Machine Intelligence for Floods and the Built Environment under Climate Change

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Abstract

While intensification of precipitation extremes has been attributed to anthropogenic climate change using statistical analysis and physics-based numerical models, understanding floods in a climate context remains a grand challenge. Meanwhile, an increasing volume of Earth science data from climate simulations, remote sensing, and Geographic Information System (GIS) tools offers opportunity for data-driven insight and action plans. Defining Machine Intelligence (MI) broadly to include machine learning and network science, here we develop a vision and use preliminary results to showcase how scientific understanding of floods can be improved in a climate context and translated to impacts with a focus on Critical Lifeline Infrastructure Networks (CLIN).

1. Introduction

Flooding is one of costliest natural hazards in the United States and globally, driving more insured losses than any other catastrophe (Aerts et al., 2014). Flooding in the midwestern United States during the spring of 2019 caused more than $1.3 billion dollars in structural damage and agricultural losses in Nebraska alone (Bacon, 2019). Despite these impacts, understanding of floods in a climate context remains a major challenge, as does translating insights to actionable information for adaptation (Sharma et al., 2018). Climate-informed risk assessment frameworks for floods must consider changes in attributes of precipitation extremes, uncertainty in our understanding of flood generation, exposure, and vulnerability. Risk management requires a focus on development pathways, which should consider principled approaches to flood hazards management (including preventive measures, consequence management, and recovery), time-phased and flexible adaptation, and longer-term mitigation (Rosner et al., 2014; Ganguly et al., 2018).

Based on emerging success stories across multiple sectors, a recent climate action plan (Moss et al., 2019a;b) suggests broader use of that MI, including artificial and intelligence and citizen science, for climate risk management.

2. A Vision for Flood Risk Management

Figure 1 outlines a vision for leveraging MI for the advancement of climate-informed flood risk management. A risk management framework for floods under global change needs to consider key challenges in changing weather patterns, aging infrastructures and consequent vulnerabilities, and evolving attributes of urbanization and exposure.

One challenge in predictive understanding of floods is estimating statistics of hydrometeorological extremes, which can translate to indices for risk-informed decision-making. Hybrid approaches blending physics and data sciences have shown value in extracting credible scientific insights from Earth System Model (ESM) simulations and translating insights to information relevant for adaptation (Ganguly et al., 2014; Vandal et al., 2017). Gaps also exist in understanding of the integrated climate-water system and the complex physical processes that generate floods. Machine Learning (ML) is being used estimate parameters of high-resolution ESM processes, address fundamental gaps in process understanding, as well as post-process ESM outputs and compare with observations to improve predictions and uncertainty quantification (Schneider et al., 2017; Rasp et al., 2018; Reichstein et al., 2019; Wang et al., 2015).

Improvements in predictive understanding of floods can be measured through statistical metrics and the consequences for impacted systems such as CLINs. For CLIN systems, network science and engineering approaches have demonstrated potential for robustness and recovery modeling, leading to enhanced resilience (Bhatia et al., 2015; Gao et al., 2016). CLIN systems, in this context, could include interdependent built systems such as communication, power, transport, and water, as well as natural systems such as food webs and ecological networks (Tessler et al., 2015).

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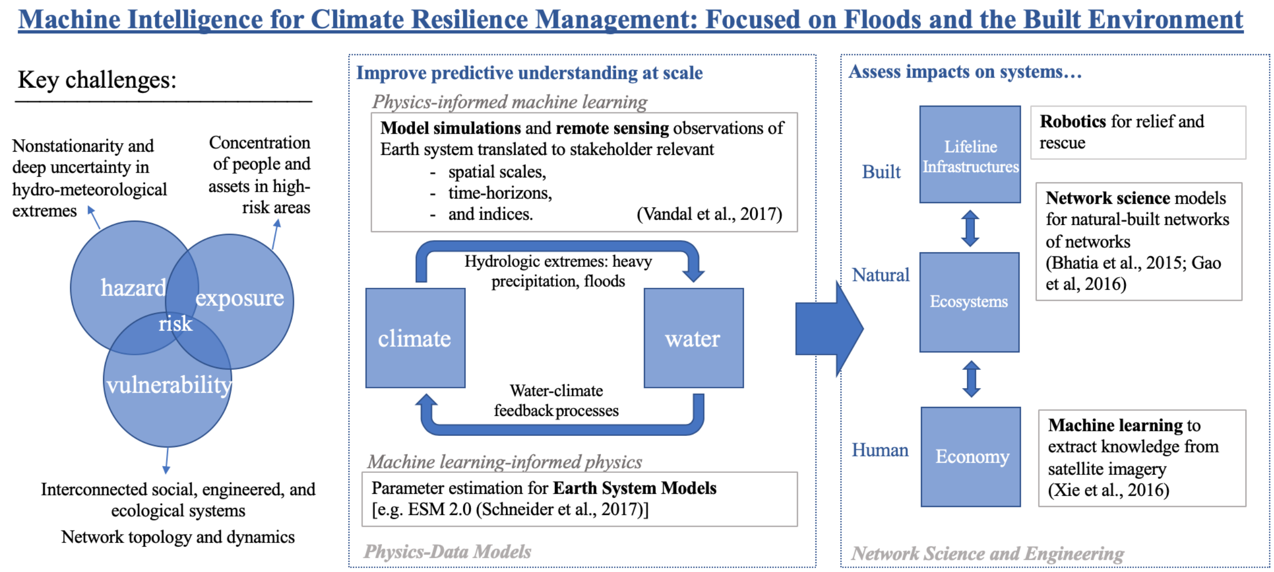

Figure 1. Machine intelligence can be embedded within comprehensive flood risk management.

3. Proof of Concept Results and Case Study

Figure 2 presents a proof of concept which illustrates the value of MI (specifically, spatiotemporal data sciences, machine learning, and network science, blended with physics and process understanding) for flood risk management under climate change in the context of built infrastructures.

The climate case study (top left) extracts predictive insights about extremes (return levels of precipitation) together with uncertainty quantification from model simulations and remotely sensed observations. The water case study (top right) examines the role of antecedent soil moisture in flood generation, which may confound the relation between precipitation and floods. Specialized statistical tools, such as extreme value theory, and machine learning approaches, which can extract actionable insights from complex processes and datasets, have shown value in genrating novel science insights and translating to them to impacts.

The infrastructure resilience case (bottom) demonstrates how compound weather hazards (in this case blizzard from Nor'easters followed storm surge in the hurricane season) can impact the recovery of CLIN systems such as Boston's Massachusetts Bay Transportation Authority (MBTA) mass transit system. Here, we considered a case where the system is subjected to successive disruptions without adequate time for full recovery between the first disruption and consequent events. Network science and engineering in this context have demonstrated value to inform robustness and recovery of networked assets and systems.

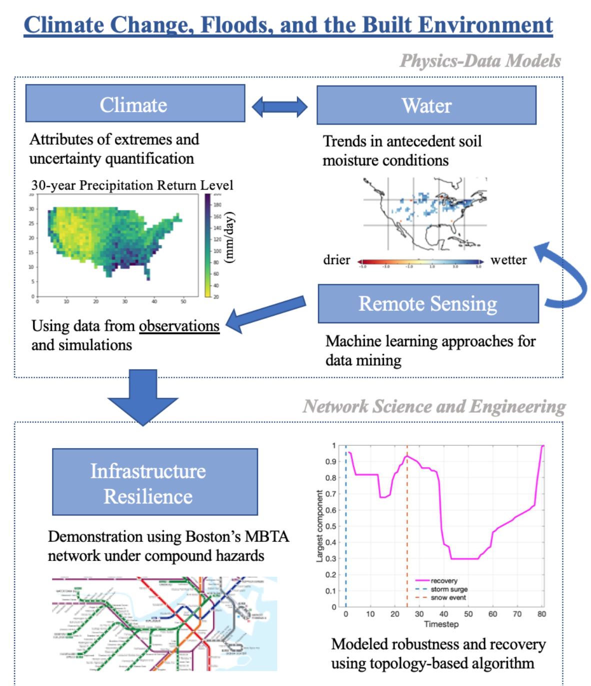

Figure 2. Case study using machine intelligence to study hydrologic extremes and built network resilience.

4. Future Work

Future work needs to examine how MI may work in conjunction with developments such as citizen science and networked Digital Earth to inform climate risk management.

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