Title: Leveraging machine learning to improve understanding and predictability of weather/climate extremes and the resilience of human systems

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Focal Area(s): Developing hybrid models for predicting weather/climate extremes at the intersection of the urban environment (focal area #2).

Science Challenge: Limited by many sources of uncertainty, numerical models are unable to accurately simulate weather and climate processes and this problem is particularly acute for modeling extreme events, including hurricanes. Moreover, computational limits within these numerical models bound our ability to develop large ensembles to explore this uncertainty and the implications relative to characterization of risk and resilience within the human systems that are impacted by changes in extremes.

Rationale: Numerical simulation of weather and climate extremes is often challenging due to several reasons. Extremes, such as hurricanes are often influenced by processes at wide ranging spatial and temporal scales. At typical resolutions that are used (~ 25 km to 100 km), models employ parametrizations of convective and cloud microphysical processes which are not explicitly resolved by the models. Although cloud-resolving resolution (< ~ 4 km) models are becoming feasible for weather and climate simulations, global-scale cloud-resolving simulations are still computationally prohibitive for long climate simulations or large ensemble simulations. Although the problem has been alleviated to an extent through the use of super-parameterizations, the community is still divided on the efficacy of this approach, which is also computationally demanding. In light of this, the potential use of hybrid approaches in which machine learning techniques, which can learn highly non-linear features from complex data, are combined with physics-based numerical models can be explored.

Narrative: One of the main areas of improvement for climate models is their ability to resolve clouds and related heat transport processes. In the horizontal, the main mechanism of heat transport is through mid-latitude storms that span thousands of kilometers, and, consequently are well-resolved by most models. However, vertical transport of heat occurs primarily through convective processes that span a few kilometers, and hence are poorly resolved. Hurricanes constitute one of the most important phenomena associated with convection. They are also the most destructive weather systems that impact millions of people annually in the global tropics and sub-tropics. Although there may be other forms of damages due to hurricanes, the primary impact from the storms is through coastal and inland flooding. While coastal flooding is primarily related to sea-level and winds, inland flooding results from the torrential rains during storms. Combining the effects of storm surge and streamflow, coastal flooding may be compounded and threaten the resilience of coastal populations and infrastructure. Considering the above it becomes really important to better understand co-evolving processes, including wind, precipitation, storm surge, and the human system response.

A hybrid approach to address coastal flood risk would encompass several models including one for precipitation. However, as mentioned previously, dynamical models typically tend to struggle...
with generating accurate estimates of rainfall. To overcome this limitation, one potential method would be the use of deep neural networks. Deep learning is one of the most ground-breaking and powerful techniques of machine learning that is making its inroads into most areas of research. Notable examples include computer vision, object recognition, etc. In our case for example, using a variety of data of the large-scale environment from satellite observations and reanalysis based on dynamical models, we can train the model to predict direct estimates of precipitation. Previously, neural networks were often used as a black box without an ability to explain the significance of various features and the inter-relationships among them. This was an issue for the scientific community and hampered the use of these methods in research for years. However, recent advancements have been made in the field that allow us to not only understand the relative feature relevance, but also the inter-relationships between the predictors and data. Consequently, the machine learning model thus developed can also provide valuable feedback to the human-earth system modeling community through identification of critical parameters that need better representation to improve model performance.

Previously, we have successfully implemented a hybrid approach to improve the prediction of hurricane intensity (see figure 1). By training a Multi Layer Perceptron (MLP) on historical observations, we demonstrated that the model can outperform well-known statistical-dynamical models (e.g. SHIPS) and even fully dynamical models (e.g. HWFI). These results are encouraging and suggest that similar or more complex neural network-based methods can be applied to improve our ability to understand and predict other processes, including extreme precipitation. However, compared to predicting hurricane intensity, precipitation on the other hand will be more challenging for several reasons. First, while intensity modeling is often related to predicting a point value, such as the maximum near-surface windspeed, precipitation involves generating a spatial distribution. Second, while intensity prediction involves parameters in the atmosphere and ocean, precipitation also includes terrain effects and hence is more complicated.

Figure 1: The 24-hour intensity change Mean Absolute Error (kt) from MLP, models used at the NHC (SHIPS, DSHP, LGEM, HWFI) and the NHC official forecast, tested on 2010–2019 Atlantic hurricanes over the same 6-hourly locations. While the MLP model was tested in a hindcast mode for the period 2010-2018, it was tested for 2019 as if in a real-time mode. The shading around the MLP line denotes the 95% confidence interval based on the bootstrap method Figure reproduced from Xu et al. (under review at WAF).
Nevertheless, the utility of hybrid models, once developed, also extends to assessment of probabilistic risk from extreme climate events, including hurricanes. This approach overcomes the issue of sample size that is typically encountered when attempting to perform robust risk quantification based on observations or direct numerical simulations. The Risk Analysis Framework for Tropical Cyclones (RAFT) is an example of the hybrid approach that is being used in ICOM to understand human system risk due to hurricanes (see figure 2). Thus, an improvement in predicting concurrent events, such as extreme wind and precipitation, storm surge, etc. using machine learning can also enhance our ability to accurately quantify risk. Also, it can pave the way for the development of surrogate models for extreme climate events, and the human system response to them. Although we have used the example of hurricanes to illustrate our point, the method could also be applied to model other types of extremes, such as atmospheric rivers, summertime convective storms, etc. Finally, the data generated from the hybrid approach could potentially be made available for community use to foster more collaborations that would further drive advancements in these areas.

**Figure 2**: The framework of Risk Analysis Framework for Tropical Cyclones (RAFT) is depicted. It includes 6 components, 3 related to storm characteristics (Track, Intensity, Rainfall) and 3 related to impacts from storms (Storm Surge, Inland Flooding and Electric Power Outages). For each component, the methodology employed is indicated beside them.