# Carbon Cycle Extremes in the 22$^{nd}$ and 23$^{rd}$ Century and Attribution to Climate Drivers

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Friday, December 15, 2017

# Sources and Sinks of Carbon Dioxide

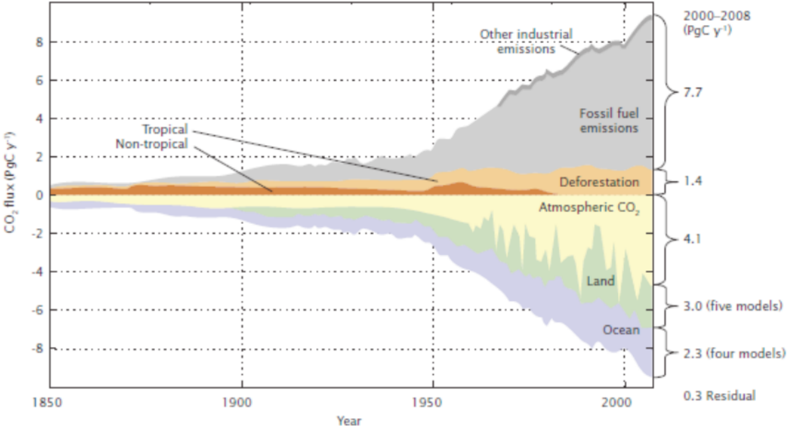



Figure 1: Sources and sinks of carbon dioxide, *Source : CSIRO 2011, Figure 2.5*

# Carbon Cycle and GPP

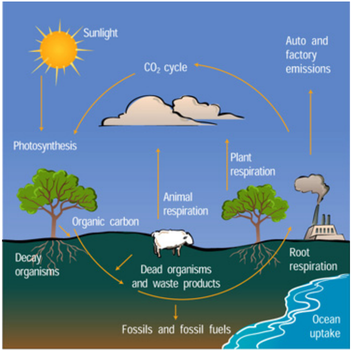



Figure 2: Carbon cycle, *Source:ucar.edu 2017*

- Due to increasing $CO_2$ levels, understanding of the $CO_2$ sinks is necessary.
- Gross Primary Production (GPP) is a major driver for land sink.
- Extreme events in GPP can significantly affect the $CO_2$ uptake.

# Data Source

Community Earth System Model Biogeochemistry Working Group, CESM1-BGC

- 1850–2005: Historical
- 2006–2100: Representative Concentration Pathway 8.5
- 2101–2300: Extended Concentration Pathway 8.5
- Resolution: $0.9375^\circ$ x $1.25^\circ$ (lat x lon)
- Monthly Mean Data
- Constant Land Use: Pre-industrial forcing

# Definition of Extreme Events

1. Original signal of GPP at every pixel.
2. Calculate annual (seasonality) and decadal+higher signals (trend).
3. Anomalies = Original − Trend − Seasonality
4. Select the time period(s) [**25 years**].
5. Thresholds for that time period(s) based on a defined percentile [**1.0**].
6. Global GPP extreme events.

# What Qualifies as an Extreme Events?

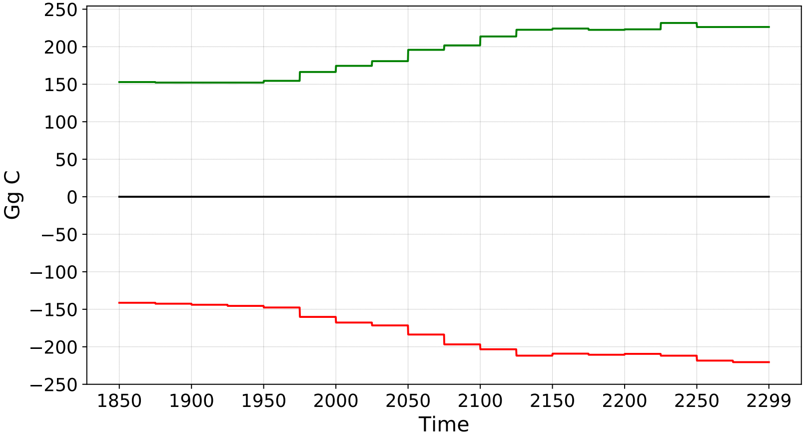



Figure 3: Thresholds when percentile is 1.0 and time period is 25 years

# Spatial Distribution of Frequency of Negative Extremes

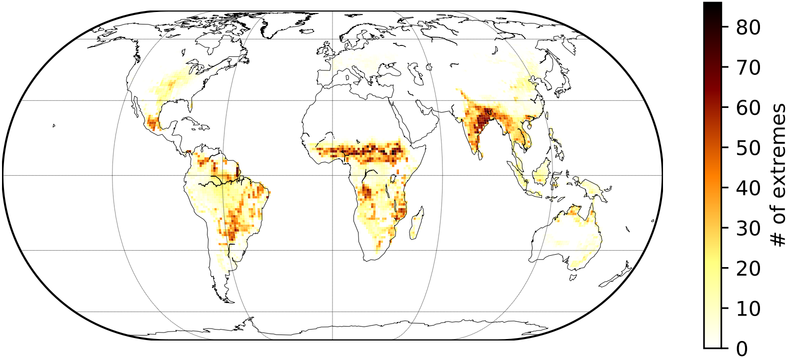



Figure 4: Frequency of negative extreme events for 2175–2199, percentile: 1.0

# Timeseries of Frequency of Extreme Events

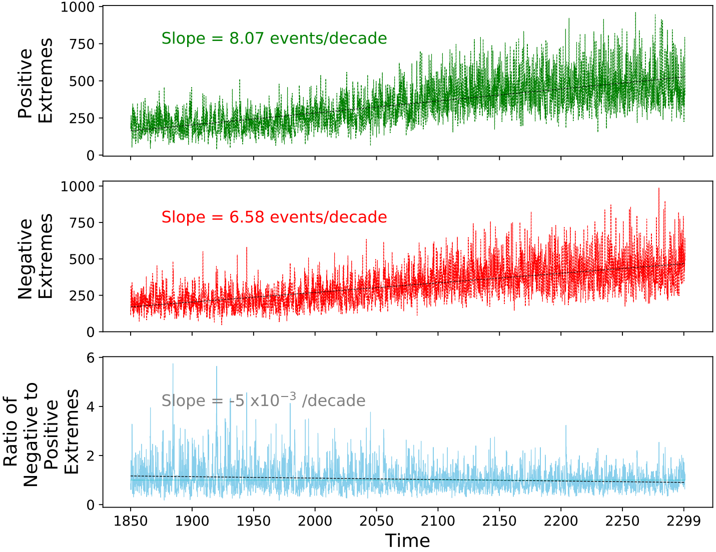



Figure 5: Counts of extremes relative to the threshold of 1850–1999

# Global Timeseries of Extreme Events

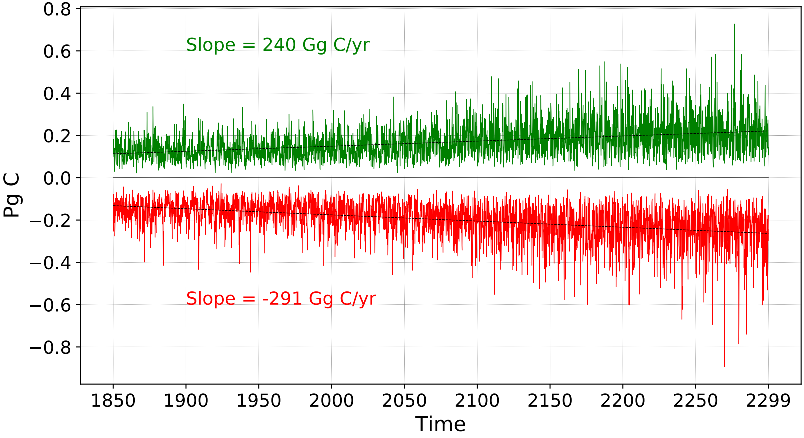
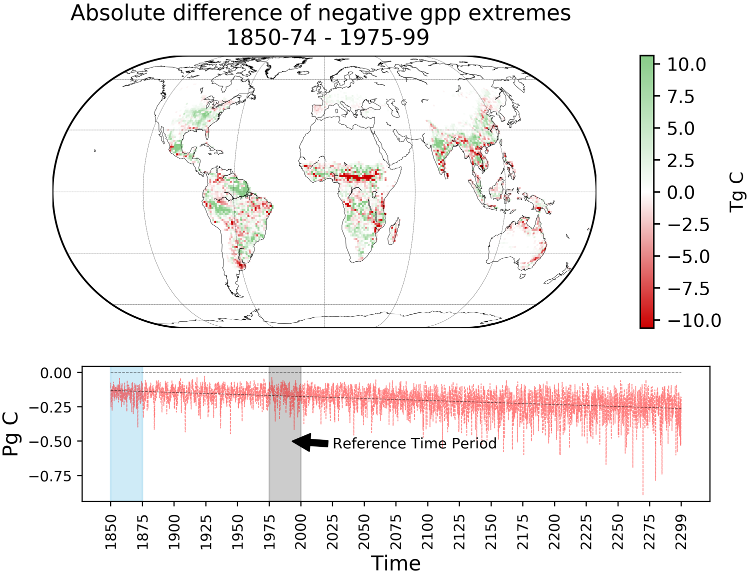
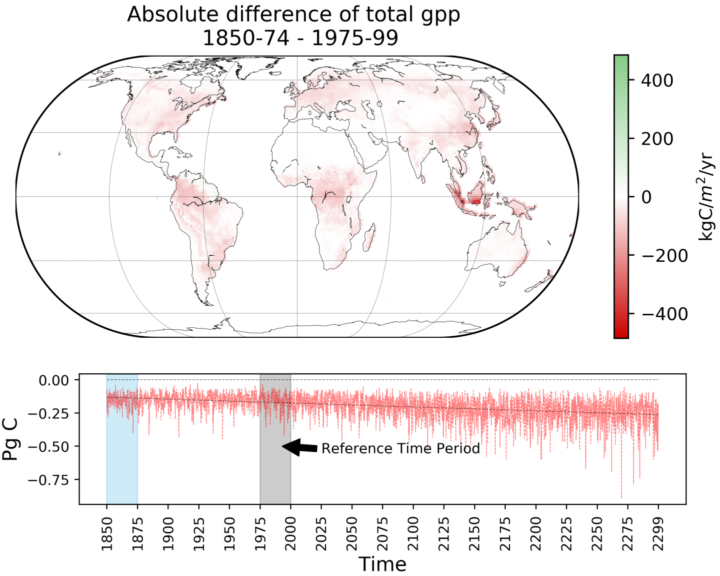



Figure 6: Global timeseries of extreme events when percentile is 1.0 and time period is 25 years

# Changes in Spatial Distribution of Negative Extremes



# Changes in Spatial Distribution of GPP



# What led to GPP Extreme Events?

The correlation coefficients of GPP anomalies and extremes were computed:

- at every pixel
- for all 18 25-year time-periods from 1850-2299
- for prior lags from 0 to 12 months

with original, detrend and anomalies of following climate drivers:

Table 1: Drivers

| | |
|---|---|
| Prcp | Atmospheric rain + snow |
| Soilmoist | Soil moisture to 1-m depth |
| $T_{av}$ | Monthly Mean daily temperature |
| $T_{max}$ | Monthly Maximum daily temperature |
| P-ET | Precipitation minus Evapotranspiration |
| Fire-pft | Total pft-level carbon loss due to fire |
| Fire | Total column level carbon loss due to fire |

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Table 2: Selected Drivers

| | | |
|---|---|---|
| **Prcp** | Atmospheric rain + snow | **Anomalies** |
| **Soilmoist** | Soil moisture to 1-m depth | **Anomalies** |
| Tav | Monthly Mean daily temperature | |
| **Tmax** | Monthly Maximum daily temperature | **Anomalies** |
| **P-ET** | Precipitation minus Evapotranspiration | **Anomalies** |
| Fire-pft | Total pft-level carbon loss due to fire | |
| **Fire** | Total column level carbon loss due to fire | **Original** |

# Multi Linear Regression - Spatial Distribution

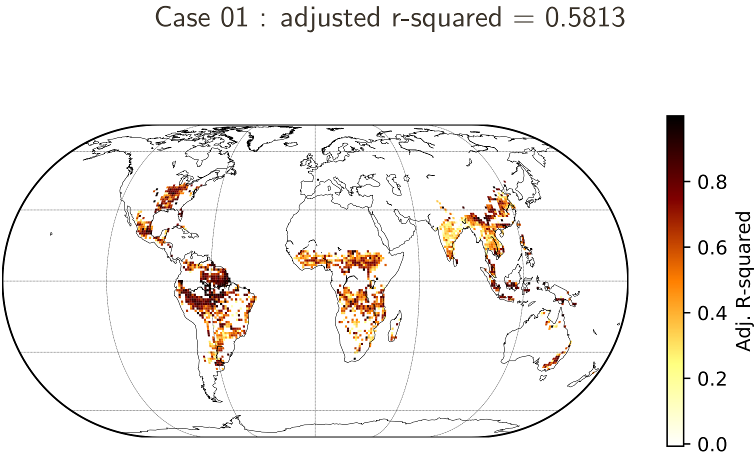


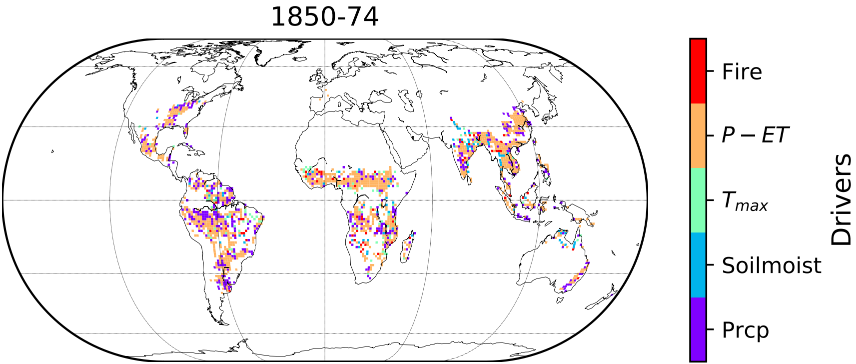

Figure 7: Spatial distribution of adjusted r-squared for gpp extreme events with percentile 1.0 and for time period 1975–99

# Multi Linear Regression - adj. R-squared

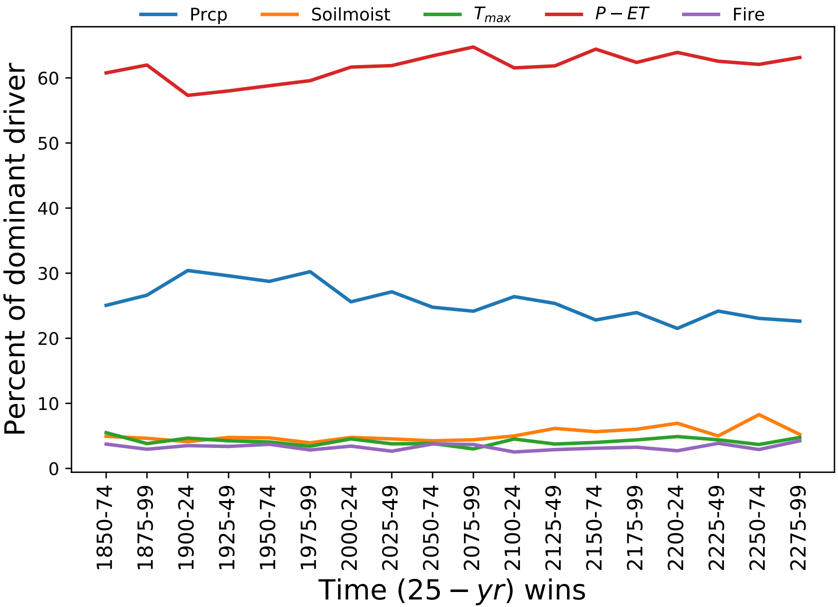
Numbers = prior month lags ; X = excluded

| **Cases** | Prcp | Soilmoist | $T_{max}$ | P-ET | Fire | Rsq_adj |
|---|---|---|---|---|---|---|
| Case 1 | 0 | 0 | 0 | 0 | 0 | **0.5813** |
| Case 2 | 1 | 1 | 1 | 1 | 1 | 0.4094 |
| Case 3 | 2 | 2 | 2 | 2 | 2 | 0.3369 |
| Case 4 | 0 | 0 | 0 | 0 | 1 | 0.5531 |
| Case 5 | 0 | 0 | 0 | 1 | 0 | 0.4033 |
| Case 6 | 0 | 0 | 1 | 0 | 0 | 0.5651 |
| Case 7 | 0 | 1 | 0 | 0 | 0 | 0.5768 |
| Case 8 | 1 | 0 | 0 | 0 | 0 | 0.4361 |
| Case 9 | 0 | 0 | 0 | 0 | X | 0.5361 |
| Case 10 | 0 | 0 | 0 | X | 0 | 0.4022 |
| Case 11 | 0 | 0 | X | 0 | 0 | 0.5503 |
| Case 12 | 0 | X | 0 | 0 | 0 | 0.5545 |
| Case 13 | X | 0 | 0 | 0 | 0 | 0.4209 |
| Case 14 | 0 | X | X | X | X | 0.3394 |
| Case 15 | X | X | X | 0 | X | 0.3195 |
| Case 16 | 0 | X | X | 0 | X | 0.4672 |

# Spatial Distribution of Dominant Driver



# Dominant Climate Driver



# Conclusions

The CESM1-BGC (ecp 8.5) suggests that:

- The intensity of both negative and positive carbon cycle extreme events is increasing with time
- Compared to historic threshold, the frequency of positive extreme events is increasing at higher rate than that of negative extremes
- The slope of absolute total carbon mass from negative extreme events is at least 20% more than from the positive extreme events
- The adjusted R-squared value is highest for zero time lag and all five drivers considered
- The $P - ET$ anomalies are the most dominant climate driver, followed by Prcp anomalies

# Future steps

- Define spatio-temporal carbon cycle extreme events
- Perform similar analyses with dynamic land use change

# Acknowledgments

This research was performed for the Reducing Uncertainty in Biogeochemical Interactions through Synthesis and Computation Scientific Focus Area (RUBISCO SFA), which is sponsored by the Regional and Global Climate Modeling (RGCM) Program in the Climate and Environmental Sciences Division (CESD) of the Biological and Environmental Research (BER) Program in the U.S. Department of Energy Office of Science. Oak Ridge National Laboratory (ORNL) is managed by UT-Battelle, LLC, for the U.S. Department of Energy under Contract No. DE-AC05-00OR22725.

# Thank you!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