

Growing-season Arctic carbon fluxes are changing relatively faster in tundra than in boreal ecosystems

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Article

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Abstract

Rapid Arctic warming is altering ecosystem functioning and challenging the view of the terrestrial Arctic as a sustained carbon sink. Drawing on independent evidence from warming experiments, satellite observations, data-driven eddy-covariance-based flux products, and atmospheric inversions, we assess growing-season carbon dioxide (CO_2) fluxes across the terrestrial Arctic (60°N – 90°N) between 2001 and 2020. We find that tundra ecosystems exhibit larger relative increases in gross primary productivity (median 7–8%) than boreal regions (median 4–5%), which is also reflected in larger relative increases in solar-induced chlorophyll fluorescence (median 9% versus 5%) and an overall strengthening of carbon uptake (median of 9–11% versus 3–5%) between the two decades. Despite differences among datasets, their agreement on broad-scale patterns suggests that Arctic warming is reshaping tundra carbon dynamics faster than those of boreal ecosystems.

Keywords: Solar-Induced Chlorophyll Fluorescence, Gross Primary Productivity, Ecosystem Respiration, Tundra, permafrost, Arctic

Over the past four decades, the Arctic has warmed nearly four times faster than the global average, a phenomenon known as Arctic amplification [1–3]. This rapid warming, together with rising atmospheric carbon dioxide (CO_2), has increased vegetation productivity across the extratropical Northern Hemisphere since the 1980s [4, 5]. However, the persistence of these trends under continued climate change remains uncertain [5, 6]. Satellite and in situ observations reveal widespread Arctic greening, driven by longer growing seasons, enhanced photosynthesis, and shifts in plant community composition [7–12]. Yet, this trend is punctuated by regional browning events linked to disturbances (e.g., winter warming, wildfires) and processes such as permafrost thaw and hydrological change [13–17].

These vegetation dynamics directly affect the Arctic carbon cycle [10, 18]. Most terrestrial carbon exchange occurs during the growing season, when both gross primary productivity (GPP) and ecosystem respiration (ER) increase. However, because NEE represents the relatively small difference between these two large fluxes, it remains difficult to constrain and varies strongly across space and time [19–23]. For a broader overview of Arctic terrestrial carbon cycling, see Natali et al. [24].

56 In the terrestrial Arctic (60°N–90°N), while early growing-season increases in
57 photosynthesis may enhance carbon uptake, they can be offset by increased late-
58 season respiration, limiting annual net sequestration [25, 26]. As a result, some regions
59 may already function as annual net CO₂ sources [27], even though the broader Arc-
60 tic–Boreal region has remained a net sink over recent decades [28]. The magnitude and
61 direction of these responses are likely to differ between tundra and boreal ecosystems
62 owing to contrasts in vegetation structure, productivity, disturbance regimes, hydrol-
63 ogy, and permafrost influence. These uncertainties are further amplified by the sparse
64 and uneven distribution of in situ observations, complicating efforts to quantify the
65 carbon balance in the terrestrial Arctic zone [29].

66 To address these limitations, machine-learning approaches have been developed
67 to upscale CO₂ flux observations from eddy covariance (EC) and chamber measure-
68 ments using satellite and meteorological data [30–36]. In parallel, satellite-derived
69 solar-induced chlorophyll fluorescence (SIF) has emerged as a robust proxy for pho-
70 tosynthetic activity and is increasingly used to evaluate large-scale GPP estimates
71 [37–41].

72 Here, we examine how tundra and boreal ecosystems differ in their responses to
73 recent warming, with particular emphasis on relative changes in growing-season car-
74 bon fluxes. We test whether independent datasets spanning up to two decades in most
75 cases converge on a consistent picture of the Arctic growing-season carbon balance.
76 In particular, we use independent model-driven datasets based on (i) experimental
77 warming responses of ecosystem respiration [19], (ii) eddy covariance–based estimates
78 of GPP and NEE combined with satellite predictors [36, 42], and (iii) satellite obser-
79 vations of SIF [43]. Also, to complement the bottom-up data-driven C flux balance
80 assessment, we use an ensemble of different top-down atmospheric inversion models
81 [44].

82 Results

83 Heterogeneous increases in Arctic gross primary productivity

84 Across the terrestrial Arctic, growing-season (June–August, JJA) gross primary pro-
85 duction (GPP) increased robustly between the two decades of our study period
86 (2001–2010 vs. 2011–2020), with remarkably consistent median increases of approxi-
87 mately 5–6% across two independent, data-driven products, X-BASE [36] and FluxSat
88 [42] (Table 1). This tendency aligns with previous observations [45, 46] and is sup-
89 ported by an increase in solar-induced fluorescence (SIF; median of 6.5%), reinforcing
90 evidence for a widespread intensification of photosynthetic activity during the growing
91 season.

92 The spatial pattern of change (Fig. 1.a–c) is heterogeneous across the terrestrial
93 Arctic but remains broadly consistent across datasets. After restricting the analysis
94 to pixels with relative changes between -100 and 100% , relative changes in SIF were
95 positively correlated with relative changes in GPP from both X-BASE ($r = 0.38$,
96 $n = 1.21 \times 10^6$) and FluxSat ($r = 0.79$, $n = 1.12 \times 10^6$), supporting the consis-
97 tency of the large-scale spatial patterns across independent products. The strongest
98 increases, in relative terms, occur in tundra-dominated regions, including eastern
99 Canada (CAN.E) and the Taymyr Peninsula (RUS), where GPP increases exceed 10%
100 and are accompanied by even larger SIF enhancements (10% – 17% , see Table 1). In
101 contrast, other localized regions exhibit weak or negligible changes lower than 2% , such
102 as parts of the southern Canadian Archipelago (CAN.A.S) and northern Fennoscan-
103 dia (FEN), while Alaska (AK) shows a mixed response. Notably, areas with limited
104 or negative GPP transitions consistently coincide with weak SIF changes, suggesting
105 the expected physically consistent link between SIF and GPP across datasets.

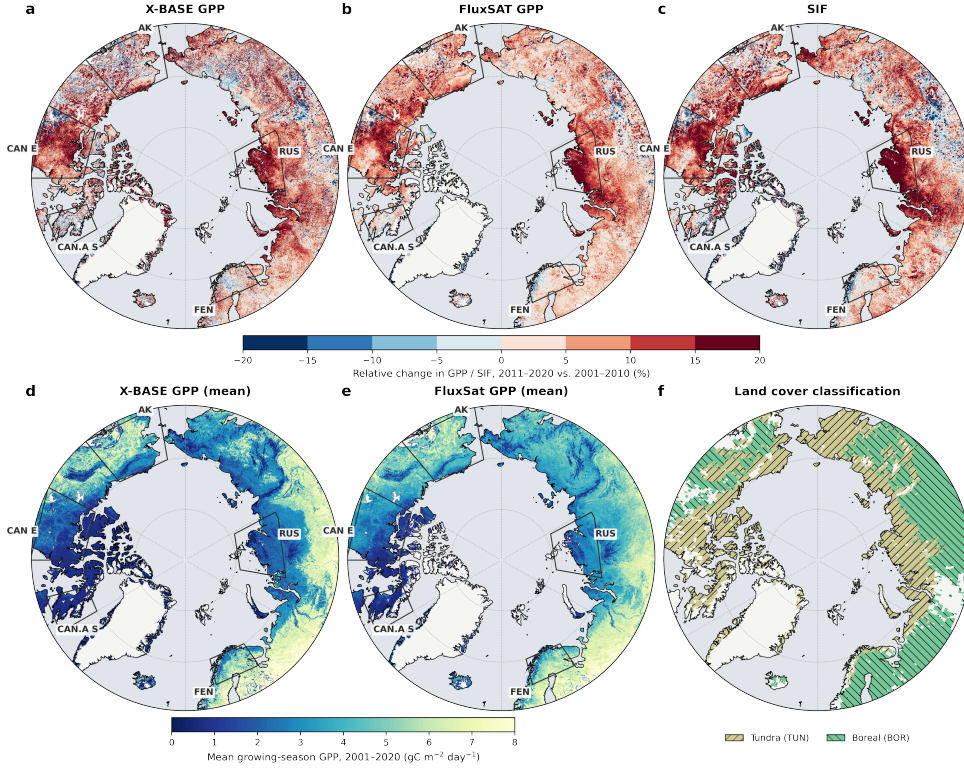


Fig. 1: Spatial Patterns in gross primary productivity (GPP) and Solar-induced Fluorescence (SIF) decadal changes. GPP transition between the second (2011-2020) and first (2001-2010) periods evaluated for the X-BASE and FluxSat datasets (**a** and **b**, respectively). SIF transition between the same periods (**c**). Mean climatological GPP values for the entire period of 2001-2020 for the X-BASE and FluxSat datasets (**d** and **e**, respectively). Tundra and Boreal areas according to the BALWD classification [47] (**f**). Geographical abbreviations refer to Alaska (AK), eastern Canada (CAN.E), the southern Canadian Archipelago (CAN.A.S), northern Fennoscandia (FEN), and the Taymyr Peninsula, Russia (RUS).

Comparison of relative changes of GPP between decades against long-term mean productivity (referred here as “GPP climatology”) across the 2001–2020 period reveals a clear biome-dependent pattern (Fig. 1). Low-productivity tundra systems exhibit the largest relative increases (5–6%), whereas more productive boreal regions show smaller relative gains (2-3%) (see Table 1). In this manuscript, we refer to tundra and boreal regions (Fig. 1.f) as defined by the BAWLD classification [47], where tundra

112 and boreal classes correspond to pixels with the highest percentage cover of dry tun-
 113 dra and boreal forest, respectively (See Supplementary Fig. A2 for percent maps). We
 114 also observe a higher sensitivity of SIF response to warming (air temperature increase,
 115 see Methods for this analysis) in those pixels with a higher percentage of dry tundra
 116 presence compared to boreal forest (Supplementary Fig. A3), while this behaviour is
 117 more inconclusive for GPP (Supplementary Fig. A3, A9, A10 and Tables A4 and A5).
 118 Many factors potentially drive the response of GPP, such as the subclimatic zone [48],
 119 the vegetation type and abundance, nutrient availability [49], the C stock (including
 120 the above-ground biomass) [50, 51] or the permafrost presence [52, 53], which mod-
 121 ulate the resilience of the biome to increasingly more frequent drastic changes [17]
 122 and Arctic warming. Consistent with this interpretation, we further observe enhanced
 123 sensitivity of GPP to air temperature—expressed through its linear response (Sup-
 124 plementary Table A6)—in regions characterized by higher permafrost presence, as
 125 identified from thermokarst classifications [52]. Although indirectly, this points to the
 126 role of permafrost-affected landscapes as key modulators of productivity and greening
 127 responses under warming [54, 55].

128 When comparing the decadal changes in GPP reported by each dataset, i.e.,
 129 FluxSat and X-BASE, an interesting spatial pattern emerges differentiating between
 130 over- and under-estimated areas (Fig. 2.a). These highlighted areas perfectly align with
 131 the biome boundaries defined by the IGBP classification used in the X-BASE con-
 132 struction [56]. According to the IGBP classification, X-BASE estimates higher GPP
 133 changes in boreal forests (e.g., IGBP classes of Deciduous and Evergreen Needle-leaf
 134 Forest in Fig. 2.c), whereas FluxSat reports higher values of decadal change in tun-
 135 dra ecosystems (e.g., Open Shrubs and Grasslands) and Wetlands. Such an observed
 136 dependency on the IGBP classification most likely reflects sensitivities to model struc-
 137 ture and training data in the generation of the X-BASE dataset. Because GPP is a
 138 dominant component of the growing-season carbon balance, these discrepancies do

not obscure the broad large-scale patterns observed across datasets, but instead highlight remaining uncertainties in the magnitude and spatial distribution of productivity responses to warming. This calls for targeted experiments and benchmarking to disentangle how differences in machine-learning architectures, predictor variables, and training datasets shape spatial patterns of Arctic carbon fluxes.

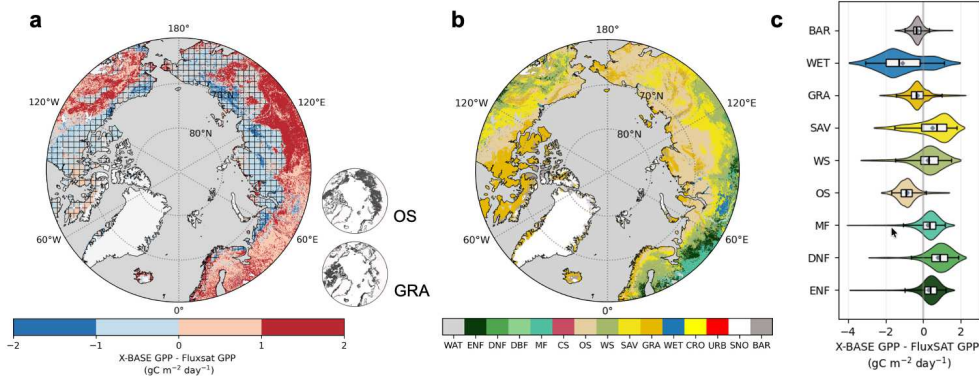


Fig. 2: Divergent Decadal GPP Transitions Across the terrestrial Arctic Land-Cover Types. Discretized map of the decadal GPP transition differences between X-BASE and FluxSat with an overlapping gridded square pattern on the IGBP classes of Open Shrublands (OS) and grasslands (GRA) (a). Classification of the IGBP land-cover class map [56], using data from year 2020 (b). Violin plots showing the statistics of the decadal GPP transition differences between the X-BASE and FluxSat databases during the growing season (JJA) (c). IGBP land-cover classes: Evergreen Needleleaf Forest (ENF), Evergreen Broadleaf Forest (EBF), Deciduous Needleleaf Forest (DNF), Deciduous Broadleaf Forest (DBF), Mixed Forest (MF), Closed Shrublands (CSH), Open Shrublands (OSH), Woody Savannas (WSA), Savannas (SAV), Grasslands (GRA), Permanent Wetlands (WET), Croplands (CRO), Urban and Built-up (URB), Cropland–Natural Vegetation Mosaic (MOS), Snow and Ice (SNO), Barren or Sparsely Vegetated (BAR), and Water Bodies (WAT).

Table 1: Summary of growing-season (JJA) carbon flux changes across datasets. Values are reported as the median and the interquartile range (IQR). The $\Delta\text{GPP}(\text{NEE})$ refers to changes between the two decades, i.e., 2011–2020 minus 2001–2010. GPP units are $\text{gC m}^{-2} \text{ day}^{-1}$ or in percent. Negative NEE values indicate a shift towards enhanced C uptake. For the ER, the reported values correspond to the slope of the linear regression following $\Delta\text{ER} = \alpha\Delta T_{\text{air}} + n$ for the combined (ER_{COM}) and the X-BASE ($\text{ER}_{\text{X-BASE}}$) products. The ER experiment section reports the percent median values of the regions and the (IQR) associated with the percent maps provided in [19]. The values marked with * correspond to the whole map provided by [19] which mostly covers tundra landscapes. For more details regarding the statistics, see Supplementary Tables A2 and A3. The acronyms of the regions refer to CAN.E (Canada East), RUS (Taymyr region in Russia), CAN.A S (Canadian Archipelago South), FEN (Northern Fennoscandia) and AK (Alaska); the ER-experiment section instead uses Y-G (Yamal–Gydan), CAN.A (Canadian Archipelago) and RUS.E (East Russia) – a different, coarser set of polygons specific to that dataset (see note below). The limits used to define all regions are given in Supplementary Table A2.

Gross Primary Production (GPP)			
	$\Delta\text{GPP}_{\text{X-BASE}}$ (%)	$\Delta\text{GPP}_{\text{FluxSat}}$ (%)	ΔSIF (%)
Metric / Region	median (IQR)	median (IQR)	median (IQR)
Pan-Arctic change	5.56 (0.66–11.6)	5.61 (2.25–9.81)	6.5 (1.29–12.29)
CAN.E	9.99 (5.23–15.95)	9.57 (5.72–13.39)	10.41 (5.52–15.15)
RUS (Taymyr)	12.64 (8.19–18.59)	13.22 (9.85–17.42)	17.36 (11.09–24.93)
CAN.A S	0.34 (–5.42–4.64)	0.95 (–2.38–4.35)	1.31 (–4.56–7.05)
FEN	1.94 (–2.22–5.95)	1.45 (–1.22–3.89)	1.23 (–2.11–4.27)
AK	3.19 (–1.49–9.27)	5.90 (2.96–9.12)	5.61 (1.2–11.01)
Tundra change	7.34 (1.69–13.62)	7.46 (3.46–11.65)	9.1 (3.73–14.95)
Boreal change	3.98 (0.02–8.24)	4.35 (1.72–7.58)	4.13 (–0.05–8.54)
	$\Delta\text{GPP}_{\text{X-BASE}}$ ($\text{gC m}^{-2} \text{ day}^{-1}$)	$\Delta\text{GPP}_{\text{FluxSat}}$ ($\text{gC m}^{-2} \text{ day}^{-1}$)	
Metric / Region	median (IQR)	median (IQR)	
Tundra (climatology)	2.12 (0.92–2.82)	3.00 (1.88–3.82)	—
Boreal (climatology)	5.94 (3.88–6.92)	5.28 (4.27–6.41)	—
Net Ecosystem Exchange (NEE)			
	$\Delta\text{NEE}_{\text{X-BASE}}$ (%)	$\Delta\text{NEE}_{\text{COM}}$ (%)	$\Delta\text{C flux}_{\text{atm-inv}}$ (%)
Metric / Region	median (IQR)	median (IQR)	median (IQR)
Pan-Arctic	–5.58 (–20.12–4.21)	–6.58 (–17.95–3.71)	—
CAN.A S	5.33 (–10.85–22.72)	1.58 (–18.93–15.49)	—
RUS (Taymyr)	–19.07 (–37.02––7.48)	–16.47 (–26.75––9.68)	—
Tundra	–10.1 (–27.71–2.25)	–8.91 (–19.1––0.3)	–11.48 (–30.75–6.13)
Boreal	–2.71 (–11.38–4.81)	–4.39 (–16.69–7.11)	–5.18 (–15.71–10.64)
Ecosystem Respiration (ER)			
	$\alpha(\Delta\text{ER}_{\text{X-BASE}})$	$\alpha(\Delta\text{ER}_{\text{COM}})$	Experiment (%)
Metric / Region	slope (CI)	slope (CI)	median (IQR)
Y-G	0.11 (0.09–0.13)	0.17 (0.15–0.20)	35.73 (24.24–49.93)
CAN.A	0.04 (0.02–0.05)	0.07 (0.05–0.10)	26.85 (21.93–33.46)
RUS.E	0.09 (0.06–0.12)	0.12 (0.08–0.17)	38.57 (28.77–49.62)
Tundra	0.06 (0.04–0.10)	0.11 (0.07–0.15)	27.52 (21.41–35.81)%*

Contrasting ecosystem respiration responses to warming

In tundra ecosystems, controlled warming experiments (+1.4°C in air and +0.4°C in soil) reported an overall increase in ecosystem respiration (ER) of approximately 30% [19]. We use the ER change map (Fig. 3a) derived from warming experiment data during the growing season [19] as a benchmark against warming-induced ER changes inferred from X-BASE and FluxSat. Given that the extension of the experimental-based map of ER covered only tundra regions, we use the Circumpolar Arctic Vegetation Map (CAVM) [57] to enrich the interpretation (Fig. 3.b) and capture the heterogeneity of tundra-dominated landscapes.

According to the experimental-based map [19], the Yamal–Gydan region (Y-G) shows the strongest increase in ER (median of $\approx 37\%$), whereas the Canadian Archipelago (CAN.A) exhibits consistently weaker (median of $\approx 27\%$) responses to warming. Eastern Siberia (RUS.E) presents a more heterogeneous pattern, with both high and low responses depending on local vegetation composition (Table 1). These contrasts align with differences in vegetation structure and biomass: Y-G is characterized by shrub- and sedge-dominated tundra with relatively high aboveground biomass, while CAN.A is dominated by sparsely vegetated barrens and low-productivity tundra types (see Fig. 3.b). Eastern Siberia (RUS.E) reflects a mixture of these tundra types, resulting in intermediate and spatially variable ER warming-induced change.

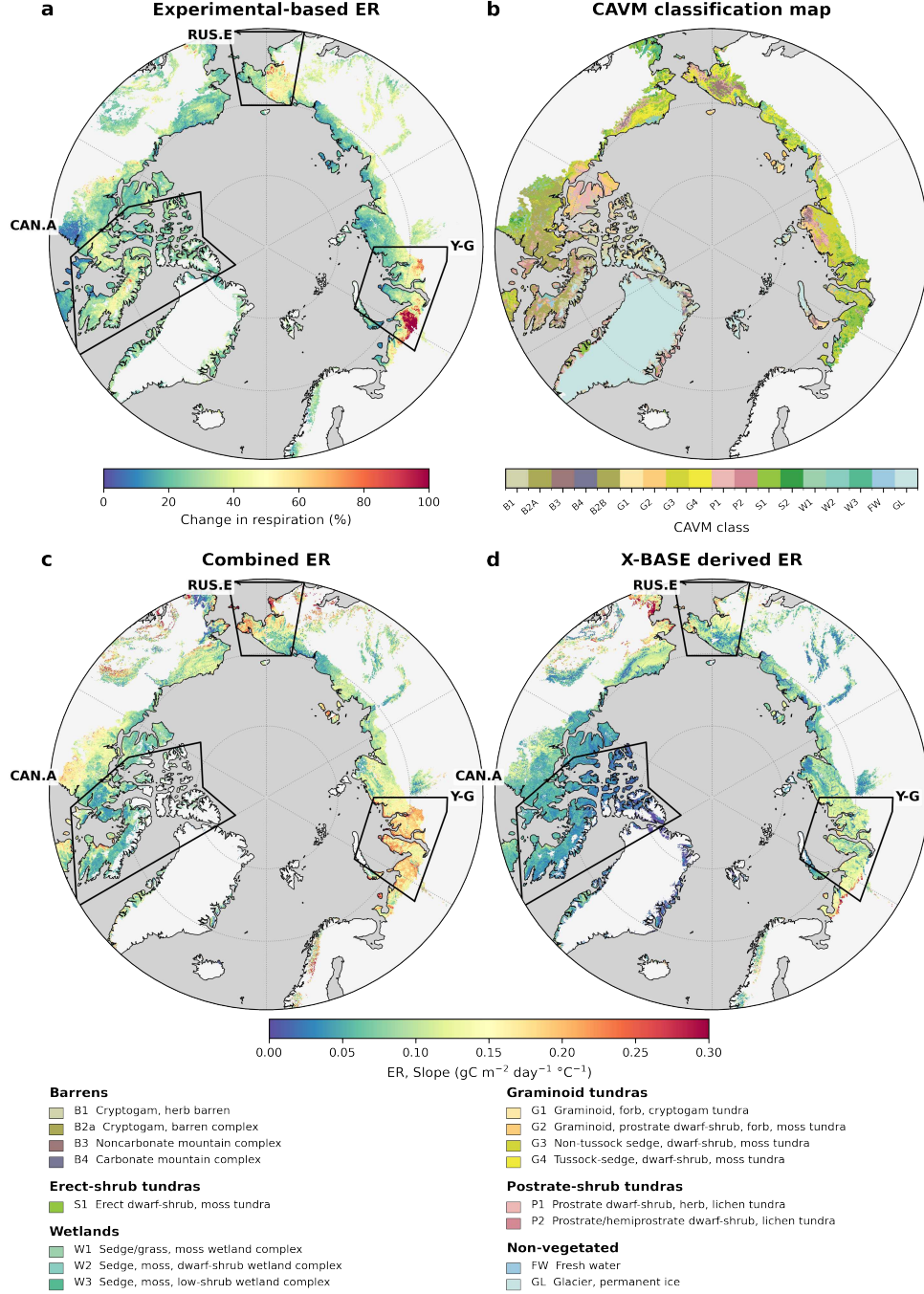


Fig. 3: Ecosystem Respiration (ER) warming response. Change in percent of ER due to an increase in temperature of 1.4°C in air and 0.4°C in soil. Data origin [19](a). CAVM tundra classification map (b). ER change associated with an increase in air temperature of 1.4°C and represented by the slope (α) of the linear regression in $\Delta ER = \alpha \Delta T_{air} + n$ for the combined (ER_{COM}) and the X-BASE (ER_{X-BASE}) products (c) and (d), respectively.

163 Because ER is not directly provided in FluxSat or X-BASE, we derive it from
 164 GPP and NEE using $NEE = ER - GPP$, assuming a closed C cycle. This results in
 165 two products: ER_{X-BASE} and ER_{COM} , the latter from combining FluxSat GPP with
 166 X-BASE NEE. To enable an spatial comparison with the experimental-based map
 167 (ER_{exp}), we adopt a simplified linear temperature response of ER to air tempera-
 168 ture changes across 2001-2020 during the growing season, e.g., $\Delta ER = \alpha \Delta T_{air} + n$,
 169 expressing anomalies of ΔER and ΔT_{air} relative to the 2001–2020 climatology (see
 170 Methods). Although ER responses to temperature are often represented as non-linear
 171 functions—either monotonic (with or without saturation) or exhibiting an optimum
 172 [20]—this linear approximation is assumed to facilitate the spatial comparison across
 173 datasets.

174 The spatial distribution of the inferred response of ER to warming, that is indi-
 175 cated by the slope α (Fig. 3.c,d), is consistent with the spatial pattern derived from the
 176 experimental datasets ER_{exp} (Fig. 3.a). Regions with low-biomass content and domi-
 177 nated by barrens (e.g., CAN.A) show weaker temperature sensitivity, whereas shrub-
 178 and sedge-dominated tundra regions (e.g. Y-G) exhibit stronger responses. Across
 179 all tundra regions, despite the general agreement on the spatial gradients, ER_{COM}
 180 consistently shows higher sensitivities to warming than ER_{X-BASE} .

181 A direct one-to-one comparison between ER_{exp} and the linear responses modelled
 182 in ER_{X-BASE} and ER_{COM} must be done cautiously due to the different assumptions
 183 underlying each dataset. Nevertheless, it is possible to estimate the absolute change in
 184 ER ($\text{g C m}^{-2} \text{ day}^{-1}$) for ER_{X-BASE} and ER_{COM} by assuming a 1.4 °C increase in air
 185 temperature and using the climatological ER mean for 2001–2020 (see Supplementary
 186 Material). The estimates from the warming-induced experiment report higher values
 187 (Supplementary Material, Fig. A4) most probably reflecting discrepancies associated
 188 with the data origin and differing auxiliary datasets used for spatially continuous

upscaling. For instance, while the campaign-based experiments incorporated soil carbon (C) and nitrogen (N) spatial information for the metaregression-modeled maps [19], these auxiliary variables were not explicitly used in the EC-derived linear regression products [36, 42]. However, despite the expected discrepancies among datasets derived from fundamentally different approaches and datasets, the emergence of coherent spatial patterns across all evaluated regions lends confidence to the identified hotspots of ecosystem response to warming.

Implications for growing-season net ecosystem exchange

The warming-induced response of the growing-season C balance reflects the interplay between enhanced GPP and ER. Decadal changes (ΔNEE), defined as differences between 2011–2020 and 2001–2010 in JJA, indicate shifts in the strength of net carbon exchange. Because NEE is defined as positive (C release) and negative (C uptake), ΔNEE does not indicate whether an ecosystem functions as a net carbon source or sink, but rather whether carbon exchange has shifted towards greater uptake or release between decades. Accordingly, a negative ΔNEE indicates stronger carbon uptake or weaker carbon release, whereas a positive ΔNEE indicates stronger carbon release or weaker carbon uptake.

Both NEE products ($\text{NEE}_{\text{X-BASE}}$ and NEE_{COM} , see Methods) show consistent spatial patterns (see Supplementary Figs. A5, A6, A7, and A8 for yearly basis), with an overall median decrease of $\approx 6\text{--}7\%$ between the two decades evaluated across the terrestrial Arctic during the growing season, indicating a tendency towards reduced C release (Fig. 4 and Table 1).

Regionally, however, the magnitude of this shift towards reduced C release (or increase) varies substantially. Both products report in the southern Canadian Archipelago (CAN.A S) a weak positive ΔNEE , accompanied by high variability,

214 suggesting that low-productivity systems may not fully offset warming-enhanced respi-
215 ration. In contrast, the Taymyr Peninsula (RUS) exhibits a marked decrease in ΔNEE
216 (enhanced carbon uptake), consistent with stronger increases in GPP.

217 However, when comparing relative changes in NEE with those in net land carbon
218 flux derived from atmospheric inversion models over the same period [44], some dis-
219 crepancies appear in the regional patterns. A direct one-to-one evaluation between
220 the atmospheric inversion models and bottom-up land flux estimates would require
221 accounting for lateral carbon transport (e.g., aquatic fluxes), which is not consid-
222 ered here. Instead, we focus on assessing the consistency of spatial variability and
223 decadal shifts across approaches and the overall statistics. In Fig. 4, relative decadal
224 changes of the net C land flux are shown together with the data-driven ΔNEE corre-
225 sponding shifts. Despite the observed spatial variability, a consistent large-scale signal
226 emerges across both data-driven and atmospheric inversion products: tundra ecosys-
227 tems exhibit larger relative changes than boreal regions. Atmospheric inversion models
228 indicate changes of approximately -11% in tundra compared with -5% in boreal
229 areas, whereas EC-based products indicate changes ranging from -9 to -10% and
230 from -3 to -4% , respectively (Fig. 5; Table A2). This pattern is further reinforced
231 by the distribution of decadal transitions, for which the integrated area associated
232 with negative flux changes is consistently larger in tundra than in boreal ecosystems
233 across both atmospheric inversion models and EC-based products. The fraction of the
234 distribution associated with negative transitions reaches 68.6% , 70.8% , and 75.6% for
235 the atmospheric inversion ensemble, $\text{NEE}_{\text{X-BASE}}$, and NEE_{COM} , respectively, in tun-
236 dra ecosystems, compared with 60.8% , 59.8% , and 61.5% in boreal regions (Fig. 5;
237 Table A2). Notably, the integrated negative area exceeds 50% in all cases, indicating
238 a prevailing tendency towards enhanced carbon uptake during the decadal transi-
239 tion, with this tendency being consistently more pronounced in tundra than in boreal
240 ecosystems.

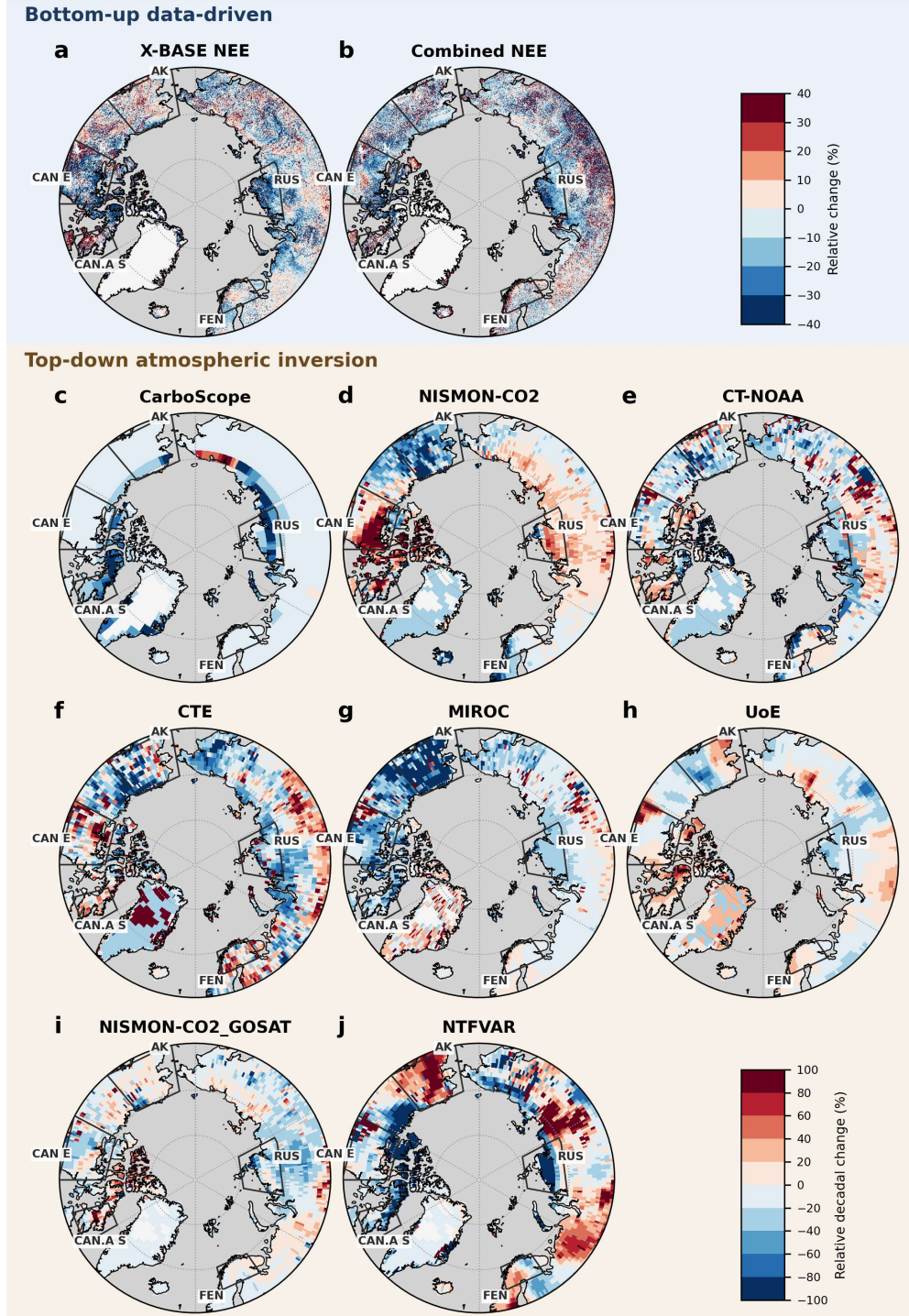


Fig. 4: NEE decadal relative changes. Decadal relative changes—defined as differences between 2011–2020 and 2001–2010— with respect to the mean absolute NEE value, e.g., $\Delta\text{NEE}/|\overline{\text{NEE}}|$ in percent. Using absolute mean values makes the sign of the relative change reflect the direction of the shift, rather than its source–sink state. Data-driven X-BASE NEE_{X-BASE} dataset (a) and the Combined NEE_{COM} dataset (b). Also, decadal relative transitions of the net land C flux reported by different atmospheric inversion models of CarboScope, NISMON-CO2, MIROC, UoE, NISMON-CO2.GOSAT, NTFVAR, CT-NOAA, CTE (c-j) [44]. The mean absolute value of NEE (or net C flux) is used, so the sign of the relative change indicates a relative increasing or decreasing tendency.

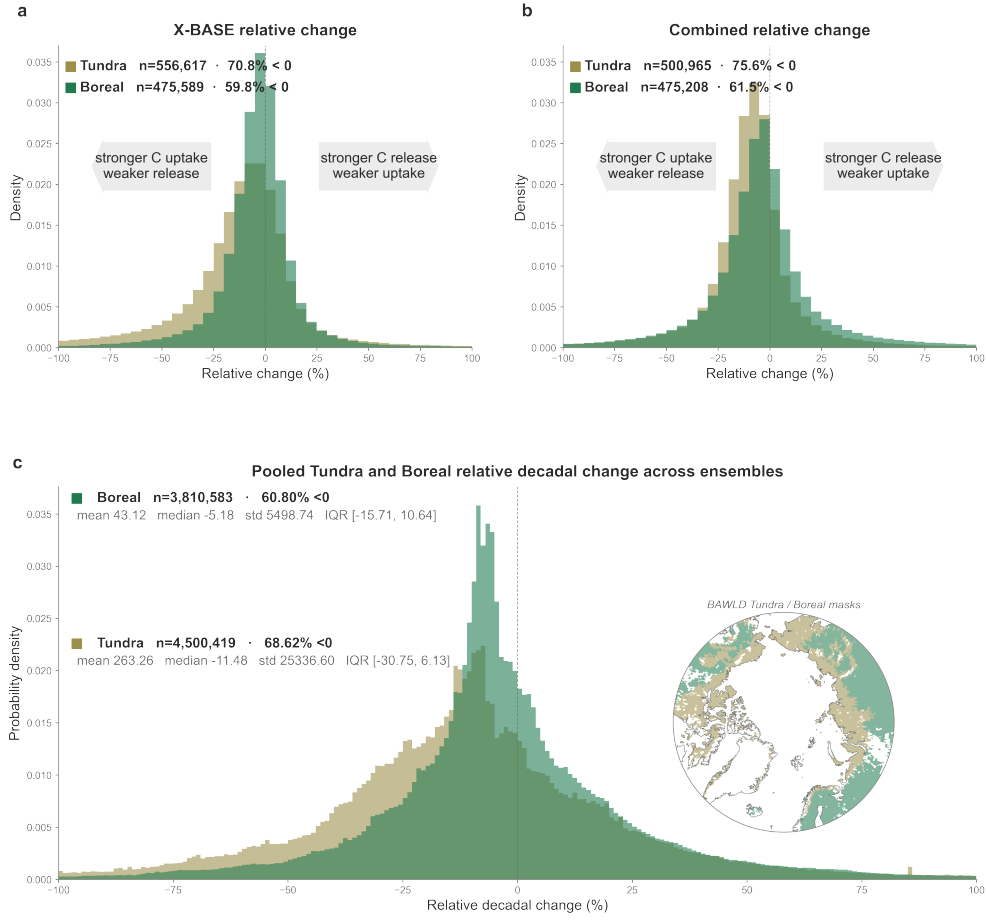


Fig. 5: Distribution of the NEE and net C flux relative change across two decades. Probability Density Function (PDF) of the NEE_{X-BASE} (a) and NEE_{COM} (b) decadal transitions. Probability Density Function (PDF) of the net C flux from an ensemble of different atmospheric inversion C models (CarboScope, NISMOM-CO₂, CT-NOAA, MIROC, UoE, NISMOM-CO₂-GOSAT, NTFVAR [44]). Decadal transitions are reported in percent and are defined as differences between 2011–2020 and 2001–2010 with respect to the mean absolute NEE (or C flux) value. The mean absolute value is used so the positive (negative) values in the transition indicate regions pointing either toward a stronger (weaker) C release or a weaker (stronger) C uptake (a). PDFs are evaluated according to the BALWD dominant class of tundra or boreal forest.

241 Growing-season C source–sink behaviour across Arctic 242 vegetation classes

243 We assess the distribution of growing-season NEE daily values across the two decades
244 at the ecosystem level. According to the CAVM classification (Fig. 3.b), most barren
245 complexes (B1, B2a, B3, B4), prostrate shrub tundra (P1, P2), wet tundra complexes
246 (W1, W2), and some graminoid tundra classes (G1, G3) exhibit a larger fraction of
247 positive NEE values in the NEE_{X-BASE} product, indicating a tendency towards net
248 carbon release during the growing season (Fig. 6; Supplementary Fig. A12). The prob-
249 ability density functions (PDFs) of growing-season NEE values over 2001–2020 reveal
250 that this source-like tendency is consistently more pronounced in NEE_{X-BASE} than in
251 NEE_{COM} . Differences in distribution shape (predominantly unimodal in NEE_{X-BASE}
252 versus bimodal in NEE_{COM}) likely reflect contrasting sensitivities to methodological
253 constraints associated with the IGBP land-cover classification and the low number of
254 flux sites in some of these classes [29].

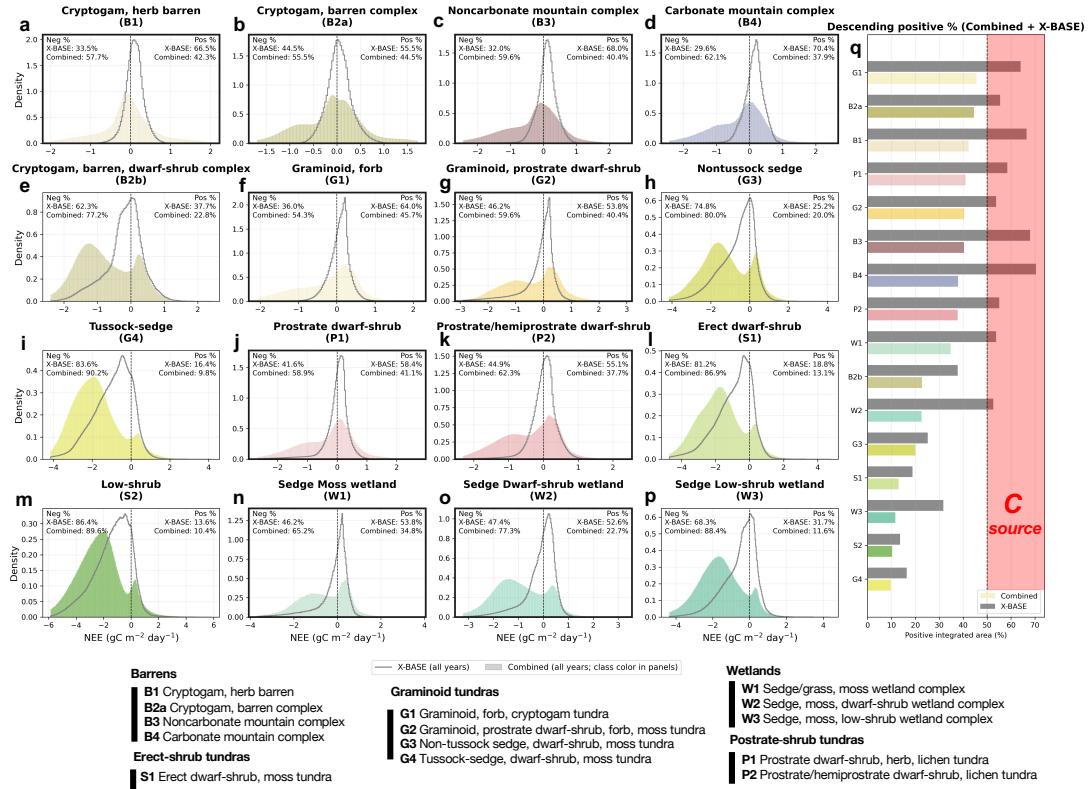


Fig. 6: Probability Density function (PDF) of NEE_{X-BASE} and NEE_{COM} values for the 2001-2020 period across the CAVM classification. Histograms of NEE_{X-BASE} (shaded color) and NEE_{COM} (gray line edge) PDF normalized for the 2001-2020 period across the CAVM classification (a-p). Panels of classes with the highlighted frame (B1, B2a, B3, B4, G1, G2, P1, P2, W1, and W2) are those with higher than 50% percent of NEE_{X-BASE} positive values. Horizontal bar graph sorted in descending order of the percentage of NEE_{COM} positive values per CAVM class (q). NEE_{COM} in the color bar and NEE_{X-BASE} in gray. For this per-class comparison, only those pixels for which data were available in both products were selected (see Methods).

255 The relative contribution of positive NEE values further highlights these dif-
 256 ferences. For several ecosystem classes, the NEE_{X-BASE} estimates exceed the 50%
 257 threshold, indicating that positive NEE values dominate the distribution (Fig. 6.q).
 258 By contrast, NEE_{COM} generally shows a greater contribution from negative NEE

values, consistent with a prevailing growing-season carbon sink across both decades (Supplementary Fig. A11).

Discussion

Our results show that growing-season carbon cycling changed more strongly in tundra than in boreal ecosystems between 2001–2010 and 2011–2020. Both satellite- and EC-based data-driven products indicate larger relative increases in GPP and SIF in tundra regions than in boreal areas (Fig. 1, Table 1, and Supplementary Fig. A1). These results suggest that the largest responses to recent warming are occurring in low-productivity Arctic landscapes. However, the undergoing more rapid transformation in tundra than boreal systems, may respond not only to the lower productivity in absolute terms but to a set of different mechanisms likely involving interacting controls related to vegetation composition, hydrology, nutrient availability, disturbance regimes, and permafrost dynamics [8, 13, 58–60]. The strongest increases in productivity were concentrated in tundra-dominated regions of eastern Canada and the Taymyr Peninsula, whereas weaker or locally negative changes occurred in parts of Alaska, Fennoscandia, and the Canadian Archipelago. Such contrasts reinforce the notion that Arctic greening is not a spatially uniform process [8]. Instead, ecosystem responses emerge from the interaction of regional climate forcing with local environmental constraints [16, 60]. We also observed that an enhancement of GPP sensitivity overlaps regions with extensive permafrost and large carbon reservoirs (Supplementary Table A6)[50, 61], which further indicates the role played by warming-induced changes in soil thermal regimes, hydrology, and nutrient cycling in shaping future ecosystem productivity [62, 63]. Permafrost thaw can initially enhance vegetation productivity through increased nutrient availability and active-layer deepening, but these potential benefits may be offset by waterlogging, surface subsidence, and vegetation disturbance. The

284 balance between these effects likely depends on the extent and hydrological conse-
285 quences of thaw and may shift over longer timescales [54]. Understanding how such
286 transient belowground changes translate into shifts in vegetation abundance, plant
287 species composition, productivity, and photosynthetic activity remains a key challenge
288 for predicting Arctic carbon–climate feedbacks.

289 Our results demonstrate that, despite substantial spatial variability, experimental
290 and data-driven approaches converge on similar large-scale patterns of ER sensitiv-
291 ity [64] (Fig. 3, Supplementary Fig. A4). This consistency suggests that the primary
292 controls governing the spatial distribution of ER responses to warming are well cap-
293 tured across fundamentally different approaches. However, the systematically weaker
294 temperature sensitivities inferred from data-driven products relative to experimen-
295 tal warming estimates indicate that deriving ER from NEE and GPP products using
296 a simplified linear dependence on air temperature may not fully capture respiration
297 responses to warming [65]. Nevertheless, the recurrent identification of regions such
298 as the Yamal–Gydan Peninsula as hotspots of ER sensitivity increases confidence in
299 the location of the strongest respiration responses, even if their absolute magnitude
300 remains uncertain.

301 Decadal changes in growing-season net carbon balance revealed a consistent large-
302 scale pattern across both EC-based data-driven and atmospheric inversion models:
303 tundra ecosystems exhibited a more pronounced strengthening of carbon uptake than
304 boreal regions (Fig. 5). Despite differences among products, this consistent pattern
305 indicates that tundra landscapes are undergoing the largest relative changes in carbon
306 cycling across the terrestrial Arctic. Our findings therefore suggest an Arctic carbon
307 balance that is strengthening on average during the growing season, but in a highly
308 heterogeneous way. Low-productivity systems such as the Canadian Archipelago show
309 weak positive NEE transitions between decades, suggesting that respiration increases
310 can outpace productivity gains, whereas more productive tundra regions such as the

311 Taymyr Peninsula exhibit strong shifts toward carbon uptake, supported by both
312 higher baseline productivity and stronger GPP increases [8, 16]. The temporal anal-
313 ysis further indicates that warmer growing seasons do not systematically translate
314 into enhanced carbon uptake (Supplementary Fig. A11), reflecting the tight coupling
315 between GPP and ER and the influence of interannual variability, ecosystem-specific
316 sensitivities, and legacy effects from previous seasons [66–71].

317 Importantly, stronger carbon uptake in tundra does not imply that all Arctic
318 vegetation types are becoming stronger carbon sinks. Several High Arctic ecosystem
319 classes, including barren, graminoid, prostrate-shrub, and wet tundra systems, fre-
320 quently exhibit source-like behaviour during the growing season. However, the extent
321 of this behaviour remains sensitive to the observational framework employed. Given
322 the sparse and uneven distribution of in situ observations across large regions of the
323 Arctic, estimating ecosystem-scale carbon fluxes inevitably requires the use of auxiliary
324 information to generate spatially continuous products. Differences in how these auxil-
325 iary constraints are represented, including land-cover classifications and environmental
326 predictors, contribute to uncertainty in source–sink attribution at the ecosystem level.
327 These results therefore highlight both the complexity of Arctic carbon dynamics
328 and the continued need for improved observational constraints in sparsely monitored
329 regions [29]. Advancing observational capabilities will therefore be critical, particu-
330 larly in regions where strong productivity responses overlap extensive permafrost and
331 large carbon reservoirs. In particular, current and emerging satellite observations of
332 vegetation fluorescence, together with visible, thermal infrared, and microwave mea-
333 surements, offer new opportunities to characterize ecosystem productivity, respiration
334 controls, hydrological change, and ecosystem responses to permafrost thaw [53, 72–
335 75]. These advances will be crucial for understanding why tundra is changing faster
336 than boreal ecosystems and for predicting the future trajectory of the terrestrial Arctic
337 carbon cycle.

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Methods

Data spatial and temporal harmonization

To harmonize all datasets onto a common grid over the terrestrial Arctic (i.e. latitudes $\geq 60^\circ\text{N}$), all variables were re-gridded to a spatial resolution of $0.05^\circ \times 0.05^\circ$, covering latitudes 60°N – 90°N and longitudes 180°W – 180°E . The CSIF, FluxSat GPP, and X-BASE GPP and NEE datasets were spatially cropped to the study domain without

543 further interpolation, as their native resolution and grid already matched the tar-
544 get grid. Daily mean air temperatures from the ARCLIM dataset, originally derived
545 from hourly ERA5-Land data at 0.1° resolution, were interpolated to the 0.05° grid.
546 The growing season period of JJA is set to be consistent with the warming-induced
547 experiment for the ER [19].

548 Among the ancillary land cover datasets, the IGBP land cover classification is
549 originally provided on the target grid. The BAWLD land cover classes (glaciers and
550 permanent snow, rocklands, dry tundra, boreal forest, wetlands, lakes, and rivers) were
551 originally available as fractional coverage of each class at a resolution of $0.5^\circ \times 0.5^\circ$.
552 Each class was rasterized individually from the shapefile to the common grid. After
553 rasterizing onto the common grid, the dominant BAWLD land cover type for each
554 grid cell was then defined as the class with the highest fractional coverage. All seven
555 classes were represented, although the river class did not dominate in any grid cell.
556 The CAVM land cover dataset, originally at $1 \text{ km} \times 1 \text{ km}$ resolution, was resampled
557 to the Arctic grid using mode resampling, assigning each target grid cell the most
558 frequently occurring source class.

559 For temporal sampling, hourly X-BASE variables were aggregated to daily values
560 by computing daily means, whereas all other datasets were already provided as daily
561 values. Data was evaluated for the growing season, defined here as June–July– August
562 (JJA). To ensure temporal consistency across datasets, all variables were subsampled
563 to match the 4-day temporal resolution of the CSIF dataset, resulting in 23 observa-
564 tions per year. In 2020, however, the cSIF time series ended on the 9th of August,
565 yielding only 18 observations for that year. The remaining datasets were subsampled to
566 follow the same temporal sampling scheme as in previous years. FluxSat GPP values,
567 originally provided in units of $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$, were converted to $\text{gC m}^{-2} \text{ day}^{-1}$.

568 The machine-learning-based carbon flux datasets included: FluxSat GPP, X-BASE
569 GPP ($\text{GPP}_{\text{X-BASE}}$), and X-BASE NEE ($\text{NEE}_{\text{X-BASE}}$). In addition, three derived flux
570 variables were defined as follows:

$$ER_{X-BASE} = NEE_{X-BASE} + GPP_{X-BASE},$$

$$ER_{COM} = NEE_{X-BASE} + GPP_{FluxSat},$$

$$NEE_{COM} = ER_{X-BASE} - GPP_{FluxSat}.$$

In total, six flux variables were analysed, comprising two GPP, two NEE, and two ER datasets.

Decadal and climatological means were computed for all temporally varying variables using the 4-day resolution JJA datasets. Decadal means were calculated separately for the periods 2001–2010 and 2011–2020, whereas the climatological mean was derived from the full 2001–2020 time series.

Reported main statistics

All summary statistics in the main text and Table A3 are reported as medians rather than means, as no explicit filtering of outliers was applied to the flux distributions. Given their potentially skewed and non-Gaussian nature, the median provides a more robust and representative measure of central tendency, minimizing the influence of extreme values. Interquartile ranges (IQRs) are also reported, corresponding to the 25th and 75th percentiles.

Statistics provided in Tables A3 and A2 include the metrics of mean, median, minimum, maximum, standard deviation, number of pixels evaluated, and the 25th and 75th percentiles.

C flux and SIF air temperature sensitivity

To quantify the sensitivity of SIF and carbon flux variables (GPP, ER, NEE) to air temperature, a linear relationship of the form $f(x) = \alpha x + n$ was assumed, where $f(x)$ denotes the anomaly of the response variable (δSIF , δGPP , δER , δNEE) and $x = \delta T_{air}$ represents the air temperature anomaly. Anomalies were defined relative to the climatological mean over the period 2001–2020. For example, for temperature, $\delta T_a = T_a - T_{mean}$, where T_a corresponds to the 4-day observations and T_{mean} corresponds to the climatological mean. An analogous definition was applied to all response variables.

598 The regression analysis was conducted using Orthogonal Distance Regression
 599 (ODR), which accounts for uncertainties in both dependent and independent variables.
 600 The implementation was carried out using the SciPy ODR package. This method was
 601 selected due to its robustness in the presence of higher uncertainties and outliers,
 602 particularly when uncertainties are estimated from the data [76].

603 Uncertainties were assigned at the 4-day temporal resolution for all variables. The
 604 conversion from absolute values to anomalies was assumed to represent a constant
 605 shift and, therefore, not to introduce additional uncertainty. Consequently, uncer-
 606 tainties of the anomaly variables were assumed to be equal to those of the original
 607 values. For air temperature, a constant uncertainty of 0.21°C was applied, based
 608 on the reported summer mean bias between station observations and ERA5-Land
 609 data [77]. For clear-sky daily SIF, the uncertainty was defined as 11% of the daily
 610 value, with a minimum threshold of $0.08 \text{ mW m}^{-2} \text{ nm}^{-1} \text{ sr}^{-1}$, reflecting an approx-
 611 imately 11% overestimation relative to the daily average satellite-based SIF, with
 612 RMSE below the minimum threshold [43]. For X-BASE GPP and NEE, which were
 613 derived from hourly data, uncertainty was estimated using the standard error of the
 614 daily mean, computed as $\sigma = \sigma_{\text{daily}}/\sqrt{24}$. For FluxSat GPP, the uncertainty provided
 615 with the dataset was used. For the derived flux variables (ERX-BASE, ERcombined,
 616 and $\text{NEE}_{\text{combined}}$), uncertainties were propagated assuming independent errors using
 617 standard error propagation, i.e. $\sigma = \sqrt{\sigma_1^2 + \sigma_2^2}$.

618 The statistical significance of the regression slopes was assessed using a two-sided
 619 Student's t-test. Resulting p-values were classified into two categories ($p < 0.05$ and
 620 $p \geq 0.05$) and visualized in Fig. A9. Model performance was further evaluated using the
 621 coefficient of determination (R^2). Only regions exhibiting statistically significant rela-
 622 tionships ($p < 0.05$) and sufficiently high explanatory power ($R^2 > 0.15$) are presented
 623 in Fig. A10. Spatial distributions of R^2 are shown in the right upper panels of Fig. A9.

624

NEE Probability Density Function (PDF) and Net PDF

Probability density functions (PDFs) were computed for each CAVM class using all available NEE values over the 2001–2020 period during the growing season (JJA) (Fig. A11). These PDFs were normalized such that the total area under each distribution equals one.

We then defined the net PDF as the difference between the integrated areas corresponding to positive and negative NEE values. Positive NEE values represent carbon release to the atmosphere, whereas negative values indicate carbon uptake. Accordingly, a negative (positive) net PDF reflects a dominance of carbon uptake (carbon release) for a given CAVM class and year.

1 Data availability

Carbon flux and Solar-induced Chlorophyll Fluorescence (SIF) dataset

Data are available from the following sites. The Solar-induced Chlorophyll Fluorescence (SIF) cSIF product [43] was downloaded from . We use the cSIF *clear* dataset. The X-BASE data [36] was accessed through the repository available in <https://gitlab.gwdg.de/fluxcom/fluxcomxdata>. Hourly values were downloaded to compute daily averages at a 0.05-degree resolution (see Methods). FluxSat [42] dataset was downloaded from NASA’s Earthdata repository <https://search.earthdata.nasa.gov/>. Ecosystem Respiration (ER) percent maps of increase due to warming were downloaded from the Zenodo repository <https://doi.org/10.5281/zenodo.10572479> associated with [64].

Classification maps

The BALWD classification maps [47] were downloaded from <https://doi.org/10.18739/A2C824F9X..> The CAVM [57] Arctic vegetation map can be accessed from <https://data.mendeley.com/datasets/c4xj5rv6kv/2>.

651 The IGBPS land-cover classification map [56] was downloaded from
652 <https://www.earthdata.nasa.gov/data/catalog/lpcloud-mcd12c1-006> (we
653 used data from 2020). The Thermokarst presence classification map
654 (used in Supplementary Material Tables) [52] was downloaded from
655 <https://dx.doi.org/10.3334/ORNLDAAAC/1332>.

656 **Atmospheric inversion net C flux model**

657 Data was accessed from https://meta.icos-cp.eu/objects/6gR_MW23fL2KEI860UX_TGoO
658 under the Creative Commons Attribution 4.0 international licence .
659 <https://creativecommons.org/licenses/by/4.0/legalcode>. The downloaded pack-
660 age was GCP2025_inversions_1x1_version1_0_20251031.nc [44] with PID
661 10.18160/VZ3B-GHYQ. We used the field land_flux_only_fossil.cement_adjusted

662 **2 Code availability**

663 All Python code used in this study is made available through the GitHub repository
664 (https://github.com/TUT-ISI/TundraBoreal_SIF_GPP_NEE_ER.git).

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670 **4 Authors contributions**

671 N.S. designed the study, coded the plots and analysis, and wrote the paper. E.K.
672 coded the plots, contributed to discussions and analysis, and participated in writing
673 the paper. A.V. and T.T. provided feedback on the data analysis and the process, as
674 well as contributed to the manuscript during reviews. A.L., J.A., M.L., S.VW., and

675 P.K. reviewed and contributed to the writing and discussion. A.A. contributed to the
676 design of the study, discussion and reviewed and commented on the manuscript.

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680 **6 Competing interests**

681 The authors declare that they have no competing interests.

682 **7 Additional information**

683 **Supplementary information** The online version contains supplementary Materials
684 are available at xx.

685 **Correspondence and requests for materials** should be addressed to Neus
686 Sabater.

Supplementary Files

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