Subseasonal-to-seasonal Prediction of Atmospheric Rivers in the Western United States

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Focal Area(s)

Our goal is to improve predictive modeling of atmospheric rivers through the use of an AI-driven model and its components. This white paper primarily aligns with the focal area 2.

Science Challenge

Atmospheric rivers (ARs) account for a large portion of winter total precipitation (especially heavy precipitation) in the coastal states of western US (Dettinger et al., 2011; Rutz et al., 2014), but accurate subseasonal-to-seasonal predictions of ARs remain challenging. The challenge stems from relatively short observational records, the interactions of different climate modes and their nonlinear impacts on ARs, and uncertainties in AR activity due to AR detection methods (Huang et al., 2021). Important sources of AR prediction skill include different climate modes, such as the El Niño/Southern Oscillation (ENSO), Madden–Julian oscillation (MJO), and quasi-biennial oscillation (QBO) (DeFlorio et al., 2018, 2019; Mundhenk et al., 2018). Nevertheless, a lack of consensus on climate mode–AR relationship limits the subseasonal-to-seasonal predictive skills on ARs.

Rationale

The studies of ARs have grown exponentially since the 1990s (Ralph et al., 2017) due to the pivotal connections of ARs to water resources, droughts, and flooding over the western US. Reanalysis and climate model data are commonly used to investigate and predict ARs (Shields et al., 2018). Reanalysis products, such as MERRA2 used in the Atmospheric River Tracking Method Intercomparison Project (ARTMIP; Shields et al., 2018), generally date back to 1979 when satellite observations first became available. The

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short observational records (~40 years), along with the chaotic nature of the climate system, hinder a robust estimation of the causal relationships between climate modes and ARs (i.e., noise outweighs signal). Moreover, climate models and their outputs suffer from intrinsic deficiencies in simulating weather and climate accurately, such as extreme weather events and the ENSO-MJO and QBO-MJO linkages. Apart from the issues with climate data, the diversity of AR detection algorithms increases the uncertainty of AR activity. It has recently been shown that AR frequency, duration, and seasonality vary substantially by AR detection algorithm in both reanalysis and future projections (Rutz et al., 2019; O'Brien et al., 2020). The barriers largely constrain accurate predictions of AR activity in the western US. In contrast, ML/AI models are well suited to fill the gap due to their advantages to deal with 1) multiple climatic controls (e.g., ENSO, MJO, QBO) on AR occurrence and landfall; 2) the nonlinear response of AR activity to these controls; and 3) detection of ARs with supervised learning.

Narrative

ML techniques have been shown to be powerful tools to detect and forecast ARs effectively and robustly (Chapman et al., 2019; Prabhat et al., 2021). For example, the Deeplab/Resnet Neural Network (Chen et al., 2018; He et al., 2016) is implemented in the Toolkit for Extreme Climate Analysis (TECA; Loring et al., 2016) to detect ARs. The TECA application is newly developed and available for experimental use, offering an opportunity to improve AR detection and prediction. The Deeplab/Resnet Neural Network within TECA is trained with labeled data (i.e., supervised learning) from the Atmospheric River Tracking Method Intercomparison Project (ARTMIP; Shields et al., 2018). Thus, the ML-based toolkit can be fully leveraged to identify ARs in a wide variety of reanalysis (e.g., MERRA2 and ERA5) and climate model data (e.g., E3SM and CMIP5/6 models).

To further predict ARs at subseasonal-to-seasonal time scale, advanced ML models such as DeepLabv3+ (Chen et al., 2018) and U-net (Ronneberger et al., 2015) can be applied to emulate the relationship between ARs and all possible sources of subseasonal-to-seasonal AR predictability (e.g., ENSO, MJO, and QBO). The ML model will first be trained with the ARs identified by TECA using historical (1979–2015) reanalysis and climate model data. Training data will be used in the ML model to optimize model parameters. Then the optimized ML model will be tested by applying it to predict ARs from 2016–2020 and using the MERRA2 reanalysis as ground truth to evaluate its prediction skill. Furthermore, the ML-based model will be compared to traditional seasonal forecasting systems (e.g., the North American Multi-

Model Ensemble and fifth generation of the ECMWF seasonal forecasting system SEAS5) to assess the values added from using the novel ML approach. The ML-based predictive model may offer a path toward accurate subseasonal-to-seasonal prediction of ARs and precipitation over the western US. Thus, it will provide governments and stakeholders a powerful tool to manage future water resources and drought and flood risks.

To meet the FAIR (Findable, Accessible, Interoperable, Reusable) principles, the AR prediction model and code will be made publicly available on Github so that it is reusable and reproducible by other researchers. A link to the Github page and model introduction will be shown in the CASCADE SFA website maintained by the Lawrence Berkeley National Laboratory (https://cascade.lbl.gov). All training and testing data will also be compiled into a list with accessible links on the CASCADE website and Github page.

Suggested Partners/Experts

Burlen Loring (Lawrence Berkeley National Laboratory)

Travis A. O'Brien (Indiana University Bloomington)

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