Spatiotemporal variation of surface albedo and its influencing factors in northern Xinjiang, China postprint

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Date: 2023-11-13T00:00:00+00:00

Abstract

Surface albedo is a quantitative indicator for land surface processes and climate modeling, and plays an important role in surface radiation balance and climate change. In this study, by means of the MCD43A3 surface albedo product developed on the basis of Moderate Resolution Imaging Spectroradiometer (MODIS), we analyzed the spatiotemporal variation, persistence status, land cover type differences, and annual and seasonal differences of surface albedo, as well as the relationship between surface albedo and various influencing factors (including Normalized Difference Snow Index (NDSI), precipitation, Normalized Difference Vegetation Index (NDVI), land surface temperature, soil moisture, air temperature, and digital elevation model (DEM)) in the north of Xinjiang Uygur Autonomous Region (northern Xinjiang) of Northwest China from 2010 to 2020 based on the unary linear regression, Hurst index, and Pearson' s correlation coefficient analyses. Combined with the random forest (RF) model and geographical detector (Geodetector), the importance of the above-mentioned influencing factors as well as their interactions on surface albedo were quantitatively evaluated. The results showed that the seasonal average surface albedo in northern Xinjiang was the highest in winter and the lowest in summer. The annual average surface albedo from 2010 to 2020 was high in the west and north and low in the east and south, showing a weak decreasing trend and a small and stable overall variation. Land cover types had a significant impact on the variation of surface albedo. The annual average surface albedo in most regions of northern Xinjiang was positively correlated with NDSI and precipitation, and negatively correlated with NDVI, land surface temperature, soil moisture, and air temperature. In addition, the correlations between surface albedo and various influencing factors showed significant differences for different land cover types and in different seasons. To be specific, NDSI had the largest influence on surface albedo, followed by precipitation, land surface temperature, and soil moisture; whereas NDVI, air temperature, and DEM showed relatively weak influences. However, the interactions of any two influencing factors on surface albedo were enhanced, especially the interaction of air temperature and DEM. NDVI showed a nonlinear enhancement of influence on surface albedo when interacted with land surface temperature or precipitation, with an explanatory power greater than 92.00%. This study has a guiding significance in correctly understanding the land-atmosphere interactions in northern Xinjiang and improving the regional land-surface process simulation and climate prediction.

Full Text

Preamble

Journal of Arid Land (2023) 15(11): 1315-1339
https://doi.org/10.1007/s40333-023-0069-5
Science Press Springer-Verlag

Spatiotemporal Variation of Surface Albedo and Its Influencing Factors in Northern Xinjiang, China

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Abstract

Surface albedo is a quantitative indicator for land surface processes and climate modeling, playing a crucial role in surface radiation balance and climate change. In this study, we analyzed the spatiotemporal variation, persistence status, land cover type differences, and annual and seasonal variations of surface albedo in northern Xinjiang, Northwest China, from 2010 to 2020 using the MCD43A3 surface albedo product derived from the Moderate Resolution Imaging Spectroradiometer (MODIS). We also examined its relationship with various influencing factors—including Normalized Difference Snow Index (NDSI), precipitation, Normalized Difference Vegetation Index (NDVI), land surface temperature, soil moisture, air temperature, and digital elevation model (DEM)—through unary linear regression, Hurst index, and Pearson' s correlation coefficient analyses. The random forest (RF) model and geographical detector (Geodetector) were employed to quantitatively evaluate the importance of these influencing factors and their interactions. The results revealed that seasonal average surface albedo in northern Xinjiang was highest in winter and lowest in summer. The annual average surface albedo from 2010 to 2020 exhibited a pattern of high values in the west and north and low values in the east and south, showing a weak decreasing trend with small and stable overall variation. Land cover types significantly impacted surface albedo variation. The annual average surface albedo in most regions was positively correlated with NDSI and precipitation, and negatively correlated with NDVI, land surface temperature, soil moisture, and air temperature. Moreover, correlations between surface albedo and various influencing factors showed significant differences across land cover types and seasons. Specifically, NDSI exerted the greatest influence on surface albedo, followed by precipitation, land surface temperature, and soil moisture, whereas NDVI, air temperature, and DEM showed relatively weak influences. However, interactions between any two influencing factors enhanced their effects on surface albedo, particularly the interaction between air temperature and DEM. NDVI demonstrated nonlinear enhancement of its influence on surface albedo when interacting with land surface temperature or precipitation, with explanatory power exceeding 92.00%. This study provides guidance for correctly understanding land-atmosphere interactions in northern Xinjiang and improving regional land-surface process simulation and climate prediction.

Keywords: surface albedo; MCD43A3; Hurst index; random forest (RF) model; geographical detector (Geodetector); Normalized Difference Snow Index (NDSI); northern Xinjiang

Citation: YUAN Shuai, LIU Yongqiang, QIN Yan, ZHANG Kun. 2023. Spatiotemporal variation of surface albedo and its influencing factors in northern Xinjiang, China. *Journal of Arid Land*, 15(11): 1315–1339. https://doi.org/10.1007/s40333-023-0069-5

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Received: 2023-02-21; Revised: 2023-08-09; Accepted: 2023-08-13

1 Introduction

Surface albedo refers to the ratio of reflected radiation to total incident radiation on the Earth' s surface (Dickinson, 1983). It is a key regulating variable of the radiation budget at the Earth' s surface (Bonan, 2008) and an important quantitative indicator in land-surface process simulation and climate prediction studies (Liang et al., 2019). Surface albedo plays a vital role in the land-atmosphere system, as underlying surface conditions (vegetation cover, soil moisture, etc.) and meteorological factors (precipitation, air temperature, etc.) directly or indirectly affect surface albedo (Wielicki et al., 2005; Gorelick et al., 2017). This, in turn, influences the transfer of surface fluxes (sensible heat, latent heat, and soil heat flux) and regional atmospheric circulation, resulting in significant climatic effects both locally and globally (Rotenberg and Yakir, 2010). Therefore, a comprehensive understanding of surface albedo variation characteristics is essential for studying land surface processes and climate change (Cess, 1978; Ollinger et al., 2008; Van De Kerchove et al., 2013; Hotaling et al., 2021).

With the assistance of remote sensing satellites, several global-coverage surface albedo products have been produced based on the Moderate Resolution Imaging Spectroradiometer (MODIS) (Lucht et al., 2000; Schaaf et al., 2002), Global Land Surface Satellite (GLASS) (Liang et al., 2013; Liu et al., 2013), GlobAlbedo (Potts et al., 2012), and others. These products provide long-term time series data for studying the spatiotemporal distribution characteristics and evolution patterns of surface albedo at large scales. Among them, MODIS-based surface albedo products have been widely and effectively used due to their excellent quality and spatiotemporal continuity (Wang et al., 2012; Wang et al., 2014b; Wen et al., 2022). Regarding influencing factors of surface albedo, previous studies have shown that surface albedo change correlates with ecological or meteorological parameters (He et al., 2014), such as snowpack (Loranty et al., 2014), land surface temperature (Shekhar et al., 2010), and soil moisture (Verheijen et al., 2013), and exhibits strong seasonal variation (Fang et al., 2007; Shi and Liang, 2013) characterized by decreasing trends in July and increasing trends in January (He et al., 2014).

Studies on surface albedo in China have primarily focused on the Qinghai-Tibet Plateau and central and eastern China (Wang et al., 2005; Tang et al., 2018; Huang et al., 2019; Chen et al., 2021), while fewer studies have been conducted in Xinjiang Uygur Autonomous Region in Northwest China. Xinjiang features diverse climate types and ecological environments, along with complex topography and landscapes in both spatial and temporal distribution (Li et al., 2018). It can be divided into northern and southern Xinjiang by the main ridgelines of the Tianshan Mountains. Northern Xinjiang is a typical arid and semi-arid region dominated by a continental climate, with low precipitation, strong evaporation, and sparse vegetation (Wang et al., 2014a; Zhang et al., 2021a). The sensitive underlying surface characteristics in this region can promptly reflect regional climate changes in dry, wet, cold, and warm processes (Alessandri et al., 2021). Land cover types in northern Xinjiang are complex, including cropland, forestland, grassland/shrubland, wetland, water bodies, impervious surface, bare land, and snow/ice. This complexity enables investigation of surface albedo variation characteristics under diverse land cover types, where snowpack changes contribute more to surface albedo variation than other factors (Pang et al., 2022). Northern Xinjiang is one of China’ s three major snowpack distribution areas (Wang et al., 2008; Zhang et al., 2021a), making it ideal for studying snowpack effects on surface albedo. Approximately 20%–70% of surface water in northern Xinjiang originates from snowmelt and glacier meltwater (Kong and Pang, 2012). Estimates from glacier surface summer albedos and snowmelt models indicate that reduced surface albedo drives about 30%–60% of glacier melting on the Tibetan Plateau and surrounding regions (Zhang et al., 2021b). Therefore, studying surface albedo variation characteristics and analyzing its influencing factors in northern Xinjiang is crucial for revealing snowmelt and glacier meltwater patterns, predicting snowmelt floods, and assessing water supply and demand. Compared to southern Xinjiang, human activities are more concentrated in northern Xinjiang and have relatively significant impacts on impervious surfaces of construction land. Future changes in surface albedo caused by urbanization represent one of the causes of global warming (Ouyang et al., 2022). Investigating these natural and human effects can provide deeper understanding of the causes of surface albedo change. However, previous studies on surface albedo in northern Xinjiang were conducted only at small spatial scales (Deng et al., 2021), and the spatiotemporal distribution and influencing factors have not been well documented.

For these reasons, this study characterized the spatiotemporal variation of surface albedo in northern Xinjiang using the daily MODIS-based MCD43A3 surface albedo product and quantitatively analyzed influencing factors including Normalized Difference Snow Index (NDSI), precipitation, Normalized Difference Vegetation Index (NDVI), land surface temperature, soil moisture, air temperature, and digital elevation model (DEM). The study comprised three main components. First, we investigated the spatial distribution and variation trend of surface albedo and the correlation between surface albedo and its influencing factors using dimensionality reduction analysis. Second, we independently analyzed the spatiotemporal variation of surface albedo using unary linear regression and Hurst index methods to reveal past trends and future changes. Third, based on correlation analysis between surface albedo and its influencing factors, we employed the random forest (RF) model and geographic detector (Geodetector) to jointly quantify the influencing factors and further explore the interrelationships between factors and the mechanisms driving surface albedo change in northern Xinjiang. This study provides guidance for correctly understanding land-atmosphere interactions in northern Xinjiang and improving regional land-surface process simulation and climate change prediction.

2.1 Study Area

Northern Xinjiang (79°53 10 -96°22 54 E, 42°15 29 -49°10 59 N) is located in the hinterland of Central Asia, north of the main ridge line of the Tianshan Mountains in Xinjiang Uygur Autonomous Region, Northwest China, covering an area of approximately 4.50$×10^{5}$ km^2 with elevations ranging from 185 to 5457 m (Fig. 1 [Figure 1: see original paper]). The region has a typical temperate continental arid and semi-arid climate (Zhang et al., 2019), with large temperature differences between winter and summer and scarce precipitation throughout the year (Luo et al., 2017). The study area is surrounded by the Tianshan and Altay Mountains, with the Junggar Basin in the central portion. The northern basin contains Ulungur Lake, the largest inland lake in northern Xinjiang (Zou et al., 2021), while the western part contains Ebinur Lake, the largest brackish water lake in Xinjiang (Wang et al., 2019). The center of the Junggar Basin features the Gurbantunggut Desert, with extensive desert grasslands and deserts, extreme drought, minimal precipitation, and obvious soil salinization (Wang et al., 2014a; Zhang et al., 2021a).

2.2 Data Sources

We obtained daily-scale MCD43A3 WSA-shortwave surface albedo product (500 m spatial resolution), daily-scale MOD10A1 NDSI product (500 m spatial resolution), and MOD13A3 NDVI product (1 km spatial resolution) from the Level-1 and Atmosphere Archive & Distribution System Distributed Active Archive Center (LAADS DAAC) (https://ladsweb.modaps.eosdis.nasa.gov) for the period from December 2009 to December 2020. NDSI provides snow cover information within MODIS pixels with an average absolute error of less than 0.1 (Salomonson and Appel, 2004). Due to the high surface albedo (above 0.7) of snow-covered land—which is much higher than other land cover types—and the fact that changes in snow-covered land surface albedo are mainly caused by snow loss rather than snow metamorphism (Qu and Hall, 2007), changing snow cover can greatly affect surface albedo. Therefore, using NDSI as a snow cover indicator is useful for studying snow impacts on surface albedo.

Meteorological datasets including monthly precipitation (mm) and monthly average temperature (°C) from December 2009 to December 2020 were obtained from the National Earth System Science Data Center (http://www.geodata.cn) at 1 km spatial resolution. Digital elevation model (DEM) data at 90 m spatial resolution were provided by the Resource and Environment Science and Data Center (https://www.resdc.cn).

Land cover data for 2020 were obtained from the Cross-Resolution Land-Cover (CRLC) mapping framework product (https://github.com/LiuGalaxy/CRLC) based on noisy label learning, with a spatial resolution of 10 m. This map was created using a deep classification network and includes categories such as cropland, forestland, wetland, grassland/shrubland, water bodies, impervious surface, bare land, and snow/ice. The final assessment showed an overall accuracy of 84.35% ($±$0.92%) (Liu et al., 2023).

Land surface temperature (°C) and soil moisture data were obtained from the National Tibetan Plateau Data Center (http://data.tpdc.ac.cn), including a daily all-weather land surface temperature dataset (1 km spatial resolution, December 2009–December 2020) and a soil moisture dataset (0.05° spatial resolution, December 2009–December 2018, missing data for 2019 and 2020 compared to other datasets).

All data were resampled to a spatial resolution of 500 m, and monthly, seasonal (spring: March–May, summer: June–August, autumn: September–November, winter: December–February of the following year), and annual average values were calculated for the study area.

2.3.1 Spatial Analysis

To visually and accurately characterize the spatial distribution of surface albedo, this study conducted dimensionality reduction analysis to reveal distribution characteristics along longitude or latitude based on seasonal and annual average values (Fig. 2a [Figure 2: see original paper]). The formula is as follows:

$$f(x, y)$$

where $g(x)$ is the mean function of surface albedo varying with longitude (or latitude); y is the latitude (or longitude); $f(x, y)$ is the spatial distribution function of surface albedo with latitude and longitude; and N_y is the number of image elements in the latitude (or longitude) direction.

2.3.2 Trend Analysis

The spatial variation trends of surface albedo and its influencing factors (NDSI, precipitation, NDVI, land surface temperature, soil moisture, and air temperature) were analyzed using unary linear regression (Tang et al., 2020) and Hurst index methods (Fan et al., 2012; Hou et al., 2012) (Fig. 2). First, pre-processed annual and seasonal average values were used to calculate the element-by-element trend (slope of the linear trend) via unary linear regression. The significance and reliability of pixel-by-pixel trends were determined by t-test. Second, confidence intervals of 99% (P<0.01) and 95% (P<0.05) were used as thresholds to classify regions with significant changes, and their distributions were analyzed through dimensionality reduction along longitude (or latitude). Classification criteria and spatial distribution function values are shown in Table 1 , where P>0.05 indicates no significant trend (Knorr et al., 2001). The formula is expressed as:

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

where slope is the trend of surface albedo (or its influencing factors) per decade; n is the total number of years; and X_i is the surface albedo (or influencing factor) in the ith year ($i = 1, 2, ..., n$). Slope>0 indicates an increasing trend, while slope<0 indicates a decreasing trend, with larger absolute values representing faster rates of change.

The Hurst index quantifies long-term dependence of time-series information based on Rescaled Range (R/S) analysis (Fan et al., 2012; Hou et al., 2012). The R/S method effectively calculates the Hurst index according to the following principle:

For a time series $\xi(t)$ (where t is time; $t = 1, 2, ..., n$), we defined another series τ ($\tau = 1, 2, ..., n$). For a given τ, the average series $\bar{\xi}$ is defined as (Sánchez-Granero et al., 2008):

$$\bar{\xi} = \frac{1}{\tau} \sum_{t=1}^{\tau} \xi(t)$$

For time t, the cumulative discrepancy $X(t,\tau)$ is calculated as:

$$X(t,\tau)=\sum_{u=1}^{t}(\xi(u)-\bar{\xi})$$

The range series $R(\tau)$ and standard deviation series $S(\tau)$ are defined as Equations 5 and 6, respectively:

$$R(\tau)=\max_{1\le t\le\tau}X(t,\tau)-\min_{1\le t\le\tau}X(t,\tau)$$

$$S(\tau)=\sqrt{\frac{1}{\tau}\sum_{t=1}^{\tau}(\xi(t)-\bar{\xi})^2}$$

The exponential law can then be derived as:

$$\frac{R(\tau)}{S(\tau)}=c\times\tau^H$$

where H is the Hurst index and c is a constant. If this exponential law is satisfied, the time series $\xi(t)$ exhibits the Hurst phenomenon. As shown in Table 2 , the Hurst index has three main forms. Values closer to 1.00 indicate stronger persistence, while values closer to 0.00 indicate stronger anti-persistence (Hou and Hou, 2020). In this study, the Hurst index was divided into seven levels to analyze the persistence status and distribution of surface albedo, with dimensionality reduction used to characterize the average distribution along longitude and latitude (Table 3).

Integrated analysis was performed based on the slope from unary linear regression and the Hurst index. Specifically, regions with significant changes in surface albedo were classified into five categories. We fully revealed past trends and future changes in surface albedo through dimensionality reduction analysis along longitude (or latitude), as shown in Table 4 .

2.3.3 Correlation Analysis

Pearson' s correlation coefficient was used to reveal relationships between average surface albedo (at annual and seasonal scales) and influencing factors (NDSI, precipitation, NDVI, land surface temperature, soil moisture, and air temperature) in northern Xinjiang (Fig. 2c), with significance tested via t-test. The dimensionality reduction method was applied to analyze the spatial distribution of Pearson' s correlation coefficients (Table 5). The formula is:

$$R_{XY} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

where R_{XY} is the correlation coefficient between variables X and Y; n is the total number of years; X_i and Y_i are values of variables X and Y in the ith year ($i = 1, 2, ..., n$), respectively; and $\bar{X}$ and $\bar{Y}$ are mean values of variables X and Y over the study period.

2.3.4 Influencing Factor Analysis

The RF model was used to measure the importance of influencing factors (NDSI, precipitation, NDVI, land surface temperature, soil moisture, air temperature, and DEM) on surface albedo. Both the factor detector and interaction detector in Geodetector were employed to reveal the influence and significance of each factor, the strength of interactions between factors, and their combined effects (Fig. 2c).

The RF model is considered a robust method for evaluating factor importance through model calculation (Liu et al., 2018; Gomes et al., 2019), producing relatively unbiased and accurate factor importance rankings (Grömping, 2009). The model provides two reliable metrics for calculating factor importance: percentage increase in mean squared error (%IncMSE) and average increase in node purity (IncNodePurity). This study used IncNodePurity to assess the importance of each influencing factor, where larger values indicate greater importance.

Geodetector is an effective method for testing single-factor spatial heterogeneity and multi-factor coupling. This study used factor detection to analyze the spatial heterogeneity of surface albedo and the influence q of each factor on this heterogeneity. The q value indicates that the factor explains $q \times 100\%$ of the spatial heterogeneity in surface albedo (Wang and Xu, 2017). Larger q values indicate stronger explanatory power. The formula is:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}$$

where h is the stratification of surface albedo (or its influencing factors); N_h and N are the number of elements in stratum h ($h = 1, 2, ..., L$) and the entire area, respectively; σ_h^2 and σ^2 are variances of surface albedo in stratum h and the entire area, respectively; and SSW and SST are the sum of variance within strata and total variance of the entire area, respectively.

Additionally, $q(X_1 \cap X_2)$ (where X_1 and X_2 are influencing factors of surface albedo) represents the influence of the interaction between X_1 and X_2 on the spatial heterogeneity of surface albedo, used to detect whether interactions among different factors are correlated or independent (Table 6).

Geodetector parameters were optimized through spatial discretization. Three discretization methods (equal, natural, and quantile) combined with 3-500 stratifications were used for each factor to calculate corresponding q values. From the perspective of spatial stratification heterogeneity, the combination of discretization method and stratification yielding the maximum q value represents the optimal parameter. We calculated seven influencing factors using the GD package (Song et al., 2020) with the quantile discretization method. The stratification numbers for NDSI, precipitation, NDVI, land surface temperature, soil moisture, air temperature, and DEM were 478, 491, 478, 485, 498, 493, and 397, respectively.

3.1 Spatial Distribution Patterns of Surface Albedo

Figure 3 [Figure 3: see original paper] shows the spatial distribution characteristics of seasonal and annual average surface albedo in northern Xinjiang from 2010 to 2020. The annual average surface albedo ranged from 0.10 to 0.56, with a mean value of 0.28. The gray area map in Figure 3e clearly shows that overall annual average surface albedo was high in the west and north and low in the east and south. The eastern part of the study area was the center of low surface albedo values, mostly below 0.20. Additionally, surface albedo values of lakes such as Ulungur Lake and Ebinur Lake were also below 0.20. Surface albedo values in the western part mostly ranged between 0.20 and 0.30. Values in most central regions, such as the Junggar Basin, exceeded 0.30, particularly in the northerly Altay Mountains (reaching 0.56), which formed the center of high surface albedo values.

The spatial distribution of seasonal average surface albedo was similar to that of the annual average—high in the west and low in the east. However, in spring, summer, and autumn, seasonal average surface albedo decreased first then increased from north to south. In winter, the pattern differed markedly: seasonal average surface albedo exceeded 0.40 in most central and western areas and was mostly below 0.30 in the eastern region. Additionally, winter seasonal average surface albedo increased then decreased from north to south, with the highest average value of 0.42 (Fig. 3d). In spring, average surface albedo was significantly lower at 0.28 (Fig. 3a), and its spatial distribution was extremely similar to that of the annual average. In summer, average surface albedo decreased to its lowest value of 0.19 (Fig. 3b), with lake values such as Ulungur and Ebinur below 0.10. Autumn average surface albedo was 0.25, higher than summer but slightly lower than spring (Fig. 3c).

3.2.1 Temporal Variation

Inter-annual variation of surface albedo generally showed a decreasing trend with a slope of -0.0069/10a from 2010 to 2020 (Fig. 4 [Figure 4: see original paper]). However, performance varied by season. Spring showed the greatest decreasing rate at -0.0348/10a; summer exhibited a weak decreasing trend at -

0.0041/10a; while autumn and winter showed increasing trends at 0.0120/10a and 0.0156/10a, respectively. Annual and seasonal average surface albedo results did not reach significance levels ($P>0.05$), indicating non-significant variation trends. Regarding influencing factors at the annual scale, NDSI and precipitation showed decreasing trends, while NDVI, land surface temperature, soil moisture, and air temperature exhibited increasing trends. In spring, NDSI decreased significantly while air temperature and NDVI increased significantly. Additionally, soil moisture increased significantly in winter.

3.2.2 Spatial Variation

Annual and seasonal average surface albedo from 2010 to 2020 showed substantial spatial variations (Fig. 5 [Figure 5: see original paper]). During the study period, annual average surface albedo decreased mainly in the southern part of the study area and increased in some northern regions (Fig. 5e). The area showing significant decrease covered approximately 8.77$\times10^{3}$ km^2 (1.95% of the study area), while the area showing significant increase covered about 16.67$\times10^{3}$ km^2 (3.71% of the study area) (Fig. 5f). Seasonal average surface albedo showed similar spatial distributions to the annual average but contributed unevenly to long-term variation of the annual average (Fig. 5a and b). Significant decreases occurred in more than 5.90% of the study area in both spring and summer, obviously higher than the area proportion showing significant increase; the opposite pattern occurred in autumn and winter, consistent with the overall trend shown in Figure 4.

Land cover types significantly impacted surface albedo change. Among different land cover types, the largest area proportion showing significant decrease was cropland in spring (9.37% of the study area) and impervious surface in summer (14.37% of the study area), whereas the largest area proportion showing significant increase was water bodies in autumn (11.56% of the study area) and bare land in winter (14.37% of the study area) (Fig. 5f).

3.2.3 Trend Analysis

The persistence status of annual and seasonal average surface albedo during the study period also exhibited spatial variations (Fig. 6 [Figure 6: see original paper]). At the annual scale, more regions showed significant persistence (14.79% of the study area) than significant anti-persistence (6.63%). Significant persistence of seasonal average surface albedo in spring and summer covered larger areas (15.78% and 20.28% of the study area, respectively) than significant anti-persistence (7.30% and 3.89%, respectively) (Fig. 6a and b), particularly in summer. The area proportions showing significant persistence in autumn and winter (9.27% and 13.27%, respectively) were close to those showing significant anti-persistence (11.05% and 7.65%, respectively) (Fig. 6c and d). Persistence status across different land cover types was similar to that of the overall study area (Fig. 6f).

The slope from unary linear regression and Hurst index were used to analyze the integrated variation trend of surface albedo (Fig. 7 [Figure 7: see original paper]). Results showed that in 1.08% of the study area, average surface albedo trended upward in the past and will continue rising in the future (slope>0.00 and Hurst index>0.50); in 2.12% of the area, it trended downward in the past and will continue declining (slope<0.00 and Hurst index>0.50); in 1.59% of the area, it trended downward in the past but will reverse direction (slope<0.00 and Hurst index<0.50); and in 0.87% of the area, it trended upward in the past but will reverse (slope>0.00 and Hurst index<0.50). Among regions with significant change in annual average surface albedo, the area proportion showing the same trend in past and future (3.20% of the study area) was significantly higher than that showing opposite trends (2.46%). Additionally, the area proportions showing future upward (2.67%) and downward (2.99%) trends were similar.

The integrated trend of seasonal average surface albedo was similar to that of the annual average. Among regions with significant seasonal variations, area proportions showing the same trend in past and future (spring: 4.34%; summer: 6.83%; autumn: 2.37%; winter: 2.94%) were much greater than those showing opposite trends (spring: 3.00%; summer: 2.81%; autumn: 1.77%; winter: 2.44%) (Fig. 7a–d). Area proportions showing future upward and downward trends were also similar. For certain land cover types, large areas shifted from decreasing trends in the past to increasing trends in the future. For instance, cropland in spring and impervious surface in summer shifted from past decreasing to future increasing trends in 4.68% and 4.12% of the study area, respectively. Meanwhile, large areas shifted from past increasing to future decreasing trends, such as water bodies in autumn (4.68%) and bare land in winter (2.05%) (Fig. 7f).

3.3.1 Correlation Analysis Results

The relationship between annual average surface albedo and various influencing factors showed strong spatial heterogeneity (Fig. 8 [Figure 8: see original paper]). Regions where surface albedo was significantly positively correlated with NDSI and precipitation accounted for 95.37% and 2.40% of the study area, respectively. Surface albedo was extremely positively correlated with NDSI in bare land (90.89% of bare land area) and all other land cover types (over 99.00% of each type) (Fig. 8g). Only some bare land regions in the eastern study area showed no significant correlation between surface albedo and NDSI (Fig. 8a). Regions where surface albedo was significantly negatively correlated with precipitation accounted for 1.84% of the study area, with only a few patches showing extreme negative (0.31%) or intermediate negative (1.53%) correlations. Regions showing extreme positive correlation between surface albedo and precipitation were scattered throughout the study area, with wetland having the highest area proportion among land cover types (3.23% of wetland area) (Fig. 8g).

Surface albedo was mainly negatively correlated with NDVI, land surface temperature, soil moisture, and air temperature (Fig. 8c–f), with significant negative correlations covering 4.54%, 7.41%, 3.65%, and 3.14% of the study area, respectively. Regions showing extreme negative correlations accounted for 1.06%, 2.00%, 0.80%, and 0.64%, respectively, while intermediate negative correlations covered 3.48%, 5.41%, 2.86%, and 2.51%, respectively. Regions with significant positive correlations accounted for 1.49%, 1.08%, 1.79%, and 1.62%, respectively, with only a few patches showing extreme positive (0.29%, 0.20%, 0.32%, 0.29%) or intermediate positive (1.20%, 0.87%, 1.46%, 1.32%) correlations. The area proportions of regions where surface albedo was significantly negatively correlated with NDVI (6.19%), soil moisture (5.04%), and air temperature (5.34%) were highest in cropland, while the proportion showing significant negative correlation between surface albedo and land surface temperature was highest in bare land (Fig. 8g).

Correlations between surface albedo and each influencing factor showed significant seasonal differences (Fig. 9 [Figure 9: see original paper]). The correlation with NDSI was most pronounced in winter, with significant positive correlation in 93.27% of the study area, followed by spring (62.23%) and autumn (53.56%). In summer, however, snow melted in most regions, leaving only a few high-altitude areas with snow, so significant positive correlation was not available in most regions, covering only 5.41% of the study area, though 88.69% of snow- and ice-covered regions showed significant positive correlation. In autumn and winter, regions with significant positive correlation between surface albedo and precipitation accounted for 4.55% and 4.39%, respectively, obviously higher than proportions showing significant negative correlation (0.78% and 2.08%, respectively). Correlations between surface albedo and precipitation showed small differences among spring, autumn, and winter, but the opposite distribution occurred in summer, with significantly fewer regions showing significant positive correlation (1.30%) than negative correlation (4.58%). For NDVI, land surface temperature, soil moisture, and air temperature, extreme negative correlations dominated in almost all seasons, except for significant positive correlations between surface albedo and land surface temperature and soil moisture in summer, and between surface albedo and NDVI in autumn.

3.3.2 Importance Analysis Results

The RF model assessed the importance of each influencing factor on surface albedo during the study period. The model explained 67.89% of average surface albedo variation from 2010 to 2018, with %IncMSE and IncNodePurity values shown in Table 7 . IncNodePurity was selected as the importance index, and overall factor importance from 2010 to 2018 ranked as: NDSI (IncNodePurity of 1.75) > precipitation (0.89) > land surface temperature (0.81) > soil moisture (0.73) > DEM (0.61) > NDVI (0.46) > air temperature (0.42).

Using this method, we evaluated the annual importance of each factor from 2010 to 2018 (Fig. 10 [Figure 10: see original paper]). Mean IncNodePurity values across these years ranked as: NDSI (2.42) > precipitation (1.52) > soil moisture

(1.39) > land surface temperature (1.36) > DEM (1.12) > air temperature (0.98) > NDVI (0.96) (Fig. 10a), indicating that NDSI, land surface temperature, precipitation, and soil moisture were dominant factors, while DEM, NDVI, and air temperature had relatively weak influences. Additionally, the influence degree of each factor fluctuated over years. For example, NDSI' s influence on surface albedo in 2012 (IncNodePurity of 3.00) and 2014 (2.88) was much higher than its average (2.42) during 2010–2018 (Fig. 10b).

To further test influencing factors, we used factor and interaction detectors to quantitatively assess individual and interactive impacts on surface albedo. Factor detector results (Fig. 11a [Figure 11: see original paper]) showed factor impacts ranked as: NDSI (q-value of 0.622) > precipitation (0.516) > land surface temperature (0.486) > soil moisture (0.454) > NDVI (0.396) > air temperature (0.327) > DEM (0.236). Only DEM had insignificant influence, while other factors met the 99% confidence interval ($P<0.01$). Spatial variation in surface albedo resulted from combined effects of various factors, with NDSI contributing most, and precipitation, land surface temperature, and soil moisture also making substantial contributions (all $q > 0.400$). In contrast, NDVI, air temperature, and DEM contributed relatively little (average $q = 0.236$). These results were highly consistent with RF model findings, confirming NDSI as the primary influencing factor, with precipitation, land surface temperature, and soil moisture also showing strong influence, while NDVI, air temperature, and DEM had relatively weak effects.

Interaction detector analysis (Fig. 11b) showed that interactions between any two factors had greater effects on surface albedo than single factors, indicating dual-factor enhancement or nonlinear enhancement. Air temperature and DEM both showed nonlinear enhancement with the other four factors (NDSI, precipitation, land surface temperature, and soil moisture), indicating that although these single factors had small effects, their influences were significantly improved through interaction, with q-values mostly exceeding those of the individual factors. Additionally, NDVI showed nonlinear enhancement when interacting with land surface temperature or precipitation, with explanatory power for spatial heterogeneity of surface albedo exceeding 92.00%. Interactions among other factors also showed varying degrees of enhancement, with explanatory power surpassing 57.70%.

4.1 Influence Mechanisms of Surface Albedo

Surface albedo is directly or indirectly affected by factors such as NDSI, NDVI, soil moisture, land surface temperature, precipitation, and air temperature (Wielicki et al., 2005; Gorelick et al., 2017). Changes in soil-related properties (e.g., soil moisture) and surface cover (e.g., NDSI and NDVI) directly affect surface albedo (Kala et al., 2014). In the context of global warming, snow is an extremely important and rapidly changing element, especially in northern Xinjiang (Bormann et al., 2018). Since snow surface albedo varies with snow conditions–0.90 for fresh snow, 0.40 for melting snow, and 0.20 for polluted snow (Moody et al., 2007)—snow changes contribute more to surface albedo variation than other factors (Figs. 10 and 11). Vegetation shading on snow significantly reduces surface albedo (Loranty et al., 2014), and NDVI changes can also alter surface albedo in snow-free regions due to optical contrast between vegetation canopy and underlying soil surface (Alessandri et al., 2017). When soil transitions from dry to wet, its color darkens, enhancing light absorption capacity (Gascoin et al., 2009). Compared to dry soil albedo above 0.70, moist soil has lower albedo below 0.50 (Alessandri et al., 2021). Therefore, increasing soil moisture reduces surface albedo and increases net radiation and evaporation rates.

Land surface temperature, precipitation, and air temperature also affect surface albedo through different mechanisms, such as influencing NDSI, NDVI, and soil moisture (Alibakhshi et al., 2019). To further understand these effects, we evaluated factor interactions. Land surface temperature changes affect vegetation growth, which influences solar radiation absorption through photosynthesis, leading to surface albedo variation (Zhao et al., 2014). This is consistent with our finding that the interaction between land surface temperature and NDVI showed nonlinear enhancement with the highest explanatory power for surface albedo spatial heterogeneity (96.76%). Previous studies have revealed that meteorological factors such as air temperature and precipitation indirectly affect surface albedo by influencing other factors (e.g., Kala et al., 2014). For example, air temperature and precipitation indirectly affect surface albedo by influencing vegetation growth (both show nonlinear enhancement effects on NDVI's impact), and precipitation changes alter snow characteristics, thus indirectly affecting surface albedo (precipitation' s explanatory power for spatial heterogeneity is 85.15%, greater than NDVI' s). These conclusions enhance understanding of feedback relationships in land-atmosphere interactions and provide scientific references for verifying and improving land-surface process simulations (Li et al., 2020).

4.2 Attribution of Spatiotemporal Variation in Surface Albedo

This study found that annual average surface albedo in northern Xinjiang showed a weak decreasing trend (Fig. 4), consistent with the slow decreasing trend in China' s regional areas in recent years (Xu et al., 2020). Similar decreasing trends in annual average surface albedo have been observed in other Northern Hemisphere areas, including high-latitude regions (Loranty et al., 2014), the Arctic (Pistone et al., 2014), France (Planque et al., 2017), the Swiss Alps (Rangwala and Miller, 2012), and Greenland (He et al., 2013).

Decreases in NDSI and precipitation, along with increases in NDVI, land surface temperature, soil moisture, and air temperature, jointly contributed to the surface albedo decrease in northern Xinjiang. NDSI change contributed significantly more than other factors (Pang et al., 2022). The decrease in NDSI was the main reason for surface albedo reduction, especially in spring. The interaction between land surface temperature and NDVI showed nonlinear enhancement, and increased land surface temperature affected vegetation growth, leading to significant NDVI increases. Similarly, land surface temperature increased most rapidly in spring, affecting vegetation growth and causing the fastest NDVI increase.

Climate change also significantly contributed to surface albedo decrease. Against the backdrop of warming temperatures and reduced precipitation in northern Xinjiang from 2010 to 2020 (Fig. 4), warming promoted vegetation expansion (Pearson et al., 2013) and snow melting (Atlaskina et al., 2015), reducing snow' s high surface albedo and increasing vegetation' s low surface albedo. Meanwhile, reduced snowfall and rainfall decreased NDSI, resulting in lower surface albedo (Fassnacht et al., 2016; Malmros et al., 2018). In spring, increased rainfall raised soil moisture, also causing surface albedo decreases in snow-free, sparsely vegetated regions.

Among land cover types, cropland in spring and impervious surface in summer contributed significantly to surface albedo decrease, with areas showing significant reduction occupying 9.37% and 14.37% of the study area, respectively—higher than average proportions for all land cover types in spring and summer (7.36% and 9.69%, respectively) (Fig. 5f). Cropland showed the highest area proportions of extreme negative correlations between surface albedo and NDVI (6.19%) and soil moisture (5.04%). This occurs because crop planting and irrigation decrease surface albedo by increasing NDVI and soil moisture, while impervious surfaces disrupt surface heat balance, causing significant summer warming and subsequent surface albedo reduction (Xu, 2009). Therefore, human activities have contributed to surface albedo decrease in northern Xinjiang, indicating that more solar radiation will be absorbed, accelerating warming in this region.

5 Conclusions

This study analyzed spatial distribution and spatiotemporal variation characteristics of surface albedo in northern Xinjiang and its responses to multiple influencing factors. The following conclusions were obtained:

(1) Surface albedo in the study area showed obvious spatial and seasonal differences. Annual average surface albedo exhibited a spatial pattern of high values in the west and north and low values in the east and south. The highest seasonal average surface albedo occurred in winter, while the lowest was in summer.

(2) During 2010–2020, annual average surface albedo in the study area showed a weak decreasing trend. The spatial distribution of regions with significant change showed increases in the north and decreases in the south, with larger areas of significant persistence than anti-persistence. Trend and persistence status of seasonal average surface albedo in spring and summer were similar to those of the annual average, while autumn and winter

showed opposite patterns. The changing trend of surface albedo was generally stable and persistent, with land cover types significantly influencing variation. NDSI and precipitation showed decreasing trends during the study period, while NDVI, land surface temperature, soil moisture, and air temperature showed increasing trends.

(3) Annual average surface albedo was significantly positively correlated with NDSI and precipitation in many regions, and mainly negatively correlated with NDVI, land surface temperature, soil moisture, and air temperature. Correlations between surface albedo and each factor showed significant seasonal differences. NDSI was the primary influencing factor, followed by precipitation, land surface temperature, and soil moisture, while NDVI, air temperature, and DEM had relatively small influences. All factors showed varying degrees of enhancement in interaction, particularly air temperature and DEM. NDVI showed nonlinear enhancement when interacting with land surface temperature or precipitation.

These findings significantly enhance our understanding of surface albedo variation and its responses to various influencing factors. This research is immensely important for accurately comprehending complex land-atmosphere interactions in northern Xinjiang, which can greatly improve regional land-surface process simulation and climate prediction.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was supported by the National Key Research and Development Program of China (2019YFC1510505), the Xinjiang University PhD Start-up Fund (BS210226), and the National College Student Research Training Plan of China (202110755004).

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Note: Figure translations are in progress. See original paper for figures.