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Snow droughts enhance carbon uptake in energy-limited ecosystems but reduce it in water-limited ones

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Abstract

Seasonal snowpack acts as a natural water reservoir, and snowmelt provides a critical water supply for many ecosystems across the Northern Hemisphere. Snow droughts, periods of reduced winter snow accumulation, are becoming a growing threat to the functioning of these ecosystems due to ongoing global warming. Here, we demonstrate how snow droughts shift gross primary productivity (GPP) across Northern Hemisphere ecosystems. Combining dynamic global vegetation model simulations with gridded snow and multi-source GPP products, we identify positive GPP anomalies in spring and negative GPP anomalies in summer following snow drought conditions over recent decades. Overall, snow droughts reduce the annual net productivity in water-limited regions and enhance it in energy-limited regions. Further, the impact of snow droughts on GPP remains largely independent of subsequent spring and summer moisture conditions. This work advances our understanding of how declining snowpacks impact the stability of the terrestrial carbon sink under climate change.

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1 Snow plays a crucial role in the Earth’s water, energy, and carbon cycles, particularly
2 in the Northern Hemisphere, where 98% of the Earth’s seasonal snow cover is located
3 [1], covering up to 50% of the land surface [2] and supplying fresh water for more than
4 2 billion people [3]. Snow directly influences ecosystems, e.g., by modulating decom-
5 position rates and nutrient availability in biogeochemical cycling [4, 5]. At the same
6 time, seasonal snowpack serves as a natural water reservoir, storing winter precipita-
7 tion and gradually releasing it during spring and early summer melt [5]. This process
8 governs the timing and magnitude of spring runoff and the growing-season onset in
9 snow-dominated ecosystems [6].

10 Evidence from recent decades shows that global warming is significantly altering
11 snowfall and snowmelt patterns [5, 7, 8]. Observations reveal a substantial decline in
12 the Earth’s winter snow cover extent in the last decades [9], with more winter pre-
13 cipitation falling as rain instead of snow and earlier spring snowmelt [10]. Because
14 ecosystem water availability depends on snow accumulation and melt timing, these
15 shifts redistribute when and how much water reaches vegetation across the year: ear-
16 lier snowmelt advances the growing season [11], can intensify spring floodings [12],
17 and leaves less water in storage for summer, increasing water scarcity later in the sea-
18 son [13], limiting water availability for hydropower production [14] and irrigation on
19 agricultural lands [15–17]. Winter snowpack further controls the seasonal availabil-
20 ity of water by recharging soil moisture [10, 18] and groundwater [19]. Reductions in
21 snow accumulation and a shorter snow season can further have legacy effects on ter-
22 restrial vegetation that persist into the growing season, limiting plant-available water
23 and increasing ecosystem water stress [20].

24 A severely reduced winter snow accumulation relative to the climatological mean
25 is known as a *snow drought*. These hydro-climatic extremes can arise either from
26 anomalously warm conditions that shift precipitation from snow to rain (warm snow
27 drought) or from a general deficit in winter precipitation (dry snow drought) [21–23].
28 Snow droughts are an emerging threat to ecosystems adapted to stable winter snow
29 conditions, which are increasingly exposed to altered thermal insulation and disrupted
30 hydrological cycles under ongoing warming [5].

31 Gross Primary Productivity (GPP), the total carbon assimilated by vegetation
32 through photosynthesis, is one of the most direct indicators of ecosystem responses
33 to such disturbances and is a key component of the terrestrial carbon cycle. Regional
34 studies demonstrate that earlier snowmelt and reduced snow storage may alter the
35 timing and magnitude of primary production, with responses varying across climate
36 zones and vegetation types [18, 24, 25]. For instance, in mountainous ecosystems,
37 which are generally energy-limited regions (vegetation growth is primarily constrained
38 by the availability of incoming radiation and temperature), waning snowfields have
39 already become hotspots of greening, suggesting a positive impact of snow droughts on
40 vegetation productivity [26]. However, snow droughts have recently been identified as
41 hydroclimatic drivers that significantly reduce GPP, often in conjunction with growing-
42 season droughts [27].

43 Despite growing evidence that snow droughts are becoming more frequent and
44 more severe under continued warming [22, 28], their consequences for ecosystem pro-
45 ductivity and the terrestrial carbon sink remain poorly understood at the global scale.

In particular, the global net effect of snow droughts on GPP has, to our best knowledge, not been quantified. Yet this is crucial for evaluating the role of snow droughts as a threat to the stability of the terrestrial carbon sink. Further, how growing-season moisture availability modulates the positive or adverse impacts of snow droughts on GPP across biomes and climatic ranges remains unresolved.

Motivated by these knowledge gaps, we systematically assess how snow droughts alter the seasonal dynamics of ecosystem primary productivity across biomes of the Northern Hemisphere (NH). By combining a process-based global dynamic vegetation model with state-of-the-art multi-source GPP datasets, we quantify the growing-season GPP impact of preceding snow drought conditions across seasons and ecosystems, and further quantify the role of in-season moisture availability in modulating the GPP response.

Results

Spatial Patterns of Snow Drought Occurrence and Vegetation Productivity Response

To determine the impact of snow droughts on ecosystem productivity, we use snow water equivalent (SWE) data from ERA5-Land and the dynamic global vegetation model LPJmL [29] after evaluating their performance (Supplementary Fig. S1), to derive a multi-month snow water equivalent index (SWEI; [5]; see Methods) that enables quantification of snow droughts. For GPP, we use an ensemble approach that integrates modeled GPP from LPJmL with GPP from three state-of-the-art multi-source datasets (FLUXCOM, VODCA2GPP, and NIRv) and retain only grid cells with robust signals (see Methods for details).

Assessed over the 1988–2018 period, Western North America, Eastern Europe, parts of Siberia, Central Asia, and Eastern China emerge as hotspots with frequencies higher than the 75th percentile (i.e., 4 snow drought years; Fig. 1a). The number of snow droughts per year has increased significantly in recent decades (Supplementary Fig. S2), predominantly due to increased temperature-driven (i.e., warm and warm-and-dry) snow droughts.

We define vegetation response to snow droughts, ΔGPP_{gs} , as the difference in the growing-season mean GPP between snow drought years and years without snow droughts. This response shows strong spatial heterogeneity across the four datasets (Fig. 1b): Most grid cells with a negative GPP response to snow droughts (red) are located at lower latitudes, whereas a positive GPP response (blue) is dominant across the higher latitudes. While some of the identified snow drought hotspots also show a strong ΔGPP_{gs} response (e.g., western North America and Central Asia), others show only a weak impact of snow droughts on vegetation (e.g., Eastern Europe). These results suggest that snow drought frequency does not necessarily drive negative vegetation responses across all ecosystems.

Overall, 37.3% [31.5 | 50.6]% (mean [min|max] across the datasets) of the grid cells exhibit a negative ΔGPP_{gs} and 62.7% [49.4 | 68.5]% a net positive ΔGPP_{gs} with a strong agreement across all four datasets (Fig. 1c). The combined cumulative ΔGPP_{gs} reveals a net-positive effect of snow droughts on GPP of 180.29 TgC across

86 the entire domain (Fig. 1d). However, we observe a substantial variation in this net
 87 effect across the four datasets: LPJmL (529.25 TgC) and VODCA2GPP (347.24 TgC)
 88 show a strongly positive ΔGPP_{gs} while NIRv (-140.16 TgC) and FLUXCOM (-22.90
 89 TgC) exhibit a net-negative GPP response to snow droughts (Fig. 1d). In general,
 90 a more widespread positive response for warm-and-dry snow droughts was identified,
 91 where only NIRv yields a net-negative GPP response (Supplementary Fig. S3). Paired
 92 t-tests and Wilcoxon signed-rank tests indicate that the mean GPP anomalies during
 93 the growing season in snow drought years differed significantly ($p < 0.001$) from years
 94 without snow droughts. In addition, we use Hedges' g , an effect size measure that
 95 quantifies the standardized difference between the two (snow drought vs. normal con-
 96 ditions) GPP group means (see Methods). We find a non-negligible ($g = 0.29$) effect
 97 size for ΔGPP_{gs} .

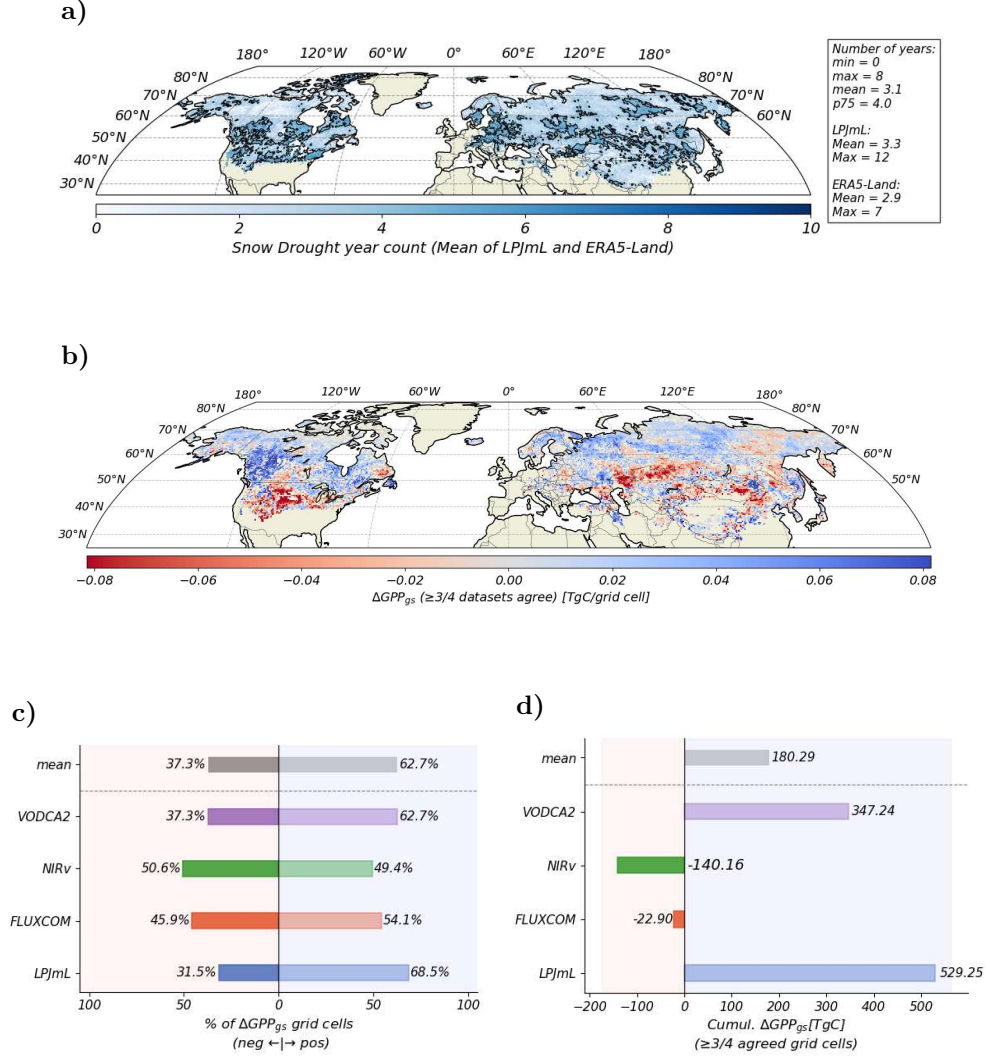


Fig. 1: Snow drought frequency and its impact on GPP. (a) Number of snow drought occurrences between 1988 and 2018 (derived as a composite of LPJmL and ERA5-Land). Here, the mean number of snow drought years per grid cell over the 1988-2018 period is 3.1, with a maximum of 8. The contoured areas correspond to snow drought hotspots, where the number of snow drought years per grid cell exceeds the 75th percentile (4 snow drought years). (b) Mean ΔGPP_{gs} [TgC/grid cell] over the growing season across the four datasets. Only grid cells where at least 3 of the 4 datasets agree on the sign are shown (see Methods). (c) Percentage of negative and positive ΔGPP_{gs} grid cells for each dataset. (d) Total cumulative ΔGPP_{gs} per dataset.

Snow drought impacts on growing-season GPP: Contrasting responses across energy- and water-limited ecosystems

Grouping ΔGPP_{gs} by ecoregion and aridity index classes (see Methods) reveals a clear pattern that contrasts ecoregions where energy (radiation and/or temperature) limits plant growth while water is generally available, with water-limited ecosystems characterized by sufficient energy availability. Energy-limited, colder, and humid ecosystems exhibit a net positive ΔGPP_{gs} , whereas water-limited, arid ecosystems show a negative response in vegetation productivity after a snow drought (Fig. 2a, 2b and Supplementary Table S1).

The positive impact is most pronounced for temperate coniferous (+0.030 TgC/grid cell) with medium effect size ($g = 0.58$) and boreal (+0.022 TgC/grid cell, $g = 0.71$) forests, with 70% and 68% of grid cells showing positive response (Fig. 2a). Boreal forests' greater extent means their hemispheric signal (169.06 TgC) exceeds that of temperate coniferous forests (30.69 TgC), dominating the net positive ΔGPP_{gs} across the NH (Supplementary Table S7). Conversely, ΔGPP_{gs} is negative for most temperate grasslands, savannas, and shrublands (-0.023 TgC/grid cell), with a 64% negative response, and desert/xeric shrublands (-0.015 TgC/grid cell) with a 60% negative response (Fig. 2a). Temperate grasslands have the greatest effect on the cumulative carbon signal (-50.75 TgC) due to their larger spatial extent (Supplementary Table S7).

Similar patterns emerge when stratifying by aridity (Fig. 2b): humid (0.021 TgC/grid cell, $g = 0.64$) and dry sub-humid (0.014 TgC/grid cell, $g = 0.43$) regions show the strongest positive ΔGPP_{gs} across 71% and 66% of the grid cells. With increasing aridity, ΔGPP_{gs} decreases and the percentage of negative grid cells increases. Hyper-arid regions show a -0.041 TgC/grid cell (large effect size, $g = 1.08$) and 81% negative response. Across arid and semi-arid regions, the response is more diverse (56% and 51% negative grid cells) and less pronounced (-0.009 and -0.006 TgC/grid cell). But their larger area means they contribute more to the total negative signal (-12.34 TgC for semi-arid and -1.90 TgC for hyper-arid; Supplementary Table S7). Consistency across ecoregion and aridity classifications indicates their similar underlying composition (Supplementary Fig. S9): energy-limited ecoregions are predominantly humid to dry sub-humid, whereas water-limited ecoregions are dominated by semi-arid and arid regions.

These patterns remain independent of snow drought severity (Supplementary Fig. S5) and type (Supplementary Fig. S4). Yet, the positive GPP signal across energy-limited ecosystems is dominated by temperature-driven snow droughts (warm and warm-and-dry) while warm-and-dry snow droughts exhibit a positive GPP response across almost all ecoregions and aridity index classes (Supplementary Fig. S4). In contrast, the positive GPP response to dry snow droughts is dampened in energy-limited ecosystems and strongly negative in water-limited ecosystems.

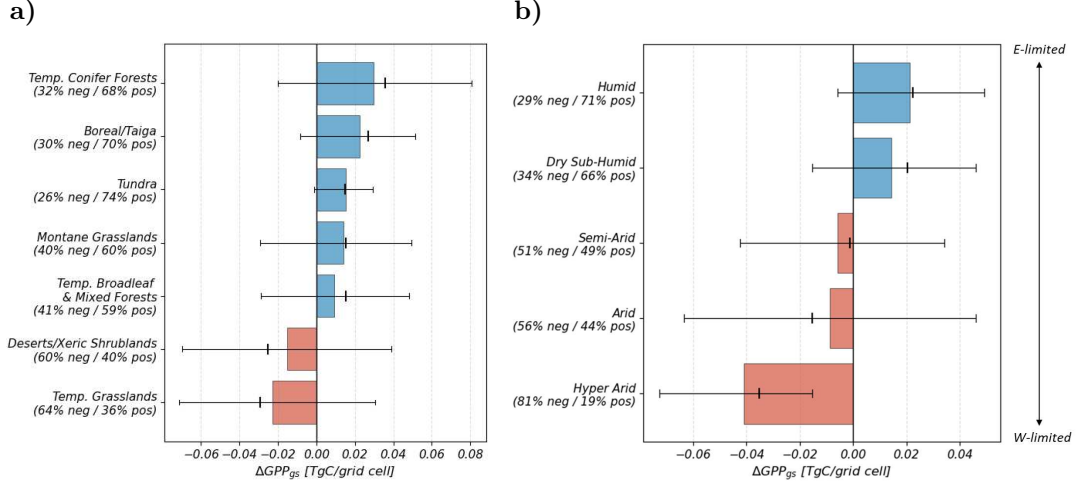


Fig. 2: Growing season ΔGPP stratified by ecosystem and aridity. Only grid cells where 3 of the 4 datasets agree are considered (see Methods). Bars refer to the mean across all grid cells, whiskers denote the inter-quartile range, and the vertical black line represents the median across all grid cells of each group. Brackets below the labels show the percentage of grid cells with positive and negative vegetation response per (a) ecoregion and (b) aridity index classes. The arrow indicates the direction of more energy-limited (E-limited) and more water-limited (W-limited) regions.

Snow droughts alter the seasonal timing of GPP anomalies

Snow droughts consistently redistribute carbon uptake and seasonal timing of ecosystem productivity from summer (ΔGPP_{su}) toward spring (ΔGPP_{sp}) across the NH (Fig. 3a and Supplementary Fig. S7). We find a positive ΔGPP_{sp} across 73.7 [57.6 | 74.6]% of the NH (Fig. 3b), and a negative ΔGPP_{su} across 62.1 [57.9 | 62.8]% of the grid cells (Fig. 3d). Cumulative NH ΔGPP_{sp} is consistently positive across all datasets (347.74 [11.21 | 690.46] TgC; Fig. 3c and Supplementary Fig. S7), while cumulative ΔGPP_{su} is consistently negative (-176.09 [-285.26 | -41.89] TgC; Fig. 3e). The positive spring response is widespread across the NH, while the negative summer response emerges mostly at lower latitudes (Supplementary Fig. S8). Both the responses are statistically significant across the four datasets (except FLUXCOM in spring; Wilcoxon $p = 0.36$), with a large effect size in spring ($g = 0.88$) and a small effect size in summer ($g = 0.41$) (Supplementary Table S2). When examining the spatial distribution of spring and summer GPP responses, 38.6% of grid cells, predominantly at higher latitudes, exhibit enhanced anomalies in both seasons. The opposite behavior (negative GPP anomalies in spring and summer) is observed in 27.0% of the NH. 25.1% show a spring enhancement followed by a summer reduction, and 9.4% of the grid cells show negative spring with summer enhancement (Fig. 3f).

155 When grouping by ecoregion and aridity index classes for spring and summer (Sup-
 156 plementary Fig. S9 and Supplementary Tables S3 and S4), positive ΔGPP_{sp} emerges
 157 across almost all regions with large-to-medium effect sizes (Supplementary Tables S5
 158 and S6). In contrast, negative ΔGPP_{su} is identified everywhere, except in the most
 159 energy-limited regions (tundra and boreal forests), where ΔGPP_{su} is close to zero.
 160 The most water-limited regions show the greatest ΔGPP_{su} effect sizes while energy-
 161 limited regions (temperate conifer forests, humid and dry sub-humid regions) show
 162 small or negligible effect sizes ($g = 0.19 - 0.43$; Supplementary Tables S5 and S6).
 163 The regional heterogeneity in negative ΔGPP_{su} highlights existing trade-offs of
 164 an earlier onset of photosynthetic activity (positive ΔGPP_{sp}) and reduced water
 165 availability during the season (ΔGPP_{su}). Which pathway dominates depends on the
 166 ecosystem's resource limitation, explaining the flip from positive to negative growing
 167 season GPP (ΔGPP_{gs}) along the energy-water-limited gradient.

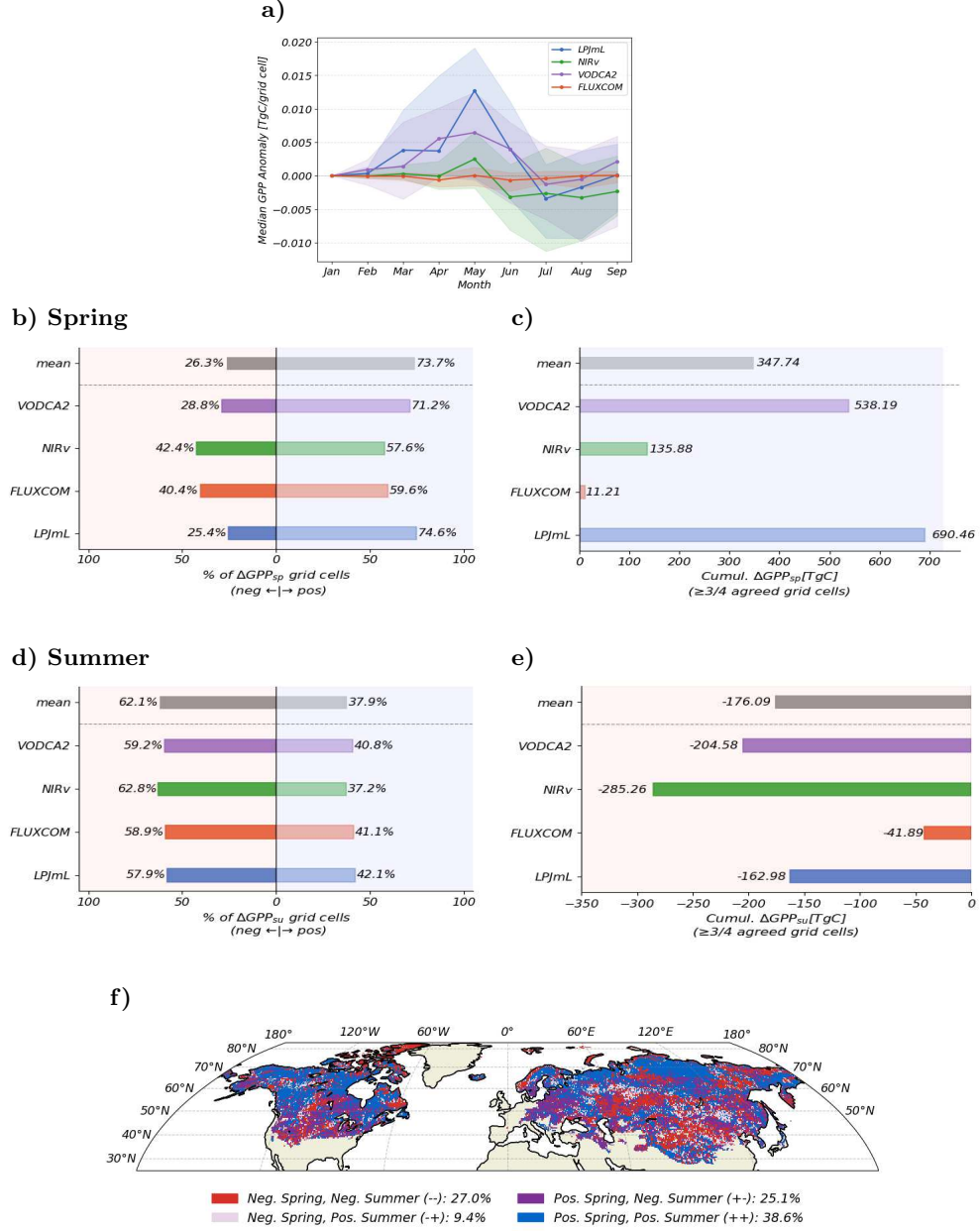


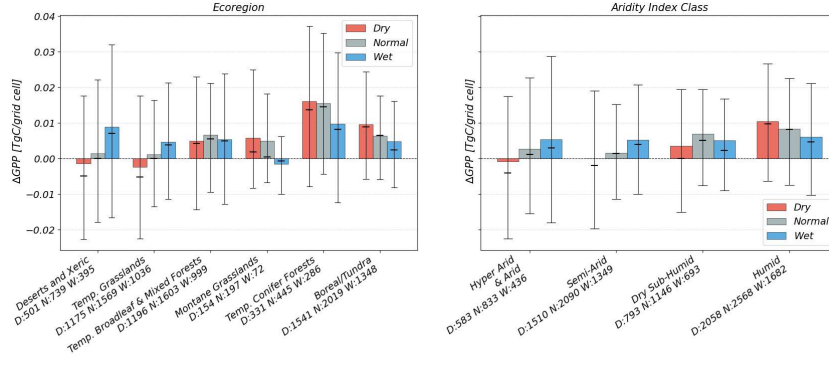
Fig. 3: Seasonal shifts of ecosystem productivity after a snow drought across the NH. (a) Cumulative mean monthly GPP anomaly per grid cell [TgC/grid cell] for years with preceding snow droughts. Solid lines show the median of the spatially averaged monthly GPP anomalies per grid cell for each of the four GPP datasets (LPJmL, NIRv, VODCA2GPP, FLUXCOM). Shading represents the interquartile range across all years. (b) Percentages of grid cells with positive/negative ΔGPP_{sp} , (c) and their total cumulative ΔGPP_{sp} response. (d) and (e) Same as (b) and (c) but for ΔGPP_{su} . (f) Spatial distribution of spring (ΔGPP_{sp}) and summer (ΔGPP_{su}) GPP responses to snow drought conditions. Blue (red) corresponds to a positive (negative) ΔGPP in spring and summer. Purple corresponds to a positive ΔGPP in spring, and a negative one in summer, light pink corresponds to the opposite case.

Precipitation and soil moisture conditions after the snow season modulate ΔGPP

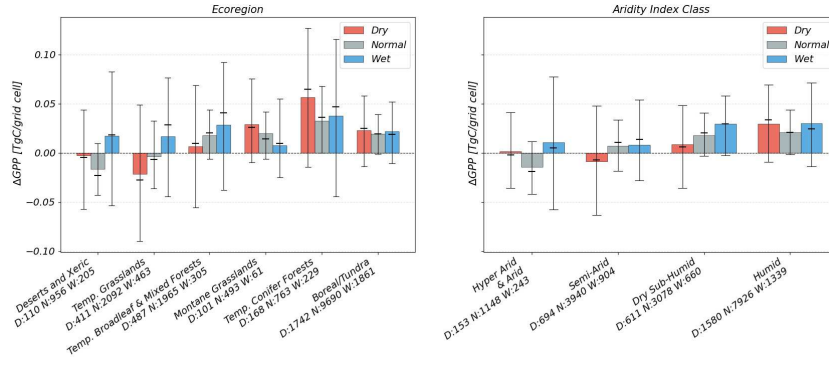
168 Next, we assess how varying moisture conditions in spring (precipitation and soil water
169 content, SWC) and summer (precipitation) modulate the ΔGPP response to snow
170 droughts. This allows us to assess whether in-season moisture offsets or worsens water
171 shortages during snow droughts. Again, the magnitude and direction of the ΔGPP
172 response vary across water- and energy-limited regions. ΔGPP_{sp} is predominantly
173 positive across all ecoregions and aridity classes independent of initial spring SWC
174 (Fig. 4a). Drier and more water-limited regions indicate an adverse impact of lower
175 spring soil moisture, with reduced or even negative ΔGPP_{sp} (Fig. 4a). Humid and more
176 energy-limited regions show the opposite, with more positive ΔGPP_{sp} for drier spring
177 soil moisture conditions (Fig. 4a). Stratifying by spring precipitation shows similar
178 but more pronounced patterns (Fig. 4b). In particular, water-limited ecosystems show
179 a strong scaling of ΔGPP_{sp} with spring precipitation, such that only a wet spring
180 can offset the adverse impact of a snow drought on spring productivity. This shows
181 that early-season productivity generally benefits from an earlier onset of the growing
182 season, regardless of ecoregion or water inputs. Only strongly water-limited regions
183 reveal that a snow drought followed by a dry spring negatively impacts productivity
184 despite an earlier growing season.

185 For summer precipitation, we consider only grid cells preceded by a normal spring
186 precipitation to isolate the snow drought effect on summer GPP. We find that ΔGPP_{su}
187 is predominantly negative across most ecoregions and aridity classes, indicating that
188 summer GPP following a snow drought is suppressed even with adequate summer
189 rainfall (Fig. 4c). Only temp. broadleaf and mixed forests and dry sub-humid regions
190 show a positive but near-zero ΔGPP_{su} through a wet summer. Considering the large
191 interquartile range, it is difficult to conclude that these regions are not adversely
192 impacted despite a wet summer.

a) Spring SWC



b) Spring precipitation



c) Summer precipitation

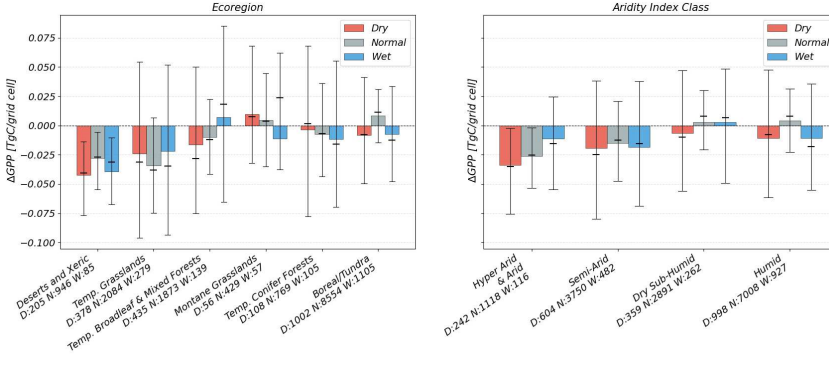


Fig. 4: Effects of soil moisture and precipitation on ΔGPP responses after a snow drought per ecoregion and aridity index classes. Bars refer to the mean across all grid cells, whiskers denote the inter-quartile range, and the vertical black line represents the median across all grid cells of each group. Numbers below the labels indicate the sample sizes for the dry (D), normal (N), and wet (W) conditions. (a) ΔGPP_{sp} the month after peak SWE for dry, normal, and wet SWC conditions at that point. (b) ΔGPP_{sp} for dry, normal, and wet spring SPI (From April to June). (c) ΔGPP_{su} for dry, normal, and wet summer SPI (June to August), considering only the grid cells that had normal spring precipitation.

As spring droughts have been shown to potentially enhance GPP [30], we contrasted the snow drought response with that to spring droughts to determine which condition drives spring enhancement in the analyzed regions (see Methods). Northern and humid regions show that both conditions contribute similarly to increased GPP anomalies in spring (Fig. 5a and 5b). In temperate conifer forests, temp. broadleaf and mixed forests, and dry sub-humid regions, snow droughts contribute more to spring enhancement than dry springs do. This implies that an earlier growing-season onset benefits these ecosystems more than low spring precipitation. Drier regions benefit to a lesser extent from a longer growing season, as long as there is normal spring precipitation. Even under normal snow conditions, a dry spring can lead to vegetation productivity losses in water-limited areas (Fig. 5a and 5b). This agrees with Fig. 4b, where dry spring precipitation adversely affects GPP in the most water-limited regions.

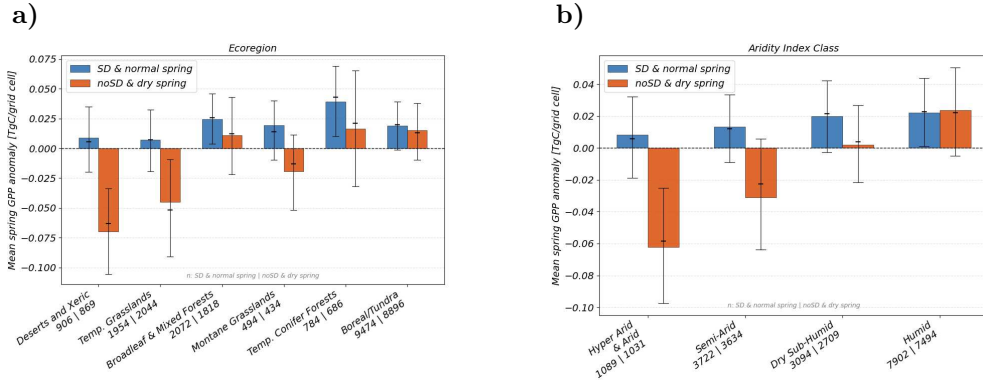


Fig. 5: Mean spring GPP anomaly per grid cell. Blue bars indicate grid cells that experienced a snow drought followed by normal spring precipitation. Red bars show grid cells with normal snow conditions followed by a dry spring. Only grid cells where 3 of the 4 datasets agree are considered (see Methods). Numbers below the labels refer to the sample size: snow drought & normal spring | no snow drought & dry spring. (a) Ecoregions (b) Aridity index classes.

We find that 71.2% of grid cells show enhanced GPP anomalies for snow droughts followed by a normal spring, amounting to 295.89 TgC with only a few regions (e.g., Central Asia and East Siberia) showing negative responses (Fig. 6a). For no snow droughts followed by a dry spring, a different pattern emerges: a spring GPP enhancement in 53.2% of grid cells, concentrated in energy-limited regions (northern latitudes and eastern US), with a strong GPP decrease in lower latitudes (water-limited areas), especially in Central Asia, with a considerably smaller cumulative net effect (7.09 TgC; Fig. 6b). There is a spatial distinction in the enhancement of spring GPP caused by snow droughts compared to dry spring conditions. While an earlier onset of the growing season benefits most of the NH, a dry spring benefits vegetation productivity only in energy-limited regions. Subtracting the two quantities per grid cell (mean

216 GPP anomalies for snow droughts followed by normal spring, minus dry spring condi-
 217 tions with preceding normal snow conditions) confirms that positive spring anomalies
 218 are primarily dominated by snow droughts (63.2% of grid cells; blue) compared to dry
 219 springs (36.8%; red; Fig. 6c).

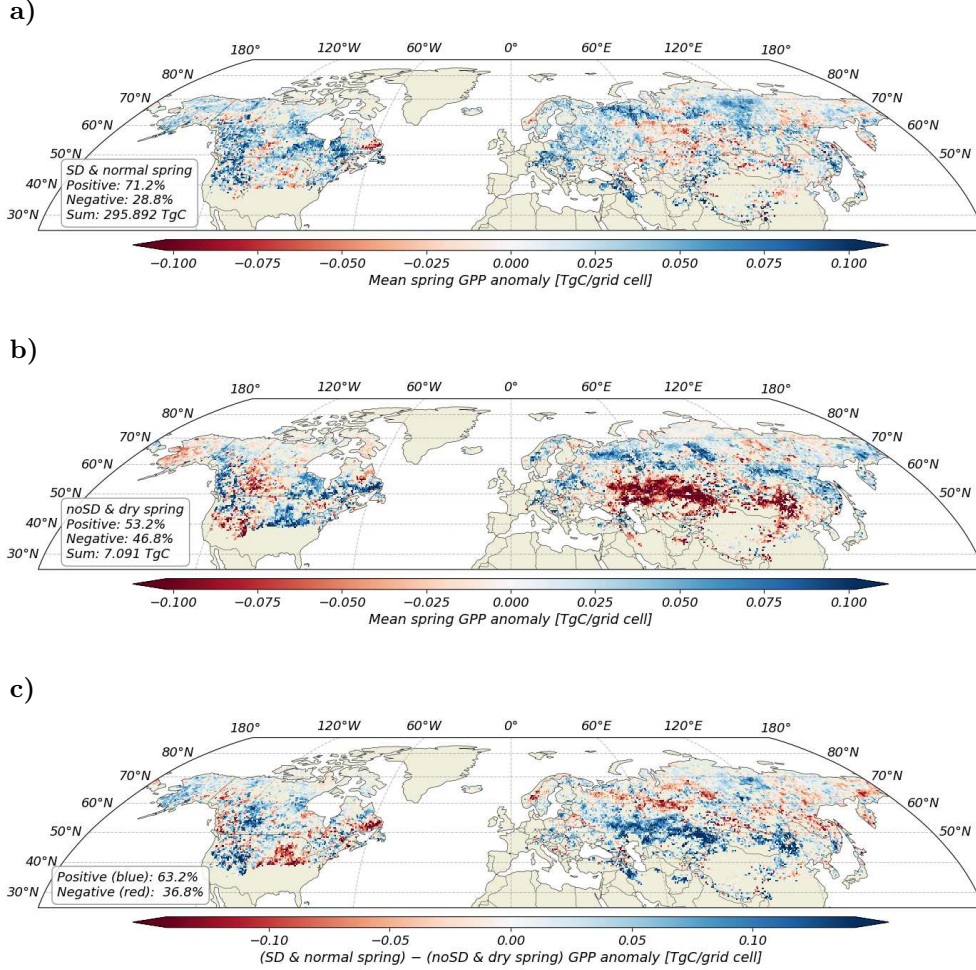


Fig. 6: Mean spring GPP Anomaly for grid cells with a (a) snow drought followed by a normal spring (b) no snow drought followed by a dry spring. (c) Mean spring Δ GPP for snow drought with normal spring vs. no snow drought with dry spring. Δ GPP = $GPP_{SD} - GPP_{dry\ spring}$. Blue (+) values correspond to snow droughts with normal spring being more productive than no snow drought with a dry spring. Red (-) values show the opposite: a dry spring without snow drought had higher positive spring anomalies.

Discussion

Our findings demonstrate that snow droughts alter the seasonal balance between spring phenological gains (ΔGPP_{sp}) and summer losses (ΔGPP_{su}) due to moisture limitation. We find widespread positive ΔGPP_{sp} values, attributable to an earlier growing-season onset in snow drought years with an extended snow-free period [31, 32]. The earlier vegetation greening then contributes to the widely observed increase in annual evapotranspiration [33–35]. This depletes soil moisture, leading to an accumulation of seasonal water deficits that may persist into summer, decreasing plant productivity [35–39]. This identified adverse lagged response acts through three main pathways: (1) enhanced early-season growth raises evaporative demand and water consumption in ecosystems [40]. (2) An earlier growing season may build up leaf area and biomass beyond what the later-season water supply can sustain, further increasing their vulnerability to summer water deficiencies [41]. (3) The advancement of the growing season may also advance the timing of peak productivity, and further limit summer carbon uptake [42]. While diminishing snowpack can directly reduce soil moisture recharge [43] and intensify soil moisture limitation on productivity [44], our findings reveal that snow droughts affect GPP through several biophysiological pathways beyond direct soil moisture limitation alone.

The balance between the opposing seasonal effects determines whether ecosystems experience net gains or losses in growing-season productivity (ΔGPP_{gs}). In energy-limited, humid regions, the positive effect of an earlier growing-season onset generally exceeds the negative impacts of snow droughts on summer GPP (Supplementary Fig. S9). Earlier snowmelt extends the growing season and reduces thermal limitations on productivity, and since annual water supply is not the binding constraint, these spring gains persist rather than being offset by summer moisture stress [45–47]. In water-limited regions, by contrast, soil moisture limitation overrides the earlier start of the growing season. Weaker spring enhancement combined with a stronger negative GPP response in summer results in negative snow drought impacts (Supplementary Fig. S9). Also, the observed spring enhancement in these arid regions might be hampered by a reduced GPP uptake rate, resulting in a less beneficial role of the expanded growing season [48]. Further, reduced snow storage here may directly intensify growing-season water stress, as snowmelt is an important moisture source [49]. Our findings further show that the identified positive spring GPP response generally occurs independently of spring soil water content or precipitation. Yet, across water-limited regions, drier spring conditions might offset the positive impact of snow droughts on GPP (Fig. 4a and 4b). The picture changes for summer precipitation. In water-limited regions, snow droughts tend to suppress GPP regardless of how wet the summer is, suggesting that the moisture deficit accumulated from reduced snowmelt and earlier growing season is not recoverable through summer rainfall alone. We find a similar, but less clear response for energy-limited regions. It is important to note that further categorizing moisture conditions reduces the sample size in each category, increasing variance and challenging the interpretation of the results.

Previous work showed that spring droughts increase spring productivity in energy-limited ecosystems through greater photosynthetically active radiation and warmer temperatures [30]. Yet, spring droughts have the opposite effect on productivity in

water-limited regions (Fig. 6b). Our results show that snow droughts, by contrast, have a positive spring GPP effect in both energy- and water-limited ecosystems (Fig. 5a and 5b). Aggregated over the NH, the cumulative GPP responses to snow droughts (295.89 TgC) exceed that of dry springs alone (7.09 TgC), showing that the longer growing-season impact due to snow droughts dominates the benefits of dry spring conditions in the early season (Fig. 6b and 6a). However, this enhanced spring productivity may exacerbate summer drought intensity through soil drying [50] and indirectly contribute to compound extremes [51–53]. As particularly large negative GPP anomalies might occur in years with stacked droughts, in which a winter snow drought is followed by a drought later in the growing season [27], the (multi-year) legacy effect of snow droughts warrants further investigation.

Our results indicate a positive net effect of snow droughts on GPP and thus the terrestrial carbon cycle, yet this quantification is limited by the underlying uncertainties in the datasets analyzed. These datasets consistently agree on the direction of the seasonal GPP response to snow droughts (Fig. 3c and 3e). However, they differ in the magnitude of these seasonal GPP effects and consequently in the growing-season net effect. A positive (negative) ΔGPP_{gs} is found for LPJmL and VODCA2GPP (FLUXCOM and NIRv). These differences can be attributed to the nature of each data product. LPJmL and VODCA2GPP show a more pronounced spring enhancement in all regions (except hyper-arid), reflected in larger effect sizes (Supplementary Table S2). As a process-based model that relies on parameterized vegetation traits, LPJmL might overestimate the spring enhancement and underestimate the summer depletion in GPP through lagged effects, as seen in other terrestrial carbon cycle models [36]. VODCA2GPP is derived from microwave vegetation optical depth, mainly driven by vegetation’s water content (above-ground biomass) [54]. As a result, it performs well in densely vegetated biomes but drops in arid and less-vegetated regions, as well as in topographically complex regions [55]. In contrast, FLUXCOM, which upscales eddy covariance measurements, is known to have lower interannual variability [56] and performs worse at high latitudes, where other datasets show a prominent spring GPP enhancement, due to lower station density [57]. This may explain the negligible effect sizes in related ecosystems (Supplementary Table S5). However, the interpretation of effect sizes might not reflect the actual ecological impact: i.e., a negligible effect might still show measurable impacts [58]. NIRv, derived from satellite canopy reflectance, focuses on the growing-season canopy signal and is known to overestimate drought impact and underestimate ecosystem recovery [59].

Lastly, we apply a grid-cell-based approach to quantify the impact of snow droughts on GPP. Our results thus do not allow us to directly evaluate and disentangle the upstream-downstream relationships among catchments, large reservoirs, irrigation, glacier melt, and deep groundwater aquifers. Rather, their contributions are reflected through modeling schemes and indirectly captured across all datasets. Nevertheless, particularly reservoirs may compensate for the negative effects of snow droughts in summer.

Conclusion

306 This study provides new evidence that snow droughts consistently alter the seasonal
307 dynamics of GPP across the NH. We show that snow droughts increase spring vege-
308 tation productivity by advancing the growing season, leading to widespread positive
309 GPP anomalies across all ecosystems. These early-season productivity gains are fre-
310 quently followed by enhanced summer water stress, revealing that ecological legacy
311 effects of snow drought extend beyond the winter season. Whether these opposing sea-
312 sonal responses translate into net gains or losses in productivity depends primarily on
313 resource limitations within the ecosystem. Our study suggests an overall positive net
314 effect of snow droughts on GPP and, thus, the terrestrial carbon sink. Specifically,
315 we find a robust net-positive impact of snow droughts on GPP across humid, energy-
316 limited ecoregions and a negative net response in arid, water-limited ecoregions. These
317 findings generally hold true independent of spring and summer moisture availability.
318 The projected increase of snow droughts under continued warming and their role in
319 forming stacked droughts demand further attention in future studies. Improving the
320 performance and methods for inferring GPP are thus urgently needed across scales
321 to better quantify the impacts of hydro-climatic extremes on the terrestrial carbon
322 sink. Our results highlight snow drought as an increasingly important, yet currently
323 under-quantified, driver of regional carbon-cycle variability. Further, we show that
324 winter snow conditions predominantly shape ecosystem functioning far beyond the
325 snow season itself. As seasonal snowpack continues to decline under climate warm-
326 ing, accurately representing snow-driven legacy effects will be essential for improving
327 projections of terrestrial carbon-cycle dynamics and assessing ecosystem resilience.

Methods

Study domain and model setup

For this study, we focus on four variables central to snow–ecosystem interactions: Snow Water Equivalent (SWE), precipitation amount in millimeters (mm), soil water content (SWC), and gross primary productivity (GPP). SWE represents the total amount of water contained within a snowpack, expressed as the depth of water in mm that would result if the snow were completely melted. During snow accumulation, SWE increases, whereas during snow ablation, the stored water is released through snowmelt into the soil and runoff. SWC gives the water volume per unit soil volume, and GPP gives the rate of carbon fixation by vegetation, expressed in TgC/month. Together, these variables primarily characterize the seasonal water storage, transfer, and corresponding ecological response. They were obtained jointly by using the Dynamic Global Vegetation Model Lund–Potsdam–Jena managed Land (LPJmL V5.8.15) [29], a process-based model that explicitly simulates coupled terrestrial carbon and water cycle dynamics, including photosynthesis, vegetation dynamics, evapotranspiration, runoff generation, soil moisture dynamics, and snow processes. In LPJmL, snow accumulates when the temperature is less than 0 °C with a constant snow density of 300 kg/m³. If the snowpack increases beyond a threshold, the surplus is released as runoff. Sublimation is assumed to be 0.1 mm/day, and a conversion factor from water to snow depth is taken to be 1 cm of water for 6.7 cm of snow [29]. Melting is calculated for temperatures above freezing using a degree–day method [60].

In this manner, we consistently obtained all variables of interest from a single model, yielding generally good snow and GPP estimates. LPJmL was forced with monthly ERA5-Land climate data [61] spanning 1950 to present and run with the default settings. The target variables are simulated globally at a monthly time step, with a spatial resolution of 0.5° × 0.5°.

Datasets

Because model-based estimates carry their own structural uncertainties, LPJmL was evaluated against multiple reanalysis, observational, and remote-sensing SWE and GPP products (Table 1). All datasets were re-gridded to the LPJmL spatial resolution and aggregated to a monthly temporal resolution to ensure consistency across products. For SWE, the seasonal (March–May) mean SWE simulated by LPJmL was compared with several snow products (GlobSnow, GLDAS, MERRA2, ERA5-Land, and ERA5) between a more than 30-year overlapping period (1979–2011) of all those products. As these datasets are well-known and widely used, both globally and regionally [62], we validated the simulated LPJmL SWE against them. However, recent findings [63, 64] show that global snowfall and SWE estimates across satellite-based and reanalysis datasets can vary widely regionally. In comparison to all chosen products, LPJmL SWE estimates were within the range of the reference products in 83.1% of grid cells, with most deviations occurring in regions with complex topography, particularly the Himalaya and Tibet region (Supplementary Fig. S1). Furthermore, the minimum and maximum SWE values of the data products show a wider spread in

such regions, suggesting increased uncertainty in the reference estimates themselves, which may explain the observed disagreement in LPJmL. In the regions where LPJmL falls outside the range of the snow products, LPJmL tends to overestimate SWE values. Overall, the datasets show good agreement: all products except GLDAS exhibit median SWE values between 75.39 and 84.48 mm, whereas GLDAS has a substantially lower median of 23.02 mm (see Supplementary Fig. S1). As we use ERA5-Land for climatological data (see Table 1), we retain ERA5-Land SWE for consistency in the subsequent analysis, while the other products (GlobSnow, GLDAS, MERRA2, and ERA5) serve to validate LPJmL SWE.

For GPP, FLUXCOM, NIRv, and VODCA2GPP data products are considered for their long-term data availability, resulting in a temporal overlap period of 1988-2018. FLUXCOM estimates GPP by upscaling in-situ eddy covariance measurements from FLUXNET tower sites using remote sensing and meteorological data from ERA5. Although it has the advantage of being based on real flux measurements, it is known to underestimate interannual variability and to have a spatially biased distribution of FLUXNET sites. VODCA2GPP uses vegetation optical depth (VOD) and FLUXNET observations to derive GPP, which have been shown to correlate significantly [65]. VODCA2GPP is known to have a number of limitations: it shows a consistent positive bias in most regions, is less reliable in areas with extreme climatic or topographic conditions, and, in arid and less vegetated regions, possibly due to plants' adapted water regulation strategies. NIRv is a spectral index derived from satellite reflectance that quantifies the presence of living green vegetation. It serves as a proxy for the fraction of absorbed photosynthetically active radiation (fAPAR), which correlates closely with GPP across many biomes. This relationship is typically calibrated empirically against eddy-covariance GPP estimates from FLUXNET towers. Limitations of this data product include the small number of flux sites for some vegetation types, which limits the ability to generate the relationship between NIRv and GPP. These products were considered following an ensemble approach to reduce uncertainty associated with the assumptions or biases of any single dataset. The resulting cross-dataset agreement is used to robustly assess GPP responses to snow droughts.

Table 1: List of data products used in the analysis with their respective available time period.

SWE	Precipitation	SWC	GPP
ERA5-Land (1950-2025)			
GlobSnow (1979-2011) [66]			FLUXCOM (1979-2018) [57, 70]
GLDAS (1948-2014) [67]	ERA5-Land	ERA5-Land	VODCA2GPP (1988-2020) [55]
MERRA2 (1980-2025) [68]			NIRv (1982-2018)[71]
ERA5 (1940-2025) [69]			

To select grid cells where snow occurs reliably across years, we define a threshold mask (Supplementary Fig. S11). Following the steps in [5], we define this mask by marking a cell as valid for a given year if its three-month SWE sum was above 0 at least

once. The grid cell is kept if this is true in at least 75% of all years. This is applied to both LPJmL and ERA5-Land SWE. In addition, we mask Greenland to ensure snow drought is not flagged in areas mostly covered by ice. An additional 0.96% (LPJmL) and 2.33% (ERA5-Land) of threshold-passing grid cells were further excluded because the mode of the peak SWE month was between October and December, meaning that over the years, their peak SWE happened more frequently in these months. These grid cells were concentrated in complex mountain terrain (e.g., European Alps, Rocky Mountains, Caucasus, Tibetan Plateau) and in high-Arctic cells. The resulting mask generally agrees with the spatial extent of the snow-dominated watersheds [10].

Snow drought identification

Snow droughts were identified using the standardized Snow Water Equivalent Index (SWEI) framework [5]. SWEI is a grid-cell-based standardized metric derived from 3-month cumulative SWE values and quantifies deviations in snow water storage relative to the local climatology. To account for regional differences in snow seasonality across the NH, SWEI was evaluated at each grid cell’s own climatological peak SWE month, rather than a single calendar month applied uniformly across the domain. The peak month was defined as the modal month with the maximum SWE over the study period for each grid cell. Overall, the spatial distribution of the modal month of peak SWE for LPJmL agrees quite well with that of ERA5-Land, as does the month of peak melt, with their magnitudes matching most closely in April and May (Supplementary Fig. S10).

Snow drought conditions were defined as $\text{SWEI} \leq -1.3$, corresponding to the severe, extreme, and exceptional drought categories on the US Drought Monitor scale [72] (See Supplementary Table S8). To assess the sensitivity of our results to this threshold, we repeated the analysis using alternative cutoffs ranging from abnormally dry ($\text{SWEI} \leq -0.5$) to extreme drought ($\text{SWEI} \leq -1.6$) (see Supplementary Fig. S5). The GPP responses were consistent across these thresholds. We retain $\text{SWEI} \leq -1.3$ because it captures a sufficiently extreme subset of events while preserving adequate sample sizes for further analysis. All remaining years were classified as no snow drought conditions.

Hydroclimatic and ecosystem variables

Precipitation anomalies were characterized using the Standardized Precipitation Index (SPI), calculated from 3-month cumulative precipitation totals. Spring precipitation conditions were represented using June SPI (April–June accumulation), whereas summer conditions were represented using August SPI (June–August accumulation). Precipitation was subdivided into dry ($\text{SPI} \leq -1.3$), normal ($-1.3 < \text{SPI} < 1.3$), and wet ($\text{SPI} \geq 1.3$) conditions in order to evaluate the ability of in-season precipitation to modulate GPP responses to snow drought. This threshold falls within the moderately-to-severely dry range of standard SPI drought classifications [73] and was chosen to match the SWEI threshold used to define snow drought, allowing direct comparability between snow and precipitation anomaly severity when evaluating their combined influence on GPP responses.

Seasonal SWC and GPP anomalies were calculated relative to the long-term climatological mean of the studied period. As for precipitation, SWC was also divided into dry, normal, and wet conditions. Above the 75th percentile, SWC was classified as wet, whereas below the 25th percentile was classified as dry. Intermediate values were considered normal conditions. During the analyzed period, LPJmL and ERA5-Land peak snowmelt occurs approximately one month after peak SWE (Supplementary Fig. S10), and therefore, SWC was evaluated during the month following peak SWE. For GPP, prior to anomaly calculation, the time series were linearly detrended to minimize the influence of long-term CO₂ fertilization and climate trends. A Mann-Kendall test was then applied to the detrended series to confirm that no significant residual trend remained. The anomalies were then calculated and aggregated over three dynamical periods: spring, summer, and the growing season. The growing season was dynamically defined for each grid cell as the period from the month following peak SWE through September. Spring was defined as the month after peak SWE through the two months after, and summer was defined as June to September, excluding months already counted in spring. GPP anomaly magnitudes were compared between snow drought and non-snow drought years. The hydroclimatic variables and season definitions are summarized in Supplementary Table S9.

Ecosystem and aridity classification

To assess ecosystem-specific responses, all grid cells were classified according to terrestrial ecoregions [74] and aridity index classes [75] (Fig. 7). This categorization enables disentangling GPP responses to snow drought across specific ecosystems and climates.

To account for potential land-use grid cells, we assessed the extent of cropland-classified grid cells within our valid-land domain using the 2016 MODIS land cover types [76]. More than 90% of cropland grid cells fall within temperate grasslands and temp. broadleaf and mixed forests ecoregions and semi-arid and dry sub-humid aridity index classes. Specifically, cropland grid cells make up 36.7% of temp. broadleaf and mixed forests, 34.3% of temperate grasslands, 13.8% of semi-arid, and 14.2% of dry sub-humid, compared to less than 6% in all other regions. Despite croplands being in a significant portion of these regions, a sensitivity comparison excluding these cropland grid cells showed no meaningful change in the results (Supplementary Fig. S6). Therefore, we retained these grid cells in the main analysis to preserve sample size.

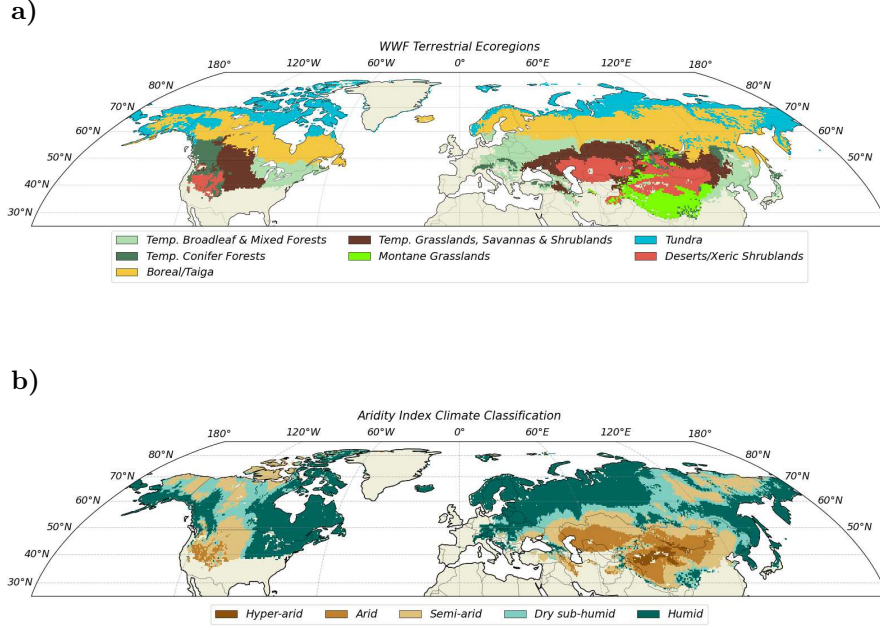


Fig. 7: Spatial distribution of the two classification approaches used to categorize GPP responses to snow drought across the NH. (a) WWF Terrestrial Ecoregions of the World [74]. From the fourteen biome classes, nine fall within the studied area. In addition, two classes were dropped due to their very small areas (flooded grasslands and savannas, and Mediterranean forests, woodlands, and scrub), leaving the final seven classes shown above. Boreal ecosystems cover an area of 14,768,632 km², followed by tundra (7,185,482 km²), temp. broadleaf and mixed forests (6,641,190 km²), temp. grasslands (6,639,605 km²), deserts and xeric shrublands (5,114,077 km²), montane grasslands (3,097,087 km²) and temp. conifer forests (2,761,283 km²). (b) Aridity Index (AI) climate classification following the FAO convention [75]. Divided into five classes: hyper-arid (AI < 0.03), arid (0.03-0.20), semi-arid (0.20-0.50), dry sub-humid (0.50-0.65), and humid (AI > 0.65). Humid areas cover an area of 20,776,054 km², followed by semi-arid regions (11,750,207 km²), dry sub-humid (8,258,755 km²), arid (5,719,075 km²) and hyper-arid regions (771,805 km²). Both maps are masked to the snow-covered domain used in this study, retaining only grid cells that meet the minimum SWE threshold for snow drought classification.

Analysis workflow

To evaluate snow drought occurrence across the NH, we computed the mean snow drought count of LPJmL and ERA5-Land, the two SWE datasets used for the analysis. Hotspot regions were identified by examining which grid cells had snow drought occurrences above the 75th percentile, corresponding to at least 4 years over the analyzed period (31 years). In addition, the study period was divided into three windows (1989–1998, 1999–2008, and 2009–2018) to assess whether snow droughts have increased over time. The year 1988 was intentionally omitted to create three decadal windows.

To quantify the overall impact of snow droughts on ecosystem productivity, we calculated for each grid cell the cumulative GPP anomaly within each year, summed over the relevant period (growing season, spring, or summer). We then calculated ΔGPP as the difference between the mean cumulative GPP anomaly across snow drought years and across years without snow droughts, following $\Delta\text{GPP} = \text{GPP}_{SD} - \text{GPP}_{noSD}$, where GPP_{SD} and GPP_{noSD} represent cumulative GPP anomalies during snow drought and no snow drought years, respectively. This was calculated separately for the growing season (ΔGPP_{gs}), spring (ΔGPP_{sp}), and summer (ΔGPP_{su}).

For a given grid cell, ΔGPP characterizes ecosystem productivity response to snow droughts, describing whether the net cumulative anomalies during snow drought years are on average higher ($\Delta\text{GPP} > 0$) or lower ($\Delta\text{GPP} < 0$) than during years with normal snow conditions. Calculating this for the growing season, spring, and summer allows us to evaluate both the net seasonal response and the underlying seasonal dynamics.

From this, we obtain a spatial distribution of the four GPP datasets, showing where snow drought cumulative anomalies are higher or lower than in normal years. The datasets are compared by examining the percentage of grid cells with positive or negative ΔGPP , as well as their net GPP sum. We summarize these results by averaging ΔGPP across the four datasets. To reduce uncertainty associated with individual products, only grid cells for which at least three of the four datasets agreed on the sign of the response were kept for the analysis. This majority-agreement criterion (3/4) was chosen over full agreement (4/4) because requiring agreement across all four products substantially reduced spatial coverage, retaining only a small minority of grid cells. A 3/4 threshold ensures that the majority of datasets support the same direction of response, while avoiding the sample-size reduction that a stricter criterion would impose.

The ensemble majorities were then grouped by terrestrial ecoregion and aridity class to evaluate ecosystem-specific responses to snow drought. For each data grouping (ecoregion and aridity index), the median, mean, and interquartile range (IQR, Q25–Q75) of ΔGPP were calculated to characterize the central tendency and variability of the region’s productivity responses.

To characterize how GPP anomalies are distributed month-by-month across snow drought and normal snow years, monthly anomalies were aggregated separately for each condition. For each year and month, GPP anomalies were summed over all valid land grid cells classified as snow drought (or no snow drought) and divided by the number of contributing grid cells, yielding a spatially averaged anomaly [TgC/grid cell] for each condition. The distributions of these yearly averages were summarized using the median and IQR over the analysis period to show the central tendency for each month. The procedure was applied to the four datasets.

We assess whether snow drought significantly altered GPP anomalies within each ecoregion and aridity class by computing the mean GPP anomaly per grid cell for snow droughts and normal years. Given paired values for snow drought and no snow drought conditions per grid cell, we applied the paired t-test and the Wilcoxon signed-rank test to the grid cell pairs for each ecoregion and aridity class. Due to the large number of grid cell samples, statistical significance is expected even for small GPP

differences, which limits the interpretation of p-values. Furthermore, spatial autocorrelation among grid cells may also inflate the statistical significance of the paired tests. Therefore, the effect sizes were additionally quantified using Hedges' g, a bias-corrected standardized mean difference, to emphasize the magnitude and ecological relevance of the observed differences across ecoregions and datasets [77]. The effect size is interpreted following Cohen's conventions [78], shown in Table 2. Because effect size thresholds are standardized conventions rather than field-derived thresholds, they may lack interpretation in ecological contexts [58], meaning a small effect size does not necessarily indicate an ecologically insignificant result. This procedure was performed for the four datasets, and for each dataset, the growing season, spring, and summer were considered.

Table 2: Cohen Rule of thumb for interpreting effect size results

Hedges' g Value	Interpretation
< 0.2	Negligible
≥ 0.2	Small
≥ 0.5	Medium
≥ 0.8	Large

To evaluate how spring soil water content and spring and summer precipitation alter the impact of snow droughts on GPP, we examine ΔGPP across ecoregions and aridity index classes, this time also classifying grid cells as wet, normal, or dry based on the thresholds discussed. Spring SWC considers ΔGPP at the month after peak SWE, spring SPI considers April to June, and summer SPI considers ΔGPP from June to August. For summer precipitation, we consider only grid cells preceded by normal spring precipitation. In this manner, we can determine whether dry conditions in a region alter the impact of a snow drought relative to normal or wet conditions. Since further dividing the regions into three categories creates groups with very few samples (e.g., hyper-arid with a wet spring), we combined hyper-arid and arid regions, as well as boreal forests and tundra. Finally, to isolate the effects of snow drought and spring precipitation deficits on spring GPP, we classified grid cells into two categories: (1) snow drought years followed by a spring with normal precipitation conditions, and (2) years with normal snow conditions followed by a dry spring. For each category, the mean ΔGPP_{sp} was calculated per grid cell and per ecoregion and aridity index classes. In this manner, we identified which effect primarily drives GPP anomalies in what region. In addition, we computed for each category the percentage of grid cells showing a positive GPP anomaly and the cumulative net anomaly in TgC. As a final step, we computed the difference between the two categories for each grid cell to visualize which regions the spring GPP anomalies are driven by snow droughts or dry springs.

To increase robustness against multiple uncertainties in both snow and ecosystem productivity estimates, we deliberately adopted conservative methodological choices throughout the analysis workflow: Restricting the analysis to regions with persistent

558 seasonal snow cover, identifying only severe snow droughts, comparing LPJmL with
559 multiple independent snow products, and retaining only grid cells where at least three
560 out of four independent GPP datasets agreed on the sign of the response. The entire
561 workflow, the thresholds selected for SWEI, SWC, and SPI, the months considered
562 for each variable, and the datasets used are summarized in Supplementary Fig. [S12](#).

Supplementary information. This article has an accompanying supplementary file.

Declarations

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- **Conflict of interest/Competing interests:** The authors declare no competing interests.
- **Ethics approval and consent to participate:** Not applicable
- **Data availability:** All data used in this study are publicly available. The ERA5-Land and ERA5 dataset is available from Copernicus Climate Change Service's Climate Data Store (<https://cds.climate.copernicus.eu/datasets>). The GlobSnow v3.0 snow water equivalent dataset is available from the PANGAEA repository (<https://doi.org/10.1594/PANGAEA.911944>). The GLDAS and MERRA2 datasets are available from the NASA Goddard Earth Sciences Data and Information Services Center (<https://disc.gsfc.nasa.gov/datasets?keywords=GLDAS>, https://disc.gsfc.nasa.gov/datasets/M2T1NXSLV_5.12.4/summary). The VODCA2GPP dataset is available from the TU Wien Data Repository (<https://doi.org/10.48436/1k7aj-bdz35>). The NIRv GPP dataset is available from figshare (<https://doi.org/10.6084/m9.figshare.12981977>). The FLUXCOM dataset is publicly available through the FLUXCOM data portal (<https://www.bgc-jena.mpg.de/geodb/fluxcom/globalandcarbonfluxes-fluxcom>). LPJmL outputs are available upon request.
- **Materials availability:** Not applicable.
- **Code availability:** The code to reproduce all the results in this study will be available upon successful submission.
- **Author contribution:** M.V., F.K. and D.G. designed and conceptualized the study, M.V. carried out the formal analysis, visualizations, data curation and wrote the initial version of the manuscript, F.K. and D.G. supervised the study. All authors contributed to the discussion and interpretation of the results and reviewed the final manuscript.

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