College of Engineering – Department of Civil, Environmental and Geodetic Engineering

Modeling water flux to WPL correct methane flux for the Ameriflux network.

Student: Noah Charlton

Principal Investigator: Dr. Gil Bohren

BACKGROUND

Methane and Greenhouse Gasses.

- · Methane (CH4) is the second most impactful greenhouse gas after carbon dioxide (CO2) and is a pollutant to Earth's atmosphere. [1]
- · In order to understand methane emissions, scientists have looked at wetlands, since they "may contribute as much as 25%–40% ... of atmospheric methane concentrations." [2]

Methane Flux, Eddy Covariances, and the Ameriflux Network.

- · To study methane emissions, scientists record a region's methane flux, which quantifies how much methane moves through an area is a certain period.
- Eddy covariance is a technique that analyzes meteorological variables and gas concentrations to measure flux.
- · Our team maintains a site at Old Women's Creek, shown below, which regularly submits data to the Ameriflux network

Old Women's Creek Flux Tower



Flux Tower at Old Women's Creek, April 2018

MOTIVATION

To correct raw methane data, water flux is needed. However, during winter 2019 and summer 2021, the water concentration sensor broke so we cannot produce methane flux data.



THE OHIO STATE UNIVERSITY

METHODOLOGY

To solve this, we hoped to model water flux and fill in the gaps in the data. To do this, we had a four-step plan:

- 1. Develop a linear regression model of water flux to identify variables that affect water flux.
- 2. Modify the data pipeline by moving the WPL correction.
- Create a neural network to model water flux.
- 4. Apply the WPL correction with the modeled water flux data.

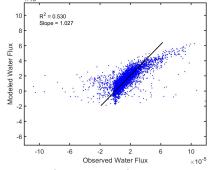
LINEAR MODEL OF WATER FLUX

Using MATLAB and data from winter 2021, we developed a linear regression model of water flux to identify driver variables for the neural network. We achieved an R^2 value of 0.53 using:

 Water temperature 	Soil Temperature
---------------------------------------	------------------------------------

- 2. Frictional Velocity 5. Air Temperature
- 3. Relative Humidity

Observed vs. Modeled Water Flux Data during Winter 2021



Modeled water flux $\left(\frac{kg}{m^2}\right)$ vs. observed water flux $\left(\frac{kg}{m^2}\right)$ from 11/1/21 to 2/28/22.

MODIFYING THE DATA PIPELINE

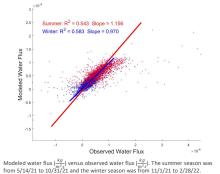
For periods where we had to model water flux, we needed to move the WPL correction to when we process the entire season because we don't create a model until we process the entire season



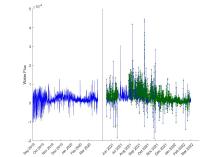
NEURAL NETWORK OF WATER FLUX

Then, we created a neural network model for summer and winter using MATLAB. The script creates 3 models for day and 3 models for night and chooses the best day and night model for the final product.

Observed vs. Modeled Water Flux Data



Time Series of Observed and Modeled Water Flux



Water flux (kg/2) versus time. Observed water flux is in green, and modeled water flux is in blue. The break in the plot is from 4/1/20 to 5/1/21.

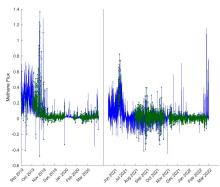
WPL CORRECTION FOR METHANE FLUX

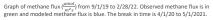
- By default, the derivation of Eddy Covariance assumes that the air is dry, so the WPL (Webb-Pearman-Leuning) correction is used to compensate for water vapor. [3]
- Below is the WPL equation for methane flux, with water flux highlighted:

 $F_c = A(w_M + B\frac{m_a\rho_m}{m_m\rho_a} w_Q + C\rho_m \left(1 + \frac{m_a\rho_q}{m_m\rho_a}\right) \frac{w_T}{T_L}$

RESULTS

Time Series of Observed and Modeled Methane Flux





CONCLUSION

- · We used machine learning to train a neural network to model water flux during the summer and winter at Old Women's Creek
- By modeling water flux, we were able to correct raw methane data during periods where missing water concentration data caused a gap in methane flux calculations.
- We now have a continuous set of methane flux data for Old Women's Creek from September 2019 to November 2020, and from May 2021 to February 2022.

REFERENCES

 [1] Myhre, G., Shindell, D., Bréon, F.-M., Collins, W., Fuglestvedt, J., Huang, J., Koch, D., Lamarque, J.-F., Lee, D., Mendoza, B., Nakajima, T., Robock, A., Stephens, G., Takemura, T., & Zhang, H. (2013). Anthropogenic antaural radiative forcing. In F. F. Stocker, D. Qin, G. A.: Platters, M. Tignor, S. K. Allen, J. Doschung, A. Nauels, Y. Xu, See, & P. M. Midgley (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (pp. 659–740). Cambridge University Press

 [2] Knox, S. H., Jackson, R. B., Poulter, B., McNicol, G., Fluet-Chouinard, E., Zhang, Z., Hugelius, G. (c) nonvo, s. hr. needon, n. t. o., nonvo, s. northog, n. t. nov. (n. t. nov. (n. t. nov.), n. t. nov. (n. t. nov.), n 100(12), 2607-2633. https

• [3] Monson, R., & Baldocchi, D. (2014). Terrestrial Biosphere-Atmosphere Fluxes. Cambridge University

ACKNOWLEDGEMENTS

I would like to thank my project advisor, Dr. Gil Bohrer, for helping me through my project.

https://ceg.osu.edu/ecohydrology-and-forest-meteorology-laboratory