (2007) found that the greatest impact and extent of cascades in Canada from the power sector was to business retail and production, whereas Rong et al. (2010) found that the greatest impact and extent of cascades in China from the power sector was to the mobile telephone sector. This implies that there were contextual aspects in each case that contributed to the occurrence and extent of cascades across specific infrastructure systems. Thus, characterizing generalized rules of cascades from interdependencies provides limited capacity for predicting outcomes of different contexts.

DISCUSSION

Since cascades from interdependencies are complex in nature, managers should not rely on the characterization or modeling of interdependencies alone in their climate change adaptation strategies, but should follow best practices recommended by complex systems science. For example, the Cynefin framework recommends that for complex systems, strategies including probing and testing, collecting and analyzing data, and lastly deploying solutions, with a commitment to reassessing the systems as conditions change should be employed (Snowden and Boone, 2007). Decision-making frameworks which would be appropriate include (but are not limited to) Decision Making Under Deep Uncertainty, and Safe-to-Fail (Leavitt et al., 2006; Ilic, 2014; Derrible, 2017; Kim et al., 2017; Chester and Allenby, 2019). These frameworks tend to establish principles that recognize complexity and call for designing and operating by recognizing uncertainty, testing, and a commitment to long-term reassessment of the asset and its performance under changing conditions.

Decision Making Under Deep Uncertainty is relevant for managing types of uncertainty that are largely unknown and which cannot necessarily be characterized through probability distributions (Helmrich and Chester, 2019). It involves a cyclical process of framing the analysis, performing an exploratory uncertainty analysis, choosing initial actions and contingent actions, and iteration and re-examination (Decision Making Under Deep Uncertainty, 2019). There are multiple approaches suggested within this framework including Robust Decision-making, and Dynamic Adaptive Planning. Robust Decision-making includes using exploratory modeling to test strategies over possible futures (Decision Making Under Deep Uncertainty, 2019). Dynamic Adaptive Planning focuses on the adaptation of plans overtime when new information is available (Park et al., 2013; Decision Making Under Deep Uncertainty, 2019). Modeling interdependencies could thus be an aspect of exploring future scenarios, but the assumptions and inputs into the model would need to be updated when new information becomes available. Information that might surface overtime regarding interdependencies might include changes in connections between systems, climate hazards, demand profiles, and infrastructure hardware and institutions.

The Safe-to-Fail framework bypasses the need to characterize uncertainty and instead assumes that assets will fail if designed for rigidity in changing conditions. The framework recommends designing with potential failure in mind, and incorporating alternative service delivery approaches to make the system more adaptable (Kim et al., 2017). In the case of managing interdependencies, this might mean that managers would assume that the other infrastructure systems they rely on will fail at some point, and would prioritize providing backup systems (e.g., generators, storage tanks, etc.) to maintain critical services.

Improving the communication and coordination between managers of different infrastructure systems could increase managers' capacity to implement strategies for complex systems (Leavitt et al., 2006; Ilic, 2014; Derrible, 2017; Chester and Allenby, 2019). Though appropriate in the past, literature suggests that separate management of infrastructure systems may limit the capacity to prepare systems for disturbances. Derrible (2017) states that the "dichotomy of responsibility" was developed due to "the global push toward safety, accountability, and higher efficiency." "The mechanistic approach has been shown to be…effective in environments that require routine operation and little change. In these environments high-level management possesses the appropriate amount of knowledge to make decisions and organize work" (Chester and Allenby, 2018). This implies that in environments with high change, one organization might not be in possession of all relevant knowledge. Because infrastructure organizations have evolved without the acute need to coordinate or consider uncertainty, "sharing of knowledge and resources across groups to address interdisciplinary challenges is typically infeasible and solutions to challenges are often prescribed with little opportunity for deviation" (Chester and Allenby, 2019). Without information sharing, flawed expectations about the behavior of the change may lead to undesired consequences (Leveson, 2002; Park et al., 2013). Thus, coordination across organizations would provide the capacity to develop more realistic expectations about the behavior of infrastructure systems and would allow for effective adaptations to be more easily made.

CONCLUSION

A common approach to managing the uncertainty of the failure of infrastructure systems in the face of climate change hazards has been to try to characterize the cause-and-effect behavior of interdependencies. Historical examples of failures from interdependencies show that the occurrence and extent of cascades of failure from one infrastructure system to another is unpredictable because the systems display essential tenets of complexity—namely non-linearities, path dependence, and emergence. Thus, in order to better prepare for an uncertain future including climate change, managers should consider the complexity of cascades and implement additional strategies which are appropriate for the complex domain of the Cynefin framework. Ultimately, if the complexity of the behavior of cascades of interdependencies is overlooked and additional strategies are not included, the surprise from the emergent cascading failures will continue to strain institutions managing infrastructure systems and the customers they serve.

DATA AVAILABILITY STATEMENT

All datasets presented in this study are included in the article/supplementary material.

AUTHOR CONTRIBUTIONS

All authors contributed to the article and approved the submitted version.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grants Nos. 1831475, 1931324, 1934933, and 1444755.

REFERENCES

Bagheri, E., Baghi, H., Ghorbani, A. A., and Yari, A. (2007). An agent-based service-oriented simulation suite for critical infrastructure behaviour analysis. *Int. J. Bus. Process Integr. Manage.* 2:312–326. doi: 10.1504/IJBPIM.2007.017756

Barrett, C. L., Beckman, R. J., Berkbigler, K. P., Bisset, K. R., Bush, B. W., and Campbell, K. (2003). *TRANSIMS : TRansportation ANalysis SIMulation System*. Los Alamos, NM: Los Alamos National Laboratory.

Barton, D. C., Edison, E. D., Schoenwald, D. A., Cox, R. G., and Rhonda, K. (2004). *Simulating Economic Effects of Disruptions in the Telecommunications Infrastructure.* Albuquerque, NM: Sandia National Laboratory.

Bartos, M. D., and Chester, M. V. (2014). The conservation nexus: valuing interdependent water and energy savings in Arizona. *Environ. Sci. Technol.* 48, 2139–2149. doi: 10.1021/es4033343

Bella, J., Cascos, G., Ciaccia, J., Tripp, J., and Qussar, S. (2004). Emergency backup power supply. *Am. Water Work. Assoc.* 96, 41–43. doi: 10.1002/j.1551-8833.2004.tb10516.x

Berardy, A., and Chester, M. V. (2017). Climate change vulnerability in the food, energy, and water nexus: concerns for agricultural production in Arizona and its urban export supply. *Environ. Res. Lett.* 12:035004. doi: 10.1088/1748-9326/aa5e6d

Birol, F., and Olerjarnik, P. (2012). *World Energy Outlook 2012,* (Paris: OECD Publishing), 1–33. doi: 10.5547/2160-5890.1.1.2

Carter, N. T. (2014). *Energy-Water Nexus : The Energy Sector' s Water Use*. Washington, DC: Congressional Research Service.

Chang, S. E., Mcdaniels, T. L., Mikawoz, J., and Peterson, K. (2007). Infrastructure failure interdependencies in extreme events: power outage consequences in the 1998 ice storm. *Natural Hazards* 41, 337–358. doi: 10.1007/s11069-006-9039-4

Chester, M. V., and Allenby, B. (2018). Toward adaptive infrastructure: flexibility and agility in a non-stationarity age. *Sustain. Resilient Infrastruct.* 4, 1–19. doi: 10.1080/23789689.2017.1416846

Chester, M. V., and Allenby, B. (2019). Infrastructure as a wicked complex process. *Elem. Sci.Anth.* 7:21. doi: 10.1525/elementa.360

Clark, S. S., Chester, M. V., Seager, T. P., and Eisenberg, D. A. (2018). The vulnerability of interdependent urban infrastructure systems to climate change: could Phoenix experience a Katrina of extreme heat? *Sustain. Resilient Infrastruct.* 4, 21–35. doi: 10.1080/23789689.2018.1448668

Decision Making Under Deep Uncertainty (2019). *The Oxford Handbook of Planning for Climate Change Hazards.* eds A. W. J. M. Vincent, E. W. Warren, J. T. M. B. Pieter, W. P. Steven (Cham: Springer).

Derrible, S. (2017). Urban infrastructure is not a tree : integrating and decentralizing urban infrastructure systems. *Environ. Plan. B.* 44, 553–569. doi: 10.1177/0265813516647063

Donzelli, P., and Setola, R. (2007). Identifying and evaluating risks related to enterprise dependencies: a practical goal-driven risk analysis framework. *Int. J. Risk Assess. Manage.* 7, 1120–1137. doi: 10.1504/IJRAM.2007.015297

Eidson, E. D., and Ehlen, M. A. (2005). *NISAC Agent-Based Laboratory for Economics (N-ABLE^{TM}): Overview of Agent and Simulation Architectures*. Sandia National Laboratories Technical Report SAND 2005-0263.

Ghorbani, A. A., and Bagheri, E. (2008). The state of the art in critical infrastructure protection : a framework for convergence. *Int. J. Crit. Infrastruct.* 4, 215–244. doi: 10.1504/IJCIS.2008.017438

Grabowski, Z. J., and Miller, T. (2017). Infrastructures as socio-eco-technical systems : five considerations for interdisciplinary dialogue. *J. Infrastruct. Syst.* 23:02517002. doi: 10.1061/(ASCE)IS.1943-555X.0000383

Haimes, Y. Y., and Jiang, P. (2001). Leontief - Based Model of Risk in Complex Interconnected Infrastructures. *J. infrastruct. Syst.* 7, 1–12. doi: 10.1061/(ASCE)1076-0342(2001)7:1(1)

Helmrich, A., and Chester, M. V. (2019). Reconciling complexity and deep uncertainty in infrastructure design for climate adaptation. *Sustain. Resilient Infrastruct.* 1–17. doi: 10.1080/23789689.2019.1708179

Hwang, H., and Lansey, K. (2015). *ARVIN : ARizona Value INtegrated Water, Energy, and Agriculture Planning Model*. ARVIN : ARizona Value INtegrated Optimization Model.

Ilic, M. (2014). *Change of Paradigms in Complexity and Interdependencies of Infrastructures : The Case for Flexible New Protocols.* Berlin: Research Gate.

Johansson, J., and Hassel, H. (2010). An approach for modelling interdependent infrastructures in the context of vulnerability analysis. *Reliab. Eng. Syst. Saf.* 95, 1335–1344. doi: 10.1016/j.ress.2010.06.010

Kim, Y., Eisenberg, D. A., Bondank, E. N., Chester, M. V., Mascaro, G., and Underwood, B. S. (2017). Fail-safe and safe-to-fail adaptation: decision-making for urban flooding under climate change. *Clim. Change* 145, 397–412. doi: 10.1007/s10584-017-2090-1

Lall, U., and Mays, L. W. (1981). Model for planning water-energy systems. *Water Resour. Res.* 17, 853–865. doi: 10.1029/WR017i004p00853

Lauge, A., Hernantes, J., and Sarriegi, J. M. (2015). Critical infrastructure dependencies : a holistic, dynamic and quantitative approach. *Int. J. Crit. Infrastruct. Prot.* 8, 16–23. doi: 10.1016/j.ijcip.2014.12.004

Leavitt, W. M., Leavitt, W. M., and Kiefer, J. J. (2006). Infrastructure interdependency and the creation of a normal disaster: the case of Hurricane Katrina and the City of New Orleans. *Public Works Manag. Policy* 10, 306–314. doi: 10.1177/1087724X06289055

Leveson, N. G. (2002). *System Safety Engineering : Back to the Future.*

Loggins, R. A., and Wallace, W. A. (2015). Rapid assessment of Hurricane Damage and Disruption to Interdependent Civil Infrastructures Systems. *J. Infrastruct. Syst.* 21, 1–19. doi: 10.1061/(ASCE)IS.1943-555X.0000249

Lubega, W. N., and Farid, A. M. (2014a). A reference system architecture for the energy-water nexus. *IEEE Syst. J.* 10, 106–116. doi: 10.1109/JSYST.2014.2302031

Lubega, W. N., and Farid, A. M. (2014b). Quantitative engineering systems modeling and analysis of the energy–water nexus. *Appl. Energy* 135, 142–157. doi: 10.1016/j.apenergy.2014.07.101

Markolf, S. A., Chester, M. V., Eisenberg, D. A., Iwaniec, D. M., Davidson, C. I., Zimmerman, R., et al. (2018). Interdependent infrastructure as linked social, ecological, and technological systems (SETS) to address lock-in and enhance resilience. *Earths Future* 6, 1638–1659. doi: 10.1029/2018EF000926

Moini, N., and Asce, M. (2014). Modeling of risks threatening critical infrastructures: system approach. *J. Infrastruct. Syst.* 22:04015010. doi: 10.1061/(ASCE)IS.1943-555X.0000263

North American Electric Reliability Council (2004). *Technical Analysis of the August 14, 2003, Blackout: What Happened, Why, and What Did We Learn?* 124.

Oughton, E. J., Usher, W., Tyler, P., and Hall, J. W. (2018). Infrastructure as a complex adaptive system. *Complexity* 2018:11–14. doi: 10.1155/2018/3427826

Panzieri, S., Setola, R., and Ulivi, G. (2003). "An approach to model complex interdependent infrastructures," in *Conference on 16th IFAC World Congress*. Prague.

Park, J., Seager, T. P., Rao, P. S. C., Convertino, M., and Linkov, I. (2013). Integrating risk and resilience approaches to catastrophe management in engineering systems. *Risk Anal.* 33, 356–367. doi: 10.1111/j.1539-6924.2012.01885.x

Pate, R., Hightower, M., Cameron, C., and Einfeld, W. (2007). *Overview of Energy-Water Interdependencies and the Emerging Energy Demands on Water Resources*. Albuquerque, NM: Sandia National Laboratories. doi: 10.1115/IMECE2007-41173

Pederson, P., Dudenhoeffer, D., Hartley, S., and Permann, M. (2006). *Critical Infrastructure Interdependency Modeling: A Survey of US and International Research*. Idaho Falls, ID: Idaho National Laboratory, 1–20.

Pye, G., and Warren, M. (2011). "Analysis and modelling of critical infrastructure systems," in *10th European Conference on Information Warfare and Security 2011* (Tallinn: ECIW), 194–201.

Reynolds, T. D., and Richards, P. A. (1982). *Unit Operation and Process in Environmental Engineering*. Wadsorth, CA: PWS Publishing Company.

Rheinheimer, D. E., Ligare, S. T., and Viers, J. H. (2012). *Water and Energy Sector Vulnerability to Climate Warming in the Sierra Nevada: Simulating the Regulated Rivers of California's West Slope Sierra Nevada*. Davis, CA: California Energy Commission.

Rinaldi, S. M., Peerenboom, J. P., and Kelly, T. K. (2001). Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control Syst. Mag.* 21, 11–25. doi: 10.1109/37.969131

Rong, M., Han, C., and Liu, L. (2010). "Critical infrastructure failure interdependencies in the 2008 Chinese winter storms," in *2010 International Conference on Management and Service Science,* (Wuhan), 1–4. doi: 10.1109/ICMSS.2010.5576239

Rübbelke, D., and Vögele, S. (2011). Impacts of climate change on European critical infrastructures: the case of the power sector. *Environ. Sci. Policy* 14, 53–63. doi: 10.1016/j.envsci.2010.10.007

Shahid, S. (2012). Vulnerability of the power sector of Bangladesh to climate change and extreme weather events. *Reg. Environ. Chang.* 12, 595–606. doi: 10.1007/s10113-011-0276-z

Smith, M. R. (2002). Energy security in Europe. *Pet. Rev.* 56, 24–26.

Snowden, D. J., and Boone, M. E. (2007). *A Leader's Framework for Decision Making*. Brighton, MA: Harvard Business Review, 1–8.

Turner, J. R., and Baker, R. M. (2019). Complexity theory : an overview with potential applications for the social sciences. *Systems* 7:4. doi: 10.3390/systems7010004

Veselka, T., Boyd, G., Conzelmann, G., and Koritarov, V. (2001). Simulating the behavior of electricity markets with an agent-based methodology : the electric market complex adaptive systems (EMCAS) model," in *Center for Energy, Environmental, and Economic Systems Analysis*. Argonne National Laboratory.

Visarraga, D. (2005). Development of a JAVA based water distribution simulation capability for infrastructure interdependency analyses. *Ewri* 2005:14. doi: 10.1061/40792(173)14

Wang, S., Hong, L., and Chen, X. (2012). Vulnerability analysis of interdependent infrastructure systems: a methodological framework. *Phys. A Stat. Mech. Appl.* 391, 3323–3335. doi: 10.1016/j.physa.2011.12.043

Wang, S., Hong, L., Ouyang, M., Zhang, J., and Chen, X. (2013). Vulnerability analysis of interdependent infrastructure systems under edge attack strategies. *Saf. Sci.* 51, 328–337. doi: 10.1016/j.ssci.2012.07.003

Wilbanks, T. J., Fernandez, S. J., and Allen, M. R. (2015). Extreme weather events and interconnected infrastructures: toward more comprehensive climate change planning. *Environ. Sci. Policy Susat. Develop.* 57, 4-15. doi: 10.1080/00139157.2015.1048134

Zhang, P., Peeta, S., and Friesz, T. (2005). Dynamic game theoretic model of multi-layer. *Netw. Spatial Econ.* 5, 147–178. doi: 10.1007/s11067-005-2627-0

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Water

PERSPECTIVE
published: 03 December 2020
doi: 10.3389/frwa.2020.545051

Check for updates

Next-Generation Intensity-Duration-Frequency Curves for Climate-Resilient Infrastructure Design: Advances and Opportunities

Hongxiang Yan[1], Ning Sun[1], Xiaodong Chen[2] and Mark S. Wigmosta[1,3]**

[1] Pacific Northwest National Laboratory, Earth Systems Science Division, Richland, WA, United States, [2] Pacific Northwest National Laboratory, Atmospheric Sciences and Global Change Division, Richland, WA, United States, [3] Department of Civil and Environmental Engineering, University of Washington, Seattle, WA, United States

OPEN ACCESS

Edited by:
Abhishek Gaur,
National Research Council Canada (NRC-CNRC), Canada

Reviewed by:
Andre Schardong,
Western University, Canada
Lauren Cook,
Swiss Federal Institute of Aquatic Science and Technology, Switzerland

***Correspondence:**
Hongxiang Yan
hongxiang.yan@pnnl.gov
Mark S. Wigmosta
mark.wigmosta@pnnl.gov

Specialty section:
This article was submitted to Water and Built Environment, a section of the journal Frontiers in Water

Received: 23 March 2020
Accepted: 09 November 2020
Published: 03 December 2020

Citation:
Yan H, Sun N, Chen X and Wigmosta MS (2020) Next-Generation Intensity-Duration-Frequency Curves for Climate-Resilient Infrastructure Design: Advances and Opportunities. Front. Water 2:545051. doi: 10.3389/frwa.2020.545051

National and international security communities (e.g., U.S. Department of Defense) have shown increasing attention for innovating critical infrastructure and installations due to recurring high-profile flooding events in recent years. The standard infrastructure design approach relies on local precipitation-based intensity-duration-frequency (PREC-IDF) curves that do not account for snow process and assume stationary climate, leading to high failure risk and increased maintenance costs. This paper reviews the recently developed next-generation IDF (NG-IDF) curves that explicitly account for the mechanisms of extreme water available for runoff including rainfall, snowmelt, and rain-on-snow under nonstationary climate. The NG-IDF curve is an enhancement to the PREC-IDF curve and provides a consistent design approach across rain- to snow-dominated regions, which can benefit engineers and planners responsible for designing climate-resilient facilities, federal emergency agencies responsible for the flood insurance program, and local jurisdictions responsible for developing design manuals and approving subsequent infrastructure designs. Further, we discuss the recent advances in climate and hydrologic science communities that have not been translated into actional information in the engineering community. To bridge the gap, we advocate that building climate-resilient infrastructure goes beyond the traditional local design scale where engineers rely on recipe-based methods only; the future hydrologic design is a multi-scale problem and requires closer collaboration between climate scientists, hydrologists, and civil engineers.

Keywords: NG-IDF curves, snowmelt, rain-on-snow, floods, nonstationarity, extreme events, atmospheric river, DHSVM

INTRODUCTION

Recurring high-profile flooding events (e.g., 2017 California) has led to major public safety concerns and motivated national security communities to explore new methods to innovate critical infrastructure (ESTCP, 2018). Currently, infrastructure design to withstand extreme flooding relies largely on precipitation-based intensity-duration-frequency (PREC-IDF) curves developed at the local scale, which is then coupled with single-event rainfall-runoff models such as the Technical Release 55 (TR-55) for estimating flood peaks, the so-called "standard IDF design workflow" (Cronshey et al., 1986; Chow et al., 1988). This PREC-IDF approach assumes that precipitation is in the form of rainfall that immediately starts the rainfall-runoff process. This assumption, however, can lead to significant underdesign risk in areas where snowmelt/rain-on-snow (ROS) are the dominant flood-generating mechanisms (e.g., the 2017 Oroville Dam crisis). Further, federal atlas's of PREC-IDF curves, such as the National Oceanic and Atmospheric Administration (NOAA) Atlas 14 (Bonnin et al., 2011), assume stationary climate, that is, the occurrence probability of extreme hydrometeorological events is not expected to change significantly within the service life of infrastructure. Given the strong evidence that climate-related hazards, including common engineering design criteria such as the 25-year storm magnitude and frequency, are no longer stationary over time (Wuebbles et al., 2014), the current hydrologic design standards are insufficient in the 21st century (Ragno et al., 2018; Wright et al., 2019).

In design practices, many surface water design manuals in the U.S. are based on the NOAA PREC-IDF curves, even in snow-dominated regions (SMMEW, 2004; SCDM, 2016). The earliest NOAA Atlas 14 product appeared for Ohio in 2004 and the latest product was for Texas in 2018 (Lopez-Cantu and Samaras, 2018). At present, the NOAA Atlas 14 is not available for the Pacific Northwest (PNW); Technical Paper 40 (Hershfield, 1961) is used instead and was developed from observations ending in the 1950s. Given the observed rapid increase in extreme precipitation (Kunkel et al., 2020), these products are becoming obsolete. For critical infrastructure with a design life often exceeding 30 years, even the latest 2018 atlas has become problematic because of the projected significant changes in extreme precipitation by 2050 (Prein et al., 2017). Currently, systematic, coordinated, and consistent surface water design manuals explicitly addressing snowmelt and nonstationary climate are not available. The recent federal guideline for flood frequency analysis, Bulletin 17C, acknowledges the significant implications of snowmelt and nonstationarity; however, it provides no explicit guidance (England et al., 2018). On the other hand, deficiencies of the standard PREC-IDF approach are well-known issues in climate and hydrologic science communities and coupled physically-based hydrologic and climate models have been applied to investigate multi-scale extreme hydrometeorological events and runoff generation mechanisms (Tohver et al., 2014). Despite significant advances made in science communities in the past decades, the current state of science has not translated into actionable information for engineers, and a gap still exists between science and engineering communities (ASCE, 2015).

This paper addresses the emerging need for a next-generation design tool by providing a review of the recently developed, science-driven "next-generation IDF" (NG-IDF) approach. In the following, Section "NG-IDF Curves vs. PREC-IDF Curves" describes the NG-IDF curves and Section "Physics-Based Hydrologic Modeling: Extending and Validating NG-IDF Curves" describes the physically-based hydrologic modeling approach to extend and validate NG-IDF curves" (i.e., advances in hydrologic science). Section "Nonstationary NG-IDF Curves Under Climate Change" describes the general circulation model (GCM) modeling approach to develop nonstationary NG-IDF curves (i.e., advances in climate science). Finally, Section "Discussion" discusses future opportunities and technology transfer.

NG-IDF CURVES VS. PREC-IDF CURVES

The authors (Yan et al., 2018) proposed the NG-IDF curves that characterize the actual amount of water reaching the land surface or "water available for runoff (W)." The W is estimated through land surface water balance as $W = P - \Delta SWE$, where P indicates precipitation, and ΔSWE indicates changes in snow water equivalent (SWE). The W can be associated with multiple mechanisms, including rainfall on the snow-free ground, snowmelt without precipitation, ROS, and mixed rainfall and snowfall. By comparing the NG-IDF value with the PREC-IDF value for events with a specified duration and average recurrence interval (ARI), they evaluated the current design risk as (1) underdesign when the NG-IDF value is greater than the PREC-IDF value, (2) overdesign when the PREC-IDF value is greater than the NG-IDF value, and (3) proper design when the differences between the two values are trivial. Underdesign occurs when ROS/snowmelt intensity exceeds precipitation intensity ($W > P$), overdesign occurs when snowfall intensity exceeds snowmelt intensity ($W < P$), and proper design occurs when the snow has minor effects ($W \approx P$).

The authors (Yan et al., 2018) first compared PREC-IDF and NG-IDF curves using Snowpack Telemetry (SNOTEL) measurements as a proof-of-concept, as even the most sophisticated hydrologic models cannot replace the observation record. SNOTEL is an automated system of snowpack and climate sensors installed in open mountainous areas of the western U.S. (WUS) and operated by the Natural Resources Conservation Service. They developed long-term bias-corrected quality-controlled (BCQC) P and SWE measurements from nearly 400 SNOTEL stations across the WUS to develop and compare PREC-IDF and NG-IDF curves. They found that the use of PREC-IDF curves can lead to underdesign at 45% of the sites. Most of the sites found to be underdesigned were in the PNW and continental regime that feature deeper snowpack and longer snow accumulation seasons. At these sites, the authors (Yan et al., 2019a) further compared the peak design flood estimates using NG-IDF and PREC-IDF curves coupled with the TR-55 rainfall-runoff model. They found that after the nonlinear runoff generation process, 70% of the sites were subject to underdesign and the PREC-IDF method underestimated peak design flood by as much as 324%.

By differentiating the precipitation phase using the change in SWE, the authors (Yan et al., 2018) also identified the dominant mechanism of extreme W at these sites, and found significant regional differences in flood-generating mechanisms across the WUS, e.g., the maritime regime is ROS dominated, and the continental regime is snowmelt dominated. The authors (Yan et al., 2019b) confirmed that this regional variability is associated with climate variability across the WUS, which includes air temperature, solar radiation, and atmospheric humidity. In the maritime regime that features high humidity, latent energy can warm the falling precipitation through condensation, leading to more frequent ROS events (Harpold and Brooks, 2018). In the continental regime that features high elevations, the late onset of above-freezing temperatures results in snowmelt in late spring, leading to high solar radiation (high solar angles) and large snowmelt events (Musselman et al., 2017).

PHYSICS-BASED HYDROLOGIC MODELING: EXTENDING AND VALIDATING NG-IDF CURVES

The inclusion of snow processes in hydrologic design vastly increases the complexity of the problem over the PREC-IDF approach. Canopy interception and release of snowfall is significantly more complicated than for rainfall. The SNOTEL observations are limited in space and time and only available for the open condition. In this regard, Hamlet (2018) and the authors (Yan et al., 2020) advocated a need for well-validated physics-based model simulations to extend snow data in space, time, and for different land covers to provide comprehensive NG-IDF products that can be adapted to the standard IDF design workflow. A well-validated model is also critical for validating the NG-IDF approach in design flood estimates because streamflow in snow-dominated regions is poorly observed due to inherent difficulties of access (Lundquist et al., 2016).

To extend NG-IDF curves for different land covers beyond the bare ground of SNOTELs, the authors (Sun et al., 2018) enhanced the capability for modeling complex snow-canopy interactions within the framework of the Distributed Hydrology Soil Vegetation Model (DHSVM) (Wigmosta et al., 1994, 2002). In an extensive review of 30 hydrologic models, Beckers et al. (2009) showed that DHSVM is the best for hydrologic modeling in forest environments because of the detailed process representation of topographic and canopy control of the energy and mass exchange in a spatially distributed manner. The authors (Sun et al., 2018) enhanced DHSVM capability in featuring a subgrid representation of snow-canopy dynamics in canopy gaps by explicitly accounting for the impact of the surrounding canopy on the gap energy balance and generating spatially varied irradiance. The enhanced model was validated at the University of Idaho Experimental Forest and showed good agreement with subhourly *SWE* observations at open, dense canopy, and canopy gap sites, e.g., correlation of determinations (R^2) were >0.9. This validated model lays the foundation for developing NG-IDF curves in complex land cover conditions (e.g., consistent with TR-55 land cover classification).

To extend NG-IDF curves in time and space beyond the limited coverage of the SNOTEL data, the authors (Sun et al., 2019) developed and validated regionally coherent DHSVM snow parameters. By using the BCQC SNOTEL data at 246 sites over the WUS, the authors (Sun et al., 2019) performed a generalized sensitivity test for the DHSVM snow model and identified sensitive snow parameters that control daily *SWE* evolution under diverse climate regimes. Regional parameters were then developed for these sensitive snow parameters for eight ecoregions (CEC, 2009) characterized by a distinct hydroclimatic regime across the WUS. The regional snow parameters were evaluated at individual SNOTEL sites and the validation results ensured that regional snow parameters were able to capture daily variations in *SWE* obversions, e.g., the simulation of daily *SWE* had Nash-Sutcliffe efficiency (NSE) >0.8 at 83% of the sites. These regional snow parameters lay the foundation for developing NG-IDF curves at ungauged sites at regional to continental scale.

To validate the NG-IDF approach in design flood estimates, the authors (Yan et al., 2020) developed an experimental hillslope appropriate for mountainous topography to allow direct comparison between the DHSVM continuous simulation and NG-IDF approach. They applied the same experimental hillslope at these 246 SNOTEL sites to examine and compare the performances of the NG-IDF approach across the WUS under various hydroclimate conditions. They used the aforementioned well-validated DHSVM continuous streamflow simulations as a performance benchmark with explicit uncertainty quantification. By comparing the design flood estimates from NG-IDF curves coupled with the TR-55 model and DHSVM streamflow frequency statistics, they suggested that the NG-IDF approach provided a satisfactory performance in design flood estimates in different hydroclimate regimes of the WUS, e.g., the averaged error over the WUS in design flood estimates was <15%. This validation study facilitates NG-IDF technology transfer and implementation practice.

NONSTATIONARY NG-IDF CURVES UNDER CLIMATE CHANGE

Instead of focusing on changes in extreme precipitation only, nonstationary NG-IDF curves further require an understanding of changes in extreme snowmelt and ROS events. Global warming will lead to a shift in rain-snow ratio and increase soil freeze-thaw cycles, resulting in more frequent ROS events and higher flood risk at higher elevations in the future (Beniston and Stoffel, 2016; Musselman et al., 2018; Li et al., 2019). Using the BCQC SNOTEL data, the authors (Yan et al., 2019b) examined the changes in snow process and frequency of ROS events over 1979–2017. They found statistically significant trends toward declining and earlier snowmelt over the WUS. Specifically, annual maximum snowmelt decreased by 21% averaged across the snowy regions of the WUS, and the frequency of ROS events increased by 32% averaged in the northwestern U.S. The changes in snowpack and extreme *W* events under future climate can be better understood with the use of climate model projections.

Despite GCMs providing useful information at global and climatic scales, they cannot present some fine-scale weather systems that are critical in the formation of precipitation given their relatively coarse resolution. To make these projections useful in hydrological design, they need to be downscaled to a finer resolution, through either a statistical or dynamical process. Statistical downscaling is computationally efficient but depends upon choices of predictors and suffers from the possible change of predictor-predictand relationship under future climate (Fowler et al., 2007). On the contrary, dynamical downscaling uses regional climate simulation to resolve the atmospheric processes but is computationally intense (Chen et al., 2018). Currently, there are two approaches to develop nonstationary NG-IDF curves: (1) top-down method using GCMs and hydrologic models (Clark et al., 2016; Hou et al., 2019) and (2) statistical modeling with time-varying parameters (Cheng and AghaKouchak, 2014; Ren et al., 2019). The first approach physically simulates both climate and hydrological processes; however, the outcome is subject to a cascade of uncertainties that arise from assumptions in each step of the modeling chain. The second approach is straightforward, yet the extrapolation of parameter trends into the future should be cautious because it is not known when or where the change point may occur.

Figure 1A presents the top-down end-to-end modeling chain that connects emission scenarios to next-generation design tools and **Figures 1B,C** present the associated steps to develop both stationary and nonstationary PREC-IDF and NG-IDF curves. The top-down modeling chain includes eight uncertainty sources: (1) climate change scenario, (2) global model structure, (3) internal climate variability, (4) downscaling method, (5) hydrologic model structure, (6) hydrologic model parameter, (7) statistical model structure, and (8) statistical model parameter. Characterizing and reducing uncertainties remains challenging and requires improving process understanding and increasing computational resources.

Based on the top-down method, the authors (Hou et al., 2019) developed nonstationary NG-IDF curves for two Department of Defense (DoD) mountainous sites: Fort Carson in Colorado and Marine Corps Mountain Warfare Training Center in California. Using the Weather Research and Forecasting (WRF) model (Skamarock et al., 2008) to dynamically downscale phase 5 of the Coupled Model Intercomparison Project (CMIP5) Community Earth System Model (CESM), the authors (Hou et al., 2019) developed nonstationary NG-IDF curves at the two DoD sites through the end of 21 century under the representative concentration pathway RCP4.5 and RCP8.5 scenarios. If NG-IDF curves are used while ignoring climate nonstationarity, the resulting projections showed that the two DoD installations are at risk for underdesign by up to 80% through the end of the century. This result, however, has large uncertainty because it was based on one GCM using one initial condition. Dynamically downscaled ensemble simulation is desired and undergoing in our next study.

DISCUSSION

Currently, a systematic and consistent local surface water design manual is not available for snow-dominated regions of the U.S. The documented "recipe-based" methods vary from the "blind method" of simply using the PREC-IDF curves to the "tuning factor method" of adding a snowmelt factor to the PREC-IDF curves. For example, Snohomish County in Washington State extends from the Puget Sound lowland to the crest of the Cascade Range. Despite Snohomish County's large portion of snow-dominated regions, the Snohomish County Drainage Manual still recommends the use of NOAA PREC-IDF curves for hydrologic design such as wetpool treatment facilities (SCDM, 2016). Chelan County in Washington State, located in the snow-dominated regions of the Eastern Cascade Ranges, follows the turning factor method in the Stormwater Management Manual for Eastern Washington (SMMEW, 2004). Data to support this method, however, are only available for nine sites and are based on several implicit assumptions (e.g., snow will melt during a 72-h ROS). Alternatively, the federal Unified Facilities Criteria (UFC) recommends using PREC-IDF curves for small infrastructure design such as detention pond and using a hydrologic model such as the Storm Water Management Model for large, high-risk design projects (UFC, 2013).

Despite significant efforts that have been made in physics-based climate and hydrologic modeling over the past decades, advances in hydrologic and climate science communities have not been broadly translated into actionable information in engineering communities. One possible reason is that the use of a physics-based, coupled hydrologic and climate model can be cost-prohibitive in the design of local smaller infrastructure, such as highway culverts or residential drainage systems. Another more important reason is the required adherence to local surface water design manuals. Updating design manuals is a complex process that may take years to accomplish. Therefore, technology transfer is critical to bridge the gap and a new science-driven engineering tool that can be adapted to the current standard codes is most likely to be implemented and considered in the following updated design manual.

To provide a consistent IDF design method for both rain-dominated and snow-dominated regions, we proposed the NG-IDF curves that captured multiple flood-generating mechanisms including rainfall, snowmelt, and ROS. The NG-IDF curve is a science-driven engineering product from the collaboration between climate scientists, hydrologists, and civil engineers. Climate scientists used the WRF model to dynamically downscale GCM simulations and understand the atmospheric mechanism of extreme precipitation; hydrologists used DHSVM to simulate snow process and understand dominant mechanisms of extreme water available for runoff and also worked with civil engineers on technology transfer such as adaption to the standard IDF design flow by including snow process into IDF curves (i.e., NG-IDF) and validation sites selection (i.e., the aforementioned two DoD sites).

Looking forward, there is an increasing awareness that hydrologic design under nonstationary climate is a multi-scale problem and requires the linkage across scales, such as linking global-scale atmospheric circulation to regional-sale water flux, linking watershed-scale hydrological processes to design-scale flood response (**Figure 2A**). This process-oriented hydrologic design will require a shift in thinking from a purely statistical inference problem to a broader understanding of physical flood-generating mechanisms at both watershed and synoptic scales

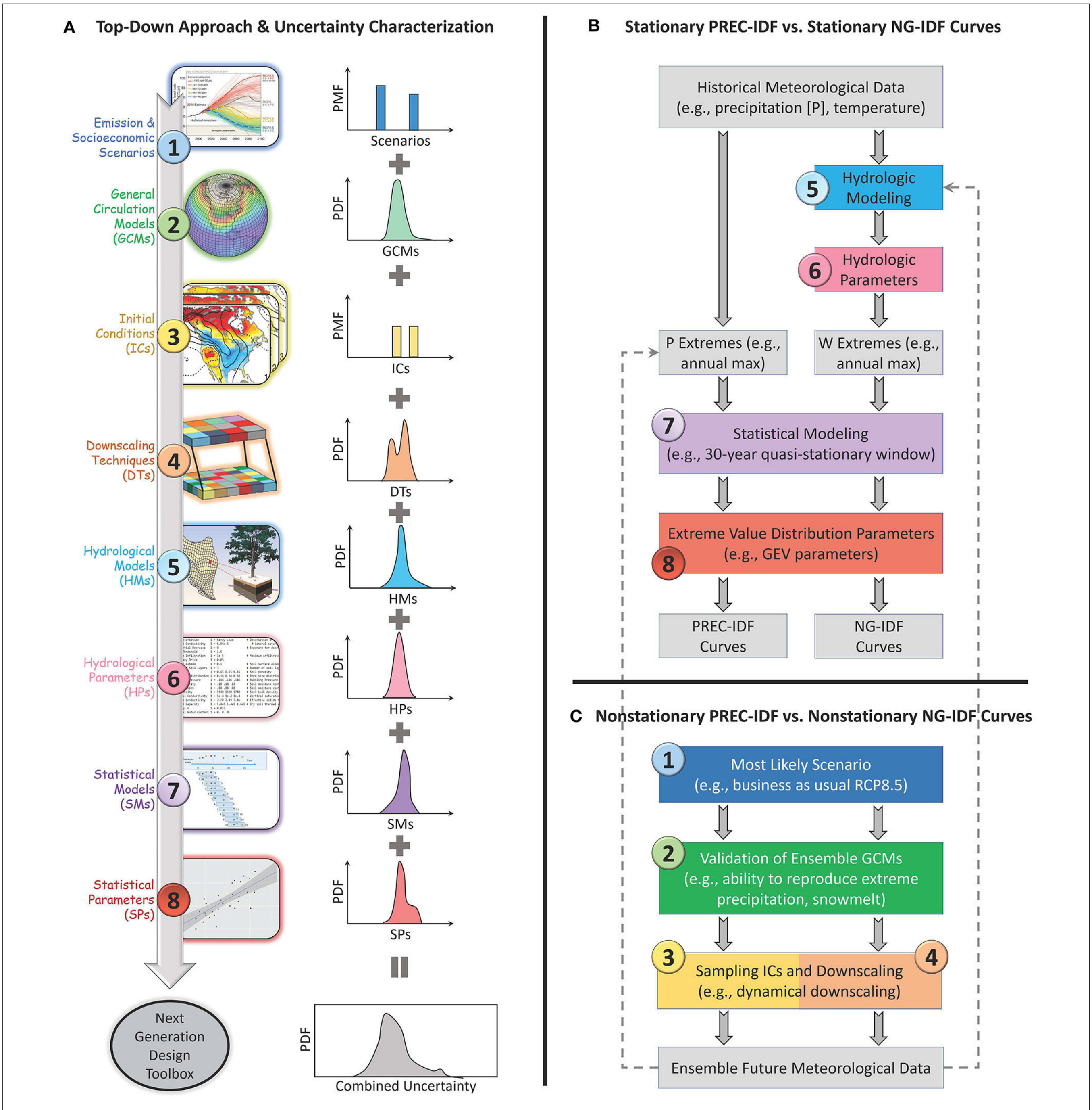

FIGURE 1 | (A) Top-down approach to develop nonstationary next-generation hydrologic design toolbox. To make the projection actionable to engineers, deliberate approaches are necessary to characterize and reduce uncertainties in each step. The final nonstationary design toolbox should be probabilistic (i.e., projections of the most likely, the least, and worst cases) and adapted to the standard risk management design framework. **(B)** Developing stationary PREC-IDF and NG-IDF curves following the top-down approach. **(C)** Developing nonstationary PREC-IDF and NG-IDF curves following the top-down approach.

(Milly et al., 2008; Mailhot and Duchesne, 2010; Arnbjerg-Nielsen et al., 2013; Chester et al., 2020; Cook et al., 2020).

In **Figure 2B**, the authors (Chen et al., 2018) suggested that atmospheric rivers (ARs), a long and narrow band of intense moisture transport, is a key predictor of extreme precipitation occurrence and magnitude in the WUS watersheds. The authors (Chen et al., 2019a) also found out that ARs are the main driver of ROS events and responsible for 11–20% of intense snowmelt

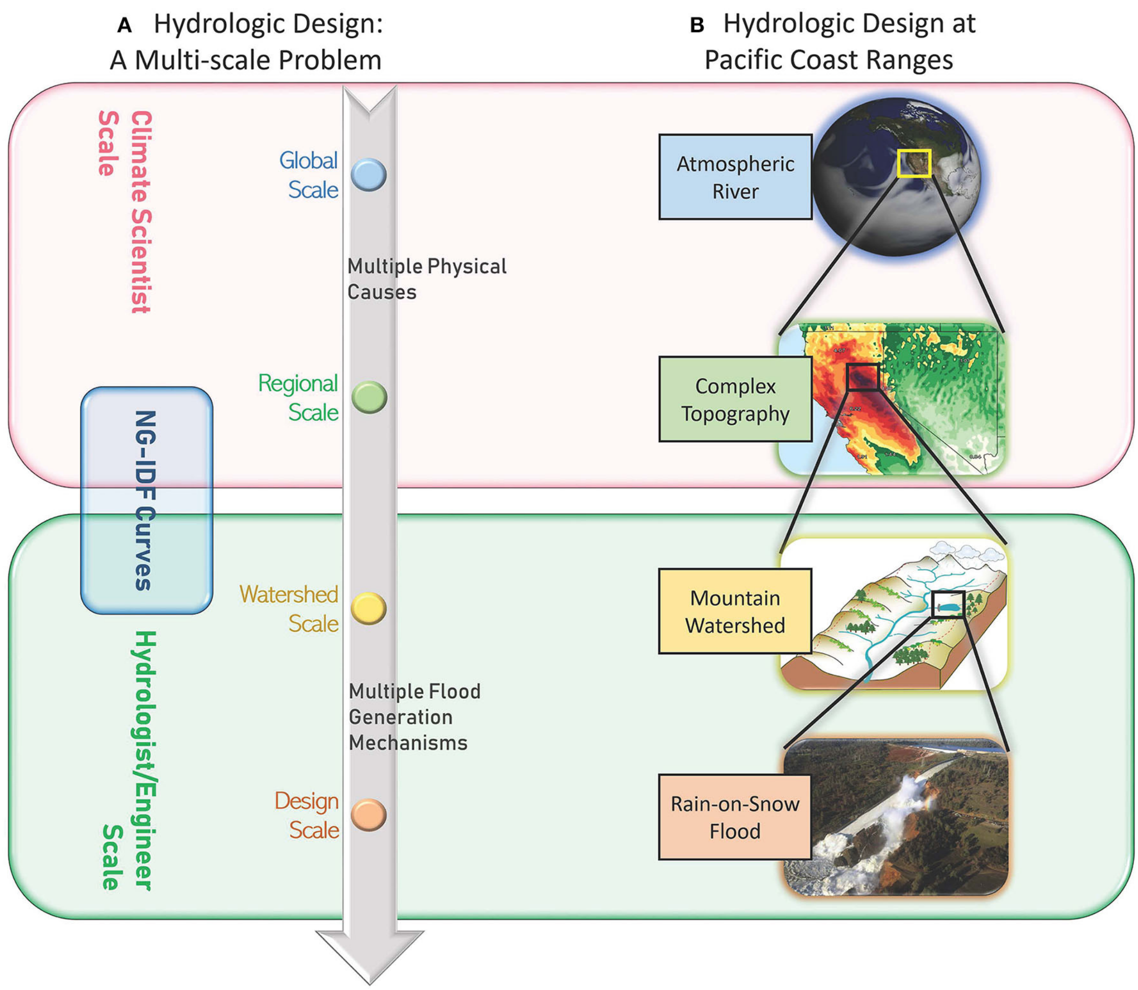

FIGURE 2 | (A) Illustration of hydrologic design under nonstationary climate: a multi-scale problem that links climate scientists, hydrologists, and engineers. **(B)** An example of a flooding event at the Sierra Nevada caused by rain-on-snow at watershed-scale and atmospheric river at global-scale.

events in Pacific Coast Ranges. Further, the authors (Chen et al., 2019b) provided a comprehensive evaluation of land surface energy and hydrologic responses to ARs over the WUS. They identified that strong radiation and warm air temperature during ARs enhanced snow ablation and increased the likelihood and strength of ROS. Therefore, projecting future design floods for Pacific Coast Ranges not only requires a better understanding of extreme precipitation change but also the interacted change of AR storms on snowpack.

DATA AVAILABILITY STATEMENT

The datasets generated for this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://dhsvm.pnnl.gov/.

AUTHOR CONTRIBUTIONS

HY, NS, and XC drafted the manuscript. MW was the Principle Investigator. All authors contributed to the article and approved the submitted version.

FUNDING

This material is based upon work supported by the Strategic Environmental Research and Development Program under Contract No. RC-2546.

ACKNOWLEDGMENTS

Battelle Memorial Institute operates the Pacific Northwest National Laboratory for the U.S. Department of Energy under contract DE-AC06-76RLO-1830.

REFERENCES

Arnbjerg-Nielsen, K., Willems, P., Olsson, J., Beecham, S., Pathirana, A., Bülow Gregersen, I., et al. (2013). Impacts of climate change on rainfall extremes and urban drainage systems: a review. *Water Sci. Technol.* 68, 16–28. doi: 10.2166/wst.2013.251

ASCE (2015). "Adapting infrastructure and civil engineering practice to a changing climate," in: *Technical Report*, ed. J. R. Olsen (Reston, VA: American Society of Civil Engineers; Committee on Adaptation to a Changing Climate). Available online at: https://ascelibrary.org/doi/book/10.1061/9780784479193 (accessed October 10, 2018).

Beckers, J., Smerdon, B., and Wilson, M. (2009). *Review of Hydrologic Models for Forest Management and Climate Change Applications in British Columbia and Alberta*. Kamloops, British Columbia: Forum for Research and Extension in Natural Resources Society.

Beniston, M., and Stoffel, M. (2016). Rain-on-snow events, floods and climate change in the Alps: events may increase with warming up to 4°C and decrease thereafter. *Sci. Total Environ.* 571, 228–236. doi: 10.1016/j.scitotenv.2016.07.146

Bonnin, G. M., Martin, D., Lin, B., Parzybok, T., Yekta, M., and Riley, D. (2011). *Precipitation-Frequency Atlas of the United States, NOAA Atlas 14. vol. 1, version 5.0*. Silver Spring, MD: U.S. Department of Commerce, National Oceanic and Atmospheric Administration.

CEC (2009). *Ecological Regions of North America, Level III*. Corvallis, OR: Commission for Environmental Cooperation.

Chen, X., Duan, Z., Leung, L. R., and Wigmosta, M. (2019a). A framework to delineate precipitation-runoff regimes: precipitation versus snowpack in the Western United States. *Geophys. Res. Lett.* 46, 13044–13053. doi: 10.1029/2019GL085184

Chen, X., Leung, L. R., Gao, Y., Liu, Y., Wigmosta, M., and Richmond, M. (2018). Predictability of extreme precipitation in Western U.S. watersheds based on atmospheric river occurrence, intensity, and duration. *Geophys. Res. Lett.* 45, 11693–11701. doi: 10.1029/2018GL079831

Chen, X., Leung, L. R., Wigmosta, M., and Richmond, M. (2019b). Impact of atmospheric rivers on surface hydrological processes in Western U.S. watersheds. *J. Geophys. Res. Atmos.* 124, 8896–8916. doi: 10.1029/2019JD030468

Cheng, L., and AghaKouchak, A. (2014). Nonstationary precipitation intensity-duration-frequency curves for infrastructure design in a changing climate. *Sci. Rep.* 4:7093. doi: 10.1038/srep07093

Chester, M. V., Underwood, B. S., and Samaras, C. (2020). Keeping infrastructure reliable under climate uncertainty. *Nat. Clim. Chang.* 10, 488–490. doi: 10.1038/s41558-020-0741-0

Chow, V. T., Maidment, D. R., and Mays, L. W. (1988). *Applied Hydrology*. New York, NY: McGraw-Hill.

Clark, M. P., Wilby, R. L., Gutmann, E. D., Vano, J. A., Gangopadhyay, S., Wood, A. W., et al. (2016). Characterizing uncertainty of the hydrologic impacts of climate change. *Curr. Clim. Chang. Rep.* 2, 55–64. doi: 10.1007/s40641-016-0034-x

Cook, L. M., McGinnis, S., and Samaras, C. (2020). The effect of modeling choices on updating intensity-duration-frequency curves and stormwater infrastructure designs for climate change. *Clim. Change* 159, 289–308. doi: 10.1007/s10584-019-02649-6

Cronshey, R., McCuen, R. H., Miller, N., Rawls, W., Robbins, S., and Woodward, D. (1986). *Urban Hydrology for Small Watersheds—TR-55*. Washington, DC: U.S. Department of Agriculture.

England, J. F. Jr., Cohn, T. A., Faber, B. A., Stedinger, J. R., Thomas, W. O. Jr., et al. (2018). *Guidelines for Determining Flood Flow frequency—Bulletin 17C. U.S. Geological Survey Techniques and Methods*, Reston, VA: U.S. Geological Survey.

ESTCP (2018). *Nonstationary Weather Patterns and Extreme Events: Informing Design and Planning for Long-Lived Infrastructure. Project RC-201591*. ESTCP. Available online at: https://www.serdp-estcp.org/News-and-Events/Blog/Nonstationary-Weather-Patterns-and-Extreme-Events-Workshop-Report (accessed April 23, 2018).

Fowler, H. J., Blenkinsop, S., and Tebaldi, C. (2007). Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *Int. J. Climatol.* 27, 1547–1578. doi: 10.1002/joc.1556

Hamlet, A. F. (2018). New observed data sets for the validation of hydrology and land surface models in cold climates. *Water Resour. Res.* 54, 5190–5197. doi: 10.1029/2018WR023123

Harpold, A. A., and Brooks, P. D. (2018). Humidity determines snowpack ablation under a warming climate. *Proc. Natl. Acad. Sci.* 115, 1215–1220. doi: 10.1073/pnas.1716789115

Hershfield, D. M. (1961). *Rainfall Frequency Atlas of the United States for Durations From 30 Minutes to 24 Hours and Return Periods From 1-100 Years*. Washington, DC: Weather Bureau, Department of Commerce.

Hou, Z., Ren, H., Sun, N., Wigmosta, M. S., Liu, Y., Leung, L. R., et al. (2019). Incorporating climate nonstationarity and snowmelt processes in intensity–duration–frequency analyses with case studies in mountainous areas. *J. Hydrometeorol.* 20, 2331–2346. doi: 10.1175/JHM-D-19-0055.1

Kunkel, K. E., Karl, T. R., Squires, M. F., Yin, X., Stegall, S. T., and Easterling, D. R. (2020). Precipitation extremes: trends and relationships with average precipitation and precipitable water in the contiguous United States. *J. Appl. Meteorol. Climatol.* 59, 125–142. doi: 10.1175/JAMC-D-19-0185.1

Li, D., Lettenmaier, D. P., Margulis, S. A., and Andreadis, K. (2019). The role of rain-on-snow in flooding over the conterminous United States. *Water Resour. Res.* 55, 8492–8513. doi: 10.1029/2019WR024950

Lopez-Cantu, T., and Samaras, C. (2018). Temporal and spatial evaluation of stormwater engineering standards reveals risks and priorities across the United States. *Environ. Res. Lett.* 13:074006. doi: 10.1088/1748-9326/aac696

Lundquist, J. D., Roche, J. W., Forrester, H., Moore, C., Keenan, E., Perry, G., et al. (2016). Yosemite hydroclimate network: distributed stream and atmospheric data for the Tuolumne River watershed and surroundings. *Water Resour. Res.* 52, 7478–7489. doi: 10.1002/2016WR019261

Mailhot, A., and Duchesne, S. (2010). Design criteria of urban drainage infrastructures under climate change. *J. Water Resour. Plan. Manag.* 136, 201–208. doi: 10.1061/(ASCE)WR.1943-5452.0000023

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., et al. (2008). Stationarity is dead: whither water management? *Science* 319, 573–574. doi: 10.1126/science.1151915

Musselman, K. N., Clark, M. P., Liu, C., Ikeda, K., and Rasmussen, R. (2017). Slower snowmelt in a warmer world. *Nat. Clim. Chang.* 7, 214–219. doi: 10.1038/nclimate3225

Musselman, K. N., Lehner, F., Ikeda, K., Clark, M. P., Prein, A. F., Liu, C., et al. (2018). Projected increases and shifts in rain-on-snow flood risk over western North America. *Nat. Clim. Chang.* 8, 808–812. doi: 10.1038/s41558-018-0236-4

Prein, A. F., Rasmussen, R. M., Ikeda, K., Liu, C., Clark, M. P., and Holland, G. J. (2017). The future intensification of hourly precipitation extremes. *Nat. Clim. Chang.* 7, 48–52. doi: 10.1038/nclimate3168

Ragno, E., AghaKouchak, A., Love, C. A., Cheng, L., Vahedifard, F., and Lima, C. H. R. (2018). Quantifying changes in future intensity-duration-frequency curves using multimodel ensemble simulations. *Water Resour. Res.* 54, 1751–1764. doi: 10.1002/2017WR021975

Ren, H., Hou, Z. J., Wigmosta, M., Liu, Y., and Leung, L. R. (2019). Impacts of spatial heterogeneity and temporal non-stationarity on intensity-duration-frequency estimates—A case study in a mountainous California-Nevada watershed. *Water* 11:1296. doi: 10.3390/w11061296

SCDM (2016). *Snohomish County Drainage Manual Volume III Hydrologic Analysis and Flow Control BMPs*. Available online at: https://snohomishcountywa.gov/1130/Drainage-Manual (accessed March 5, 2018).

Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Barker, D. M., Duda, M. G., et al. (2008). *A Description of the Advanced Research WRF Version 3 Tech. Rep. NCAR/TN-475+STR*. Boulder, CO: National Center for Atmospheric Research.

SMMEW (2004). *Stormwater Management Manual for Eastern Washington*. Washington State Department of Ecology. Available online at: https://fortress.wa.gov/ecy/publications/documents/0410076.pdf (accessed March 5, 2018).

Sun, N., Wigmosta, M., Zhou, T., Lundquist, J., Dickerson-Lange, S., and Cristea, N. (2018). Evaluating the functionality and streamflow impacts of explicitly modelling forest-snow interactions and canopy gaps in a distributed hydrologic model. *Hydrol. Process.* 32, 2128–2140. doi: 10.1002/hyp.13150

Sun, N., Yan, H., Wigmosta, M. S., Leung, L. R., Skaggs, R., and Hou, Z. (2019). Regional snow parameters estimation for large-domain hydrological applications in the Western United States. *J. Geophys. Res. Atmos.* 124, 5296–5313. doi: 10.1029/2018JD030140

Tohver, I. M., Hamlet, A. F., and Lee, S.-Y. (2014). Impacts of 21st-century climate change on hydrologic extremes in the Pacific Northwest region of North America. *J. Am. Water Resour. Assoc.* 50, 1461–1476. doi: 10.1111/jawr.12199

UFC (2013). *Surface Drainage Design (150/5320-5D)*. Washington, DC: U.S. Department of Transportation, Federal Aviation Administration. Available online at: https://www.faa.gov/documentLibrary/media/Advisory_Circular/150_5320_5d.pdf (accessed August 11, 2017).

Wigmosta, M. S., Nijssen, B., and Storck, P. (2002). "The distributed hydrology soil vegetation model," in *Mathematical Models of Small Watershed Hydrology and Applications*, ed. V. P. Singh (Highlands Ranch, Colorado: Water Resources Publication), 7–42.

Wigmosta, M. S., Vail, L. W., and Lettenmaier, D. P. (1994). A distributed hydrology-vegetation model for complex terrain. *Water Resour. Res.* 30, 1665–1679. doi: 10.1029/94WR00436

Wright, D. B., Bosma, C. D., and Lopez-Cantu, T. (2019). U.S. hydrologic design standards insufficient due to large increases in frequency of rainfall extremes. *Geophys. Res. Lett*. 46, 8144–8153. doi: 10.1029/2019GL083235

Wuebbles, D., Meehl, G., Hayhoe, K., Karl, T. R., Kunkel, K., Santer, B., et al. (2014). CMIP5 climate model analyses: climate extremes in the United States. *Bull. Am. Meteorol. Soc.* 95, 571–583. doi: 10.1175/BAMS-D-12-00172.1

Yan, H., Sun, N., Wigmosta, M., Leung, L. R., Hou, Z., Coleman, A., et al. (2020). Evaluating next-generation intensity–duration–frequency curves for design flood estimates in the snow-dominated western United States. *Hydrol. Process.* 34, 1255–1268. doi: 10.1002/hyp.13673

Yan, H., Sun, N., Wigmosta, M., Skaggs, R., Hou, Z., and Leung, L. R. (2019a). Next-generation intensity–duration–frequency curves to reduce errors in peak flood design. *J. Hydrol. Eng.* 24:04019020. doi: 10.1061/(ASCE)HE.1943-5584.0001799

Yan, H., Sun, N., Wigmosta, M., Skaggs, R., Hou, Z., and Leung, R. (2018). Next-generation intensity-duration-frequency curves for hydrologic design in snow-dominated environments. *Water Resour. Res.* 54, 1093–1108. doi: 10.1002/2017WR021290

Yan, H., Sun, N., Wigmosta, M., Skaggs, R., Leung, L. R., Coleman, A., et al. (2019b). Observed spatiotemporal changes in the mechanisms of extreme water available for runoff in the Western United States. *Geophys. Res. Lett.* 46, 767–775. doi: 10.1029/2018GL080260

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Water

POLICY AND PRACTICE REVIEWS
published: 22 January 2021
doi: 10.3389/frwa.2020.544141

Evidence-Driven Approach for Assessing Social Vulnerability and Equality During Extreme Climatic Events

Ram A. Barankin[1]*, Michelle E. Portman[2], Paul Kirshen[1] and Robert E. Bowen[1]

[1] School for the Environment, University of Massachusetts Boston, Boston, MA, United States, [2] Faculty of Architecture and Town Planning, Technion - Israel Institute of Technology, Haifa, Israel

Climate change adaptation policy requires assessing a community's vulnerability based on its socio-economic characteristics. A predominant approach to vulnerability assessment is indicator-based, wherein variables are aggregated to assess the vulnerability of units in a system (e.g., neighborhoods in a city). Here we show that a particular evidence-based predictive statistics approach can address two shortcomings of the most commonly-used indicator-based approach: lack of a means of validation and problematic weighting of individual indicators. We demonstrate how robust evidence-based models can produce frameworks that overcome these limitations. Using the case study of Hurricane Sandy in the State of New Jersey, we conducted two-pronged validated vulnerability assessments, based on insurance claim payouts and assistance grants. The latter *needs-based* assessment shows that "Minorities" are substantially more vulnerable than others based on a significant negative association with assistance *approval rate* (approved claims divided by all claims). Our findings highlight issues discussed in the literature within the context of climate justice and equity. Such an approach is helpful locally, but also when adaptation plans are developed over broad scales of time and space considering disparities between regions or across multiple jurisdictions.

Keywords: climate change, social vulnerability assessment, social vulnerability, indicator-based assessment, climate adaptation, climate policy

Edited by:
Abhishek Gaur,
National Research Council Canada (NRC-CNRC), Canada

Reviewed by:
Sepideh Yazdekhasti,
Xylem, United States
Auroop Ratan Ganguly,
Northeastern University, United States

****Correspondence:***
Ram A. Barankin
ram.barankin@gmail.com

Specialty section:
This article was submitted to Water and Built Environment, a section of the journal Frontiers in Water

Received: *19 March 2020*
Accepted: *10 December 2020*
Published: *22 January 2021*

Citation:
Barankin RA, Portman ME, Kirshen P and Bowen RE (2021) Evidence-Driven Approach for Assessing Social Vulnerability and Equality During Extreme Climatic Events. Front. Water 2:544141. doi: 10.3389/frwa.2020.544141

BACKGROUND

Climate change is one of the most pressing issues of our time, one that puts many communities at risk from multiple types of catastrophic hazards (O'Neill et al., 2017). For example, sea level rise puts coastal communities at risk, especially when combined with intensive storms and high tides, which create storm surge and flooding (Walsh et al., 2016). Mitigating these risks requires new and proven ways of adaptation planning.

There are several challenges inherent to the adaptation planning process that require significant improvement, including dealing with uncertainties in climatic system forecasting (Nicholls and Cazenave, 2010; Walsh et al., 2016) while incorporating physical, ecological, and socio-economic aspects of human activities within coastal zones (Nicholls et al., 2015; Shao et al., 2017). Socio-economic aspects of adaptation planning involve consideration of social vulnerability and environmental justice issues related to climate change; both need to be addressed for efficient adaptation planning (Kim et al., 2018; van den Berg and Keenan, 2019). Despite its urgency, the practicalities of assessing the *vulnerability* of human communities and populations, which lays the foundation for designing adaptation plans and for allocating the resources necessary to make plans a reality, need further investigation.

A commonly used vulnerability assessment approach uses indicators (hereafter "indicator-based assessment") (Zhang et al., 2018). This approach has been widely implemented by governments as part of adaptation policy efforts (e.g., Rowan et al., 2013; Boston, 2016). In the social vulnerability domain, using socio-economic variables (social indicators), such as age, race, and income, the predominant indicator-based *vulnerability* assessment should enable the prediction of the susceptibility of communities to the negative effects of climate-driven events, whether they be physical, financial, or psychological (Benevolenza and DeRigne, 2019). However, such assessments are based largely on theoretical assumptions of what is perceived to reflect vulnerability and therefore are less accurate than they would be if they were based on empirical findings.

Evidence-based approaches to vulnerability assessment could supplement and improve the standard "indicator-based" approach and thus lead to better allocation of resources for adaptation. Here we show that an evidence-based predictive statistics approach, often claimed infeasible in the past (Hinkel, 2011), can indeed be used as a possible solution for two shortcomings of the most commonly-used indicator-based approach: (1) the lack of a means of validation, and (2) problematic weighting (Tonmoy et al., 2014; Nguyen et al., 2016).

Due to the availability of large quantities of socio-economic data to choose from as indicators (e.g., as a result of increased data from national census programs), it is a common practice to remove correlating indicators, or to perform some type of dimension reduction statistical technique. The most common of these methods is the Principal Component Analysis (PCA). As a case in point, one of the most influential works in the field of indicator-based vulnerability assessments introduced the PCA-based social vulnerability index over a decade and a half ago and trademarked SoVi (R)—the Social Vulnerability Index.

Methods, such as PCA, minimize redundancy, and produce a lower and more manageable number of indicators (alias, "components" in PCA) for the assessment. While the PCA approach is sometimes mistaken to be a predictive data-driven approach, in practice it only analyzes variability in the explanatory dataset while offering no evaluation of its predictive power. Like other works over the years, the original introduction of the social vulnerability index approach explicitly acknowledged the problematic nature of indicator equal-weights practices back in 2003 (Cutter et al., 2003). Now, with new types of information and with the relative abundance and accessibility of big data, previously unforeseen research opportunities have become available and can be used to remedy this situation.

We propose validation of common theoretical assumptions by utilizing harm indicators, i.e., harm experienced by subjects during a climate-related event (e.g., heat waves or hurricanes), in robust predictive statistical models. PCA and other dimension reduction techniques are an important first step in analyses that utilize an initially large number of variables (especially correlating variables), however, these unsupervised approaches (i.e., for which there is no outcome/dependent variable) only analyze the explanatory data (social indicators in this case). They do not analyze how these social indicators come into play in real events which can themselves be analyzed by using a supervised predictive approach, i.e., ones that use an outcome variable.

Predictive supervised statistical models (as opposed to, for example, the unsupervised PCA) tell us whether certain vulnerability indicators are appropriate for predicting *de facto* vulnerability, always measured based on harm indicators. Furthermore, the results of such predictive models denote the relative importance of each vulnerability indicator and thus can help in (a) deciding on the final set of indicators to include in the assessment (e.g., that are the social indicators shown to be significant in predicting the outcome), and (b) assigning different weights to each indicator in that set.

Such ideas have been addressed in the literature in the past (see Discussion), however, indicator-based vulnerability assessments in general and particularly indicator-based social vulnerability assessments, have rarely used a predictive approach based on empirical observation of outcomes (i.e., harm indicators). Furthermore, they usually employ equal-weighted aggregation, wherein indicators are considered equally important without justification (Tonmoy et al., 2014; Nguyen et al., 2016). As a result, quantitative vulnerability assessments that are available to policy-makers today are largely not based on real-world experience; they are not sufficiently modified or improved based on recent and actual climate events, and thus they remain limited.

The methodology we present here follows several evidence-based predictive statistics studies while addressing some technical and practical limitations of these studies (see Discussion). We demonstrate, using a case study, how robust predictive statistical analysis can produce a validated evidence-based vulnerability assessment. Our case study is based on the impact of Hurricane Sandy (2012) on the State of New Jersey (NJ), USA. We analyzed the relationship between observed harm as reflected by insurance payout data, FEMA assistance data and using various social indicators while controlling for environmental factors. We hypothesize that certain indicators are significant in predicting harm and that the level of impact varies across indicators.

METHODS

Data and Variables

Harm Indicators (Outcome Variables)

Harm indicators (the outcome/dependent variables) were derived from two main datasets (**Figure 1**). The first, containing data related to insurance payouts after Hurricane Sandy was provided by the NJ Department of Banking and Insurance at the zip code level in NJ (Request Number: C115955). It reflects over four billion US dollars paid to subjects who experienced financial damage as a result of Hurricane Sandy. The second dataset contains information about the Federal Emergency Management Agency's (FEMA) Individual and Housing Assistance Program

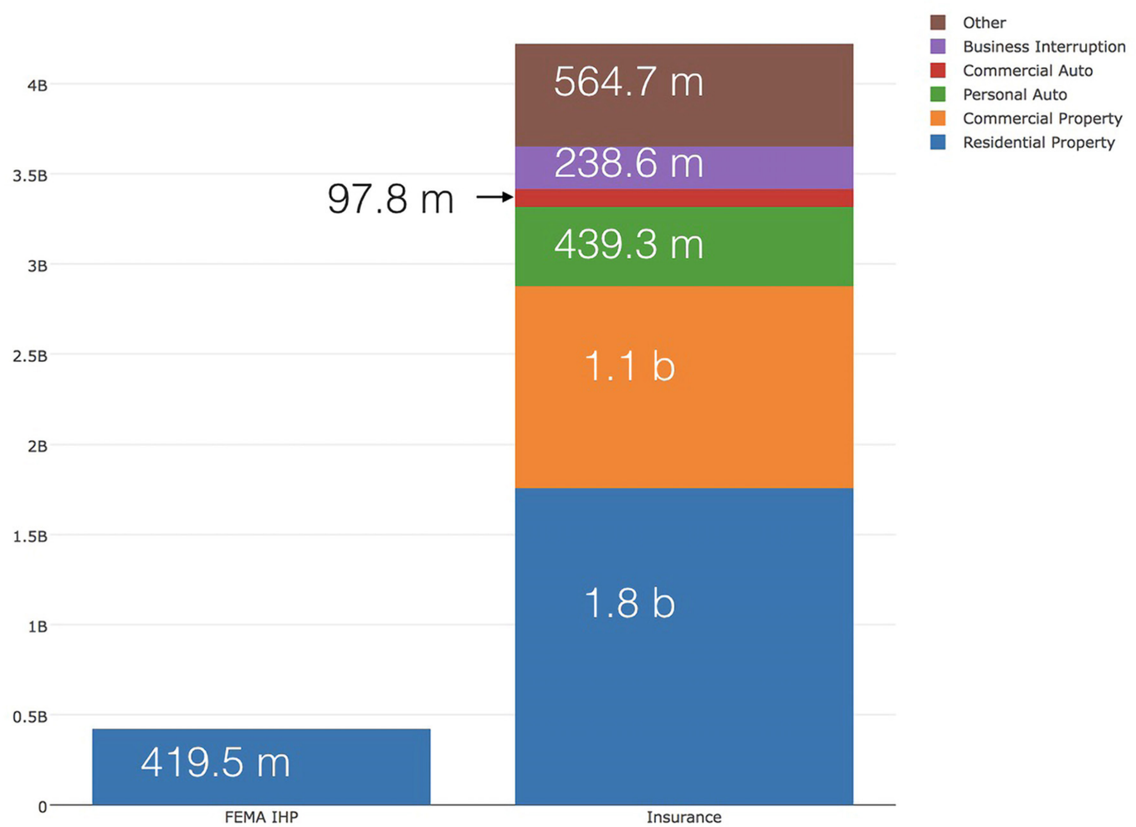

FIGURE 1 | Datasets used in the study to derive harm indicators (US $).

(IHP) of over 400 million US Dollars during Hurricane Sandy (hereinafter: "FEMA assistance" or "government assistance") which is also available at the zip code level (FEMA, 2014).

IHP provides assistance to those who had necessary expenses and significant needs, and only if they are unable to meet those needs through other means. It provides temporary housing assistance as well as other grant money that assists in activities, such as the replacement of lost furniture and clothing (Lindsay, 2017). Some typos were identified in the FEMA dataset's zip code numbers (invalid numbers or numbers outside the relevant states) and were subsequently removed from the database before it was used in the analysis.

Social Indicators (Explanatory Variables)

Initially, 15 social indicators (explanatory variables) were considered (see **Table 1**). These were consistent with the literature and were obtained from the US Census Bureau's American Community Survey (ACS) aggregated for the years of 2008–2012. Since Hurricane Sandy occurred toward the end of 2012, it was assumed that the majority of samples are relevant for the pre-event conditions as required for the analysis.

Exposure Indicators (Explanatory/Control Variables)

Three exposure indicators were used: distance from the storm track, maximum wind speed, and flood extent, as presented in **Figure 2** (see **Supplementary Material** for additional information).

Spatial Resolution

The availability of data at the zip code level offers a sufficient number of observations (a sample size of 516–583 areas) at a relatively fine geospatial resolution for implementing predictive statistical modeling. Consequently, the association between socio-economic characteristics (indicators) of different communities (based on zip codes) and observed harm (insurance payouts and FEMA assistance) could be empirically explored.

Statistical Methodologies

General

Harm indicators derived from the two aforementioned datasets (insurance and FEMA assistance) were used as dependent (outcome) variables in various predictive statistical models in order to explore socio-economical risk and vulnerability patterns. Three main statistical methodologies were used. First, *Partial Least Squares Regression* (known as PLS or PLSR) was implemented for selecting the relevant social indicators. PLS is a methodology that performs dimension reduction, like PCA but considering an outcome variable(s) in addition to the explanatory variables. Then, *multivariate linear regression* (hereinafter: "simple regression"), as well as *spatial autoregressive regression* (hereinafter: "spatial regression" or "spatial lag regression") was

TABLE 1 | Social indicators considered in the initial analysis.

Indicator	Date source	Variable type
Per capita income (Income)	ACS B19301_001	Mean
Income over $75 k	ACS B19001_013-017	Ratio of households
Income below poverty (Poverty)	ACS B17017_002	Ratio of households
Household size	ACS B25010_001	Mean
Social security receivers (Social security)	ACS B19055_002	Ratio of households
Unemployment (Unemployed)	ACS HC04_EST_VC24	Ratio of population
Age dependency -under 6 (Under 6)	ACS B23008_002	Ratio of population
Age dependency—over 64 (Over 64)	ACS B11007_002	Ratio of households
Women who had birth (Women had birth)	ACS B13012_002	Ratio of population
Single-parent women (Single Moms)	ACS B11001_006	Ratio of households
High school diploma—age over 25 (Diploma)	ACS B15003_017-025	Ratio of population
International migrants (Migration)	ACS B07201_014	Ratio of population
Minorities African American or Hispanic (Minorities)	ACS B02009_001, 003	Ratio of population
Renter occupied housing units (Renters)	ACS B25003_003	Ratio of housing units

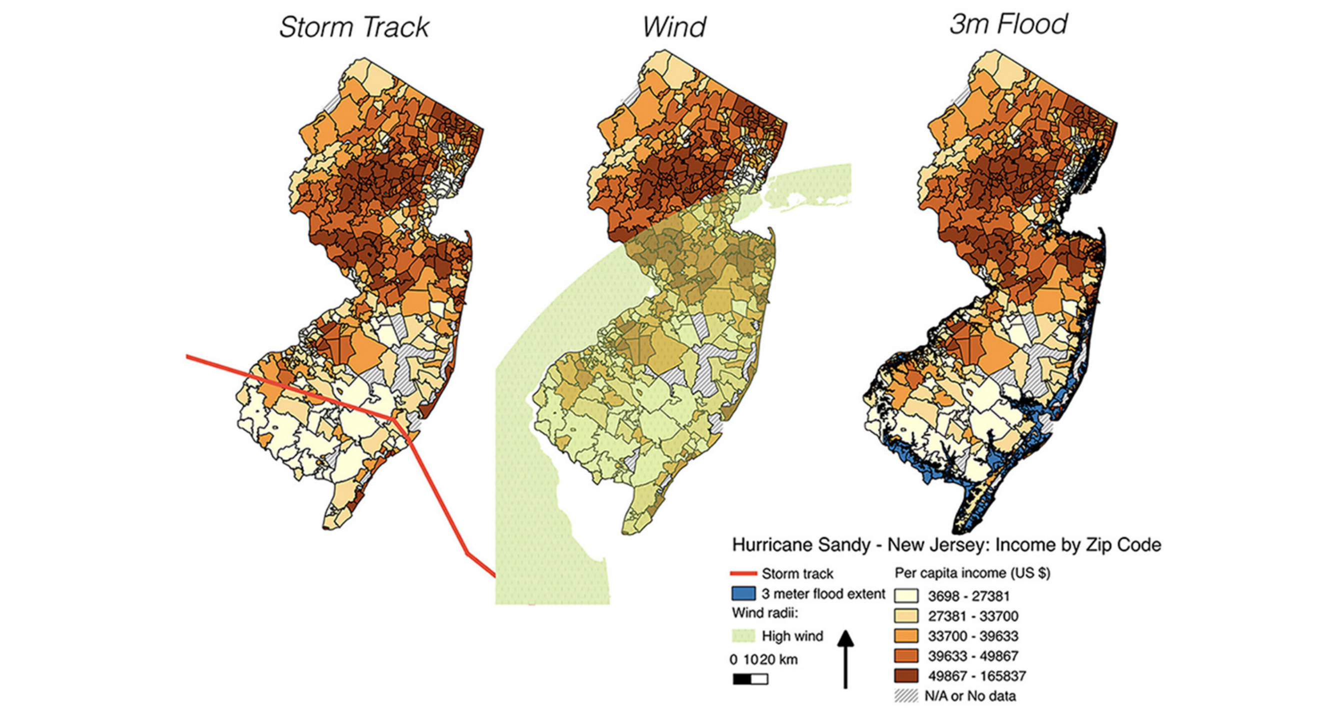

FIGURE 2 | Physical exposure in New Jersey during Hurricane Sandy and income by zip code.

used to explore the relationship between the indicators in the models (i.e., the direction and estimate of coefficients—weight).

Following the results of the statistical models, further analysis was performed to explore potential disparities in *approval rates* (i.e., approved claims divided by number of claims). The models' results were used to create weighted vulnerability indices as described below. Furthermore, the weighted vulnerability index that was based on the FEMA dataset analysis was validated using available data concerning other neighboring states that experienced harm as a result of Hurricane Sandy (New-York, Connecticut, Rhode Island, and Maryland). Notably, the insurance data were only available for NJ and thus could not be validated in a similar manner. The study workflow is presented in **Figure 3**.

PLS: Reducing the Number of Social Indicators

A total of 19 PLS models were created by a combination of various harm indicators and different datasets. The pre-selected social indicators were used as the independent variables among all models.

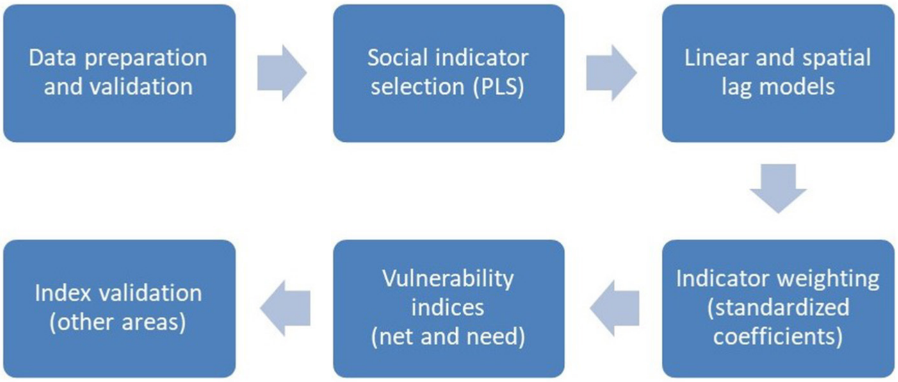

FIGURE 3 | Study workflow.

Seven harm indicators were used as outcome (dependent) variables in the different models:

- Reported claims (the total claims that were reported in the dataset).
- Reported claims per household.
- Approved claims (the total claims that were approved for payment).
- Approved claims per household.
- Approval rate (approved claims divided by the reported claims).
- Total amount paid.
- Total amount paid per household.

Each of these indicators was used in several separated models, using different datasets, as follows:

1. All claims aggregated by zip code.
2. Only FEMA assistance claims.
3. Only private insurance's residential property claims.
4. Private insurance's residential property claims and FEMA assistance claims aggregated.

All variables were log-transformed to fulfill the assumptions of normality and linearity and centered by their means for the PLS analysis. The PLS models' results demonstrated several dominant social indicators that thus were selected to be used in the linear and spatial regression models as discussed below (see **Supplementary Material** for detailed results).

Multivariate Linear Regression: Finding Weights

Linear regression models were used to assess the direction (indicate by plus or minus) and relative weight or importance (thorough standardized coefficients) of the social indicators. The social indicators selected through the PLS analysis were used as the independent (explanatory) variables in the regression models. The three exposure indicators described above were also added to the regression models as independent variables, as well as an additional variable: the number of households. The latter indicator was added in order to control for various sizes of areas captured in a single zip code.

Two outcome (dependent) variables were used in several models: number of approved claims and actual payouts/assistance amounts. These variables were assumed to reflect experienced harm (harm indicators). Approval rate was used in a post-analysis discussed separately below.

The two dependent variables were modeled using four datasets (a total of 8 linear and 8 spatial regression models):

- All aggregated.
- FEMA assistance only.
- Residential—insurance only.
- Private insurance's residential property and FEMA assistance aggregated.

Similar to what was done for the PLS analysis, the socio-economical independent variables and the outcome variables were log-transformed. The exposure indicators were not transformed since two of them are categorical and it was not necessary to transform them to satisfy the regression model assumptions. Furthermore, Variance Inflation Factor (VIF) analysis indicated that multicollinearity did not occur in the model.

Spatial Regression: Correcting for Autocorrelation

The regression models were tested for spatial autocorrelation (*Moran I* test) and their results were compared with the results of the spatial lag regression models. These analyses revealed that spatial autocorrelation was present in all the regular (non-spatial) models.

To solve this problem, we used spatial lag regression models with a log-likelihood function. For the application of this method, spatial weights are assigned to each observation and considered in generalized linear regression models. The weights list is created through two steps. First, a neighbors list is built based on regions with contiguous perimeters that are sharing one or more boundary points. Then the weighting list is created based on the neighbor list, by summing row-standardized values over links among regions. Detailed results and additional details about the methodologies are provided in the **Supplementary Material** section.

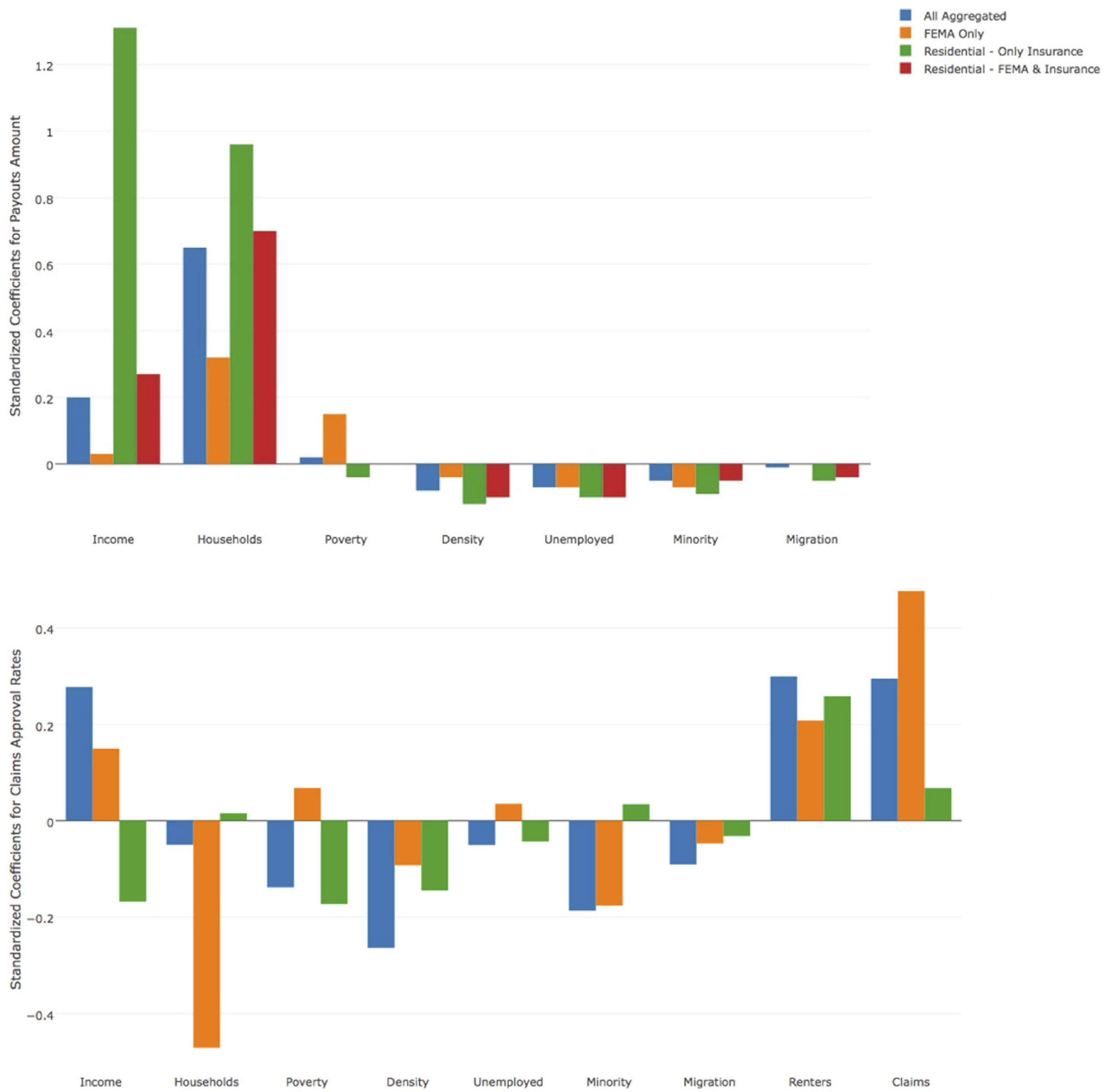

FIGURE 4 | Social indicators' weights according to the predictive model results. These weights were used to create the example vulnerability assessments. Notably, the *minority* indicator had a negative coefficient for *payouts* and a significant negative coefficient for assistance *approval rate*.

RESULTS

General

The results of the main spatial regression models (standardized coefficients) are presented in **Figure 4**, wherein the upper graph represents the *overall payouts* as the dependent variable and the lower graph *approval-rate* as the dependent variable. The main influential social indicators, as selected through PLS, were mean income, density, and rates of poverty, unemployment, minority population, and immigration.

Using these coefficients as aggregation weights (**Table 2**) of the actual values by zip code (modified as discussed below), we demonstrate the creation of two vulnerability assessments (**Figure 5**): *net-value based* (meaning, that the models used the net paid claims) and *need-based* (meaning, that the models used the FEMA assistance paid grants), with the former based on all payouts and the latter using only FEMA assistance data. Beyond their general importance for setting adaptation policy, net-value may be of use to entities such as insurance companies and real-estate organizations for anticipating losses and for planning investments. Need-based vulnerability will likely be most useful for governments and aid organizations seeking to assist communities at high risk.

From the needs-based assessment, it became clear that the variable "Minorities," which had a negative coefficient in the FEMA payouts model, actually reflects a substantially higher vulnerability than others since this indicator also demonstrated a significant negative relationship with approval rate (**Figure 4**, lower graph).

TABLE 2 | Indicator weights for the vulnerability indexes aggregation.

Indicator	Weight
NET-VALUE INDEX	
Income	0.20
Migration	−0.01
Poverty	0.02
Minority	−0.05
Unemployed	−0.07
Density	−0.08
Households	0.65
NEED-BASED INDEX	
Poverty	0.15
Minority	0.07
Households	0.32

Validation

An important part of the study presented here and an aspect that directly addresses one of the two shortcomings of the most commonly used indicator-based approaches mentioned in the introduction of this paper is the facilitation of validation. Thus, as another means of validating the methodology used in our study (and thus the vulnerability indexes we produced), we extrapolated the selected social indicators' weights (**Table 2**, Need-based index) to create a need-based vulnerability index for neighboring states that were also affected by Hurricane Sandy.

We used the need-based vulnerability index for these other states in regression models to investigate the index's predictive power and did the same using the traditional PCA-based equal-weights approach. In the latter, we used the same initial list of indicators, selected a smaller number of indicators according to the result of a PCA model (four factors), and aggregated their values into a single index (using equal weighs). Three spatial regression models were produced, in all of them the dependent variable was FEMA assistance and the explanatory variables were the physical exposure variables along with the newly produced indexes as follows: one using our proposed need-based vulnerability index, one using the PCA equal-weights vulnerability index, and one using both.

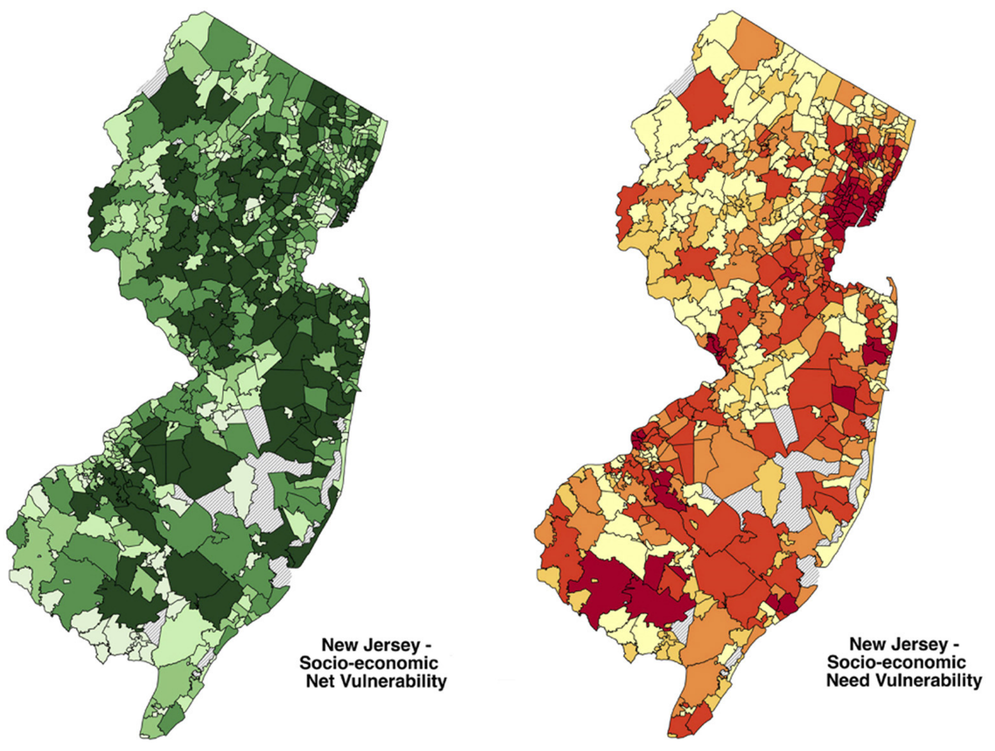

FIGURE 5 | Vulnerability maps: net **(Left)** for net financial terms and need **(Right)** for communities in need of assistance. The darker the shade the higher the vulnerability.

TABLE 3 | Linear regression results.

	Dependent variable:		
	FEMA IHP (log US $)		
	(1) Including the weighted vulnerability index	(2) Including PCA-based index	(3) Including both
Weighted Vulnerability index	1.66*** [0.24]		1.61*** [0.23]
	(0.20)		(0.22)
Regular Vulnerability index (PCA-based)		0.07*** [0.10]	0.01 [0.01]
		(0.02)	(0.02)
Surge level	6.05***	5.97***	6.08***
	(0.31)	(0.33)	(0.32)
Wind Level: High	1.14***	1.36***	1.14***
	(0.15)	(0.15)	(0.15)
Track Distance	−0.87***	−1.33***	−0.88***
	(0.17)	(0.16)	(0.17)
Constant	10.95***	11.99***	10.99***
	(0.37)	(0.36)	(0.37)
Observations	616	614	614
R^2	0.57	0.53	0.57
Adjusted R^2	0.57	0.53	0.57
Residual Std. Error	1.64 (df = 611)	1.71 (df = 609)	1.64 (df = 608)
F Statistic	200.83*** (df = 4; 611)	172.31*** (df = 4; 609)	160.29*** (df = 5; 608)

*[] = Standardized coefficients. *,**,***p < 0.01.*

Subsequently, we found that our proposed method can better predict harm using fewer variables, as shown in **Table 3**. This may signal to researchers and policy-makers that there is higher value in monitoring specific social indicators over others.

DISCUSSION

The shortcomings of the common indicator-based methodological approaches often used to conduct vulnerability assessments, such as lack of validation frameworks and the unjustified equal-weighting approach, have been acknowledged in the literature as described above. Only a few studies have taken on the task of validating the relationship between social indicators and observed climate change-driven impact (harm indicators) using robust predictive statistical models (Tonmoy et al., 2014). Even fewer use the results of such models to modify how vulnerability is assessed (i.e., what weight is given to individual indicators in the assembly of the vulnerability index). However, the grave consequences of lethal climate events recently experienced lead us to contend that these common indicator-based methodological limitations must be addressed and that methods can and should be improved. We demonstrate how robust evidence-based models can produce frameworks that overcome these limitations.

Two explanations for not using studies that are based on evidence and predictive statistics are usually offered. The first explanation highlights the lack of proper data at the required geographic resolution used for analysis (Hinkel, 2011). The second explanation originates in the difficulties related to communicating the results of complex methodologies (Beccari, 2016), an argument which renders simplistic approaches preferable over those that could provide more accurate results.

The few studies that implemented predictive statistical techniques that we reviewed (e.g., Burton, 2010) introduce some statistical shortcomings that may bias results. Particularly methodological issues include: not including environmental/exposure as possible predictors in the model (e.g., Finch et al., 2010; Burton, 2015); lack of transparency or misreporting of model results, such as missing information concerning model results and the preprocessing of the data (e.g., Flanagan et al., 2011); not accounting for geographic dependencies in the data (spatial autocorrelation) (e.g., Myers et al., 2008; Fekete, 2009); reliance on correlation without considerations to causation (e.g., Borden et al., 2007; Finch et al., 2010); use of spatial units that may be too large to reflect socio-economic variability (e.g., Fekete, 2009); use of simulated results (e.g., Schmidtlein et al., 2011) or political decisions as outcome variables (e.g., Borden et al., 2007), both which do not serve as evidence of vulnerability; and other statistical assumption violations.

The first shortcoming mentioned above, which is particularly grave and common, results in a particularly low explanatory power of the model. This leads to biases, especially when performing an analysis based on a single climatic event with its unique physical features. The physical exposure (e.g., flood level) would carry a high explanatory power of the climatic event's consequences. Thus, including exposure in the statistical model allows a better examination of the other factors (socio-economic indicators/variables) that impact vulnerability.

Some limitations of this work are that it used only one case study. It also used similar datasets (though with different variables) for the first (supervised dimension reduction) and second (regression) steps of the study due to relatively small sample size (though with different target variables to overcome this limitation), and it explored only a single statistical approach for variable weighing (standardized coefficients). We therefore recommend additional evidence-based regional vulnerability assessments use data from several hurricane/flooding events and explore possible modifications to the model design by using additional statistical techniques, including those incorporating interactions between variables and standardizing model coefficients differently. Furthermore, we suggest exploring the normalization of indicators within a spatial unit using additional types of data from myriad sources, keeping in mind that the interpretability of models is especially important in such cases for driving adaptation policy.

In any case it is important to point out that a crucial aspect of this study that is seldom performed in other studies in this field is the validation of the proposed vulnerability index using a different geographical area. Other methods of validation can be explored, such as holding off some of the internal units (zip codes in this case) for validation when there is a sufficient sample size.

Perhaps most notable in our analysis results is the negative coefficient associated with the minority indicator for *approval rate* (i.e., successful assistance application rate). This result highlights issues that have been discussed in the literature, particularly within the context of justice and equity when facing the consequences of climate change (Rydin, 2006; Kim et al., 2018). These could be helpful on a local scale, but also when climate change adaptation plans are developed over broader scales of time (i.e., for long-term planning) and space considering disparities between regions or across multiple jurisdictions (Barbier, 2014; van den Berg and Keenan, 2019).

CONCLUSION

Our analysis suggests a strong association between social indicators and observed vulnerability, empirically demonstrating that some indicators are more meaningful than others. Consequently, adaption planning should consider and prioritize the most vulnerable communities, as reflected by the indicators, with consideration to the indicators' weights. Most importantly, this work sets another steppingstone for methodological advancement for the assessment of hurricane-related vulnerability to climate change. Moving consideration of social vulnerability to climatic events forward, and especially with regard to events related to storm surge and flooding, is of vast importance as new data reveals increased risk of damage to extensive areas and the crucial consequences such damage involves, especially among already vulnerable communities (Flavelle et al., 2020).

Researchers, policy-makers, and other climate change adaptation practitioners should promote additional evidence-based predictive statistics approach implementations, thus expanding knowledge for adaptation planning and increasing the likelihood that appropriate and supportive policies for such planning to be put in place. In view of this position, we call on others to build upon, as well as to question, the proposed vulnerability assessment methodology, consequently improving adaptation planning and mitigating harm caused by climate change to communities at risk.

AUTHOR CONTRIBUTIONS

RBa developed and performed the statistical analysis, co-wrote the main article, and wrote the Supplementary material document. MP co-wrote the main article and the parts about environmental justice. PK provided expertise in the parts about adaptation planning. RBe provided expertise on the indicator-based approach. All authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frwa.2020.544141/full#supplementary-material

REFERENCES

Barbier, E. B. (2014). A global strategy for protecting vulnerable coastal populations. *Science* 345, 1250–1251. doi: 10.1126/science.1254629

Beccari, B. (2016). A comparative analysis of disaster risk, vulnerability and resilience composite indicators. *PLoS Curr.* 8. doi: 10.1371/currents.dis.453df025e34b682e9737f95070f9b970

Benevolenza, M. A., and DeRigne, L. (2019). The impact of climate change and natural disasters on vulnerable populations: a systematic review of literature. *J. Hum. Behav. Soc. Environ.* 29, 266–281. doi: 10.1080/10911359.2018.1527739

Borden, K. A., Schmidtlein, M. C., Emrich, C. T., Piegorsch, W. W., and Cutter, S. L. (2007). Vulnerability of US cities to environmental hazards. *J. Homel. Secur. Emerg. Manage.* 4, 1–21. doi: 10.2202/1547-7355.1279

Boston, C. R. (2016). *Climate Ready*. Boston, MA: Final Report.

Burton, C. G. (2010). Social vulnerability and hurricane impact modeling. *Nat. Hazards Rev.* 11, 58–68. doi: 10.1061/(ASCE)1527-6988(2010)11:2(58)

Burton, C. G. (2015). A validation of metrics for community resilience to natural hazards and disasters using the recovery from hurricane katrina as a case study. *Ann. Assoc. Am. Geogr.* 105, 67–86. doi: 10.1080/00045608.2014.960039

Cutter, S. L., Boruff, B. J., and Shirley, W. L. (2003). Social vulnerability to environmental hazards*. *Soc. Sci. Q* 84, 242–261. doi: 10.1111/1540-6237.8402002

Fekete, A. (2009). Validation of a social vulnerability index in context to river-floods in Germany. *Nat. Hazards Earth Syst. Sci.* 9, 393–403. doi: 10.5194/nhess-9-393-2009

FEMA. (2014). *Archived Housing Assistance Program Data.* Available online at: https://www.fema.gov/media-library/assets/documents/30714 (accessed April 28, 2017).

Finch, C., Emrich, C. T., and Cutter, S. L. (2010). Disaster disparities and differential recovery in New Orleans. *Popul. Environ.* 31, 179–202. doi: 10.1007/s11111-009-0099-8

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., and Lewis, B. (2011). A social vulnerability index for disaster management. *J. Homel. Secur. Emerg. Manage.* 8:3. doi: 10.2202/1547-7355.1792

Flavelle, C., Lu, D., Penney, V., Popovich, N., and Schwartz, J. (2020). *New Data Reveals Hidden Flood Risk Across America. The New York Times*. Available online at: https://www.nytimes.com/interactive/2020/06/29/climate/hidden-flood-risk-maps.html (accessed December 18, 2020).

Hinkel, J. (2011). "Indicators of vulnerability and adaptive capacity": towards a clarification of the science–policy interface. *Glob. Environ. Change* 21, 198–208. doi: 10.1016/j.gloenvcha.2010.08.002

Kim, H., Marcouiller, D. W., and Woosnam, K. M. (2018). Rescaling social dynamics in climate change: the implications of cumulative exposure, climate justice, and community resilience. *Geoforum* 96, 129–140. doi: 10.1016/j.geoforum.2018.08.006

Lindsay, B. (2017). *FEMA Disaster Housing: The Individuals and Households Program Implementation and Potential Issues for Congress*. Washington, DC: Congressional Research Service.

Myers, C. A., Slack, T., and Singelmann, J. (2008). Social vulnerability and migration in the wake of disaster: the case of hurricanes katrina and rita. *Popul. Environ.* 29, 271–291. doi: 10.1007/s11111-008-0072-y

Nguyen, T. T., Bonetti, J., Rogers, K., and Woodroffe, C. D. (2016). Indicator-based assessment of climate-change impacts on coasts: a review of concepts, methodological approaches and vulnerability indices. *Ocean Coast. Manage.* 123, 18–43. doi: 10.1016/j.ocecoaman.2015.11.022

Nicholls, R. J., and Cazenave, A. (2010). Sea-level rise and its impact on coastal zones. *Science* 328, 1517–1520. doi: 10.1126/science.1185782

Nicholls, R., Zanuttigh, B., Vanderlinden, J. P., Weisse, R., Silva, R., Hanson, S., et al. (2015). "Developing a holistic approach to assessing and managing coastal flood risk," in *Coastal Risk Management in a Changing Climate* (London: Elsevier), 9–53. doi: 10.1016/B978-0-12-397310-8.00002-6

O'Neill, B. C., Oppenheimer, M., Warren, R., Hallegatte, S., Kopp, R. E., Pörtner, H. O., et al. (2017). IPCC reasons for concern regarding climate change risks. *Nat. Clim. te Change* 7:28. doi: 10.1038/nclimate3179

Rowan, E., Evans, C., Riley-Gilbert, M., Hyman, R., Kafalenos, R., Beucler, B., et al. (2013). Assessing the sensitivity of transportation assets to extreme weather events and climate change. *Transport. Res. Rec.* 5, 16–23. doi: 10.3141/2326-03

Rydin, Y. (2006). Justice and the geography of hurricane katrina. *Geoforum* 37, 4–6. doi: 10.1016/j.geoforum.2005.10.002

Schmidtlein, M. C., Shafer, J. M., Berry, M., and Cutter, S. L. (2011). Modeled earthquake losses and social vulnerability in Charleston, South Carolina. *Appl. Geogr.* 31, 269–281. doi: 10.1016/j.apgeog.2010.06.001

Shao, W., Xian, S., Lin, N., Kunreuther, H., Jackson, N., and Goidel, K. (2017). Understanding the effects of past flood events and perceived and estimated flood risks on individuals' voluntary flood insurance purchase behavior. *Water Res.* 108, 391–400. doi: 10.1016/j.watres.2016.11.021

Tonmoy, F. N., El-Zein, A., and Hinkel, J. (2014). Assessment of vulnerability to climate change using indicators: a meta-analysis of the literature. *Wiley Interdiscip. Rev.* 5, 775–792. doi: 10.1002/wcc.314

van den Berg, H. J., and Keenan, J. M. (2019). Dynamic vulnerability in the pursuit of just adaptation processes: a Boston case study. *Environ. Sci. Policy* 94, 90–100. doi: 10.1016/j.envsci.2018.12.015

Walsh, K. J., McBride, J. L., Klotzbach, P. J., Balachandran, S., Camargo, S. J., Holland, G., et al. (2016). Tropical cyclones and climate change. *Wiley Interdiscip. Rev.* 7, 65–89. doi: 10.1002/wcc.371

Zhang, Q., Xue, H., and Tang, H. (2018). Knowledge domain and emerging trends in vulnerability assessment in the context of climate change: a bibliometric analysis (1991-2017). *KO* 45, 467–483. doi: 10.5771/0943-7444-2018-6-467

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Water

PERSPECTIVE
published: 27 January 2021
doi: 10.3389/frwa.2020.551598

Opportunities and Challenges for Artificial Intelligence Applications in Infrastructure Management During the Anthropocene

Samuel A. Markolf, Mikhail V. Chester and Braden Allenby*

School of Sustainable Engineering and The Built Environment, Arizona State University, Tempe, AZ, United States

Pervasive and accelerating climatic, technological, social, economic, and institutional change dictate that the challenges of the future will likely be vastly different and more complex than they are today. As our infrastructure systems (and their surrounding environment) become increasingly complex and beyond the cognitive understanding of any group of individuals or institutions, artificial intelligence (AI) may offer critical cognitive insights to ensure that systems adapt, services continue to be provided, and needs continue to be met. This paper conceptually links AI to various tasks and leadership capabilities in order to critically examine potential roles that AI can play in the management and implementation of infrastructure systems under growing complexity and uncertainty. Ultimately, various AI techniques appear to be increasingly well-suited to make sense of and operate under both stable (predictable) and chaotic (unpredictable) conditions. The ability to dynamically and continuously shift between stable and chaotic conditions is critical for effectively navigating our complex world. Thus, moving forward, a key adaptation for engineers will be to place increasing emphasis on creating the structural, financial, and knowledge conditions for enabling this type of flexibility in our integrated human-AI-infrastructure systems. Ultimately, as AI systems continue to evolve and become further embedded in our infrastructure systems, we may be implicitly or explicitly releasing control to algorithms. The potential benefits of this arrangement may outweigh the drawbacks. However, it is important to have open and candid discussions about the potential implications of this shift and whether or not those implications are desirable.

Keywords: climate change, infrastructure, artificial intelligence, complexity, anthropocene

OPEN ACCESS

Edited by:
Auroop Ratan Ganguly, Northeastern University, United States

Reviewed by:
Munir Ahmad Nayak, Indian Institute of Technology Indore, India
Abhishek Gaur, National Research Council Canada (NRC-CNRC), Canada

****Correspondence:***
Samuel A. Markolf
smarkolf@asu.edu

Specialty section:
This article was submitted to Water and Built Environment, a section of the journal Frontiers in Water

Received: *14 April 2020*
Accepted: *19 November 2020*
Published: *27 January 2021*

Citation:
Markolf SA, Chester MV and Allenby B (2021) Opportunities and Challenges for Artificial Intelligence Applications in Infrastructure Management During the Anthropocene. Front. Water 2:551598. doi: 10.3389/frwa.2020.551598

INTRODUCTION

If future infrastructure resembles that of the past, or even of today, it will represent a profound failure on the part of engineers and infrastructure managers. Pervasive and accelerating climatic, technological, social, economic, and institutional change signal that the challenges of the future will likely be vastly different and more complex than they are today (Allenby, 2011; Marchant et al., 2011; Markolf et al., 2018). The relationship of the human species to the planet is changing dramatically given a rapidly urbanizing global population of roughly 7.7 billion, and a parallel growing middle class with changing consumption and food demands. These dynamics play a key role in driving and accelerating the integration of human, natural, and built systems to create complex, interlinked, and rapidly evolving systems at all scales—from local infrastructure to regional and global systems (Lo and Yeung, 1998; NRC (US National Research Council)., 2003; Chester et al., 2019).

The need for infrastructure to adapt, transform, and perform competently under conditions of complexity and accelerating change is increasingly being met by integrating infrastructure and information systems [including various artificial intelligence (AI) capabilities] into infrastructure design, construction, operation, and maintenance. However, successfully implementing this strategy requires a clear and concise understanding of relevant information, communication, and computational frameworks, as well as how they functionally couple together in practice—a particularly difficult task in today's environment. Therefore, it is not surprising that the rise of a new global infrastructure with profound implications for humans, their institutions, and their planet has gone both unperceived and unremarked. This is the *cognitive infrastructure*, and it already permeates virtually every aspect of our world (Allenby, 2019). In particular, each infrastructure system and sector has its own companies, experts, investors, and users. But what is often not recognized is that many of these infrastructures and technologies are not only coherent entities themselves, but also being integrated into an emergent infrastructure that includes integrated functionality from many sources: the "cognitive infrastructure."

Taking a functional definition of "cognition" (i.e., information processing, reasoning, remembering, learning, problem-solving, decision-making, etc.) (Squire, 2009), the accelerating rise of cognitive infrastructure becomes evident. For example, machine-to-machine connections are anticipated to increase from 6.1 billion in 2018 to 14.7 billion in 2023 (Cisco, 2020). Similarly, spending on sensors and other technologies related to the Internet-of-Things (IoT) is expected to reach $1.2 Trillion in 2022 (Columbus, 2018). Most of these sensors and devices will generate vast amounts of data and integrate some cognitive capability via accelerating deployment of AI technology such as neural nets (Lee, 2018). In short, accelerating capability and capacity across a number of apparently unrelated infrastructures and technologies is generating an infrastructure, tied together by AI and a vast array of institutional structures, that (1) contains the functional components of cognition and ever-more powerful networks operationally linking them together, (2) is distributed around the world, and (3) contains evolving and emergent systemic and behavioral capabilities. Simply put, we are building a pervasive cognitive infrastructure without fully recognizing it, and we are doing so rapidly and at global scale.

Cognitive infrastructure offers challenges that more traditional infrastructure systems do not. For one, it operates at a level that humans can neither fully understand nor perceive—people are relatively low bandwidth cognitive mechanisms in a world where even contemporary cognitive infrastructure operates at far higher bandwidths, much faster speeds, and higher levels of complexity than individuals can access. This can unfortunately be seen in the tragic Lion Air Flight 610 and Ethiopian Airlines Flight 302 incidents. Although many factors appeared to have been at play, the disconnect between the development of the automated flight control systems in the Boeing 737-MAX planes and the training and implementation by the pilots was a key element in the accidents (Gelles, 2019; Wise, 2019; Herkert et al., 2020; U.S. House Committee on Transportation Infrastructure., 2020). Thus, determining how to effectively integrate human and machine cognition into infrastructure systems becomes a significant professional challenge that, so far, appears to have not been adequately and effectively considered.

Integrating cognitive infrastructure is a critical capability as engineers, technologists, and policymakers try to develop infrastructure systems that are as resilient, agile, and adaptive as current (and future) conditions demand. But knowing that incorporating sensor and AI-driven adaptability into infrastructure can make it more efficient and responsive to changing conditions is only the beginning. Understanding the cognitive infrastructure as a whole is required to fully and responsibly meet the demands for better infrastructure. For example, designers of IoT devices embed sensors and communication capabilities in their products as a matter of required functionality. But, absent a systemic perspective on security and the devices' place within the overarching cognitive infrastructure, there is the potential for underappreciating/misunderstanding issues like the vulnerability to adversarial attacks that the embrace of AI technologies can create. These potential drawbacks are ultimately a symptom of understanding a few of the constituent technologies (e.g., AI) in isolation, but failing to understand that it is the cognitive infrastructure, not just those individual technologies, that their infrastructure design is integrating.

It is premature to consider tantalizing questions such as how humans should respond as critical cognitive functions migrate to higher level techno-human systems embedded in a global cognitive infrastructure. However, it is not premature to recognize that this new infrastructure, itself a reflection and driver of the complexity and challenges of the Anthropocene, is already emergent. Additionally, trying to perceive and understand some of these implications is an increasingly imperative and necessary professional responsibility. Without that first step, ethical, rational, and appropriate infrastructure design, construction, operation, maintenance (as well as the educational and institutional structures to support them) will remain beyond reach. As such, this paper provides a broad discussion about what AI is and how it relates to infrastructure. We then explore various tasks and services within infrastructure systems that may be enhanced and/or replaced by AI. Finally, we conclude with a discussion of some of the broader implications that may emerge as AI and infrastructure systems become increasingly entwined in the coming decades.

AI AND INFRASTRUCTURE LEADERSHIP IN THE CONTEXT OF COMPLEXITY

"AI" is a fuzzy term. As the U. S. National Science and Technology Council says in its 2016 report, "There is no single definition of AI that is universally accepted by practitioners. Some define AI loosely as a computerized system that exhibits behavior that is commonly thought of as requiring intelligence.

Others define AI as a system capable of rationally solving complex problems or taking appropriate actions to achieve its goals in whatever real world circumstances it encounters." Herein, we use "AI" to include big data and analytics dimensions, but ultimately describe the leadership and intelligence capabilities that are needed to replace or augment people. In doing so we envision a future where humans employ AI to make sense of an increasingly complex world.

In managing dynamic and complex systems and environments, several leadership capabilities are needed to address continually changing conditions (Uhl-Bien et al., 2007). *Administrative Leadership*, what we largely practice today, is well-suited for stable conditions and is made up of bureaucracies that formalize the structure and function of organizations. However, in the changing or chaotic conditions that define complex environments, *Adaptive Leadership* is preferred. Under this approach, adaptability, creativity, and learning are emphasized in order to make sense of and navigate complex and uncertain conditions. Perhaps of most importance is *Enabling Leadership*, the ability to shift between *Administrative* and *Adaptive Leadership* practices as conditions shift from stable to chaotic. *Enabling Leadership* involves creating structural, financial, and knowledge conditions for flexibility (Uhl-Bien et al., 2007). In assessing the AI landscape, evaluating which techniques are best positioned to support each leadership style is increasingly useful.

Given this context, there are several tasks for which AI applications in infrastructure are well-suited, including pattern recognition, classification, clustering, categorization, system control, function approximation (e.g., regression analysis), optimization, and prediction/forecasting (Chen et al., 2008; Brynjolfsson and Mcafee, 2017; Eggimann et al., 2017). In order to accomplish these tasks, a variety of techniques and approaches can be applied, such as rule-based systems (RBS), genetic algorithms, cellular automata, Fuzzy Systems, Multi-agent systems, Swarm Intelligence, Case-based reasoning (CBR), and Artificial Neural Networks (ANN) (Chen et al., 2008). For example, AI (particularly genetic algorithms, Artificial Neural Networks, and Deep Learning) has been applied in a variety of civil engineering contexts including optimum design of structures (Hajela and Berke, 1991; Adeli and Park, 1995; Camp et al., 2003; Hadi, 2003), concrete strength modeling (Yeh, 1999; Ni and Wang, 2000; Lee and Ahn, 2003; Al-Salloum et al., 2012), predicting geotechnical settlement and liquefaction (Shahin et al., 2002; Young-Su and Byung-Tak, 2006), earthquake engineering (Lee and Han, 2002; Arslan, 2010; Yilmaz, 2011), concrete design mix (Jayaram et al., 2009), prediction and forecasting of water resources and flooding (Maier and Dandy, 2000; Mitra et al., 2016; Alexander et al., 2018; Lin et al., 2018; Yu et al., 2018; Zamanisabzi et al., 2018; Li et al., 2019), water quality and sediment modeling (Nagy et al., 2002; Zhang et al., 2010; Barzegar et al., 2016; Sabouri et al., 2016), irrigation and water-delivery scheduling (Nixon et al., 2001; Karasekreter et al., 2013), rainfall-runoff modeling (Minns and Hall, 1996; Tokar and Johnson, 1999; Cheng et al., 2005, 2017; Dixon, 2005; Jeong and Kim, 2005; Abrahart and See, 2007; Young et al., 2017), and evapo-transpiration modeling (Tabari et al., 2010; Kumar et al., 2020)—additional examples can also be found in **Figure 1** (e.g., Liu et al., 2016; Mounce et al., 2016; Amanollahi et al., 2017; Beh et al., 2017; Conniff, 2017; Ghalehkhondabi et al., 2017; Matias, 2017; Rezaeianzadeh et al., 2017; Yang et al., 2017; Zhang et al., 2017, 2018; Corominas et al., 2018; Pisa et al., 2019; Rastegaripour et al., 2019; Suh, 2019). The scope and purpose of this article is not to provide a comprehensive overview and discussion of these different techniques. For that, we refer the readers to works by Flood and Kartam, 1994a,b; Kartam et al., 1997; Adeli, 2001; Flood, 2001; Flintsch and Chen, 2004; Chandwani et al., 2013; Ye et al., 2019); and (Falcone et al., 2020). Nonetheless, a brief discussion about the ways in which various AI techniques may (or may not) support infrastructure leadership in stable and chaotic environments appears warranted and is included below.

Some AI techniques may be well-suited for enhancing operations during stable conditions, while others may be more appropriate for supporting leadership during unstable times (e.g., extreme events, funding uncertainty, pandemics, etc.). For example, techniques that establish algorithms to solve novel problems by recalling and referencing similar problems from the past (e.g., CBR) are particularly suitable for the well-defined and stable conditions endemic of *Administrative Leadership*. In this context, these approaches can be particularly useful for applications related to system control, planning, prediction, and diagnosis (Chen et al., 2008). Conversely, techniques that mimic the manner in which human brains process information via a series of layered and interconnected processing units (e.g., ANN) are increasingly well-suited for the complex, data-intensive, multivariable, and dynamic conditions (i.e., instability) that warrant *Adaptive Leadership*. In this context, AI can help make predictions (based on a series of input patterns) and/or intuit relationships between various inputs—even in situations where the underlying rules and structure of the problem may be unknown or hard to express (Chen et al., 2008). Overall, various forms of AI appear poised to greatly complement (or even in some cases replace) *Administrative* and *Adaptive Leadership* activities and roles within our infrastructure systems. In turn, the humans and institutions that interact with and govern our infrastructure systems may play an increasingly important role as the primary source of *Enabling Leadership* within our systems. Thus, it will be crucial for humans and institutions to recognize the benefits and tradeoffs among the different types of leadership, roles, and services provided by various AI. Perhaps most importantly, additional consideration appears warranted regarding the frameworks, resources, structures, and knowledge systems that may be needed to facilitate the smooth and agile transition between leadership approaches as future conditions continually fluctuate between stable and chaotic. The following section explores this issue further by examining some of the various roles and tasks AI may fill in infrastructure systems moving forward.

AI INTELLIGENCES AND TASKS WITHIN INFRASTRUCTURE SYSTEMS

Evaluating the potential for AI to augment or replace existing capabilities requires a critical examination of the intelligences involved. Huang and Rust (2018) assert that AI job replacement fundamentally occurs at the task level, and that "lower" intelligence tasks (e.g., repetitive, routine tasks) are easier for AI to replace than "higher" intelligence tasks (e.g., highly emotional/empathetic tasks). Given that, at their core, infrastructure systems are service providers, we adapt Huang and Rust's framework to (1) link various infrastructure services to the four types of intelligences described by Huang and Rust (i.e., *Mechanical*, *Analytical*, *Intuitive*, and *Empathetic*), and (2) outline cases (and examples where possible) of how AI has and/or could potentially replace various infrastructure-related tasks at each level of intelligence—see **Figure 1**.

Mechanical Intelligence

The "lowest" level of intelligence is *Mechanical*, which is defined by routine and repeated tasks, minimal creativity, and an emphasis on efficiency and consistency (Huang and Rust, 2018). AI at this level are rule-based and are well-suited for homogenous tasks that are repetitive, performed often, and unsophisticated (Sawhney, 2016; Huang and Rust, 2018). As a result, AI at this level often have an advantage over humans with respect to consistency, reliability, and work-rate (Huang and Rust, 2018).

One of the primary challenges associated with *Mechanical* AI is that it can be difficult to scale to the systems level, which in turn can limit its applicability to the large-scale and dynamic infrastructure systems typical of modern cities. *Mechanical* tasks are typically conducted by a single unit (or small, tightly integrated group of components). As a result, this type of AI is best suited for well-bounded and tightly constrained situations. Thus, increasing the network, scale, and/or state of operations adds complexity that can eventually overwhelm the system. Under these circumstances, AI at higher levels of intelligence will likely be more appropriate and effective.

Analytical Intelligence

The second level of intelligence is *Analytical*, which relies on the ability to process information, make decisions, problem solve, and adjust to new information (Huang and Rust, 2018). *Analytical* Intelligence is defined by tasks that can be complex (often data-intensive), yet consistent and predictable. AI at this level use algorithms to iteratively learn and gain insights from large and/or continuous data sets. *Analytical* AI increasingly consist of networked units rather than a stand-alone machine. Human interpretation and intuition are still vital complements to AI at this level. AI provides increasingly varied and valuable decision support, but humans are still the ones ultimately making the decision.

One of the biggest potential challenges with *Analytical* AI is that it is likely not well-suited for problems that do not have similar analogs from the past (Chen et al., 2008). This drawback is particularly important to consider in the context of managing infrastructure systems under a changing climate. Non-stationarity, the concept that past conditions and data are not indicative of future trends and conditions, is increasingly a reality for urban and infrastructure systems (Milly et al., 2008; Koutsoyiannis, 2011; Lins, 2012). Thus, *Analytical* AI should not be treated as an "off-the-shelf" or "plug-and-play" solution for a wide range of problems. Engineers and infrastructure managers should take great care to understand the nuances, strengths, and weaknesses of AI when applying it to infrastructure that has significant interaction with climatic variables (e.g., weather prediction, stormwater systems, flood management systems, etc.).

Intuitive Intelligence

The next level of intelligence is *Intuitive*, which relies on experience-based thinking and creativity. Tasks related to *Intuitive* Intelligence are contextual, chaotic, complex, and idiosyncratic (Huang and Rust, 2018). AI at this level function in a more human-like manner by learning and adapting based on previous experience and new information. Understanding a problem or situation based on context and prior experience is a hallmark characteristic of *Intuitive* Intelligence in both humans and AI.

One potential challenge with *Intuitive* AI is that the problems to which it may be applied are often "wickedly complex" and do not have one "right" solution (e.g., the allocation and management of natural resources) (Chester and Allenby, 2019a). The algorithms supporting this type of AI often learn from human-defined data as to what the outcome should be. Thus, the training of and learning by the AI can be severely inhibited in situations where the outcome/solution is not clear (Meserole, 2018). Under these circumstances, AI can still be very helpful in generating, exploring, and analyzing various scenarios. However, human stakeholders will ultimately be responsible for deciding on the final outcomes or course of action.

Another potential challenge associated with *Intuitive* AI is that there can be a "black-box" element to the analysis and outcomes due to the fact that it provides solutions and insights with minimal knowledge of the underlying systems and processes (Chen et al., 2008). For example, the AI may produce outputs that are non-intuitive and/or fail to converge on a solution, and it may be difficult to ascertain why. Ultimately, some level of this "black box" is likely unavoidable. Presumably, one of the main reasons to deploy *Intuitive* AI is because the system in question is already operating at a scale and/or level of complexity beyond human cognitive capabilities. If total understanding and mastery of system dynamics and complexity (i.e., elimination of the "black box") is achievable, then *Intuitive* AI was likely not needed in the first place. Thus, the critical question is not "how do we eliminate the black-box?," but rather, "what degree of black-box are we comfortable with?" As AI systems continue to evolve and become further embedded in our infrastructure systems, we may be implicitly or explicitly releasing control of our infrastructure systems to software and algorithms. The potential benefits of this arrangement may very well outweigh the drawbacks in certain circumstances. However, it is important for communities, policy-makers, and infrastructure managers to have open and candid discussions about the potential implications of this shift in control and whether or not those implications are desirable.

Empathetic Intelligence

The "highest" level of intelligence is *Empathetic*, which relies on empathy, social interaction, and communication. *Empathetic* tasks relate to the ability to understand emotions, appropriately respond to emotions in others, and influence other's emotions (Huang and Rust, 2018). AI at this level "relates to, arises from, or influences emotions (Picard, 1995)," and behaves as if it has feeling. *Empathetic* AI are still in the nascent stages of development, with initial applications tending to relate to emotional analytics (Abou-Zeid and Ben-Akiva, 2010; Quercia et al., 2014). Nonetheless, the high level of social and communication skills needed for *Empathetic* Intelligence seem to indicate that humans will remain integral at this level for the foreseeable future.

Similar to *Intuitive* AI, aspects of wicked complexity and wicked problems can be especially challenging for *Empathetic* AI. One of the elements of a wickedly complex problem is the presence of a wide degree of norms and values among the various stakeholders within the system. These values/interests may not always be clearly stipulated or coded in anyway. Additionally, they can shift and fluctuate over time. As a result, it is very difficult for the AI to understand the different (and often conflicting) values among the stakeholders, let alone "train" the AI around a centrally agreed upon solution/outcome (Baum, 2020).

Related to the issue above, *Empathetic* AI can be particularly susceptible to various biases. The biases may be implicit or explicit, and can be the result of the individuals who wrote the algorithms or the data from which the algorithm was trained (Tomer, 2019). For example, facial recognition AI has been found to contain racial bias (Grother et al., 2019). It is unlikely that biases can fully be eliminated from *Empathetic* (and other) AI systems. Thus, similar to the "black box" issue, perhaps the best approach is for citizens, decision makers, and AI developers to have open and candid discussions about the appropriate applications of *Empathetic* AI given the potential unintended consequences that may result from these biases.

Figure 1 provides a summary of the key elements of each intelligence, examples from infrastructure systems, and current/potential applications of AI in infrastructure across each level of intelligence.

How Might AI Disrupt Infrastructure Services and Introduce New Capabilities?

Exploration of the four levels of intelligences in the context of infrastructure systems reveals a few key insights. First, it appears that AI (or at least automation) has already been widely implemented for *Mechanical* tasks. Although there is still some potential for AI growth and evolution at this level, it appears that we may have already reached a saturation point, thereby making fundamental transformations less likely. This outcome further underscores the potential for AI to complement and supplement *Administrative Leadership* roles within infrastructure systems. On the other hand, *Analytical* tasks are where AI appears poised to have the largest disruption (at least in the near-to-medium term). As AI capabilities continue to improve (especially due to the combination of ever-increasing data availability, ever-decreasing computing costs, and advancements in techniques like ANNs), *Analytical* tasks (and *Adaptive Leadership* roles) will increasingly be accomplished by AI. Considering that the vast majority of engineering and infrastructure jobs are analytical by nature, the augmentation and/or replacement of *Analytical* tasks by AI is likely to have a fundamental, profound, and transformative impact on infrastructure systems as we know them. Thus, moving forward, a key adaptation for engineers and infrastructure managers will be to strengthen and place increasing emphasis on *Intuitive* and *Empathetic* tasks/intelligences, which in turn should strengthen *Enabling Leadership* capabilities. This is particularly important, because even though humans exhibit much higher levels of *Intuitive* and *Empathetic* Intelligence than AI (and are likely to remain that way for quite a while), there is still room for improvement. Human error is always a concern when operating under both mundane and surprise conditions. Similarly, *Empathetic* Intelligence currently does not appear to be widely incorporated or considered in the development of engineered/infrastructure systems. Thus, in order to most effectively balance the *Mechanical* (i.e., *Administrative Leadership*) and *Analytical* (i.e., *Adaptive Leadership*) advantages of AI with the *Intuitive* and *Empathetic* (i.e., *Enabling Leadership*) advantages of humans, we (humans) will need to continually learn from past mistakes and develop skills to make effective decisions under surprise conditions. Additionally, substantial and continual efforts should be made toward enhancing our ability to incorporate social, emotional, and equity dynamics into engineering/infrastructure planning and implementation.

DISCUSSION AND CONCLUSION

It is useful to consider how AI technologies in infrastructure are likely to create new capabilities that, if leveraged correctly, can help us adapt to the rapidly changing conditions in which infrastructure systems must thrive. As evidence emerges of the accelerating and increasingly uncertain conditions that characterize infrastructure environments (Steffen et al., 2015), design and management must be able to respond to these conditions with agility and flexibility (Chester and Allenby, 2019b; Gilrein et al., 2019). With any new technology, control processes are created to harness and guide the new capabilities toward the goals of the managing institution (Beniger, 1989). For example, the advent of engines and novel processes during the industrial revolution released energy at rates and scales never before seen. In turn, these technological advancements required new institutions and processes to channel this power. Whether AI follows historical patterns of technological control is questionable. AI technologies are fundamentally focused on augmenting and replacing cognition. Cognitive infrastructure that learns and makes decisions for us implies that control may not be fully attainable (like it was for the steam engines in the industrial era). Instead, our control efforts may need to focus on establishing relationships with AI that recognize that cyber-technologies will be guiding us in ways that we may not always fully understand.

AI may be uniquely positioned to help us learn about and navigate increasingly complex environments. In designing knowledge systems, institutions enable sensing and analytical

	Task Description:	Examples from Infrastructure Systems:	AI Capabilities:	AI Applications in Infrastructure Systems:
Mechanical Intelligence	• Routine, repeated tasks • Minimal creativity • Consistency and efficiency are paramount	• System components (e.g., traffic lights, water pumps, etc.) • Traditional thermostats • 'Simple' supply/ demand systems based on time-of-day (e.g., time-of-day scheduling of traffic lights, time-of-day pricing and provision of water) • Fixed schedule airport trams/ people movers	• AI with minimal learning and adapting • Actions are efficient, consistent, and precise • Actions and reactions are repetitive and based on observation	• Simple rule-based controllers (e.g., automated diversion of water through pipe network) • Drones/Robots for infrastructure inspection • Limited (Level 3) vehicle automation (e.g., Smart Circuit Bus in Columbus, OH) • Wastewater treatment control and operation (Zhang et al, 2017; Corominas et al., 2018) • Water quality and pollution control (Liu et al., 2016; Mounce et al., 2016)
Analytical Intelligence	• Process information • Problem-solving • Decision-making • Learn from new information • Data/ information intensive • Tasks can be complex, yet systematic, consistent, and predictable	• Intelligent Transportation Systems (e.g., cameras and loop detectors to alter timing and sequence of traffic lights) • Electricity load management and demand forecasting (e.g., real-time pricing, real-time demand management) • 'Smart' thermostats and irrigation systems • Navigation/ traffic routing (e.g., incorporation of network conditions and travel behavior in system routing)	• AI learn/ adapt systematically based on data • Actions are logical, rational, and rule-based	• Automated maintenance scheduling based on factors such as system age, use, or projected demand • Navigation and traffic management informed by citywide cell-phone data and environmental sensors • 'Highly' (Level 4) autonomous transportation systems • Forecasting of water demand (Yang et al., 2017) • Estimating & controlling water quality (Amanollahi et al., 2017; Pisa et al., 2019) • Predicting precip. /water levels (Rezaeianzadeh et al., 2017)
Intuitive Intelligence	• Experience-based thinking • Creativity/ creative problem solving • Tasks can be complex, chaotic, contextual, idiosyncratic	• Long-term forecasting (e.g., 10-year plans by regional water suppliers and electric utilities) • User and/or system manager improvisation during abnormal/ surprise conditions • Project/ location specific design changes based on local variables & past experiences (e.g., designing a bridge foundation more robust than minimum standards due to potential local extremes)	• AI learn and adapt intuitively based on understanding • AI function in more flexible and 'human-like' manners • Unlikely that that the same mistake is made twice	• Intelligent air traffic control systems • 'Fully' (Level 5) autonomous transportation systems • Automated allocation and dispatch of resources (e.g., dynamic public transportation supply and routing) • Disaster evacuation/ preparedness (e.g., predictive & automated resource diversion) • Water demand forecasting (Ghalehkhondabi et al., 2017) • Optimization and planning of water infrastructure (Beh et al., 2017; Zhang et al, 2018; Rastegaripour et al.,2019)
Empathetic Intelligence	• Recognize/ understand emotions • Respond (appropriately) to other's emotions • Influence other's emotions • Relies on communication, empathy, and social interaction	• Planning based on 'quality of life'/sense of place/ community • Incorporating equity and social justice issues into planning/ implementation • Understanding how people feel about comfort/ safety/ etc. of different infrastructure systems	• AI learn and adapt empathetically based on experience • Decisions/ outputs incorporate emotions • Signified by affective computing, emotion recognition, and highly advanced communication	• Communicating service outages/ quality changes • Automated disaster planning and recovery based on community emotions, needs, and capabilities • AI for negotiating wicked problems across various stakeholders • Social nudges for behavioral change/demand management (Conniff, 2017; Matias, 2017; Suh, 2019; Baum, 2020) • Altering service provision based on emotional analytics/needs (Abou-Zeid & Ben-Akiva, 2010; Quercia et al., 2014)

FIGURE 1 | Summary of the "Four Intelligences," examples from infrastructure systems, and current/potential applications of AI to infrastructure systems across each level of intelligence.

capabilities (coupled with different leadership styles) to operate in both calm and chaotic environments (Miller and Munoz-Erickson, 2018). As our systems, and the environments in which they operate, become increasingly complex and beyond the cognitive understanding of any group of individuals or institutions, AI may offer critical cognitive insights to ensure that systems adapt, services continue to be provided, and needs continue to be met.

The mapping of AI applications to intelligences and leadership roles appears to support the varying approaches needed to address domains of complexity. The Cynefin framework classifies systems as *simple*, *complicated*, *complex*, or *chaotic*, and as we transition from one domain to another, disorder governs (Snowden and Boone, 2007; Chester and Allenby, 2019a). Each domain requires a fundamentally different approach to address challenges. Infrastructure have historically been *complicated* systems and are now increasingly viewed as *complex* (Chester and Allenby, 2019b). A *complicated* system calls for data collection, analyzing and decision-making, while a *complex* system shifts toward probing, testing, and a commitment to adaptability and transformation. The intelligence mapping presented in **Figure 1** provides a useful set of AI applications that can be applied to infrastructure in *complicated* and *complex* environments. The *Mechanical* and *Analytical* Intelligences appear to align well with *complicated* situations where the emergent behaviors of systems are predictable and their environments somewhat stable. The *Intuitive* and *Empathetic* Intelligences appear to align with *complex* systems, where perturbations can result in unpredictable emergent behaviors, and "*satisficing*" is needed to manage wicked problems across technical and social requirements (Chester and Allenby, 2019a). While all intelligences are needed at various times during the operation of a system, the development and deployment of *Intuitive* and *Empathetic* Intelligences (and *Enabling Leadership*) in humans and institutions, as well as the development and deployment of *Administrative* and *Adaptive Leadership* via AI appears necessary to address the growing complexity and non-stationarity of our systems and the environments in which they operate.

Ultimately, we are in the nascent stages of AI development and application to infrastructure systems. The topics in this paper are intended to be an initial discussion of some of the key opportunities and challenges associated with AI in infrastructure systems—especially in the context of the leadership and skills needed to face the complex challenges of the Anthropocene. Avenues for future work that can build on this endeavor include interviews and surveys aimed at gaining a better understanding of infrastructure practitioner's current thoughts and expectations about the possible benefits and downsides of AI. Additionally, it would be beneficial to further explore which level of intelligence appears most appropriate for specific problems/contexts, as well as a more detailed assessment of the specific AI techniques likely to be most effective/appropriate in these circumstances. Finally, in conjunction with (if not prior to) these efforts, open, candid, and iterative discussions are required amongst society writ large to debate what level of cognitive infrastructure we are comfortable with and the level of "control" (or at least perceived control) we are comfortable offloading to cognitive infrastructure. By doing so, engineers and infrastructure users/managers can hopefully ensure that they are striking the right balance between human and AI capabilities required to effectively and equitably navigate our increasingly complex world.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary materials, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

SM: conception of the work, drafting of the work, and revisions. MC: conception of the work, drafting of the work, and review and editing of the work. BA: drafting of the work and review and editing of the work. All authors contributed to the article and approved the submitted version.

FUNDING

This work is supported by multiple U.S. National Science Foundation grants including the Urban Resilience to Extremes Sustainability Research Network (UREx SRN) (Award # SRN-1444755) and Resilience Convergence (Award # GCR-1934933).

REFERENCES

Abou-Zeid, M., and Ben-Akiva, M. (2010). "A model of travel happiness and mode switching," in *Choice Modelling: The State-of-the-art and The State-of-practice,* ed S. Hess (Bingley: Emerald Group Publishing Limited), 289–305. doi: 10.1108/9781849507738-012

Abrahart, R. J., and See, L. M. (2007). Neural network modelling of non-linear hydrological relationships. *Hydrol. Earth Syst. Sci.* 11, 1563–1579. doi: 10.5194/hess-11-1563-2007

Adeli, H. (2001). Neural networks in civil engineering: 1989-2000. *Comp. Aided Civil Infrastruct. Eng.* 16, 126–142. doi: 10.1111/0885-9507.00219

Adeli, H., and Park, H. S. (1995). A neural dynamics model for structural optimization-theory. *Comput. Struct*. 57, 383–390. doi: 10.1016/0045-7949(95)00048-L

Alexander, A., Thampi, S. G., and Chithra, N. R. (2018). Development of hybrid wavelet-ANN model for hourly flood stage forecasting. *ISH J. Hydraulic Eng.* 24, 266–274. doi: 10.1080/09715010.2017.1422192

Allenby, B. R. (2011). *The Theory and Practice of Sustainable Engineering.* Upper Saddle River, NJ: Pearson/Prentice-Hall.

Allenby, B. R. (2019). 5G, AI, and big data: We're building a new cognitive infrastructure and don't even know it. *Bull Atomic Sci.* Available online at: https://thebulletin.org/2019/12/5g-ai-and-big-data-were-building-a-new-cognitive-infrastructure-and-dont-even-know-it/?utm_source=Newsletter&utm_medium=Email&utm_campaign=Newsletter12232019&utm_content=DIsruptiveTechnology_CognitiveInfrastructure_12192019 (accessed December 19, 2019).

Al-Salloum, Y. A., Shah, A. A., Abbas, H., Alsayed, S. H., Almusallam, T. H., and Al-Haddad, M. S. (2012). Prediction of compressive strength of concrete using neural networks. *Comp. Concrete* 10, 197–217. doi: 10.12989/cac.2012.10.2.197

Amanollahi, J., Kaboodvandpour, S., and Majidi, H. (2017). Evaluating the accuracy of ANN and LR models to estimate the water quality in Zarivar International Wetland, Iran. *Nat. Hazards* 85, 1511–1527. doi: 10.1007/s11069-016-2641-1

Arslan, M. H. (2010). An evaluation of effective design parameters on earthquake performance of RC buildings using neural networks. *Eng. Struct*. 32, 1888–1898. doi: 10.1016/j.engstruct.2010.03.010

Barzegar, R., Adamowski, J., and Moghaddam, A. A. (2016). Application of wavelet-artificial intelligence hybrid models for water quality prediction: a case study in Aji-Chay River, Iran. *Stochast. Environ. Res. Risk Assess*. 30, 1797–1819. doi: 10.1007/s00477-016-1213-y

Baum, S.D. (2020). Social choice ethics in artificial intelligence. *AI Soc*. 35, 165–176. doi: 10.1007/s00146-017-0760-1

Beh, E. H. Y., Zheng, F., Dandy, G. C., Maier, H. R., and Kapelan, Z. (2017). Robust optimization of water infrastructure planning under deep uncertainty using metamodels. *Environ. Modell. Softw*. 93, 92–105. doi: 10.1016/j.envsoft.2017.03.013

Beniger, J. R. (1989). *The Control Revolution: Technological and Economic Origins of the Information Society*. Cambridge, Massachusetts: Harvard University Press.

Brynjolfsson, E., and Mcafee, A. (2017). The business of artificial intelligence: what it can and cannot do for your organization. *Harvard Business Review Digital Articles*, 1–20.

Camp, C. V., Pezeshk, S., and Hansson, H. (2003). Flexural design of reinforced concrete frames by genetic algorithm. *J. Struct. Eng.* 129, 105–115. doi: 10.1061/(ASCE)0733-9445(2003)129:1(105)

Chandwani, V., Agrawal, V., and Nagar, R. (2013). Applications of soft computing in civil engineering: a review. *Int. J. Comp. Appl*. 81, 13–20. doi: 10.5120/14047-2210

Chen, S. H., Jakeman, A. J., and Norton, J. P. (2008). Artificial Intelligence techniques: an introduction to their use for modelling environmental systems. *Math. Comput. Simul.* 78, 379–400. doi: 10.1016/j.matcom.2008.01.028

Cheng, C.-T., Wu, X.-Y., and Chau, K. W. (2005). Multiple criteria rainfall-runoff model calibration using a parallel genetic algorithm in a cluster of computers. *Hydrol. Sci. J*. 50:1069. doi: 10.1623/hysj.2005.50.6.1069

Cheng, K. S., Lien, Y. T., Wu, Y. C., and Su, Y. F. (2017). On the criteria of model performance evaluation for real-time flood forecasting. *Stoch. Environ. Res. Risk Assess*. 31, 1123–1146. doi: 10.1007/s00477-016-1322-7

Chester, M. V., and Allenby, B. (2019a). Infrastructure as a wicked complex process. *Elementa* 7:360. doi: 10.1525/elementa.360

Chester, M. V., and Allenby, B. (2019b). Toward adaptive infrastructure: flexibility and agility in a non-stationarity age. *Sustai Resil Infrastruc*. 4, 173–191. doi: 10.1080/23789689.2017.1416846

Chester, M. V., Markolf, S., and Allenby, B. (2019). Infrastructure and the environment in the anthropocene. *J. Ind. Ecol*. 23, 1006–1015. doi: 10.1111/jiec.12848

Cisco. (2020). *Cisco Annual Internet Report (2018–2023)*. Cisco. Available online at: http://grs.cisco.com/grsx/cust/grsCustomerSurvey.html?SurveyCode=4153&ad_id=US-BN-SEC-M-CISCOASECURITYRPT-ENT&KeyCode=000112137

Columbus, L. (2018). *2018 Roundup of Internet of Things Forecasts and Market Estimates*. Forbes. Available online at: https://www.forbes.com/sites/louiscolumbus/2018/12/13/2018-roundup-of-internet-of-things-forecasts-and-market-estimates/#3a269b967d83

Conniff, R. (2017). *Pushy AI Bots Nudge Humans to Change Behavior*. Scientific American. Available online at: https://www.scientificamerican.com/article/pushy-ai-bots-nudge-humans-to-change-behavior/

Corominas, L., Garrido-Baserba, M., Villez, K., Olsson, G., Cortés, U., and Poch, M. (2018). Transforming data into knowledge for improved wastewater treatment operation: a critical review of techniques. *Environ. Modell. Softw*. 106, 89–103. doi: 10.1016/j.envsoft.2017.11.023

Dixon, B. (2005). Applicability of neuro-fuzzy techniques in predicting ground-water vulnerability: a GIS-based sensitivity analysis. *J. Hydrol*. 309, 17–38. doi: 10.1016/j.jhydrol.2004.11.010

Eggimann, S., Mutzner, L., Wani, O., Schneider, M. Y., Spuhler, D., Moy De Vitry, M., et al. (2017). The potential of knowing more: a review of data-driven urban water management. *Environ. Sci. Technol*. 51, 2538–2553. doi: 10.1021/acs.est.6b04267

Falcone, R., Lima, C., and Martinelli, E. (2020). Soft computing techniques in structural and earthquake engineering: a literature review. *Eng. Struct. 207*:110269. doi: 10.1016/j.engstruct.2020.110269

Flintsch, G. W., and Chen, C. (2004). Soft computing applications in infrastructure management. *J. Infrastruct. Syst*. 10, 157–166. doi: 10.1061/(asce)1076-0342(2004)10:4(157)

Flood, I. (2001). Neural networks in civil engineering: a review," in *Civil and Structural Engineering Computing: 2001*, ed B. H. Topping (Kippen: Saxe-Coburg Publications), 185–209.

Flood, I., and Kartam, N. (1994a). Neural networks in civil engineering I: principles and understanding. *J. Comp. Civil Eng*. 8, 131–148. doi: 10.1061/(ASCE)0887-3801(1994)8:2(131)

Flood, I., and Kartam, N. (1994b). Neural networks in civil engineering II: systems and application. *J. Comp. Civil Eng.* 8, 149–162. doi: 10.1061/(ASCE)0887-3801(1994)8:2(149)

Gelles, D. (2019). *Boeing 737 Max: What's Happened After the 2 Deadly Crashes*. The New York Times. Available online at: https://www.nytimes.com/interactive/2019/business/boeing-737-crashes.html

Ghalehkhondabi, I., Ardjmand, E., Young, W. A., and Weckman, G. R. (2017). Water demand forecasting: review of soft computing methods. *Environ. Monit. Assess*. 189:313. doi: 10.1007/s10661-017-6030-3

Gilrein, E. J., Carvalhaes, T. M., Markolf, S. A., Chester, M. V., Allenby, B. R., and Garcia, M. (2019). Concepts and practices for transforming infrastructure from rigid to adaptable. *Sustain. Resilient Infrastruct*. 1–22. doi: 10.1080/23789689.2019.1599608

Grother, P., Ngan, M., and Hanaoka, K. (2019). *Face Recognition Vendor Test (FRVT) Part 3: Demographic Effects*. doi: 10.6028/NIST.IR.8280

Hadi, M. N. S. (2003). Neural networks applications in concrete structures. *Comp. Struct*. 81, 373–381. doi: 10.1016/S0045-7949(02)00451-0

Hajela, P., and Berke, L. (1991). Neurobiological computational models in structural analysis and design. *Comp. Struct*. 41, 657–667. doi: 10.1016/0045-7949(91)90178-O

Herkert, J., Borenstein, J., and Miller, K. (2020). The Boeing 737 MAX: Lessons for Engineering Ethics. *Sci Eng Ethics*. 0123456789. doi: 10.1007/s11948-020-00252-y

Huang, M. H., and Rust, R. T. (2018). Artificial intelligence in service. *J. Serv. Res*. 21, 155–172. doi: 10.1177/1094670517752459

Jayaram, M. A., Nataraja, M. C., and Ravikumar, C. N. (2009). Elitist genetic algorithm models: optimization of high performance concrete mixes. *Mater. Manufact. Process*. 24, 225–229. doi: 10.1080/10426910802612387

Jeong, D. I. L., and Kim, Y. O. (2005). Rainfall-runoff models using artificial neural networks for ensemble streamflow prediction. *Hydrol. Process*. 19, 3819–3835. doi: 10.1002/hyp.5983

Karasekreter, N., Basciftci, F., and Fidan, U. (2013). A new suggestion for an irrigation schedule with an artificial neural network. *J. Exp. Theoret. Artif. Intell*. 25, 93–104. doi: 10.1080/0952813X.2012.680071

Kartam, N., Flood, I., and Garrett, J. H. (eds.). (1997). *Artificial Neural Networks for Civil Engineers: Fundamentals and Applications*. New York, NY: American Society of Civil Engineers.

Koutsoyiannis, D. (2011). Hurst-kolmogorov dynamics and uncertainty. *J. Am. Water Res. Assoc*. 47, 481–495. doi: 10.1111/j.1752-1688.2011.00543.x

Kumar, M., Raghuwanshi, N. S., Singh, R., Wallender, W. W., and Pruitt, W. O. (2020). Estimating of evapotranspiration using artificial neural network. *J. Irrigat. Drainage Eng*. 37, 81–94. doi: 10.21608/mjae.2020.94971

Lee, C., and Ahn, J. (2003). Flexural design of reinforced concrete frames by genetic algorithm. *J. Struct. Eng*. 129, 762–774. doi: 10.1061/(asce)0733-9445(2003)129:6(762)

Lee, K. (2018). *AI Superpowers: China, Silicon Valley, and the New World Order*. Harcourt, Boston, MI: *Houghton Mifflin*.

Lee, S. C., and Han, S. W. (2002). Neural-network-based models for generating artificial earthquakes and response spectra. *Comp. Struct*. 80, 1627–1638. doi: 10.1016/S0045-7949(02)00112-8

Li, S., Kazemi, H., and Rockaway, T. D. (2019). Performance assessment of stormwater GI practices using artificial neural networks. *Sci. Total Environ*. 651, 2811–2819. doi: 10.1016/j.scitotenv.2018.10.155

Lin, J., Kandra, H., Choudhury, T. A., and Barton, A. (2018). "Prediction of clogging in stormwater filters using artificial neural network," in *IEEE International Symposium on Industrial Electronics* (Cairns, QLD). 771–776.

Lins, H. F. (2012). *A Note on Stationarity and Nonstationarity*. Available online at: http://www.wmo.int/pages/prog/hwrp/chy/chy14/documents/ms/Stationarity_and_Nonstationarity.pdf (accessed November 30, 2020).

Liu, R., Jiang, J., Guo, L., Shi, B., Liu, J., Du, Z., et al. (2016). Screening of pollution control and clean-up materials for river chemical spills using the multiple case-based reasoning method with a difference-driven revision strategy. *Environ. Sci. Pollut. Res*. 23, 11247–11256. doi: 10.1007/s11356-016-6283-3

Lo, F., and Yeung, Y (eds). (1998). *Globalization and the World of Large Cities.* Tokyo: *United Nations University* Press.

Maier, H. R., and Dandy, G. C. (2000). Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. *Environ. Modell. Softw*. 15, 101–124. doi: 10.1016/S1364-8152(99)00007-9

Marchant, G. E., Allenby, B. R., and Herkert, J (eds). (2011). *The Growing Gap Between Emerging Technologies and Legal-Ethical Oversight*. New York, NY: Springer Press.

Markolf, S. A., Chester, M. V., Eisenberg, D. A., Iwaniec, D. M., Davidson, C. I., Zimmerman, R., et al. (2018). Interdependent infrastructure as linked social, ecological, and technological systems (setss) to address lock-in and enhance resilience. *Earth's Future* 6, 1638–1659. doi: 10.1029/2018EF000926

Matias, J. N. (2017). *Persuading Algorithms With and AI Nudge*. MIT Media Lab. Available online at: https://medium.com/mit-media-lab/persuading-algorithms-with-an-ai-nudge-25c92293df1d

Meserole, C. (2018). *Artificial Intelligence and the Security Dilemma.* Available online at: https://www.brookings.edu/blog/order-from-chaos/2018/11/06/artificial-intelligence-and-the-security-dilemma/ (accessed November 30, 2020).

Miller, C. A., and Munoz-Erickson, T. A. (2018). *The Rightful Place of Science: Designing Knowledge*. Tempe, AZ: Consortium for Science, Policy & Outcomes.

Milly, P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., et al. (2008). Stationarity is dead: whither water management? *Science* 319, 573–574. doi: 10.1126/science.1151915

Minns, A. W., and Hall, M. J. (1996). Artificial neural networks as rainfall-runoff models. *Hydrol. Sci. J.* 41, 399–417. doi: 10.1080/02626669609491511

Mitra, P., Ray, R., Chatterjee, R., Basu, R., Saha, P., Raha, S., et al. (2016). "Flood forecasting using Internet of things and artificial neural networks," in *7th IEEE Annual Information Technology, Electronics and Mobile Communication Conference* (Vancouver, BC: IEEE IEMCON), 1–5.

Mounce, S. R., Mounce, R. B., and Boxall, J. B. (2016). Case-based reasoning to support decision making for managing drinking water quality events in distribution systems. *Urban Water J.* 13, 727–738. doi: 10.1080/1573062X.2015.1036082

Nagy, H. M., Watanabe, K., and Hirano, M. (2002). Prediction of sediment load concentration in rivers using artificial neural network model. *J. Hydraul. Eng.* 128, 588–595. doi: 10.1061/(ASCE)0733-9429(2002)128:6(588)

Ni, H.-G., and Wang, J.-Z. (2000). Prediction of compressive strength of concrete using neural networks. *Comput. Concr.* 30, 1245–1250. doi: 10.1016/S0008-8846(00)00345-8

Nixon, J. B., Dandy, G. C., and Simpson, A. R. (2001). A genetic algorithm for optimizing off-farm irrigation scheduling. *J. Hydroinformat*. 3, 11–22. doi: 10.2166/hydro.2001.0003

NRC (US National Research Council). (2003). *Cities Transformed.* Washington, DC: National Academies Press.

Picard, R. W. (1995). *Affective Computing.* MIT Media Laboratory Perceptual Computing Section Technical Report No. 321. Available online at: https://affect.media.mit.edu/pdfs/95.picard.pdf (accessed November 30, 2020).

Pisa, I., Santín, I., Vicario, J. L., Morell, A., and Vilanova, R. (2019). ANN-based soft sensor to predict effluent violations in wastewater treatment plants. *Sensors* 19:1280. doi: 10.3390/s19061280

Quercia, D., Schifanella, R., and Aiello, L. M. (2014). "The shortest path to happiness: Recommending beautiful, quiet, and happy routes in the city," in *HT 2014 - Proceedings of the 25th ACM Conference on Hypertext and Social Media* (Santiago), 116–125.

Rastegaripour, F., Saboni, M. S., Shojaei, S., and Tavassoli, A. (2019). Simultaneous management of water and wastewater using ant and artificial neural network (ANN) algorithms. *Int. J. Environ. Sci. Technol*. 16, 5835–5856. doi: 10.1007/s13762-018-1943-0

Rezaeianzadeh, M., Kalin, L., and Anderson, C. J. (2017). Wetland water-level prediction using ANN in conjunction with base-flow recession analysis. *J. Hydrol. Eng*. 22, D4015003-1–D4015003-11. doi: 10.1061/(ASCE)HE.1943-5584.0001276

Sabouri, F., Gharabaghi, B., Sattar, A. M. A., and Thompson, A. M. (2016). Event-based stormwater management pond runoff temperature model. *J. Hydrol*. 540, 306–316. doi: 10.1016/j.jhydrol.2016.06.017

Sawhney, M. (2016). Putting products into services. *Harvard Business Review*, 82–89. Available online at: https://hbr.org/2016/09/putting-products-into-services (accessed November 30, 2020).

Shahin, M. A., Maier, H. R., and Jaksa, M. B. (2002). Predicting settlement of shallow foundations using neural networks. *J. Geotechn. Geoenviron. Eng*. 128, 785–793. doi: 10.1061/(asce)1090-0241(2002)128:9(785)

Snowden, D. J., and Boone, M. E. (2007). *A Leader' s Framework for Decision Making*. Harvard Business Review. Available online at: www.hbr.orgorcall800-988-0886.www.hbrreprints.org

Squire, L. R. (ed.). (2009). "*Cognition*," in *Encyclopedia of Neuroscience* (Elsevier).

Steffen, W., Broadgate, W., Deutsch, L., Gaffney, O., and Ludwig, C. (2015). The trajectory of the Anthropocene: the great acceleration. *Anthropocene Rev*. 2, 81–98. doi: 10.1177/2053019614564785

Suh, B. (2019). *Can AI Nudge Us to Make Better Choices?* Harvard Business Review. Available online at: https://hbr.org/2019/05/can-ai-nudge-us-to-make-better-choices

Tabari, H., Marofi, S., and Sabziparvar, A. A. (2010). Estimation of daily pan evaporation using artificial neural network and multivariate non-linear regression. *Irrigat. Sci*. 28, 399–406. doi: 10.1007/s00271-009-0201-0

Tokar, B. A. S., and Johnson, P. A. (1999). Rainfall-runoff modeling using artificial neural networks. *J. Hyrdol. Eng*. 4, 232–239. doi: 10.1061/(ASCE)1084-0699(1999)4:3(232)

Tomer, A. (2019). *Artificial Intelligence in America's Digital City.* Available online at: https://www.brookings.edu/research/artificial-intelligence-in-americas-digital-city/ (accessed November 30, 2020).

U.S. House Committee on Transportation and Infrastructure. (2020). *The Boeing 737 MAX Aircraft: Costs, Consequences, and Lessons from it Design, Development, and Certification*. (Washington, DC: U.S. House Committee on Transportation and Infrastructure. Available online at: https://transportation.house.gov/imo/media/doc/TI Preliminary Investigative Findings Boeing 737 MAX March 2020.pdf

Uhl-Bien, M., Marion, R., and McKelvey, B. (2007). Complexity Leadership Theory: Shifting Leadership from the industrial age to the knowledge era. *Leadersh. Q.* 18, 298–318. doi: 10.1016/j.leaqua.2007.04.002

Wise, J. (2019). *The Boeing 737 Max and the Problems Autopilot Can't Solve*. The New York Times. Available online at: https://www.nytimes.com/2019/03/14/opinion/business-economics/boeing-737-max.html

Yang, B., Zheng, W., and Ke, X. (2017). Forecasting of industrial water demand using case-based reasoning—A case study in Zhangye City, China. *Water* 9:626. doi: 10.3390/w9080626

Ye, X. W., Jin, T., and Yun, C. B. (2019). A review on deep learning-based structural health monitoring of civil infrastructures. *Smart Struct. Syst*. 24, 567–585. doi: 10.12989/sss.2019.24.5.567

Yeh, I.-C. (1999). Design of high-performance concrete mixture using neural networks and nonlinear programming. *J. Comp. Civil Eng*. 13, 36–42. doi: 10.1061/(ASCE)0887-3801(1999)13:1(36)

Yilmaz, S. (2011). Ground motion predictive modelling based on genetic algorithms. *Nat. Hazards Earth Syst. Sci*. 11, 2781–2789. doi: 10.5194/nhess-11-2781-2011

Young, C. C., Liu, W. C., and Wu, M. C. (2017). A physically based and machine learning hybrid approach for accurate rainfall-runoff modeling during extreme typhoon events. *Appl. Soft Comp. J*. 53, 205–216. doi: 10.1016/j.asoc.2016.12.052

Young-Su, K., and Byung-Tak, K. (2006). Use of artificial neural networks in the prediction of liquefaction resistance of sands. *J. Geotech. Geoenviron. Eng*. 132, 1502–1504. doi: 10.1061/(asce)1090-0241(2006)132:11(1502)

Yu, F., Li, X. Y., and Han, X. S. (2018). Risk response for urban water supply network using case-based reasoning during a natural disaster. *Safety Sci*. 106, 121–139. doi: 10.1016/j.ssci.2018.03.003

Zamanisabzi, H., King, J. P., Dilekli, N., Shoghli, B., and Abudu, S. (2018). Developing an ANN based streamflow forecast model utilizing data-mining techniques to improve reservoir streamflow prediction accuracy: a case study. *Civil Eng. J*. 4:1135. doi: 10.28991/cej-0309163

Zhang, F. X., Wai, O. W. H., and Jiang, Y. W. (2010). Prediction of sediment transportation in deep bay (Hong Kong) using genetic algorithm. *J. Hydrodyn. Ser. B* 22, 599–604. doi: 10.1016/S1001-6058(09)60260-2

Zhang, J., Du, C., and Feng, X. (2017). Research on a soft measurement model of sewage treatment based on a case-based reasoning approach. *Water Sci. Technol*. 76, 3181–3189. doi: 10.2166/wst.2017.417

Zhang, J., Fu, D., Urich, C., and Singh, R. P. (2018). Accelerated exploration for long-term urban water infrastructure planning through machine learning. *Sustainability* 10:4600. doi: 10.3390/su10124600

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Advantages of publishing in Frontiers

OPEN ACCESS
Articles are free to read for greatest visibility and readership

FAST PUBLICATION
Around 90 days from submission to decision

HIGH QUALITY PEER-REVIEW
Rigorous, collaborative, and constructive peer-review

TRANSPARENT PEER-REVIEW
Editors and reviewers acknowledged by name on published articles

Frontiers
Avenue du Tribunal-Fédéral 34
1005 Lausanne | Switzerland

Visit us: www.frontiersin.org
Contact us: frontiersin.org/about/contact

REPRODUCIBILITY OF RESEARCH
Support open data and methods to enhance research reproducibility

DIGITAL PUBLISHING
Articles designed for optimal readership across devices

FOLLOW US
@frontiersin

IMPACT METRICS
Advanced article metrics track visibility across digital media

EXTENSIVE PROMOTION
Marketing and promotion of impactful research

LOOP RESEARCH NETWORK
Our network increases your article's readership