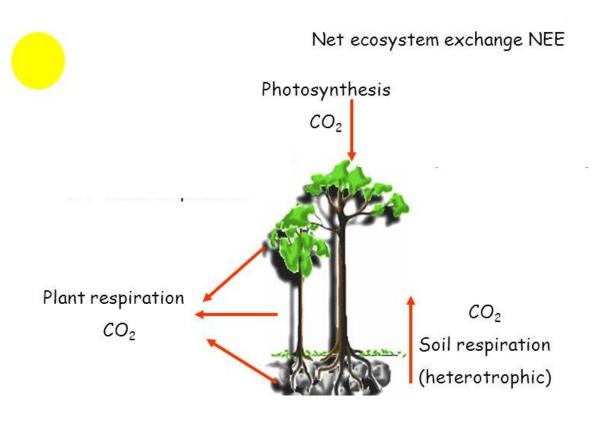
Decipher Climate Clues via Carbon Flux Simulation

Winter Incubator

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Overview



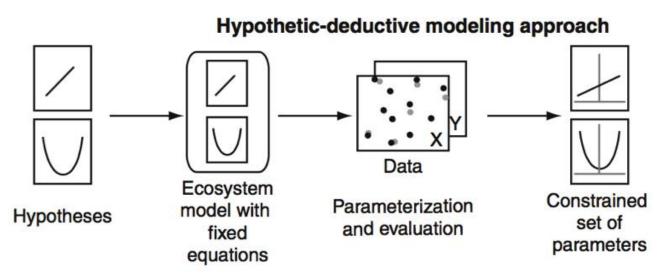
- Knowledge of the amount of carbon dioxide (CO₂) flux into and out of the atmosphere is important for understanding climate change.
- Mapping and modeling of carbon fluxes in different ecosystems are essential for understanding the contribution of these ecosystems to the global carbon budget.
- This information will be useful for decision making regarding various carbon-related climate change mitigation strategies.

• Study sites (from Fluxnet)



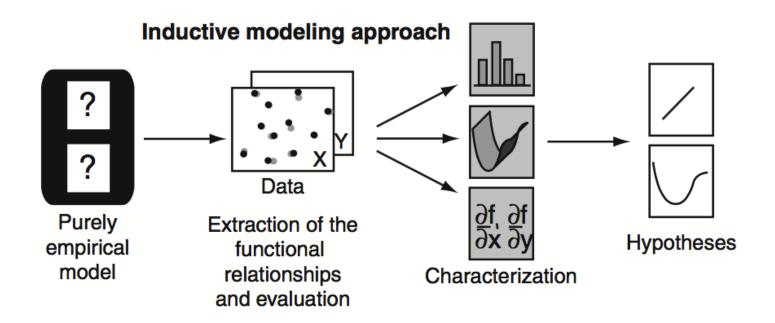
Pre-Incubator

- Large, complex, and multidimensional datasets from which the causalities cannot be obtained just by visual evaluation of the measurements.
- Process-based models: the non-linearity of the relationship between CO₂ flux and other micrometeorological flux parameters (such as energy fluxes) limits the applicability of common carbon flux models to accurately estimate the flux dynamics.



During Incubator

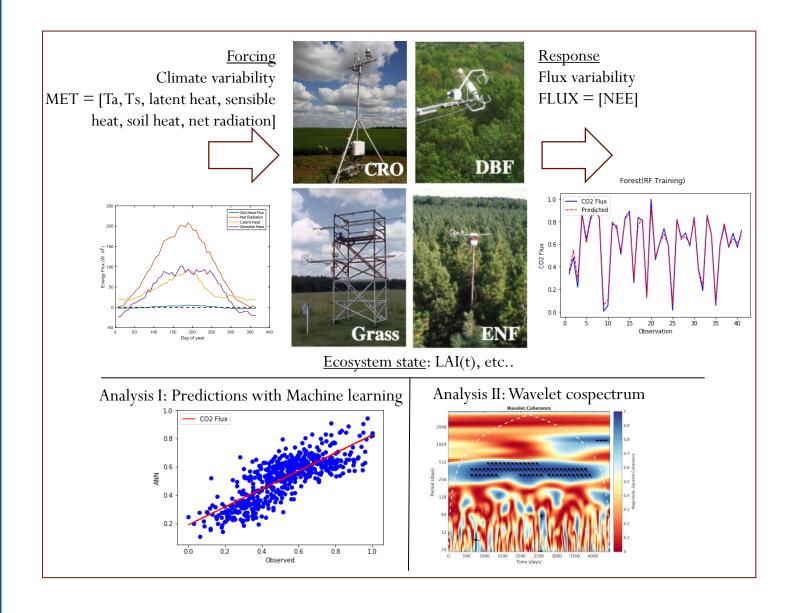
- A fully inductive approach
- A priori assumptions are avoided as much as possible.
- The functional relationships of the carbon fluxes to the climatic controls are inferred solely and directly from the observations.



Scientific questions we try to answer:

- Can we model CO₂ fluxes with micrometeorological variables? If so, what statistically meaningful performance could we achieve?
- What's the relative contributions and temporal scale of different drivers?
- How does disturbance (eg. drought, fire...) impact input variables, and further, impact CO, flux?

Methods



Goal 1:

Use climate forcing (drivers) to model and predict CO2 flux dynamics in different ecosystems

- Method 1:

ML methods including ANN and random forest

- <u>Method 2</u>:

Wavelet scale decomposition

Goal 2:

Capture disturbance (eg. drought; fire) effects at the site scale

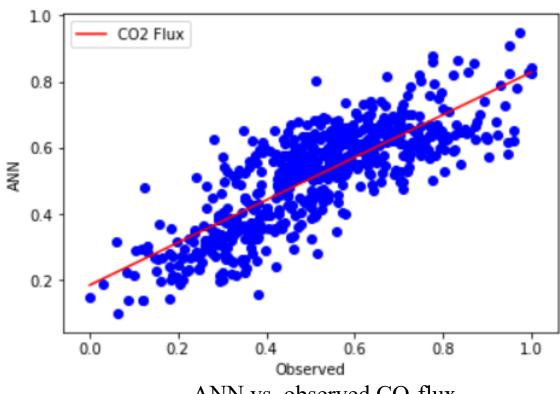
Method:

Add Leaf Area Index (LAI) as a proxy for disturbance.

Results

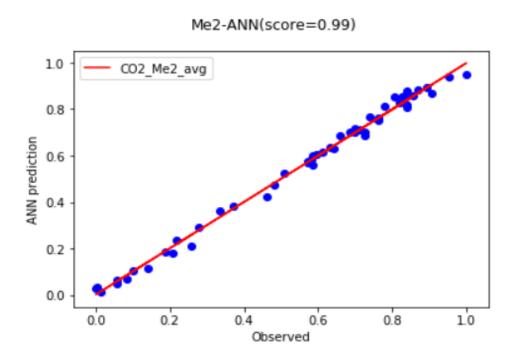
• ANN: training set — forests; testing set — Me2 (weekly data)

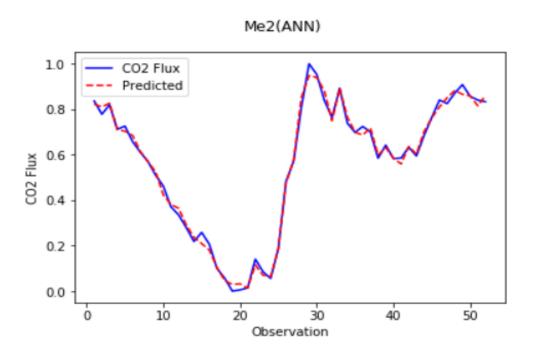


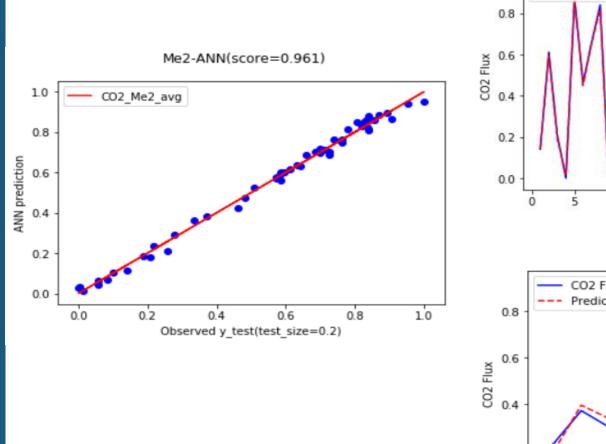


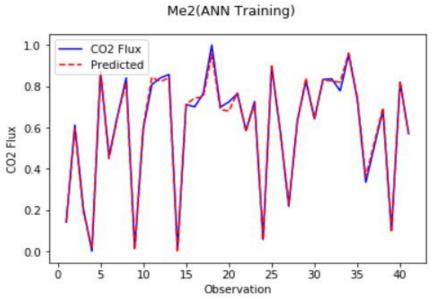
ANN vs. observed CO₂ flux

• ANN: training set — forests; testing set — Me2 (annual average data)

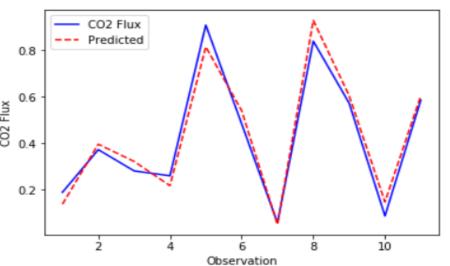








Training set: 80% of the annual dataset

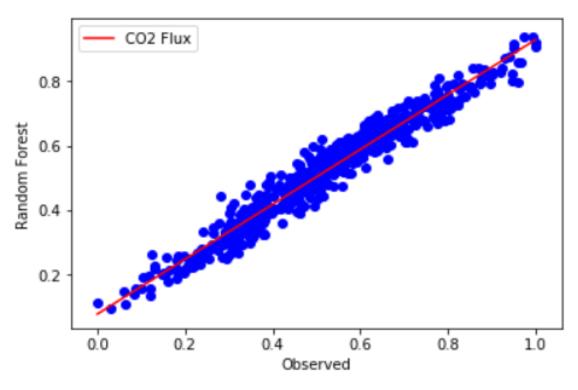


Me2(ANN Testing)

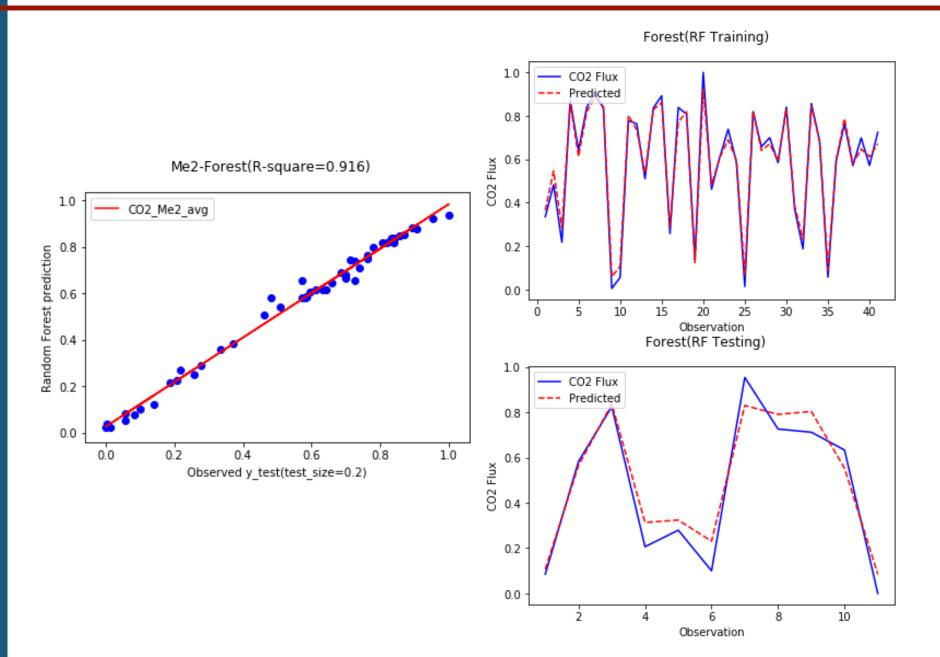
Testing set: 20% of the annual dataset

• Random Forest

Me2-Forest(score=0.942)



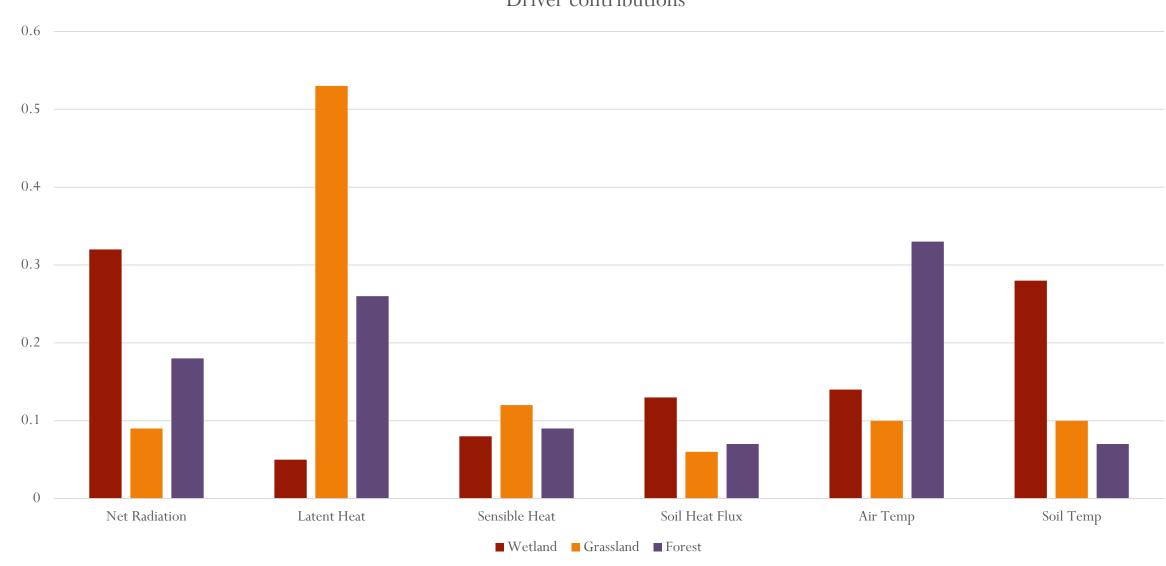
RF vs. observed CO₂ flux



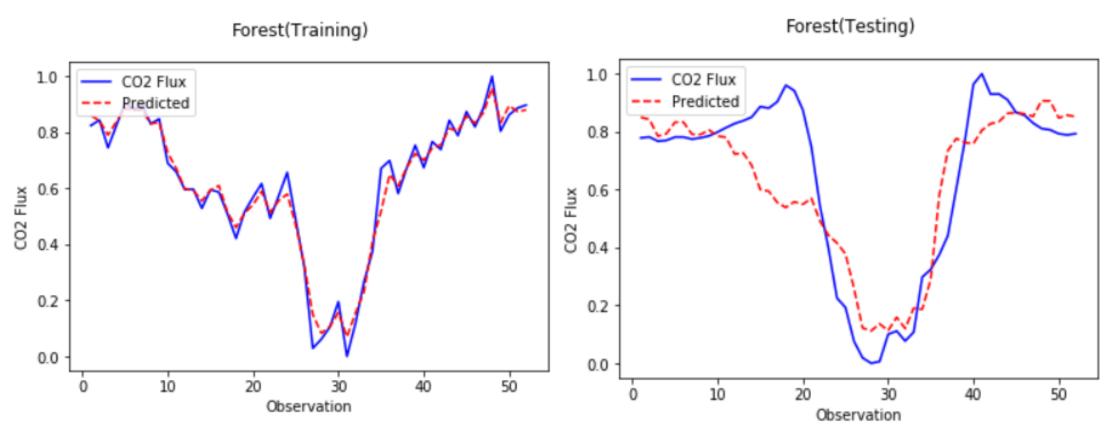
Training set: 80% of the annual dataset

Testing set: 20% of the annual dataset





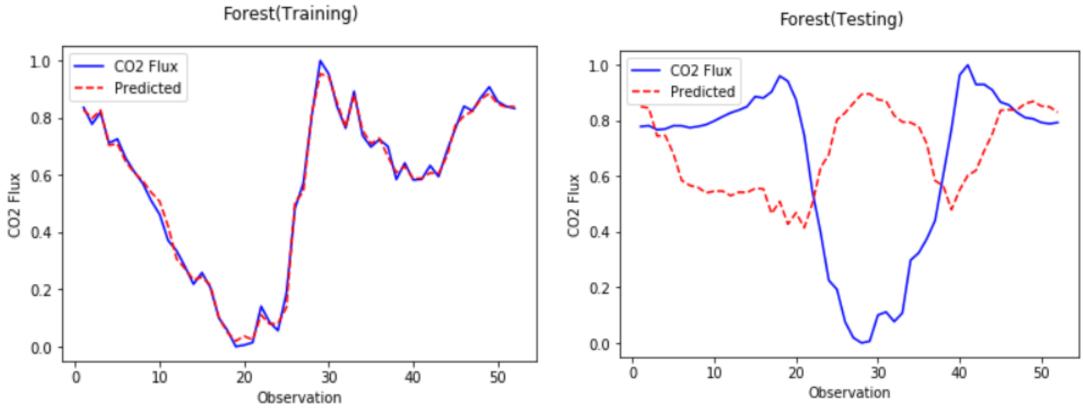
• Random Forest: Blo vs WCr-Annual



Training set: Blo annual average data

Testing set: WCr annual average data

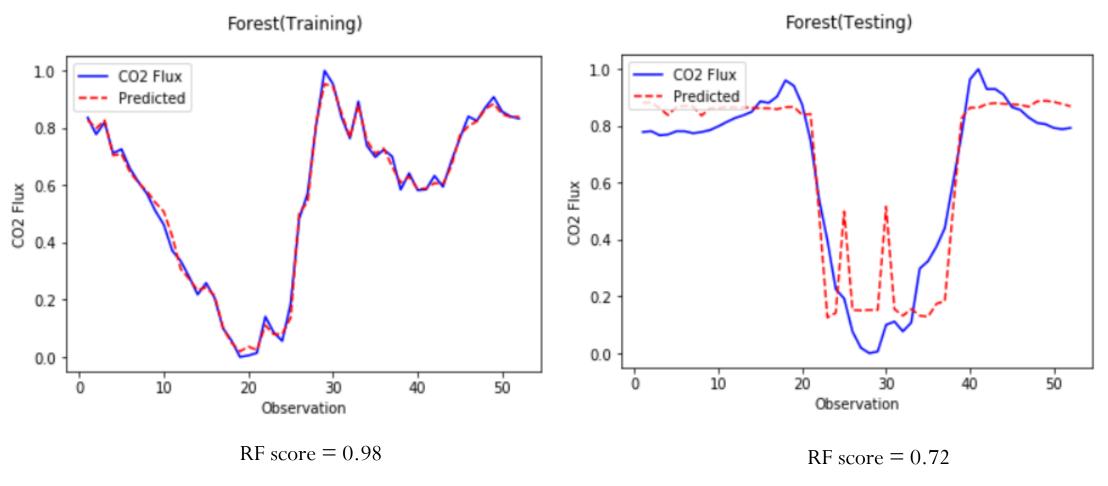
• Random Forest: **Me2 vs WCr-Annual**



Training set: Me2 annual average data

Testing set: WCr annual average data

• Fire influence on CO2 flux: Me2 vs WCr-Annual

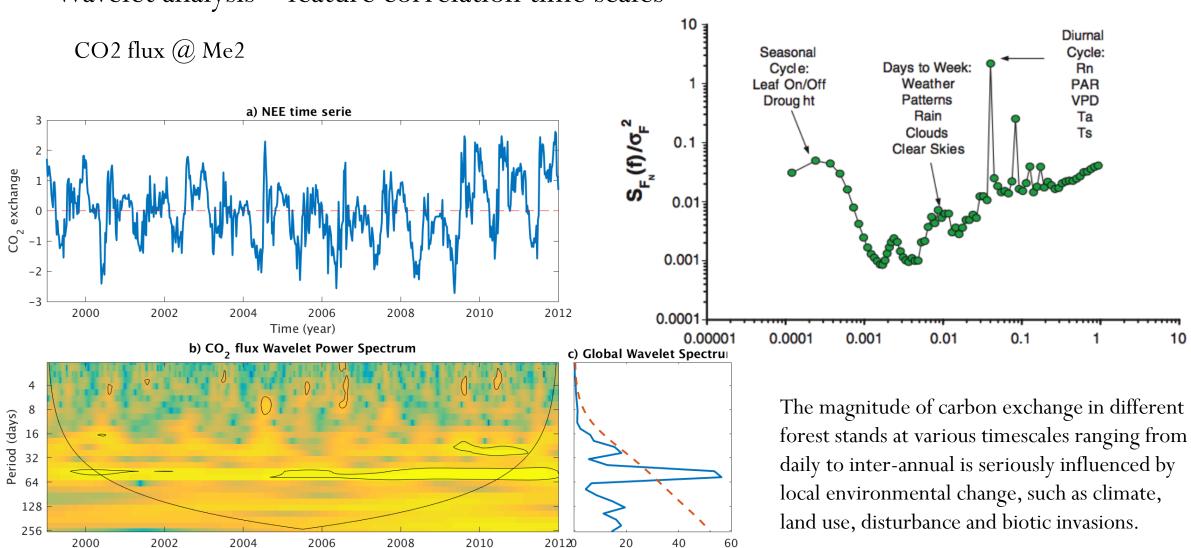


Training set: Me2 annual average data with LAI added

Testing set: WCr annual average data with LAI added

• Wavelet analysis – feature correlation time scales

Time



Power

Next steps

• Model spatial carbon flux using ANN covering larger areas with remotely sensed meteorological data to provide carbon information at the spatial and timescale of interest.

• The approach is not limited to the net carbon flux, but can be extended to the energy and momentum flux, or other greenhouse gases.

Questions?