High-Resolution Mapping of Wetland CO_2 Fluxes Using Sentinel-2 Imagery and Deep Learning

Name: Yehuda Yungstein

ID: 205487143

Introduction

Wetlands are crucial ecosystems for global carbon cycling and climate regulation, storing 20-30 precents of global carbon despite covering only 1-2% of Earth's surface(Dinsa & Gemeda, 2019). These environments both sequester and emit greenhouse gases, primarily carbon dioxide (CO_2) and methane (CH_4), through complex processes influenced by water level, temperature, and vegetation (Shindell et al., 2009). Quantifying these carbon fluxes is essential for effective wetland management and climate change mitigation strategies. Traditional carbon flux measurement methods, such as eddy covariance (EC) towers, provide accurate point-based data but are limited in spatial coverage (Göckede et al., 2004). Remote sensing offers a solution to this limitation by providing spatially and temporally continuous data over large areas (Helman, 2018). While satellite-based observations have been used to monitor vegetation dynamics and estimate carbon fluxes in various ecosystems, their application in modeling wetland carbon fluxes remains relatively unexplored (McGowan et al., 2022).

Recent studies have shown promise in integrating satellite data with EC measurements to map CO_2 fluxes in wetlands. For instance, (Zhang et al., 2021) mapped CO_2 fluxes in the Greater Everglades using Landsat data and EC measurements. However, there is still a need for higher spatial and temporal resolution data to capture the fine-scale heterogeneity and rapid changes characteristic of wetland environments.

This project aims to address this gap by developing a neural network model that predicts CO_2 fluxes in wetlands using high-resolution Sentinel-2 satellite data. The model will utilize Sentinel-2's multi-spectral imagery with a 10-meter spatial resolution and up to 5-day temporal resolution. By focusing solely on satellite-derived spectral information as input, this approach has the potential to provide a more widely applicable method for monitoring wetland carbon fluxes. The project will explore both Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) architectures to capture the complex spatial and temporal dynamics of CO_2 fluxes in wetland ecosystems.

Methods

CO_2 Measurements

The study of CO_2 flux was conducted at Agamon Hula, a shallow (<0.6 m deep) lake of approximately 1.1 km² in the Hula Valley, northern Israel. An Eddy Covariance (EC) system was installed at the center of the lake, positioned more than 200 m from vegetated areas to ensure measurements primarily reflected the open water surface. The EC station, mounted on a tripod 2 m above the mean water level, was equipped with a CO_2 Infrared Gas Analyzer (IRGA, LI-7500A, Li-Cor, USA), which measured the half-hourly CO_2 flux.

Data Acquisition and Preprocessing

Sentinel-2 satellite imagery was acquired through the Google Earth Engine (GEE) platform. Data were collected with a temporal resolution of 5 days, applying a 20% cloud cover filter. The spatial resolution of the utilized bands was 10 meters per pixel. Each sample represents an average of the wetland area corresponding to the open water surface without vegetation, covering the area measured by the CO_2 flux station.

The satellite data were preprocessed by converting reflectance values to float, scaling them by 0.0001, and removing values below 0.25. Missing values were linearly interpolated. A jump in values on 2022-01-24 was adjusted using a custom function. Data were resampled to daily frequency.

CO_2 flux data were resampled to daily mean frequency. The two datasets were merged and smoothed using a 5-day rolling window average. Missing values were removed, resulting in a final dataset of 937 samples. Day of year (DOY) was added as additional feature to capture seasonal variations in CO_2 fluxes.

Model Development

The dataset was split into training (60%), validation (20%), and testing (20%) sets. Features were scaled using MinMaxScaler. The target variable (CO_2 flux) was also scaled.

An Artificial Neural Network (ANN) was implemented using PyTorch. Extensive experimentation was conducted to optimize the model architecture, including the search for an appropriate loss function, number of epochs, batch size, optimization method, number of layers, neurons per layer, and dropout ratio.

The final model architecture consisted of five hidden layers (512, 256, 128, 64, and 32 neurons) with ReLU activation functions, batch normalization, and dropout (probability 0.5) between layers. The output layer had one neuron. The model was trained for 1500 epochs using RMSprop optimizer with a learning rate of 0.001 and Huber loss (SmoothL1Loss) as the criterion. Batch size was set to 64.

In addition, a Long Short-Term Memory (LSTM) model was implemented with similar hyperparameters, using a sequence length of 30 and 5 layers but 1000 epochs.

Model Evaluation

Model performance was evaluated using R-squared (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) on the validation and test sets. Learning curves, time series plots of observed vs. predicted CO2 flux, and scatter plots were generated to visualize model performance.

Results & Discussion

Model Performance and Validation

The performance of the ANN and LSTM models in predicting CO2 flux at Agamon Hula was evaluated on both validation and test datasets (Table 1).

Table 1: Performance metrics of ANN and LSTM models for CO_2 flux prediction in Agamon Hula, compared with results from Zhang et al. (2021) for ENP and BCNP sites. MAE and RMSE are in g C m^{-2} day^{-1}.

Model	**Validation**			**Test**		
	MAE	R^2	*RMSE*	*MAE*	R^2	*RMSE*
ANN	0.67	0.65	0.92	0.65	0.60	0.89
LSTM	0.56	0.7	0.76	0.59	0.69	0.83
Zhang et al ENP	-	-	-	0.91	0.59	1.22
Zhang et al BCNP	-	-	-	1.21	0.79	1.67

The ANN and LSTM models demonstrated consistent performance across validation and test sets, suggesting good generalization. For the ANN model, MAE values were 0.67 and 0.65 g C m^{-2} day^{-1}, R^2 values were 0.65 and 0.60, and RMSE values were 0.92 and 0.89 g C m^{-2} day^{-1} for validation and test sets, respectively. The LSTM model showed slightly better performance with MAE values of 0.56 and 0.59 g C m^{-2} day^{-1}, R^2 values of 0.7 and 0.69, and RMSE values of 0.76 and 0.83 g C m^{-2} day^{-1} for validation and test sets, respectively.

The learning curves for both models reveal interesting insights (Figure 1). For the LSTM model, there is a noticeable gap between the training and validation loss, which could indicate some degree of overfitting. However, the continued decrease in validation loss suggests that the model was still learning and improving its generalization. The ANN model's learning curve shows a smaller gap between training and validation loss, indicating better generalization. Notably, the LSTM model required fewer epochs to reach optimal performance, demonstrating its efficiency in capturing temporal dependencies in the data.

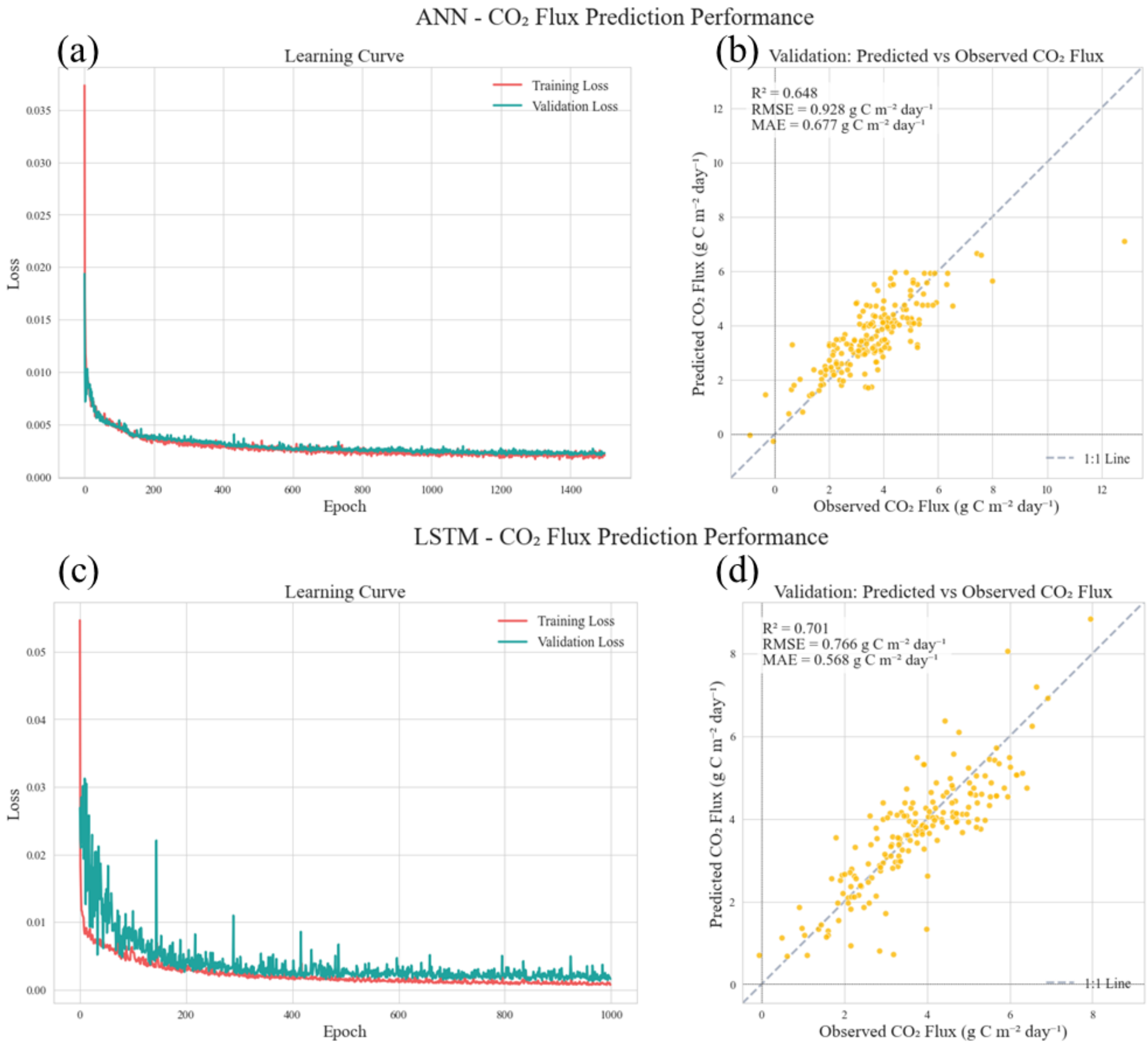

Figure 1. Comparison of Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) model performance on training and validation sets in predicting CO_2 flux at Agamon Hula. (a) ANN learning curve showing training and validation loss across epochs. (b) ANN scatter plot of predicted vs. observed CO_2 flux for the validation set, with R^2, RMSE, and MAE metrics. (c) LSTM learning curve showing training and validation loss across epochs. (d) LSTM scatter plot of predicted vs. observed CO_2 flux for the validation set, with R^2, RMSE, and MAE metrics.

To further evaluate the models' performance, scatter plots of predicted versus observed CO_2 flux for both ANN and LSTM models on the test set were generated (Figure 2). The LSTM model demonstrates a tighter clustering around the 1:1 line compared to the ANN model, indicating better predictive performance in this range (Figure 2).

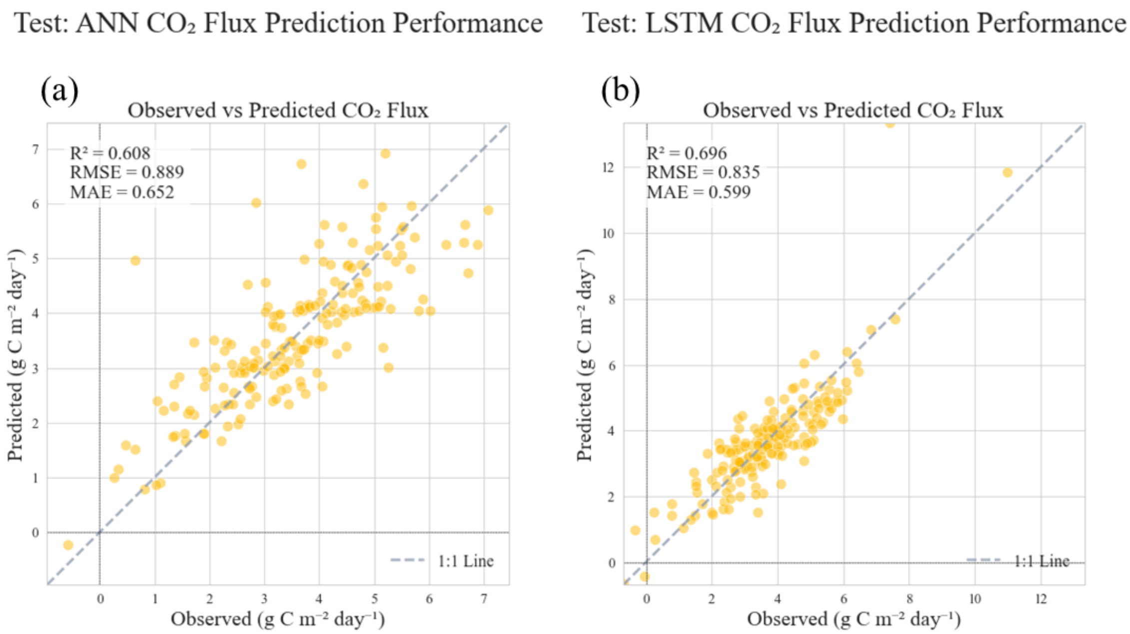

Figure 2. Scatter plots of predicted versus observed CO_2 flux on the test set for (a) Artificial Neural Network (ANN) and (b) Long Short-Term Memory (LSTM) models. The dashed line represents the 1:1 line. R^2, RMSE, and MAE values are provided for each model, with RMSE and MAE in g C m^{-2} day^{-1}.

ANN vs LSTM Performance

The LSTM model outperformed the ANN model across all metrics, particularly in terms of R^2 values. This superiority can be attributed to the LSTM's ability to capture and utilize temporal dependencies in the data, which is crucial for time-series predictions like daily CO2 flux. The improved performance of the LSTM model suggests that incorporating temporal context enhances the accuracy of CO2 flux predictions in wetland environments.

Interestingly, the computational efficiency of the models differed significantly. The ANN model completed training in just 1.5 minutes, while the LSTM model required 10.3 minutes. This substantial difference in training time can be attributed to several factors. First, LSTMs have a more complex architecture with multiple gates (input, forget, and output gates) that need to be computed for each time step. This increased complexity results in more parameters and computations per epoch. Second, LSTMs process data sequentially, considering the temporal relationships between data points, which can be more time-consuming than the parallel processing possible in standard ANNs.

Comparison with Zhang et al. (2021)

Comparing my results to those reported by Zhang et al. (2021) for the Everglades National Park (ENP) and Big Cypress National Preserve (BCNP) sites, my models generally outperformed the ENP model in terms of MAE and RMSE. The LSTM model showed particular improvement (MAE: 0.59 vs 0.91 g C m^{-2} day^{-1}; RMSE: 0.83 vs 1.22 g C m^{-2} day^{-1}). R^2 values were also higher for my models (0.60-0.69 vs 0.59). When compared to the BCNP model, my models showed lower MAE and RMSE values, indicating better accuracy in predicting CO_2 flux. However, the BCNP model achieved a higher R^2 (0.79), suggesting it captured more of the variance in the data.

It's important to note that Zhang et al.'s model provided quarterly forecasts, while my models predict daily CO_2 flux. This difference in temporal resolution may partly explain the performance variations, as daily predictions are typically more challenging due to higher variability in short-term environmental factors.

Model Optimization

During the model development process, several optimizations were found to improve performance. The RMSprop optimizer outperformed Adam, leading to faster convergence and better overall results. Additionally, using ReLU activation functions proved more effective than sigmoid activations, likely due to ReLU's ability to mitigate the vanishing gradient problem and provide non-linear transformations without saturating.

Increasing the number of layers and neurons in the network architecture improved model performance to a certain extent. However, it's worth noting that there was a point of diminishing returns, beyond which additional complexity did not yield significant improvements and risked overfitting.

These results demonstrate the potential of using high-resolution satellite data with advanced machine learning techniques for accurate daily CO_2 flux predictions in wetland ecosystems. The models developed in this project offer improved accuracy over previous work, particularly for short-term predictions, which could be valuable for more detailed monitoring and understanding of carbon dynamics in these important ecosystems.

References

Dinsa, T. T., & Gemeda, D. O. (2019). The Role of Wetlands for Climate Change Mitigation and Biodiversity Conservation. Journal of Applied Sciences and Environmental Management, 23(7), 1297. https://doi.org/10.4314/jasem.v23i7.16

Göckede, M., Rebmann, C., & Foken, T. (2004). A combination of quality assessment tools for eddy covariance measurements with footprint modelling for the characterisation of complex sites. Agricultural and Forest Meteorology, 127(3), 175–188. https://doi.org/https://doi.org/10.1016/j.agrformet.2004.07.012

Helman, D. (2018). Land surface phenology: What do we really ‘see’ from space? Science of The Total Environment, 618, 665–673. https://doi.org/https://doi.org/10.1016/j.scitotenv.2017.07.237

McGowan, H., Lensky, N., Abir, S., Shaked, Y., & Wurgaft, E. (2022). Direct Measurement of CO2 Air-Sea Exchange Over a Desert Fringing Coral Reef, Gulf of Eilat (Aqaba), Israel. Journal of Geophysical Research: Oceans, 127(10). https://doi.org/10.1029/2022JC018548

Shindell, D. T., Faluvegi, G., Koch, D. M., Schmidt, G. A., Unger, N., & Bauer, S. E. (2009). Improved Attribution of Climate Forcing to Emissions. Science, 326(5953), 716–718. https://doi.org/10.1126/science.1174760

Zhang, C., Brodylo, D., Sirianni, M. J., Li, T., Comas, X., Douglas, T. A., & Starr, G. (2021). Mapping CO2 fluxes of cypress swamp and marshes in the Greater Everglades using eddy covariance measurements and Landsat data. Remote Sensing of Environment, 262, 112523. https://doi.org/https://doi.org/10.1016/j.rse.2021.112523