Extreme Learning

A challenge to develop and apply novel math to capture, characterize and predict extreme events in a warming world

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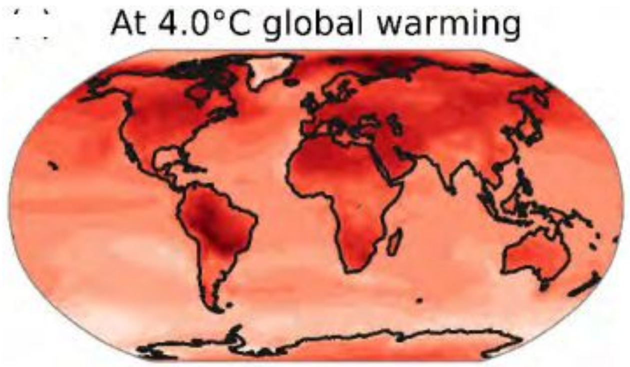
Motivation and Impact

- Climate extremes have devastating societal impact
  - Temperature, heavy precipitation and flood, droughts, storms, wildfires, compound events
- Long-term prediction of extreme events is impossible, short term is “merely” hard
- By definition, data for extreme events are sparse
- With a changing climate background, extremes are even harder to assess
  - Even modest changes in global temperature can cause large changes in frequency and severity
  - These may be concentrated regionally, even locally
  - Tipping points may introduce qualitative changes in the climate background
- How can we understand future extremes without knowing their background?



Projected MAX temperature
(from IPCCAR 6)

State of the Art for AI/ML and Physical Modeling for extremes

Build on initial efforts in this space: NSF AI Institute on Weather, Climate and Oceanography (AI2ES), CNRS's XAIDA: Artificial Intelligence for Detection and Attribution, etc.

- Assumptions that limit us
  - Stable climate
  - Gaussian distributions
  - ML/AI methods are typically based on gaussians, not tails
- We have models of the future: but imperfect and few data points
  - Coarse grid data
  - Assumptions about future required
- Physics-based models are currently riddled with uncertainties in parameters, parameterizations, multiple scaling issues, stale algorithms.

Grand challenge: assess frequency and magnitude of local extremes within a globally changing world

- Anticipate future conditions, incorporating
  - global trends (current state of the art)
  - tipping points
  - catastrophic events
- Create scenarios for probability distribution of extremes
  - at unprecedented spatial and temporal resolution
  - with more physical understanding
- Improve decision-making by accurate prioritization
- Advance scientific knowledge
  - create new tools to understand and predict extremes
- Increase climate change resilience to
  - heat waves and wildfires
  - drought, flooding, extreme rain
  - blizzards, hurricanes, tornado/hail clusters
  - epidemics, die-offs

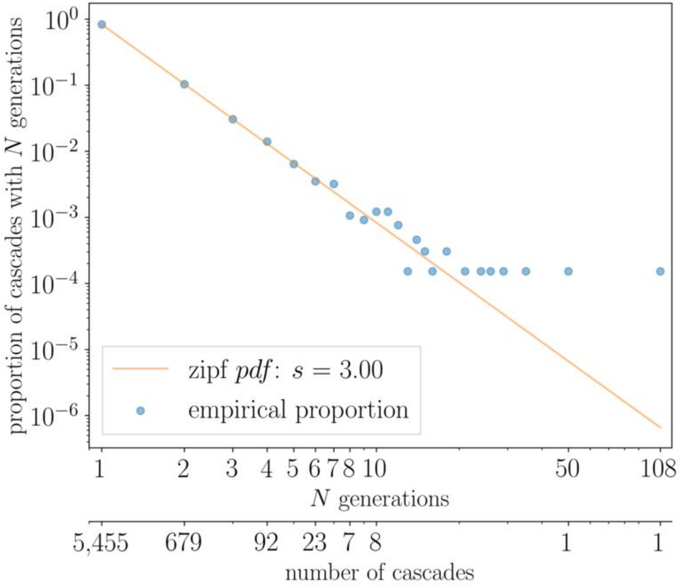
Stakeholders:

- Local (e.g. cities, counties, communities)
- National (NOAA, DHS, FEMA, USACE, USDA, USFS)
- Public, private, commercial (e.g., insurance)

Concerns: Lack of concrete ways of moving forward, add specific systems/examples, capture financial modeling, multiscale, dependence on current/past climate

What ML and Math research is needed?

- New ML techniques: Novel loss functions, their mathematical properties, and robust algorithms to carry out training with them.
- Scientific Machine Learning: merging physics-based models with ML while focusing on the precursors and process chains leading to extreme event models.
- Statistical methods for nonstationary and spatially distributed extremes.
- Improvements in physical and computational models. Numerical methods cannot currently reliably simulate and predict extreme events with reliability and error bounds.
- New insights in characterizing and propagating uncertainty in all relevant variables



BPA cascading failure data (courtesy Ian Dobson, Iowa State), prob(size)=C*size^(-3) (Gaussian =exp(-size^2)).

PARM	VAL
[illegible]	nan
[illegible]	nan
T_{casc}	60.0
T_{gen}	1.0
freq-type	casc-gens

Roth, Jacob, et al. "A Kinetic Monte Carlo Approach for Simulating Cascading Transmission Line Failure." *Multiscale Modeling & Simulation* 19.1 (2021): 208-241.

Concens: limits of ML, Generic ML hampered by space-time auto-correlation, variability, and tele-connection, Incorporate non-ML approaches, How to validate?

Additional requirements

- Determining data sources and needs for future data collection efforts, assessing quality of data.
- Convene stakeholder meetings, including infrastructure planners and operators, to identify initial types of extremes for our focus
  - Prioritize diverse stakeholder representation to maximize value of research in improving equitable outcomes
- Workforce development:
  - interdisciplinary training in mathematics, domain sciences, computational science, data science, statistics, etc.
  - Broaden the diversity of the workforce
- Computing/data storage/networking
- Experimental campaigns
- Interdisciplinary connections to economists, environmental scientists, biologists, physicists, computer scientists, etc.
- Create infrastructure and policies for verification, validation, and assurance

Concerns: Are rare events frequent enough to be predictable and analyzable?