



Winter snow cover influences growing-season vegetation productivity non-uniformly in the Northern Hemisphere

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Ongoing changes in snow cover significantly affect vegetation productivity, but the actual effect of snow cover remains unclear due to a poor understanding of its lagged effect. Here, we used multisource datasets to investigate the lagged effect of snow cover on vegetation productivity in Northern Hemisphere ($> 40^{\circ}\text{N}$) ecosystems from 2000 to 2018. We found a widespread lagged effect of snow cover ($> 40\%$, $P < 0.05$) on growing season vegetation productivity (mean -73 -day lag). The effect of snow cover on vegetation productivity was underestimated by over 10% of the areas without considering regional lagged time differences. A longer lagged effect generally occurred in warm and humid areas, and areas with increased lagged time (66%) were greater than those with decreased trends. Moreover, changes in lagged effect were strongly driven by climate factors, followed by soil and topography factors. These findings emphasize the need to consider lagged time differences of snow cover when investigating snow-vegetation productivity interactions.

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Snow covers nearly half of the land surface in the Northern Hemisphere (NH) during winter¹, and it plays a fundamental role in hydrological and biogeochemical processes^{2–4}. As one of the most sensitive indicators of climate, snow cover has experienced substantial changes in NH ecosystems over the past several decades^{5–7}, and the Intergovernmental Panel on Climate Change warns that spatiotemporal changes in snow cover significantly affect vegetation dynamics, thereby altering vegetation productivity⁸. Specifically, snow cover affects vegetation productivity through various physiological and phenological processes. For example, a high snow water equivalent (SWE) not only improves soil moisture and nitrogen status, but the deep snow layer also protects vegetation from frost damage and reduces root mortality in winter, promoting vegetation productivity^{9,10}. Furthermore, delayed snowmelt typically leads to a later spring vegetation phenology and a shorter growing season, which can limit vegetation productivity¹¹. Understanding the interaction between snow cover and vegetation productivity is critical for gaining insight into climate feedback mechanisms and thus has recently attracted widespread attention^{12–16}.

Numerous efforts have been made to investigate the effect of snow cover on the growing season vegetation productivity (hereafter called vegetation productivity)^{17–19}, but findings regarding the magnitude and direction of vegetation productivity responses to snow cover changes are not always consistent. For example, in the European Alps and the Tibetan Plateau, snow cover changes were significantly correlated with vegetation productivity when seasonal scales were used^{11,20}, but no significant effect of snow cover was found at annual scales^{21,22}. Such a biased result was also obtained for different vegetation types at vegetation development stage scales, e.g., snow cover significantly affects the early vegetation productivity for grasslands in temperate China but not for forests and shrublands²³. The above studies chose to use fixed temporal scales to capture the sensitive period of snow cover affecting vegetation productivity, lacking a comprehensive understanding of the lagged effect of snow cover (hereafter called lagged effect), which may lead to inconsistent results.

In fact, vegetation productivity does not respond directly to the changes in snow cover but instead responds to actual soil hydrothermal conditions (e.g., soil temperature and moisture), and the effect of snow cover on soil hydrothermal conditions may take several weeks or months to dissipate after snowmelt^{24,25}. This leads to a time lag between changes in snow cover and their effect on vegetation productivity (i.e., the lagged effect of snow cover). Meanwhile, the direction of the lagged effect can be positive (increased snow cover increases vegetation productivity) or negative, depending on different geographical conditions²⁶. More importantly, the lagged time of snow cover (no direction) on vegetation productivity varies considerably regionally.

Although the lagged effect is a common climatic phenomenon^{27,28}, it is still unclear how long the lagged response of vegetation productivity to snow cover changes is, especially over large areas. This severely limits the understanding of snow cover-vegetation interactions and is a major knowledge gap recognized by the Arctic Monitoring and Assessment Program²⁹. Moreover, due to an insufficient understanding of the lagged effect, snow cover information is rarely used correctly in climate change impact models⁴, which increases the uncertainty in quantifying the dynamics of the vegetation carbon budget. Efforts to develop climate adaptation policies are also hampered by the difficulty of identifying the areas of NH ecosystems that may be most vulnerable to future changes in snow cover.

Here, we investigated the lagged effect on vegetation productivity in NH ecosystems (>40° N) based on multisource datasets from 2000 to 2018 and found that the main reason for underestimation of the effect of snow cover on vegetation

productivity was the neglect of regional differences in the lagged time of snow cover, which has received little attention to date. Furthermore, we identified the spatiotemporal pattern of the lagged time of snow cover on vegetation productivity and used the random forest model to determine a series of biotic and abiotic factors driving changes in the lagged time of snow cover. Our study is expected to contribute to a deeper understanding of how vegetation productivity responds to snow cover changes and to provide crucial insight for improving the assessment of snow-vegetation interactions.

Results

Underestimated impact of snow cover on vegetation productivity without considering lagged time differences. We first compared the lagged effect on vegetation productivity with and without considering regional differences in the lagged time of snow cover (WITH_LTSC and WITHOUT_LTSC). The scenario WITHOUT_LTSC was conducted at four commonly used fixed temporal scales separately, including monthly, seasonal, vegetation development stage, and whole growing season scales (Fig. 1b–m, “Methods”). The results showed that the proportion of pixels with significant correlations between snow cover and vegetation productivity was small, and the affected regions varied in different periods, which led to a large inconsistency and uncertainty in the results. For instance, the highest proportion of significant correlations was only 11.6% (at the spring scale) across different fixed temporal scales, giving the illusion that snow cover had no significant effect on vegetation productivity in most regions (Fig. 1h). In contrast, the area proportion of the lagged effect on vegetation productivity was apparently larger (45.7%, Fig. 1a) under the scenario WITH_LTSC, indicating that the sensitive period of snow cover affecting vegetation productivity cannot be captured at a fixed temporal scale.

We further merged significant correlation pixels for each fixed temporal scale (Fig. 1n–p) to quantify the difference between the two scenarios mentioned above. The results showed that the proportion of both positive and negative significant correlations between snow cover and vegetation productivity under the scenario WITH_LTSC was 12.5–38.9% ($\sim 3.3\text{--}10.1 \times 10^6 \text{ km}^2$) greater than that of the scenario WITHOUT_LTSC. Spatially, the area proportion was the least underestimated (e.g., mean of $\sim 0.3\%$ at monthly scale) in Europe compared to North America ($\sim 5.0\%$), Central Asia ($\sim 3.2\%$), and East Asia ($\sim 3.9\%$) (Fig. 1q). Among the different vegetation types, the underestimated areas of forests and shrublands were greater than those of grasslands (Supplementary Fig. 1). In addition to significantly affected areas, the magnitude of lagged effect on productivity was underestimated under the scenario WITHOUT_LTSC (Fig. 1r–u). The positive differences in absolute partial correlation coefficients between scenarios WITH_LTSC and WITHOUT_LTSC occurred in most ecosystems, especially at the vegetation development stage and whole growing season scales (over 35%). The above results were generated from the Global Orbiting Carbon Observatory-2-based solar-induced fluorescence (SIF) gross primary productivity (GPP) dataset (GOFGPP). Similarly, these underestimated phenomena were observed in three other independent productivity datasets: Moderate Resolution Imaging Spectroradiometer MOD17A2H GPP (MODGPP), Boreal Ecosystem Productivity Simulator model GPP (BEPGPP), and clear-sky contiguous SIF (CSIF) (Supplementary Fig. 2).

Spatial patterns of the lagged time of snow cover on vegetation productivity. The time scale of lagged effect was further determined and showed high heterogeneity in NH ecosystems. There was a widespread significant lagged effect (concentrated below the

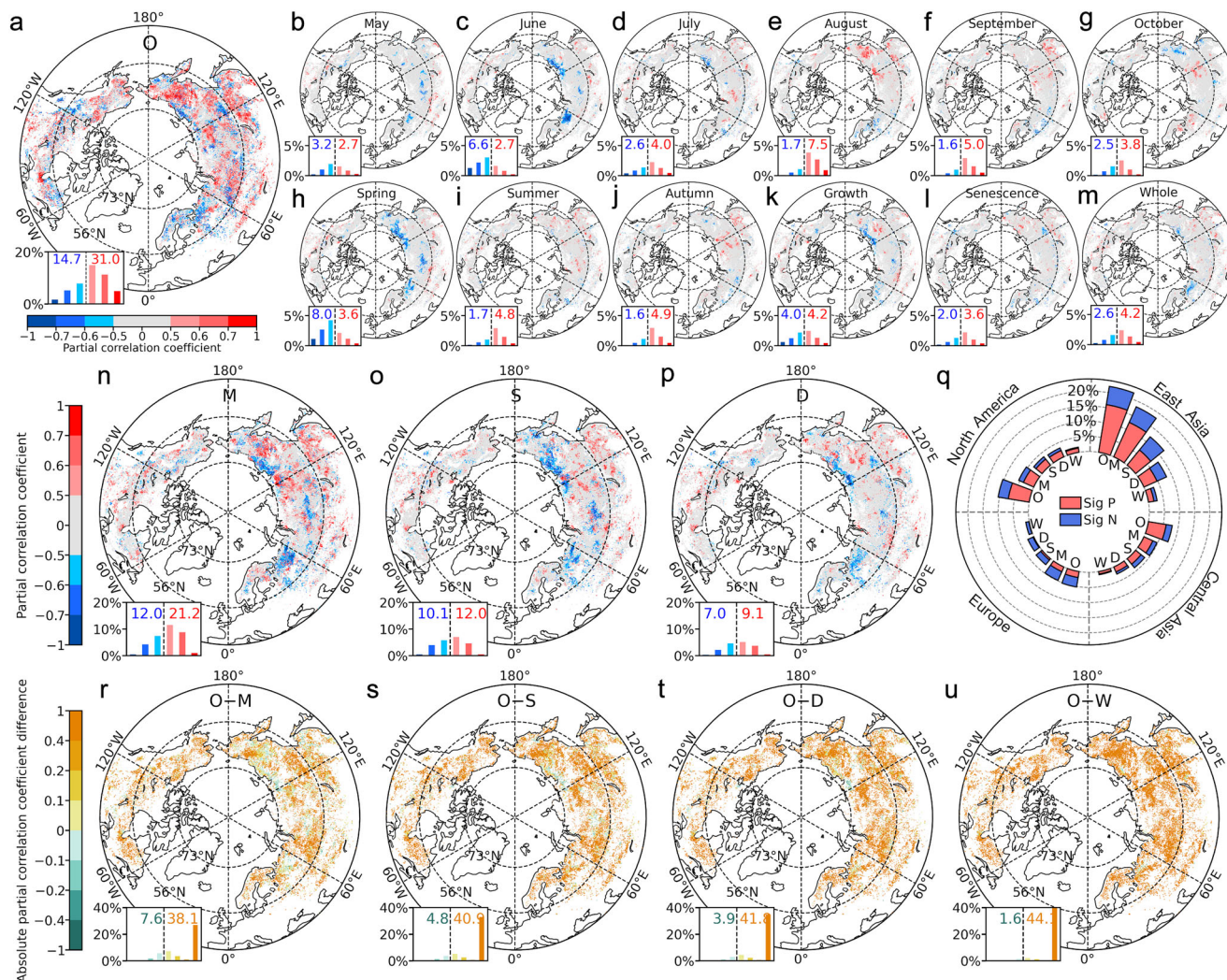


Fig. 1 Comparisons of the lagged effect on vegetation productivity (based on the GOFGPP dataset) under scenarios WITH_LTSC and WITHOUT_LTSC in Northern Hemisphere ecosystems from 2000 to 2018. **a–m** Spatial distribution of the partial correlation coefficient between SWE and vegetation productivity under scenarios WITH_LTSC (O) (**a**) and WITHOUT_LTSC (**b–m**) at monthly (May–October), seasonal (spring–autumn), vegetation development stage (growth and senescence), and whole growing season (W) scales. Non-grey pixels show significant partial correlations at $P < 0.05$. **n–p** Spatial distribution of merged partial correlation coefficients between SWE and vegetation productivity at monthly (M), seasonal (S), and vegetation development stage (D) scales. **q** Proportion of the significant positive (Sig P) and negative (Sig N) partial correlation coefficients in East Asia (90°E–180°, 40°N–90°N), Central Asia (60°E–90°E, 40°N–90°N), Europe (25°W–60°E, 40°N–90°N), and North America (180°–25°W, 40°N–90°N). **r–u** Spatial distribution of differences in the absolute partial correlation coefficient between O and M, O and S, O and D, and O and W.

105-day lag, mean ~73-day lag) on vegetation productivity (45.7% of the study area, $P < 0.05$), with a clear latitudinal pattern with a decreasing trend of 1.05-day lag from south to north (Fig. 2a). The positive lagged effect mainly occurred at relatively long lags (over a month) and peaked at ~3-month, while the negative lagged effect mainly occurred at shorter lags, and its area proportion decreased with increasing lagged time scales (Fig. 2b). Meanwhile, the absolute significant positive correlations between SWE and vegetation productivity was greater than negative correlations, which decreased with increasing lagged time scales. From the perspective of vegetation types, the mean positive lagged effect on vegetation productivity in forests (76-day lag) and shrublands (73-day lag) was longer than that in grasslands (69-day lag) (Fig. 2c). However, the mean negative lagged effect on grasslands (74-day lag) was longer than that on forests and shrublands. Additionally, the above-mentioned spatial patterns were generally similar to the results of the MODGPP, BEPSGPP, and CSIF datasets (Supplementary Fig. 3).

Temporal dynamics of the lagged time of snow cover on vegetation productivity. In general, the temporal trends in the time scale of positive and negative lagged effects from 2000 to 2018 were opposite in NH ecosystems. Specifically, four vegetation productivity proxies (GOFGPP, MODGPP, BEPSGPP, and CSIF) generally showed significant increasing (mean of $0.39 \text{ d yr}^{-1} \text{ lag}$) and decreasing (mean of $-0.45 \text{ d yr}^{-1} \text{ lag}$) trends for positive and negative lagged effects, respectively (Fig. 3a, b). Among the different vegetation types, a consistent and significant increasing trend in the time scale of positive lagged effect was observed in forests, and a significant decreasing trend in the time scale of negative lagged effect was observed in grasslands (Fig. 3c). In comparison, there was no significant increasing or decreasing trend for shrublands based on most of the observational datasets. Spatially, most of Europe and Eastern North America showed decreasing trends in the lagged time of snow cover over the last two decades, while Central and East Asia mainly showed increasing trends in the lagged time (Fig. 3d). In addition, we

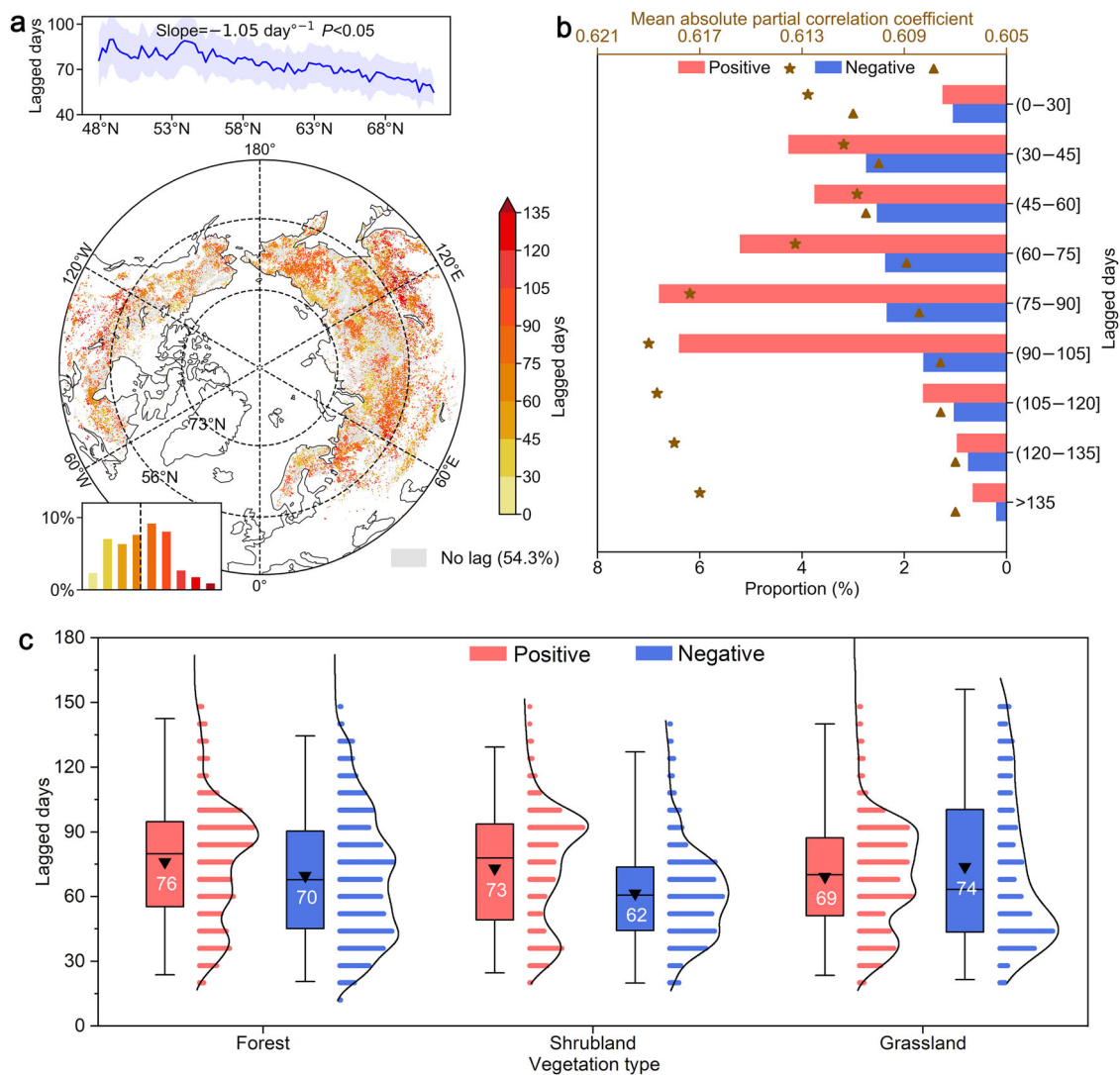


Fig. 2 Spatial patterns of the lagged time of snow cover on vegetation productivity (based on the GOFGPP dataset) in Northern Hemisphere ecosystems from 2000 to 2018. **a** Geographical and latitudinal distribution of the lagged time of snow cover. The inset histogram indicates the proportion of lagged time, and the dashed vertical line indicates the mean lagged time. The blue shaded area indicates ± 0.5 standard deviation. **b** Proportion of the significant partial correlation coefficient between SWE and vegetation productivity ($P < 0.05$) at different lagged time scales. **c** Distribution of the lagged time of the positive and negative effects of snow cover in different vegetation types. The mean value in **c** is marked by triangles (with digits), centerlines indicate the median values, whiskers indicate the $1/99$ th values, and the right part of the boxplots shows the distribution of lagged time.

tested the robustness of temporal results by applying different moving windows (11-year and 12-year) and consistent results were obtained (Supplementary Fig. 4).

Drivers of the lagged time of snow cover on vegetation productivity. Evaluating which environmental factors contribute to the lagged time of snow cover was vital to understanding the effect and underlying mechanisms of snow cover on vegetation productivity. We thus constructed random forest models to predict the time scales of positive and negative lagged effects using 12 biotic and abiotic variables closely related to snow cover status and vegetation carbon uptake (“Methods”). The models performed with moderate to high accuracy in predicting the time scales of the positive lagged effect ($R = 0.65$, $P < 0.05$) and negative lagged effect ($R = 0.76$, $P < 0.05$) (Supplementary Fig. 5), which successfully identified the most important drivers explaining positive and negative lagged effects on vegetation productivity (Fig. 4).

Based on the built random forest models, the ranked importance of the variable and the partial dependence of each

variable were acquired. The results showed that climate factors played a vital role in regulating variations in the time scales of positive (43%) and negative (39%) lagged effects (Fig. 4). The time scales of the lagged effect increased with increasing mean air temperature and precipitation and decreasing wind. This was followed by topography and soil factors, but their importance for positive and negative lagged effects differed. For example, the topography factors accounted for a larger proportion of variations in the time scale of the positive lagged effect, while soil factors did the opposite. Furthermore, some considerably important variables, such as biodiversity and soil organic carbon, had opposite effects on variations in the time scales of positive and negative lagged effects. In addition, other related factors, including land cover and human activity, showed relatively low contributions.

Discussion

Importance of considering lagged time differences when assessing the effect of snow cover on vegetation productivity. Vegetation dynamics are affected not only by concurrent climatic

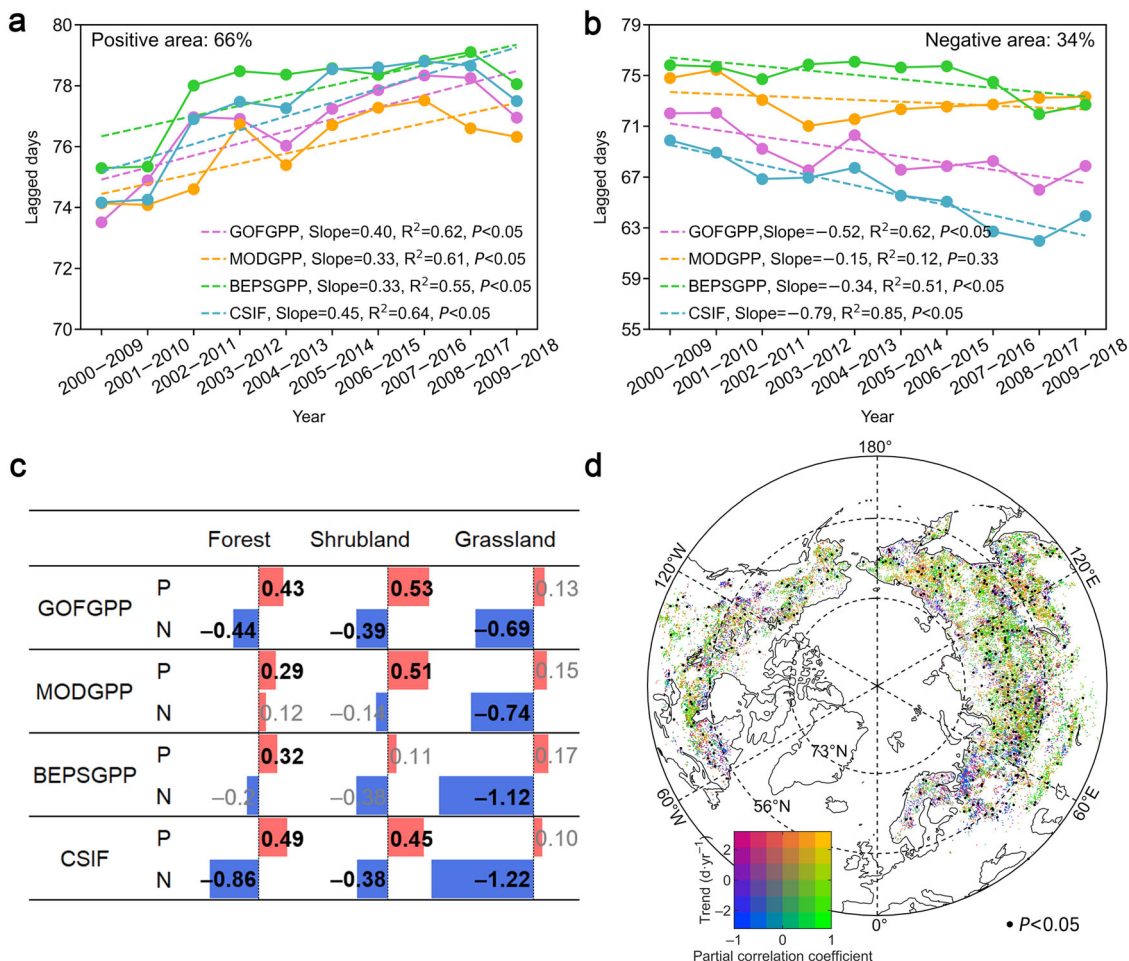


Fig. 3 Temporal dynamics of the lagged time of snow cover on vegetation productivity in Northern Hemisphere ecosystems from 2000 to 2018. **a, b** Changes in the mean lagged time of snow cover based on the 10-year moving window for positive (**a**) and negative (**b**) lagged effects, respectively. Solid and dotted lines present the mean lagged time and linear regression, respectively. **c** Trends (d yr⁻¹) of the lagged time of positive (P) and negative (N) effects of snow cover in different vegetation types, and black numbers denote the significant trend ($P < 0.05$). **d** Spatial pattern of lagged time trends averaged by GOFGPP, MODGPP, BEPGPP, and CSIF datasets.

factors but also by previous climatic factors^{30,31}. In this study, we found that the actual effect of snow cover cannot be fully revealed without considering lagged time differences (i.e., directly using a fixed temporal scale, Fig. 1). The results showed that significant variations in vegetation productivity in nearly one-half of the NH (45.7%) were related to snow cover changes (Fig. 1a). In contrast, the area proportion of the effect of snow cover on vegetation productivity was lower in the scenario WITHOUT_LTSC, where the significant areas at monthly, seasonal, vegetation development stage, and whole growing season scales were 33.2%, 22.1%, 16.1%, and 8.8%, respectively. This could explain why the document using the development stage scale reported that areas with significant snow-vegetation productivity correlations were relatively small and the magnitude of significant correlations was spatially scattered³².

In addition to finding the underestimation of the lagged effect on vegetation productivity under the scenario WITHOUT_LTSC, we improved the understanding of the lagged effect and revealed the reasons for the inconsistent findings of previous studies. Since the response time of vegetation productivity to snow cover varied in different ecosystems, the use of fixed temporal scales in previous studies proved inadequate in capturing the sensitive period of snow cover affecting vegetation productivity, even within the same region. For example, a previous study based on a vegetation development stage scale reported that snow depth has

a significant impact on early productivity for grasslands in temperate China but not for forests and shrublands²³. Conversely, another study found a significant effect of snow depth on productivity for these vegetation types using a seasonal scale²⁰. Although the lagged effect on vegetation productivity has been widely acknowledged^{12,16,19}, most observational and model simulation studies, have only used fixed response time scales to characterize the effect of snow cover. In light of these findings, we emphasize that lagged time differences should be considered to improve assessments of snow-vegetation productivity interactions.

Differences in spatiotemporal patterns of the lagged time of snow cover on vegetation productivity and underlying mechanisms. Based on multiple observational datasets, we found that the time scales of the lagged effect on vegetation productivity mainly occurred below the ~4-month time scale (mean of 73-day lag) across NH ecosystems (>40°N, Fig. 2a). The lagged effect was similar to the temporal effect of other climatic factors, such as air temperature, precipitation, and drought, which were generally shorter than a quarter of the year^{27,28,33}. The significant positive lagged effect (31% of the NH) predominated at a 2–3-month lag and was mainly distributed in Western North America, Central Siberia, and Eastern Asia, while the significant negative lagged

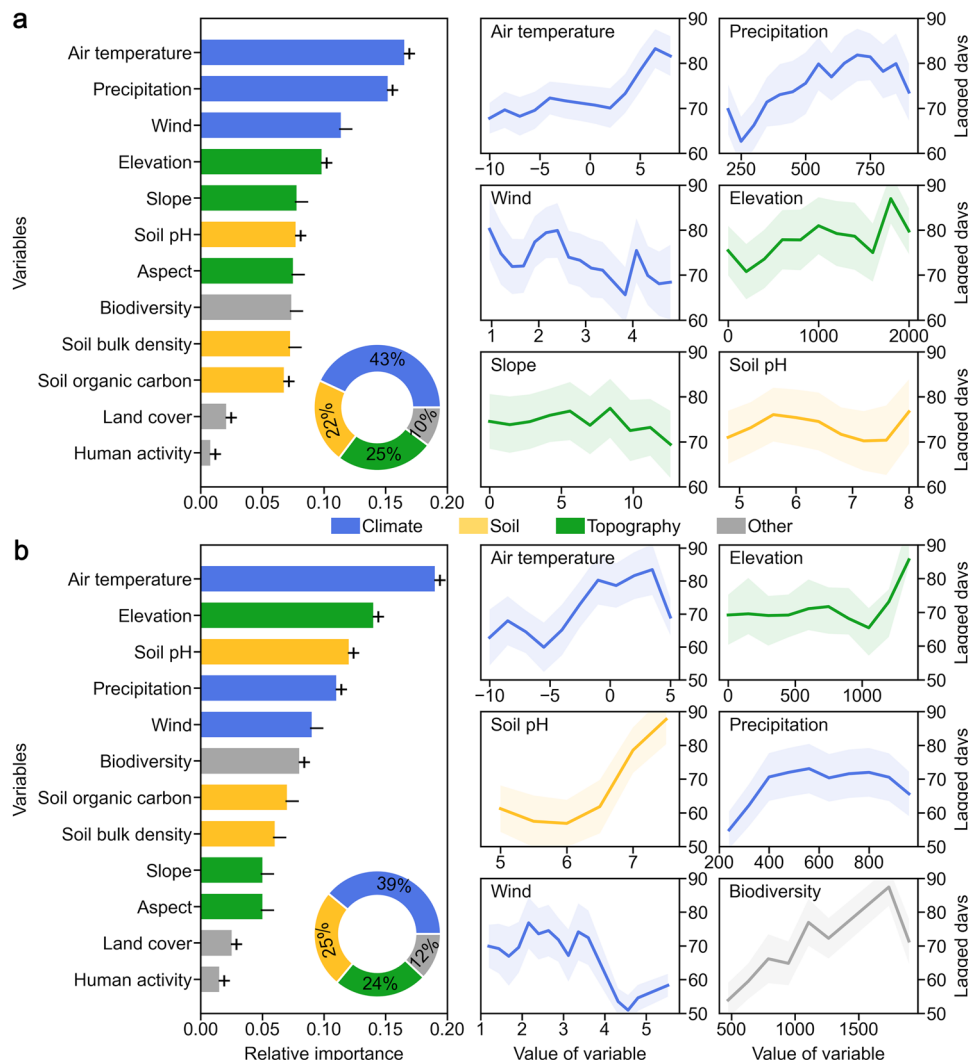


Fig. 4 Drivers accounting for the lagged time of snow cover on vegetation productivity in Northern Hemisphere ecosystems from 2000 to 2018.

a, b Ranked relative importance of four categories of factors for time scales of positive (**a**) and negative (**b**) effects of snow cover, and right line plots show the partial contribution of the six most important variables. The partial contribution plot presents the effect of an independent variable (x-axis) on the lagged time (y-axis) while controlling for the impacts of all other variables, and the shaded area indicates the 95% confidence interval. The markers “+” and “-” in the bar plots indicate positive and negative correlations between the variable and lagged time of snow cover based on the partial contribution analysis, respectively. The inset circles in the bar plots indicate the cumulative contribution of the variables from the same category.

effect (14.7%) predominated at a short-term time scale (below 2 months) and was mainly distributed in Northern Europe and Northern Canada. This difference in geographical distribution could be attributed to different major ecological processes of snow cover affecting vegetation productivity^{7,34,35}. For example, previous studies found that the “moisture effect” of snow cover predominated in Northeast China²⁰, Eastern Asia, and Western North America³², with positive snow-productivity relations. However, the negative “growth period” effect predominated in Central Europe¹⁵ and Northern Canada³², i.e., more snow cover delayed spring phenology and inhibited early vegetation productivity.

Furthermore, there was a significant increasing trend of positive lagged effect over the past two decades (Fig. 3a), especially for forests and shrublands. In comparison, a significant decreasing trend in the negative lagged effect was observed only in grasslands (Fig. 3c). These phenomena may be related to root functional traits of different vegetation. Woody vegetation with deep roots can benefit from deeper water from snowmelt infiltration, enabling them to grow in the later growing

season^{36,37}, while low herbaceous vegetation with shallow roots mainly absorbs water from snowmelt in upper soil layers and may be covered by snow more completely, resulting in the early light and heat deficits and impeding vegetation recovery in spring^{26,38}. Thus, under the same environmental change conditions, the trend of positive lagged effect trend was greater in forests and shrublands than in grasslands, while the negative lagged effect trend was greater in grasslands. Notably, the decreasing trend in the time scale of both negative and positive lagged effects mainly occurred in most parts of Northern Europe and Northern Canada (Fig. 3d). This implies that these regions would likely be subject to greater water stress in the later growing season, and therefore, more attention should be given to maintaining their ecological stability.

Attribution analysis of which environmental factors influence the lagged effect was performed to better clarify the differences in spatiotemporal patterns of the lagged time of snow cover on vegetation productivity. The factors associated with climate conditions (e.g., annual mean air temperature and precipitation) were the most important drivers of changes in the lagged time of snow cover

(Fig. 4), which agreed with previous documents that the lagged effect on vegetation growth was strongly related to heat-water conditions^{12,26,39}. Specifically, the longer-lagged effect tended to occur in high-temperature and precipitation regions. The was probably there is no permafrost in warm and humid regions⁴⁰, where snowmelt water would not immediately be lost to water runoff. This could result in more snowmelt water being retained, promoting or limiting vegetation growth³² and consequently longer positive and negative lagged effects in these regions.

It is noteworthy that some variables (biodiversity and soil organic carbon) had the opposite impact on changes in positive and negative lagged effects timescales. Ecosystems with high biodiversity generally have a greater demand for water⁴¹, and thus, the positive lagged effect tends to have a shorter time. Similarly, high biodiversity could lead to more intense competition for resources, which may exacerbate the negative lagged effect, particularly in some species struggling to obtain sufficient resources for environmental adaptation. In comparison, an increase in soil organic carbon increased soil nutrient and water infiltration^{42,43}, which in turn improved the adaptability of vegetation to snow cover and mitigated its negative duration effect. Meanwhile, high water retention (reducing water runoff) was beneficial to prolong the moisture effect of snow cover in regions with a positive lagged effect. In addition, although the human factor was identified as an important driver of vegetation productivity variations^{44,45}, it showed relatively small contributions, which was largely due to the exclusion of agricultural land and the relatively low level of human activity at mid-to-high latitudes. The deeper significance of understanding these control factors was to enable accurate predictions of the future responses of vegetation productivity to lagged effect.

Uncertainties and prospects. It is necessary to consider the uncertainties of our data and analyses. However, most of the datasets used in this study showed good agreement with station observations and were regarded as state-of-the-art datasets currently available. It inevitably causes errors when interpolated to the same spatiotemporal scale. Meanwhile, the applicability of our findings at other scales may need to be further explored due to different scale effects. The lagged effect is also expected to be related to other factors such as soil freeze–thaw cycles⁴⁶, fire disturbances⁴⁷, and extreme climate events⁴⁸. It is not feasible, however, to analyze these impacts completely at hemisphere scales in this study, and they therefore warrant further study. Moreover, a combination of long-term in situ observations, higher quality remote sensing data, and improved model simulations are needed to better understand the changes in the lagged effect on vegetation productivity in the future.

Conclusion

This study provided the first estimation of the lagged time of snow cover on vegetation productivity and its drivers in NH ecosystems from 2000 to 2018. The results showed that snow cover had a significant lagged effect on vegetation productivity in over 40% of NH ecosystems and that the lagged effect on vegetation productivity was underestimated when regional differences in the lagged time of snow cover were neglected. The positive and negative lagged effect on vegetation productivity mainly predominated at lags of ~2–3 months and 1–2 months, respectively. Furthermore, the mean time scale of the positive lagged effect increased significantly, mainly due to climate factors changes. If this trend continues, it could potentially alleviate water stress and promote vegetation productivity during the later growing season, especially in arid regions. These findings have important implications for improving the modeling of the terrestrial carbon cycle,

including the lagged effect and developing effective climate adaptation strategies in NH ecosystems.

Materials and methods

Datasets. We used two vegetation indicators to enhance the robustness of our results, namely, GPP and SIF, as proxies for vegetation productivity. Specifically, three types of GPP datasets were used, including the 8-day GOFGPP at a 0.05° spatial resolution⁴⁹, the 8-day MODGPP product at a 500 m spatial resolution⁵⁰, and the daily BEPSGPP product at a ~0.07° spatial resolution⁵¹. These GPP products demonstrated good reliability through comparisons with ground observations in different ecosystems and exhibited high agreement with one another (Supplementary Fig. 7 and Fig. 8). SIF data with a 0.05° spatial resolution were derived from the state-of-the-art 4-day CSIF product⁵², which was widely used in ecological analysis.

SWE was used to characterize snow cover status. This comprehensive parameter includes not only information on snow depth and snow density but also allows calculations related to snow cover phenology. It refers to the amount of water (mm) contained in snow cover when it is completely melted and directly affects hydrological and ecological processes⁵³. SWE data were derived from the GlobSnow daily product with a 0.25° spatial resolution, which combined SWE retrieved from multi-satellite passive microwave and ground snow depth data for non-mountainous regions. It demonstrated high stability and reliability compared to ground observations and other SWE products^{54,55} and was regarded as the best SWE product currently available for climate analysis⁵⁶.

In addition to vegetation productivity and snow cover data, several types of datasets were collected to explore drivers of the lagged effect of snow cover, including climate, soil, elevation, and human activity data. The daily air temperature, precipitation, wind, downward shortwave radiation, and soil temperature data were obtained from the ERA5-Land daily product at a 0.1° grid⁵⁷. The soil property data (soil organic carbon⁵⁸, soil bulk density⁵⁹, and soil pH⁶⁰) were extracted from the Open Land Map dataset at a 250-m grid. Elevation data were obtained from the Shuttle Radar Topography Mission (STRM) digital elevation dataset at a 90-m grid⁶¹. Human activity and biodiversity data were obtained from the LandScan Global⁶² and the plant species⁶³ datasets.

Data preprocessing. All datasets were aggregated to the same spatial resolution of 0.25°. Vegetation productivity datasets with high temporal resolution were aggregated to 8-day temporal resolution using the mean value to reduce interpolation uncertainty. We focused on the seasonal snow-dominated regions >40°N with snow cover duration >60 days (Supplementary Methods S1) and masked the non-vegetation, sparse vegetation, and cultivated areas using the ESA CCI land cover map⁶⁴. Moreover, pixels with a constant vegetation type (total study area of ~26 × 10⁶ km²) were retained for analysis to minimize the influence of land cover changes.

Estimation of the lagged effect of snow cover. Considering differences in the lagged time of snow cover on vegetation productivity in different regions, we applied an adaptive time scale based on per-pixel partial correlation analysis to identify the lagged effect on vegetation productivity. Firstly, the maximum SWE (SWE_{max}) within snow cover duration was extracted to indicate SWE status since it can reflect the amount of snowmelt for the whole snow cover season compared to the mean SWE. Secondly, the partial correlation coefficient (PCC) between SWE_{max} and vegetation productivity of each period (*istep*) was computed (Eq. 1) during the growing season, removing the effects

of the pre-season and current mean air temperature, precipitation, solar radiation, and wind. Additionally, all variable data were detrended before correlation analysis. Then, the optimal lagged effect on vegetation productivity was determined when the absolute significant maximum PCC ($|R_{\max\text{-lag}}|$ at $P < 0.05$) occurred (Eq. 2), and the $R_{\max\text{-lag}}$ was regarded as the magnitude of lagged effect (the direction of $R_{\max\text{-lag}}$ could be either positive or negative). Finally, the corresponding time (DOY) of $R_{\max\text{-lag}}$ subtracted by snow cover end date (SCED, Supplementary Methods S1) was identified as the time scale of the lagged effect (Eq. 3). Namely, the lagged time of snow cover was the difference between SCED and the date when the response of vegetation productivity to snow cover was the strongest.

$$r_{i\text{step}} = \text{PCC}(SWE_{\max}, VP_{i\text{step}}), i = (1, 2, 3, \dots, n), \text{SOS} \leq i\text{step} \leq \text{EOS} \quad (1)$$

$$R_{\max\text{-lag}} = \max(r_{1\text{step}}, r_{2\text{step}}, r_{3\text{step}}, \dots, r_{n\text{step}}), -1 \leq R_{\max\text{-lag}} \leq 1 \quad (2)$$

$$\text{Lagged time} = \text{DOY}_{R_{\max\text{-lag}}} - \text{SCED} \quad (3)$$

where $r_{i\text{step}}$ is the PCC with a lagged period of $i\text{step}$; EOS is the end of the growing season (Supplementary Methods S2); $VP_{i\text{step}}$ is the vegetation productivity with a lagged time interval of $i\text{step}$ ($i\text{-step}$ lag); and step is the temporal resolution of vegetation productivity datasets (8-day). Only pixels with SCED below the start of the growing season (SOS) were retained for analysis.

Analysis of spatiotemporal dynamics of the lagged time of snow cover on vegetation productivity. We first calculated the partial correlation coefficient between snow cover and vegetation productivity at four fixed temporal scales to investigate the lagged effect on vegetation productivity under scenarios WITH_LTSC and WITHOUT_LTSC. The fixed temporal scales included monthly (six periods: May–October), seasonal (three periods: spring (May–June), summer (July–August), and autumn (September–October)), vegetation development stages (two periods: growth and senescence), and the whole growing season. Growth and senescence were defined as the increasing and decreasing vegetation productivity phases, respectively⁶⁵. Due to the regional differences in the lagged effect on vegetation productivity at different fixed temporal scales, we then merged the lagged effect on vegetation productivity at monthly, seasonal, and vegetation development stage scales, respectively, based on the significant partial correlation coefficient between snow cover and vegetation productivity, and quantified the difference between the scenarios WITH_LTSC and WITHOUT_LTSC.

Next, we analyzed the time scale of the lagged effect at different biome scales. Three typical vegetation types were analyzed, including forests, shrublands, and grasslands. The classes of broadleaf, coniferous, and mixed forests were grouped into forest class based on the ESA CCI land cover map. Finally, temporal variations in the lagged time of snow cover on vegetation productivity were examined using a 10-year moving window. We calculated the lagged effect over the NH with each moving window from 2000 to 2018 using four vegetation productivity datasets. The mean value of all pixels in each moving window was used to evaluate the overall temporal dynamics of the lagged time of snow cover. Meanwhile, 11-year and 12-year moving windows were also used to enhance the temporal results (Supplementary Fig. 4). Furthermore, we used the Theil–Sen method⁶⁶ for slope calculation and the modified Mann–Kendall test method⁶⁷ for trend detection in time series of the lagged effect.

Identification of drivers of the lagged time of snow cover on vegetation productivity. The random forest method was used to quantify the relative contributions of drivers to the time scale of

the lagged effect on vegetation productivity in NH ecosystems. It is a data-driven machine learning algorithm based on a bootstrap aggregating strategy, which not only has a strong predictive ability but also evaluates the importance of features⁶⁸. Four categories of environmental factors were considered in the contribution analysis (Supplementary Table 1), including climate, soil, topography, and other related factors.

Among these, we calculated the annual mean air temperature, mean total precipitation, mean wind, and mean solar radiation as climate factors that were important limiting factors. For soil factors, we took soil properties such as soil organic carbon, soil pH, and soil bulk density into account since they were strongly related to vegetation photosynthetic rates and dynamics of soil resource distribution. Topography factors include elevation, slope, and aspect. Meanwhile, other factors closely related to snow cover changes and vegetation growth were extracted, including the human activity impact, land cover types, and biodiversity (number of plant species). All variables were first standardized using the Z-score method to eliminate the effect of numerical differences in different variables.

For the time scales of positive and negative lagged effects, we separately developed two random forest regression models. The lagged time of snow cover and four types of factors were regarded as response variables and explanatory variables, respectively. For each model, we randomly stratified to use 80%/20% of the data to train/test the model and used the correlation coefficient and mean absolute error to evaluate the performance of models. Although collinearity between variables would not influence the accuracy of the random forest model, it did affect the ranking of variable importance⁶⁹. We further used the variance inflation factor (VIF) method to exclude the strong collinearity variable (i.e., solar radiation (VIF > 3), Supplementary Fig. 6). The optimal parameters (numbers of estimators, maximum features, and maximum depth) for each model were then determined based on the training data (Supplementary Table 2). Finally, according to the out-of-bag score of the model, we ranked the importance of each explanatory variable to characterize the contribution of drivers to lagged time and evaluated how variables regulated its changes. Note that we repeated the run ten times for each model to avoid random errors and averaged the results of 10 runs as the final result.

Data availability

All datasets used in the study are openly available. The MODGPP, GOFGPP, BEPSGPP, and CSIF data are available at <https://pdaac.usgs.gov/products/mod17a2hv006>, <https://cstr.cn/15732.11.nesdc.ecodb.2016YFA0600200.02.001>, https://data.globalecology.unh.edu/data/GOSIF-GPP_v2/, and <https://osf.io/8xqy6/>, respectively. Snow cover data from the GlobSnow v3.0 product are available at <https://www.globsnow.info/swe/>. Air temperature, precipitation, wind, solar radiation, and soil temperature data from the ERA5-Land product are available at <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=form>. The plant species datasets are available at <https://databasin.org/datasets/43478f840ac84173979b22631c2ed672/>. The data for plotting the figures in the study are available at <https://zenodo.org/records/10252501>.

Code availability

The processing codes for analysis are available from the corresponding author on request.

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Author contributions

P.X., X.Z., and H.L. conceived and designed the study. H.L. conducted the analysis and drafted the paper. S.C., Y.W., and W.W. processed data. All authors contributed to the interpretation of results and paper revision.

Competing interests

The authors declare no competing interests.

Additional information

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