



1 **The impact of climate extremes on northern and southern**
2 **hemisphere seasonal ecosystem productivity over four decades to**
3 **2018**

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13
14 **Abstract**

15 Climate extremes affect ecosystem performance across the globe, including net seasonal
16 productivity (NSP), the difference between land surface carbon uptake in summer and release
17 in winter. In this study we correlated estimates of NSP, obtained from atmospheric carbon (C)
18 observations, with curated climate extreme indices that span from 1977 to 2018, split between
19 the Northern (NH) and Southern hemispheres (SH). In the NH, wet climate extremes correlated
20 with an increase in summer uptake of C, and hot climate extremes were correlated with reduced
21 winter release of C. Together, hotter and wetter climate extremes in the NH correlated with
22 increased NSP, a finding that supports a beneficial effect of warming climates in high latitude
23 seasonal NH forests, where cold temperatures typically limit ecosystem productivity. In the
24 SH, all 10 hot climate extremes examined correlated negatively with summer C uptake, and
25 NSP in the SH was negatively correlated with hot extremes but positively correlated with wet
26 and cold extremes. The results indicate that seasonality in the SH, which is predominately
27 located in warm tropical and subtropical forests, seem to be more deleteriously impact by heat
28 than the NH, presumably due to the ambient temperature of SH forests being already close to
29 biological heat thresholds such as photosynthetic heat stability. Increases in the Southern
30 Oscillation Index (SOI) in the NH was associated with wetter and hotter climates that drove
31 down winter C loss and led to increases in NSP. In the SH an increase in the SOI was associated
32 with wetter climates that correlated with increased summer C uptake and NSP. The findings
33 highlight the contrast between NH and SH seasonal C flux responses to climate extremes, and



34 the importance of climate drivers of temperature and rainfall extremes in determining global
35 ecosystem performance.

36

37

38 **1 Introduction**

39 Attributing the seasonal fluctuation in atmospheric carbon (C) concentrations to the terrestrial
40 biosphere is well established, particularly for the Northern hemisphere (NH) and at higher
41 latitudes (Graven et al., 2013; Forkel et al., 2016; Liu et al., 2024b). Fossil fuel use can vary
42 seasonally, with as much as 5% more C released from fossil fuel burning in the NH winter than
43 summer (Rotty, 1987). However, the seasonal cycle in anthropogenic C release is no more than
44 10% of the total seasonal atmospheric C cycle (Levin et al., 2003), with much of the seasonal
45 cycle being driven by C exchange by plants and soils. Seasonal uptake in atmospheric C, and
46 an increase in atmospheric $\delta^{13}\text{C}$ (due to $^{12}\text{CO}_2$ being fixed preferentially by Rubisco), directly
47 link seasonal photosynthetic C uptake and atmospheric C concentrations (Von Caemmerer,
48 2020). Moreover, increases in seasonal ecosystem productivity from atmospheric CO_2 records
49 and through global vegetation models closely align (Graven et al., 2013; Haverd et al., 2020;
50 Ruehr et al., 2023; Zhu et al., 2016). With seasonal fluctuations in the atmospheric C cycle
51 reflecting photosynthetic and respiratory flux, studies have used the atmospheric C data to infer
52 patterns of change in seasonal ecosystem productivity (Forkel et al., 2016; Graven et al., 2013;
53 Liu et al., 2024b).

54 Increases in the amplitude of the seasonal fluctuation in atmospheric C and net
55 ecosystem productivity over recent decades have been linked to increasing seasonal
56 productivity due to CO_2 fertilisation of photosynthesis, with that effect being stronger than
57 negative influences on ecosystem productivity such as climate extremes and land clearing
58 (Ruehr et al., 2023; Zhu et al., 2016). Importantly, the increase in amplitude of seasonal C is
59 stronger the more north in latitude observations are made, suggesting that the CO_2 fertilisation
60 effect is primarily occurring in boreal and temperate forests across northern land masses (Dunn
61 et al., 2020).

62 A key area that needs to be addressed is understanding how greenhouse-gas induced
63 increases in climate extremes (historically uncommon hot, cold, wet, and dry weather events)
64 are influencing global patterns in seasonal productivity and associated seasonal changes in
65 atmospheric C. Climate extreme indices derived from weather records can provide clear
66 indicators of erratic changes in weather systems due to global warming. One such set of indices
67 is held within the HadEX3 global climate extreme database (Dunn et al., 2020). Given that



68 there is climate extreme data that can be paired with seasonal ecosystem C exchange data, the
69 opportunity exists to determine which climate extreme events have had an impact on seasonal
70 changes in atmospheric C and associated patterns in ecosystem performance. An important
71 driver of climate is the Southern Oscillation Index (SOI). The SOI captures differences in
72 eastern and western equatorial Pacific Ocean sea-level pressures and temperatures that drive
73 El Niño (wet eastern Pacific – low SOI) and El Niña (wet western Pacific – high SOI)
74 (Rasmusson and Wallace, 1983). SOI has the potential to influence climate extremes, with
75 knock-on effects on ecosystem productivity, atmospheric C and the global climate system.

76 While the NH is thoroughly studied in terms of its seasonal biosphere C exchange, the
77 southern hemisphere (SH) has not been explored in a similar way, understandable as the SH
78 has less of the seasonal forests found in the NH (seasonal atmospheric CO₂ fluctuations is much
79 less evident in the SH - Fig. 1). Another difference between the NH and SH is that, unlike the
80 NH, most of SH seasonality occurs in the lower < 25° latitudes, where most of the SH land
81 vegetation resides. Despite reduced seasonality in the SH (Liu et al., 2024b), it is important to
82 understand how climate extremes are impacting the forests in the SH, as much of the world's
83 vegetation resides in SH tropical rainforests.

84 In this study we investigate hemisphere-specific relationships between seasonal
85 variations in atmospheric C and climate extremes. We correlate seasonal summer C uptake,
86 winter release, and seasonal uptake minus release (net seasonal productivity - NSP) with
87 climate extremes by matching mean yearly data between seasonal C exchange and climate
88 extreme records. By combining yearly seasonal productivity with yearly climate extreme data
89 and changes in SOI, our goal was to provide generalised hemisphere-scale insights into which
90 extremes in climate are driving seasonal C uptake and release from ecosystems. We explore
91 factors determining differences in the response of vegetation above and below the equator to
92 climate change drivers. The findings point to increases in the availability of water driving
93 greater seasonal productivity, and the widening of the daily temperature range (DTR) driving
94 reduced seasonal summer C uptake, across both hemispheres. Importantly, we show that there
95 are clear differences in the impact of climate extremes on vegetation that are hemisphere based,
96 the most evident being the impact of hot extremes. While NH seasonal productivity has mostly
97 benefitted from an increase in hot climate extremes, the opposite has occurred in the SH,
98 emphasising the difference in forest seasonality between the hemispheres and the importance
99 of understanding SH seasonality despite it being less pronounced than the NH.

100



101 **2 Materials and Methods**

102 *2.1 Data acquisition*

103 Four datasets were used in this analysis: (1) Northern Hemisphere atmospheric CO₂
104 concentration records from Mauna Loa (MLO, 20°N), Hawaii (NOAA); (2) Southern
105 Hemisphere atmospheric CO₂ concentration records for Kennaook/Cape Grim (CGO, 41°S),
106 Tasmania, Australia (Australian Bureau of Meteorology; CSIRO Oceans & Atmosphere); (3)
107 The HadEX3 climate extreme indices with reference period of 1961-1990 for the years 1977
108 to 2018 (Dunn et al., 2020); and (4), the southern oscillation index (SOI) recordings derived
109 from sea-level atmospheric pressure differences between Tahiti and Dawin (Australian Bureau
110 of Meteorology). All analysis was limited to the years 1977 to 2018 based on CO₂ concentration
111 data for Kennaook/Cape Grim starting in 1977, and the HadEX3 climate extreme database
112 being limited to 2018. The HadEX3 data can be accessed from the Climdex online repository
113 (<https://www.climdex.org/access/>). The atmospheric CO₂ concentration and SOI datasets used
114 are available from the websites of the named government agencies above. The mean 1977 to
115 2018 annual values spit by hemisphere, covering all data used to generate results (the
116 atmospheric C exchange data, HADEX3 data, and SOI data) can be found at
117 <https://dx.doi.org/10.25911/cfej-9t96>.

118

119 *2.2 A segmented linear model analysis of seasonal atmospheric carbon exchange*

120 Mauna Loa and Kennaook/Cape Grim are two of the three Premier Global Baseline stations of
121 the World Meteorological Organisation's Global Atmospheric Watch programme, making them
122 ideal representatives of atmospheric C observations for the NH and SH, respectively.
123 Kennaook/Cape Grim observatory data consisted of monthly observations starting in 1977 and
124 Mauna Loa observatory data (although available on a weekly basis and beginning in 1974) was
125 limited to 1977 and monthly data for consistent analysis between the two observation sites.
126 CO₂ was converted from a concentration to a mass in petagrams of atmospheric carbon (Pg C)
127 by multiplying by a factor of 2.12 Pg C per ppm of CO₂ for all subsequent analysis; all results
128 are thus presented on a C mass basis. To de-trend the interannual increases in atmospheric C, a
129 quadratic equation was fitted through least-squares regression to the mean yearly atmospheric
130 C over the years for which data were analysed (Fig. S1). From this quadratic equation, predicted
131 atmospheric C values (C_p) at each datapoint were used to obtain the baseline atmospheric C
132 independent of the annual upward trends as follows:

133



$$134 \quad \text{Baseline } C_{[t_n]} = C_{o[t_n]} - (C_{p[t_n]} - C_{p[t_1]}) \quad \text{Eq.1}$$

135

136 where $C_o[t_n]$ is the observed atmospheric C at any given observation point, $C_p[t_n]$ is the
137 predicted atmospheric C at any given observation point, and $C_p[t_1]$ is the predicted atmospheric
138 C at the baseline observation year of 1977. Thus, all influences on inter-annual shifts in
139 atmospheric C - notably rises in anthropogenic C emissions - were not factored into our
140 seasonal analysis. The annual sea-air C flux was also assumed to not influence the analysis,
141 being less than 10% of the NH seasonal C cycle (Zhang et al., 2022), but may have had a
142 greater influence on the much smaller SH seasonal atmospheric cycle.

143 A linear model framework with break-points determined through fitted piecewise terms
144 in the regression model, as described by Muggeo (2003), was used to determine the peak and
145 trough of each yearly seasonal fluctuation in atmospheric C, with the model providing
146 estimates of atmospheric C at the peak and trough of each cycle. Firstly, the baseline
147 atmospheric C data were subset by time of year so that the peak and trough of seasonal
148 atmospheric C was separately analysed using the segmented linear model. For the NH, January
149 to July observations captured the peak in atmospheric C (equivalent to the end of vegetative
150 carbon release), and July to December for the trough of atmospheric C (equivalent to the end
151 of vegetative carbon uptake). For the SH, January to July observations captured the trough in
152 atmospheric C and June to December for the peak of atmospheric C. Linear models using the
153 ‘segmented’ package in R (Muggeo, 2003; Muggeo et al., 2014) were able to fit a break-point
154 at the seasonal peak and trough and linear regressions either side (Fig. S2). Seasonal uptake
155 rate (Tg C day^{-1}) was derived from the slope of the linear regression between a peak and trough.
156 Seasonal release rate was derived from the slope of the linear regression between a trough and
157 peak. The seasonal uptake span (days) was derived from the number of days between a peak
158 and trough, or between a trough and peak for release span. A seasonal uptake and release (Pg
159 C) were derived from the seasonal uptake and release rates multiplied by the span of uptake
160 and release days. Finally, net seasonal productivity was derived by subtracting the seasonal
161 release from the seasonal uptake of C.

162

163 2.3 Global climate extreme indices

164 The HadEX3 global climate extreme index covers weather indices interpolated from annual
165 and monthly observations from weather stations on a $1.875 \times 1.25^\circ$ grid derived from daily in
166 situ weather station observations from the years 1950 to 2018 and referenced to the years 1961-



1990, as described by Dunn et al. (2020). We averaged indices for the entire NH and SH geographical regions by year from 1977-2018. The dataset is curated until 2018, limiting our analysis to that year. We categorised the indices into five climate categories: temperature range (one index), dry (one index), hot (10 indices), cold (five indices), wet (nine indices). The single temperature range index was the diurnal temperature range (DTR), which was the annual mean difference between daily max and min temperatures ($^{\circ}\text{C}$). The single dry index was the consecutive dry days (CDD), which was the highest number of consecutive days when precipitation < 1 mm. The 10 hot indices were: TXx, the annual highest value of maximum daily temperature; TXn, the annual lowest value of the maximum daily temperature; TX90p, the percentage of days when maximum daily temperature is $> 90^{\text{th}}$ percentile; TNx, the annual highest value of daily minimum temperature; TNn, the minimum value of daily minimum temperature; TN90p, the percentage of days when maximum nighttime temperature $>$ the 90th percentile; GSL, the annual growing season length; SU, the number of summer days when the daily maximum temperature was $> 25^{\circ}\text{C}$; TR, the number of tropical nights when maximum nighttime temperature was $> 20^{\circ}\text{C}$; and WSDI, the warm spell duration index - annual count of days with at least 6 consecutive days when maximum daily temperature was $> 90^{\text{th}}$ percentile. The five cold indices were: TN10p, the percentage of days when the daily minimum temperature was $<$ the 10^{th} percentile; TX10p, the percentage of days when the daily maximum temperature was $< 10^{\text{th}}$ percentile; CSDI, the cold spell duration index - annual count of days with at least 6 consecutive days when the daily minimum temperature was $<$ the 10^{th} percentile; FD, the number of frost days with daily minimum temperature below 0°C ; and ID, the number of icing days when the daily maximum temperature was $<$ than 0°C . The nine wet indices were: R95p, the annual total PRCP when the daily precipitation amount was $> 95^{\text{th}}$ percentile; R99p, the annual total PRCP when the daily precipitation amount was $> 99^{\text{th}}$ percentile; Rx1day, the maximum 1-day precipitation; Rx5day, the maximum consecutive 5-day precipitation; R10mm, the annual count of days when precipitation was $\geq 10\text{mm}$; R20mm, the annual count of days when precipitation was $\geq 10\text{mm}$; CWD, the maximum length of a wet spell - daily precipitation amount $\geq$ than 1 mm; PRCPTOT, the annual total precipitation on wet days; and SDII, the simple precipitation intensity index. For a more detailed explication of how each indices was calculated, refer to Dunn et al. (2020). Note that categorisation of an indices as hot or cold was based on a positive association with the climate category. For instance, TXn and TNn although measuring the lowest value of the annual maximum and minimum daily temperature are classified as hot extreme indices because a higher TXn or TNn value indicates a hotter climate.



201

202 *2.4 Data analysis by year or SOI*

203 Data was analysed using base R programming language. Correlations between seasonal C
204 exchange (seasonal uptake, seasonal release, and net seasonal productivity) and year, or
205 between seasonal C exchange and SOI, were based on linear regression analysis of the mean
206 value for each variable, segmented by year of observation. The yearly mean seasonal carbon
207 exchange variables and SOI were further correlated with corresponding yearly means of
208 extreme climate indices, and the presented correlation coefficients between the variables of
209 interest are based on a Persons correlation matrix performed in Base R programming language.

210

211 **3 Results**

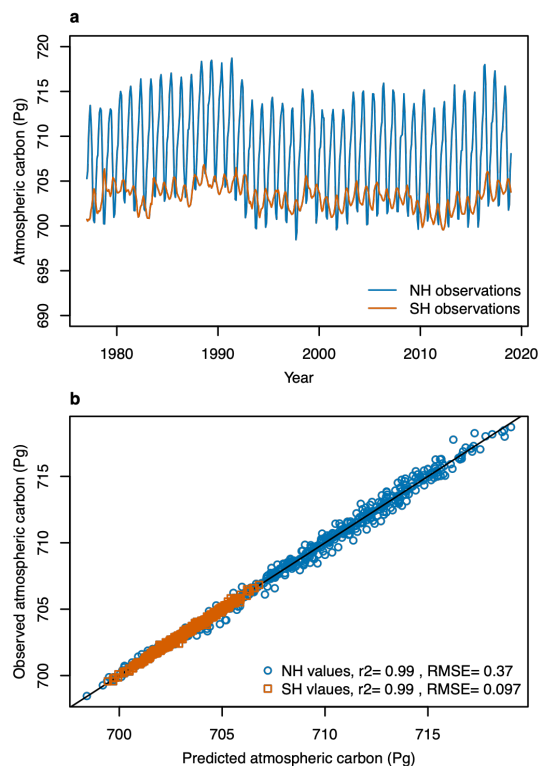
212 *3.1 Seasonal carbon exchange in the northern and southern hemisphere*

213 Yearly fluctuations in atmospheric C attributed to variations in vegetative C cycles were evident
214 in both the NH and SH (for the years 1977-2018) when subtracting background anthropogenic
215 rises in atmospheric C (Fig. 1a). Predictions of atmospheric C using the segmented linear model
216 closely matched observations over all the years analysed, with a RMSE value of 0.37 Pg for
217 the NH and 0.097 Pg for the SH and an $r^2=0.99$ for both (Fig. 1b). The model accuracy gives
218 support to our seasonal uptake and release calculations that were based on the slopes and
219 identified peak and trough positions of the segmented linear model.

220 There were weak and non-significant ($P > 0.05$) linear relationships in seasonal C
221 exchange rates (Fig. 2a), C uptake and release spans (Fig. 2b), total seasonal C uptake and
222 release (Fig. 2c), and NSP for both the NH and SH (Fig. 2d; Table S1). Taken together, the
223 combination of (1) a faster seasonal uptake rate multiplied by a shorter uptake season, and (2)
224 a slower seasonal release rate multiplied by a longer release season, led to almost matching
225 total seasonal uptake and release of C each year in the NH. The resulting net seasonal
226 productivity (NSP) in the NH was close to zero across the years 1977-2018 with an upward
227 trend through time by 0.015 Pg C yr⁻¹ (Fig. 2d); while this upward trend was not significant, it
228 equated to a 0.1% increase in NSP yr⁻¹ relative to the 15 Pg C of seasonal uptake in 1977.
229 Interestingly, the SH seasonal uptake span was longer than the release span (Fig. 2b) and the
230 seasonal C uptake rate was slower than the release rate (Fig. 2c), the reverse of the relationship
231 between rates and seasonal span in the NH. As with the NH, SH differences in seasonal rates
232 between uptake and release were largely counteracted by the span of the uptake and release
233 season, leading to near zero NSP that was almost constant from the years 1977-2018, barely
234 increasing by 0.001 Pg C yr⁻¹.



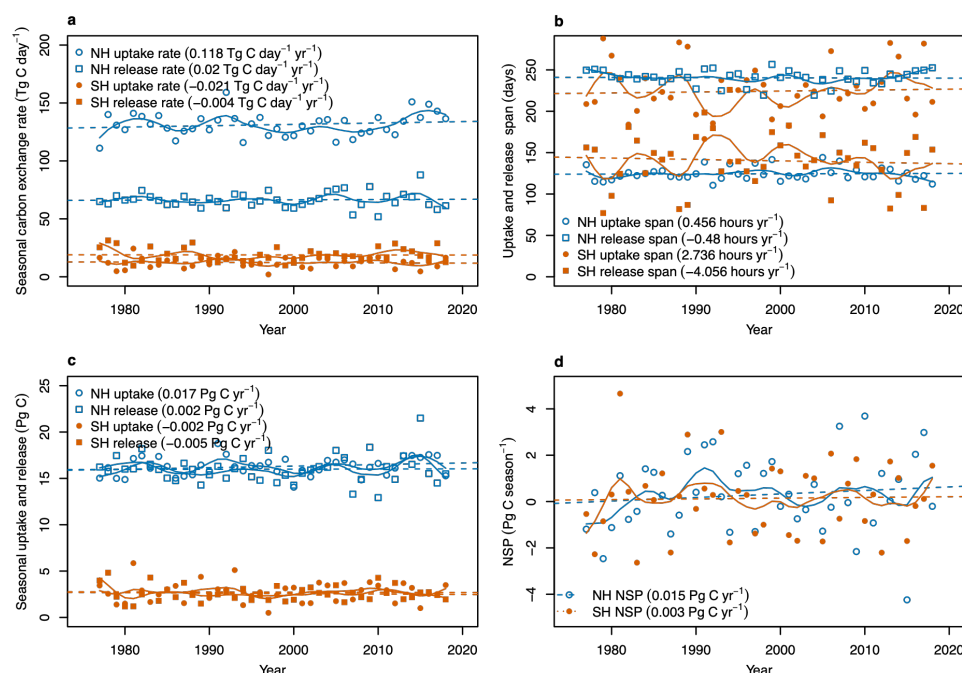
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236

237 **Figure 1.** Atmospheric carbon (C) observed from Mauna Loa, Hawaii (NH) and Kennaook/Cape Grim, Tasmania
 238 (SH), two of the three Premier Global Baseline stations of the World Meteorological Organisation's Global
 239 Atmospheric Watch programme. (a) Observations were limited to the years 1977-2018 with the yearly upward
 240 trend in emissions removed (refer to Eq.1 and Fig. S1). (b) Model analysis of observed atmospheric C compared
 241 to predicted atmospheric C based on a segmented linear model of observed data to derive seasonal C uptake and
 242 release. The r^2 and the Root Mean Square Error (RMSE) values of the modelled versus observed values are
 243 presented on the graph.

244



245

246 **Figure 2.** Seasonal ecosystem carbon exchange in the Northern (NH) and Southern hemisphere (SH) based on a
 247 segmented linear model that determined the peak and trough, and the rate of seasonal uptake and release of each
 248 yearly seasonal fluctuation in atmospheric carbon. (a), Seasonal C exchange rates based on the linear rate of
 249 decline or incline in atmospheric C between the peak and trough (uptake) or trough and peak (release) during the
 250 warmer and cooler months in each hemisphere. (b) The seasonal C uptake and release span based on the days
 251 between the peak and trough (uptake) or trough and peak (release) during the warmer and cooler months in each
 252 hemisphere. (c) The total seasonal C uptake and release based on the uptake and release rates in Panel a multiplied
 253 by the seasonal span presented in Panel b. (d), The Net Seasonal Productivity (NSP) based on subtracting seasonal
 254 uptake from seasonal release as presented in Panel c. Stright dashed lines represent the linear regression fits
 255 between seasonal C exchange variables and year with the slope coefficients of regression fits presented in
 256 parenthesis in the figure legends and more detailed regression statistics presented in Table S1. Curved lines
 257 represent a cubic smoothing spline fit.

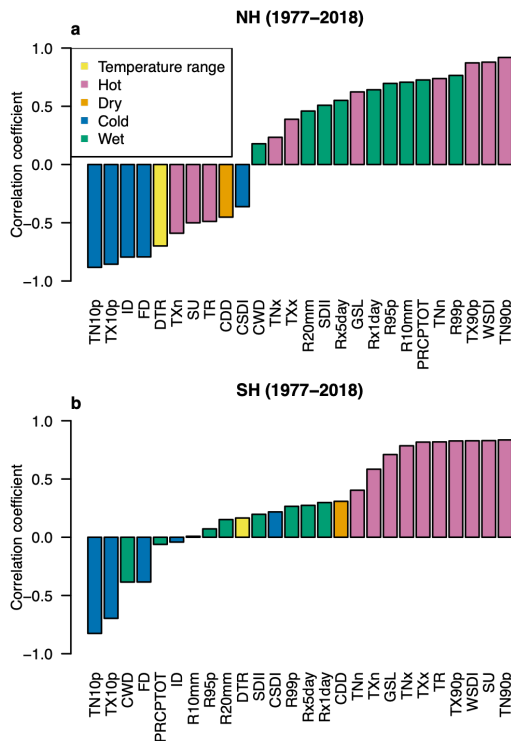
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259 3.2 Climate extreme correlations with time and seasonal carbon exchange

260 When averaged by year, a range of indices of hot climate extremes exhibited strong positively
 261 correlations with chronological time from 1977 to the 2018 (Fig. 3). Stronger correlations were
 262 evident in the SH, where all 10 hot climate extreme indices were most positively correlated
 263 with progression of time. While the top three climate extremes positively correlated with year
 264 in the NH were also hot extremes (TN90p, WSDI, and TX90p), other hot climate extremes
 265 were negatively correlated with year in the NH (TR, SU, and TXn). The other clear difference



266 between the two hemispheres in climate extreme patterns with time was a positive correlation
267 between wet climate extremes and year in the NH, with all eight wet climate extremes
268 positively correlating with progression of year in the NH, and to a much greater extent than
269 wet climate extremes in the SH (Fig. 3).
270



271
272 **Figure 3.** Pearson correlation matrix derived correlation coefficients for the relationships between the annual
273 mean values of each temperature extreme index and chronological time spanning the years 1977-2018 in the
274 northern hemisphere (a) and the southern hemisphere (b). The HadEX3 climate extreme indices are colour coded
275 by climate category as presented in the legend. Climate index acronyms are described in the Methods section of
276 this report, and are described in detail by Dunn et al. (2020).

277
278 Pearson correlation matrices further allowed for associations between annual mean
279 changes in seasonal C exchange (i.e. uptake, release, and NSP) and climate extremes among
280 the years 1977-2018 to be ascertained. In both the NH and SH, seasonal C uptake was to the
281 greatest extent positively correlated with wetter climate extremes (Fig. 4). Hot and cold climate
282 extremes had differing relationships with seasonal C uptake depending on the hemisphere (Fig.
283 4a,b). Hot climate extremes were often correlated with increased seasonal C uptake in the NH



284 (TN90p, WSDI, TX90p, GSL) but all hot extremes had a negative correlation with seasonal
285 carbon uptake in the SH. Indeed, in the SH, eight of the nine climate extremes most negatively
286 correlated with C seasonal uptake were heat related. All five cold climate extremes were
287 negatively correlated with seasonal C uptake in the NH, while in the SH three of the five cold
288 extremes (indices FD, TN10p, and TX10p) all correlated positively with seasonal carbon
289 uptake. In both hemispheres, the climate extreme variable that had the strongest negative
290 correlation with seasonal C uptake was Daily Temperature Range (DTR) (Fig. 4a,b).

291 There were distinct differences in climate extreme relationships with seasonal C release
292 between the hemispheres (Fig. 4c,d). Most strikingly, hot climate extremes negatively
293 correlated with seasonal C release in the NH, most notably TNx and TXx were the two hot
294 indices that correlated most negatively with C release (Fig. 4c). However, many hot extremes
295 were positively correlated with seasonal C release in the SH (most notably, TX90p and WSDI).
296 In the NH, wet and hot climate extremes positively correlated with NSP (Fig. 4e), while in the
297 SH, wet and cold climate extremes positively correlated with NSP and hot extremes correlated
298 with reduced NSP (Fig. 4f).

299

300 *3.3 Seasonal carbon exchange and the southern oscillation index*

301 To determine if the southern oscillation index (SOI) impacted on seasonal C uptake or release
302 over the past few decades for both the NH and SH, the mean yearly seasonal C exchange values
303 were further compared to SOI values for the same years (Fig. 5). The SOI had a significant
304 negative relationship with NH seasonal release, and a subtle non-significant negative
305 relationship with NH uptake. In the SH, SOI had a positive and significant relationship with
306 SH seasonal C uptake and non-significant relationship with SH release. The resulting impact
307 of the SOI on overall NSP was a significant positive relationship in both hemispheres (Fig. 5b).
308 The significant positive relationship between SOI and NSP in the NH can be attributed to the
309 SOI being strongly correlated with wetter and hotter climate extremes in the NH (Fig. 5c),
310 extremes that were shown to correlate with reduced NH seasonal release and increased NSP
311 (Fig. 4 c,e). The significant positive relationship between SOI and NSP in the SH can be
312 attributed to the SOI being strongly correlated with wetter climate extremes in the SH (Fig. 5d)
313 and these extremes being positively correlated with seasonal uptake and NSP in the SH (Figs.
314 4b,f & 5d).

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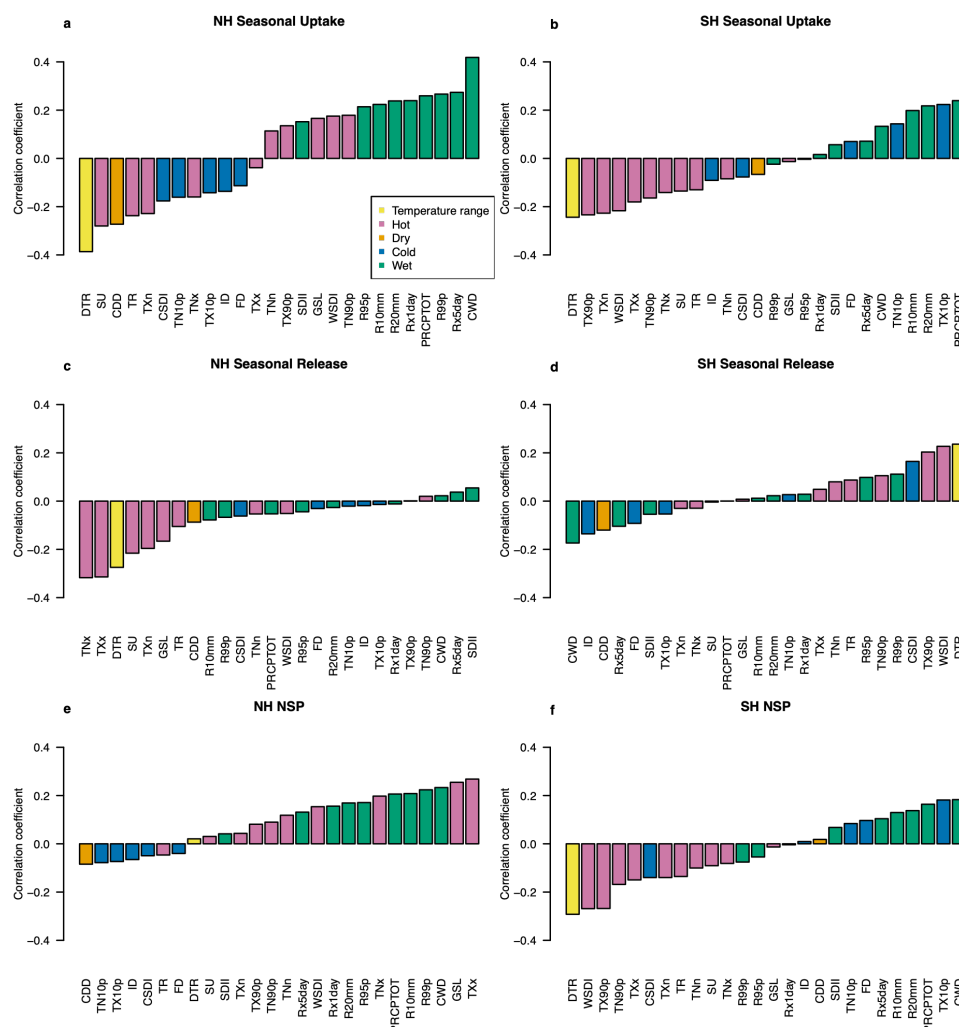


Figure 4. Pearson correlation matrix derived correlation coefficients for the relationships between the annual mean values of each temperature extreme index and annual mean seasonal C ecosystem exchange variables, for the northern (NH) and southern hemispheres (SH). (a,b), The relationships between seasonal C uptake (as presented in Fig. 2c) and climate extreme indices. (c,d), The relationships between seasonal C release (as presented in Fig. 2c) and climate extreme indices. (e,f), The relationships between net seasonal productivity (NSP) (as presented in Fig. 2d) and climate extreme indices. The HadEX3 climate extreme indices are colour coded by climate category as presented in the legend. Climate index acronyms are described in the methods section of this report, and are described in detail by Dunn et al. (2020).

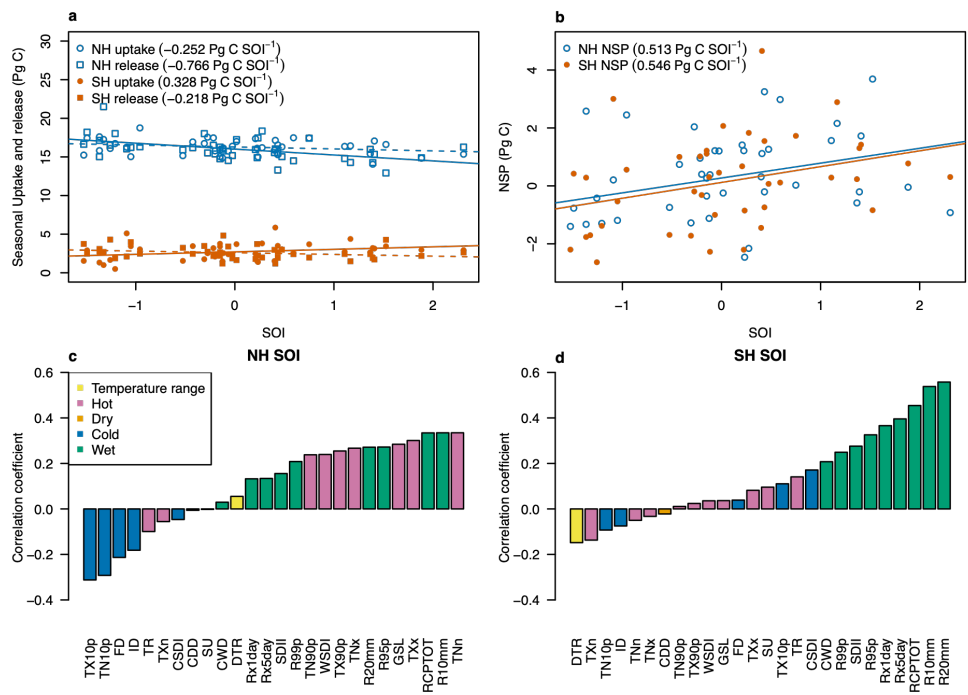


Figure 5. The relationships between seasonal C exchange variables and the Southern Oscillation Index (SOI) for the northern (NH) and southern hemispheres (SH). (a) The annual mean seasonal ecosystem uptake and release plotted against the annual SOI for the years. (b), The annual mean net seasonal productivity (NSP) plotted against the annual SOI. (c,d) Pearson correlation matrix derived correlation coefficients for the relationships between the annual mean values of each temperature extreme index and the annual mean southern hemisphere SOI for NH and SH, respectively. (a,b) Lines represent the linear regression fits between seasonal C exchange variables and SOI, with dashed lines representing no-significance ($p > 0.05$) and solid line representing significance ($P < 0.05$). The slope coefficients of regression fits are presented in parenthesis in the figure legends and more detailed regression statistics presented in Table S1.

4 Discussion

Ecosystem productivity has been rising steadily over past decades driven by atmospheric CO_2 fertilisation that has so far over-compensated for the negative impacts of climate extremes on photosynthetic performance (Ruehr et al., 2023). The impact of climate extremes on evergreen forests - particularly globally dominant tropical evergreen forests - will be the greatest contributor to carbon sequestration in plants (Pan et al., 2011). However, the positive and negative influences of climate extremes on seasonal C uptake, C release and resulting NSP, and differences between the NH and SH in seasonality responses to climate extremes is of urgent consideration. Indeed, shifts in seasonal productivity due to temperature dependence has



347 recently been identified as contributing most to CO₂ driven changes in global gross primary
348 productivity, more so than changes in global mean annual temperature, mean annual
349 precipitation, or aridity (Tang et al., 2025). Here, we identify that a rise in hot extremes and
350 reduction in cold extremes benefits seasonal productivity in forests of the NH but are
351 detrimental to SH seasonal productivity. This may have profound implications on the balance
352 of seasonal vegetation and its distribution across the globe.

353 The NSP of the NH trended upwards at 0.1% NSP yr⁻¹ (Fig. 2). A similar weak and non-
354 significant increasing trend of 0.076% yr⁻¹ was obtained from Mauna Loa observations
355 analysed over a similar timeframes of 1970 to 2011 using amplitude of the seasonal C cycle
356 (Forkel et al., 2016). However, others have reported a more substantial ~0.3% yr⁻¹ increase in
357 seasonal amplitude over similar timeframes based on Mauna Loa observations (Cuntz et al.,
358 2025; Graven et al., 2013), demonstrating variability in seasonal estimates of C uptake and
359 release, likely due to the specifics of methodology and the years analysed. Observations based
360 on vegetative indices from aeroplane surveys and satellite data, combined with biophysical
361 models of photosynthesis, derive much higher increases in seasonal uptake for latitudes of >
362 40°N, ranging from 10 to 60% (or 0.1 to 0.8% yr⁻¹) over the years 1960-2010 (Haverd et al.,
363 2020). There is, however, a positive relationship between seasonal productivity and NH
364 latitude, attributable to more climate stimulation of boreal and tundra forests that are benefiting
365 not only from atmospheric CO₂ fertilisation but also climate warming (Forkel et al., 2016;
366 Haverd et al., 2020).

367 The atmospheric observations we present demonstrate seasonal C exchange differences
368 that can be attributed to differences in the NH and SH biomes. In the NH, faster seasonal uptake
369 rates were paired with shorter seasonal C uptake spans, reflecting cool environments with short
370 but substantive warm season growth. By contrast, slower seasonal C uptake rates in the SH
371 were paired with longer seasonal uptake spans, reflecting warm environments with limited
372 seasonality but a longer growing season due to less distinct winter seasons in the SH forests
373 (Fig. 2). This is consistent with the peak in C uptake by the land sink in the NH occurring at
374 latitudes between 40 and 60°N (colder temperate forests), while land surface C uptake peaks
375 at latitudes between 0 and 20°S (tropical and subtropical forests) in the SH (Haverd et al.,
376 2020).

377 Hotter extremes are often associated with reduced plant performance (Margalef-
378 Marrase et al., 2020; Teskey et al., 2015). This is evident in our SH analysis, with essentially
379 all hot extreme indices correlating negatively with seasonal C uptake, positively with seasonal
380 C release, and negatively with NSP (Fig. 4). This is despite the possibility of a small



381 confounding effect of hot extremes rising alongside CO₂ fertilisation, the latter, as previously
382 stated, having a positive influence on plant productivity. Hot weather extremes can therefore
383 be considered as one of the main drivers of loss of net seasonal C productivity by plants in the
384 SH. Most of the vegetation in the SH is within the tropical and subtropical regions of central
385 and southern parts of Africa, South America, southern part of Asia, and the north of Australia,
386 regions where plant metabolism is not cold limited, but rather closer to the upper thermal limits
387 of photosynthetic functionality. For example, a study of the tropical rainforests of the Amazon
388 basin and the African Congo, showed that C uptake by the forests was negatively correlated
389 with rising temperature, even more so than drier conditions (Hubau et al., 2020). Moreover,
390 recent studies have reported that leaf temperatures in SH tropical forests often exceed their
391 photosynthetic temperature optimum and may be reaching critical heat loads above
392 photosynthetic biochemical stability that impact on survival (Doughty et al., 2023; Slot and
393 Winter, 2017). The detrimental impact of hot climate extremes on NSP in the SH was not
394 evident in the NH. Rather, warmer climate extremes were correlated with increased NSP in the
395 NH. For example, the indices WSDI and TN90p that indicate spells of warm weather and mild
396 nights during summer months were two of the climate extremes with strongest positive
397 correlation to increase seasonal C uptake in the NH. The positive effect of hot climate extreme
398 indices on NSP in the NH but not SH matches patterns of more climate resilience in northern
399 latitude forests attributed to the positive influence of rising temperature and CO₂ fertilisation
400 on biomass production in these high latitude NH forests (Forzieri et al., 2022).

401 The climate extremes indices with the greatest negative relationship with seasonal
402 summer C uptake, for both hemispheres, was the diurnal temperature range (DTR). This
403 suggests that a greater difference between the minimum and maximum daily temperature has
404 a strong negative impact daily net C gain in summer months. One potential reason may be that
405 a greater rise in diurnal air temperature would cause a rise in the atmospheric vapour pressure
406 deficit (VPD) that can lead to stomata closure to limit accelerated leaf water loss, at a cost to
407 photosynthetic C fixation, especially in afternoons as VPD rises (Grossiord et al., 2020; Liu et
408 al., 2024a). Additionally, dynamic rises in temperature initiate kinase receptors that induce heat
409 shock transcription factors and heat shock proteins for stabilisation of membrane lipids (Wang
410 et al., 2026), all of which would presumably require energy and contribute to C loss. Of note,
411 DTR is declining with time in the Northern hemisphere (Fig. 3a), likely driven by asymmetric
412 warming in daily nighttime minimum relative to maximum temperatures, which is more
413 pronounced in the NH (Davy et al., 2017). This yearly reduction in DTR is likely having a



414 positive influence on net C uptake in the NH considering the negative relationship between
415 DTR and seasonal uptake.

416 Driven by a decline in NH seasonal release and an increase in SH seasonal uptake with
417 increasing SOI, the SOI significantly correlate with positive changes in NSP in both
418 hemispheres (Fig. 5). In the NH this positive correlation between SOI and NSP could be
419 attributed to the SOI being associated with hotter climate extremes that were linked to reduced
420 NH seasonal winter C release (Figs. 4c & 5c). In the SH the positive correlation between SOI
421 and NSP could be attributed to much wetter climates with increased SOI driving increased SH
422 seasonal summer C uptake and NSP (Figs. 4b,f & 5d). This is consistent with lower SOI (i.e.
423 El Niño events) leading to drought, including in southern tropical rainforests, which severely
424 reduces forest C uptake (Nath et al., 2024). As far back as the years 1997/1998, increases in
425 tree mortality of 11 to 22% with an El Niño (i.e. low SOI) associated drought have been
426 observed in the tropical forests of Borneo in Indonesia, just south of the equator (Slik, 2004).
427 Of concern is a report that there may be an increase in the occurrence of intense El Niño SOI
428 events associated with the human induced climate change (Cai et al., 2021), which will likely
429 have a strong negative impact on seasonal productivity across the globe based the findings we
430 present here.

431

432 **5 Conclusions**

433 In conclusion, ecosystems that seem to benefit the most from current changes in climate are
434 seasonal cool temperate forests in the NH that are stimulated by wetter summers that increase
435 C uptake, and hotter climate extremes that reduce winter C release. By contrast, hot climate
436 extremes have reduced seasonal ecosystem performance in the SH through being negatively
437 correlated with summer C uptake, most likely due to seasonality in the SH being concentrated
438 in forests close to the equator that are already close to their photosynthetic temperature
439 optimums. If these relationships between hot climate extremes and seasonal photosynthetic and
440 respiratory C fluxes hold over the coming years, in essence, the NH may become greener and
441 the SH less so. The extent to which seasonal productivity is detrimentally impacted upon by
442 climate change may be most heavily dependent on the SOI, which is positively correlated with
443 NSP across the hemispheres due to higher SOI (La Niña events) driving wetter climates in the
444 SH and hotter and wetter climates in the NH. Whether these patterns hold as climate extremes
445 become more intense over the coming decades and to what extent seasonal responses reflect
446 general ecosystem performance to climate extremes needs to be further explored.

447



448 *Data availability.* All data used were accessed through publicly available sites: NOAA GML
449 atmospheric CO₂ data was accessed at <https://gml.noaa.gov>. and Cape Grim atmospheric CO₂
450 data from <https://capegrim.csiro.au>. The SOI data from the Australian BOM at
451 <https://www.bom.gov.au/climate/enso/soi/>. HadEX3 climate extreme data is available from the
452 Climdex <https://website www.climdex.org>. Compiled annual mean values of all data split by
453 hemisphere are located at the DOI: <https://dx.doi.org/10.25911/cfej-9t96>.

454
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456
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458
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