LETTER

Attribution of the spatial heterogeneity of Arctic surface albedo feedback to the dynamics of vegetation, snow and soil properties and their interactions

Linfei Yu1, Guoyong Leng1,2,* and Andre Python3

1 Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Science and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, People’s Republic of China
2 University of Chinese Academy of Sciences, Beijing 100049, People’s Republic of China
3 Center for Data Science, Zhejiang University, Hangzhou 310058, People’s Republic of China

* Author to whom any correspondence should be addressed.
E-mail: lenggy@igsnrr.ac.cn

Keywords: Arctic, surface albedo feedback, land warming, interaction effects, spatial heterogeneity

Supplementary material for this article is available online

Abstract

The Arctic warming rate is triple the global average, which is partially caused by surface albedo feedback (SAF). Understanding the varying pattern of SAF and the mechanisms is therefore critical for predicting future Arctic climate under anthropogenic warming. To date, however, how the spatial pattern of seasonal SAF is influenced by various land surface factors remains unclear. Here, we aim to quantify the strengths of seasonal SAF across the Arctic and to attribute its spatial heterogeneity to the dynamics of vegetation, snow and soil as well as their interactions. The results show a large positive SAF above $-5\% \, K^{-1}$ across Baffin Island in January and eastern Yakutia in June, while a large negative SAF beyond $5\% \, K^{-1}$ is observed in Canada, Chukotka and low latitudes of Greenland in January and Nunavut, Baffin Island and Krasnoyarsk Krai in July. Overall, a great spatial heterogeneity of Arctic land warming induced by positive SAF is found with a coefficient of variation (CV) larger than 61.5%, and the largest spatial difference is detected in wintertime with a CV > 643.9%. Based on the optimal parameter-based geographic detector model, the impacts of snow cover fraction (SCF), land cover type (LC), normalized difference vegetation index (NDVI), soil water content (SW), soil substrate chemistry (SC) and soil type (ST) on the spatial pattern of positive SAF are quantified. The rank of determinant power is SCF > LC > NDVI > SW > SC > ST, which indicates that the spatial patterns of snow cover, land cover and vegetation coverage dominate the spatial heterogeneity of positive SAF in the Arctic. The interactions between SCF, LC and SW exert further influences on the spatial pattern of positive SAF in March, June and July. This work could provide a deeper understanding of how various land factors contribute to the spatial heterogeneity of Arctic land warming at the annual cycle.

1. Introduction

Surface albedo refers to the ratio of the total reflected radiation to the incident radiation for a certain surface (Henderson-Sellers and Wilson 1983), and how its variations can significantly regulate regional temperature anomalies (Dai et al 2019, Alessandri et al 2021). Generally, surface albedo feedback (SAF) includes positive and negative effects. A negative SAF refers to an increase in highly reflective factors (e.g. snow and sea ice) of the underlying surface and a decrease in the absorption of incoming solar radiation, thus strengthening surface cooling (Hall and Qu 2006, Alessandri et al 2021). In contrast, the phenomenon of increased temperature triggered by reduced albedo is often referred to as a positive SAF (Hall and Qu 2006). It has long been known that the loss of snow and ice under global warming greatly contributes to the decrease in Arctic surface albedo (Walsh 2014, Andry et al 2017, Huang et al 2017,
Jakobs et al. 2020), which enhances the absorption of solar radiation and thus amplifies the warming rate over the Arctic (see figure S1 (available online at stacks.iop.org/ERL/17/014036/mmedia), feedback loop). Therefore, understanding the mechanisms behind historical positive SAF is fundamental for predicting future climate warming in the Arctic due to global climate change.

Previous studies have mainly focused on quantifying the strengths of SAF and its components, as well as its seasonal cycle at various time and space scales (Hall and Qu 2006, Wegmann et al. 2018, Thackeray and Hall 2019, Alessandri et al. 2021). For example, Qu and Hall (2014) indicated that approximately 5%–10% of the global warming rate is contributed by the variation in SAF via changes to the top of atmosphere radiation balance. However, SAF can exert a greater impact on regional climate and hydrological cycles because this feedback tends to be larger in the regions where snow and ice dynamics are susceptible to climate change (Bowman et al. 2018, Kim et al. 2018, Thackeray et al. 2018, Webb et al. 2021). A number of studies have estimated that an approximately 1% reduction in land albedo over the Northern Hemisphere could cause an average of 1 °C of near surface warming, equivalent to a radiative effect of approximately 0.1 W m⁻² K⁻¹ (Qu and Hall 2006, 2014, Flanner et al. 2011, Fletcher et al. 2014). As would be expected due to low snow and ice cover, Qu and Hall (2014) found a low SAF (0.1% K⁻¹–0.3% K⁻¹) during summertime compared to other seasons (0.6% K⁻¹–0.9% K⁻¹) across Northern Hemisphere extratropical land areas. Similarly, over the Arctic, the SAF exerts an impact mainly in spring and/or summer, which is closely associated with the seasonal cycling of sea ice area (Andry et al. 2017). Spatially, both observational and modeling analyses reveal stronger feedback strengths in high latitudes from 50 °N to 70 °N (Fletcher et al. 2012, 2014, Thackeray et al. 2021) with a large positive SAF (+0.87 W m⁻² K⁻¹) in snow-dominated areas (annual mean areal fraction of snow cover >10%) (Alessandri et al. 2021).

In recent decades, a considerable reduction in snow cover extent/area has been detected in spring and summer by satellite-derived observations in polar and high mountainous regions due to climate warming (Estilow et al. 2015, Hartfield et al. 2018, Notarnicola 2020). Moreover, extensive greening of the Earth was reported under anthropogenic climate warming (Forzieri et al. 2017), which could influence SAF in snow-covered regions (e.g. polar areas and high mountains) by altering the masking effect of vegetation over snow and land surface albedo (Loranty et al. 2014, Yu et al. 2021). In addition to snow and vegetation, albedo can also be modulated by soil parameters, including soil type (ST) and soil moisture. For instance, dry soil often shows high albedo, and vice versa for wet soil (Yang et al. 2020). In addition, a smaller soil particle size tends to increase soil albedo because incident radiation is more easily trapped in large soil aggregates with more inter-aggregate spaces and cracks (Cierniewski et al. 2013). These results suggest that the dynamics of snow, vegetation and soil properties could interact with each other and modulate the spatial pattern of land surface albedo, affecting the spatial heterogeneity of Arctic land warming induced by positive SAF. To date, however, quantitative attribution of the spatial pattern of Arctic land warming induced by positive SAF across Arctic land areas is still lacking.

To fill this gap, this study aims to quantify the strengths of SAF across the Arctic and to identify the key influencing factors governing its spatial heterogeneity during the historical period of 1982–2015. The three key scientific questions addressed in this study are as follows: (a) how is the seasonal SAF spatially distributed across Arctic land near the surface? (b) How do the dynamics of vegetation, snow and soils control the spatial pattern of seasonal positive SAF? (c) How do vegetation, snow and soils interact with each other and affect the positive SAF? The results can enhance our understanding of the regional differences in SAF across the Arctic and can have large implications for predicting future Arctic climate under global warming.

2. Materials and methods

2.1. Study area

Here, the Arctic is defined as the areas north of the Arctic Circle (66°34′), including the Arctic Ocean, adjacent seas, and parts of Alaska, Northwest Territories, Nunavut, Chukotka, eastern Yakutia, western Yakutia, Krasnoyarsk Krai, Yamalo-Nenets Autonomous Okrug (Y aNAO) and Greenland (figure 1). Cool summers and cold winters are typical features of the Arctic climate. Generally, most regions of the Arctic receive annual precipitation below 500 mm, mainly in the form of snow (Przybylak 2003). The average winter temperature can be as low as −40 °C, and the coldest temperature recorded is approximately −68 °C (Przybylak 2003). Dwarf shrubs, graminoids, herbs, lichens and mosses are the main vegetation types over the Arctic (Walker et al. 2005, Raynolds et al. 2019). Nonvascular plants such as lichens and mosses tend to grow in the colder areas of the Arctic, while shrubs dominate in relatively warmer regions (Walker et al. 2005).

2.2. Datasets

2.2.1. Land surface albedo dataset

The Global LAnd Surface Satellite (GLASS) phase-2 broadband surface albedo product is adopted in this study (www.glass.umd.edu/Download.html), which is characterized by long time series and spatiotemporal continuity (Liang et al. 2013, 2021). This
product is derived from advance very-high-resolution imaging spectroradiometer (AVHRR) data at a spatial resolution of 0.05° and a temporal resolution of 8 d. During the process of generating the GLASS phase-2 surface albedo product, the broadband surface albedo (shortwave, visible, and near infrared) is first estimated using the direct-estimation algorithm from the cloud-detected moderate-resolution imaging spectroradiometer and AVHRR data and then filled and fused by statistics-based filter approaches (Liang et al. 2013, 2021, Jia et al. 2018). The GLASS albedo product provides information on the directional hemispherical reflectance (black sky albedo) and bihemispherical reflectance (white sky albedo). The shortwave broadband (0.3–5.0 µm) black sky albedo is used in this study and is defined as the reflection of direct radiation in the absence of a diffuse component of illumination (Liang et al. 2021).

2.2.2. NDVI dataset

The GIMMS3g normalized difference vegetation index (NDVI) is produced by the National Oceanic and Atmospheric Administration of the USA from AVHHR data (Tucker et al. 2005) and is available at https://ecocast.arc.nasa.gov/data/pub/gimms/3g/v1/. The 15 d GIMMS3g NDVI data have a spatial resolution of 1/12° (~8 km) covering the period from 1982 to 2015. This set of data has eliminated the effects of sensor replacement and orbital drift during the production process and is widely applied for measuring ecosystem carbon cycles, vegetation phenological changes and climate responses (Kong et al. 2016, Pan et al. 2018, Yu et al. 2021). In this study, the maximum value composite (MVC) technique is used to produce a monthly NDVI. The specific introduction of the MVC method can be seen in the supplementary information (SI).

2.2.3. Land parameter data

The 2 m air temperature (T2m), snow cover fraction (SCF), soil water content (SW) and ST data are obtained from the land component of the 5th generation of European ReAnalysis (ERA5-Land) (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=form). ERA5-Land is mainly used to describe the evolution of land parameters in an accordant mode in recent decades (Muñoz-Sabater et al. 2021). Furthermore,
ERAS5-Land shares most parameterizations with ERAS5, thus, ensuring the use of a state-of-the-art land surface model (Muñoz-Sabater et al 2021). Another great merit of ERAS5-Land is its improved spatial resolution to 9 km from the 31 km ERAS5 and 80 km ERA-Interim products (Muñoz-Sabater et al 2021).

2.2.4. Circumpolar Arctic vegetation map (CAVM)

The CAVM is the first vegetation map covering the entire Arctic based on a single and unified legend (www.arcticatlas.org) (CAVM Team 2003). The CAVM is a vector map compiled from hand-drawn polygons that are interpreted by a geobotanical method (Walker et al 2005). This map contains 15 vegetation types using a relatively simple legend (Walker et al 2005). In addition, the map also includes the outlines of different bioclimate subzones, lake cover, physiography and substrate chemistry. The land cover types (LCs) (mainly vegetation cover types) and soil substrate chemistry (SC) are used in this study. The spatial patterns of LC and SC are shown in figure S2 in the SI.

2.3. Methods

2.3.1. Data preprocessing

All the above raster data are re-projected and resampled to the 25 km equal-area scalable Earth grid (EASE-grid), which is a widely used format for data analysis and visualization for polar regions (Atlaskina et al 2015, Yu et al 2021, Yu and Leng 2022). For albedo data, first, the ~0.05° resolution datasets are re-projected to the EASE 5 km grid using the nearest neighbor approach such that each 25 km grid contains 5 × 5 smaller grids. Second, the data are aggregated using an averaging method to the 25 km EASE grid in ArcGIS software. Similarly, the T2m, SCF, SW and ST data are homogenized over the Arctic to a 25 km spatial resolution based on the bilinear interpolation method.

2.3.2. Evaluation of the strength of surface albedo feedback (SAF)

Following Hall and Qu (2006) and Qu and Hall (2014), the strength of SAF is defined as the relative percentage change in albedo ($\Delta_{\text{Albedo}} \times 100$), divided by the corresponding change in near surface (2 m) air temperature ($\Delta T_{2m}$). The specific calculation formula is as follows:

$$\text{SAF} = \frac{\Delta_{\text{Albedo}} \times 100}{\text{Albedo} \times \Delta T_{2m}}$$

(1)

where $\Delta$ denotes the month-to-month change, which represents 1 month to the next successive month. From this equation, it can be seen that an increase in albedo from 1 month to the next month, as expected in autumn with increasing snow and ice cover, leads to a negative SAF, while a decrease in albedo, as expected in spring, leads to a positive SAF.

2.3.3. Evaluation of the spatial heterogeneity of positive SAF

Following previous studies (e.g. Hall and Qu 2006, Qu and Hall 2014), negative values of SAF indicate a positive SAF, while a decrease in albedo could enhance the near surface temperature. Consequently, we only evaluate the spatial heterogeneity of positive SAF over the Arctic in this study. The coefficient of variation (CV), which describes the relative deviation of a series of data from its mean value, is adopted to evaluate the spatial heterogeneity of positive SAF in this study. The calculation formula is as follows:

$$\text{CV} = \frac{\text{P-SAF}_{SD}}{\text{P-SAF}_{M}} \times 100\%$$

(2)

where P-SAF$_{SD}$ indicates the standard deviation of positive SAF across the Arctic land areas, and P-SAF$_{M}$ denotes the averages of these positive SAFs.

2.3.4. Changing trend calculation and test

Based on a regression analytical method, the changing trend of CVs of positive SAF can be calculated in different months for the 1982–2015 period. The trends are estimated using equation (3):

$$\text{Trend} = \frac{n \times \sum_{i=1}^{n} i \times X_i \sum_{i=1}^{n} i \times \sum_{i=1}^{n} X_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

(3)

where $i$ is the serial number of each year; $X_i$ is the value of CV in year $i$; and $n$ is the cumulative number of years during the study periods.

The Mann–Kendall trend test, commonly known as the Kendall statistic, is a non-parametric evaluation of monotonic trends of a variable over time that does not require measurements to be normally distributed or the trend to be linear (Mann 1945, Kendall 1948). In the Mann–Kendall test, the null hypothesis $H_0$ assumes that if no trend exists, the $n$ measurements $X_1$, ..., $X_n$ obtained over time are realizations of the independently and identically distributed random variables $X_1$, ..., $X_n$. The alternative hypothesis $H_1$ for a two-sided test assumes that the distributions of $X_i$ and $X_j$ are not independently and identically distributed. For all $k, j \leq n$ with $k \neq j$.

The test statistics, with zero mean and asymptotically normal variance, can be calculated using equations (4) and (5):

$$S = \sum_{j=1}^{n} \sum_{k=j+1}^{n} \text{Sign} (x_k - x_j)$$

(4)

$$\text{Sign} (x_k - x_j) = \begin{cases} 1 & x_k > x_j \\ 0 & x_k = x_j \\ -1 & x_k < x_j \end{cases}$$

(5)

where $S$ is the Gaussian distribution, and the mean value is 0. The variance can be calculated by $\text{Var}(S) =$
The OPGD model is adopted to investigate the spatial heterogeneity of a geographic phenomenon and potential influencing factors (Song et al. 2020). This technique is based on the following hypotheses: if the driving factors have a significant influence on the warming of Arctic land, the spatial patterns of the independent and dependent variables should be similar (Song et al. 2020). Compared to the traditional linear model, the OPGD model has the advantage of being able to detect the relationship between driving factors and geographical phenomena without any assumption of linearity. Furthermore, OPGD has four modules, two of which are adopted in this study: the factor detector and interaction detector. We establish the relationship between six factors and positive SAF (LC + SCF + NDVI + SW + SC + ST → positive SAF) and run the OPGD model for each month with a total of 408 runs (34 years × 12 months).

Details on the parameter optimization of the OPGD model are provided in the SI. The factor detector uses a OGD model are provided in the SI. The factor detector and interaction detector. We established the following principles of the interaction detector: the spatial heterogeneity of positive SAF.

The interaction detector identifies the interactive effects of two covarying spatial variables on the spatial heterogeneity of positive SAF based on the relative importance of interactions calculated by q values of the factor detector (Song et al. 2020). The spatial interaction represents an overlay of two spatial explanatory variables. The weakening, enhancement or independence of two spatial variables can be quantified by the interaction detector. Specifically, there are five interaction types that can be examined using the interaction detector, including nonlinear weakening, univariable weakening, bivariable enhancement, independent, and nonlinear enhancement (Song et al. 2020) (table 1). The detailed principles of the interaction detector of OPGD are introduced in the SI.

### 3. Results

#### 3.1. The spatial pattern and heterogeneity of SAF

The spatial patterns of SAF from 1982 to 2015 are presented in figure 2. From January to March, most Arctic land areas exhibit negative SAFs except for Baffin Island and high latitudes of Greenland in January, Yanao, parts of Krasnoyarsk Krai and Alaska in February and Chukotka, Banks Island and Victoria Island in March (figures 2(a)–(c)). In April, a positive
SAF is found in Alaska, Chukotka and the Northwest Territories, with feedback strengths ranging from $-5\% \text{ K}^{-1}$ to $0\% \text{ K}^{-1}$ (figure 2(d)). From May to June, all Arctic land shows a positive SAF except for the midland of Greenland in May (figures 2(e) and (f)). In particular, high positive SAFs are found in Chukotka, eastern Yakutia, Alaska, Northwest Territories, Banks Island and Victoria Island in June, with feedback strengths above $-5\% \text{ K}^{-1}$ (figure 2(f)). Notably, in July, most Arctic land areas show a negative SAF, especially in the Krasnoyarsk Krai and Baffin Islands, with a large feedback strength above $10\% \text{ K}^{-1}$ (figure 2(g)). From August to December, the positive SAF dominates most regions of Arctic land, with feedback strength ranging from $-5\% \text{ K}^{-1}$ to $0\% \text{ K}^{-1}$ (figures 2(i)–(l)).

Figure 2. Maps of SAF in different months from 1982 to 2015 over the Arctic. The CVs are calculated only for the positive SAF. CV$_{P-SAF}$ denotes the coefficient of variation of positive SAF.
Overall, a large spatial difference in positive SAF is observed for each month, with CV values beyond 61.5% (figure 2). The largest spatial heterogeneities of positive SAF are found in winter (from December to February), with CV values ranging from 643.9% to 2462.2% (figures 2(a), (b) and (l)). Despite fluctuations, the CV of positive SAF shows an overall decreasing trend at a rate ranging from 0.1% to 3.1% per decade except for February, March, June and November (figure 3). In addition, the Mann–Kendall test shows that the temporal changes in CV are statistically significant ($p < 0.05$) for October and December, which decrease at rates of 2.0% and 3.1% per decade, respectively (figure 3).

### 3.2. Attribution of the spatial heterogeneity of positive SAF

Figure 4 shows the determinant power ($q$) of six factors on the spatial pattern of positive SAF for each month. Overall, the LC and SCF are the dominant factors determining the spatial pattern of positive SAF in all seasons (figure 4). Specifically, from January to March, LC, SCF and SW have relatively higher determinant power on the spatial pattern of positive SAF, with average $q$ values of 0.22–0.34, 0.14–0.39 and 0.13–0.32, respectively (figures 4(a)–(c)). In addition to LC and SCF, the NDVI also exerts a large influence on the spatial pattern of positive SAF from April to May, with mean $q$ values above 0.32 (figures 4(d) and (e)). During early summer (from June to July), all selected factors have relatively weak determinant power ($q \leq 0.08$) for the spatial pattern of positive SAF (figures 4(f) and (g)). In August, the LC and SCF again have strong contributions to the spatial pattern of positive SAF, with $q$ values of 0.38 and 0.39, respectively (figure 4(h)). In September, SCF has the highest determinant power, followed by LC, NDVI, SW, ST and SC (figure 4(i)). From October to December, the SCF is the key factor controlling the spatial pattern of positive SAF, with average $q$ values ranging from 0.09 to 0.30 (figures 4(j)–(l)).

Changing trends of the determinant power ($q$) for six factors in different months from 1982 to 2015 are summarized in table 2. A decreasing trend is detected in all six factors regarding determinant power in winter (from December to February) (table 2). More
Figure 4. Box plots of the determinant power ($q$) of six factors on positive SAF in different months from 1982 to 2015. The red number indicates the averages of $q$ for each influencing factor.

Table 2. The results of Z values based on the Mann–Kendall trend test for determinant power ($q$) of six land factors in different months over the Arctic from 1982 to 2015.

| Land factors | Month    | LC      | NDVI    | SC      | SCF     | ST      | SW      |
|--------------|----------|---------|---------|---------|---------|---------|---------|
|              | January  | −1.95** | −3.74** | −1.72   | −2.46   | 0.21    | −3.44** |
|              | February | −3.49** | −3.38** | −2.94** | −2.28** | −2.45** | −4.03** |
|              | March    | −0.59   | −1.31   | 0.32    | −3.62** | 0.39    | −2.69** |
|              | April    | −0.44   | 1.60    | 0.51    | −0.89   | 0.68    | −1.07   |
|              | May      | −0.92   | −1.57   | −1.27   | −1.01   | −1.54   | −1.93   |
|              | June     | −1.01   | −0.72   | −2.31*  | −2.36*  | −2.02*  | −0.99   |
|              | July     | 0       | 0.92    | −0.59   | −0.21   | −1.04   | −3.05** |
|              | August   | 0.97    | −0.15   | 1.33    | 0.59    | 1.01    | −0.21   |
|              | September| 1.42*   | 2.69**  | 2.76**  | 1.04    | −0.53   | 0.21    |
|              | October  | 2.67**  | 1.89    | 2.15*   | 1.07    | 1.54    | 2.19*   |
|              | November | 1.19    | 0.15    | 0.62*   | 0.33    | −0.12   | 1.42    |
|              | December | −1.39   | −1.81*  | −2.49** | −0.21   | −1.39   | 0.47    |

Note: The positive Z values indicate an increasing trend, and negative Z values indicate a decreasing trend. * and ** represent significance at the 95% and 99% confidence levels, respectively.

Specifically, a significant ($p < 0.05$) decreasing trend is found for the determinant power of LC, NDVI, SCF and SW in January and February (table 2). In March, the determinant power of SCF and SW shows a significant ($p < 0.05$) reduction over time across the Arctic (table 2). Similarly, the SC, SCF and ST exhibit a significantly ($p < 0.05$) decreasing determinant power for the spatial pattern of positive SAF in June (table 2). In contrast, the contributions of the NDVI and SC to the spatial pattern of positive SAF increased significantly during September, and the same results are found for LC, SC and SW during October (table 2).
Figure 5. Interaction effects and types between influencing factors on positive SAF in different months from 1982 to 2015. The number indicates the 34 year average of the interaction effect in the same month; NE, BE, UW and IND indicate different interaction types; (a)–(l) represent January to December.

### 3.3. The interaction effects between influencing factors on the positive SAF

Figure 5 shows 15 pairs of interactions between the six factors affecting the spatial pattern of positive SAF. Specifically, in January, the LC∩SCF and LC∩SW have the largest BE and IND interaction effects, respectively, with an average value of 0.66 (figure 5(a)). From February to April, the NE and BE interactions between LC and NDVI are the dominant interaction types for the spatial pattern of positive SAF, with average $q(LC\cap NDVI)$ values ranging from 0.49 to 0.66 (figures 5(b)–(e)). Similar to the individual effect of a single factor, the interactions of influencing factors have relatively low values in June and July (figures 5(f) and (g)). However, the greatest NE interaction is found between LC and SCF, with $q$ values of 0.17 and 0.19, respectively (figures 5(f) and (g)). In August and September, the BE interaction between SCF and LC has the highest effect on positive SAF, with $q(SCF\cap LC)$ values of 0.76 and 0.84,
respectively, followed by the interaction of SCF and NDVI, with $q$ values of 0.56 and 0.83, respectively (figures 5(h) and (i)). For October and December, all pairs of interactions have relatively low values compared to other seasons, with the largest NE and UW interactions found for LCs–SW, with $q$ values ranging from 0.26 to 0.28 (figures 5(j)–(l)). More detailed interaction information between different land factors in different months can be found in the SI (tables S1–S12).

4. Discussion

Changes in snow cover area/extent are recognized as the major drivers of albedo changes in the Arctic (Webb et al 2021). Consequently, the influence of climate perturbation on snow cover is a key process governing Arctic land warming. Generally, snow has a high albedo, and as snow cover decreases, more land surface, which has a much lower albedo, is exposed (Webb et al 2021). In recent decades, most Arctic land areas experienced a significant ($p < 0.05$) reduction in snow cover during the study period except for Greenland (figure S3), which further contributed to the amplified warming of Arctic land due to the snow-cover-albedo-warming feedback. In addition, the factor detector suggests a high contribution of SCF causes spatial differences in positive SAF at the annual cycle, which is due to the high correlation ($p < 0.05$) between SCF and albedo at the spatial scale (figure S4).

In addition to snow cover, this study indicates that the vegetation type and coverage also have high contributions to the spatial heterogeneity of Arctic land warming induced by positive SAF. Changes in vegetation coverage inevitably result in changes in surface albedo, which could further affect the regional climate and energy budget of the Earth (Swann et al 2010, Willard et al 2019). For example, in snow-covered areas such as the Arctic, the growth of leaves in springtime and summertime enhances solar absorption due to the reduction in surface albedo (Kelsey et al 2021), which is the reason for the higher contribution of the NDVI to the spatial heterogeneity of positive SAF in this period (figures S5 and 4). In addition, because leaves play a key role in the transpiration process of the hydrological cycle (Seo and Kim 2021), changes in albedo and transpiration rate between different vegetation types induces climate feedbacks. In combination, these processes could result in varying contributions to the spatial pattern of positive SAF. Consequently, the spatial differences in vegetation types over the Arctic further amplifies the spatial heterogeneity of land warming because different types have different albedos and transpiration rates. From figure 2, a higher positive SAF (above $-5$% K$^{-1}$) is found across western Yukon and Alaska in June. These regions are generally dominated by dwarf shrubs (figure S2), which have a higher variability in albedo than other LCs, such as herb barrens, moss and wetlands (Loranty et al 2011). In addition, broad-leaved deciduous trees may invade tundra ecosystems more effectively than boreal evergreen trees under climate warming, and because deciduous broad-leaved trees have a higher transpiration rate than needle-leaf evergreen trees, the climate responses may be different (Swann et al 2010).

SW also plays an important role in the spatial pattern of positive SAF because land surface albedo is strongly related to SW. Previous studies have reported that surface albedo has a linear relationship with soil moisture (Roxy et al 2010, Li et al 2019, Yang et al 2020). Generally, dry soil has a higher albedo (above 0.7), while wet soil has a lower albedo (below 0.5) (Atlaskina et al 2015). As indicated by figure S6, the SW in the Northwest Territories, Nunavut, and Baffin Island is relatively low. Hence, these regions are more likely to be affected by the different types of vegetation, resulting in greater SAF, which is confirmed in figure 2. In addition, the spatial differences in SW also have a great impact on vegetation growth and soil respiration. In general, vegetation growth is highly sensitive to soil moisture, and therefore spatial differences in SW could affect the distribution, composition and abundance of vegetation (Otkin et al 2016, Geruo et al 2017, Joiner et al 2018). Moreover, spatial differences in soil moisture determine soil respiration rates associated with gas emissions from soil (Peng et al 2015, Liu et al 2016). Specifically, soil water saturation is regulated by permafrost thaw, thus changing the soil oxygen content and tundra soil carbon decomposition under climate warming (Peng et al 2015, Gibson et al 2019).

This study quantifies the strengths of seasonal SAF and explores the contributions of different land factors to spatial patterns of positive SAF over Arctic land. Although it is out of the scope of this paper to consider other influencing factors, such as aerosols, solar irradiance, greenhouse gases, sea ice, and clouds, it is worth giving attention to the nonlinear interactions between different land and atmospheric components of the climate system. Indeed, sea ice–albedo feedback, cloud feedback, and water vapor feedback could also amplify or restrain climate perturbations. For example, the feedbacks related to sea ice reduction are shown to be critical to polar amplification (Dai 2021, You et al 2021), which could further accelerate the melting of snow and/or the expansion of vegetation (Mudryk et al 2017). Additionally, the distribution and frequency of rainfall and snowfall are impacted by aerosols, water vapor and cloud feedbacks (Pan et al 2020). More importantly, the deposition of aerosols (e.g. black carbon, dust, and nitrate) also contributes to the reduction of albedo in polluted regions, although the forcing is less compared to the preindustrial period (Alessandrini et al 2021). Nevertheless, the deposition of nitrogen and phosphorus may enhance biogeochemical cycles and improve
the productivity of terrestrial ecosystems (Mahowald et al. 2017). Under this circumstance, the expansion or reduction of vegetation cover could cause feedback by regulating the emission of bioaerosols and their precursors, whereas the release of mineral dust could also be affected because it is preferentially emitted from dry and unvegetated soils (Ganzeveld et al. 2010). Moreover, the multiple biophysical interactions among snow, vegetation and soil tend to have larger effects than the absorption of solar radiation. It has been shown that when snow is present, the expansion of forested areas will lead to positive surface net longwave radiation due to increasing longwave radiation, which could cause feedback to seasonal warming, especially in temperate and subarctic areas (Todt et al. 2019). The future increase in regional temperature is highly affected by these complex interactions and cumulative effects at various space and time scales.

Representing the dynamics of snow, vegetation and soil, Earth system models (ESMs) are valuable tools for understanding the role of SAF in amplifying or reducing anthropogenic climate warming at the regional scale (Winton 2006). However, a range of results are found among state-of-the-art ESMs due to uncertainties in setting land surface parameter schemes (Thackeray and Fletcher 2016, Andry et al. 2017, Thackery and Hall 2019). As a result, current ESMs must be improved and better constrained to achieve reliable projections of future climate change, especially for warming amplification induced by SAF. Thus, this work could provide a benchmark for improving the representation of the processes governing the variations in seasonal SAF in the next generation of ESMs. More importantly, the impacts of different land parameters and their interactions have large implications for optimizing relevant parameterizations of ESMs.

5. Conclusions

In this study, the strengths of seasonal SAF are quantified for the period between 1982 and 2015 in the Arctic. A large positive SAF (above −5% K⁻¹) is observed across Baffin Island in January and eastern Yakutia in June. In contrast, a large negative SAF (beyond 5% K⁻¹) is estimated in Nunavut, Banks Island, Victoria Island, Chukotka and low latitudes of Greenland in January and Nunavut, Baffin Island and Krasnoyarsk Krai in July. As indicated by the CV, large spatial differences in positive SAF are found in the Arctic, which contribute to the high spatial heterogeneity of Arctic land warming. Furthermore, based on the OPGD model, the determinant power and the interactive effects of six factors are examined. Generally, the rank of determinant power is SCF (0.26 ± 0.14) > LC (0.23 ± 0.13) > NDVI (0.18 ± 0.12) > SW (0.13 ± 0.08) > SC (0.07 ± 0.03) > ST (0.06 ± 0.03).

In addition, the interactions between SCF, LC and SW exhibit a further influence on the spatial heterogeneity of Arctic land warming induced by positive SAF in March, June and July.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files). Data will be available from 02 August 2021.

Acknowledgments

This research is supported by the National Key Research and Development Program of China (No. 2020YFA0608502) and the National Natural Science Foundation of China (No. 42077420).

References

Alessandri A, Catalano F, Felice M D, Hurk B and Balsamo G 2021 Varying snow and vegetation signatures of surface-albedo feedback on the Northern Hemisphere land warming Environ. Res. Lett. 16 034023

Andry O, Bintanja R and Hazeleger W 2017 Time-dependent variations in the Arctic's surface albedo feedback and the link to seasonality in sea ice J. Clim. 30 393–410

Atlaskina K, Beringer F and Leewu G 2015 Satellite observations of changes in snow-covered land surface albedo during spring in the Northern Hemisphere Cryosphere 9 1879–93

Bowman K W, Cressie N, Qu X and Hall A 2018 A hierarchical statistical framework for emergent constraints: application to snow-albedo feedback Geophys. Res. Lett. 45 13050–9

CAVM Team 2003 Circumpolar Arctic vegetation map, scale 1: 7500000 Conservation of Arctic Flora and Fauna (CAFF) Map No.1. US Fish and Wildlife Service (Anchorage, Alaska)

Ciertrwenski J, Karmiel A, Kuiniekerk K, Goldberg A and Herrmann I 2013 Approximating the average daily surface albedo with respect to soil roughness and latitude Int. J. Remote Sens. 34 3416–24

Dai A, Luo D, Song M and Liu J 2019 Arctic amplification is caused by sea-ice loss under increasing CO₂ Nat. Commun. 10 121

Dai H 2021 Roles of surface albedo, surface temperature and carbon dioxide in the seasonal variation of Arctic amplification Geophys. Res. Lett. 48 e2020GL090301

Estilow T W, Young A H and Robinson D A 2015 A long-term Northern Hemisphere snow cover extent data record for climate studies and monitoring Earth Syst. Sci. Data 7 137–42

Flannner M G, Shell K M, Barlage M, Perovich D K and Tschudi M A 2011 Radiative forcing and albedo feedback from the Northern Hemisphere cryosphere between 1979 and 2008 Nat. Geosci. 4 151–5

Fletcher C G, Thackery C W and Burgers T M 2014 Evaluating biases in simulated snow albedo feedback J. Geophys. Res. Atmos. 120 122–26

Fletcher C G, Zhao H, Kushner P J and Fernandes P 2012 Using models and satellite observations to evaluate the strength of snow albedo feedback J. Geophys. Res. Atmos. 117 D11117

Forzieri G, Alkama R, Miralles D G and Cescatti A 2017 Satellites reveal contrasting responses of regional climate to the widespread greening of Earth Science 356 1180–4

Ganzeveld L, Bouwman L, Stehfest E, van Vuuren D P , Eickhout B and Lelieveld J 2010 Impact of future land use and land cover changes on atmospheric chemistry-climate interactions J. Geophys. Res. Atmos. 115 D23301
Geruo A, Velicogna I, Kimball J S, Du J, Kim Y and Njoka E 2017 Satellite-observed changes in vegetation sensitivities to surface soil moisture Environ. Res. Lett. 12 054006

Gibson C M, Estop-Aragonés C, Flannigan M, Thompson D K and Olefeldt D 2019 Increased deep soil respiration detected despite reduced overall respiration in permafrost peat plateaus following wildfire Environ. Res. Lett. 14 125001

Hall A and Qiu X 2006 Using the current seasonal cycle to constrain snow albedo feedback in future climate change Geophys. Res. Lett. 33 L03502

Hartfield G, Blunden J and Arndt D S 2018 State of climate in 2017 Bull. Am. Meteorol. Soc. 99 Si–S310

Henderson-Sellers A and Wilson M F 1983 Surface albedo data for climatic modeling Rev. Geophys. 21 1743–78

Huang J et al 2017 Recently amplified arctic warming has contributed to a continual global warming trend Nat. Clim. Change 7 875–9

Jakobs C L, Reijmer C H, van den Broeke M R, van de Berg W J and van Wessem J M 2020 Spatial variability of the snowmelt-albedo feedback in Antarctica J. Geophys. Res. Earth Surf. 126 e2020JF005696

Jia K, Yang L, Liang S, Xiao Z, Zhao X, Yao Y, Zhang X, Jiang B and Liu D 2018 Long-term Global Land Surface Satellite (GLASS) fractional vegetation cover product derived from MODIS and AVHRR data IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 12 508–18

Joiner J, Yoshida Y, Anderson M, Holmes T, Hain C, Reichle R, Koster R, Middleton E and Zeng F 2018 Global relationships among traditional reflectance vegetation indices (NDVI and NDI), evaportranspiration (ET), and soil moisture variability on weekly timescales Remote Sens. Environ. 219 339–52

Kelsey K C, Pederson S, Laflèr A J, Sexton J O, Feng M and Welker J M 2021 Winter snow and spring temperature have differential effects on vegetation phenology and productivity across Arctic plant communities Glob. Change Biol. 27 1572–82

Kendall M G 1948 Rank Correlation Methods (London: Griffin; American Psychological Association)

Kim Y, Kimball J S, Du J, Scaife C L B and Kirchner P B 2018 Quantifying the effects of freeze-thaw transitions and snowpack melt on land surface albedo and energy exchange over Alaska and Western Canada Environ. Res. Lett. 13 075009

Kong D, Qiang Z, Singh V P and Shi P 2016 Seasonal vegetation response to climate change in the northern hemisphere (1982–2013) Glob. Planet Change 148 1–8

Li Z, Yang J, Gao X, Yu Y, Zheng Z, Liu R, Wang C, Hou X and Wei Z 2019 The relationship between surface spectral albedo and soil moisture in an arid Gobi area Theor. Appl. Climatol. 136 1475–82

Liang S et al 2013 A long-term Global Land Surface Satellite (GLASS) data-set for environment studies Int. J. Digital Earth 6 5–33

Liang S et al 2021 The Global Land Surface Satellite (GLASS) product suite Bull. Am. Meteorol. Soc. 102 E323–37

Liu X et al 2016 Biochar has no effect on soil respiration across Chinese agricultural soils Total. Environ. 534 259–65

Loranty M M, Berner L T, Goetz S J, Jin Y and Randerson J T 2014 Assessing the evolution of soil moisture and vegetation conditions during the 2012 United States flash drought Agric. For. Meteorol. 218 230–42

Pan N, Feng X, Fu B, Wang S, Ji F and Pan S 2018 Increasing global vegetation browning hidden in overall vegetation greening: insights from time-varying trends Remote Sens. Environ. 214 59–72

Pan S, Dou T, Lin L, Yang J, Zhang F, Duan M, Zhao C, Liao H and Xiao C 2020 Larger sensitivity of Arctic precipitation phase to aerosol than greenhouse gas forcing Geophys. Res. Lett. 47 e2020GL090452

Peng F, Xu M, You Q, Zhou X, Wang T and Xue X 2015 Different response of soil respiration and its components to experimental warming with contrasting soil water content Arctic Antarct. Alp. Res. 47 59–68

Przybylak R 2003 The Climate of the Arctic (Dordrecht: Kluwer) (available at: https://link.springer.com/book/10.1007%2F978-94-017-1298-6)

Qu X and Hall A 2006 Assessing snow albedo feedback in simulated climate change J. Clim. 19 2617–30

Qu X and Hall A 2014 On the persistent spread in snow-albedo feedback Clim. Dyn. 42 69–81

Raynolds M K et al 2019 A raster version of the circumpolar Arctic vegetation map (CAVM) Remote Sens. Environ. 233 112297

Roxy M S, Sumithranand V B and Renuka G 2010 Variability of soil moisture and its relationship with surface albedo and soil thermal diffusivity at astronomical observatory, Thiruvananthapuram, south Kerala J. Earth Syst. Sci. 119 507–17

Seo H and Kim Y 2021 Role of remotely sensed leaf area index assimilation in eco-hydrologic processes in different ecosystems over East Asia with community land model version 4.5—biogeochemistry J. Hydrol. 594 125957

Song Y, Wang J, Ge Y and Xu C 2020 An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: cases with different types of spatial data GISci. Remote Sens. 57 593–610

Swann A L, Fung I Y, Levis S, Bonan G B and Doney S C 2010 Changes in Arctic vegetation amplifies high-latitude warming through the greenhouse effect Proc. Natel Acad. Sci. USA 107 12925–300

Thackeray C W and Fletcher C G 2016 Snow albedo feedback: current knowledge, importance, outstanding issues and future directions Prog. Phys. Geogr. 40 392–408

Thackeray C W and Hall A 2019 An emergent constraint on future Arctic sea-ice albedo feedback Nat. Clim. Change 9 972–8

Thackeray C W, Hall A, Zelinka M D and Fletcher C G 2021 Assessing prior emergent constraints on surface albedo feedback in CMIP6 J. Clim. 34 3889–904

Thackeray C W, Qu X and Hall A 2018 Why do models produce spread in snow albedo feedback? Geophys. Res. Lett. 45 6223–31

Todt M, Rutter N, Fletcher C G and Wake L M 2019 Simulated single-layer forest canopies delay Northern Hemisphere snowmelt Cryosphere 13 3077–91

Tucker C J, Pinzon J E, Brown M E, Slavoy D A, Pak E W, Mahoney R, Vermote E F and El Saeouli N 2005 An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data Int. J. Remote Sens. 26 4485–98

Walker D R et al 2005 The circumpolar Arctic vegetation map J. Vegetation Sci. 16 267–82
Walsh J E 2014 Intensified warming of the Arctic: cause and impacts on middle Glob. Planet Change 117 52–63

Webb E E, Lorantz M M and Lichstein J W 2021 Surface water, vegetation, and fire as drivers of the terrestrial Arctic-boreal albedo feedback Environ. Res. Lett. 16 084046

Wegmann M, Dutra E, Jacobi H W and Zolina O 2018 Spring snow albedo feedback over northern Eurasia: comparing in situ measurements with reanalysis products Cryosphere 12 1887–98

Willard D A, Donders T H, Reichgelt T, Greenwood D R, Sangiorgi F, Peterse F, Nierop K G J, Frieling J, Schouten S and Sluijs A 2019 Arctic vegetation, temperature, and hydrology during Early Eocene transient global warming events Glob. Planet Change 178 139–52

Winton M 2006 Amplified Arctic climate change: what does surface albedo feedback have to do with it? Geophys. Res. Lett. 33 L03701

Yang J, Li Z, Zhai P, Zhao Y and Gao X 2020 The influence of soil moisture and solar altitude on surface spectral albedo in arid area Environ. Res. Lett. 15 035010

You Q et al 2021 Warming amplification over the Arctic pole and third pole: trends, mechanisms and consequences Earth Sci. Rev. 217 103625

Yu L and Leng G 2022 Identifying the paths and contributions of climate impacts on the variation in land surface albedo over the Arctic Agric. For. Meteorol. 313 108772

Yu L, Leng G and Python A 2021 Varying response of vegetation to sea ice dynamics over the Arctic Sci. Total Environ. 799 149378