Integrating Physical and Remote Sensing Models to Map Inundation at High Spatiotemporal Resolution

Jenna Abrahamson[1] and Josh Gray[1,2]

[1]Center for Geospatial Analytics, North Carolina State University

[2] Forestry and Environmental Resources, North Carolina State University

Center for Geospatial Analytics

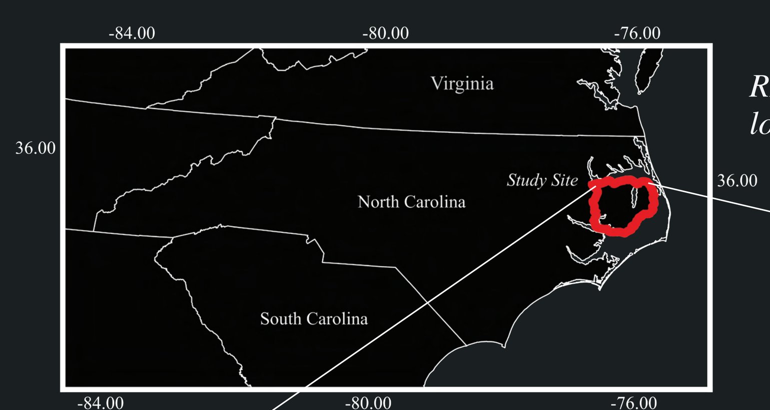
jnabraha@ncsu.edu

@JennaAbrahamson

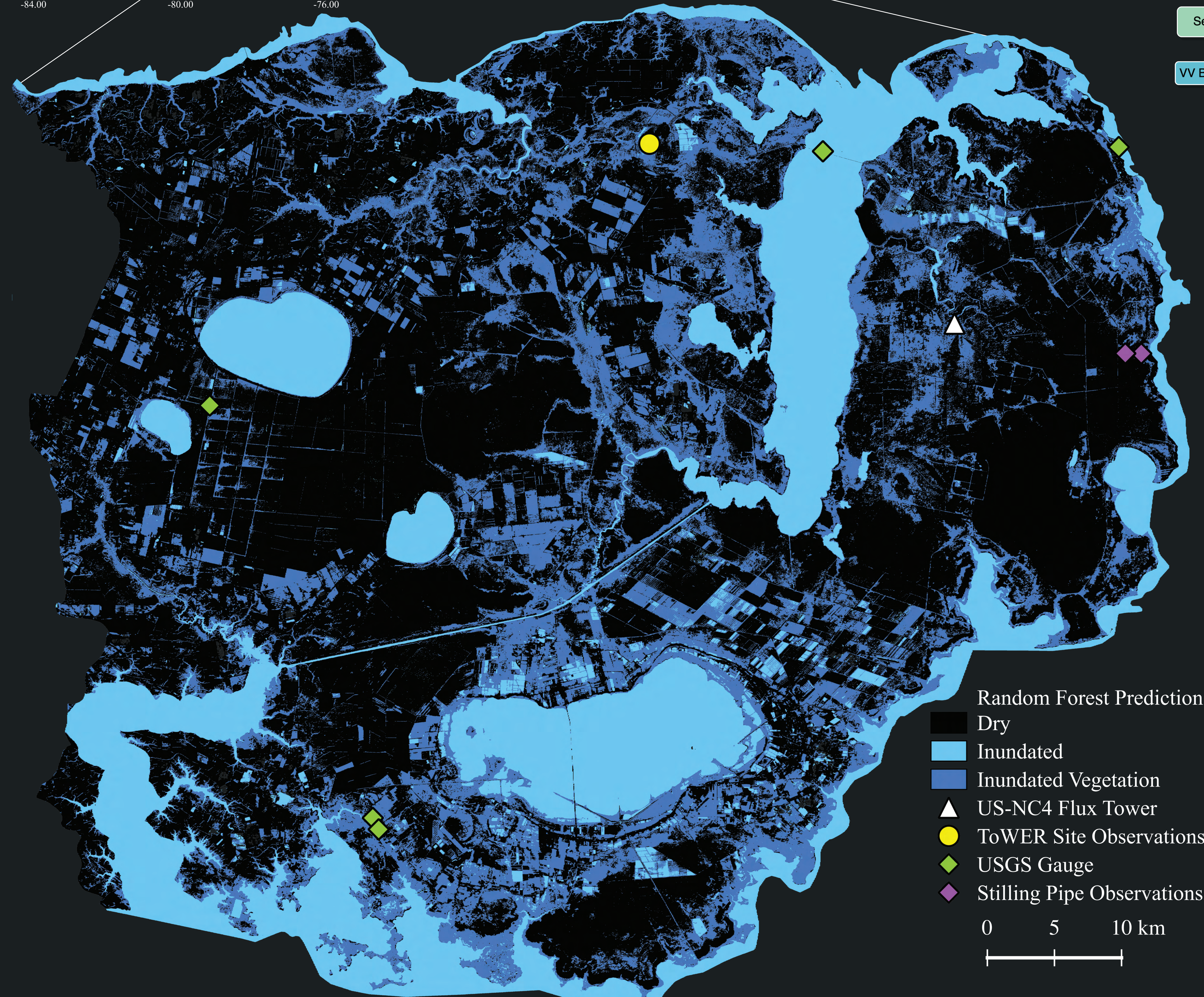
@jen-abrahamson

I. Motivation

- **The biogeochemistry of coastal wetlands is driven by hydrologic processes.**
- Wetlands are vital to carbon sequestration and are known to be hotspots of methane (CH_4) emissions when inundated.
- The ability to map short-term inundation events in these ecosystems is **a critical component in understanding global biogeochemical cycles.**
- Current methods tend to rely on moderate resolution (30 m) remote sensing data or hydrologic models alone to map inundation at monthly or yearly time steps, at which spatial and temporal resolutions are insufficent for understanding biogeochemial impacts.



RF predicted inundation map for 2018-01-31. Study area is a low-lying coastal wetland in Eastern North Carolina.



II. Objectives

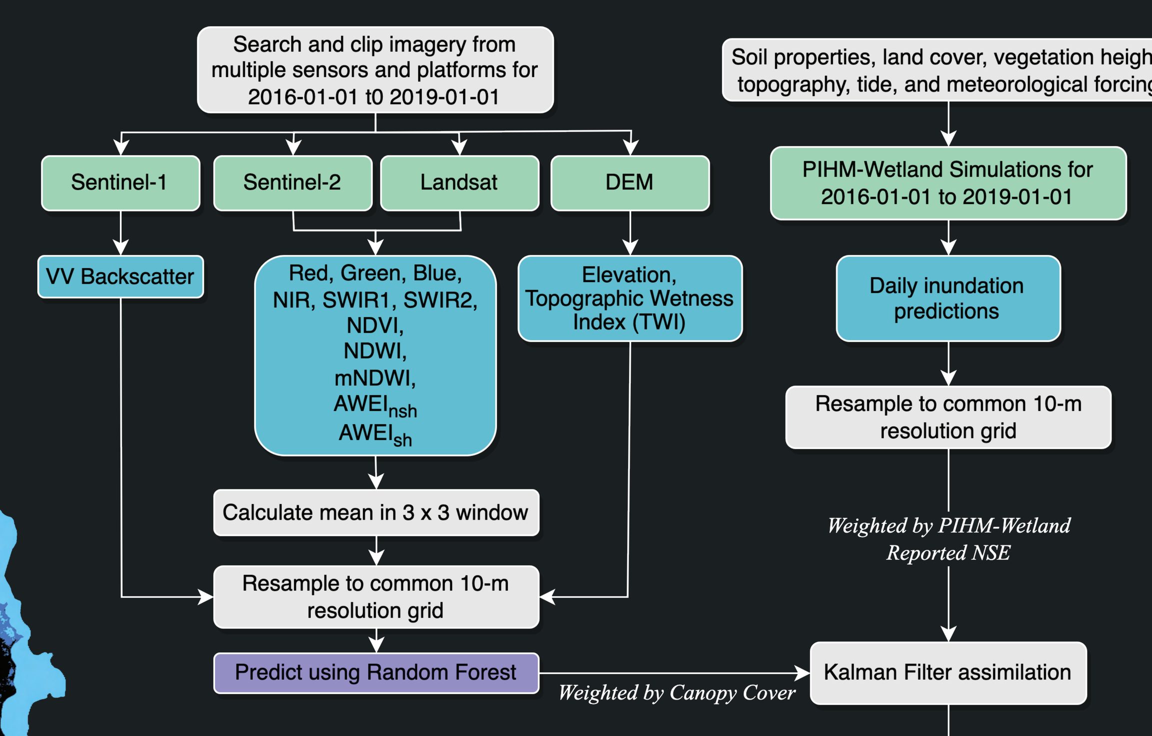
- Can we develop a framework that integrates a multi-sensor remote sensing model with a process-based hydrologic model using data assimilation methods to produce **daily inundation probabilites at 10-m resolution**?
- How does daily monitoring of inundation using this framework compare to monitoring inundation using either method alone?

Key Takeaways

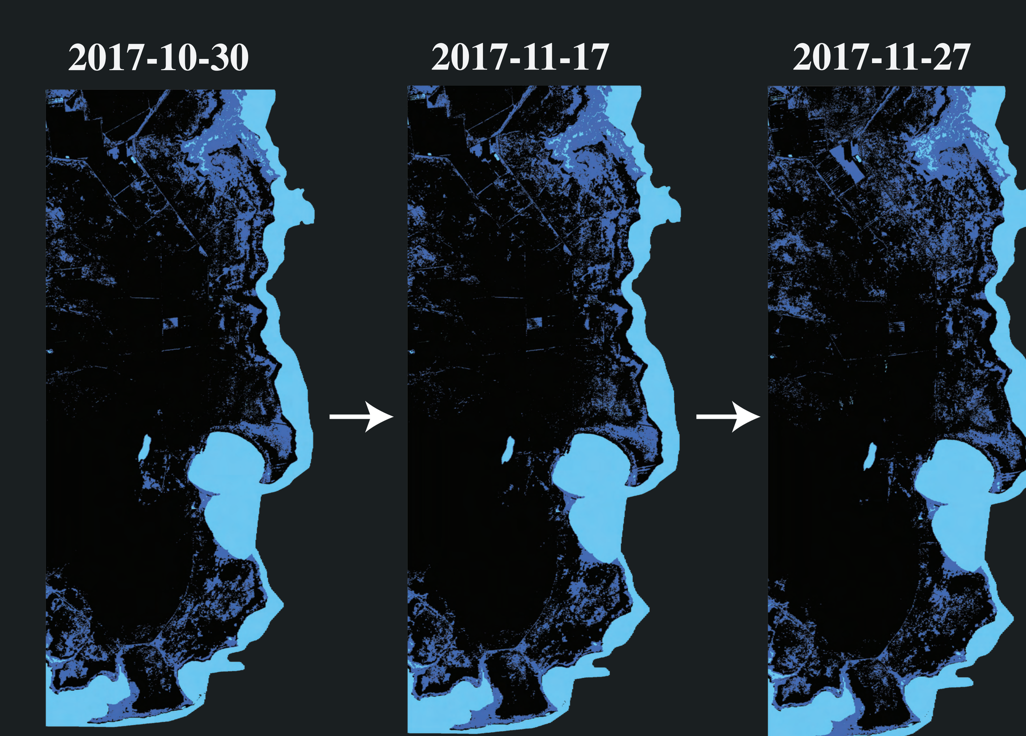
- Data assimilation allows us to monitor inundation in coastal wetland ecosystems daily at 10-m resolution.
- Integrating with a hydrological model provides improvements in estimating inundation underneath forest canopies and during times of cloud cover.
- Satellite data allows for increased accuracy in low-lying coastal plains where topographic gradients can be difficult to simulate at a regional scale.

III. Machine Learning-Based Remote Sensing Model

- The **random forest (RF) machine-learning algorithm** was used to map inundation.
- Training data (4,926,513 pixels) were acquired through visual interpretation of Google Earth, NAIP, and PlanetScope imagery and stratified by land cover categories.
- 26 predictors were used to classify pixels as *inundated*, *dry*, and *inundated vegetation*.
- The reported out-of-bag error and 10-fold cross-validation error for the model was 0.084

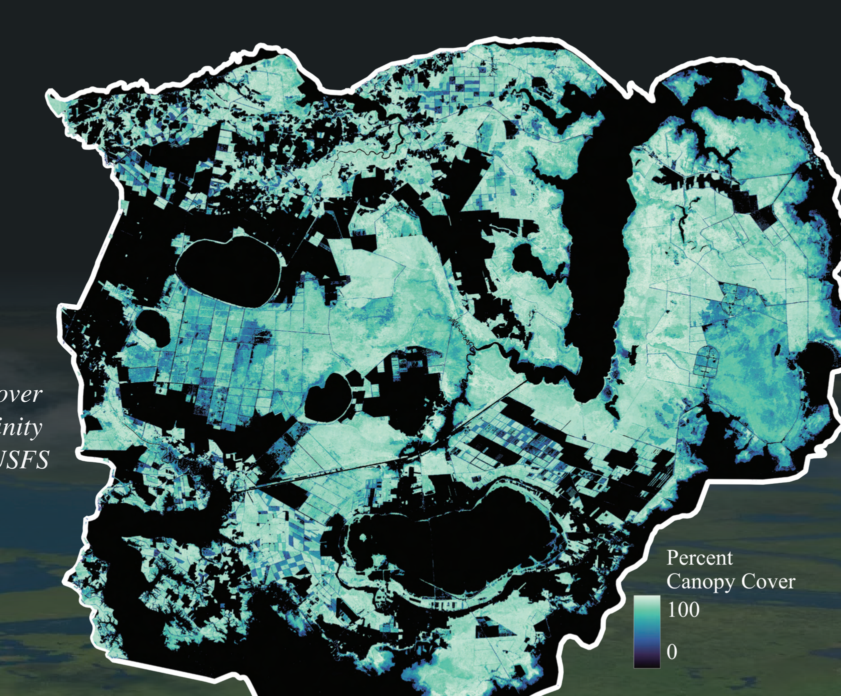


Flow chart detailing methodology and input data



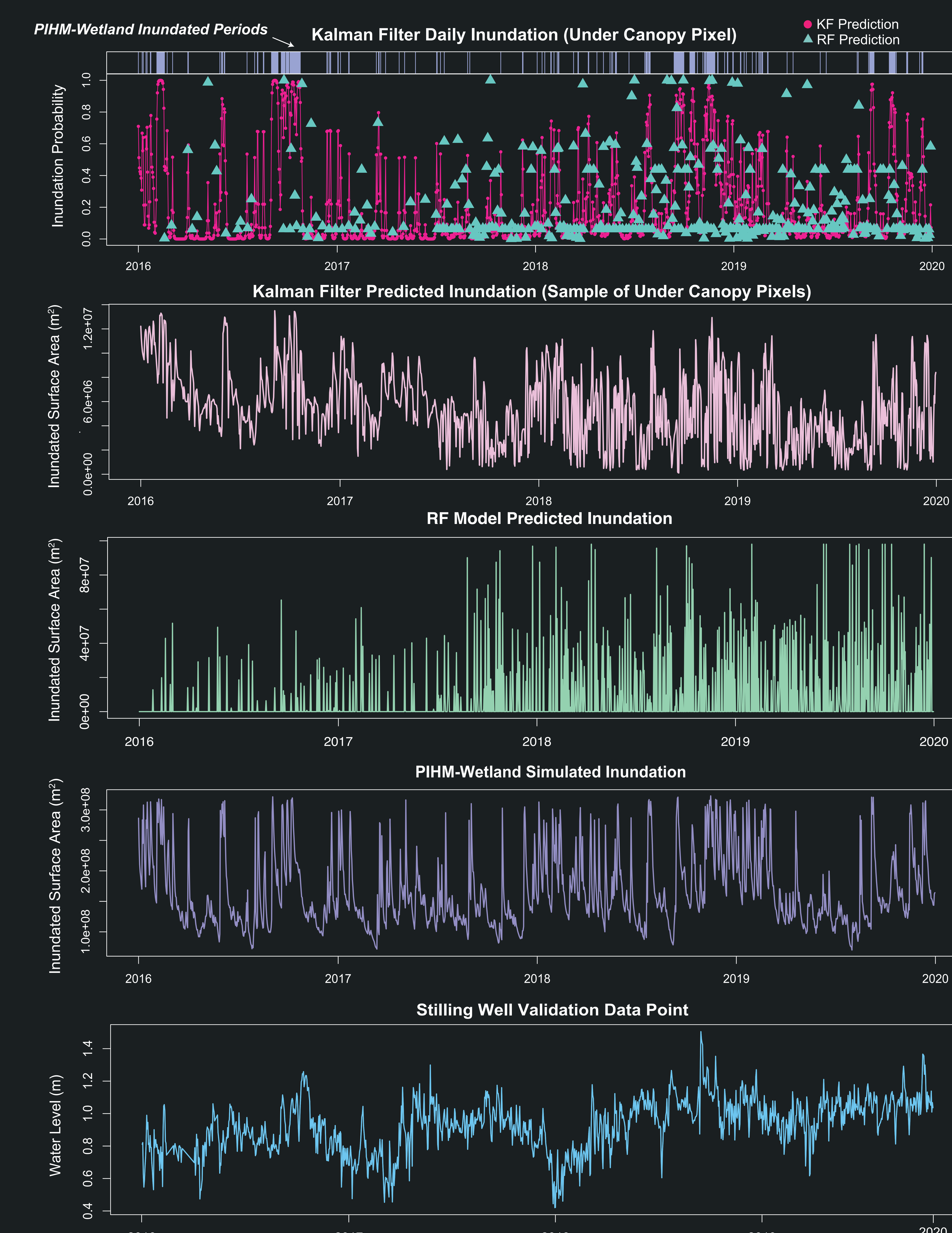
Example RF predictions from satellite observations input into Kalman Filter. This extent was used to calculate time series figures to the right.

Percent Canopy Cover for Kalman Filter uncertainity weighting obtained from USFS



IV. Data Assimilation via State-Space Modeling

- We developed a data assimilation framework using the **Kalman filter** to combine results from the remote sensing RF model with the process-based PIHM-Wetland hydrologic model (Zhang et al., 2018).
- The Kalman filter estimates a posterior probability via uncertainty weighted averaging.
- Uncertainty was weighted for each pixel by canopy cover to leverage the ability of PIHM-Wetland to "see" or be favored under dense canopies. The OOB error estimate for predicting inundated vegetation from the RF model was used to weight the RF model predictions for pixels whose canopy cover was greater than 50%.



The time series above show the inundation probability for an under canopy pixel predicted with KF, total inundated surface area predicted by KF, RF and PIHM-Wetland compared to a validation data set of water levels calculated for a subset of the study region (subsection extent seen left).

V. Next Steps

- Refine RF model and add high-resolution PlanetScope data as an input
- Test different uncertainty weighting schemes for use with Kalman filter
- Apply at a regional scale to study impacts on biogeochemistry

NC STATE UNIVERSITY College of Natural Resources

Acknowledgements

Special thanks to Keqi He for sharing PIHM-Wetland inundation simulations (He et. al., 2022) and Dr. Justine Neville for sharing stilling well data.

Photo Credit: Drew Angerer/Getty Images

Lab Website