Resilience Quantification of Nonstationary and Compounding Threats

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Introduction

Technological advancements and management adaptations have improved engineered systems functions in response to flooding. Other natural and anthropogenic disturbances such as pandemics, utility hijacking, infrastructure destruction, and biochemical releases can stress a system beyond acceptable limits or in ways not previously conceived. Such threats can be direct or indirect and often result in large-scale disruption to the critical functions of the system. Traditional risk management approaches, while effective for known and predictable threats, are not adequate preparation for compound disturbances that are often unpredictable and not well defined. These approaches are additionally flawed when applied to non-stationary threats such as future coastal flooding impacted by sea level rise and changing riverine inflows.

Resiliency, though often conflated with concepts including robustness and risk, is unique in that it considers a system or networks performance past the initial threat or failure. Resiliency includes preparation, absorption, recovery, and adaption (Galaitsi et al. 2022). Compound threats are defined as multiple events that impede an infrastructure network or system while magnifying the impact of one another (Kruczkiewicz et al. 2021). As weather and related flooding events become both more frequent and extreme the likelihood of engineered systems in coastal areas facing compound threats increases or is nonstationary (Kirezci, et al., 2020).

In order to evaluate the resiliency of areas used for case studies in this work, a network science approach was taken. Ego networks are a network science methodology that analyzes networks centered around a central point or ego (Arnaboldi et al. 2012). For the purposes of this work critical points were identified to form these ego networks. These points are unique to the goals of each study and can be adjusted dynamically for each area of concern.

Methods

Of the case studies described below, ego network based analysis has been completed for New York City. The remaining case studies are still in progress, the results of which are the subject of future work. Ego network analysis requires four main steps:

1) Data gathering and processing

2) Unstressed networking analysis

3) Stressed network analysis including each threat scenario and the compounding threat scenario

4) Comparison of results from steps two and three

The ego networks discussed in this work relate directly to transportation infrastructure. As a part of data gathering and processing, a set of important points are identified. From there the larger network is divided into individual ego nets centered around the important points and threat information is applied. In the case of transportation network resiliency analysis, connectivity within these ego nets is used to quantify local resiliency.

Case Studies

To explore the concept of resiliency as it relates to nonstationary and compounding threats three case study sites were selected. Each of these sites had a primary threat of coastal flooding and examines the impacts of this threat on the selected infrastructure system(s).

New York City Case Study: The New York City case study exclusively investigates the impacts of compounding threat on the transportation infrastructure network. The primary threat in this case study is inundation due to Super Storm Sandy with a secondary threat of mass bridge closures due to a credible threat (Figure 1). Inundation extents and depth were provided by an existing GSSHA model (Gridded Surface/Subsurface Hydrologic Analysis) of Super Storm Sandy (Massey et al. 2013).

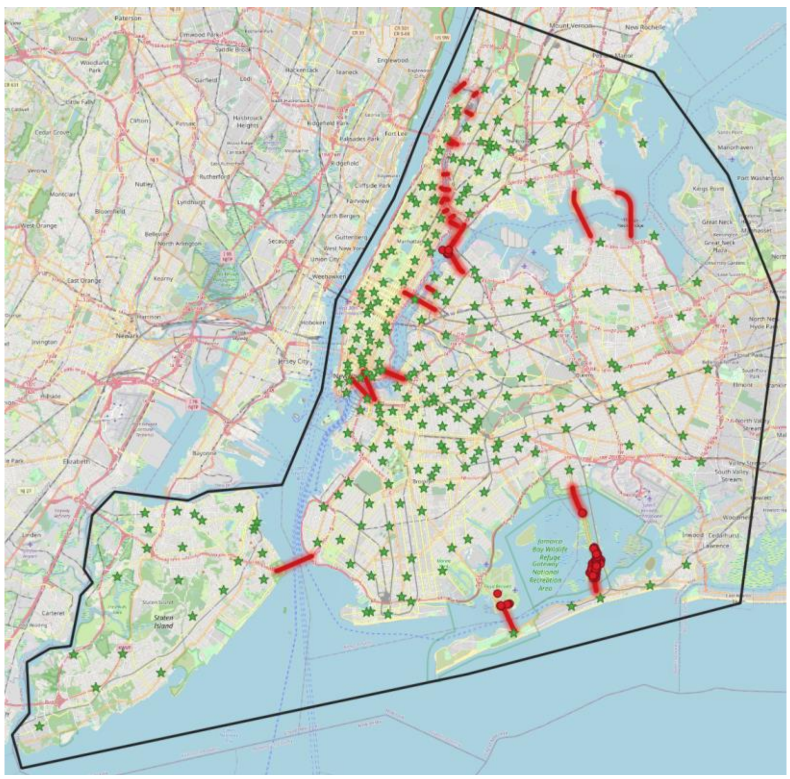

Figure 1. Location of Critical Points, Bridge Failures, and GSSHA Model Extents

North Carolina Case Study: The North Carolina case study expands to multiple, layered networks while incorporating both compound threats and nonstationarity of threats. The eastern seaboard region of the state is used to examine the impacts of flooding from Hurricane Florence provided by the FIMAN-T model and power grid failures on the recovery period of both power restoration and roadway connectivity (Figure 2).

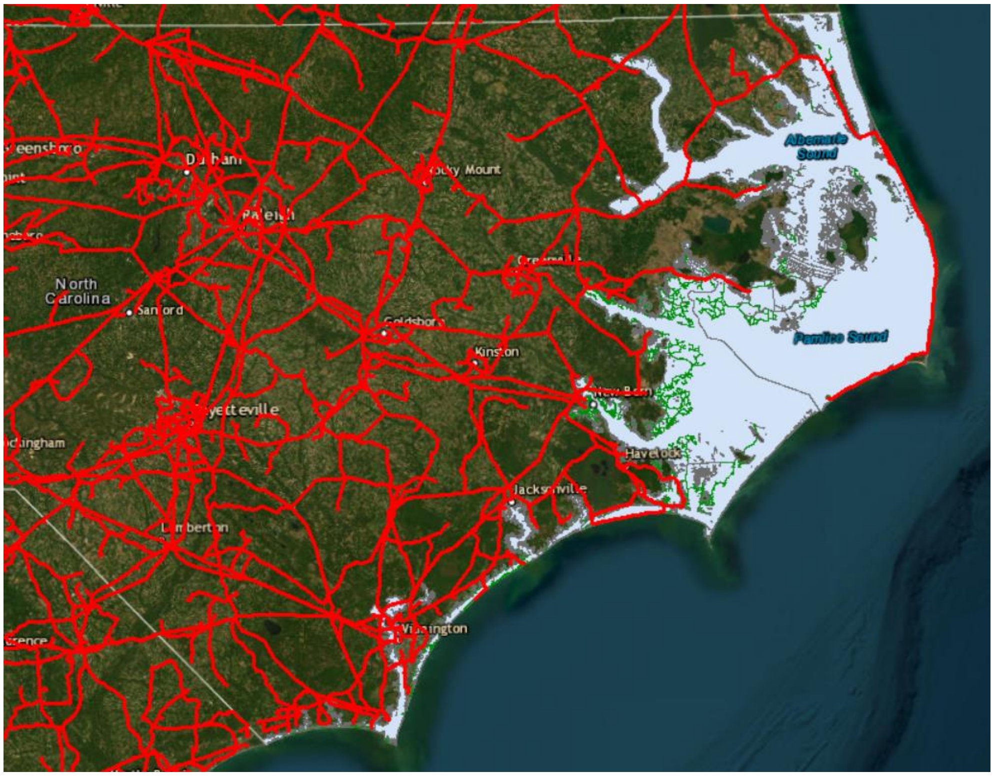

Figure 2. Map of FIMAN-T Inundation Extents and Major Power Lines on the Eastern Seaboard of North Carolina

Nonstationarity is addressed by this case study locally in Camp Lejeune. Tidal harmonics were used to generate local tidal elevations from 2000 to 2100 and the low, intermediate, and high USACE sea level rise curves were applied. A two-dimensional Adaptive Hydraulics (AdH) model was constructed with the calculated sea level rises (Savant et al, 2011). This provided the flood data which will be applied to assess base infrastructure resiliency.

Gulfport Case Study: The Gulfport Mississippi case study addressed nonstationarity exclusively. Similarly to the Camp Lejeune case study, a two-dimensional AdH model was run with the tidal boundary driven by calculated tidal harmonics and applied sea level rise equations. River levels were also varied using the return intervals provided by the StreamStats tool.

Preliminary Results and Conclusions

Within the New York Case study ego networks, bridges were shown to have a much less significant impact than flooding to the connectivity of roadways (Figure 3). However, previous work has shown a compounding impact across the larger network (Zimmerman et al. 2022).

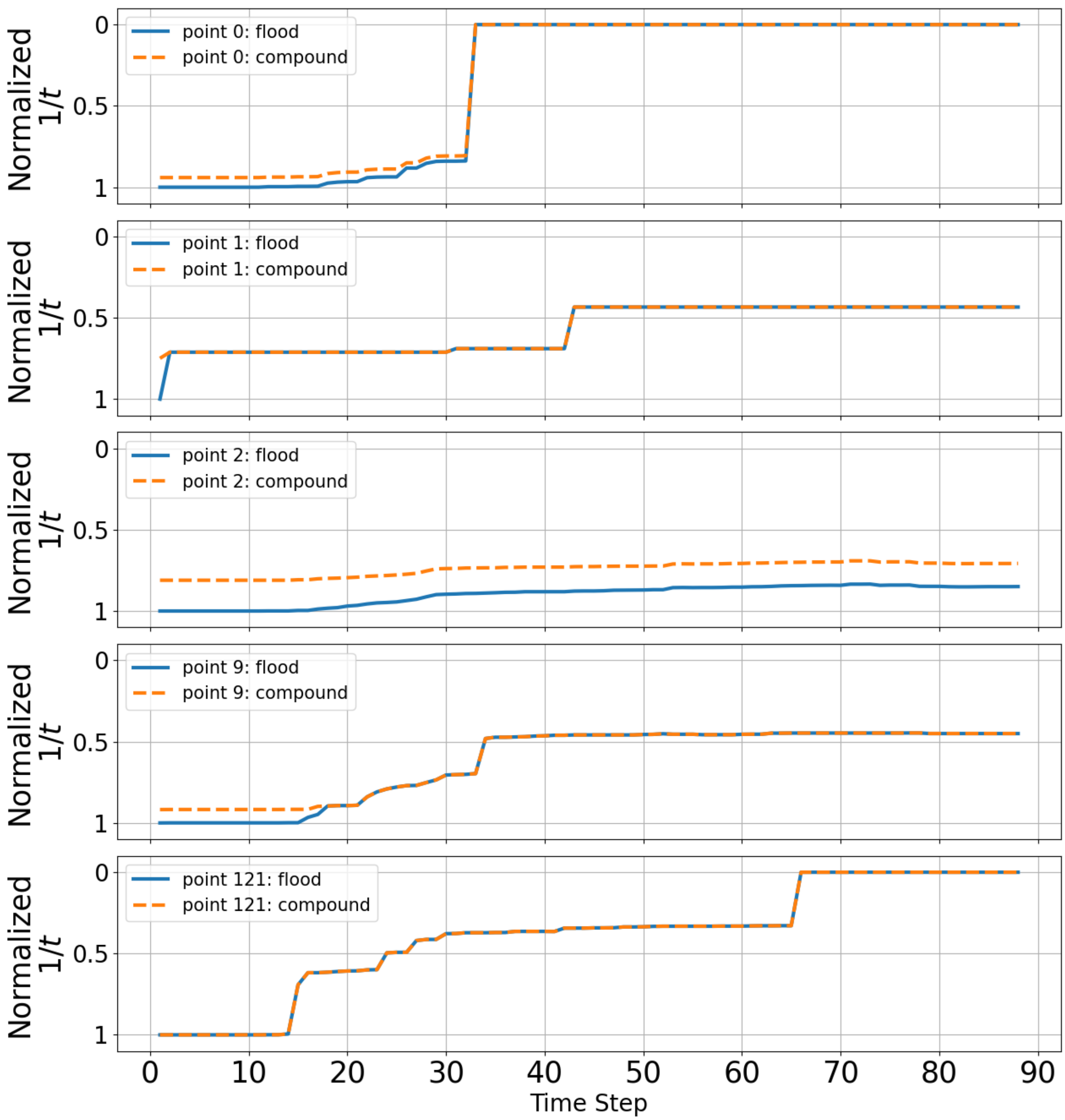

Figure 3. Normalized inverse travel time impacts across each GSSHA model time step for flood threatened network and compound threatened network in New York City

The y axis in Figure 3 shows normalized, inverse average travel time in order to represent the impact of disconnected nodes which have an infinite travel time. The axis is inverted to show the increase in disconnectivity which is linearly correlated to the travel time.

Future applications of clearly identifying areas likely to be isolated include improved emergency disaster response, targeted remediation and future flood mitigation. Areas identified as being more resilient could be used as a design guide for future transportation network and city planning. Work on the case studies outlined in this paper is ongoing and includes the ability to consider multiple interconnected infrastructure networks and the impact of each network on the others ability to recover along with consideration to non-stationary threats such as future coastal flooding impacted by sea level rise and changing riverine inflows.

References

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