AI-Based Approach for Advancing the Understanding of Spatiotemporal Drought Characteristics

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Focal Area

(3) Our proposal will focus on insight gleaned from observed and simulated complex data by using artificial intelligence (AI), big data analytics, and other advanced methods.

Science Challenge

We will advance the understanding of water cycle extremes by evaluating the interactions between hydroclimate and land surface processes across spatiotemporal scales.

Rationale

A prolonged period of atmospheric, surface, or subsurface water shortage in a region is referred to as a *drought*. Droughts can result in the loss of agricultural productivity, ecosystem damage, water scarcity, and negative socioeconomic impacts. Therefore, the ability to estimate drought in a timely manner is crucial for emergency preparedness and planning. The state of drought in a region is determined by understanding the interaction among hydroclimate and land surface characteristics and by identifying the dominant drivers, and it is estimated by using deficit indicators (Miralles et al. 2019). Thus far, many indicators have been developed to quantify drought, and the most popular are the standardized precipitation index, Palmer drought severity index (PDSI), and standardized precipitation evapotranspiration index. The utility of these indices varies by region and applications. These indices are generally calculated at aggregate timescales with respect to a reference period with a deficit over a certain period indicating drought (Hao, Singh, and Xia 2018).

With the intensification of the hydrological cycle in response to enhanced radiative forcing, the frequency and intensity of extreme precipitation events are projected to change (Rastogi et al. 2020). This could lead to heavy precipitation concentrated over a few days, which might be insufficient to improve drought conditions, as opposed to more uniformly spread precipitation over a month. Similarly, the land-atmosphere interactions, which occur at short timescales, can trigger other extreme mechanisms, such as heatwaves, that can further intensify droughts (Mukherjee and Mishra 2020). However, most drought indices are not estimated in a way that fully account for these mechanisms. The more sophisticated indexes, such as PDSI, capture these interactions to a certain extent by incorporating a range of hydroclimate variables, including precipitation, temperature, evapotranspiration, and soil moisture. However, not even PDSI can depict drought on shorter timescales (<12 months), despite being computationally intensive and time consuming. This implies that relying on traditional indices might not provide a holistic picture of the state of drought in a region, especially for sub-seasonal to seasonal scale impacts. Furthermore, drought occurrence is spatially widespread and can lead to extensive damages as opposed to more localized extremes (Brunner et al. 2020). Understanding the spatial extent of drought and cooccurrence across regions can help improve risk assessment and provide more adequate resources planning and management. However, few studies have focused on evaluating the spatial dependence of drought thus far. To overcome these limitations, we propose to apply AI-based approaches that can help develop a generalized way to quantify drought, capture the interactions between land-atmosphere interactions at relevant timescales, and account for spatial dependence.

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Narrative

Our goal is to develop a generalized approach to improve our understanding of drought by incorporating the spatial and temporal dependencies of various drivers for sub-seasonal- and seasonal-scale assessments. To achieve this objective, we propose to apply advanced deep learning approaches based on convolutional and recurrent neural network architectures for the analysis of large volumes of spatiotemporal data. The existing literature on this topic already includes multiple examples of the successful application of these approaches to evaluate atmospheric patterns in observed and simulated data. For instance, convolutional neural networks (CNNs) were used to identify and classify patterns associated with hot and cold extremes in the climate data (Chattopadhyay, Hassanzadeh, and Pasha 2020). Similarly, convolutional long short-term memory (ConvoLSTM) recurrent network was used for precipitation nowcasting over a region for a relatively short time by treating it as a spatiotemporal sequence forecasting problem in which both input and output sequences are spatiotemporal in nature (Shi et al. 2015). However, these approaches have not been applied to evaluate spatiotemporal drought characteristics. Moreover, they are commonly derived as an extension of the existing state-of-the-art supervised learning techniques which rely on the availability of large amounts (10,000 or more) of preprocessed and labeled training datasets and do not account for the specifics of climate and environmental data, which is often unlabeled, inherently multi-scale, and multi-modal.

To address the multi-scale nature of environmental data, we propose to adapt the existing architectures for multi-scale image and time series processing (Pelt and Sethian 2017, Xiao, et al. 2018, Ke, Maire and Yu n.d., Liu, et al. 2020). Such networks allow for simultaneous extraction of multi-scale features, enable the flow of information across the scales, often require less data and better adopt to a specific problem allowing the same model to be applied for various applications and types of data. We also intend to extend these architectures with our recent results on robust learning of dynamical systems (Reshniak and Webster 2021) and hierarchical design of neural networks with a goal to enable the simultaneous utilization of data coming from different sources and at different resolutions.

To overcome the limited availability of labeled data, we propose an approach that builds on existing work and employs unsupervised machine learning algorithms—such as k-means and self-organizing maps—to cluster various drought-related variables, such as precipitation, temperature, evapotranspiration, soil moisture, and land use type. We will identify historically known events by using existing drought indices in the reanalysis as well as observations. In addition to spatial clustering, we also propose using a temporal method of clustering these variables so that the resulting clusters can capture the spatiotemporal drought characteristics. Further, we will label various spatio-temporal cluster representing drought characteristics. We also plan to incorporate the output from earth system models, such as the Energy Exascale Earth System Model in this entire process. We anticipate that our proposed deep-learning based approach will improve our understanding of drought by capturing spatial and temporal variations among drought related indicators at sub-seasonal and seasonal scales.

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