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Disentangling the mechanisms behind winter snow impact on vegetation activity in northern ecosystems

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Abstract

Although seasonal snow is recognized as an important component in the global climate system, the ability of snow to affect plant production remains an important unknown for assessing climate change impacts on vegetation dynamics at high-latitude ecosystems. Here, we compile data on satellite observation of vegetation greenness and spring onset date, satellite-based soil moisture, passive microwave snow water equivalent (SWE) and climate data to show that winter SWE can significantly influence vegetation greenness during the early growing season (the period between spring onset date and peak photosynthesis timing) over nearly one-fifth of the land surface in the region north of 30 degrees, but the magnitude and sign of correlation exhibits large spatial heterogeneity. We then apply an assembled path model to disentangle the two main processes (via changing early growing-season soil moisture, and via changing the growth period) in controlling the impact of winter SWE on vegetation greenness, and suggest that the "moisture" and "growth period" effect, to a larger extent, result in positive and negative snow–productivity associations, respectively. The magnitude and sign of snow–productivity association is then dependent upon the relative dominance of these two processes, with the "moisture" effect and positive association predominating in Central, western North America and Greater Himalaya, and the "growth period" effect and negative association in Central Europe. We also indicate that current state-of-the-art models in general reproduce satellite-based snow–productivity relationship in the region north of 30 degrees, and do a relatively better job of capturing the "moisture" effect than the "growth period" effect. Our results therefore work towards an improved understanding of winter snow impact on vegetation greenness in northern ecosystems, and provide a mechanistic basis for more realistic terrestrial carbon cycle models that consider the impacts of winter snow processes.

KEYWORDS
northern ecosystems, path model, snow water equivalent, snowmelt date, soil moisture, vegetation greenness

1 | INTRODUCTION

Studies of remote sensing and tree ring records indicate that the past few decades have witnessed an overall increase in vegetation productivity in the northern high latitudes (Piao et al., 2011; Salzer, Hughes, Bunn, & Kipfmueller, 2009), but the magnitude and direction of productivity responses are not spatially uniform. For example, remote sensing studies found increasing plant growth ("greening") over tundra and shrublands in the arctic (e.g. Bi, Xu, Samanta, Zhu, & Myneni, 2013; Macias-Fauria, Forbes, Zetterberg, & Kumpula, 2012),

but declining productivity ("browning") over a certain portion of boreal forests particularly in North America (e.g. Beck & Goetz, 2011; Bi et al., 2013; Peng et al., 2011). Such transformations are widely recognized as a result of climatic warming (the releases of low temperature constraints on plant growth) and warming-invoked increasing drought stress in the growing season although other processes such as spring cooling (Wang et al., 2011), fire disturbance (Goetz, Bunn, Fiske, & Houghton, 2005) and the expansion of woody shrubs (Forbes, Fauria, & Zetterberg, 2010) also play a certain role. Despite these compelling lines of evidence, uncertainty remains as to the extent of change in vegetation that has occurred across the northern high latitudes owing to changes in winter snow accumulation. Quantifying the effect of winter snow accumulation on productivity in the northern high latitudes becomes urgent, since there is a widespread decline in winter snow accumulation over the past few decades and climate models unanimously project a decrease in snow-to-rain ratio during winter season in a warmer future (Bintanja & Andry, 2017; Stocker et al., 2013).

There is a growing body of experimental and observational (e.g. satellite-derived observations, annual-growth-ring) studies providing evidence that winter snow accumulation can affect plant productivity during the growing season (e.g. Grippa et al., 2005; Jonas, Rixen, Sturm, & Stoeckli, 2008; Mark et al., 2015; Matsumura & Yamazaki, 2012; Matsumura, Yamazaki, & Tokioka, 2010; Peng, Piao, Ciais, Fang, & Wang, 2010; Trujillo, Molotch, Goulden, Kelly, & Bales, 2012; Vaganov, Hughes, Kirdyanov, Schweingruber, & Silkin, 1999; Wipf & Rixen, 2010; Wipf, Stoeckli, & Bebi, 2009). Although there was no direct relationship between snow and plant productivity, changes in snow can have cascading effects on known drivers of growing-season productivity such as the soil moisture status (e.g. Matsumura & Yamazaki, 2012; Matsumura et al., 2010). Yet, how plant productivity responds to winter snowpack is still not well understood. Cross-study synthesis of snow manipulation experiments alpine tundra ecosystems at high latitudes (Mark et al., 2015; Wipf & Rixen, 2010) offers us a well-supported conceptual framework for understanding the underlying processes in explaining how winter snow affects plant productivity. Variation in winter snow could affect plant productivity through a variety of processes (Figure 1). First, less winter snow is generally related to advanced snowmelt date. This earlier snowmelt could, on the one hand, allow plants to initiate growth or leaf onset earlier (Ernakovich et al., 2014; Inouye, 2008; Korner, 2003; Shaw et al., 2002), thus enhancing vegetation productivity through extending the growing period available for plant growth and resource allocation (e.g. Piao et al., 2017). On the other hand, an increase in evapotranspiration because of earlier spring could lead to drier soils in the growing season if an increase in growing-season precipitation cannot subsequently compensate for an earlier soil drying, thereby decreasing vegetation productivity. Second, changes in winter snow would affect soil moisture availability in the growing season since the soil moisture anomaly formed from the melting snowpack might take months to dissipate, therefore having indirect effects on growing-season productivity particularly in water-limited ecosystems. However, it remains unclear what is the main ecological process and how these processes interact in controlling the apparent snow–productivity relationship?

The objectives of this paper are therefore to characterize vegetation productivity–winter snow accumulation relationships, and identify the role of each process in controlling snow–productivity
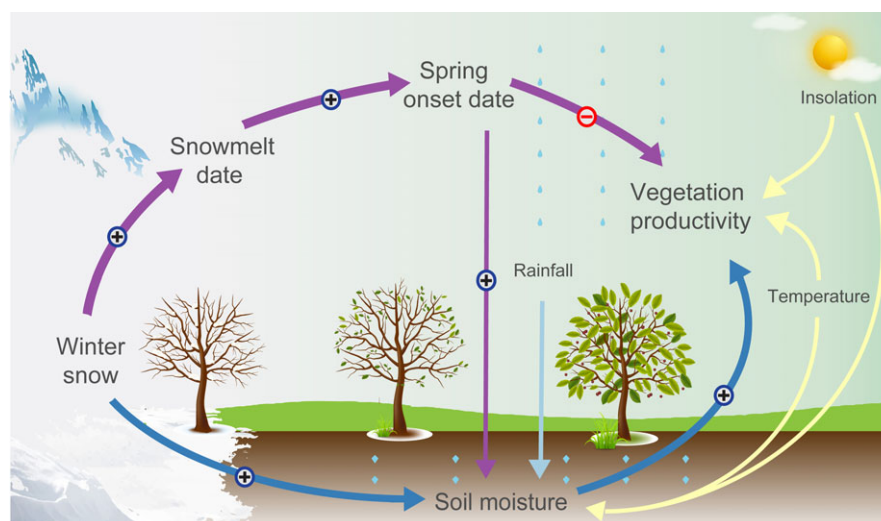

FIGURE 1 Schematic path diagram showing the effect of winter snow accumulation on early growing-season vegetation productivity through changing the growing period (in purple) and moisture conditions (in blue). The two main pathways (or effects) are identified. The first one is referenced as the "growth period" effect, which mainly works through changing the snowmelt date and in turn spring onset date. The second one is identified as the "moisture" effect that operates through modulating the early growing-season soil moisture. Note that in the "moisture" effect, the potential impact of spring onset date on soil moisture is also considered. The + and − in circle indicate positive and negative bivariate correlation, respectively, while the signs may change with location. Other drivers including precipitation, temperature and solar insolation during the early growing season are also included in the path diagram [Colour figure can be viewed at wileyonlinelibrary.com]

relationship across the northern ecosystems based upon our established framework (Figure 1). To do so, we compile data on satellite observation of vegetation greenness and spring onset date, soil moisture product relying on the process-based model to combine satellite observations, climate data (temperature, precipitation and insolation) and passive microwave snow water equivalent and its derived snowmelt date across the northern high latitudes (Table S1). The expected results will enable us to evaluate the generality of previously documented snow–productivity relationships within tundra and taiga ecosystems for which they were originally developed. Our satellite-based analyses might also provide insights into the potential role of snow in non-uniform responses of productivity to recent climate change in high-latitude ecosystems, and works towards a more mechanistic and quantitative understanding of how winter SWE influences vegetation productivity. Furthermore, current state-of-the-art terrestrial ecosystem models are widely used to evaluate the climate change impact on land ecosystems (e.g. Ciais et al., 2005; Peng et al., 2015; Piao et al., 2013), and we therefore also use results from satellite-based analysis to make a quantitative assessment of how the models simulate the vegetation response to winter snow change.

2 | MATERIALS AND METHODS

2.1 | Observational datasets

Satellite-derived Normalized Difference Vegetation Index (NDVI) as a proxy for vegetation productivity (e.g. Gamon et al., 1995; Myneni, Keeling, Tucker, Asrar, & Nemani, 1997; Piao et al., 2014; Wang et al., 2014, 2016, 2017) is retrieved from the third generation of Advanced Very High-Resolution Radiometer (AVHRR) developed by the Global Inventory Modeling and Mapping Studies (GIMMS) group (Tucker et al., 2005). This new GIMMS NDVI spans from 1981 through 2011 and has a spatial resolution of one-twelfth of a degree (~8 km) and 15-day interval (available at https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/). Grid cells with NDVI <0.1 were excluded to eliminate the influence of permanent snow and ice on NDVI analysis.

Daily snow water equivalent (SWE) observations at a spatial resolution of 25 km for the 1982–2011 period is obtained from GlobSnow SWE product that is derived from a combination of ground-based observations of snow depth and passive microwave radiometer data (SMMR, SSM/I and AMSR-E sensors) in an assimilation scheme (Pulliainen, 2006; Takala et al., 2011). Compared to GlobSnow, the SWE retrieval based solely on passive microwave radiometer data shows spurious features during snowmelt and would overestimate SWE because of strong thermal gradients and erroneous forest cover correction factors (Hancock, Huntley, Ellis, & Baxter, 2014). In this study, we use the GlobSnow SWE product with mountainous regions unmasked, and restrict our analysis to pixels with SWE estimates larger than a previously suggested minimum detectable value of 15 mm since shallow snowpack could be missed by microwave sensors (Solberg et al., 2010).

Monthly temperature, insolation and precipitation data at a spatial resolution of $0.5° \times 0.5°$ covering the period 1982–2011 are compiled from Climatic Research Unit–National Centers for Environmental Prediction (CRU-NCEP) climate dataset (Le Quéré et al., 2009). Since soil moisture directly controls soil water availability for plants (Mendez-Barroso, Vivoni, Watts, & Rodriguez, 2009; Rodriguez-Iturbe, Porporato, Laio, & Ridolfi, 2001), we use monthly root-zone soil moisture data from the version 3.0a of Global Land Evaporation Amsterdam Model (GLEAM) dataset at a spatial resolution of $0.25° \times 0.25°$ (Miralles et al., 2011). This dataset assimilates microwave observations of surface soil moisture from the European Space Agency–Climate Change Initiative (ESA–CCI) dataset in a multi-layer water balance module, and shows a general good agreement with soil moisture measurements from eddy-covariance towers and soil moisture sensors across a broad range of ecosystems (Martens, Miralles, Lievens, Fernández-Prieto, & Verhoest, 2016).

2.2 | Determination of snowmelt date, spring onset date and peak photosynthesis timing

Snowmelt date is defined as the last continuous 5 days when daily SWE from GlobSnow larger than 1 mm is observed (e.g. Peng et al., 2010). We adopt the four methods (HANTS-Maximum, Polyfit-Maximum, double logistic and piecewise logistic) to extract spring onset date from the seasonal cycle of NDVI, and then determine the spring onset date by taking the ensemble mean of the four methods. The detection of spring onset date is sensitive to the presence of snow during the non-growing season (Wang, Peng, Lin, & Chang, 2013). Therefore, before applying phenology extraction method on NDVI data, we use the criterion of daily air temperature below 0°C for five consecutive days to exclude pixels that are potentially covered by snow, and replace this snow-affected NDVI with that from the temporally nearest snow-free date (Liu et al., 2016). We use ployfit maximum (Cong et al., 2013; Piao, Friedlingstein, Ciais, Zhou, & Chen, 2006) to estimate daily NDVI time series based on the original bimonthly data, and the satellite-derived peak photosynthesis timing is then defined as the day with maximum NDVI (Xu, Liu, Williams, Yin, & Wu, 2016). The early growing season (early GS) in this study is therefore defined as the period between spring onset date and peak photosynthesis timing.

2.3 | Terrestrial ecosystem models

To evaluate the model performance in simulations of snow–productivity relationship, we use monthly gross primary production (GPP), net primary productivity (NPP) and snow depth from a suite of terrestrial ecosystem models participating in the historical climate carbon cycle model intercomparison project (Trendy) (http://dgvm.ceh.ac.uk/files/Trendy_protocol%20_Nov2011_0.pdf). Based on the availability of productivity and snow data, we use only four terrestrial ecosystem models: Community Land Model Version 4 for carbon (CLM4C), Community Land Model Version 4 with explicit carbon and nitrogen processes (CLM4CN), Lund-Potsdam-Jena

DGVM (LPJ) and Top-down Representation of Interactive Foliage and Flora Including Dynamics (TRIFFID) (Table S2). Each model was run from its pre-industrial equilibrium (assumed at the beginning of the 1900s) to 2012 and was forced by both observed historic climate changes and rising CO_2 concentrations. All the model outputs are regridded to $0.25° \times 0.25°$ with the first-order conservative remapping technique to facilitate the comparison with observations. We use polyfit maximum to estimate daily snow depth, GPP time series based on the original monthly data, and the snowmelt date is then defined as the last continuous 5 days when daily snow depth larger than 1 mm. Spring onset date was extracted from modelled GPP when daily GPP becomes larger than zero (Cong et al., 2013), and the method used to determine peak photosynthesis timing from modelled GPP is similar to that from NDVI.

2.4 | Path analysis

Path analysis is a multivariate statistical analysis technique that requires the formal establishment of a model to be estimated based on previous studies. Note that path analysis is used to test the fit of the given model with the observed data but not for informing whether the given conceptual model is correct or not. Compared to standard statistical methods such as simple or partial correlation analyses, path model is capable of dealing with multiple independent and dependent variables, and allows an integration of different processes in which direct and indirect effects of the forcing variable on the response variable could be represented. Here, we develop a conceptual model by specifying relationships between winter SWE and vegetation productivity through including intervening variables in the multiple pathways by which one entity can influence another. Specifically, we include the following variables in the conceptual path model linking winter SWE to vegetation productivity based on previous recognition and data availability at the continental scale: snowmelt date, spring onset date, soil moisture during the period between snowmelt date and spring onset date, and soil moisture during the early GS (Figure 1 and Table S1). The two main processes are identified to indicate how winter SWE affects early GS productivity: via soil moisture (that change the water supply for plant growth) and via spring onset date (that initiates the growing season and changes the duration of plant growth period) (Figure 1). The aim of using path analysis is to compare the magnitude of these two underlying processes responsible for the potential correlation between winter SWE and early GS productivity. In addition, we also include climatic drivers (temperature, precipitation and solar insolation) during the growing season in the path diagram.

Technically, the path analysis permits the partitioning of bivariate SWE-productivity correlation coefficients into components as path coefficients. A path coefficient is analogous to the partial correlation coefficient that describes the strength and sign of the relationship between two variables. For example, in our path model shown in Figure 1, the path coefficient describing the effect of spring onset date on early GS productivity can be considered as their partial correlation coefficient whilst controlling for the effect of early GS soil

moisture, temperature and insolation. The effect of winter SWE on early GS productivity via soil moisture (or via spring onset date) can then be estimated as follows. By assuming several pathways tracing from winter SWE to productivity via a certain variable, we first compute the product of the standardized path coefficients along each pathway, and then sum up the products over all pathways. We should inform that the interpretation of the standardized path coefficients relies on a good fit of the path model. To assess goodness of model fit, we use the root mean square error of approximation (RMSEA) that measures the model fit in comparison to the null model and comparative fit index (CFI) that gauges the model fit with respect to the null model where all variables are uncorrelated. We adopted the recommended cut-off values with RMSEA <0.10, and CFI larger than 0.95. All variables are standardized before conducting the path analysis. The path analysis model is applied over $0.75°$ by $0.75°$ moving windows centred on each pixel to satisfy the minimum sample size requirements in the north of 30 degrees.

Path analysis is also conducted in exploring the effect of winter snow depth on early GS NPP in each terrestrial ecosystem model. This approach represents a novel opportunity to evaluate the way in which lagged and indirect effects of winter snow on vegetation productivity are represented in the models. In addition, we do not expect that the model-data comparison would be biased by the use of snow depth instead of SWE (not provided in the model output list), since all variables are standardized and path coefficients are estimated from correlations.

2.5 | Statistical analyses

We compute partial correlation coefficient between early GS vegetation greenness and winter SWE ($R_{NDVI-SWE}$) whilst controlling for the effects of early GS soil moisture, temperature and insolation during the period 1982–2011. Using the similar method, we calculate the partial correlation coefficient linking early GS vegetation greenness to early GS temperature. We also estimate the temporal sensitivity of early GS vegetation greenness to early GS temperature (S_{NDVI-T}) as the slope in a multiple regression of early GS vegetation greenness against winter SWE, early GS soil moisture and early GS insolation. All analyses are only performed over mean winter SWE larger than 15 mm and the vegetated land area north of 30°N, which is defined as mean annual NDVI during the period 1982–2011 larger than 0.1.

3 | RESULTS

3.1 | The relationship between winter snow and vegetation productivity

We analyse the temporal correlation between winter (December throughout February) SWE and vegetation productivity from 1982 to 2011 during the early growing season (early GS) over the north of 30 degrees in the Northern Hemisphere. Figure 2 provides the region-wide overview of the correlation between SWE and early GS
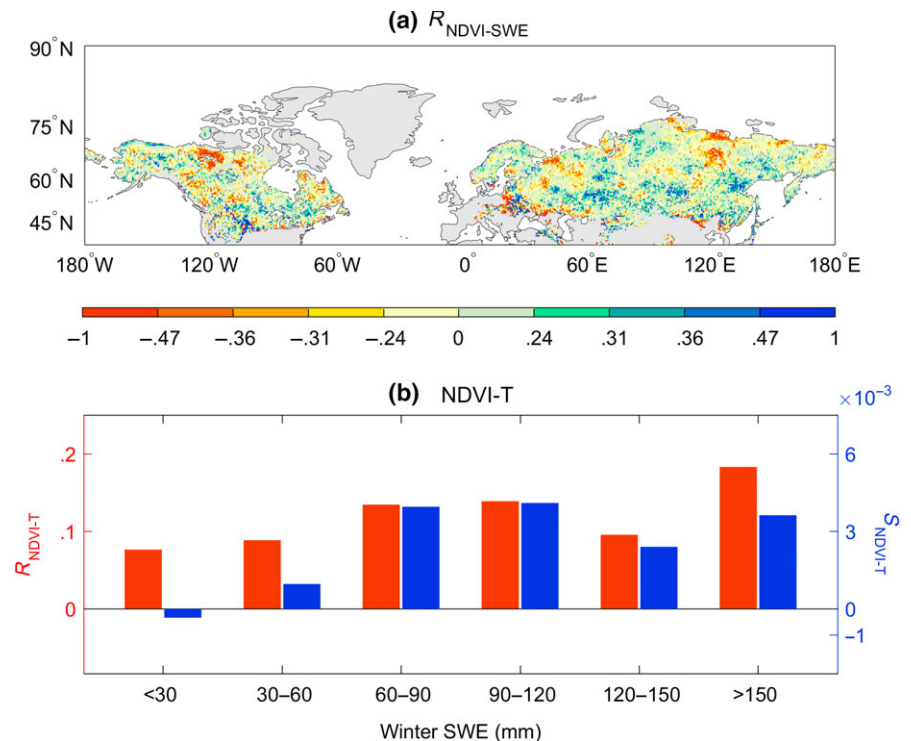
FIGURE 2 Spatial distribution of the partial correlation coefficient of early growing-season vegetation greenness and winter SWE ($R_{NDVI-SWE}$) (a), and changes in early growing-season vegetation greenness-temperature relationship with climatological SWE (b). R_{NDVI-T} represents the partial correlation coefficient between vegetation greenness and temperature during the early growing season, and S_{NDVI-T} denotes the sensitivity of vegetation greenness to temperature during the early growing season [Colour figure can be viewed at wileyonlinelibrary.com]

NDVI. About 20.4% and 13.1% of the total areas display statistically significant correlation ($p < .1$ and $p < .05$), respectively, with 10.1% (6.0%) being positive and 10.3% (7.1%) being negative that are significant at .1 (.05) level. The significant negative correlation localized in taiga and tundra regions such as northern part of eastern Siberia and northwestern Canada, and the significant positive correlation is mainly found in the western and central North America and boreal region such as southern part of Siberia.

But the magnitude and sign of SWE–productivity correlation is somewhat scattered on the spatial scale, which could be expected since early GS productivity is co-determined or predominated by temperature and/or soil moisture (Figs S1 and S2). In addition, if the pixels were classified into different winter SWE bins, the correlation coefficient between temperature and early GS productivity appears to increase with winter SWE (Figure 2b), as also found in the sensitivity of productivity to temperature. This result suggests that winter SWE could also influence early GS productivity through changing the productivity responses to temperature.

3.2 | The role of ecological processes in controlling snow–productivity relationship

Next, we quantify the relative importance of the two main processes (via soil moisture referring to "moisture" effect, and via spring onset date referring to "growth period" effect) contributing to the observed temporal winter SWE–productivity correlation (see Methods) based on the assembled path diagram from previous studies (Figure 1). As an example, the "moisture" effect is measured by the product of the path coefficient relating winter SWE to soil moisture and that relating soil moisture to GS productivity. Figure 3 shows

the spatial distribution of the magnitude of "moisture" effect and "growth period" effect over the north of 30 degrees in the Northern Hemisphere. The "growth period" effect mostly carries a negative value, which is mainly because an increase in winter SWE generally delays snowmelt date (Fig. S3a1) and in turn spring onset date (Fig. S3a2), thereby shortening plant growth period and reducing early GS productivity (Fig. S3a3). In contrast, the "moisture" effect generally has a positive value, since increased winter SWE can enhance soil moisture conditions available for the following plant growth (Fig. S3b1, b2 and ab). The "growth period" effect predominates over the Europe and Alaska, and the "moisture" effect over southern part of Siberia, western and central North America. The interpretation of these two effects, which are measured by products of path coefficients along different pathways (see Methods), would provide useful information only when the path model passes through an acceptable goodness of model fit and the temporal SWE–productivity correlation is significant at a certain level such as $p < .1$ adopted in this study (see Methods). If these requirements were met, the spatial median of negative "growth period" effect and positive "moisture" effect is estimated to be −0.02 and 0.11, respectively. These values indicate a unit change of one standard deviation in winter SWE causes 0.02 and 0.11 unit change in standard deviation of early GS productivity via "growth period" effect and "moisture" effect, respectively.

To examine regional characters of these two effects, we limit the analysis to pixels with significant temporal winter SWE–productivity relationship ($p < .1$) and path analysis model passing through the goodness-of-fit test. Within each of 11 regions over the north of 30 degrees, we average these effects over selected pixels to represent regional characters. Figure 4 compares the relative importance of
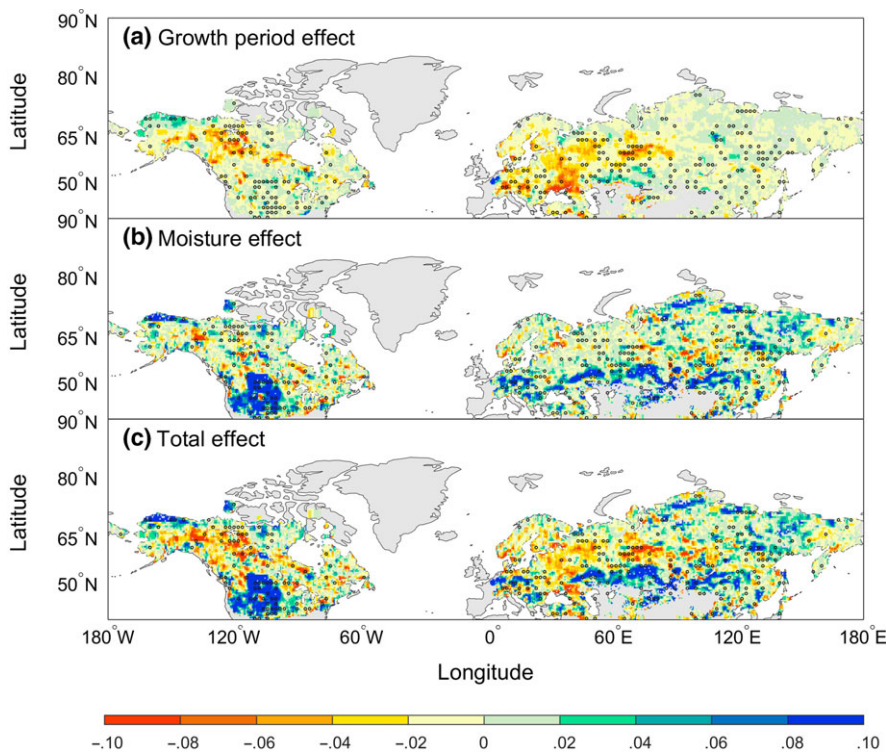
FIGURE 3 Spatial distribution of the magnitude of winter SWE impact on early growing-season productivity through the growth period effect (a), moisture effect (b) and their summed effect (c) over north of 30 degrees in the Northern Hemisphere based on the satellite analysis. The dots indicate the pixels with significant partial correlation between winter SWE and early growing-season productivity during the period 1982–2011 ($p < .1$) [Colour figure can be viewed at wileyonlinelibrary.com]

the two effects shaping the observed temporal SWE–productivity relationship within each region. The "moisture" effect predominating over the "growth period" effect is found in western and central North America, and Greater Himalaya. In contrast, the "growth period" effect plays a dominant role in central Europe (Figure 4). When comparing across different regions, Greater Himalaya, western and central North America have a relatively high "moisture" effect, but central Europe has a high "growth period" effect. In addition, we should inform that all variables included in our correlation and path analyses are original time series without removing the temporal trend, and hence the calculated path coefficients linking the variables in the path analysis include the influence of trend of one variable on that of another variable. For example, in part of arctic and subarctic northeast Eurasia (blue rectangle in Fig. S4c, S4d), there is a widespread delay in snowmelt date (around 60.8% of the region), but an advance in spring onset date (around 88.6% of the region) over the past three decades. Their opposing patterns are consistent with our path analysis showing that the regional path coefficient linking snowmelt date and spring onset date is −0.04. In Central America (red rectangle in Fig. S4b, S4e), there is a widespread increasing trend in both soil moisture (59.4% of the region) and vegetation activity (66.0% of the region) in the last three decades, and their coherent patterns are also confirmed by the regional positive path coefficient (0.15).

To inquiry which bivariate coupling mainly contributes to the observed pattern in different regions (Figure 4), we calculate the path coefficient linking the two variables (Fig. S5) and find that the relatively high "growth period" effect in Central Europe is mainly contributed by the high path coefficient (0.36) relating winter SWE to the snowmelt date, and that (0.47) relating the timing of

snowmelt to spring onset date (Figure 5). But the relatively low correlation between spring onset date and productivity appears to be a primary factor limiting the "growth period" effect. The relatively high "moisture" effect, as notably found in western North America and Greater Himalaya, is due to the relatively high coupling between soil moisture and productivity (Figure 5 and Fig. S5). The memory effect of winter SWE on spring and summer soil moisture seems to exert a major control on limiting the size of "moisture" effect.

In comparison with satellite-based results, terrestrial ecosystem models in general reproduce snow–productivity relationship across the whole north region, in terms of percentage of pixels having significant correlations at $p < .1$ (Figure 6). But this model-data match does not always hold in some sub-regions. For example, in Greater Himalaya, the models have a much lower percentage of pixels (1.7%) showing positive correlations at $p < .1$ than that from satellite analysis (14.7%). Concerned with the two processes (via changing soil moisture and via changing the growth period) in controlling snow–productivity relationship, the models (0.024 ± 0.01) faithfully simulate the positive value of "moisture" effect (0.025), but underestimate the "growth period" effect based on satellite observations for the whole north region (Figure 6). Of particular concern is the moderate success of the models in simulating the positive "moisture" effect in western and central North America that rank the largest among all sub-regions. But there is still a large model spread in the magnitude of these two effects, and some models even having the opposite sign with that analysed from satellite data in some sub-regions. Most notably in Central Europe, the model ensemble erroneously simulates a positive "growth period" effect and a negative "moisture" effect.
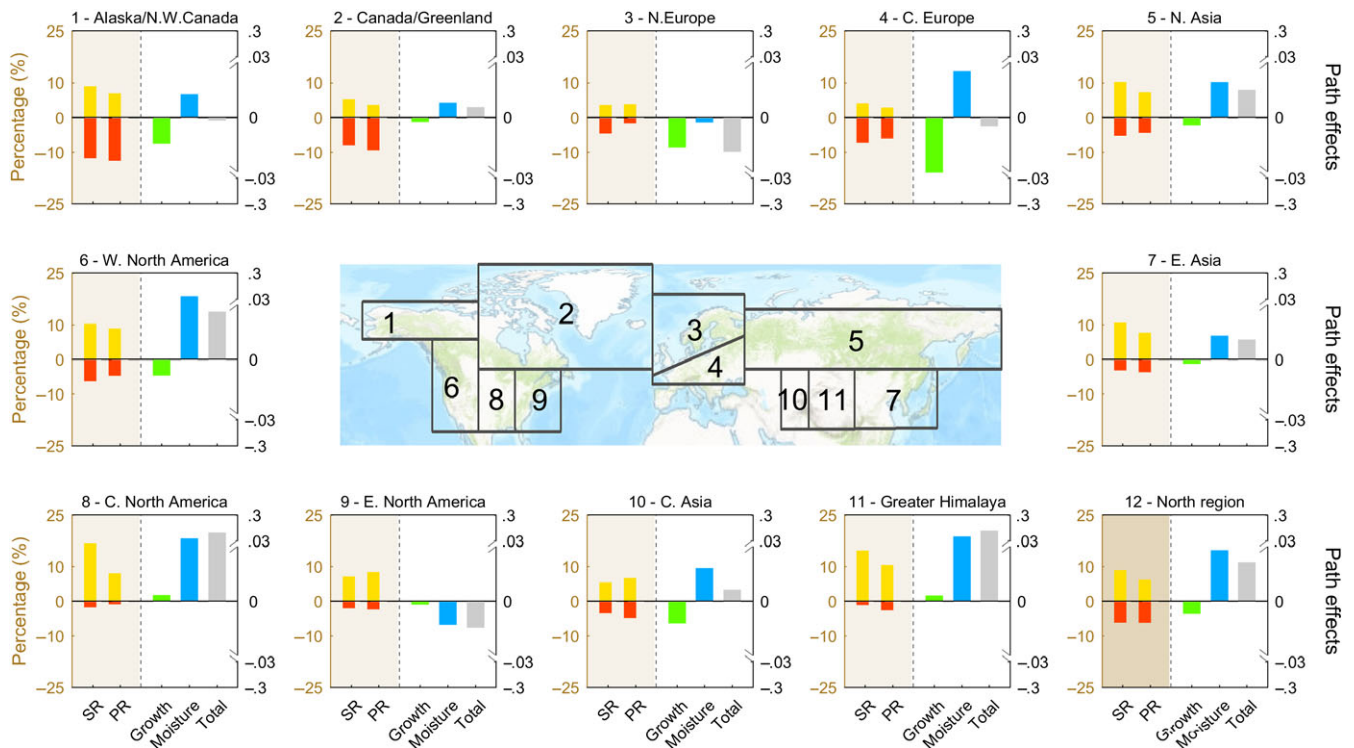
FIGURE 4 Comparison of the magnitude of winter SWE impact on early growing-season productivity through growth period effect, moisture effect and their summed effect over 11 different regions and the whole northern region. The percentages of statistically significant (at $p < .1$) simple correlation (SR) and partial correlation (PR) between winter SWE and early growing-season productivity during the period 1982–2011 are also shown for each region. The regional path coefficient is averaged from the pixels with winter SWE larger than 15 mm, their own path model passing through an acceptable goodness of model fit and their partial correlation between SWE and early growing-season productivity being statistically significant at $p < .1$. Exact coordinates of each region is provided in Table S3 [Colour figure can be viewed at wileyonlinelibrary.com]

4 | DISCUSSION

4.1 | Large spatial variation in the change of vegetation greenness with winter SWE

Our results indicate that winter SWE accumulation, as it could affect the growing-season length and moisture condition, is significantly tied to satellite-based vegetation greenness during the early GS over nearly one-fifth of land surface in the region north of 30 degrees. However, previously documented strong dependence of vegetation productivity on winter snow in mountainous regions (e.g. Trujillo et al., 2012) or over specific vegetation type (e.g. grasslands in Peng et al., 2010) are not always realized at large geographic scales that encompass a broad climatic range. This is mainly because a significant portion of the variability in vegetation greenness is explained by the interannual variations of temperature and/or soil moisture during the early GS (Figs S1 and S2), which agrees with the previous recognition that environments at lower latitudes are water-limited and at higher latitudes are energy (or temperature) limited. We show that increases in winter SWE can enhance the responses of vegetation productivity to temperature variation according to the spatial gradient analysis (Figure 2b). If space-for-time substitution was assumed, the decrease in winter SWE with the on-going global

warming might continue to weaken the temperature sensitivity of vegetation productivity, as found by Piao et al. (2014).

4.2 | Regionally variable role of different ecological processes in controlling vegetation response to snow change

Our results from correlation analyses indicate that the response of vegetation greenness to winter snow change is not uniform in magnitude and direction, and varies with the region. It therefore highlights that snow–productivity relationship is dependent on an interaction of different processes such as those (via changing soil moisture and changing the growth period) encapsulated in our experimental derived framework (Figure 1).

The strong negative impact of increasing (decreasing) SWE on productivity through shortening (extending) the "growth period" is predominantly found in part of Alaska and Central Europe (known as "growth period" effect), but not in arctic and subarctic northeast Eurasia, and North America. It well explains the result that part of Alaska and Central Europe has more percentage of pixels with negative snow–productivity correlations, since more snow is generally expected to delay the date of snowmelt and spring onset and then suppress plant growth (Figure 3a). Nevertheless, the magnitude of
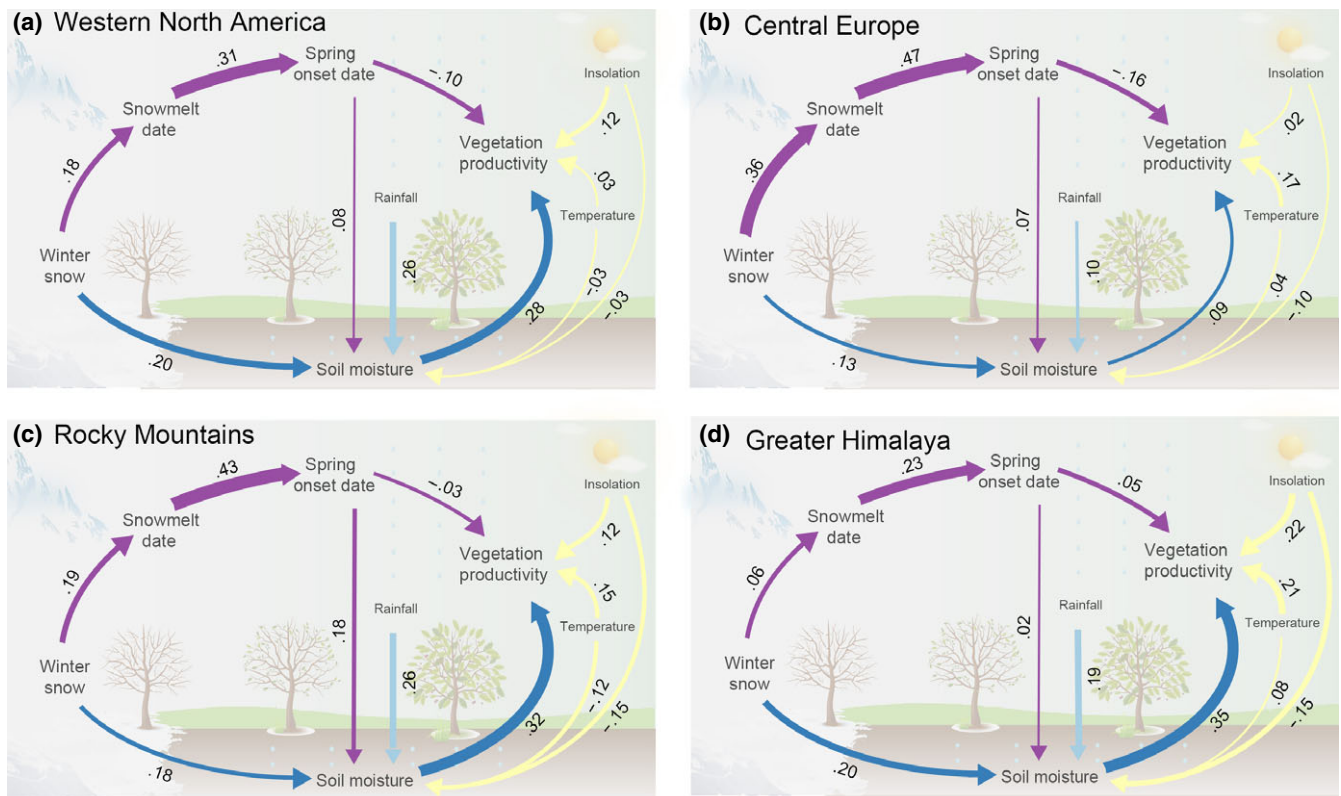
FIGURE 5 Path models are shown for the western North America (a), central Europe (b), Rocky Mountains (c) and Greater Himalaya (d). Numbers adjacent to arrows are regional path coefficient indicative of the effect-size of the bivariate relationship, and the width of arrows is proportional to the strength of path coefficients. The regional path coefficient is averaged from the pixels with winter SWE larger than 15 mm, their own path model passing through an acceptable goodness of model fit and their partial correlation between SWE and early growing-season productivity during the period 1982–2011 being statistically significant at $p < .1$ [Colour figure can be viewed at wileyonlinelibrary.com]
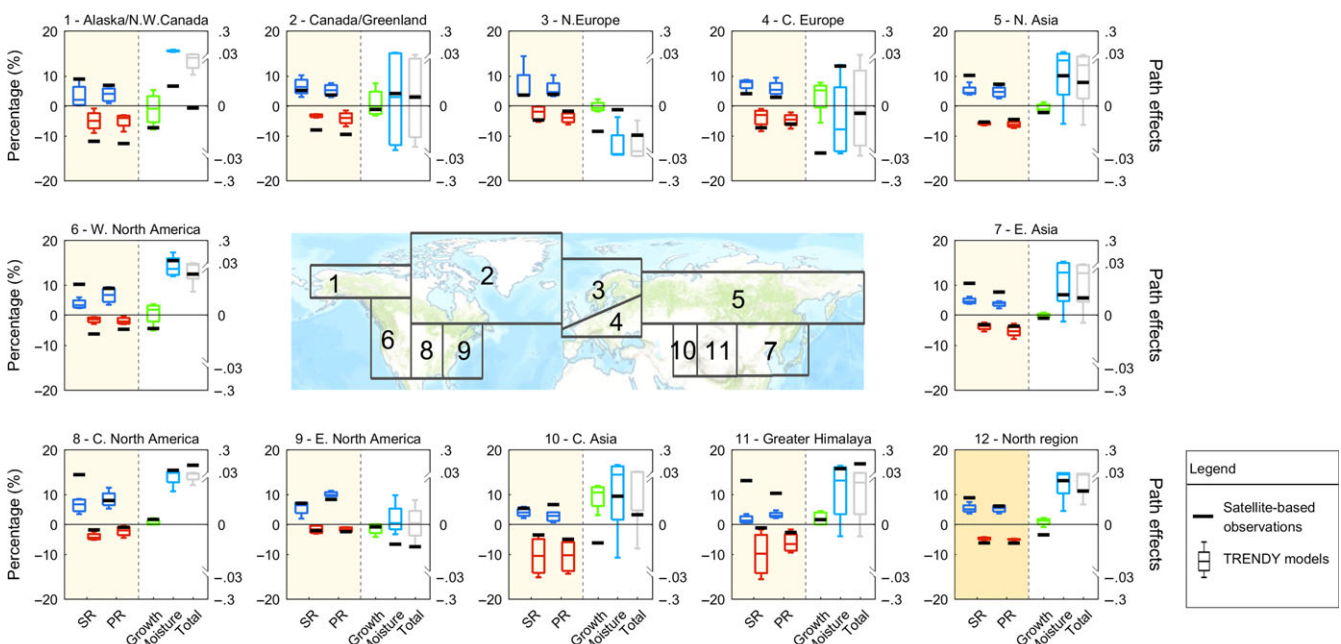

FIGURE 6 Comparison of satellite-derived observations and TRENDY model-based growth period effect, moisture effect and their summed effect over 11 different regions and the whole northern region. The percentages of statistically significant (at $p < .1$) simple correlation (SR) and partial correlation (PR) between winter SWE and early growing-season productivity during the period 1982–2011 are also shown for both satellite and models at each region [Colour figure can be viewed at wileyonlinelibrary.com]

this effect and its role in shaping snow–productivity correlation is not uniform across the northern ecosystems. As exemplified in Figure 1, the magnitude of "growth period" effect is co-determined by the three bivariate correlations: the effect of winter SWE accumulation on the snowmelt date, the linkage between the timing of snowmelt and spring onset date, and the impact of spring onset date on vegetation productivity. In arctic and subarctic northeast Eurasia, the weak "growth period" effect is mainly induced by the weak relationship (low path coefficient) linking between winter SWE and snowmelt date (Fig. S3a1), and that between snowmelt and spring onset date (Fig. S3a2). For example, part of this region experiences an increase in winter SWE over the past three decades (Fig. S4a), but increased winter snow accumulation did not proportionally translate into delayed snowmelt (Fig. S4c and Fig. S3a1), which is probably due to increased spring atmospheric heat transport from lower latitudes (e.g. Kapsch, Graversen, & Tjernstrom, 2013). Earlier snowmelt is always accompanied with increased temperature that is widely recognized as the most ecologically relevant cue for spring onset in many species, and a tight coupling between spring onset date and snowmelt date is therefore expected (e.g. Borner, Kielland, & Walker, 2008; Galen & Stanton, 1995; Høye, Post, Meltofte, Schmidt, & Forchhammer, 2007; Sweet, Gough, Griffin, & Boelman, 2014). But in this region spring onset date is not synchronized with snowmelt date (Fig. S4d and Fig. S3a1), tentatively suggesting that multiple environmental constraints, such as insufficient heat accumulation after snowmelt and light limitation (Basler & Korner, 2012; Zohner & Renner, 2015), might prevent plants from taking advantage of earlier snowmelt. Besides arctic and subarctic northeast Eurasia, North America also has a weak "growth period" effect, which is mainly attributable to the weak correlation between spring onset date and vegetation productivity. In general, the advance of spring onset date, that extends the growing period, could turn the longer growing season into increased vegetation growth (e.g. Piao et al., 2017) and productivity in many parts of the Northern Hemisphere (Fig. S3a3). But the spring phenological shift in most of North America seems to be uncorrelated with GS productivity (Fig. S3a3). This decoupling is related to the possibility that soil moisture mainly determines the productivity, as shown in Figs S1 and S2.

The strong positive impact of increasing (decreasing) winter SWE on early GS productivity through increasing (decreasing) soil moisture conditions is mainly concentrated in western, central North America and Greater Himalaya (known as "moisture" effect), therefore resulting in much more pixels having positive snow–productivity correlations. The effect-size represents the degree of dependence of winter snow as a water resource for vegetation growth, which is determined by the legacy effect of winter SWE on GS soil moisture and the reliance of vegetation growth on moisture conditions (Figure 1). Our results are consistent with previous studies focusing on temperate and alpine grasslands of China (Peng et al., 2010), and forested ecosystems of western North America (Angert et al., 2005; Buermann et al., 2007), where melting snow provides an important contribution to spring and summer soil moisture and in turn the vegetation growth. In contrast, the "moisture" effect is not pronounced

in pan-arctic region such as Alaska and northern Canada characteristic with long snow season and thick winter snowpack. This result could be related to the possibility that the underlain permafrost prevents the infiltration of snowmelt water into the soils. Much of snowmelt would immediately be lost to surface runoff and less is therefore retained for plant growth.

Our model-data comparison suggests that models do a relatively better job of capturing the "moisture" effect than the "growth period" effect, suggesting that there is a critical need for improved representation of "growth period" effect in current models. This model deficiency might be anticipated since current models have a poor performance in simulating spring phenology (Richardson et al., 2012). It therefore requires a further understanding of the controls of spring phenology (particularly the role of snowmelt date), and hastens the development of an accurate characterization of the relationship between phenology and its controls in models. In addition, the model characterization of the degree to which spring phenology controls productivity, which also determines the "growth period" effect according to our assembled path model, needs also to be improved (e.g. Richardson et al., 2010).

4.3 | Limitations and future perspectives

It is important to consider the limitations of our data and analyses. First, the underlying relationships between winter SWE and vegetation productivity through including intervening variables (snowmelt date, spring onset date and soil moisture) have been reported in previous experimental studies, which could provide evidence that the proposed links are of general significance. But the current path model (Figure 1) is still incomplete. An advance of snowmelt date might increase the probability of spring frost damage to the growth of frost-sensitive species (Inouye, 2000, 2008; Inouye, Morales, & Dodge, 2002; Wipf et al., 2009). For example, in a long-term study of flowering phenology conducted at the Rocky Mountain Biological Laboratory (Colorado, USA), Inouye (2008) found that larger winter snowpack leads to later snowmelt and later beginning of the growing season, but increased abundance of flowering in the summer mainly because of less spring frost mortality of buds. Furthermore, changes in winter snowpack modify the soil thermal regime and soil freeze-thaw cycles that could significantly affect the nutrients available for plant growth (e.g. Weintraub & Schimel, 2003). Unfortunately, these processes cannot be explicitly considered in the path model largely due to data scarcity on soil nutrients and the risk of frost damage at the continental scale.

Second, our results are not always consistent with previously documented snow–productivity relationships in the same studied region. Grippa et al. (2005) found that vegetation greenness increased with winter snowpack over central Siberia, but we reported a mixed relationship (Figure 2). This discrepancy could be tied to the use of different NDVI and snow data. Compared to the pathfinder AVHRR land (PAL) NDVI used in Grippa et al. (2005), we adopt the latest version of GIMMS-NDVI3g that should have an improved algorithm in accounting for various deleterious effects,

such as calibration loss, orbital drift and volcanic eruptions. In terms of snow data, Grippa et al. (2005) used Special Sensor Microwave/Imager (SSM/I) to retrieve snow depth based on the spectral gradient algorithm (Grippa, Mognard, Le Toan, & Josberger, 2004). The use of GlobSnow SWE in this study should have an enhanced accuracy in the retrieval of SWE over central Siberia especially in forested regions, since which implements specific modifications to SWE retrieval algorithm over forests and integrates different satellite-based passive microwave measurements including SSM/I. But we should inform that GlobSnow is still subject to certain uncertainties in estimating SWE above 150 mm or in the forested regions with dense canopy cover (Takala et al., 2011).

We also find that the satellite-based result is not consistent with the tree-ring study in subarctic Eurasia, which shows that earlier snowmelt can advance the initiation of cambial activity necessary for forming wood cells (Vaganov et al., 1999). It highlights the necessity in developing high-resolution maps of SWE since current GlobSnow SWE maps (25 km^2) are too low resolution for precise estimates in small spatial scales. The on-going SnowEx Campaign will serve to produce these highly detailed maps (e.g. even down to 1.5-m resolution) in the future, through combining lidar instruments (laser altimeter) and different types of radar in a design for a snow-sensing satellite (Witze, 2016). Finally, our results have significant implications for understanding vegetation browning in boreal North America (Beck & Goetz, 2011). The decline of winter snow accumulation, together with the detectable imprint of winter snow on early GS soil moisture and in turn vegetation activity, could partly contribute to this browning trend. In a warmer world, the decline in winter snow accumulation because of reduced snow-to-rain ratio is likely to occur, which will further aggravate the browning trend that could potentially induce the tree mortality across the boreal zone.

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SUPPORTING INFORMATION

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