

ARTICLE

Climate Ecology

Unraveling the effects of snow cover change on vegetation productivity: Insights from underlying surface types

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Funding information

National Natural Science Foundation of China, Grant/Award Number: 42171307; "GeoX" Interdisciplinary Research Funds for the Frontiers Science Center for Critical Earth Material Cycling, Nanjing University

Handling Editor: Yude Pan

Abstract

Changes in snow cover have an important effect on vegetation gross primary productivity (GPP), but the role of underlying surface types in this effect still remains unclear. The underlying surface refers to the surface of the Earth and is located at the bottom of the snow cover during the snow season. Here, we focus on the influence of snow cover change on GPP in Northeast China from 1982 to 2015, revealing the various dependencies of the association between snow cover and GPP on forest, grassland, and dryland. The results show that the increases in GPP in dryland and grassland are primarily influenced by the increase in snow water equivalent, while the variations in GPP in forest are primarily influenced by snow phenological indicators, with snow cover end date and snow cover days dominating GPP in the early and peak growing seasons, respectively. Additionally, snow cover can have a rather strong time-lagged effect on GPP by changing the soil temperature in dryland. Our findings emphasize the importance of considering underlying surface types in the snow–GPP relation and provide insight into how climate change may affect ecosystems in regions with comparable underlying surface types.

KEYWORDS

gross primary productivity, Northeast China, snow cover change, underlying surface type

INTRODUCTION

Escalating global warming and an associated change in snow cover are identified to have complex effects on the regional carbon cycle (Knowles et al., 2018; Qiu et al., 2019; Zeeman et al., 2017). As the measurement of vegetation carbon uptake through photosynthesis, gross primary productivity (GPP) is an essential part of the terrestrial environment, contributing to offsetting carbon emissions and balancing the carbon budget (Beer et al., 2010;

Lewis et al., 2009). Meanwhile, GPP is an important proxy index of vegetation growth, with greater productivity indicating increased vegetation greening (Rumpf et al., 2022). As a connection between the ground surface and the atmosphere, snow can strongly affect vegetation growth by altering soil, radiation, water, and so on (Callaghan et al., 2011; Chen, Huang, & Wang, 2019; Chen, Ju, et al., 2019; Slatyer et al., 2022), thus having considerable impacts on GPP.

Changes in snow cover can affect GPP in various ways, such as by influencing soil hydrothermal

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conditions and altering the start and end of the growing season (Mark et al., 2015; Matsumura et al., 2010; Matsumura & Yamazaki, 2012; Piao et al., 2017), and different snow cover indicators dissimilarly impact GPP (Galvagno et al., 2013; Knowles et al., 2017; Scholz et al., 2018; Wipf & Rixen, 2010). An earlier snow cover end date (SCED) enhances carbon uptake by advancing spring phenology (Pulliainen et al., 2017). The length of the growing season is negatively correlated with snow cover days (SCDs), which means that longer SCD may lead to lower GPP (Choler, 2015). Additionally, the augmentation of snow water equivalent (SWE) can enhance GPP by elevating the soil moisture in water-limited areas (Chen, Huang, & Wang, 2019; Chen, Ju, et al., 2019) and raising soil temperature due to its insulating effect (Freppaz et al., 2008).

However, the reactions of GPP to snow cover change could be inconsistent under different conditions (Humphreys & Lafleur, 2011; Wang, Wang, et al., 2018; Wang, Wu, et al., 2018; Winchell et al., 2016; Zona et al., 2022). Thicker snowpack with warmer soil may hinder vegetation growth by delaying spring phenology in some plants (Yu et al., 2013). If the water lost during springtime evaporation cannot be made up by summer precipitation, increased snow cover, which promotes vegetation growth in the early growing season, can also induce water stress and constrain GPP in summer (Wang, Wang, et al., 2018; Wang, Wu, et al., 2018; Yu et al., 2013). In addition, the impacts of snow cover change on vegetation productivity vary throughout the growing season and can even lead to opposite outcomes. For instance, less SWE and earlier SCED are associated with lower early growing season GPP despite the extended growing season due to the influence of snow aridity, while SWE is negatively correlated with the late growing season GPP (Knowles et al., 2018). Such results illustrate the complexity and heterogeneity of the impacts and mechanisms of snow cover change on vegetation productivity, but it is unclear what factor primarily governs the snow–GPP relation.

In general, the heterogeneity in the snow–GPP relation could be associated with differences in hydrothermal conditions, topography, and underlying surface types. For instance, earlier snowmelt greatly enhances carbon uptake in a high Arctic tundra (Lund et al., 2012), while reduced vegetation productivity is caused by the loss of winter snow in shrubs in northern Sweden (Bokhorst et al., 2008). In the Sierra Nevada Mountains of California, the effects of snow cover on forest productivity are elevation-dependent, reaching a peak in the mid-elevations with water restrictions (Trujillo et al., 2012). The response of tundra productivity to delayed snowmelt strongly depends on local water

and temperature constraints in Alaska (Kim et al., 2021). However, when exploring the role of hydrothermal conditions and topographic conditions, studies usually unravel the impacts of changing snow cover on vegetation productivity based on a specific underlying surface type. The underlying surface refers to the surface of the Earth and is located at the bottom of the snow cover during the snow season, which can highlight the effects of snow cover on the underlying vegetation and soil during the snow season. Besides, the underlying surface type is a comprehensive reflection of the regional environment, as heavily influenced by climate conditions, terrain, elevation, latitude, and soil. A consistent message emerges from these studies: the types of underlying surface have a significant impact on how changing snow cover affects vegetation productivity.

It is anticipated that the different underlying surface types would cause dissimilarities in the direction and magnitude of the snow–vegetation growth relation (Peng et al., 2010; Qi et al., 2021). For grassland, the start of the growing season is strongly regulated by snow depth (Yu et al., 2013), and decreased snow cover leads to a substantial seasonal uptake of carbon dioxide (Zeeman et al., 2017). For forest, studies have shown that boreal springtime carbon uptake can be significantly promoted by early snowmelt (Pulliainen et al., 2017), and snow-driven changes can explain up to 25% of the annual carbon sink enhancement (Yu et al., 2016). Regarding cropland, snow depth greatly influences soil moisture, which may in turn have an impact on the areas suitable for crop cultivation (Li et al., 2022; Liang et al., 2020). Although the impacts of snow cover change on GPP based on one specific type of underlying surface have been studied extensively, investigations of the comprehensive role of various underlying surface types in the snow–GPP relation are rare, and opinions on the magnitude and direction of these effects are widely divergent.

Northeast China (NEC) is taken as the study area to thoroughly characterize the snow–GPP relation from insights into underlying surface types in this study. NEC is one of the three major regions in the country that experiences stable seasonal snow cover (Huang et al., 2016) and has diverse ecosystems, such as forests, grasslands, and croplands, with large carbon stocks in terrestrial ecosystems (Mo et al., 2014; Wang et al., 2010; Xin et al., 2020). Besides, NEC has witnessed the most significant rise in mean annual temperature in China (Piao et al., 2010). Hence, it is optimal to investigate the potential effects of snow cover changes on GPP in different underlying surface types within the context of climate change in the NEC region.

This study aims to comprehensively disentangle the effects and mechanisms of snow cover change on GPP in different underlying surface types based on long-term

remote sensing data. In particular, our objectives are to (1) unravel the impacts of variations in snow cover on GPP across different underlying surface types, (2) identify the dominant indicators of snow cover that exert the most significant influence on the snow–GPP relation determined by underlying surface types, and (3) elucidate the mechanism of snow cover change on GPP, considering the diverse underlying surface types. The results will advance the scientific comprehension of the relation between snow and vegetation and provide insight into how climate change may affect ecosystems in regions with comparable underlying surface types.

MATERIALS AND METHODS

Study area

NEC covers an area of 1.24 million km² (115°05′–135°02′ E, 38°40′–53°34′ N). The topography of NEC is complex

and diverse, with the northwestern, northeastern, and southeastern parts surrounded by the Greater Khingan Mountains, Lesser Khingan Mountains, and Changbai Mountains, and the central part distributed by the Sanjiang Plain, Songnen Plain, and Liao River Plain from north to south (Figure 1). The annual mean temperature and precipitation are −4 to 12°C from north to south and 250–1100 mm from west to east, respectively (Mao et al., 2012). NEC has a cold and extended winter period characterized by a mean temperature of −12.37°C, a snow duration of up to 8 months, and a maximum annual snow depth of over 30 cm (Ao et al., 2021; Guo et al., 2022). Besides, NEC boasts rich terrestrial ecosystems, including forests, cropland, and grassland, with vast carbon reserves. Its natural forest region is the largest in China, constituting a vital carbon pool (Yin et al., 2022). Meanwhile, the region has a significant proportion of cropland (including dryland and paddy field), producing almost one third of China's grain (Chen et al., 2012). At the same time, the maximum total carbon

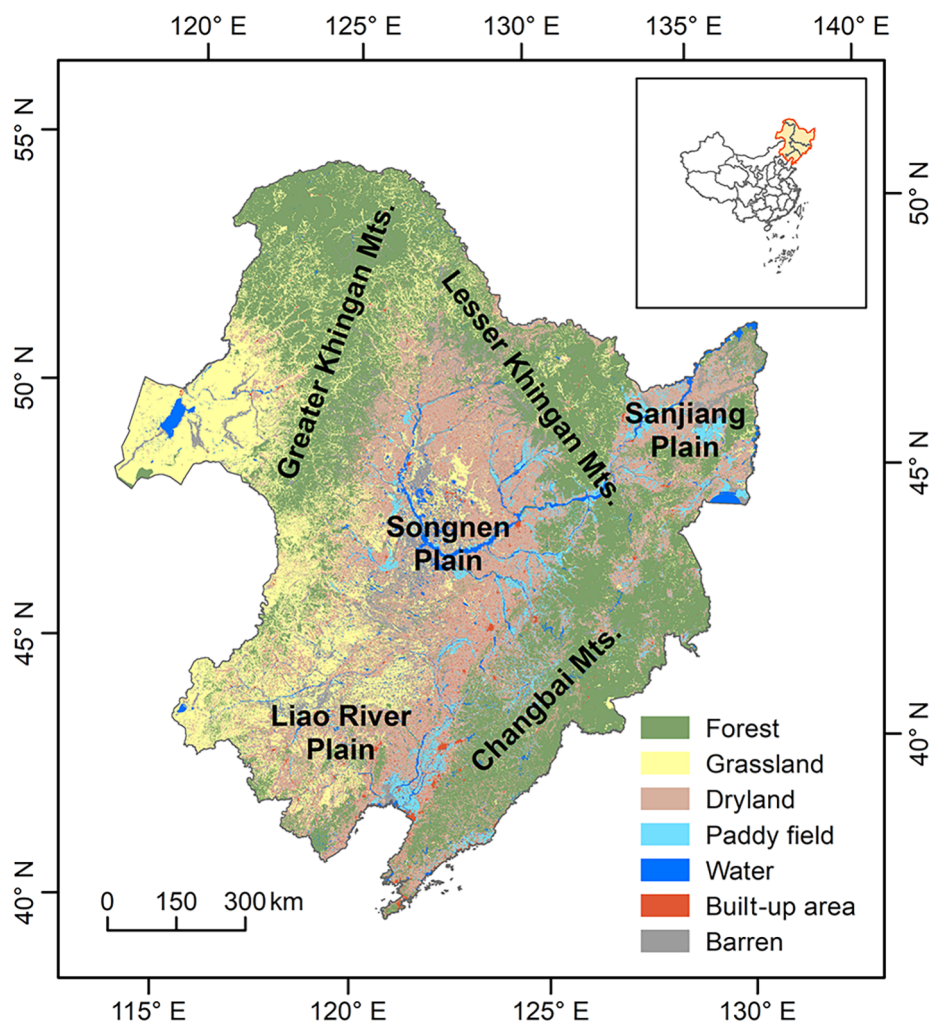


FIGURE 1 Geographical location, underlying surface types, and general geographic features of Northeast China. Mts., Mountains.

uptake reduction in grassland has been found in the center of NEC (Ren et al., 2007). Therefore, with typical and multiple underlying surface types, ample snow cover, large stores of carbon, and a substantially changing climate, NEC is an optimal area for conducting this study.

Datasets

The datasets utilized in this study include snow cover, GPP, Normalized Difference Vegetation Index (NDVI), underlying surface types, climate data, soil moisture, and soil temperature.

Snow cover indicators were acquired from the Advanced Very High Resolution Radiometer (AVHRR) snow cover extent (SCE) dataset (Hao, 2021; Hao et al., 2021) and the China snow depth long time series dataset (Che, 2019; Che et al., 2008; Dai et al., 2015). The daily SCE dataset with a spatial resolution of 5 km from 1981 to 2019 was derived from AVHRR data through a cloud detection, snow discrimination, and a gap-filling algorithm. The overall accuracy of the SCE dataset has reached 87.4%, as validated by ground snow depth measurements. The snow phenology was calculated using the SCE dataset, including SCD and SCED. The daily snow depth dataset with a spatial resolution of 25 km from 1979 to 2016 in China used different passive microwave brightness temperature data through intercalibration to increase the consistency of snow depth. This dataset was proven to present the highest accuracy of snow depth in NEC (Che et al., 2016). The annual maximum SWE (SWE_{max}) was extracted from the snow depth dataset.

The daily GPP dataset from 1981 to 2019 with a $0.07^\circ \times 0.07^\circ$ grid was generated by the boreal ecosystem productivity simulator (BEPS), which is an ecological process-based model driven by atmospheric CO_2 concentration, meteorological information, and vegetation characteristics (Liu et al., 1997). BEPS has been successfully and extensively applied for simulating terrestrial carbon flux (Chen, Ju, et al., 2019; Chen, Huang, & Wang, 2019; Liu et al., 2014, 2022; Wang et al., 2021). The daily GPP dataset has the highest temporal resolution among the existing long-term GPP data products, allowing for a more accurate assessment of the impacts of snow cover change on GPP. To evaluate the accuracy of the daily

GPP dataset for NEC, we used two flux tower sites collected from the FLUXNET2015 dataset for validation (Table 1). When the Nash–Sutcliffe efficiency (NSE) surpasses 0.5, the performance of the simulation is considered satisfactory, and when the NSE exceeds 0.65, the simulation is very good (Moriassi et al., 2007). The results showed that the daily GPP dataset performed well in NEC.

NDVI was provided by the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI3g 15-day dataset with a $1/12^\circ \times 1/12^\circ$ grid from 1981 to 2015. As the longest NDVI dataset in existence, GIMMS NDVI3g has been extensively used in studies of vegetation (Pinzon & Tucker, 2014; Ye et al., 2021). We used the NDVI dataset to calculate vegetation phenology and divide the growing season in this study.

The underlying surface type data were acquired from the 1-km land use dataset in China from 1980 to 2015 (Xu et al., 2018). The dataset includes land use data in 1980, 1990, 1995, 2000, 2005, 2010, and 2015. A two-level classification scheme is used for this dataset. The first level includes six categories, forest, grassland, cropland, water, built-up area, and barren, and the second level includes 23 types. Specifically, cropland is divided into dryland and paddy field. Most dryland crops are rainfed in NEC, which implies that the water source is mostly natural precipitation rather than artificial irrigation water (Yang et al., 2015). Considering that paddy fields are mostly distributed in areas with abundant water sources and guaranteed irrigation, the impact of snow on GPP is significantly reduced, especially through the influence of soil moisture. As crops cultivated on dryland directly and strongly depend on soil moisture to grow (Li et al., 2022), we use dryland for analysis without considering paddy field. To prevent the interference effect caused by changes in the type of underlying surface from 1980 to 2015, we extracted areas where the land cover did not change over the study period for analysis. Considering that the impacts of snow cover change on GPP can vary among underlying surface types, we investigated the role of three major vegetation types, forest, grassland, and dryland, in this study.

Daily climate data, including radiation, precipitation, and daily temperature, were provided by the China Meteorological Forcing Dataset (CMFD) from 1979 to

TABLE 1 Flux tower site information and validation results.

Site_ID	Time period	Vegetation type	Latitude	Longitude	NSE	NRMSE
CN-Cha	2003–2005	Forest	42.40	128.10	0.79	0.13
CN-Cng	2007–2010	Grassland	44.59	123.51	0.50	0.13

Note: The Nash–Sutcliffe efficiency (NSE) and normalized root mean squared error (NRMSE) were calculated.

2018 with a $0.1^\circ \times 0.1^\circ$ grid (Yang & He, 2019). The CMFD has been validated to have good performance at various independent stations and to be utilized extensively in climatic studies (He et al., 2020; Yang et al., 2010).

Soil moisture data and soil temperature data were acquired from the Global Land Evaporation Amsterdam Model (GLEAM) daily root-zone soil moisture version 3.5a dataset and the ERA5-Land hourly soil temperature dataset separately. Soil moisture data, which span the years 1980–2021 of $0.25^\circ \times 0.25^\circ$, have been proven to perform well in the validation of all plant types from 43 stations (Martens et al., 2017; Miralles et al., 2011). Daily soil temperature data were derived from the mean values of the hourly ERA5-Land dataset with a $0.1^\circ \times 0.1^\circ$ grid from 1950 to the present, which has been proven to be cutting-edge and widely used in ecological research (Muñoz-Sabater, 2019; Muñoz-Sabater et al., 2021). Soil moisture and soil temperature data were used for mechanism analysis in this study.

Due to the fact that GIMMS only provides data till 2015 and the temporal coverages of the other datasets exceed the NDVI dataset, the study period was restricted to 1982–2015, in accordance with the NDVI series. Additionally, each dataset was resampled to a geographic resolution of 5 km using the nearest neighbor resampling method.

Calculation of snow cover indicators and vegetation phenology

Snow indicators, including $SWE_{\max}$, SCED, and SCD, were used for analysis, as these indicators have been proven to strongly impact vegetation growth. SWE is defined as the product between the depth and density of the snow layer. We adopted 0.18 g cm^{-3} as the snow density in this study because it is the mean value of NEC based on in situ snow course data (Yang et al., 2019). $SWE_{\max}$ is the maximum value of SWE in a hydrological year (from September 1 to August 31 of the following year), which is used as a proxy for snow cover magnitude (Marshall et al., 2019). The final day of the last 5 days in a row with snow cover is defined as SCED in a hydrological year (Sun et al., 2020). The determination of SCD is the total number of days with snow cover in each hydrological year. Besides, the snow cover onset date (SCOD), which is the first day of the first 5 days in a row with snow cover, is also calculated for mechanism analysis.

The dynamic change in vegetation growth in the whole year (WY) can be divided into three stages: the early growing season (EGS), the peak growing season (PGS), and the late growing season (LGS) (Lian

et al., 2021). We extracted the upturn date (UD) as the time when NDVI starts to increase consistently, the stabilization date (SD) as the time when NDVI reaches maximum, the downturn date (DD) as the time when NDVI begins to constantly decrease, and the recession date (RD) as the time when NDVI approaches a seasonal low based on the Gu method (Gu et al., 2009), which has been widely applied for phenological studies (Diao & Li, 2022; Filippa et al., 2018; Richardson et al., 2021; Snyder et al., 2016; Zhang et al., 2018). We defined EGS as days between UD and SD, PGS as days between SD and DD, and LGS as days between DD and RD. As snow cover has the most direct influence on the vegetation growth in EGS and the vegetation growth in PGS directly reflects the vegetation growth throughout the WY (Zhang et al., 2022), we only calculated the effects of snow cover change on GPP in EGS and PGS.

Statistical analysis

To explore the spatiotemporal dynamics of snow cover and GPP, we first calculated the annual mean values of snow cover indicators ($SWE_{\max}$, SCED, and SCD) and GPP from 1982 to 2015, obtained their temporal trends of anomaly values using the Theil–Sen method, and examined the trends using the Mann–Kendall test. Then, the partial correlation coefficients between snow indicator anomalies and GPP anomalies in EGS and PGS are calculated to explore the snow–GPP relation, controlling the impacts of meteorological data (air temperature, precipitation, and solar radiation). Besides, as the partial correlation analysis excludes the influence of meteorological factors, the possibility of circular reasoning caused using the GPP data generated by the ecological process-based model to participate in the analysis is also avoided. Stepwise regression, a powerful method for choosing a subset of effects for a regression model, is used to explore the dominant snow cover indicator anomalies among $SWE_{\max}$, SCED, and SCD in the snow–GPP relation in EGS and PGS. In the stepwise regression procedure, bidirectional elimination, which is a combination of forward and backward selection processes, is adopted as the selection approach. This method allows for the addition or removal of variables at each stage, ensuring a thorough exploration of predictor variables while maintaining statistical rigor. We utilized the F test as our criterion for stepwise regression to ascertain the significance of variable addition or removal, and the α -value adopted in this study is 0.1.

We used the partial least squares structural equation modeling (PLS-SEM) to examine the mechanisms of snow cover change on GPP because it can estimate

complex cause–effect relations with less demand for samples and there is no need for data to conform to the normal distribution. PLS-SEM can test a theoretical model from a prediction perspective, and then the model can be modified based on the goodness of fit (GOF). When the GOF is higher than 0.36, the performance of the model is considered to be good (Wetzels et al., 2009). The model quantifies three influence paths (Figure 2): the first is the “soil moisture effect,” indicating that snow has a direct influence on soil moisture and subsequently affects GPP; the second is the “soil temperature effect,” which means changes in snow cover can affect GPP by altering soil temperature; and the third is the “growing period effect,” meaning that snow cover change can have an impact on GPP by changing the start and end of the growing season. The path coefficient is used to describe the magnitude and direction of the relation between two variables, and the “influence effect” of a path can be regarded as the product of the standard path coefficients along the path. For instance, the “soil temperature effect” in the SCD–GPP relation can be quantified as the product of the standard path coefficient between SCD and soil temperature and the standard path coefficient between soil temperature and GPP. The impacts of meteorological factors (solar radiation, air temperature, and precipitation) are considered in the model: on the one hand, to better fit the path of snow cover affecting GPP, and on the other hand, to alleviate the risk of circular reasoning arising from the GPP data simulated using the BEPS model. The intermediate factors (including soil moisture and soil temperature) and meteorological factors are calculated from SCOD to SD and DD, which are the end dates of EGS and PGS, respectively. The analysis is restricted to pixels, with a significant snow–GPP relation ($p < 0.1$). All variables

are standardized to eliminate the effect of different units before conducting the analysis.

RESULTS

Spatiotemporal dynamics of snow cover and GPP

The spatial distribution and interannual variations in snow cover indicators (SWE_{max} , SCED, and SCD) and GPP (in WY, EGS, and PGS) in NEC from 1982 to 2015 are shown in Figures 3 and 4. All snow cover indicators exhibit similar distribution characteristics, with more snow distributed in mountains (mainly forest) and less snow distributed in plains (mainly dryland), ascending step by step from southwest to northeast. The Greater Khingan Mountains have the latest SCED (>90 day of year) and longest SCD (>120 days), majorly as a result of the high latitude and elevation. The distribution of GPP is similar to that of snow cover, which is high in the mountains and low in the plains. The highest GPP in all stages of the growing season exists in the Changbai Mountains, mostly exceeding 1500 g C m^{-2} in the WY, 300 g C m^{-2} in the EGS, and 750 g C m^{-2} in the PGS. Snow cover and GPP are both low in the Liao River Plain, probably because of the low latitude and underlying surface types of dryland and grassland.

The interannual variations in SWE_{max} , SCED, and SCD anomalies show great spatial heterogeneity in NEC (Figure 4a–c). SWE_{max} anomalies mainly increase in the Sanjiang Plain and part of the Songnen Plain, and 29.9% of dryland exhibits a significant increasing trend ($p < 0.1$). Part of the Greater Khingan Mountains and Lesser Khingan Mountains show a significant decreasing

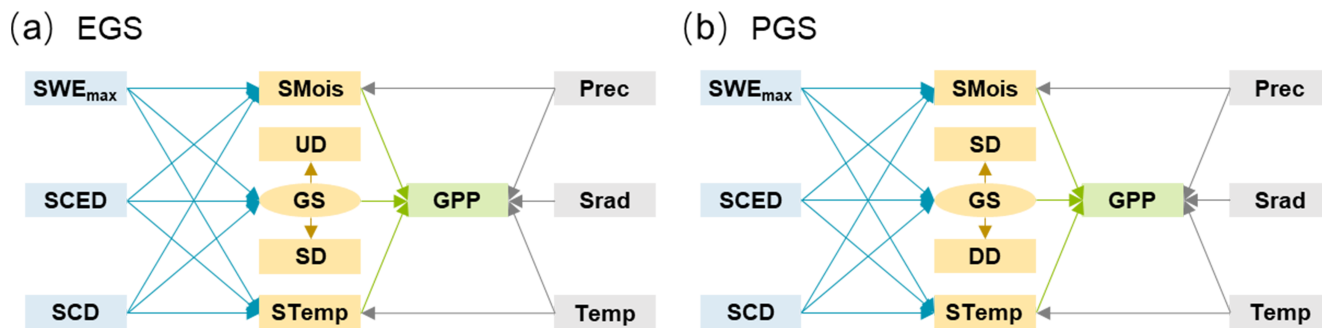


FIGURE 2 Mechanism models of snow cover change on gross primary productivity (GPP) in the early growing season (EGS) and peak growing season (PGS). As a latent variable, growing season (GS) includes the start and the end of the growing season. Specifically, for EGS, the season initiates at the upturn date (UD) and concludes at the stabilization date (SD), while for PGS, it begins at SD and concludes at downturn date (DD). Meteorological factors including precipitation (Prec), air temperature (Temp), and solar radiation (Srad) are also considered in the model. SCD, snow cover days; SCED, snow cover end date; SMOis, soil moisture; STemp, soil temperature; SWE_{max} , annual maximum snow water equivalent.

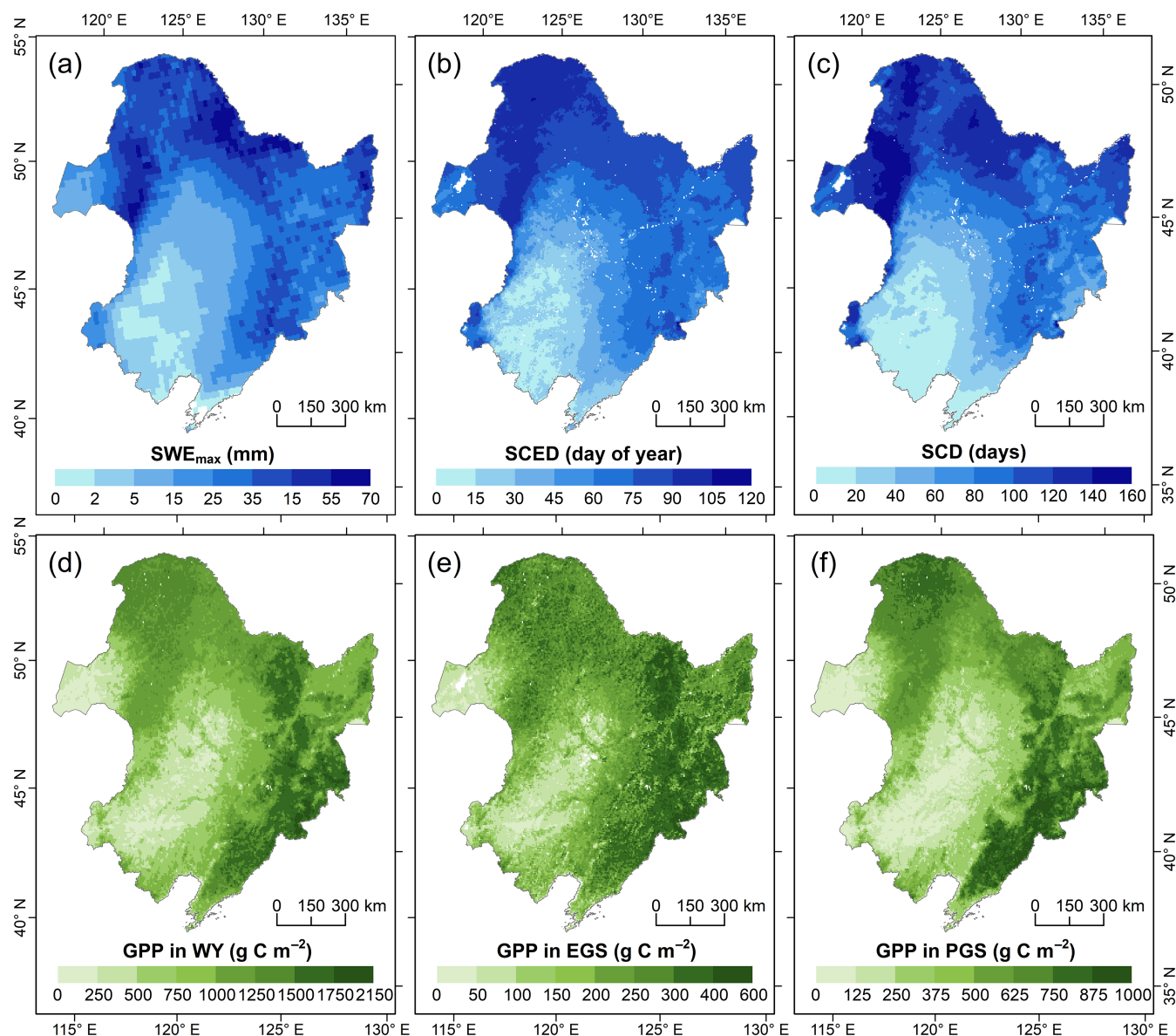


FIGURE 3 Spatial distribution of interannual mean values of snow cover indicators (annual maximum snow water equivalent [SWE_{max}], snow cover end date [SCED], and snow cover days [SCDs]) and cumulative gross primary productivity (GPP) for each stage (in the whole year [WY], early growing season [EGS], and peak growing season [PGS]) in Northeast China from 1982 to 2015.

trend in SWE_{max} anomalies. Approximately 42.6% of forests have a significant decreasing trend in SCD anomalies, mostly distributed in the Greater Khingan Mountains and Lesser Khingan Mountains. SCED anomalies have a delayed pattern in most areas (79.5% of pixels), but the spatial patterns of interannual variation in SCED anomalies show less regularity compared with other snow indicators. As for GPP anomalies in the WY (Figure 4d), 75.2% of the regions show an increasing trend, 45.0% of which are significant. Among them, 66.4% of dryland increases significantly, primarily distributed in the Sanjiang Plain, Songnen Plain, and Liao River Plain. In EGS, GPP anomalies exhibit a noteworthy

downward trend in the Greater Khingan Mountains, Lesser Khingan Mountains, and Changbai Mountains as indicated by Figure 4e. Conversely, an upward trend is observed in the same regions in PGS, as demonstrated in Figure 4f. And 82.7% of dryland have a significant increasing trend in GPP anomalies in PGS.

Effects of snow cover change on GPP

In order to quantify the impacts of snow on GPP variability, partial correlation analysis between snow indicator anomalies and GPP anomalies is conducted in NEC from

1982 to 2015 (Figure 5). The impacts of air temperature, precipitation, and solar radiation are controlled when calculating the correlation coefficients. In EGS, GPP shows a significant positive correlation with SWE_{max} (13.7% of the area) and SCD (7.3% of the area) mainly in the Greater Khingan Mountains ($p < 0.1$), and a significant negative correlation is found between GPP and SCED (7.4% of the area), mainly in the Changbai Mountains. While in PGS, GPP is significantly and positively correlated with all of the three snow cover indicators in the central part of NEC (Figure 5d–f). The pixels exhibiting strong positive correlations between GPP and SWE_{max} account for 19.0% of the area, SCED for 12.1%, and

SCD for 6.7%. In parts of the Greater Khingan Mountains and Lesser Khingan Mountains, SCD is significantly and negatively correlated with GPP in PGS, approximately 6.3% of the total region.

We calculated the percentage of pixels with significant correlation in different underlying surface types in order to further investigate the snow–GPP relation (Figure 6). For dryland, the pixels that show strong positive correlation between all the three snow indicators and GPP in both EGS and PGS are more than pixels with strong negative correlation. In EGS, grassland is the underlying surface with the strongest positive correlation in the snow–GPP relation, while dryland is the

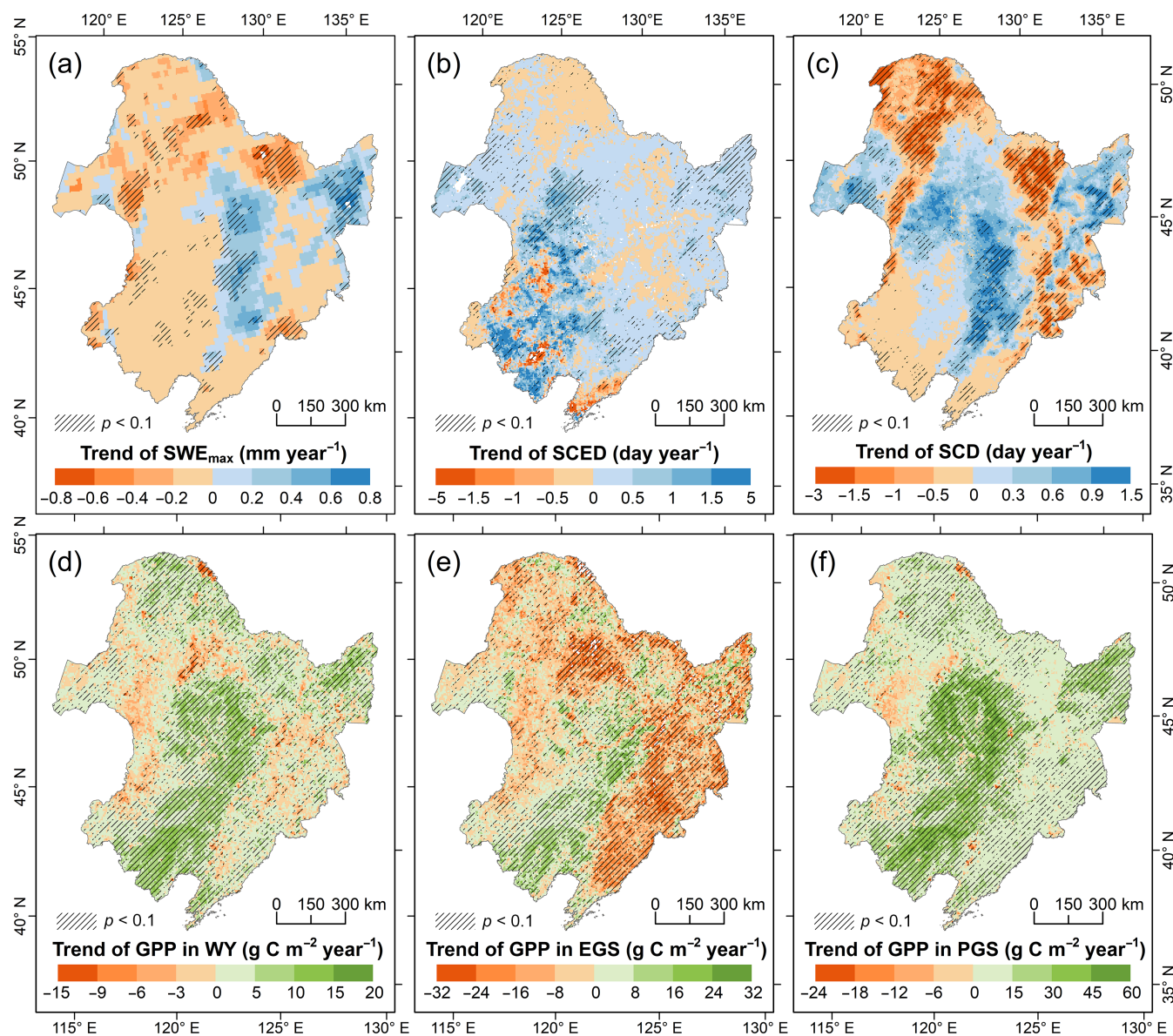


FIGURE 4 Interannual variations in snow cover indicator (annual maximum snow water equivalent [SWE_{max}], snow cover end date [SCED], and snow cover days [SCDs]) anomalies and cumulative gross primary productivity (GPP) (in the whole year [WY], early growing season [EGS], and peak growing season [PGS]) anomalies in Northeast China from 1982 to 2015. The gray slash indicates that the variable has changed significantly ($p < 0.1$).

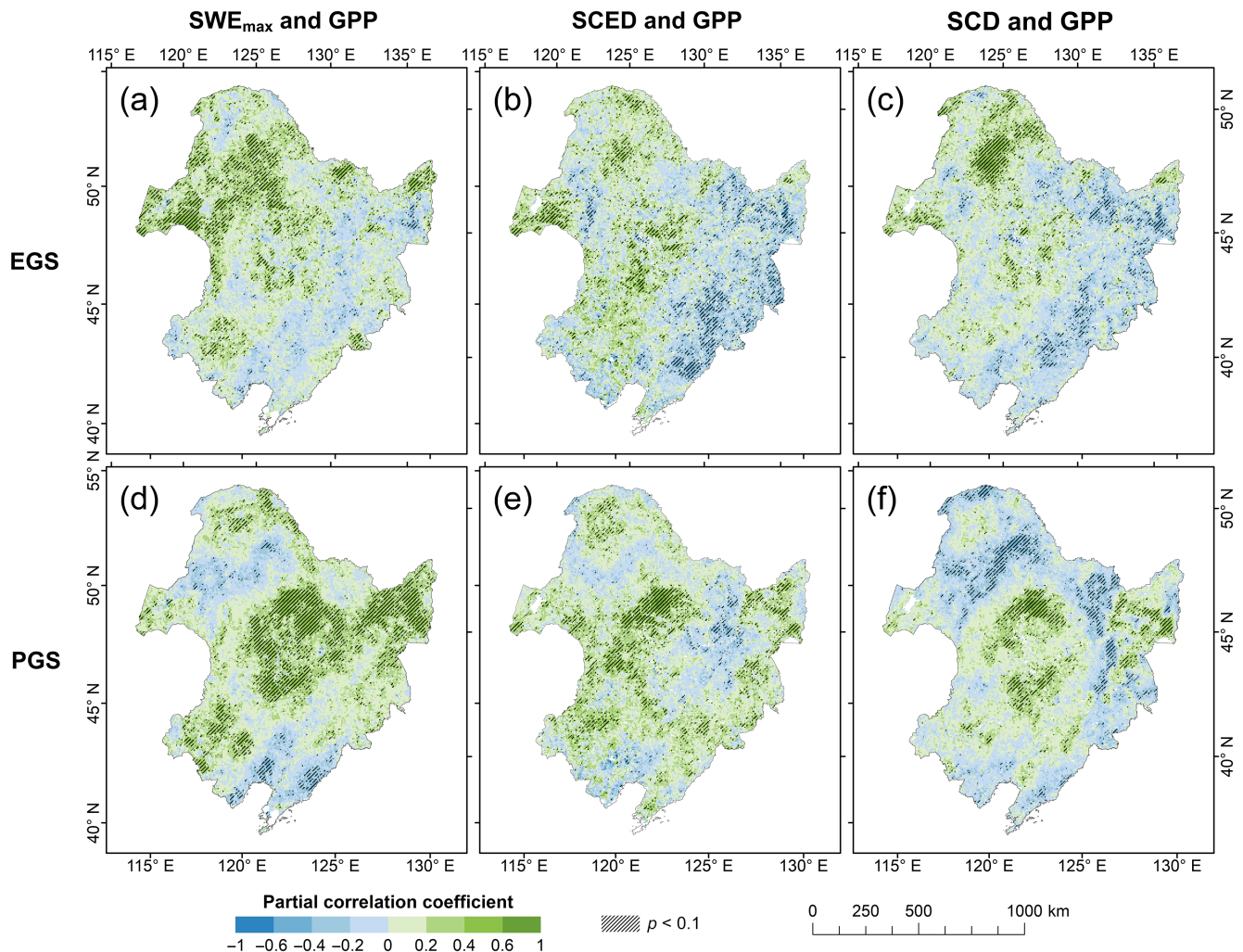


FIGURE 5 Spatial pattern of the relations between snow cover anomalies and gross primary productivity (GPP) anomalies in the different growing seasons in Northeast China from 1982 to 2015. The gray slash indicates the pixels at a significance level of $p < 0.1$. EGS, early growing season; PGS, peak growing season; SCD, snow cover days; SCED, snow cover end date; SWE_{max} , annual maximum snow water equivalent.

strongest in PGS. Specifically, GPP in PGS of dryland has a strong positive correlation with SWE_{max} , with 36.9% of pixels having a significant positive relation. In contrast, for forest, SCED has a negative relation with GPP in EGS (Figure 6b), and SCD has a negative relation with GPP in PGS (Figure 6f). The negative impacts of snow phenology indicators (SCED and SCD) on GPP in forest are greater than those in dryland and grassland. The snow–GPP relation is highly dependent on the underlying surface types.

Dominant snow cover indicators in the snow–GPP relation

Due to the interaction between different snow cover indicators and the joint effect on GPP, a stepwise regression model is applied to explore the contribution of each snow

cover indicator anomaly to variations in GPP anomalies (Figure 7). The variance (R^2) in GPP explained by snow cover indicators is reported in Figure 7b,e. Between 8.2% and 77.6% of the variance in GPP can be explained by snow cover indicators in EGS, and 8.2%–64.0% of the variance in GPP can be explained in PGS. In EGS, snow cover indicators with a positive effect on GPP account for 59.8%, and SWE_{max} accounts for 38.7% among them. The negative effect is mainly caused by SCED (24.4% of the total area), distributed in the Changbai Mountains. In PGS, the central part of NEC shows a strong positive effect dominated by SWE_{max} (47.3% of the total area), while the negative effect is mostly dispersed throughout the Greater Khingan Mountains and Lesser Khingan Mountains, which is dominated by SCD. We then calculated the percentage of each snow cover indicator that is dominant in the snow–GPP relation in different

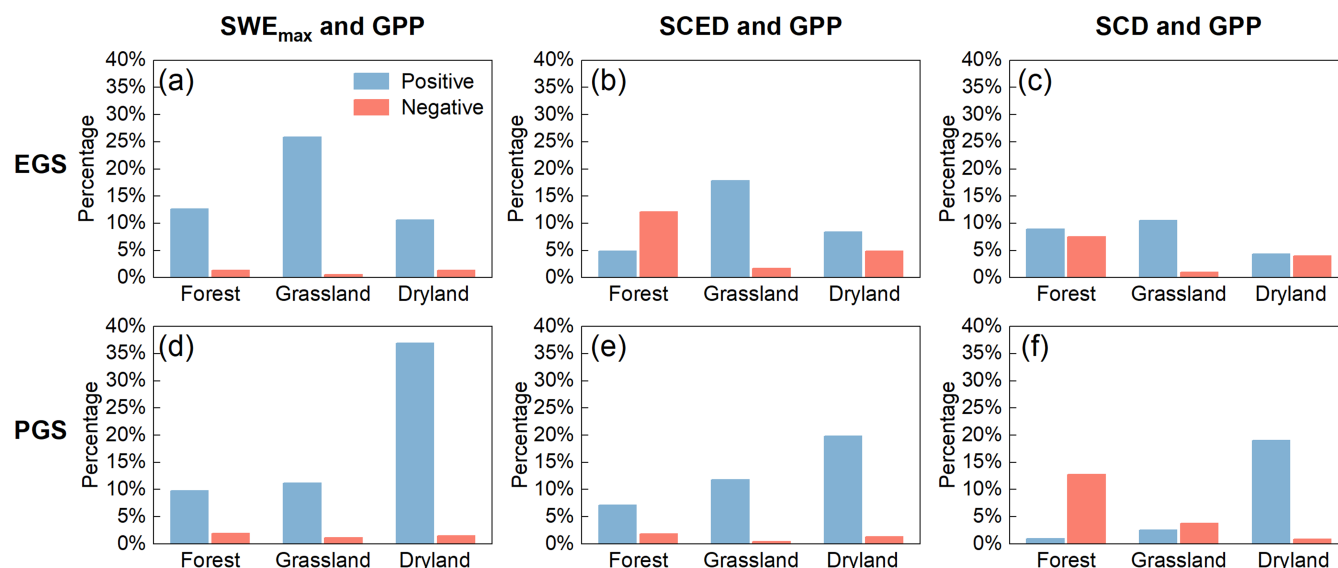


FIGURE 6 Comparison of the impacts of changes in snow cover (annual maximum snow water equivalent [SWE_{max}], snow cover end date [SCED], and snow cover days [SCDs]) on gross primary productivity (GPP) in different underlying surface types. The percentage of pixels with significant partial correlation ($p < 0.1$) is shown in each histogram. (a)–(c) present the impact of SWE_{max}, SCED, and SCD change on GPP in the early growing season (EGS), and (d)–(e) present the effects of SWE_{max}, SCED, and SCD change on GPP in the peak growing season (PGS).

underlying surface types (Figure 7c,f). For dryland and grassland, SWE_{max} plays a positive dominant role in both EGS and PGS. However, for forest, SCED and SCD show negative effects on GPP in EGS and PGS, respectively, indicating a great difference between dryland and grassland.

Mechanism of snow cover change on GPP

Because of the complex relation between snow cover change and GPP, the mechanism models were constructed based on the empirical correlations among variables in forest, grassland, and dryland (Figure 8). The SEs for the path coefficients in each model range from 0.00 to 0.06, indicating that the fitting results are relatively stable. Except for the model conducted in the forest of PGS, the GOF values of other models are higher than 0.36, and the SEs for all the path coefficients are lower than 0.1, meaning that the overall performance of the models is considered to be good.

We counted the magnitude and direction of the soil moisture effect, soil temperature effect, and growing period effect on each underlying surface type in EGS and PGS, as shown in Figure 9. For forest, SCED and SCD have a relatively stronger impact on GPP in EGS, primarily through their impact on soil moisture. In PGS, SWE_{max} has a considerable influence on GPP mainly by altering the soil temperature. For grassland and dryland, SWE_{max} plays the most important role among the three snow indicators, primarily altering GPP through its effect

on soil temperature in both EGS and PGS. Besides, changes in snow cover have the capacity to affect GPP by altering the start and end of the growing season, with the greatest effect notably seen in SCED. Furthermore, we found that the impact of snow cover changes on GPP in PGS is predominantly mediated through the soil temperature effect.

DISCUSSION

Snow–GPP relation regulated by the underlying surface types

The results of our investigation indicate that the snow–GPP relation is greatly associated with the underlying surface types. This can be observed through various aspects, including but not limited to the interannual variation, partial correlation, dominant snow cover indicator, and the potential mechanism. For forest, GPP exhibits a larger value, accompanied by higher annual maximum SWE (SWE_{max}), later SCED, and longer SCDs compared with grassland and dryland. Over time, the snow cover trends in forest decrease, while increasing trends are observed in grassland and dryland. Furthermore, GPP shows an increasing trend mainly in dryland and grassland, while a decreasing trend is observed in large areas of forest in PGS. For forest, SCED with a negative effect mainly dominates GPP in the EGS due to the relatively strong soil moisture effect, while SCD negatively

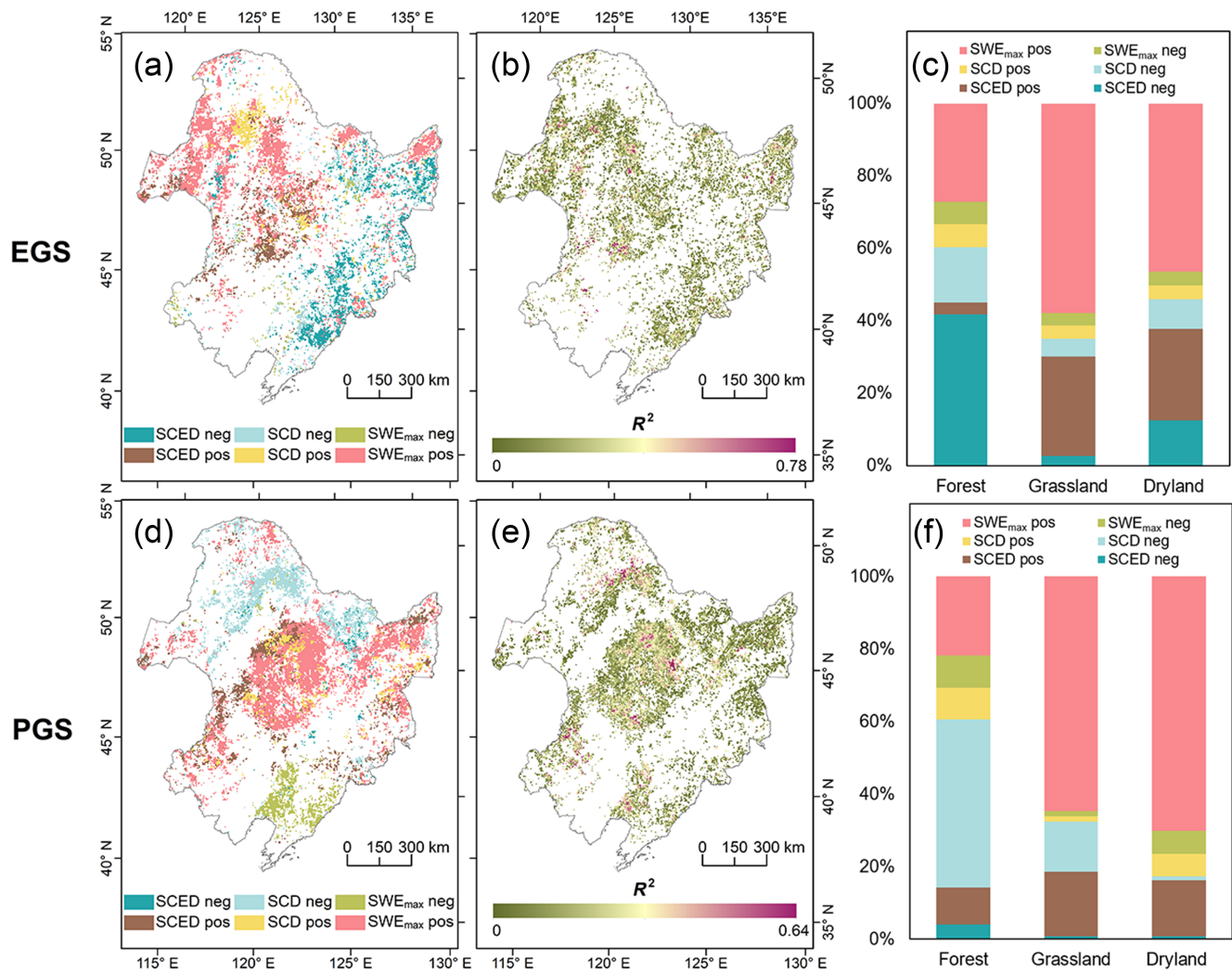


FIGURE 7 Dominant snow cover indicators in the snow–gross primary productivity (GPP) relation. (a) and (d) are the spatial distribution of dominant snow cover indicators impacting GPP. (b) and (e) report the variance (R^2) in GPP explained by snow cover indicators. (c) and (f) present the percentage of each snow cover indicator in different underlying surface types. EGS, early growing season; neg, negative; PGS, peak growing season; pos, positive; SCD, snow cover days; SCED, snow cover end date; SWE_{max}, annual maximum snow water equivalent.

dominates GPP in the PGS mainly through the growing period effect. For grassland and dryland, changes in SWE_{max} regulate GPP in both EGS and PGS, and the primary influence path of the snow–GPP relation is the soil temperature effect.

The impacts of climate warming on different underlying surface types are not uniform and can be nonlinear (Qi et al., 2021; Wang et al., 2017; Wang, Wang, et al., 2018; Wang, Wu, et al., 2018; Zhang et al., 2018), and the reasons behind the role of different underlying surface types in the snow–GPP relation may be as follows. The type of underlying surface is critical in regulating the distribution and ablation of snow cover. It has been observed that the rate of snow ablation is often slow in regions with high vegetation cover (Vikhamar & Solberg, 2003). Specifically, snow cover melts more

slowly in woodland areas than in grassland and barren, even under the same altitude conditions. Vegetation cover can influence the distribution of snow on the surface via multiple pathways, such as snow interception by the canopy, changes in radiation flux, and alterations in wind fields (Musselman et al., 2008; Niu & Yang, 2004). For instance, the distribution pattern of snow cover shows a discernible contrast between forested and nonforested areas due to the interception effect of tree branches. Grassland and cropland exhibit different responses to snow cover compared with forest due to their lack of canopy shade, leading to exposure to greater solar radiation, higher wind speed, reduced snow accumulation, and altered soil temperature and moisture (Guo et al., 2018). Thus, compared with nonforested areas, the influence period of the snow cover on

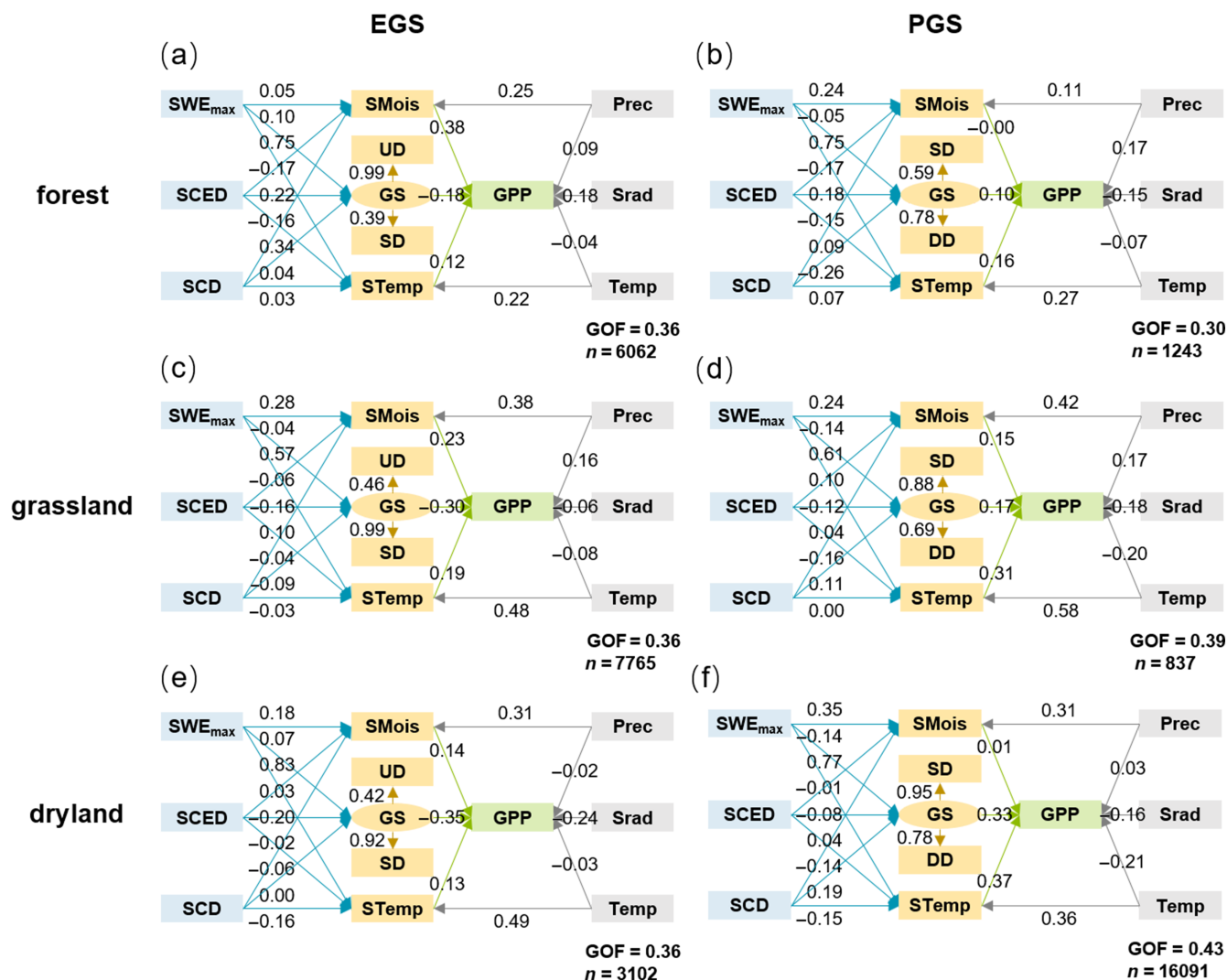


FIGURE 8 Mechanism models of snow cover change on gross primary productivity (GPP) are conducted in forest, grassland, and dryland. As a latent variable, growing season (GS) includes the start and the end of the growing season. Specifically, for the early growing season (EGS), the season initiates at the upturn date (UD) and concludes at the stabilization date (SD), while for the peak growing season (PGS), it begins at SD and concludes at the downturn date (DD). Meteorological factors including precipitation (Prec), air temperature (Temp), and solar radiation (Sradi) are also considered in the model. GOF, the goodness of fit; n , number of data points used for the analysis; SCD, snow cover days; SCED, snow cover end date; SMOis, soil moisture; STemp, soil temperature; SWE_{max}, annual maximum snow water equivalent.

vegetation growth in forest may be prolonged, which explains the reason why SCD and SCED are of greater importance in forest than in grassland and dryland.

Against the background of global warming, NEC is projected to experience reductions in SWE and SCD throughout this century (Ji & Kang, 2013; Yang et al., 2022; Zou et al., 2022). Building upon the results of this study, it is noteworthy that SCD exerts a negative influence on GPP in forests. Consequently, these findings suggest that the productivity of forest ecosystems in NEC may increase, as forests are likely to sequester more carbon from the atmosphere. Conversely, SWE emerges as a critical positive determinant of GPP in both grassland and dryland ecosystems. A decrease in SWE could lead to

diminished GPP in these areas, resulting in grassland and dryland ecosystems absorbing less carbon. These anticipated shifts in vegetation productivity have far-reaching ecological and environmental implications, underlining the importance of understanding the interplay between changing snow dynamics and ecosystem processes.

Potential explanation for the varied reactions of GPP to snow cover changes in EGS and PGS

This study demonstrates that the snow–GPP relation differs significantly in different stages of the growing season,

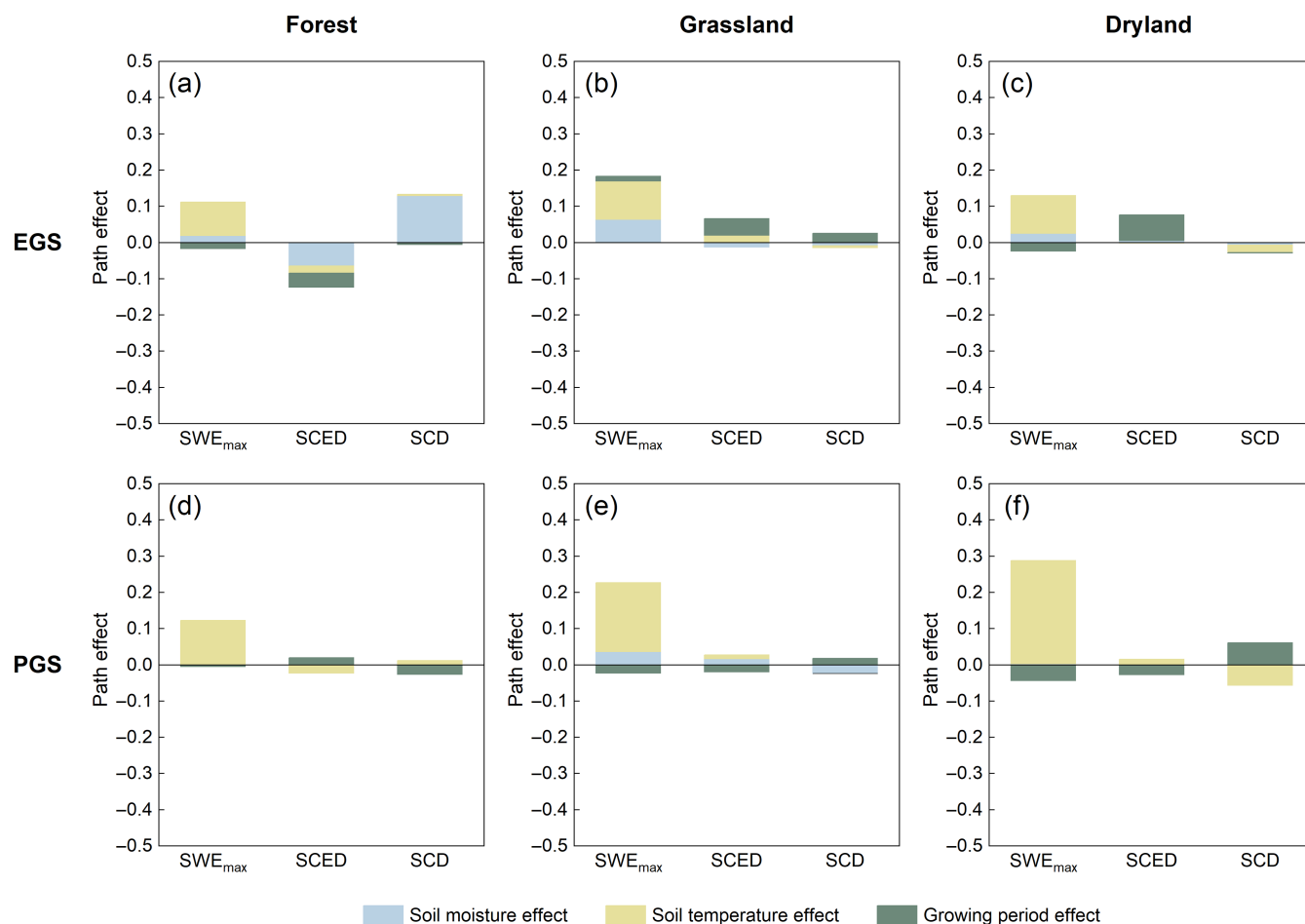


FIGURE 9 Comparison of the path effects (soil moisture effect, soil temperature effect, and growing period effect) of each snow cover change on gross primary productivity in different underlying surface types. EGS, early growing season; PGS, peak growing season; SCD, snow cover days; SCED, snow cover end date; SWE_{max}, annual maximum snow water equivalent.

which is consistent with earlier findings (Knowles et al., 2018). The response of GPP to snow cover change in different growing seasons may be reflected by lagged effects, in which soil temperature plays a major role. Snow accumulation during the winter months can raise the soil temperature due to its insulating effect, which can reduce soil freezing, protect vegetation roots (Yu et al., 2013), improve the nutrient utilization efficiency of vegetation (Semenchuk et al., 2015), subsequently promote plant growth, and increase carbon uptake throughout the following growing season. Although the lagged effect of snow cover change on GPP is not clearly understood, existing studies have realized that the underlying surface types mostly determine the magnitude of this lagged effect (Peng et al., 2010), which is highly compatible with our findings. In EGS, grassland exhibits the highest positive effect, while forest demonstrates the highest negative effect. During PGS, dryland displays the most significant positive effect, while forest exhibits the most pronounced negative effect.

This observation indicates a strong reflection of the lagged effect in dryland. Consequently, future studies should account for these differences and develop underlying surface-type-specific models to accurately forecast the influence of changing snow cover on plant growth and carbon absorption.

Limitations and future perspective

Taking NEC as a representative area, this study unravels the impacts of snow cover change on GPP in forest, grassland, and dryland. However, other underlying surface types such as shrub and tundra may also have different impacts on the snow–GPP relation (Bjorkman et al., 2015; Francon et al., 2020; Kim et al., 2021; Zong et al., 2022). To further investigate the role of a more comprehensive range of underlying surface types, future studies could either expand the scope of this study or involve other representative study areas. Additionally, we

also find that the results of the mechanism analysis are not completely consistent with the above analysis results. This may be due to some potential pathways that were not taken into account in our analysis. Snow cover can also affect GPP by influencing the soil freeze–thaw cycle, soil nutrients, and other factors (Bokhorst et al., 2008; Semenchuk et al., 2015). However, as relevant data on these factors are lacking, they have not been clearly considered in the mechanism analysis, and thus, inconsistencies in the results may arise. A more comprehensive dataset may facilitate further exploration of how snow cover change affects GPP. In addition, the GOF value of the model conducted in forest during PGS is 0.30, indicating that the model does not fit well, which may make the mechanism analysis of forest during PGS inaccurate. Furthermore, the underlying surface is a comprehensive reflection of the regional environment, heavily influenced by climate conditions, terrain, elevation, latitude, hydrology, and soil. Although we aimed to investigate the specific impact of variations in snow cover on GPP across different underlying surface types, other factors may have greatly influenced snow–GPP relations. Future studies can conduct a more comprehensive analysis regarding this issue.

CONCLUSIONS

This study thoroughly unravels the effects of snow cover change on GPP in NEC from insights of underlying surface types based on long-term satellite observations. Our findings emphasize the importance of underlying surface types in the snow–GPP relation. For forest, SCED has a negative impact on GPP change in EGS, while SCD has a negative impact on GPP change in PGS, with relatively strong soil temperature and soil moisture effects. For grassland and dryland, SWE_{max} change primarily controls GPP in both EGS and PGS, and the soil temperature effect is the main influencing factor in the snow–GPP interaction. In dryland, we also see a rather strong lagged effect brought on by the soil temperature effect. This study broadens our understanding of how changes in snow cover impact GPP in forest, grassland, and dryland, which may be used as a foundation for predicting how ecosystems in regions with comparable underlying surface types will be influenced by future climate change.

ACKNOWLEDGMENTS

This study was supported by the National Natural Science Foundation of China (Grant No. 42171307) and the “GeoX” Interdisciplinary Research Funds for the Frontiers Science Center for Critical Earth Material Cycling, Nanjing University.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The AVHRR SCE dataset was acquired from <https://www.tpdc.ac.cn/en/data/44ddd191-4123-427d-8170-de435fab01f8>. The daily snow depth dataset is available at <http://www.ncdc.ac.cn/portal/metadata/d9a9e8ae-3e8f-4c1a-b1a6-a739a405c971>. The daily GPP dataset was downloaded from <http://www.nesdc.org.cn/sdo/detail?id=612f42ee7e28172cbcd3d809&subjectCode=613ebcd17e28175ae245f762>. The FLUXNET2015 dataset was acquired from <https://fluxnet.org/data/fluxnet2015-dataset/>. The GIMMS NDVI3g dataset was obtained from <https://iridl.ldeo.columbia.edu/SOURCES/.NASA/.ARC/.ECOCAST/.GIMMS/.NDVI3g/.v1p0>. The land use dataset in China was acquired from <https://data.tpdc.ac.cn/en/data/a75843b4-6591-4a69-a5e4-6f94099ddc2d/>. The CMFD is available at <http://poles.tpdc.ac.cn/en/data/8028b944-daaa-4511-8769-965612652c49/>. The GLEAM daily soil moisture dataset was downloaded from <https://www.gleam.eu>. The ERA5-Land hourly soil temperature dataset was obtained from <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=form>. Code (Wang, 2024) is available from Zenodo: <https://doi.org/10.5281/zenodo.10518757>.

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How to cite this article: Wang, Yunhan, Pengfeng Xiao, Xueliang Zhang, Hao Liu, Youlv Wu, and Liyang Sun. 2024. "Unraveling the Effects of Snow Cover Change on Vegetation Productivity: Insights from Underlying Surface Types." *Ecosphere* 15(5): e4855. <https://doi.org/10.1002/ecs2.4855>