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Weakened constraint of start of the season on autumn senescence in the Northern Hemisphere

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Abstract

Vegetation autumn phenology is critical in regulating the ecosystem carbon cycle and regional climate. However, the dominant drivers of autumn senescence and their temporal shifts under climate change remain poorly understood. Here, we conducted a multi-factor analysis considering both direct climatic controls and biological carryover effects from start-of-season (SOS) and seasonal peak vegetation activities on the end-of-season (EOS) to fill these knowledge gaps. Combining satellite and ground observations across the northern hemisphere, we found that carryover effects from early-to-peak vegetation activities exerted greater influence on EOS than the direct climatic controls on nearly half of the vegetated land. Unexpectedly, the carryover effects from SOS on EOS have significantly weakened over recent decades, accompanied by strengthened climatic controls. Such results indicate the weakened constraint of leaf longevity on senescence due to prolonged growing season in response to climate change. These findings underscore the important role of biological carryover effects in regulating vegetation autumn senescence under climate change, which should be incorporated into the formulation and enhancement of phenology modules utilized in land surface models.

KEYWORDS: acclimation, autumn senescence, biological carryover effect, climate change, phenology, vegetation dynamic

INTRODUCTION

Plant's regulation on terrestrial carbon cycle and surface energy balance is strongly modulated by plant phenology, a crucial component which has changed considerably in the context of climate change^{1, 2}. However, our current understandings of the drivers and mechanisms underlying the autumnal senescence lags behind that of spring phenology, leaving significant knowledge gaps^{3, 4}. Previous studies have identified several important drivers for the end of the season (EOS), including climate factors (e.g. temperature^{5, 6}, solar radiation^{7, 8}, soil moisture^{9, 10}, wind speed¹¹) and preceding vegetation activities (e.g. timing of spring phenology^{12, 13} and summer productivity^{14, 15}, namely biological carryover effects which describe the influence of vegetation activities in past stages on that of current stage). However, the dominant factors regulating autumn phenology remains unclear due to only one or few of these drivers considered in previous studies.

Moreover, evidence suggest that plant responses to climate variations are dynamic and can vary over time¹⁶⁻¹⁹. The date of autumnal senescence, which demarcates the end of the growing season, has also been found to exhibit shifted responses to climate variations under rapid climate change^{7, 9, 19}. For instance, the strengthening controls of soil-moisture concentration on autumnal senescence were discovered and predicted due to late-season droughts associated with warming^{7, 9}. Temperature and light availability were also found to exert greater controls over senescence in recent decades by mechanisms that are still under debate¹⁹. Changes in direct environmental controls over senescence may potentially alter the effects (e.g. SOS and summer vegetation activity) carried over from earlier seasons^{14, 15}. However, the evolution of the multi-

factor regulation on EOS remains poorly understood, also mainly due to the limited inclusion of a diverse range of factors in previous analyses.

In order to fill these critical knowledge gaps, we take a holistic approach by considering all these factors simultaneously, aiming to identify the dominant drivers of autumn phenology, unravel the complex regulation of senescence in plants, and further provide insight into the temporal evolution of these factors. Our study addresses two primary objectives: (1) identifying the key controllers of autumn phenology by examining the role of various drivers, and (2) investigating the past shifts in the dominance of multiple regulators.

To address these objectives, we conducted a comprehensive analysis utilizing long-term remotely sensed data and site-level phenological observations in the Northern Hemisphere (NH, $>30^{\circ}\text{N}$) from 1982 to 2016. We considered four environmental regulators (solar radiation, wind speed, soil-moisture concentration and temperature) and incorporated biological carryover effects from spring phenology (SOS) and summer vegetation activity (annual maximum normalized difference vegetation index (NDVI_{max})) in our investigation. By employing partial correlation analysis, we disentangled the intercorrelations among these factors and determined the dominant roles in regulating EOS based on the highest absolute value of partial correlation coefficients (see Methods). Furthermore, we examined the shifts in multi-factor regulation and dominance on EOS between two distinct time periods (1982-1999 and 2000-2016).

Non-negligible dominance of carryover effects from spring and summer vegetation activities on EOS

In our investigation, we conducted partial correlation analyses between EOS and driving variables encompassing environmental factors, SOS and NDVI_{max} (Fig. 1). Our findings highlighted the strong carryover effects of spring and summer vegetation activities on autumn senescence, with large areas showing significantly positive effects of SOS and NDVI_{max} on EOS (Fig. 1e and 1f). Specifically, the largest significant regions were found for $R_{EOS-NDVI_{max}}$ (partial correlation coefficient between EOS and NDVI_{max} after controlling for other factors, see Methods) that take up 31.5% of the NH vegetated land (Fig. 1f), indicating an enhanced summer growth can propagate to autumn and induce later senescence²⁰. Significant positive $R_{EOS-SOS}$ were lesser but also accounted for 21.6% of the lands (Fig. 1e). Compared to NDVI_{max}, portion of regions with significant climatic controls of senescence were fewer, with temperature, radiation and soil moisture occupying 16.5%, 18.2% and 21.6% of the NH vegetated land, respectively, and mainly showing positive correlations with EOS (Fig. 1a, c and d). Though wind speed were regarded as another important factor in driving senescence in a previous study¹¹, we found its effect only being significantly negative in 12.6% of the NH vegetated pixels (Fig. 1b).

Based on these correlations, we assumed that each factor had a limiting direction for the delay in EOS, and omitted all non-limiting pixels. We retained positively correlated pixels for temperature, radiation, soil-moisture concentration, SOS and NDVI_{max}, and negatively correlated pixels for wind speed. The dominant factors were identified as the driver having the

highest absolute value of the partial correlation coefficient, which accounted for 98.5% of the NH vegetated land (Fig. 1g). Carryover effects exerted more prominent controls on EOS variations than climatic factors for nearly half (47.0%, 31.1% for NDVI_{max} and 15.9% for SOS) of the pixels with a dominant factor identified (Fig. 1g). In line with their significant correlated regions with EOS (Fig. 1e and 1f), NDVI_{max} and SOS were both more dominant in high-latitude areas like northern Eurasia and northern America (Fig. 1g). Interestingly, the effects of radiation and temperature in these regions were mostly concealed by that of SOS and NDVI_{max}, though they were popularly considered as the primary limiting factors in these colder regions^{7, 13}. For warmer temperate dry lands, we found clear dominance of soil moisture, indicating that plant late-season growth was mostly hindered by water shortages. However, no distinct occupation of dominance of wind speed can be observed on the map, indicating its lesser role in driving senescence.

Previous studies suggest that plant phenology might respond differently to day and night-temperatures^{21, 22}. To test it, we conducted the same analyses by replacing daily mean temperatures with minimum and maximum temperatures. However, we did not find contrasting effects of day- and night-time warming given the consistent results yielded using different temperature indicators (Supplementary Fig. 1 and Supplementary Fig. 2). Additionally, site-level field observations in Europe also reinforced above satellite-based results with good regional similarities (Supplementary Fig. 3).

Overall, the above results indicate the non-negligible role of carryover effects from spring and summer vegetation activities in regulating autumn senescence. Zohner et al. (2023) found opposite effects of early-season and late-season warming on leaf senescence, and speculated that earlier and enhanced vegetation activity before summer solstice would drive earlier autumn senescence¹⁵. Our results provide direct evidence for the constraint of growing season length (leaf longevity) and further explore the strong linkage between the seasonal peak of vegetation activity and autumn senescence. Therefore, current process-based phenological models that only incorporate a limited number of environmental drivers may be insufficient, and improved models under climate change will need to incorporate the non-negligible carryover effects of earlier vegetation activities.

Weakened impacts of SOS on EOS over the past decades

We further explored the shifts in partial correlations and dominant factors of EOS over the past decades by comparing them between two periods (1982-1999 vs. 2000-2016). Consistent spatial patterns of correlation between EOS and controlling variables were observed in the two periods (Supplementary Fig. 4), but the changes in correlations showed spatial heterogeneity (Fig. 2). Compared with the former period, we observed an increase in partial correlations for most of the climatic drivers, including temperature (from 0.38 to 0.42, Fig. 2d), soil moisture (from 0.19 to 0.24, Fig. 2c) and radiation (from 0.32 to 0.35, Fig. 2a), while that of wind speed remained nearly invariant (Fig. 2b). Among all the spatial heterogeneity in changes of correlations between EOS and climatic drivers (Fig. 2g-j), consistent increasing patterns of R_{EOS-SM} from negative to positive were found in high-latitude regions (Fig. 2i), indicating that

warming-accompanied droughts in recent decades might have started to exert adversities to higher-latitude plants^{9, 10}. The growing environmental controls over senescence indicated by R were further supported by increased dominance for most of the environmental drivers between the two periods, despite a marginal decrease of dominant pixels for soil-moisture by 0.7% (Fig. 3a-d).

Conversely, for carryover effects, $R_{EOS-SOS}$ decreased significantly from 0.55 to 0.48 from the earlier to the later period (Fig. 2e), while $R_{EOS-NDVI_{max}}$ stays nearly the same (Fig. 2f). The decrease in $R_{EOS-SOS}$ was mainly found in high-latitude regions, where $R_{EOS-SOS}$ were significant and positive during the study period (Fig. 1e), indicating an alleviation of the tight SOS constraint on autumnal senescence in these colder regions (Fig. 2k). Such weakened SOS impact was further corroborated by substantial decrease of the dominant regions occupied by SOS over the NH vegetated land from 20.1% to 15.8%. (Fig. 3e). Using 15-year moving window analysis, we show that the dominance of carryover effects decreased consecutively from 42.4% to 36.6% ($NDVI_{max}$ did not change much), while the control of environmental drivers gradually increased, with minor interannual fluctuations (Fig. 3g).

The shifts in carryover effects of SOS over EOS might not be homogenous over the NH and are regional specific. For example, in European forest, $R_{EOS-SOS}$ showed increased values (Supplementary Figs. 5j and 6a), and $R_{EOS-NDVI_{max}}$ exhibited a reversal from positive to negative values (Supplementary Figs. 5l and 6b). Such results were consistently revealed by both remote sensing and field observations, again confirming the robustness of our results. Compared to the

other NH ecosystems, the relatively fertile and warmer European forests may be nearing their maximum carbon sequestration capacities in the CO₂-rich world¹⁴. In such cases, sink limitation could induce negative correlations between EOS and NDVI_{max}, further triggering stronger connections between leaf-out and senescence^{12, 13, 23}.

Overall, the observed decline in the constraint of SOS over EOS indicated by the decreases both in $R_{EOS-SOS}$ and the prevalence of dominant pixels suggests a weakening of the phenological carryover effects from leaf-out over senescence across the NH. This weakening was mainly originated from the high-latitude regions (>50°N), where significant and positive $R_{EOS-SOS}$ were prevalent (Fig. 1e). High-latitude plants in these cold environments face higher risks of damage from late-autumn frost, necessitating earlier nutrient resorption from leaves^{24, 25}. To avoid harsh environments late in the season, cold-adapted plants should activate earlier programmed cell death, which could lead to limited lengths of the growing season (LOS, <120 days, Supplementary Fig. 7a), and further trigger tighter connections between leaf-out and senescence given the short interval for the variability of early phenological date to propagate through the life cycle of plants. In recent decades, the rapid warming of the Arctic and subsequent reduction in frost-related growth stresses²⁶, has considerably extended the LOS²⁷, as demonstrated in Figure 4b. The prolonged LOS consequently leads to an extended interval between leaf-out and senescence, which appears to underlie the attenuated phenological carryover effect from SOS to EOS, as evidenced by a noteworthy negative correlation between $\Delta R_{EOS-SOS}$ and ΔLOS over the land north of 50°N (Fig. 4a and Supplementary Fig. 7b).

The inverse relationship between the interval duration and the correlation of dates between the two phenophases revealed by satellite observations were also supported by a regional field-based research²⁸. This phenomenon underscores the essential role of plant biological memory (i.e. carryover effect) in determining the timing of subsequent phenophases. The tight positive correlations between leaf-out and senescence, which were thought to partially counterbalance the elongation of the growing season^{12, 29}, have progressively waned as SOS-to-EOS intervals lengthen due to ongoing climate warming based on our results. It thus implies that the acclimation of plant phenology would yield an extended growing season, transcending the constraints of leaf longevity or premature carbon sink saturation, thereby further elongating the period during which plants can take up CO₂³⁰, unless climatic factors end up imposing limitations (Penuelas et al, 2017)

Conclusion

In summary, our comprehensive analysis has effectively pinpointed the primary drivers of EOS by accounting for an array of environmental factors and biological carryover effects. Our findings uncover substantial carryover effects from spring and summer vegetation activities, exerting significant sway over the year-to-year fluctuations of EOS across almost half of the vegetated land in the northern hemisphere. However, the carryover effects from SOS to EOS have markedly waned in recent decades, while direct climatic controls strengthened, likely due to the prolonged growing season induced by rapid climate warming. Previous studies, which concentrated on a limited spectrum of drivers, may have overemphasized the direct climatic influences on EOS due to the ignorance of the carryover effects from earlier seasons. Moreover,

models of phenology rooted solely in environmental triggers like temperature and solar radiation may have generated unreliable outcomes³¹. Integrating ecological theories of carryover effects into the formulation and enhancement of phenology models utilized in land surface models could prove indispensable for the accurate projection of vegetation dynamics and the global carbon cycle.

Methods

Satellite-derived phenological data.

The seasonal trajectories of canopy greenness can be tracked by the normalized difference vegetation index (NDVI), a commonly used proxy in analysis of plant phenology³². Here, we utilized the biweekly NDVI time series from third generation of the Global Inventory Modeling and Mapping Studies (GIMMS) from the Advanced Very High-Resolution Radiometer (AVHRR, i.e., GIMMS NDVI3g)³³ to identify the dates for start of season (SOS) and end of season (EOS). The study region was restricted to the Northern Hemisphere (NH>30°N), where plants have clear seasonal cycles. Before applying algorithms for extracting phenology data, we first eliminated the influence of snow cover by replacing pixels with temperatures lower than 0 °C for at least five days with their neighboring values. Air temperature at daily timestep was derived from monthly temperature interpolated by a spline function. Then a 5-point median moving filter was applied to the seasonal cycle of NDVI to replace abnormal values with smoothed ones. After the above preprocessing procedures, we determined SOS and EOS using four methods: (1) Hants-Maximum method³⁴, (2) Polyfit-Maximum method³⁵, (3) double logistic method³⁶ and (4) piecewise logistic method^{37, 38}.

244

245 For the Hants-Maximum method, NDVI thresholds for SOS and EOS were first derived from
246 the multi-year averaged NDVI seasonal cycle. The threshold corresponds to NDVI at time $t+1$
247 with the maximum (for SOS) or minimum (for EOS) ratio of relative change ($NDVI_{ratio}$):

$$248 \quad NDVI_{ratio}(t) = \frac{NDVI(t+1) - NDVI(t)}{NDVI(t)} \quad (1)$$

249 where t is the Julian date, and $NDVI(t)$ is NDVI at time t . The NDVI seasonal cycle for each
250 year was then fitted into daily curves using a harmonic analysis of time series:

$$251 \quad NDVI(t) = a_0 + \sum_{i=1}^n a_i \cos(w_i t - \varphi_i) \quad (2)$$

252 where t , a_0 , a_i , w_i and φ_i are fitting parameters. SOS and EOS were determined by the time
253 when the fitted NDVI curves crossed their prescribed thresholds.

254

255 For the Polyfit-Maximum method, we adopted the same criteria as the Hants-Maximum method
256 for determining SOS and EOS, except that the yearly NDVI seasonal cycle was fitted into daily
257 curves using a sixth polynomial function:

$$258 \quad NDVI(t) = \alpha_0 + \alpha_1 t^1 + \alpha_2 t^2 + \dots + \alpha_6 t^6 \quad (3)$$

259 where $\alpha_0, \alpha_1, \dots, \alpha_6$ are fitting parameters.

260

261 For the double logistic method, we used two functions to simulate the vegetation seasonal cycle
262 for the middle (Eq. 4) or later (Eq. 5) part of the curve:

$$263 \quad NDVI(t) = wNDVI + (mNDVI - wNDVI) \times \left(\frac{1}{1 + e^{-mS(t-S)}} + \frac{1}{1 + e^{mA(t-A)}} - 1 \right) \quad (4)$$

$$264 \quad NDVI(t) = mNDVI - (mNDVI - wNDVI) \times \left(\frac{1}{1 + e^{-mS(t-S)}} + \frac{1}{1 + e^{mA(t-A)}} - 1 \right) \quad (5)$$

where mNDVI and wNDVI are the peak and lowest NDVIs in a year, S and A represent the dates of spring green-up (SOS) and autumnal senescence (EOS), respectively, and mS and mA are derivations of the curve at S and A, respectively.

For the piecewise logistic method, we divided the yearly NDVI curves into the periods of green-up and senescence based on their peak values. Each part was fitted into daily curves using sigmoidal functions with a unique set of parameters:

$$NDVI(t) = \begin{cases} \frac{c_1}{1 + e^{a_1 + b_1 t}} + d_1 & t \leq \alpha \\ \frac{c_2}{1 + e^{a_2 + b_2 t}} + d_2 & t > \alpha \end{cases} \quad (6)$$

where α indicates the inflection point, a_1 , a_2 , b_1 and b_2 are fitting parameters, c_1 and c_2 are peak values minus the background values and d_1 and d_2 are the background values. SOS and EOS were determined using the local maxima and minima of the derivations of the fitted senescence curves, respectively.

The multi-method derived EOS was required from Liu (2016), which indicates that the four methods generally derive comparable outcomes¹³. Further analyses were based on mean SOS and EOS obtained by these four methods.

Ground observed phenological data.

Site-level SOS and EOS dates were obtained from the Pan European Phenology Project (PEP725), which provides long-term in-situ data across European forests for a variety of phenophases³⁹. Phenological stages in PEP725 are defined by the BBCH (Biologische

Bundesanstalt, Bundessortenamt und Chemische Industrie) codes. We used the dates when the first true leaves unfolded (BBCH=11) and when foliar coloration was >50% (BBCH=205) to represent SOS and EOS, respectively. The period was restricted to 1982-2016 consistent with the satellite records. Values 2.5-fold higher and lower than the median absolute deviations were removed as outliers⁴⁰, and time series less than 30 years were discarded. After the data were cleaned, a total of 15933 time series at 1721 sites were available for further analysis.

Climatic data sets.

We acquired the following data sets for analyzing the factors controlling satellite-derived EOS. Data for monthly mean, minimum and maximum 2-m surface temperature and precipitation were obtained from the CRU.TS v4.05 data set, with a spatial resolution of 0.5°⁴¹. Note that the minimum and maximum temperatures were monthly means of the daily maximum and minimum temperatures. We acquired data for 6-hourly surface downward shortwave solar radiation from the CRU.JRA v2.2.5 data set, with spatial resolution of 0.25°⁴², which was resampled to 0.5° by computing mean values of every four pixels. Surface (0-7cm) soil-moisture concentration and 10-m wind speed with a monthly temporal resolution and 0.1° spatial resolution were derived from the fifth generation of the ERA5-land reanalysis data set of the European Center for Medium-Range Weather Forecast (ECMWF)⁴³, and was resampled to 0.5° for analysis. These datasets have been widely used to investigate the environmental controls of plant phenology^{9, 11, 44}.

We also used the same data sets of surface soil-moisture concentration and wind speed from ERA5 for correlation analysis with site-level EOS due to their fine (0.1°) spatial resolutions. We also acquired data for mean temperature and radiation from E-OBS daily gridded meteorological data set, which covers Europe with a resolution of 0.1° ⁴⁵. The daily data sets were aggregated to monthly values prior to the analysis of the site-level EOS data.

Data analysis.

To determine the lagged effects of the climatic factors (i.e., radiation, wind speed, soil-moisture concentration and temperature), we first identified preseason length by conducting simple correlation analysis between EOS and the climatic factors for 1982-2016 for up to three months prior to the EOS^{9, 13}. The preseason was the period when the means of the variables were most strongly correlated with EOS (Supplementary Fig. 8). Note that all variables were detrended before analysis. We then sequentially performed a partial correlation analysis between EOS and mean temperature, radiation, soil-moisture concentration, wind speed, SOS and annual maximum NDVI (NDVI_{max}, maximum value of biweekly NDVI) for 1982-2016, with the other factors acting as controlling variables, to remove multi-driver interactions. The factors were all regarded as being highly relevant to autumnal senescence^{11, 13, 14, 46}. We assume that each factor had a limiting direction for EOS delay and excluded all nonlimiting pixels (sites) based on the signs of the partial correlations. For temperature, radiation, soil-moisture concentration, SOS and NDVI_{max}, only pixels (sites) positively correlated with EOS were retained, whereas negative pixels (sites) were solely reserved for wind speed. Finally, we defined the dominant factor controlling EOS as the factor with the highest absolute partial correlation coefficient.

Pixels that could be identified by a dominant factor accounted for 98.5% of the NH vegetated land. Mean temperature was also replaced by maximum and minimum temperatures to determine if they produced similar outcomes.

We also investigated the shifts in the partial correlation coefficient and EOS-dominant factors during the study period, which was separated into the first eighteen (1982-1999) and latter seventeen (2000-2016) years. Random samplings containing 15-year time series were conducted 100 times for the two independent periods. Partial correlations and dominant factors were correspondingly obtained 100 times for each period, which gives us the frequency distributions of the NH-averaged correlations and the fraction of dominant pixels for each factor during specific periods, and helped to minimize the influence of anomalous years. To ensure the robustness of our results, we repeated the samplings using 13-year time series, which produced comparable outcomes with the original 15-year samples (Supplementary Figs. 9 and 10). In addition to the independent time periods, consecutive shifts were acquired by adopting 15-year moving windows, with the central years of the windows running from 1989 to 2009. Partial correlations and dominant factors were calculated for each window. Shifts in dominant factors were only investigated during the two independent periods due to the inability of site-level EOS data to produce consecutive records, and time series ≤ 10 years were discarded for each period before analysis.

To identify the factors responsible for the decrease in the partial correlation coefficient between EOS and SOS ($\Delta R_{\text{EOS-SOS}}$), we determined the length of the growing season (LOS) as the

difference between EOS and SOS, and calculated its shift between two periods (Δ LOS, equals mean of 1982-1999 minus mean of 2000-2016). Linear regressions were used to identify if there exist significant relationships between $\Delta R_{EOS-SOS}$ and Δ LOS spatially. Binned $\Delta R_{EOS-SOS}$ in the space of LOS and Δ LOS gives further support for the linear regressions (Supplementary Fig. 7).

Data availability

All observational data sets we used are publicly available. The GIMMS3g NDVI data set is publicly available at <https://data.tpdc.ac.cn/en/data/9775f2b4-7370-4e5e-a537-3482c9a83d88/>. The phenological records from the Pan European Phenology Project (PEP725) can be downloaded from <http://www.pep725.eu/>. The CRU.TS.4.05 data sets for mean, minimum and maximum 2-m surface temperature and precipitation are available at https://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.05. The CRU.JRA v2.2 6-hour insolation data sets are available at https://data.ceda.ac.uk/badc/cru/data/cru_jra/cru_jra_2.2. The ERA5 reanalysis data for surface soil-moisture concentration and wind speed are available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/10.24381/cds.68d2bb30?tab=overview>. The E-OBS daily gridded meteorological data set is available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/insitu-gridded-observations-europe?tab=overview>.

Code availability

All computer codes are available from the co-authors upon reasonable request.

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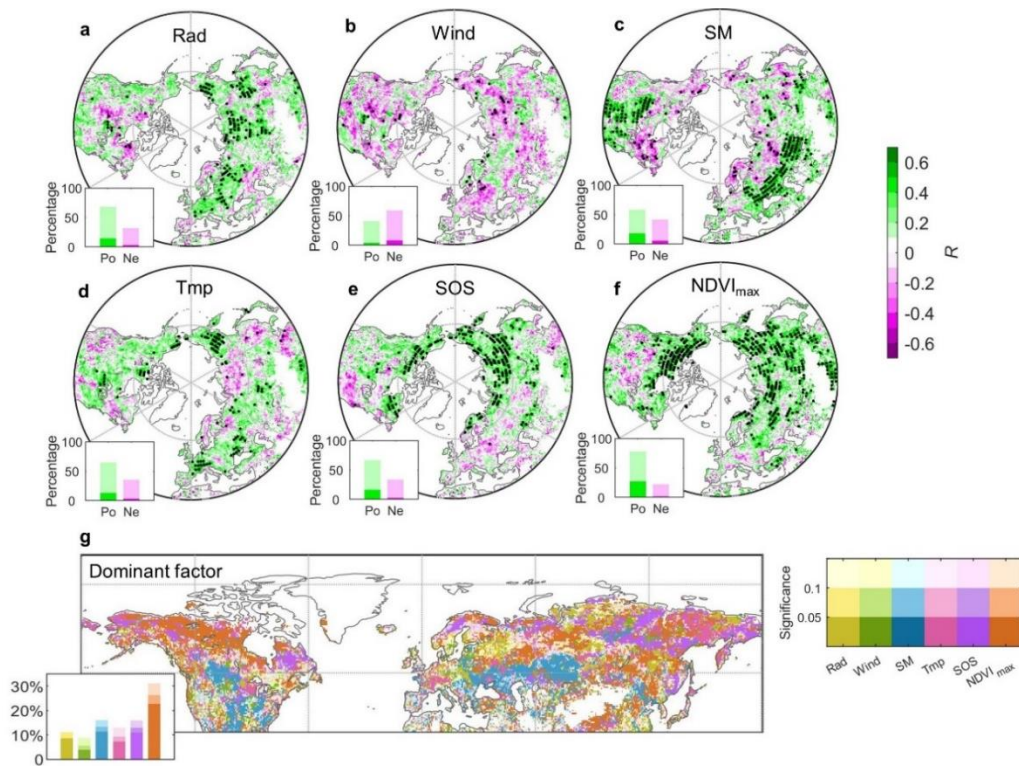
Author contributions

Competing interests

The authors declare no competing interests.

Figures

Figure 1. Factors underlying the variations of end-of-season (EOS) during 1982-2016. a-f, Partial correlation coefficients between EOS and solar radiation (Rad, a), wind speed (Wind, b), soil-moisture concentration (SM, c), temperature (Tmp, d), start-of-season (SOS, e) and annual maximum NDVI (NDVI_{max}, f), with the other factors serving as controlling variables. The black dots indicate significant correlations at $P<0.05$. The bar charts indicate the frequencies of positive (Po) vs negative (Ne) correlations, with darker colors denoting significant fractions. g. Dominant factors underlying EOS variations (defined as factors having the highest absolute partial correlation coefficient, with the sign limiting the delay of EOS). Color intensity represents the level of significance of the partial correlation coefficient for the dominant factor. The bar chart shows the fractions of pixels dominated by each factor.



505 **Figure 2. Shifts in the partial correlation coefficient between end-of-season and**
506 **controlling variables between the two periods (1982-1999 and 2000-2016). a-f.** Shifts in the
507 partial correlation coefficient (R) between EOS and solar radiation (Rad, **a**), wind speed (Wind,
508 **b**), soil-moisture concentration (SM, **c**), temperature (Tmp, **d**), start-of-season (SOS, **e**) and
509 annual maximum NDVI (NDVI_{max} , **f**) between 1982-1999 and 2000-2016. The histograms
510 indicate the frequency distributions of significant R averaged over NH obtained from 100
511 randomly selected 15-year time series. **g-l.** Spatial patterns of differences in R (ΔR) between
512 2000-2016 and 1982-1999 for Rad (**g**), Wind (**h**), SM (**i**), Tmp (**j**), SOS (**k**) and NDVI_{max} (**l**).
513 The average of 100-time sampled R was first calculated for each period before identifying the
514 difference. The first rows of bars for $\Delta R < 0$ denote pixels transforming from negative to more
515 negative (Ne->Ne), positive to negative (Po->Ne) and positive to less positive (Po->Po). The
516 second rows of bars convey similar meanings.

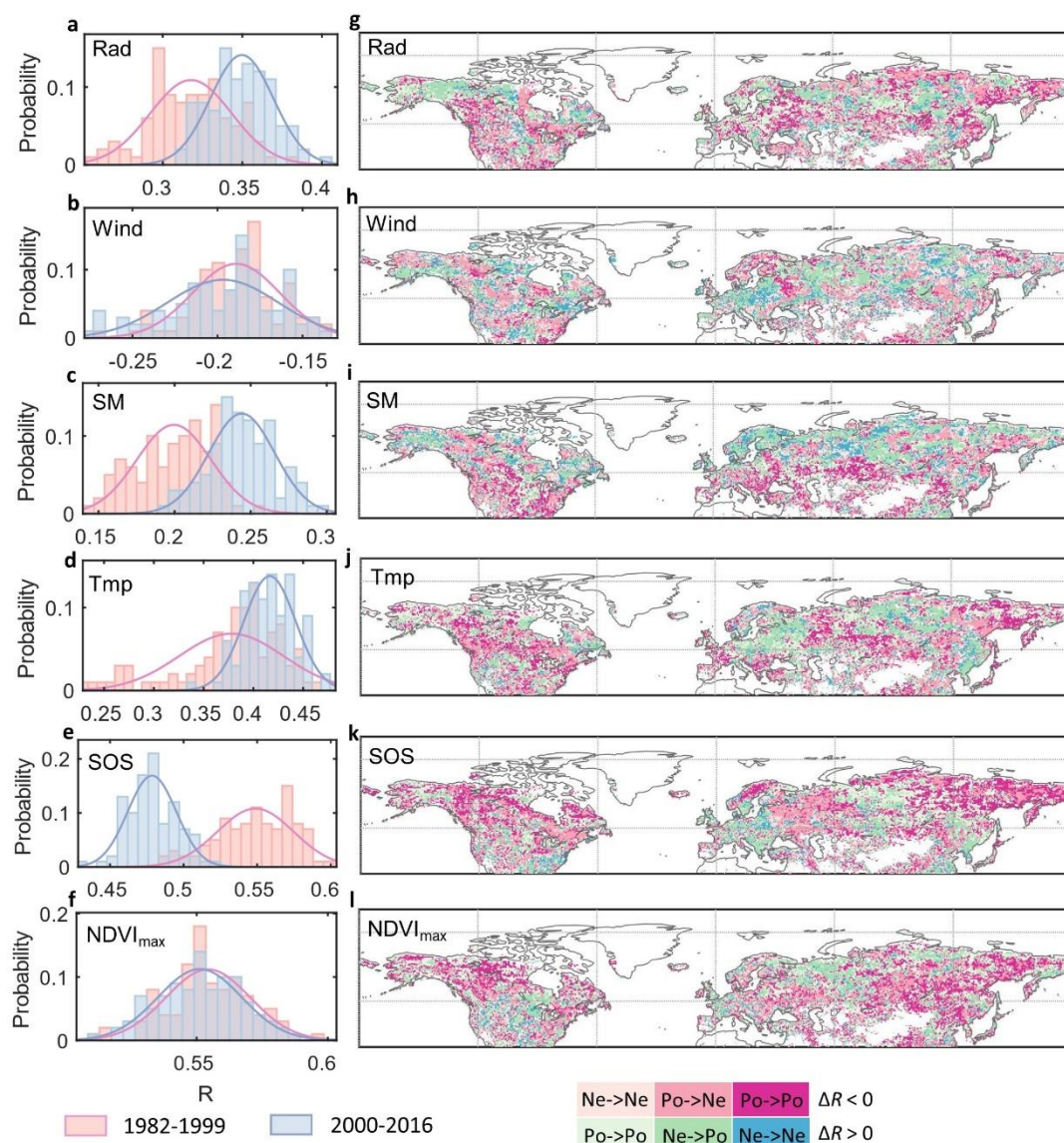


Figure 3. Shifts in the fraction of pixels with EOS variations dominated by different factors over time. **a-f**, Shifts in the percentage of pixels with EOS variations dominated by solar radiation (Rad, **a**), wind speed (Wind, **b**), soil-moisture concentration (SM, **c**), temperature (Tmp, **d**), start-of-season (SOS, **e**) and annual maximum NDVI (NDVI_{max}, **f**) between 1982-1999 and 2000-2016 relative to overall dominant pixels. The histograms indicate the frequency distributions of the percentage of dominant pixels obtained from 100 randomly selected 15-year time series. **g**. Consecutive changes in the percentage of pixels dominated by carryover effects and autumnal climates from 1989 to 2009 relative to overall dominant pixels. Carryover effects include the effects of SOS and NDVI_{max}, and Rad, Wind, SM and Tmp are referred to as autumnal climates. The dates on the x-axis are the central-years of 15-year moving windows for the partial correlation analysis and subsequent identification of the dominant factors.

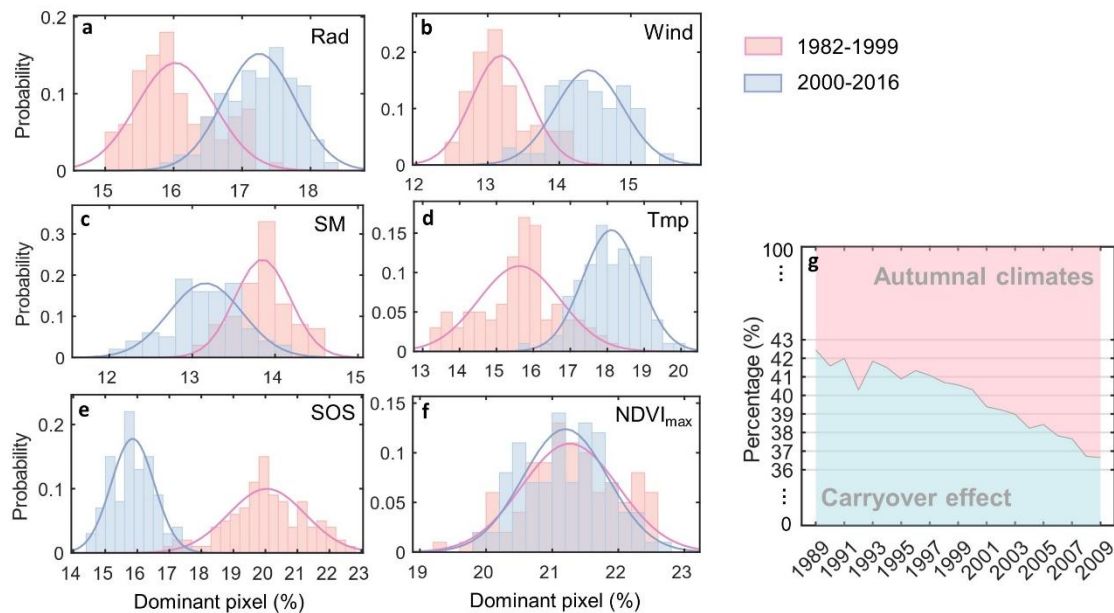


Figure 4. Underlying mechanisms for the weakened impacts of SOS on EOS. a.

Relationship between changes in length of the growing season (ΔLOS) and changes in partial

correlations between EOS and SOS ($\Delta R_{\text{EOS-SOS}}$) for two periods (1982-1999 vs. 2000-2016). **b.**

Relationship between ΔLOS and changes in mean annual temperature (ΔTmp) for two periods.

$\Delta R_{\text{EOS-SOS}}$ and ΔTmp were averaged in 1-day bins of ΔLOS if more than 50 pixels are available.

Only pixels northern of 50°N (blue lines) and meanwhile having significant $R_{\text{EOS-SOS}}$ (red lines)

were considered. *** denotes a significant level of 0.001.

