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Using Deep Learning for a High-Precision Analysis of Atmospheric Rivers in a High-Resolution Large Ensemble Climate Dataset

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Atmospheric rivers (ARs) are elongated corridors of water vapor in the lower Troposphere that cause extreme precipitation over many coastal regions around the globe. They play a vital role in the water cycle in the western US, fueling most extreme west coast precipitation and sometimes accounting for more than 50% of total annual west coast precipitation (Gershunov et al. 2017). Severe ARs are associated with extreme flooding and damages while weak ARs are typically more beneficial to our society as they bring much needed drought relief.

Precipitation is particularly difficult to predict in traditional climate models. Predicting water vapor is more reliable (Lavers et al. 2016), allowing IVT (integrated vapor transport) and ARs to be a favorable method for understanding changing patterns in precipitation (Johnson et al. 2009). There are a variety of different algorithms used to track ARs due to their relatively diverse definitions (Shields et al. 2018). The Atmospheric River Tracking Intercomparison Project (ARTMIP) organizes and provides information on all of the widely accepted algorithms that exist. Nearly all of the algorithms included in ARTMIP rely on absolute and relative numerical thresholds, which can often be computationally expensive and have a large memory footprint. This can be particularly problematic in large climate datasets. The vast majority of algorithms also heavily factor in wind velocity at multiple vertical levels to track ARs, which is especially difficult to store in climate models and is typically not output at the temporal resolution that ARs occur.

A recent alternative way of tracking ARs is through the use of machine learning. There are a variety of neural networks that are commonly applied towards identifying objects in cityscapes via semantic segmentation. The first of these neural networks that was applied towards detecting ARs is DeepLabv3+ (Prabhat et al. 2020). DeepLabv3+ is a state of the art model that demonstrates one of the highest performances of any present day neural network when tasked with the objective of identifying objects in cityscapes (Wu et al. 2019). We employ a light-weight convolutional neural network adapted from CGNet (Kapp-Schwoerer et al. 2020) to efficiently track these severe events without using wind velocity at all vertical levels as a predictor variable. When applied to cityscapes, CGNet's greatest advantage is its performance relative to its memory footprint (Wu et al. 2019). It has two orders of magnitude less parameters than DeepLabv3+ and is computationally less expensive. This can be especially useful when identifying ARs in large datasets. Convolutional neural networks have not been used to track ARs in a regional domain. This will also be the first study to demonstrate the performance of this neural network on a regional domain by providing an objective analysis of its consistency with eight different ARTMIP algorithms.