Multiscale climate drivers of extreme carbon sinks and sources in the western USA

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Introduction

Increasing climate variability is impacting the carbon cycle in unprecedented ways, demanding an understanding of the conditions leading to extreme carbon (CO_2) flux states. Spatiotemporal variation in drivers of carbon fluxes is poorly characterized; therefore, we sought to determine the strength and influential timescales of key environmental drivers governing unusually high daily gross primary production (GPP) or ecosystem respiration (Reco) fluxes across diverse ecosystems in the western USA. We evaluated drivers of extreme GPP and Reco fluxes using long-term (11-22 years/site) flux data from 14 AmeriFlux sites.

Objectives

This study aims to understand the environmental conditions that govern extreme GPP and Reco fluxes across multiple years and multiple sites distributed across the western USA. In doing so, we address three primary questions.

- **Question 1:** Which environmental drivers govern extreme carbon sink (GPP) and carbon source (Reco) states, and which of these drivers are shared between, or unique to, extreme carbon sink and source events?
- **Question 2:** How do antecedent timescale dependencies of extreme carbon sinks and sources vary across environmental conditions, and to what extent does this variation reflect additive versus synergistic effects?
- **Question 3:** How do the environmental drivers of extreme carbon fluxes differ across sites varying in their long-term climate histories?

Methods

To address our questions, we used daily flux and meteorological data from 14 AmeriFlux sites across the western USA (see Figure 2). Key analysis steps include:

- **Extreme sinks and sources** defined as daily GPP and Reco surpassing a 95th percentile threshold, determined by a seasonal quantile spline regression (see Figure 1).
- **Covariates were evaluated at different timescales**; timescales were represented by calculating the average and standard deviation of each variable at a given site over differ lag periods (e.g., concurrent, previous day, previous week) (Table 1).
- **Classification random forest (RF)** were fit across all sites to classify extreme sinks and sources (Q1 & Q2).
- **SHAP analysis** was performed to evaluate trends in variable contribution across climatic and geographic groups (Q3).

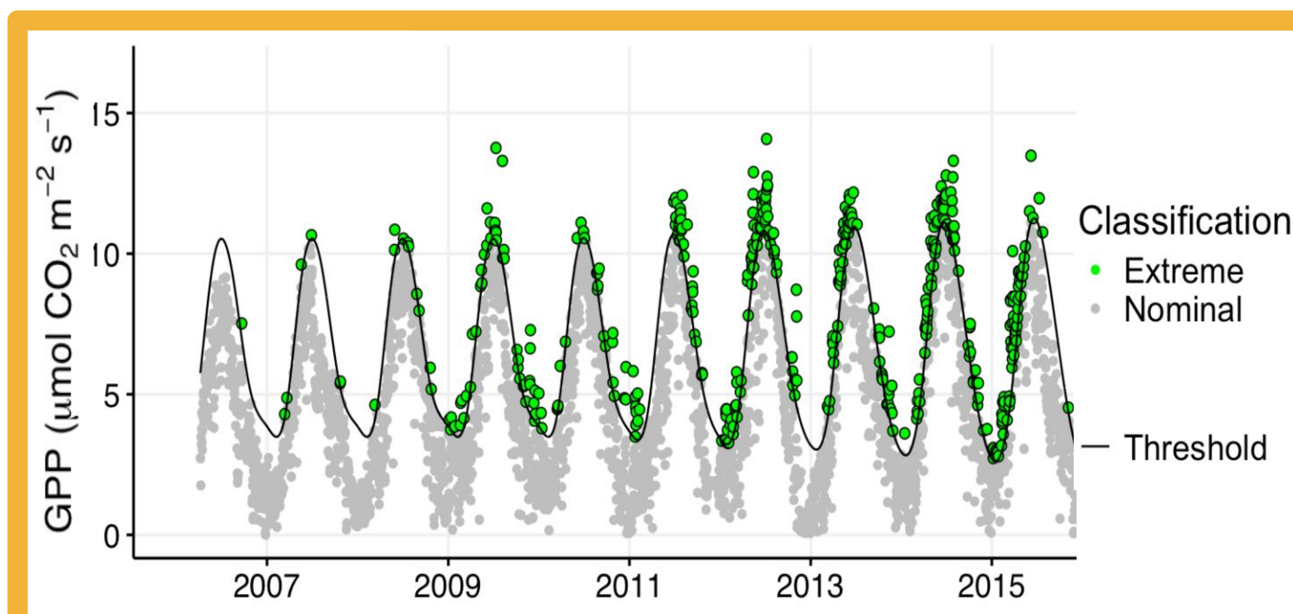
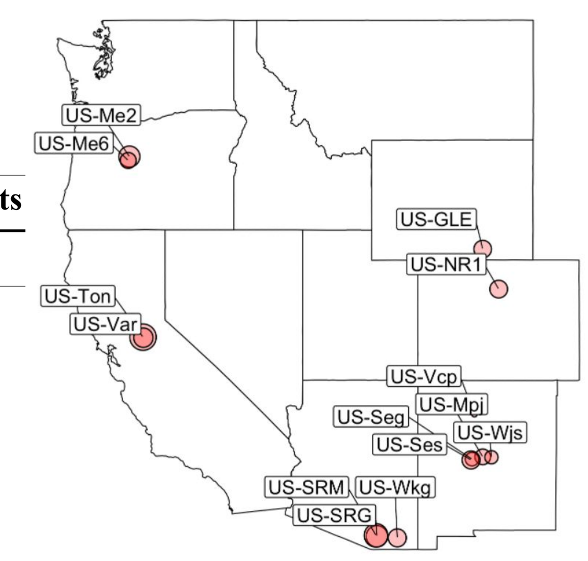


Figure 1. An example of extreme and nominal gross primary production (GPP) fluxes, based on the US-Me6 site, an evergreen needleleaf forest. The smooth black line represents a 95th percentile threshold estimated using quantile spline regression, fitted separately to the first and last four years of data and interpolated linearly for intermediate years.

Figure 2. Locations of 14 AmeriFlux towers across the western USA, representing a total of 211 site-years and 65,737 days of daily flux data.



Variables	Description	Units
Site and Climate		
MAT	Mean annual temperature	°C
MAP	Mean annual precipitation	cm
elev	Height above sea level	m
lat	Latitude	°N
lon	Longitude	°W
Meteorological and Fluxes		
GPP	Daily gross primary production	μmolCO2 m^{-2} s^{1}
Reco	Daily ecosystem respiration	μmolCO2 m^{-2} s^{1}
TA	Daily temperature	°C
P	Daily precipitation	mm
SW	Daily shortwave radiation, incoming	W m^{-2}
VPD	Daily vapor pressure deficit	hPa
SWC	Soil water content (volumetric)	%

Suffix	Description	Example
.D	Value of previous day	TA.D = temperature on previous day
.W	Mean over previous week (7 days)	TA.W = previous 7-day mean TA
.M	Mean over previous month (30 days)	TA.M = previous 30-day mean TA
.Y	Mean over previous year (365 days)	TA.Y = previous 365-day mean TA
σ(.X)	Standard deviation over lag of X	σ(TA.W) = SD of TA over previous 7-days

Table 1. Summary of variable definitions (fluxes and covariates) and timescale definitions for covariates. Meteorological and flux data were obtained from AmeriFlux; climate data wer from PRISM.

Results

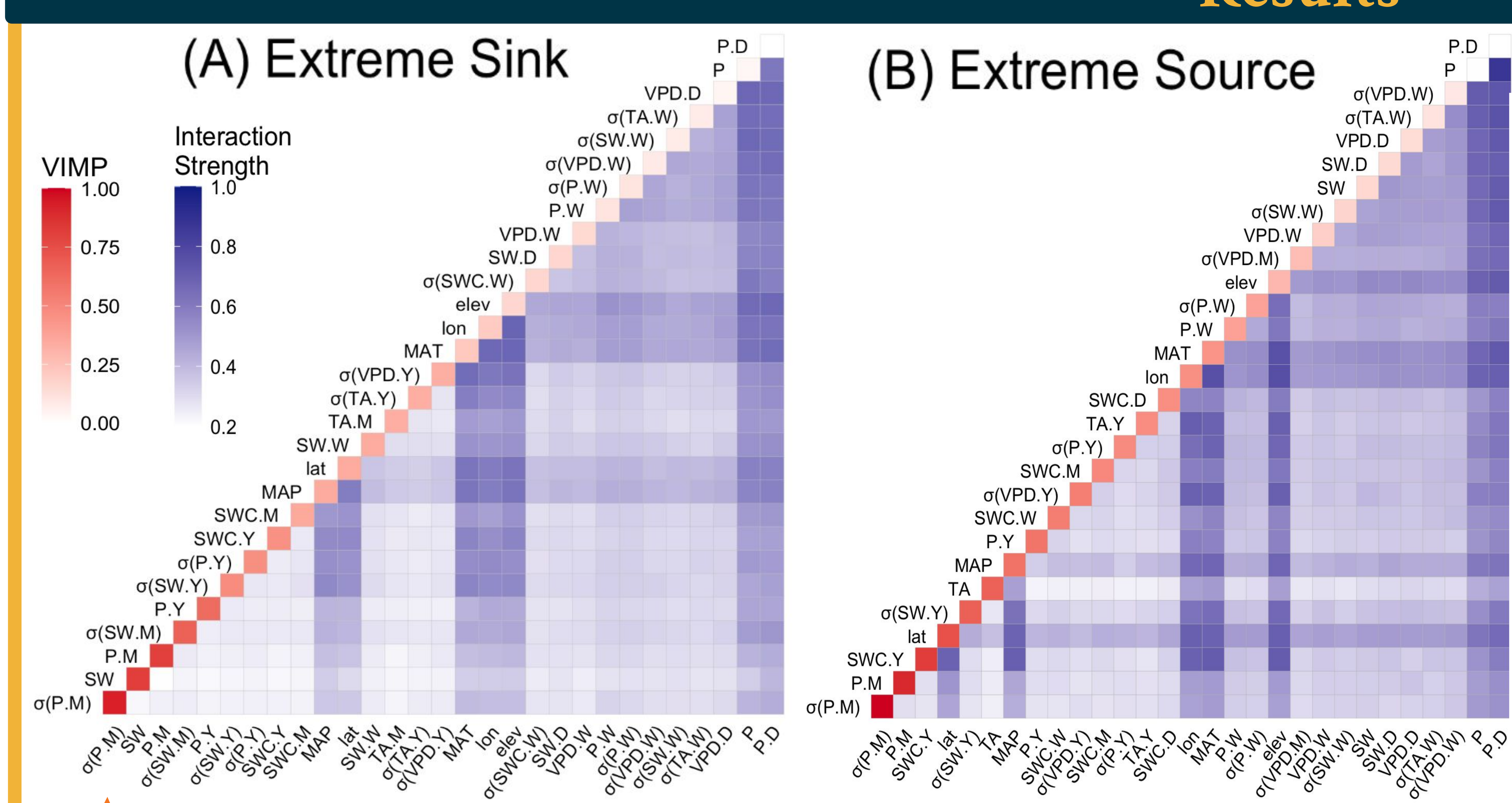


Figure 3. Heatmaps showing variable importance (VIMP; diagonal) and maximum subtree interaction strengths (off-diagonal) for predictors in the **(A)** extreme sink and **(B)** extreme source random forest classifiers. Displayed variables are those ranked among the top 15 by either variable importance (VIMP) or average interaction score. See Table 1 for definitions of the variables.

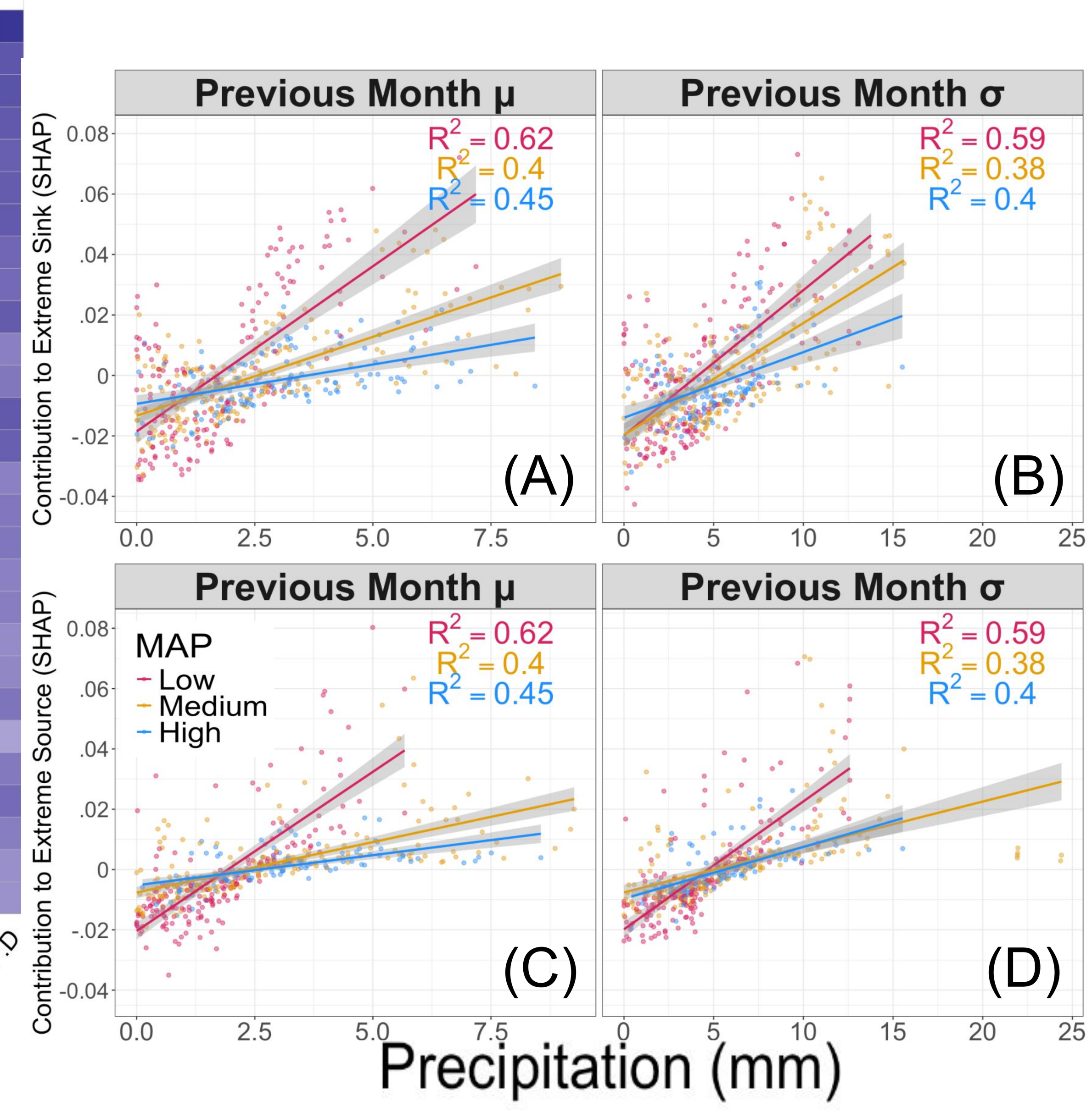


Figure 4. SHAP values for key precipitation predictors in the **(A-B)** extreme sink and **(C-D)** extreme source RF classifications, selected based on top variable importance, including **(A, C)** precipitation over the past month and **(B, D)** variation in daily precipitation over the past month. Points are colored by mean annual precipitation (MAP): red for MAP < 40 cm (low), orange for 40 ≤ MAP < 50 cm (medium), and blue for MAP > 50 cm (high). Linear regressions are fit within each MAP category, and R² values are shown for models with statistically significant slopes ($p < 0.05$).

Key Findings

- **Q1:** Greater precipitation inputs and greater variation in daily precipitation over the preceding month contribute positively to the probability of both extreme sinks and sources (Fig. 4). Thus, **larger, less frequent precipitation events over the previous month are likely to trigger both extreme sink and source events.** Key drivers of extreme sinks and sources **differed at the concurrent timescale** (shortwave radiation for extreme sinks, temperature for extreme sources), and **site-level characteristics** (e.g., MAP, MAT, latitude) were more **important for extreme sources** than extreme sinks.
- **Q2: Important drivers of extreme fluxes interact across timescales** such that long-term conditions establish a site's state of limitation, within which shorter term variation in resource availability governs extreme fluxes. For example, long-term moisture conditions (e.g., monthly, annual, and historical climate such as MAP or MAT), govern how short-term (daily to weekly) moisture deficits impact fluxes (Fig. 3).
- **Q3: Water limitation amplifies the effect of precipitation packaging effects.** Short-term precipitation inputs (total and variability) over the preceding month and year are up to 5.2 times more influential on extreme fluxes in more arid (e.g, low MAP) sites than more mesic (high MAP) ecosystems (Fig. 4). Thus, long-term climate history (e.g., MAP) partly determines the degree to which precipitation packaging influences the probability of an extreme flux event.