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Multi-Sensor Space-Time Data Fusion of Machine Learning Generated Time Series for Wetland Inundation Monitoring

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The biogeochemistry of wetland ecosystems is driven by the presence and absence of water. Wetlands are known hotspots of methane (CH_4) emissions, particularly when inundated. Monitoring short-term, and possibly small-scale changes in inundation is therefore critical to quantifying both local and global CH_4 emissions. Despite their importance, these short-term changes have historically been under-reported in efforts to monitor CH_4. As sea levels rise and flood events increase, it's imperative to account for these events to better project CH_4 cycle variation in a changing climate. Remote sensing is the only method capable of monitoring these changes over time at scale; however, no current remote sensing product has the spatial and temporal resolutions required to map ephemeral changes in inundation extents accurately. To address this, we developed a method to generate high spatiotemporal resolution inundation maps combining SAR and optical data from Sentinel-1 and Sentinel-2 imagery supplemented with commercial PlanetScope imagery from 2017–2022. This method was evaluated in the Albemarle-Pamlico Peninsula, a coastal wetland region in North Carolina, United States characterized by frequent and variable inundation.

Two decision-tree based machine learning algorithms were tested to map inundation extents: a random forest (RF) model and an extreme gradient boosted (XGBoost) model. The models were trained for each sensor based on a suite of spectral signals, terrain-derived features, and precipitation data for each image at the sensor's native resolution. This work revealed minor differences between machine learning classifiers across the 5 years, with RF accuracies of 94.0%, 98.2%, and 98.6% and XGBoost accuracies of 89.1%, 98.3%, and 97.8% for PlanetScope, Sentinel-2, and Sentinel-1 respectively. The RF classified inundation maps from each sensor were then fused using a hierarchical spatiotemporal random effects model within a probit link function, to generate daily time series of inundation probabilities at 5 m resolution. This approach is unique in that we 1) address the differing sensor resolutions using a statistical change-of-support formulation with observations mapped to process locations, 2) fuse non-Gaussian (binary) responses from machine learning outputs, and 3) model spatial and temporal autocorrelation through spatial basis functions and a first-order autoregressive time series model. Overall, this work produced a novel 5-year inundation dataset, capturing both long-term and ephemeral changes in inundation extents that are critical for quantifying components of the water cycle and their interactions with biogeochemical cycles on Earth.