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## Leveraging advances in hyper-resolution soil moisture and vegetation land data assimilation for S2S hydroclimate applications

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Due to soil moisture and vegetation's critical role in controlling land-atmosphere interactions, detailed and accurate hydrological and ecological information is essential to understand, monitor, and predict hydroclimate extremes (e.g., droughts and floods), natural hazards (e.g., wildfires and landslides), irrigation demands, weather, and climate dynamics. While in-situ soil moisture and vegetation biomass measurements can provide detailed information, their representativeness is limited, and networks of sensors are not widely available. Multispectral satellite observations offer global coverage, but retrievals can be infrequent or too coarse to capture the local extremes. This observation data gap limits the use of such information to adequately represent land surface processes and their initialization conditions for seasonal to sub-seasonal (S2S) prediction models. To bridge this gap, the assimilation of remote sensing observations into land surface models at hyper-resolution spatial scales (< 100 meters) provides a pathway forward to (i) reconcile model and observation scales and (ii) enhance S2S hydroclimate predictability in Earth System Models.

To this aim, we introduce a scalable approach that leverages advances in machine learning, radiative transfer modeling, and in-situ observations to assimilate satellite observations into unstructured tile-based land surface models. In this approach, a machine learning model is trained to harness information from big environmental datasets and in-situ observations to learn how the physical model and satellite biases are related to specific hydrologic conditions and landscape characteristics and how these biases evolve over time. We demonstrate the added value of this approach for improving soil moisture and vegetation dynamics at the hyper-resolution scales by assimilating MODIS Leaf Area Index and NASA's SMAP brightness temperature observations into the LM4.0 – the land model component of the NOAA-GFDL Earth System Model. To this end, we performed stand-alone LM4.0 simulations between 2000 to 2021 over the Continental United States, with the MODIS and SMAP assimilation performed from 2002 and 2015, respectively, until the present day. Soil moisture estimates are evaluated against independent in-situ observations. To quantify the approach added value for S2S predictability, we compare the impact of soil moisture and vegetation data assimilation on root zone soil moisture, runoff, vegetation biomass, surface temperature, and evapotranspiration.