1. Title: Identifying precursors of daily to seasonal hydrological extremes over the USA using deep learning techniques and climate model ensembles

2. Authors/Affiliations:

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3. Focal Area(s):

We focus on two areas of crosscutting interest for DOE: 1) predictability of extreme precipitation and drought in the USA and 2) the integration of climate models with new AI tools, such as convolutional neural networks (CNN) and methods to understand their output (e.g. layerwise relevance propagation; LRP). This project fits into focus area 3 of this call for white paper *using AI to gain insight from complex data, including explainable AI tools*.

4. Science Challenge:

Predicting hydrological extremes is important due to their impacts on people, agriculture and infrastructure. This prediction is difficult due to the infrequent occurrence of extremes and their complexity. However, extreme events can be related to more predictable conditions in the ocean, such as El Niño, long-term soil moisture or large scale modes of climate variability, such as the North Atlantic Oscillation (NAO).

Our goal is to identify slowly varying climate conditions preceding the occurrence of hydrological extremes over the USA. These precursors will be identified in a variety of global climate fields over a 3 to 18 month window preceding extreme events in climate model simulations. The CNN will be trained using output from three multi-model ensembles of CMIP-class global earth system models, minimizing the effect of model errors and biases in line with previous work (Barnes et al, 2019). The predictors identified through this approach will be evaluated against observations. We will additionally assess the role of model resolution in successfully identifying precursors by contrasting our results for high and low resolution models and including the DOE E3SM high resolution large ensemble when available.

5. Rationale:

Predicting hydrological extremes such as anomalous precipitation events is limited by the short observational record and infrequent occurrence of extremes. This means that within the large noise of the climate system it is difficult to identify precursors that consistently result in such extremes.

Thus, while new AI and deep learning techniques open opportunities, the relatively short and spatially incomplete observational record limits the full utilization of these techniques (e.g. Gil et

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al, 2018; Karpante et al, 2019; Reichstein et al, 2019). Fortunately, global climate models (GCMs) provide extensive and complete datasets that are ideal for the application of AI approaches. While GCMs contain biases when compared to the real world they can in general represent processes across the Earth surface and add to our understanding of the Earth system. By applying a CNN to multi-model climate ensembles that contain many models we can minimize model biases (Barnes et al, 2019). The output from the network can then be used to improve predictability. This provides benefits for farmers, hazard planners and water resource managers as well as improving our scientific knowledge on how the Earth system works.

This project fits into two of DOEs grand challenges. First, Grand Challenge 1 on the Integrated Water Cycle addresses how the frequency and intensity of precipitation events is affected by large scale variability. This project will identify large scale systems of climate variability and how they may be precursors to extreme rainfall and drought. Second, Grand Challenge 5 aims to use innovative tools. Deep learning is only beginning to be utilised to its full potential in climate science and our project will help to move this field forwards.

6. Narrative:
This project involves a collaboration between CU Boulder and NOAA scientists. Expertise in climate modelling, process analysis, USA precipitation, statistical tools, machine learning, big data, and assessing climate model uncertainties are provided by the four authors on the project (e.g. Capotondi et al, 2010, 2020; DiNezio et al, 2018; Kay et al, 2018; Lee et al, 2017; Maher et al, 2019, 2020; Thirumalai et al, 2017). This project will use a large amount of climate model data available as part of four initiatives:

1. Coupled Model Intercomparison Project phase 6 (CMIP6) - part of the World Climate Research Program (Eyring, et al 2016)
2. Multi-model large ensemble archive (Deser et al, 2020; Kay et al, 2015; Maher et al, 2019)
3. The High Resolution Model Intercomparison Project (Haarsma et al, 2016)
4. E3SM high resolution large ensemble - DOE future development project to create a higher resolution large ensemble

In this project we will use the deep learning tool CNN and the LRP tool (Barnes et al, 2020; Toms et al, 2020). CNNs provide new opportunities to learn from the large amount of climate model data we have. While many feel machine learning techniques are a black box that is difficult to interpret, methods exist to understand predictions from machine learning. Figure 1 shows a classification of El Niño events using machine learning techniques. We find that the method shows skill in identifying the evolution of events within the model limitations, demonstrating that classification succeeds for physically relevant reasons. More complicated tools, such as LRP heatmaps, which can be used to identify regions of importance for the CNN

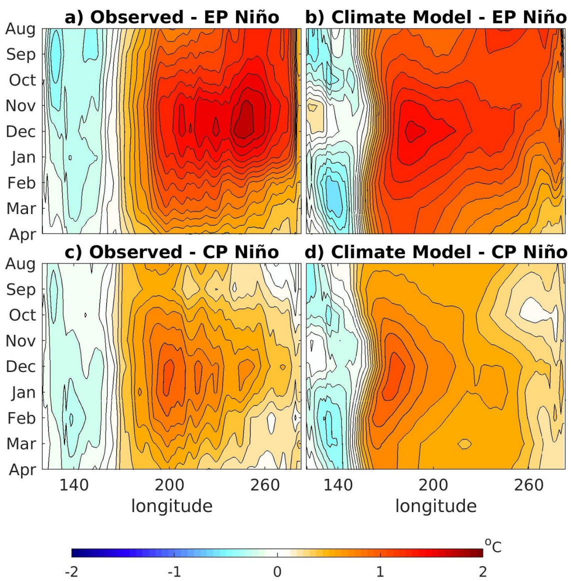

Figure 1: Evolution of equatorial SST (5S-5N) for eastern Pacific (EP) and central Pacific (CP) Niños in observations (left; HadISST) and identified by machine learning classification techniques in a climate model (right; MPI-GE).

prediction, exist to effectively look inside the black box. This method in particular has been used with climate models and shown to work well (Toms et al, 2020).

To investigate hydrological extremes over the USA we will split the country into 9 regions used by NOAA. We will consider both daily and seasonal extremes. For daily extremes we will investigate rainfall events that occur in the 99th percentile and flash droughts. For seasonal extremes we will aggregate precipitation over each region for each season of each year and identify seasons with values of precipitation in the 1st and 99th percentiles in each climate model. We will then train a convolutional neural network to predict these events and seasons. The network will use monthly values for the 3-18 months prior for quantities that are known to affect precipitation, either locally or remotely through atmospheric teleconnections. Such quantities include temperature (both over the ocean and over land), sea level pressure, outgoing longwave radiation, 500mb geopotential height, and soil moisture. The application of LRP will allow us to identify the quantities and regions that are most conducive to hydrological extremes for each region. To evaluate the results we will apply the network to NOAA-CIRES-DOE 20th Century Reanalysis product (20CRv3) and assess whether the precursors found in the climate models exist in this product.

This method will be applied to historical climate model data for each dataset individually, to assess the robustness of the results. We will additionally stratify models into low-resolution and high-resolution including HighResMIP model output and the DOE E3SM high resolution large ensemble to see if higher resolution provides more reliable precursors for precipitation in line with DOE priorities. Finally, we will characterise differences between climate models, which can be used to constrain findings and improve predictions in line with DOE pressing concerns.

The convolutional neural network predictor and LRP heatmap code and output will be made available in line with the FAIR principles. A github webpage will be made for the project where project information, metadata and explainable reusable code will be made available

7. Suggested Partners/Experts:

Dr. Celine Bonfils - Deputy Group Leader Lawrence Livermore National Laboratory

- DOE scientist with expertise in hydrology

Dr. Peter Caldwell - Research Scientist Lawrence Livermore National Laboratory

- DOE scientist, experience in climate model development and validation

Dr. Emanuele Di Lorenzo - Prof. Georgia Tech

- DOE PI responsible for the development of a E3SM Large Ensemble

Dr. Matthew Newman - Senior Research Scientist CIRES CU Boulder and NOAA/PSL

- Expert in linear inverse modelling

Dr. Angeline Pendergrass - Assistant Prof. Cornell University

- Expert in extreme precipitation and climate modelling of precipitation

Dr. Samantha Stevenson - Assistant Prof. UC Santa Barbara

- Involved in E3SM Large Ensemble Modelling effort

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