Trustworthy AI for Extreme Event Prediction and Understanding

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Focal area: We are addressing all 3 focal areas. Our center is developing novel trustworthy AI methods (focus area 1), to improve prediction and understanding (focal area 2), using trustworthy AI including explainable AI (XAI) and physics-guided AI (focal area 3).

Science challenge: Our transformational science question is: *can we revolutionize both the prediction and understanding of extreme events through trustworthy AI*? Our use-cases include extreme weather such as tornadoes and hail as well as water-based events including extreme precipitation, compound flooding, harmful algal blooms, and sea turtle cold stunnings and nest inundations.

Rationale: Extreme weather phenomena provide highly compelling use-cases where trustworthy AI can both protect lives and property and improve environmental sustainability and resilience. Billion dollar weather-related disasters are increasing in frequency (NOAA NCEI, 2021). We have demonstrated in prior work that AI techniques can skillfully predict extreme hazards (Burke et al, 2020; Gagne et al 2017, 2019; Lagerquist et al 2019, 2020; McGovern et al 2017, 2019) as well as ocean-related phenomena (e.g., Kamangir et al, 2021; Zeng et al., 2014). The ability of AI to model high impact oceanic processes, in particular at the land-sea boundary which houses large infrastructure important to our nation's economy, is still in its infancy. Machine learning has already demonstrated promise in this field (e.g., Tadesse et al. 2020). The research will develop robust and efficient AI models taking advantage of the data from multiscale observing systems and numerical weather predictions to perform atmosphere-ocean-land coupled modeling and accurately describe interactions between the atmosphere, terrestrial hydrology, and the coastal ocean.

One of the barriers to adopting AI techniques for extreme weather phenomena is the lack of trustworthy and reliable AI. We were recently funded as an inaugural NSF AI Institute to focus on the development of trustworthy AI for weather, climate, and coastal oceanography (AI2ES, 2020). Through this institute, we are focusing on the creation of trustworthy AI for the above areas. This includes synergistic work of AI researchers, meteorologists, oceanographers, and risk communication researchers. Furthermore, our institute brings together researchers from academia, national labs, government agencies, and the private sector for maximal impact. It includes a robust effort to create an effective research-to-operations pipeline that includes the active involvement of social scientists alongside domain experts and computer scientists. The institute is also active in workforce development to train a new generation of researchers with knowledge in both AI and environmental science.

Narrative: In this whitepaper, we specifically focus on the need to create trustworthy AI that can be used for scientific discovery as well as improved predictions. Creating eXplainable AI (XAI) techniques that

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integrate relevant physics directly into XAI that users can make sense of and trust appropriately provides a valuable opportunity to discover new scientific hypotheses about the dynamic of extreme events.

Opportunities: We propose to leverage the NSF-funded NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography to develop trustworthy AI specifically for applications relevant to DOE. Many of the applications we already focus on, including extreme weather, climate-scale predictions, and oceanography, are already relevant to DOE. By examining a broad set of applications, our work in AI/ML will be applicable to the following CESD grand challenges: (1) Integrated Water Cycle Scientific Grand Challenge, (4) Drivers and Responses in the Earth System Scientific Grand Challenge and (5) Data-Model Integration Scientific Grand Challenge. By expanding the existing institute to target applications relevant to the DOE, we can build on both the substantial investment by the NSF and the framework and expertise already in place in the institute, thus magnifying the potential impact of DOE funding.

Unique DOE capabilities: The development of AI that will be deemed trustworthy requires a substantial investment in computational resources. DOE's exascale computing will be highly relevant to the proposed work.

Activities that will advance the science: To develop the trustworthy AI methods for multiple environmental science applications, we will work closely in teams of computer scientists, atmospheric scientists, oceanographers, and social scientists. Specifically relevant to the science challenge that we propose in this whitepaper, we will focus on the development of physics-based XAI methods and on the interpretation and verification of these methods with scientific end-users.

AI models are traditionally driven primarily by data, which can include observations or models. While an AI data driven approach can be shown to produce realistic predictions in certain situations, it does not include the necessary understanding of the laws of physics. By incorporating the known laws of physics directly into the model, we can create models that are much more efficient and potentially more accurate. We will also incorporate the laws of physics into the XAI models that we develop to explain the AI predictions, which can then be used to identify new scientific hypotheses to improve understanding of the phenomena being studied. The team has an excellent track record of developing XAI for related applications (McGovern et al. 2019, 2019 Gagne et al. 2019, Ebert-Uphoff et al 2020, Barnes et al. 2020),

One approach to integrating AI with models that already use known physical laws is to replace computationally expensive pieces of the numerical model (e.g., atmosphere-ocean-land couplings, microphysical parameterization, radiative transfer) with AI based approaches, including deep learning. We will use this approach for improving prediction of events at both the mesoscale and the climate scale. At both scales, improving the speed of the simulation means it can be run at a higher resolution or for a longer period of time, providing more accurate and useful predictions.

A second approach that can facilitate scientific discovery is to use the AI to identify novel features and gain new insights into the dynamic of environmental non linear processes. We will explore this by learning latent space representations for specific phenomena, using autoencoders or U-net type architectures. These deep learning models learn to translate from one set of inputs to an output of similar size with a significantly smaller latent representation in the intermediate steps. This latent space representation can be used to explore additional data and to identify novel features using XAI methods. We will also explore novelty detection methods, where a deep learning model learns what is expected and then can be used to identify novel aspects of its input parameters.

Specific water-based use case example: *Coastal Compound Flooding*. Floods are one of the most common and destructive natural disasters. They cause massive damage to human life, infrastructure, and socioeconomic systems. In recent years, climate change has increased both the intensity and frequency of joint occurrence of storm surge and precipitation. Accurate predictions of these compound events and understanding the processes driving them are essential to mitigating the associated high-impact flooding risks.

We will develop physics-based AI models that will improve the prediction of compound flooding risks on U.S. coasts. In situ observations and output from a high-resolution ocean-atmosphere-land (river hydrology) coupled model designed to study impacts of major hurricanes in the U.S. in the last decade can be used as the input to develop new XAI methods constrained by physics. The AI/ML models will consider not only historical ocean parameters (such as water levels, waves, and winds), but also key environmental factors such as soil moisture, river discharge, precipitation, ground temperature, etc. to predict risk of compound flooding from storm surge and rainfall. With the resultant XAI models, both short-term and long-term compound flooding risk probability can be developed for a given U.S. coastal site.

To make the research finding and products more applicable, at least two study sites should be considered to represent distinct end members in the continuum of river-ocean coupled systems. One site represents a classic lagoonal system where river-ocean exchange is through inlets (e.g., Pamlico Sound). Complex river-ocean interactions happen in particular during high-impact events when storms, flooding, shoreline breaching, and formation of new inlets occur. The other site represents a classic estuarine system where continuous river-ocean interactions affect navigation, agriculture, and other important human activities and decisions daily.

The scientific objective is to develop an integrated coastal water predictive capability to deliver new water intelligence products and information vital for decision making both during high-impact events, such as hurricanes, nor'easters, and storm surge, and for routine water management, including marine ecosystem health, transportation, and agriculture.

Reproducible science: Our NSF institute is committed to releasing all of our code open-source. We have created a GitHub organization account and share all of our repositories there. We are also developing best practices for coding and documentation standards to enable the code to be easily used by others.

Suggested Partners/Experts:
Amy McGovern is the director of the NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography and would be happy to present at the workshop.

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