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Ph.D. DISSERTATION DEFENSE

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Date:	08/20/2025
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Title:	Application of a Coupled Modeling Framework and Machine Learning to Understand and Predict Urban Coastal-Pluvial Flooding
Chairperson:	Dr. Philip Orton, Department of Civil, Environmental & Ocean Engineering, Charles V. Schaefer, Jr. School of Engineering & Science
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ABSTRACT

Coastal urban areas face increasing flood risk from both storm surge and extreme rainfall events, with the potential for these hazards to co-occur, compounding their flooding and potentially worsening impacts. Traditional flood risk assessments and forecasting systems often neglect the complex interactions between coastal and pluvial (rainfall-driven) flooding processes, leading to underestimation of flood hazards and inadequate preparedness strategies. This dissertation advances the understanding and prediction of compound coastal-pluvial flooding through integrated modeling approaches and machine learning techniques, as informed by a novel urban flood observation network and recent extreme and record-setting flood events.

The research consists of three primary objectives that systematically address critical gaps in compound flooding science. First, a coastal system modeling framework is enhanced to incorporate pluvial flooding processes by adding volumetric effects of rainfall and parameterizing urban drainage as a simple drain rate and is validated using two recent extreme events. Second, the model is applied in scenario simulations within the context of a joint probability analysis with historical tropical cyclone rain and surge data to assess compound flood hazard. The scenario-based experiments are used to evaluate how rainfall affects coastal flood hazards and how different urban landforms influence these hazards. Third, Long Short-Term Memory (LSTM) networks are trained using flood sensor data and meteorological inputs to create a rapid flood prediction model and investigate key components affecting the predictive performance. The machine learning approach avoids the computational expense and below-ground stormwater system data availability limitations of physics-based models. The goal of this research is to create

rapid flood prediction systems integrating multiple flood drivers that are suitable for operational forecasting applications.

Key findings include publishing the first spatially continuous flood map of post-tropical Cyclone Ida showing over 23 km^2 flooded and 4,621 buildings with water depths exceeding 0.3 m. Sensitivity experiments reveal that small spatial shifts in the storm track can increase flooded areas substantially. Ignoring rainfall when evaluating coastal flood hazards significantly underestimates the threat, with compound flooding potentially increasing flood extent by up to 61%. The machine learning model achieves effective flood prediction performance across multiple stations with significantly reduced computational requirements compared to traditional hydrodynamic modeling approaches. This research contributes to flood risk science by revealing inadequacies in current risk assessment practices and establishing methodological frameworks for improved compound flood modeling. As flood risk intensifies due to climate change, sea level rise, and continued coastal urbanization, the integrated approaches developed here provide essential tools for protecting coastal communities and supporting evidence-based adaptation planning.