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# Identifying climatic drivers and their timescales of influence on extreme carbon source / sink dynamics

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## Introduction

Increasing frequency of climate extremes requires improved understanding of extreme states of ecosystem processes. The occurrence of extreme carbon cycle states—e.g., high $CO_2$ flux rates representing extreme carbon sinks or sources—and drivers of such states likely differ across spatial and temporal scales. Analyses of the drivers of extreme flux states across these different scales will provide insight into the potential responses of the carbon cycle in this era of environmental change.

## Objectives

**Objective:** Determine the strength and influential timescales of key environmental drivers governing unusually high rates of daily gross primary production (GPP) and ecosystem respiration (Reco).

**Question 1:** What are the key environmental predictors of extreme daily GPP and Reco fluxes?

**Question 2:** How do these key environmental predictors and their effects vary across concurrent and lagged timescales?

**Question 3:** How do these key environmental predictors interact to influence the probability of extreme flux states?

## Methods

**Extreme sink and source states** are defined as the upper 95[th] percentile of daily GPP and Reco values at each site.

**Growing season** is defined as the period when the average GPP over the preceding week is above the 25[th] percentile threshold. Days meeting these conditions are classified as 'in-season', while all other days are considered 'out-of-season'.

**Timescales** are represented for each environmental variable by calculating the average and standard deviation of the variable at a given site over the corresponding lag period (see Table 1).

**Classification random forest (RF) models** were fit to the extreme source/sink and add associated environmental variables. RF models were fit to all sites simultaneously, including a site ID, to classify extreme sinks and sources. Separate RF models were fit to year-round data and in-season data only.

| Variable | Definition |
|---|---|
| P | Daily precipitation |
| TA | Daily temperature |
| SW | Daily shortwave radiation |
| VPD | Daily vapor pressure deficit |
| GPP | Daily gross primary production |
| Reco | Daily ecosystem respiration |
| Site | Categorical site ID |

| Lag |
|---|
| 0 = concurrent |
| 1 = prior day |
| 7 = prior 7 days |
| 30 = prior 30 days |
| 365 = prior 365 days |
| **Measures** |
| Average and standard deviation (**sd**) over lags |

**Table 1**. Environmental variables, timescales considered, and indices (measures) used for each variable in the random forest analysis. Data obtained from FLUXNET and NEON.

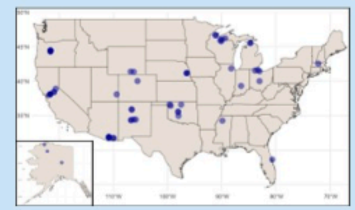


**Figure 1**. Locations of 57 FLUXNET towers across the United States, representing a total of 472 site-years and 138,306 days of observed fluxes.

## Results

### Important predictors for extreme fluxes align with physiological expectations

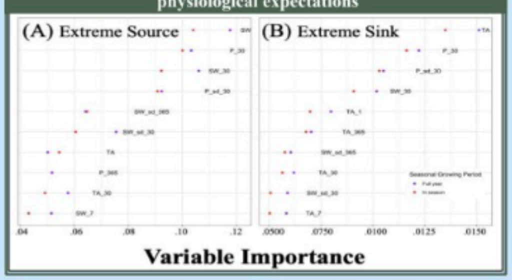


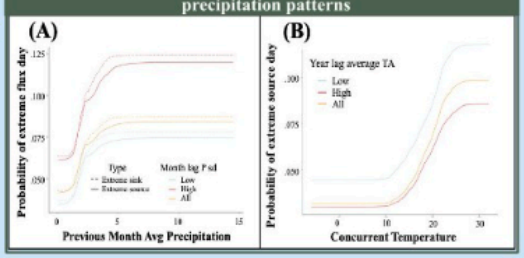

**Figure 2**. Variable importances (VIMP) of environmental variables for in-season (red symbols) and year-round (purple) for (A) extreme sink and (B) extreme source days. Of the 33 environmental predictors input to the RF models, the 10 most important (ranked by VIMP according to the in-season models) are highlighted (see Table 1 for variable_lag definitions; e.g., TA is concurrent air temperature; TA_30 is temperature over the past month).

**Figure 3**. Partial dependence plots allow visualization of how the probability of an extreme flux day depends on key environmental drivers. For example, (A) average and standard deviation of the previous month's daily precipitation interact to influence the probability of an extreme sink or source day; (B) concurrent temperature and average temperature over the previous year interact to influence the probability of an extreme source day.

**Table 2**. Misclassification error associated with each extreme flux state and timeframe. The misclassification errors are very low, indicating that the RF classification models accurately predict occurrence of extreme source and sink days.

| Model | Misclassification |
|---|---|
| Extreme sink (In-season) | 0.028 |
| Extreme sink (Overall) | 0.021 |
| Extreme source (In-season) | 0.015 |
| Extreme source (Overall) | 0.013 |

### Extreme fluxes respond to antecedent temperature and precipitation patterns




## Key Findings

- The most important predictors by VIMP (both in-season and overall) were **concurrent shortwave radiation for extreme sink (Fig. 1A) and concurrent temperature for extreme source (Fig. 1B)**. This aligns with physiological expectations given that photosynthesis (sink) is strongly coupled to light / energy, and respiration (source) is known to be strongly dependent upon concurrent temperature.
- The averages of precipitation and shortwave radiation over the previous month, as well as standard deviation of precipitation over the previous month, were also amongst the top predictors for both extreme sinks and sources (Fig. 1). **This points to the key role of moisture availability, and the packaging of moisture inputs (variability), in controlling carbon fluxes.**
- The probabilities of both an extreme sink and extreme source increase with increasing monthly precipitation (total moisture input), indicating greater moisture supply stimulates both source and sink fluxes. And, these probabilities further increased with higher variability in the previous month's precipitation (Fig. 2A), indicating a **pattern of larger, less frequent precipitation events over the previous month are most likely to trigger an extreme flux**.
- The probability of an extreme source is maximized under high concurrent temperature and low previous year average temperature. The **magnitude of a source flux in response to the current temperature will be impacted by acclimation to the previous year's temperature**, so that an ecosystem acclimated to lower temperatures the previous year is at higher risk of an extreme source flux when faced with a higher temperature day.