Machine Learning Models for Water, Energy, and Greenhouse Gas Fluxes Measured from a Dwarf Cypress Wetland Within the Greater Everglades

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Introduction:

Wetlands such as the Everglades are considered sinks for atmospheric carbon dioxide (CO_2) and sources for water vapor and methane emissions (CH_4). In this study, the magnitude and seasonality of CO_2 uptake, water vapor (ET) flux, and CH_4 emissions were defined using ensembles of machine learning models combined with a unique decadal record of water, energy, and biogeochemical cycling measured from one eddy-covariance (EC) flux station located in an area of dwarf cypress and sawgrass wetlands. ET, CO_2 flux, and CH_4 flux all can be used as the indicators of ecosystem health and are critical to understanding the status of the Greater Everglades Ecosystem.

Figure 1: Dwarf Cypress Station.

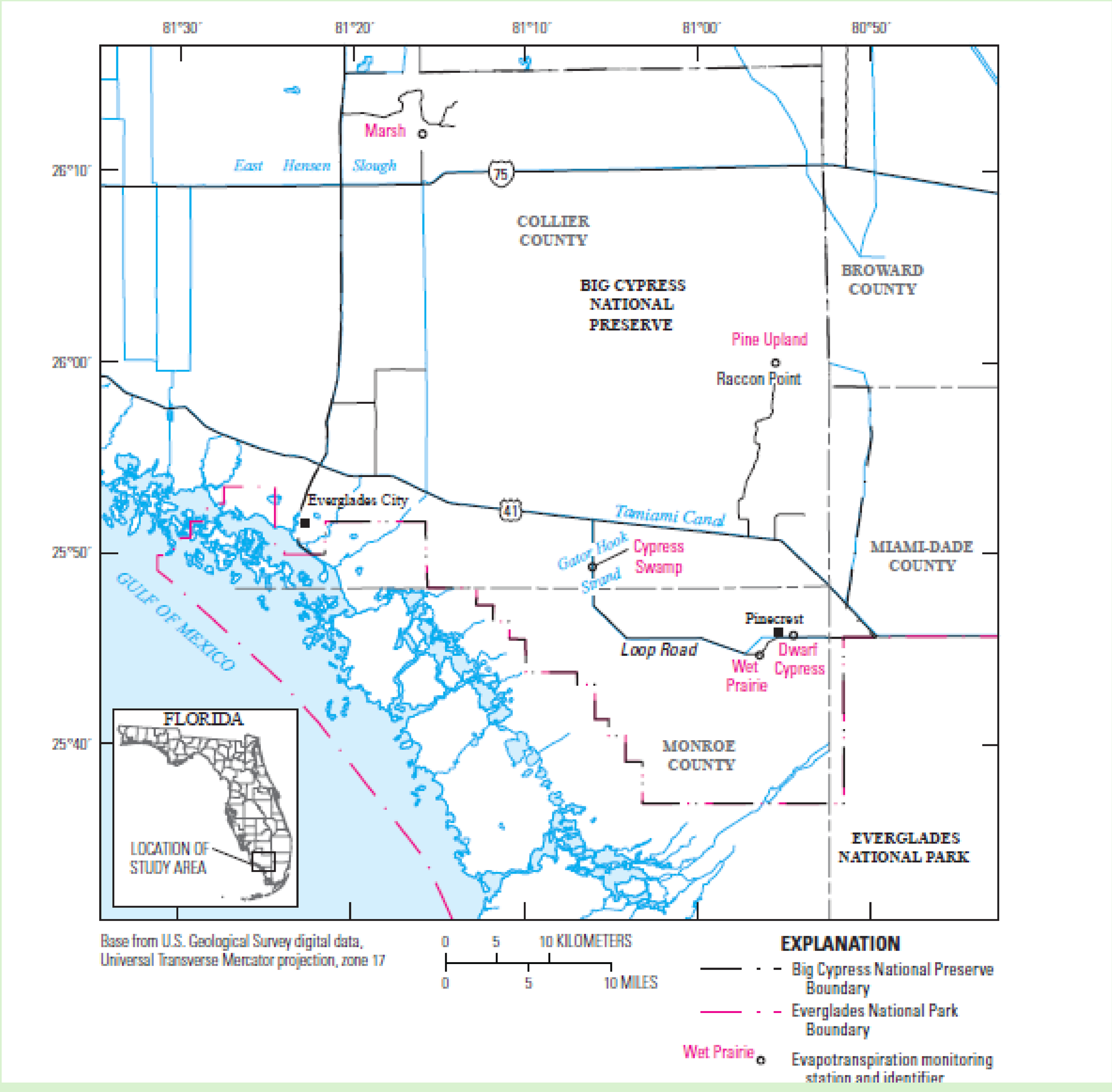

Figure 2: Map of Dwarf Cypress station location.

Methods:

- The study area is located at the Dwarf Cypress flux station off Loop Road within Big Cypress National Preserve in South Florida (Figures 1 and 2).
- EC measurements of ET were made from April 2007 to December 2024.
- Measurements of CO_2 and CH_4 were made from December 2012 to December 2024.
  - CO_2 was used to calculate Net Ecosystem Exchange (NEE)
- ET, NEE, and CH_4 fluxes were computed using eddy-covariance method (Dyer, 1961; Tanner and Greene, 1989).
- Net radiation, air temperature, soil temperature, relative humidity, and vertical wind velocity were used to calculate latent heat.

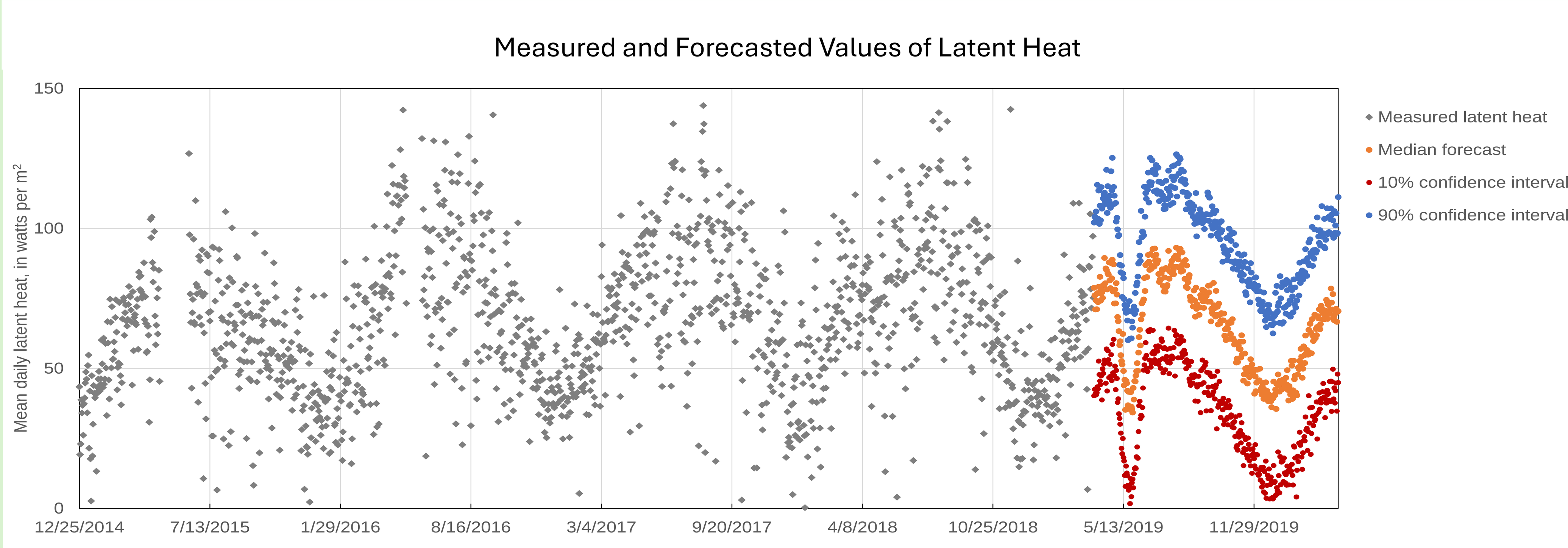

Figure 3: Measured and predicted values of latent heat.

Results:

- Machine learning tools can accurately forecast broad seasonal trends.
- Forecasting can define hard to see trends in data.

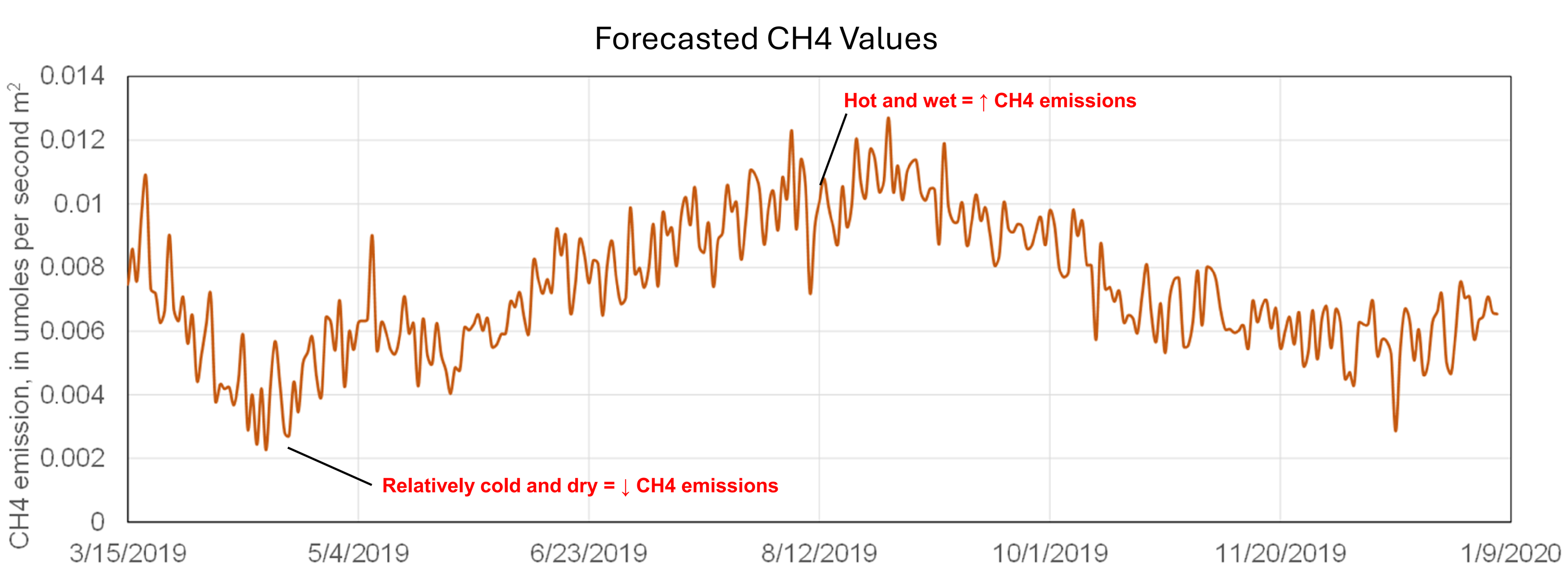

Figure 4: Forecasted trends of CH4 emission.

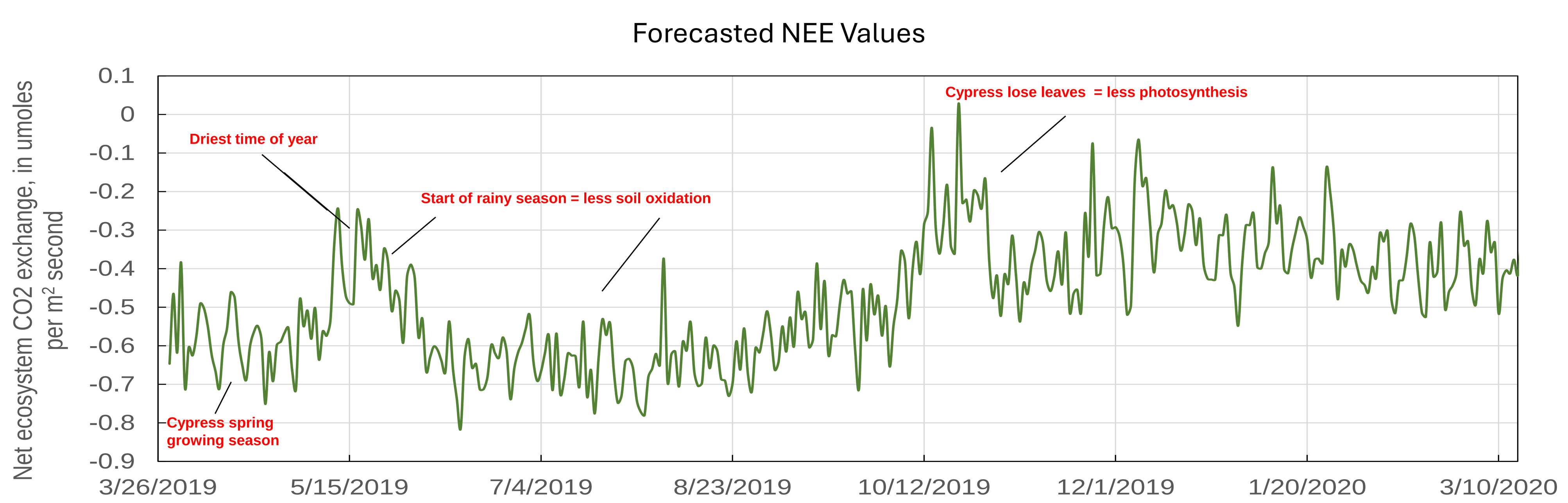

Figure 5: Forecasted values of NEE.

Discussion:

- Gap filling and forecasting technology can be incredibly useful for times when there are equipment failures and data gaps.
- Machine learning can discern minor trends and then can accurately depict them (decrease of latent heat at beginning of rainy season Figure 3).
- Machine learning can accurately predict well defined seasonal trends (Figures 4 and 5).
  - Caution should be taken as forecasting has trouble predicting unusual events.
    - Major storm events or an extended drying periods present forecasting issues.

References:

- Dyer, A. J. (1961). Measurements of evaporation and heat transfer in the lower atmosphere by an automatic eddy-correlation technique. Quarterly Journal of the Royal Meteorological Society, 87(373), 401-412. https://doi.org/10.1002/qj.49708737311
- Tanner, B. D., & Greene, J. P. (1989). Measurement of sensible heat and water vapor fluxes using eddy correlation methods. Campbell Scientific, Incorporated

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