Enhancing Resilience of Urban Systems Against Climate-Induced Floods Using Advanced Data-Driven and Computing Techniques: A Driver-Pressure-State-Impact-Response (DPSIR) Framework

Gyan Chhipi-Shrestha[1], Vipul Moudgil[1], Rachid Ouche[1], Hirushie Karunathilake[2], Kh Md Nahiduzzaman[1], Kasun Hewage[1], Boris Faybishenko[3], Lavanya Ramakrishnan[4], and Rehan Sadiq[1]

[1]School of Engineering, University of British Columbia, Okangan Campus, Kelowna, BC, Canada (corresponding: rehan.sadiq@ubc.ca)
[2]Department of Mechanical Engineering, University of Moratuwa, Katubedda, Moratuwa, Sri Lanka
[3]Energy Geosciences Division, Lawrence Berkeley National Lab, Berkeley, CA, USA
[4]Computational Research Division, Lawrence Berkeley National Lab, Berkeley, CA, USA

1. Focal Area: This white paper proposes advanced data-driven and computing techniques to improve the predictability of extreme climate events (precipitation) and focuses on comprehending their impact dynamics to enhance resilience of urban systems.

2. Science Challenge: In urban systems, climate change has presented significant challenges related to accurate spatiotemporal prediction of extreme climate events (heavy precipitation) and their impacts, i.e. flooding. The occurrence of extreme climate events and their compounding repercussions on the built environment make urban systems increasingly more vulnerable. The interactions between extreme climate events, urban systems, and the corresponding impacts are irregular, non-linear, and dynamic, making it difficult to standardize resilience. As it stands, the management of complex urban systems is affected by uncertainties related to the nature of short- and long-term consequences caused by extreme events.

3. Rationale: Extreme climate-induced events, such as floods and drought, are increasing in intensity and frequency in cities around the world. Conventional mathematical and statistical approaches are apparently insufficient in predicting these events accurately, thus hindering the ability to provide early warnings, have resilient infrastructure in place, and minimize impacts on urban systems. Moreover, the environmental, economic, and social costs of extreme climate events have made it even more necessary to internalize them in urban system design that is flexible and adaptive to future extremes. There is an urgent need to enhance the predictability of extreme events and their downstream impacts in urban systems to better understand the interaction between system components and their dynamics in the built environment. Novel and innovative analytical frameworks using advanced data-driven spatiotemporal approaches can assist in planning, managing, and advancing urban systems with increased resiliency against extreme events. Since urban systems operate under a complex nexus of pressures, stakeholders, and macro-environmental impacts, conventional approaches have a limited ability to capture the embedded dynamics. This creates the need to integrate data science and artificial intelligence (AI) in climate resilient urban system development.

4. Smart Flood Management

4.1 Background: 'Resilience' refers to the ability to sense, recognize, and withstand an external disruptive force and recover quickly, if damage occurs. It is characterized based on three pivotal criteria: (i) vulnerability (preventing damage and failures) (ii) robustness (limiting damage level) and (iii) recoverability (minimizing recovery time). Flood resilience can be assessed using an index developed by aggregating the flood-related resilience indicators against these criteria. This white paper proposes an integrated approach with AI and edge computing for real-time prediction and impact assessment and management for climate-induced floods in urban systems using a DPSIR framework.

4.2 Proposed DPSIR Framework: The proposed framework comprises five elements: drivers, pressures, state, impact, and responses (Fig. 1). The flood management timeframe is considered under the *pre*, *during*, and *post-flood* phases. Broadly, drivers and pressure are pre-flood processes; state and impact are pre- and during-flood processes, and response is during-, post-, and pre-flood of next flood cycle. The framework embraces a Cloud and Edge paradigm to inherit dedicated communication, control, management, and data-driven decision making for extreme precipitation impact management. It constitutes layered architecture to furnish local and global decision making as follows.

DOI: https://doi.org/10.2172/1769705
DOE BER, AI4ESP 2021 #AI4ESP1024 (https://www.ai4esp.org)

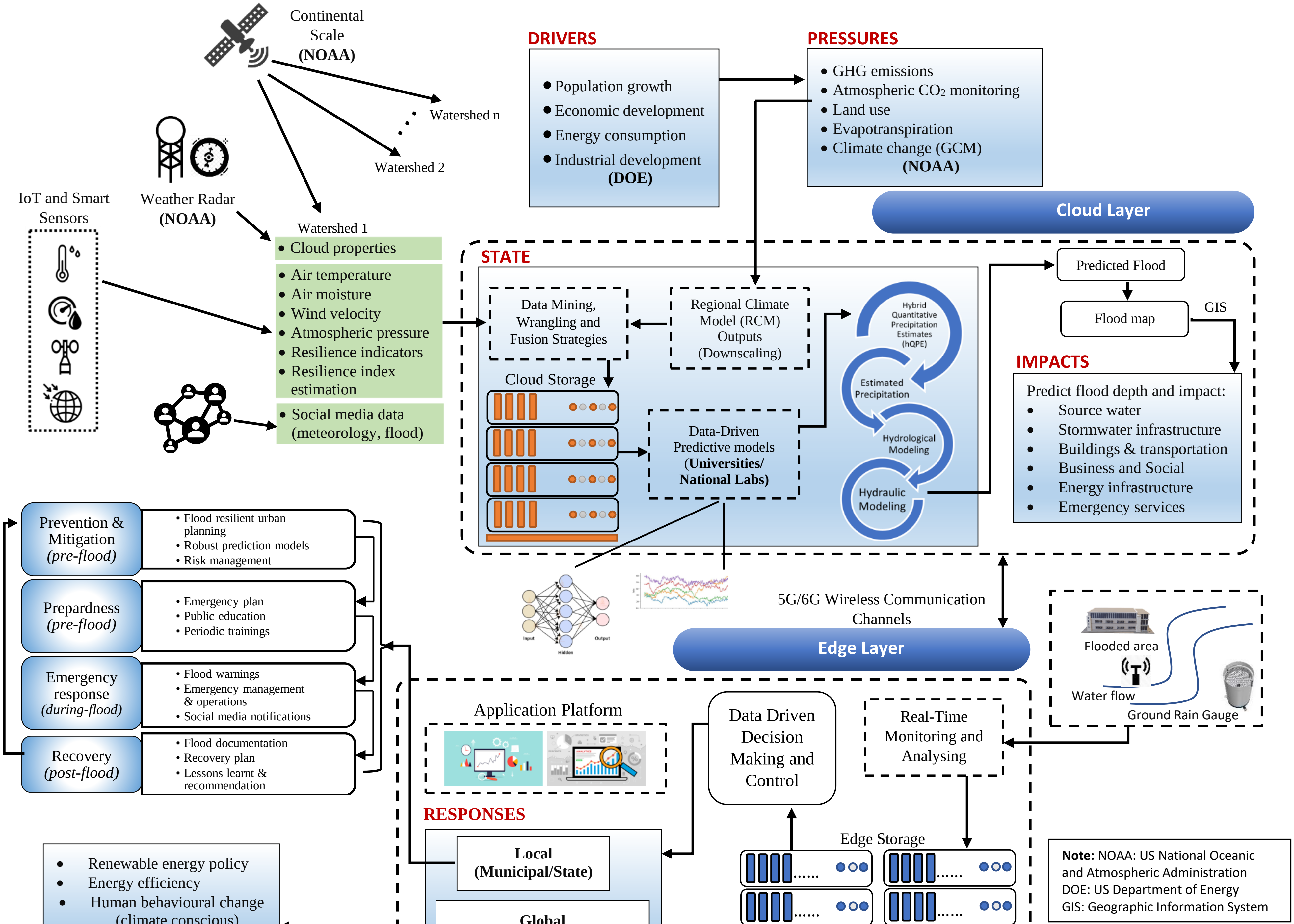

Figure 1: Smart DPSIR Framework for flood management

a) Drivers: Rapid population growth, socio-economic activities, and industrial development increase the global economy. These activities raise the demand and use of energy, other resources, infrastructure, and services.

b) Pressures: Increased energy consumption and other activities (e.g., deforestation) release more greenhouse gases (GHGs). Population growth and economic activities cause land use change that affect the global and regional climate system, causing anthropogenic climate change. The impacts of climate change on precipitation and temperature can be predicted using the Global Climate Model (GCM). However, the resolution of GCM is coarse and results in high uncertainty. The fine spatial scaled (location-specific) data can be predicted by dynamically downscaling using the high-resolution Regional Climate Model (RCM), either nested in GCM simulations or reanalyzed atmospheric fields.

c) State: For monitoring the state of watersheds, automated data collection, storage, and analysis are performed in two layers: cloud and edge.

***<u>Cloud layer</u>*:** For multiple watersheds, the cloud layer serves as a global control and storage layer for the smart DPSIR framework. This layer provides DPSIR with Infrastructure as a Services (IaaS) to store, manipulate, and control the data from all smart Internet of Things (IoT) sensors (*air temperature, humidity, pressure, etc*.), weather radar (*cloud properties*), satellite (*cloud properties & flooded area imageries*), and RCM outputs. These data are used to develop a deep learning-genetic algorithm (DL-GA) model for each watershed. The DL-GA serves as a hybrid Quantitative Precipitation Estimate (hQPE) to estimate precipitation, i.e. rain and snow. Additional data of resilience indicators are collected and a resilience index is estimated. The layer also provides decision makers with smart features like security, application hosting, scalability, quality control, loss prevention, and recovery. Additionally, it assists in regulating and using the desired data from dedicated storage and executes the DL-GA model using the secured cloud application platforms. The estimated precipitation is used to predict flooding (via hydrological and hydraulic modelling) and generate a flood map (*using Geographic Information System, GIS)* to be used in the **impact** component of DPSIR. This layer is always in consistent communication with the edge components and servers to store the historical regional data from the edge devices and also governs them by making a global and specific decision. Also, social media (e.g. Facebook, etc.) is used for localized notifications in pre- and during-flood phases, and for model validation in the post-flood phase.

***<u>Edge Layer</u>*:** For each watershed, the edge layer primarily serves as a local control and storage layer. It mainly administers local monitoring devices and stores their real-time data for instant decision making via application platforms. This layer works synchronously with the cloud layer using dedicated 5G/6G communication channels to enhance its scalability, speed, reliability, and sustainability quotient. The major responsibility of the edge layer is to incorporate and execute the **response (local)** component of DPSIR. For instant response and decisionmaking, the system administrator has the ability to use the local computation and storage power of the edge platform, whereas the edge layer supplies locally sensed data to the cloud platform to make global decisions.

d) Impact: In each watershed, using the predicted flood map, impacts are estimated in terms of source water quantity, quality, urban infrastructure (e.g. stormwater, buildings, transportation, etc.), social entities, and emergency service. The flood map is compared with the satellite-derived actual flood imagery to improve prediction efficiency.

e) Responses: In each watershed, the local response is deployed for flood disaster management and resilience enhancement via the actions suggested under prevention, preparedness, emergency response, and recovery stages. In contrast, the global response is implemented for climate change mitigation via renewable energy, etc. (Fig. 1). A resilience index is recalculated in the **state** component to evaluate the change in resilience of urban systems.

4.3 Expected benefits: The proposed framework will take extreme climate events (i.e., floods) management beyond the conventional reactive approach to a more integrated and proactive domain, where real-time data, AI, and edge computing are used for more accurate prediction as well as robust decision making. It is an automated system and allows data to be shared among the pertinent stakeholders through a central disaster prevention and management center for effective and streamlined flood management. The outcomes of this program will assist disaster resiliency initiatives at municipal, state, and federal levels, while also improving public safety, wellbeing, and quality of life.

5. Suggested Partners: US National Oceanic and Atmospheric Administration (NOAA), US Department of Energy (DOE), Universities, US National Labs, and government (municipal, state, and federal).