Decomposing terrestrial carbon flux anomalies after El Niño: process-based predictability of land carbon sinks and sources

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The obstacle in predicting atmospheric CO_2 growth

- Despite efforts to reduce carbon emissions, anthropogenic fossil fuel emissions are increasing [1]
- In accordance with this increase, ocean and land carbon sinks are removing approximately half of the emissions every year [2]
- The **ocean sink** shows relatively small interannual variability and has a predictability of 2 to 5 years [3]
- The variability of the **land sink** can reach the order of magnitude of the mean and shows little predictability beyond one year [4]
- Being able to predict the terrestrial carbon flux anomalies would allow to minimize the uncertainty in the global carbon balance and facilitate near future emission trends

Variability of the land carbon sink

Fluxes are tightly coupled to climate variables as precipitation, temperature and radiation [5], all of which having a low inherent predictability [6]. The predictive performance of land carbon fluxes is mostly due to two mechanisms:

- Predictable component due to low-frequency variability emerging from climate modes
  - → El Niño Southern Oscillation (ENSO) explains most of the interannual variability [7]

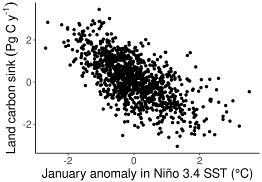


Figure 1: The annual land carbon sink and January SST variability of the Niño 3.4 region in a 1000 year control simulation with MPI ESM.

- Ecohydrological processes acting as low-pass filters between land and atmosphere [8]
  - → Processes hold memory of past climatic anomalies

Objectives and experiment setup

In this study, we want to investigate...

(a) Patterns of low-frequency carbon flux variability induced by ENSO

- Identify hotspots of ENSO related carbon flux anomalies
- Quantify flux anomaly sizes by process and region
- Decompose the land-atmosphere fluxes in the most important processes primary production (NPP) and soil respiration (Resp)

(b) Memory created by ecohydrological processes

- Decompose carbon fluxes and quantify spatial predictability patterns of carbon flux processes by using perfect model approach

  → Allows insight in relative importance of different land and vegetation processes

- Track how climatic anomalies percolate through land and vegetation processes
- Identify mechanisms within this process that contribute to a delay of the effects of climatic anomalies

Model environment

Model used: Fully coupled MPI earth system model (mpiesm-1.2.01p6 "CMIP6p6")

Simulation run: 1000 years pre-industrial control run with coupled CO_2

Ensemble experiment

Initializing ensemble simulations along control run for perfect model experiment

Number of ensemble runs	35
Ensemble size	10
Run time	2 years
Month of initialization	January

ENSO related carbon flux patterns

Data used for analysis

- July to June of next year during El Niño peak of 6 events
- Fluxes of primary production (NPP) and soil respiration

Finding hotspots of carbon flux anomalies

1. Flux anomalies of all events are scaled to unit variance
2. Events averaged to create a composite El Niño event
3. Using spectral clustering algorithm DBCLUST to identify separate areas of high flux anomalies
4. Cluster patterns applied to unscaled flux data

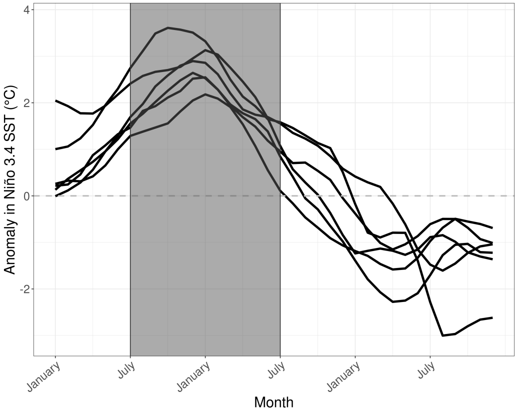


Figure 2: SST variability in the Niño 3.4 of 6 simulated El Niño events. Simulation time used for data analysis in denoted by gray area.

Clusters of post El Niño carbon flux anomalies

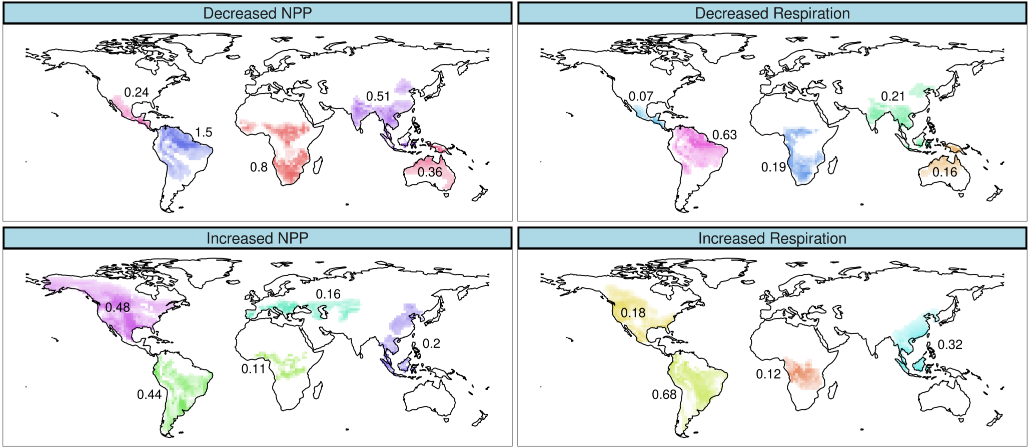


Figure 3: Clusters of carbon flux anomalies after El Niño. Numbers denote average size of the anomaly in Pg C and shading the intensity of the relative flux anomaly within clusters.

Predictability of carbon fluxes

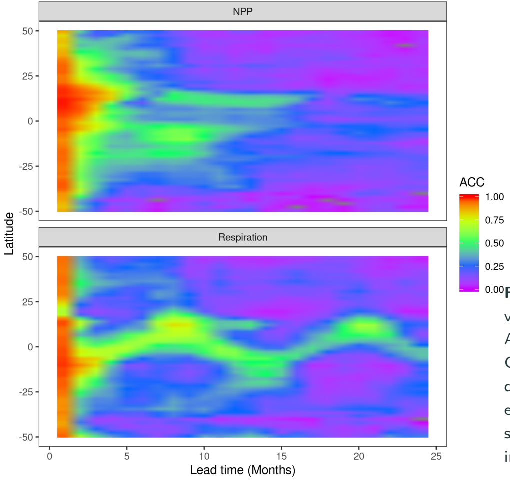


Figure 4: Zonal values of the Anomaly Correlation Coefficient (ACC) derived from 35 ensemble simulations starting in January.

Decomposition of predictability

- The perfect model approach was used to estimate the potential predictability of the two major carbon flux processes
- Predictability was measured by using the Anomaly Correlation Coefficient (ACC) calculated from the 35 2 year simulations starting in January

NPP ACC decreases slower with time and shows high, continuous predictability in the tropics for up to one year

Resp Predictability often below 0.5 for the 2nd month. However, there is a seasonally reemerging high predictability, even towards the end of the second year

Case study: Venezuela

- This region has a common pattern of predictability that can be observed across the tropics and subtropics with temporal shifts due to seasonality
- The ACC of NPP stays above 0.5 for 3 to 6 months and has a second peak with 12 months delay
- Predictability of respiration is out of phase with the predictability of NPP
- The ACC of respiration is generally higher and frequently reaches values above 0.5 even for the second peak

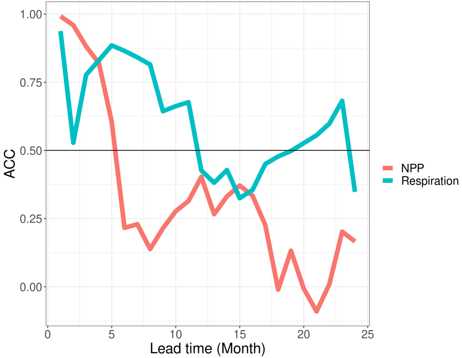
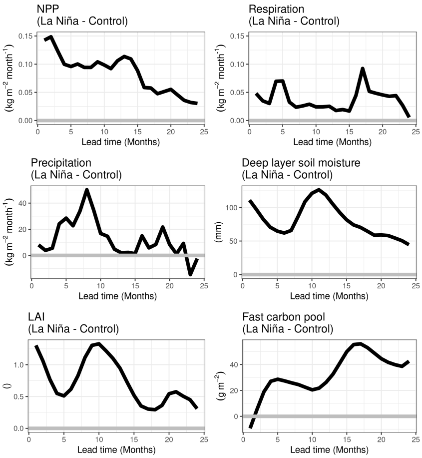


Figure 5: ACC values of NPP and respiration in Venezuela.

Land system processes contributing to predictability patterns in Venezuela

Anomalies of selected land and vegetation processes after Niña events



1. There is a strong positive increase of NPP at the beginning of La Niña events which is slowly decreasing over two years. Respiration shows two distinct peaks, separated by more or less average conditions.
2. Increased NPP and respiration can be explained by increased precipitation in both wet seasons. Respiration halts in the dry season (December to March), while NPP can still maintain the positive anomaly due to excess sol moisture.
3. Increased NPP has resulted in an extensive foliage that can't be maintained during the dry season and leads to excess carbon available for decomposition.

$\Rightarrow$ **Memory is added to the system through:**

- The successive dependence of respiration on NPP
- A delay in respiration caused by seasonality

Conclusions

Patterns of low-frequency carbon flux variability

- Hotspots of NPP and respiration are overlapping in the tropics and subtropics
- El Niño patterns differ across continents:
  - While the decrease of South American NPP is strongest in the central Amazon rainforest, the center of NPP reduction is not in the tropical forest of central African, but in drier regions
- The decrease of NPP is the strongest contributor to land-atmosphere carbon flux anomalies after El Niño

Memory of ecohydrological processes

- Differing predictability patterns of NPP and respiration
- Memory is added to the system through:
  - Long maintained NPP anomalies due to the buffering ability of soils
  - Reoccurring predictability of respiration because of excess in carbon pools produced by NPP anomaly and the halt of respiration during the dry season

References

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