AI Scaling Laws for Extremes (AISLE)

Authors

Da Yang, UC Davis, and Lawrence Berkeley National Laboratory

Paul Ullrich, UC Davis, and Lawrence Berkeley National Laboratory

Focal Area(s)

Using artificial intelligence to understand the physics of hydrologic events across temporal and spatial scales, to assess their representation in climate models, and to predict their response to climate warming. This covers both the prescribed foci of (2) predictive modeling using a hierarchy of models and (3) insight gleaned from complex data.

Science Challenge

Hydrologic extremes can result in significant loss of life, property, and damage to the environment. It is thus of primary importance to accurately predict hydrologic extremes and their responses to climate change. These extremes are often related to intense precipitation patterns, such as convective aggregation, tropical cyclones (TCs), the Madden-Julian Oscillation (MJO), and atmospheric rivers (ARs), or atmospheric blocking events that can cause extended periods of dry conditions and heatwaves. However, current climate models have large uncertainties in simulating these weather extremes, and there lacks widely accepted theories to constrain climate simulations. For example, it is unclear what environmental factors control their temporal and spatial scales—critical information to determine the impact of the extremes. Here we describe a pathway to develop quantitative theories for ascertaining theoretical relationships that fix the characteristics of hydrologic extremes by combining rapidly evolving data-science methods, automated feature tracking algorithms, with the ever-increasing computational and observational resources. These theories will help assess climate models and reduce uncertainties in predicting extremes in future climate.

Rationale

It is desirable to have both satisfying simple models and comprehensive GCMs that can truthfully simulate hydrological extremes. Simple models can help develop quantitative theories, can make physics-based predictions, and help constrain GCM results. We would then have confidence in GCM's predictions on future changes in hydrological extremes. However, we are lacking in such successful model hierarchies. For example, the MJO was first discovered five decades ago. Although tremendous progress was made by first-principle modeling, no consensus on the MJO's basic mechanism, and traditional GCMs have difficulties in reproducing its basic features (Zhang et al. 2020, Yang et al. 2021).

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Here we describe a pathway to advance theories for the hydrologic extremes by combining recent developments in machine learning methods, with the ever-increasing computational and observational resources.

Narrative

We propose to leverage recently developed capabilities in machine learning and automated feature tracking to develop successful model hierarchies for hydrologic extremes.

- ML discovery of physics laws: Recent breakthroughs in machine learning enabled accurate discoveries of symbolic expression that matches sparse data from an unknown function (e.g., PDEs and scaling laws) (Udrescu and Tegmark 2020). Such dictionary learning recently showed success in studying oceanic mesoscale eddies (Zanna and Bolton 2020). We believe that the methodology will continue to advance and can be used to discover simple models and/or scaling laws for hydrologic extremes.
- Increasing computing power: High-performance computing hardware is undergoing a transition, from CPU-based architectures to architectures with GPUs. Some climate models are rewritten to to leverage these emerging architectures. This capability allows both high-resolution simulations that require less empirical parameterization, and more ensemble simulations that explore key parameter sensitivities. The high-resolution simulations may provide valuable training data for ML algorithms, and the parameter sensitivity studies are necessary for seeking a quantitative understanding.
- Feature tracking: Both neural network-based and heuristic algorithms were developed to track a suite of hydrologic extremes, including tropical cyclones, the MJO, ARs, and blocking (Ullrich and Zarzycki, 2017; Kashinath et al., 2021; Toms et al. 2020). This capability will efficiently characterize the basic features of these phenomena and how they change with parameter values and environmental conditions.

To give an example of our proposed methodology, recent cloud-resolving models show promise in simulating realistic MJOs (Khairoutdinov and Emanuel 2018). With such tools in hand, community-driven targeted high-resolution simulations with varying parameter values, in conjunction with satellite observations, could be used to forge an unprecedented dataset for discovery of key equations and scaling laws. Automated tracking algorithms can efficiently characterize the MJO's spatial and temporal scales, and how they change with parameter values. With such information, modern ML algorithms (e.g., AI Feynman) have enabled discovery of scaling laws using dimensional analysis (a.k.a., the Buckingham Pi theorem) and neural networks (Udrescu and Tegmark 2020). These scaling laws will help to explain the inter-model spread of the simulated MJO and introduce emergent constraints that can be used to improve both climate model simulations under both historical and alternate climate states. Using an analogous approach, scaling laws and physical understanding can be assembled for tropical cyclone size and precipitation amounts, atmospheric blocking frequency, or atmospheric river intensity and spatial scale.

In summary, combining the three elements will provide a novel and potentially revolutionary pathway to advance fundamental understanding and predictive modeling of a wide range of hydrologic extremes. In turn, this understanding will enable us to identify and reduce model biases, evaluate consistency in existing modeling systems versus reality, and increase predictability on climatological and subseasonal-to-seasonal timescales.

Suggested Partners/Experts (Optional)

PCMDI Metrics Effort

References (Optional)

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