Tracking Extremes in Exascale Simulations Utilizing Exascale Platforms

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2 Focal Area

Insight gleaned from complex data (both observed and simulated) using AI, big data analytics, and other advanced methods

3 Science Challenge

There is a growing recognition in the literature that understanding variability and trends in hydrometeorological extremes relies on understanding variability and trends in the meteorological phenomena that drive these extremes. Such phenomenon-focused understanding relies critically on a robust methodology for identifying the occurrence of these phenomena in observations and model output, but a robust methodology does not currently exist. There are a variety of heuristic methods reported in the literature for identifying, and in some cases temporally tracking, meteorological phenomena. However, there have been several intercomparison projects (and resulting papers) indicating that there is a large uncertainty associated with choices in the identification methods; this is the case for extratropical cyclones (ETCs) [1], atmospheric rivers (ARs) [2], and even tropical cyclones (TCs) [3]; and we hypothesize that this is a general issue with heuristic identification methods altogether. These studies clearly show that this identification uncertainty leads to a large, and previously under-recognized, quantitative and even *qualitative* uncertainty in our understanding of these phenomena.

In light of these issues, we suggest that the field could be advanced by addressing two overarching questions. First, can we explicitly quantify uncertainty associated with detecting hydrometeorological phenomena? Second, can we decompose detection uncertainty into reducible and irreducible parts?

4 Rationale

Anthropogenically-forced climate changes in the number and character of extreme storms have the potential to significantly impact human and natural systems. Current high performance computing technologies enable multidecadal simulation of global climate models at resolutions of 25km or finer [4]. Such high resolution simulations are demonstrably superior in simulating extreme storms such as tropical cyclones than the coarser simulations available in the Coupled Model Intercomparison Project (CMIP5) and provide the capability to more credibly project future changes in extreme storm statistics and properties [5–11]. The High Resolution Model Intercomparison Project (HighResMIP), a subproject of CMIP6 [12], is an opportunity to advance understanding of extreme storms and precipitation [13].

These high-resolution climate models are inherently better able to emulate observations of strong gradients of temperature and moisture than their coarser counterparts. Hence, simulated storms of

DOI: https://doi.org/10.2172/1769788
DOE BER, AI4ESP 2021 #AI4ESP1027 (https://www.ai4esp.org)

many types including tropical cyclones exhibit greater realism in high-resolution, multidecadal simulations. A challenge in analyzing these simulations is posed by the identification and tracking of storms in the voluminous model output. In contrast to meteorological feature tracking in the real world, it is impractical to manually identify storms in such simulations due to the enormous size of the datasets and therefore automated procedures are used. Traditionally, these procedures are based on a multi-variate set of physical conditions based on known properties of the class of storms in question. For instance, tropical cyclones have been identified and tracked by numerous authors using criteria of co-located high values of low level vorticity, low surface pressure values, elevated temperatures aloft and high 10m wind speeds maintained for a specified time [14, 15] .

Extratropical cyclones (ETC) are often identified by conditions of locally maximal vorticity and minimal pressure but are considered more difficult to identify than tropical cyclones due to their larger and more asymmetric physical characteristics, faster propagation speeds, and greater numbers. The Intercomparison of Mid-Latitude Storm Diagnostics (IMILAST) project examined 15 different ETC identification schemes applied to a common reanalysis and found profound sensitivities in annual global counts, ranging from 400 to 2600 storms per year. Atmospheric rivers (AR) are characterized by "a long, narrow, and transient corridor of strong horizontal water vapor transport that is typically associated with a low-level jet stream ahead of the cold front of an extratropical cyclone" [American Meteorological Society 2017]. As a non-cyclonic event, AR identification schemes are even more heterogeneous and are based upon a wide variety of criteria involving total precipitable water, integrated water transport, and other variables. The AR community has recently organized the Atmospheric River Intercomparison Project (ARTMIP) along similar lines to the IMILAST project (www.lbl.gov/ARTMIP).

Other types of weather events are less amenable to automated identification. Blocking events are obstructions "on a large scale, of the normal west-to-east progress of migratory cyclones and anticyclones" [American Meteorological Society 2017] and are associated with both extreme precipitation and extreme temperature events. Three objective schemes were compared by [18] who found that differing block structure affects the robustness of identification. Objective identification of fronts, the "interface or transition zone between two air masses of different density" [American Meteorological Society 2017], is even less developed. Location of fronts can often be detected visually from maps of pressure and temperature, but a clear identification of the boundary usually requires the synthesis of multiple variables.

Supervised machine learning techniques tailored to identify extreme weather events offer an alternative to these objective schemes as well as provide an automated method to implement subjective schemes. The latter is critical to understanding how climate change affects weather systems, such as frontal systems, for which objective identification schemes have not been developed. In both cases, the construction of suitable labeled training datasets is necessary but the details of how they are constructed are irrelevant.

5 Narrative

Initial proof-of-principle studies by the RGMA community represent important first step towards establishing the relevance and success of Deep Learning (DL) methods in finding extreme weather patterns. There are a number of outstanding challenges at this stage, which should be addressed in future work. Over the next decade, there are also several promising avenues for future work stemming from pragmatic challenges associated with improving the performance and scaling of Deep Learning methods and hyper-parameter optimization. Extending the methods to 3D space-time grids is a natural next step, although this will require creation of large training datasets produced through community-led labeling campaigns. In addition, improving the interpretability of these methods will be essential to ensure adoption by the broader climate science community.

The next significant steps include:

- *Reducing Training Time:* Deep Learning is computationally expensive. Typically current front detection and supervised classification implementations take several days to process GBs of data on a single GPU. The semi-supervised architectures currently take 1-2 weeks to converge. For future analysis, it is very important that the climate science community have access to multi-node GPU-ready implementations of Deep Learning libraries.
- *Hyper-parameter Optimization:* Determining the right DL network architecture for a given problem is currently an art. Practitioners have to typically conduct some amount of exploration in the space of number of layers, type of layers, learning rates, training schedules, etc. If each hyper-parameter combination requires a few days to converge, this exploration quickly becomes infeasible.
- *Extension to higher-dimensional grids:* Most current results are largely based on processing instantaneous snapshots of 2D fields. Climate patterns often span 3D fields and persist for extended periods of time. It remains to be seen if we can train convolutional Long short-Term Memory (LSTM) architectures [20] with limited amount of training data. While DL-based architectures are able to do a reasonable job with classification, typical climate patterns have distinctive 3D structures, and exhibit a high-degree of spatio-temporal coherence. In future work, we would like to operate on 3D grids, and explicitly account for the temporal dimension, perhaps by using a convolutional LSTM architecture [20]. These architectures will almost certainly have more parameters than their 2D counterparts; without a corresponding increase in training data, it remains to be seen if we can train the models effectively.
- *Interpretability:* Deep Networks are complicated functions with several layers of linear and non-linear filtering. While some effort has been spent in understanding ImageNet architectures [21], there is currently a gap in mapping the learnt feature hierarchy to climate science concepts. Deep neural networks are complicated entities with many layers of linear and non-linear filtering. While there is currently a gap in our understanding of architectures for scientific applications, there has been a somewhat substantial literature in examining these networks from an interpretability point of view. For example, to examine the particular activity of a feature map in the CNN, one could zero out all feature maps save for the one of interest, and map back to the original input image using inverted layers, such as transposed convolution [21]. Another technique (also presented in the aforementioned paper) is to occlude various regions of the input image and see how the predicted class probabilities change as a function of the occlusion. In the future, we would like to explore whether imposing constraints on spaces of basis vectors (corresponding to filters) can bridge this gap.
- *Lack of Training Data:* Commercial ImageNet-style architectures operate on *millions* of labeled images. We hypothesize that Deep Learning works reasonably well in our application context because of the relatively small number of classes and lack of visual complexity encountered in natural scenes (e.g. occlusion, perspective foreshortening, illumination, material properties). Nevertheless, in order to improve the accuracy of Deep Learning-based classifiers, the climate science community will need to conduct co-ordinated labeling campaigns create curated datasets which are broadly accessible to researchers.

6 Suggested Partners/Experts

Partners could include members of a number of related RGMA-funded projects, including:

1. Scientific Focus Areas:
   (a) Water Cycle and Climate Extremes Modeling, PI: Ruby Leung (PNNL)
2. University projects:
   (a) Monsoon Extremes: Impacts, Metrics, and Synoptic-Scale Drivers, PI: William Boos (University of California, Berkeley)
   (b) Madden-Julian Oscillation, Tropical Cyclones, and Precipitation Extremes in E3SM, PI: Daehyun Kim (University of Washington)
   (c) Simulating Extreme Precipitation in the United States in the Energy Exascale Earth System Model: Investigating the importance of Representing Convective Intensity Versus Dynamic Structure, PI: Gabriel Kooperman (University of Georgia)
   (d) Assessing the influence of background state and climate variability on tropical cyclones using initialized ensembles and mesh refinement in E3SM, PI: Ramalingam Saravanan (Texas A&M University)
3. Cooperative agreements:
   (a) A Framework for Improving Analysis and Modeling of Earth System and Intersectoral Dynamics at Regional Scales (HyperFACETS), PI: Paul Ullrich (University of California, Davis)
4. Early Career Research Projects:
   (a) Multi-scale Modeling of Extreme Events and Impact Information, PI: Naresh Devineni (City College of New York)
   (b) Understanding Severe Thunderstorms in the Central United States, PI: Jiwen Fan (PNNL)

7 Data access and FAIR standards

The CASCADE SFA operates under the DOE data policies and makes all code, data, and derived products publicly available.

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