Remote Sensing Monitoring of Snowline Elevation at the End of Snowmelt Season in the Tianshan Mountains, 1991–2021: A Postprint

Authors: Jingwen Wang, Tang Zhiguang, Deng Gang, HU Guojie, Sang Guoqing, Tang Zhiguang

Date: 2022-12-20T00:00:00+00:00

Abstract

Investigating variations in snowline altitude at the end of the snowmelt period contributes to predicting future trends in cryospheric systems and understanding regional and global climate change. Based on the Google Earth Engine (GEE) platform and Landsat satellite data, a regional snowline altitude extraction model was developed to retrieve end-of-snowmelt snowline altitudes for four sub-basins in the Tianshan Mountains from 1991 to 2021, and to analyze their variation characteristics and relationships with meteorological factors. The results indicate: (1) The end-of-snowmelt snowline altitude extracted from Landsat demonstrates high consistency with the "minimized" snow cover extent at the end of snowmelt derived from Sentinel-2, achieving an overall accuracy of 91.6% and a Kappa coefficient exceeding 0.9, thereby confirming that the model can accurately obtain regional snowline altitude at the end of the snowmelt period. (2) Over the past 30 years, the end-of-snowmelt snowline altitude in the study area has exhibited a significant upward trend, with ascent rates ranging from 2.7~6.4 m · a-1; specifically, the Manas River Basin shows the fastest snowline altitude increase, while the Akyazi River Basin shows the slowest. (3) Summer temperature represents the primary factor influencing variations in end-of-snowmelt snowline altitude in the study area ($P < 0.05$), whereas precipitation exerts a relatively weaker influence.

Full Text

Monitoring of Snowline Altitude at the End of Melting Season in Tianshan Mountains from 1991 to 2021

WANG Jingwen[1], TANG Zhiguang[1], DENG Gang[1], HU Guojie[2], SANG Guoqing[1]

[1]Hunan Provincial Key Laboratory of Geo-Information Engineering in Surveying, Mapping and Remote Sensing, Hunan University of Science and Technology, Xiangtan 411201, Hunan, China
[2]State Key Laboratory of Cryospheric Sciences, Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou 730000, Gansu, China

Abstract: Studying changes in snowline altitude at the end of the melting season helps predict future trends of snow and ice systems and understand regional and global climate change. Based on Google Earth Engine and Landsat satellite data, we developed a regional snowline altitude extraction model to retrieve snowline altitudes at the end of the melting season in the Tianshan Mountains from 1991 to 2021, and analyzed the variation characteristics of snowline altitude and its relationship with meteorological factors. The results show that: (1) The "minimized" snow cover extent at the end of the melting season extracted by Landsat and Sentinel-2 has high consistency, with an overall accuracy of over 91.6% and a Kappa coefficient higher than 0.9, indicating that the model can accurately obtain regional snowline altitude at the end of the melting season. (2) The snowline altitude at the end of the melting season in the study area showed a significant upward trend over the past 30 years, with an increasing rate between 2.7-6.4 $m \cdot a^{-1}$. Among them, the Manas River Basin had the fastest rising rate of snowline altitude, while the Akeyazi River Basin had the slowest. (3) Summer temperature is the main factor affecting the change of snowline altitude at the end of the melting season in the study area ($P < 0.05$), while the effect of precipitation is relatively weak.

Keywords: snowline altitude; Landsat; remote sensing monitoring; climate change; Tianshan Mountains

1.1 Study Area Overview

The Tianshan Mountains stretch across China, Kazakhstan, Kyrgyzstan, and Uzbekistan. The complex terrain features high mountains, intermontane basins, and valleys, with abundant precipitation and low temperatures in the high-altitude zones that support extensive glacier development. The changes in snow and ice in the Tianshan Mountains are closely related to water resources and hydrological processes in numerous river basins. This study selected four typical mountain river basins as research areas: the Qiongwusankush River Basin, the Muzhati River Basin, the Akeyazi River Basin, and the Manas River Basin (Fig. 1). All four basins originate from snow-covered areas, where snow and ice meltwater constitutes an important proportion of river runoff. The Qiongwusankush and Muzhati rivers originate from the southern slope of the Tianshan Mountains and eventually flow into the Tarim River Basin. Areas above 4000 m in these basins are mainly covered by snow and ice year-round, accounting for approximately 30% of the total basin area. The Muzhati River Basin contains numerous modern glaciers, covering about 25% of the entire basin area. The Akeyazi River originates from the northern slope of the Tianshan Mountains, with areas above 4000 m permanently covered by glaciers and non-seasonal snow, accounting for about 20% of the basin area. The Manas River originates from the northern slope of the Tianshan Mountains and flows into the hinterland of the Junggar Basin, with areas above 4000 m covered by glaciers and non-seasonal snow year-round, accounting for about 30% of the entire basin area.

1.2 Data Sources

This study utilized Landsat TM/ETM+/OLI and Sentinel-2 satellite imagery, SRTM DEM data, and ERA5-LAND reanalysis datasets, all accessed and processed through the Google Earth Engine cloud computing platform.

Landsat Data: We employed Landsat Land Surface Reflectance (LSR) data from the Landsat series, which has undergone radiometric calibration and atmospheric correction to eliminate errors caused by atmospheric scattering, absorption, and reflection. The data have a spatial resolution of 30 m and a temporal resolution of 16 days. The dataset provides Quality Assessment (QA) bands generated by the CFMask cloud detection algorithm, which include identifiers for clouds and cloud shadows. This enables monitoring of snowline altitude at the end of the melting season in the study area from 1991 to the present.

Sentinel-2 Data: The Sentinel-2 MSI satellite is operated by the European Space Agency (ESA), consisting of Sentinel-2A and Sentinel-2B, launched in 2015 and 2017, respectively. The twin satellites have a revisit cycle of 5 days and both carry a Multi-Spectral Instrument (MSI). This study used the Level-2A surface reflectance product, which has undergone radiometric calibration and atmospheric correction. The selected data bands have a spatial resolution of 10 m. The higher spatial and temporal resolution of Sentinel-2 data was used to validate the accuracy of snowline altitude extraction results from Landsat data.

SRTM DEM Data: The SRTM DEM data (version 3.0) were used to extract snowline altitude information. This dataset was released by NASA, filling missing values in the original SRTM data using ASTER GDEM2 and GMTED2010 data, with a spatial resolution of 30 m. The global vertical accuracy of this data is approximately 16 m, with an absolute vertical accuracy of about 6 m in flat terrain areas and approximately 10 m in mountainous regions with rugged terrain in China.

ERA5-LAND Reanalysis Dataset: The ERA5-LAND reanalysis dataset is provided by the European Centre for Medium-Range Weather Forecasts (ECMWF), offering global precipitation, temperature, and other variables from 1981 to the present. This study used monthly average temperature and precipitation data from this dataset, with a spatial resolution of 10 km, to explore the response relationship between snowline altitude changes at the end of the melting season and climatic factors in the study area.

2 Research Methods

Using multi-temporal Landsat TM/ETM+/OLI imagery near the end of the melting season as the primary data source, we constructed a technical route for the snowline altitude extraction model (Fig. 3). The specific methods mainly include snow remote sensing identification, extraction of "minimized" snow cover extent at the end of the melting season, regional snowline altitude extraction, and accuracy validation.

2.1 Snow Remote Sensing Identification

The SNOWMAP algorithm was used to extract snow cover extent. This algorithm establishes the Normalized Difference Snow Index (NDSI) based on the characteristic that snow has high reflectance in the visible light band and strong absorption in the shortwave infrared band, using appropriate thresholds to determine snow cover extent.

$$NDSI = \frac{Green - SWIR}{Green + SWIR}$$

where *Green* and *SWIR* represent the reflectance values of the green band and shortwave infrared band in Landsat data, respectively. Since water bodies and snow have similar spectral reflection characteristics, to avoid misidentifying water bodies and shadows as snow, an additional discriminant condition was added: the near-infrared band reflectance must be greater than 0.11. Previous studies have demonstrated that the combined threshold of NDSI $>$ 0.29 & NIR $>$ 0.11 is more suitable for snow mapping in the Tibetan Plateau region. Therefore, this study identified pixels meeting these conditions as snow pixels, while those not meeting the conditions were classified as non-snow pixels. The snow, non-snow, and cloud identification results from the QA band were then combined to obtain a snow classification map (snow, cloud, non-snow).

2.2 Extraction of "Minimized" Snow Cover Extent at the End of Melting Season

Through instantaneous snowline altitude-based cloud removal and temporal fusion, the influence of clouds was reduced to obtain the "minimized" snow cover extent that best represents the end of the melting season.

2.2.1 Cloud Removal for Instantaneous Snowline Altitude

The proportion of cloud and snow areas in the region was first assessed. If the combined area proportion of cloud and snow was less than 70%, the instantaneous snowline altitude of that region was extracted for cloud removal processing. The cloud removal strategy was as follows: if the ground elevation corresponding to a cloud pixel was higher than the instantaneous regional snowline altitude, it was classified as snow; otherwise, it was classified as land. When the cloud cover proportion is too large, there are often very few snow pixels or the snow-covered area is surrounded by clouds, resulting in large deviations in the extracted instantaneous snowline altitude or making extraction impossible. To ensure the effectiveness of the extracted instantaneous regional snowline altitude, this study set a threshold where cloud and snow area proportion must be less than 70% to participate in temporal fusion processing.

2.2.2 Temporal Fusion

Temporal fusion was performed on multi-temporal snow classification images (including those after instantaneous snowline altitude cloud removal) near the end of the melting season to complete the minimization synthesis of snow cover extent, ultimately obtaining a "minimized" snow cover map representing the end of the melting season. The temporal fusion strategy was as follows: for each pixel, if it was identified as bare land in any temporal phase, it was classified as bare land; if more than 50% of the phases identified it as snow while other phases were all cloud, it was classified as snow; if more than 50% of the phases identified it as cloud while other phases were all snow, it was classified as cloud. The fused "minimized"snow cover extent map representing the end of the melting season was then used for snowline altitude extraction.

2.3 Regional Snowline Altitude (RSLA) Extraction

The principle of the regional snowline altitude method is to find an elevation within the target region that minimizes the sum of non-snow pixels above this elevation and snow pixels below it. This elevation then represents the snowline altitude within the region (Fig. 4). The specific process is as follows: starting from the lowest elevation in the region, calculate the sum of snow pixels below the target elevation and non-snow pixels above it. Repeat this calculation every 10 m until reaching the highest elevation in the region. Then use a minimum value function to retrieve the elevation corresponding to the minimum sum, which is the target region' s snowline altitude. This method allows for the existence of partial cloud cover and represents the optimal estimation of snowline altitude for the target region, making it suitable for cloud removal processing of snow images.

$$RSLA = Min\left(\sum_{elev_{min}}^{elev_{max}} C_{below} + C_{above}\right)$$

where C_{below} represents the number of snow pixels below the elevation, C_{above} represents the number of non-snow pixels above the elevation, $elev_{min}$ is the lowest elevation in the region, and $elev_{max}$ is the highest elevation in the region.

2.4 Accuracy Assessment of Snowline Altitude

Higher spatial resolution and shorter revisit cycle Sentinel-2 imagery was used to validate the accuracy of snowline altitude extraction results from Landsat data. The specific validation method was as follows: select Sentinel-2 images near the end of the melting season from 2020 to 2021 with cloud cover less than 10% in the study area (Table 1). Use visual interpretation to map snow cover extent for each image. Then perform temporal fusion on multi-temporal snow cover extent maps near the end of the melting season to obtain the "minimized" snow cover extent extracted by Sentinel-2 (serving as the "true value" of snow cover extent at the end of the melting season). Finally, based on the "minimized" snow cover extent map extracted by Sentinel-2, conduct random sampling of validation samples near the snowline position, combine them with the regional snowline altitude values extracted by Landsat, and calculate the overall accuracy (OA), precision (Pre), and recall rate (Rec) of the snowline altitude extraction model at the end of the melting season. The calculation formulas are as follows:

$$Pre = \frac{B}{B+D} \times 100$$

$$Rec = \frac{B}{A+B} \times 100$$

where A represents the number of points above the Landsat-extracted snowline altitude at the end of the melting season that are identified as snow in the Sentinel-2 "minimized" snow cover extent; B represents the number of points above the Landsat-extracted snowline altitude at the end of the melting season that are identified as non-snow in the Sentinel-2 "minimized" snow cover extent; C represents the number of points below the Landsat-extracted snowline altitude at the end of the melting season that are identified as snow in the Sentinel-2 "minimized" snow cover extent; and D represents the number of points below the Landsat-extracted snowline altitude at the end of the melting season that are identified as non-snow in the Sentinel-2 "minimized" snow cover extent. When Pre $>$ Rec, it indicates that the snowline altitude is overestimated; when Pre $<$ Rec, it indicates that the snowline altitude is underestimated.

3.1 Analysis of Accuracy Assessment Results for Snowline Altitude at End of Melting Season

By establishing a confusion matrix, the Kappa coefficient of snowline altitude extraction results at the end of the melting season in the study area was calculated to quantitatively evaluate the extraction accuracy (Table 2). The results show that the snowline altitude extraction results at the end of the melting season for all four basins have high accuracy, with overall accuracy between 87.5% and 94.4% and average Kappa coefficients between 0.86 and 0.93. This indicates that the snowline altitude at the end of the melting season extracted by Landsat is slightly underestimated compared to that extracted by Sentinel-2 with higher temporal resolution. Taking the Akeyazi River Basin as an example, the snowline altitude at the end of the melting season extracted by Landsat has high consistency with the "minimized" snow cover extent at the end of the melting season extracted by Sentinel-2, with an overall accuracy of 92.7%. The precision is 87.06%, meaning the probability that points above the Landsat-extracted snowline altitude are identified as non-snow in the Sentinel-2 "minimized" snow cover extent is 12.94%. The recall rate for this basin is 93.97%, indicating that the probability of points below the Landsat-extracted snowline altitude being identified as snow in the Sentinel-2 "minimized" snow cover extent is only 6.03%.

3.2 Spatiotemporal Variation Characteristics of Snowline Altitude During Melting Season

The snowline altitude data obtained from the model (Fig. 5) reveal strong seasonal variations from June to September. Starting in June, as snow melts rapidly, the snow cover percentage in the study area gradually decreases while the snowline altitude gradually increases. The maximum instantaneous snowline altitude mainly appears in August, after which the snowline altitude gradually decreases again. The instantaneous snowline altitude also shows strong interannual fluctuations (Fig. 6). Taking the Akeyazi River Basin in 2020 as an example (Fig. 6), the snowline altitude gradually increased from June to August, rising from 3458 m to 3967 m, and then decreased to 3775 m in September. The snowline altitude at the end of the melting season extracted by the model was 3955 m, higher than each instantaneous snowline altitude. Additionally, the standard deviation (σ) of snowline altitude at the end of the melting season was calculated to reflect the interannual fluctuation amplitude (Fig. 7). The results show that the Muzhati River Basin has the smallest standard deviation ($\sigma = 59$ m), indicating the smallest interannual fluctuation in snowline altitude at the end of the melting season for this basin. The Qiongwusankush River Basin has the largest standard deviation ($\sigma = 94$ m), indicating the largest interannual fluctuation.

3.3 Interannual Variation Characteristics of Snowline Altitude at End of Melting Season

The snowline altitude at the end of the melting season in the study area showed an overall significant upward trend from 1991 to 2021 (Fig. 7). The highest values of snowline altitude at the end of the melting season in the Qiongwusankush and Manas river basins both appeared in 2021, while the lowest values appeared in 1993 and 1992, respectively. The highest and lowest values in the Muzhati and Akeyazi river basins appeared in 2021 and 1992, respectively. The multi-year average snowline altitude at the end of the melting season was 4504 m in the Qiongwusankush River Basin, with a trend slope of 4.5 $m \cdot a^{-1}$. The Muzhati River Basin had a multi-year average snowline altitude of 4207 m at the end of the melting season, with the highest trend slope of 6.4 $m \cdot a^{-1}$, and the snowline altitude at the end of the melting season increased by about 192 m. The Manas River Basin had a multi-year average snowline altitude of 4212 m at the end of the melting season, with a trend slope of 3.1 $m \cdot a^{-1}$, and the snowline altitude at the end of the melting season increased by about 135 m. The Akeyazi River Basin had the lowest multi-year average snowline altitude of 3955 m at the end of the melting season, with the lowest trend slope of 2.8 $m \cdot a^{-1}$, and the snowline altitude at the end of the melting season increased by about 76 m.

3.4 Relationship Between Snowline Altitude Variation and Temperature/Precipitation at End of Melting Season

Snowline altitude is closely related to climate. This study analyzed the response relationship between snowline altitude at the end of the melting season and climate change by calculating the correlation between annual and summer average temperature, annual and summer total precipitation, and snowline altitude at the end of the melting season (Table 3). Annual precipitation and annual temperature refer to the total precipitation and average temperature from July of the previous year to June of the current year. The annual and summer precipitation in the Qiongwusankush River Basin showed a weak increasing trend, while the annual and summer precipitation in the Muzhati, Akeyazi, and Manas river basins showed a decreasing trend. The annual average temperature and summer average temperature in all basins showed an increasing trend (Fig. 8). The Qiongwusankush River Basin had the lowest multi-year average annual temperature (-8.9 °C) and summer average temperature (1.9 °C), while the Manas River Basin had the highest multi-year average annual temperature (-3.3 °C) and summer average temperature (8.7 °C). The Qiongwusankush River Basin had the lowest multi-year average annual precipitation (306.3 mm) and summer average precipitation (596.1 mm), while the Akeyazi River Basin had the highest multi-year average annual precipitation (485.8 mm) and summer average precipitation (930.6 mm).

The snowline altitude at the end of the melting season in the study area is positively correlated with temperature, particularly showing a significant positive correlation with summer temperature ($P < 0.05$). It shows a weak negative correlation with precipitation, indicating that summer temperature is the main factor affecting the change in snowline altitude at the end of the melting season. To explore the sensitivity of snowline altitude at the end of the melting season to climate change in the study area, a multiple linear regression model was established between snowline altitude and summer temperature and annual precipitation:

$$SLA = \lambda + aT + bP$$

where SLA is the snowline altitude at the end of the melting season, λ is a constant, T is summer temperature (°C), P is annual precipitation (mm), and

a and b are regression coefficients. The regression coefficients for the four basins are shown in Table 4. Taking the Akeyazi River Basin as an example, when summer temperature increases or decreases by 1 °C, the snowline altitude at the end of the melting season in this basin will increase or decrease by 76.2 m. When annual precipitation increases or decreases by 100 mm, the snowline altitude at the end of the melting season in this basin will decrease or increase by 36.4 m. This indicates that in the Akeyazi River Basin, the increase in snowline altitude at the end of the melting season caused by a 1 °C increase in summer temperature would require an increase of 265 mm in precipitation to compensate. The summer temperature regression coefficient is largest in the Qiongwusankush River Basin (82.9), meaning that snowline altitude change at the end of the melting season in this basin is most sensitive to summer temperature. The annual precipitation regression coefficient is largest in the Manas River Basin (-0.56), indicating that snowline altitude change at the end of the melting season in this basin is most sensitive to annual precipitation.

4.1 Uncertainty in Snow Mapping and Snowline Altitude Extraction

The uncertainty in snow mapping and snowline altitude extraction mainly comes from three aspects: (1) Terrain-induced shadows affect the accuracy of snow cover extraction when using optical remote sensing images in mountainous areas, an effect known as terrain effect. This can be better eliminated through topographic correction. Additionally, if pixel-scale snowline altitude extraction is performed, the impact of aspect on snowline altitude should be quantitatively analyzed. This study focuses on regional snowline altitude extraction, where the solved unique elevation value represents a comprehensive snowline altitude for a region. Therefore, terrain effects and micro-topographic factors such as aspect were not considered. (2) The presence of clouds and cloud shadows is also a major source of error in snow information extraction from optical remote sensing. This study used Landsat series data and employed instantaneous snowline-based cloud removal and temporal fusion methods for cloud processing. In subsequent research, Sentinel-1 SAR data, which has all-weather, all-day, and penetration capabilities unaffected by weather and solar illumination conditions, could be combined with Sentinel-2 data to enhance snow identification under clouds. (3) For forested areas, snow extraction accuracy is relatively poor as tree canopies block ground snow information. Multi-index snow identification methods based on NDFSI (Normalized Difference Forest Snow Index) and NDVI (Normalized Difference Vegetation Index) can effectively extract under-canopy snow. However, the snowline altitude at the end of the melting season is much higher than forest vegetation zones, so the impact of forests was not considered in this study. Additionally, most bare glacier surfaces are not clean (debris-covered) and have significantly lower albedo than snow, allowing them to be distinguished from snow through optical remote sensing using NDSI thresholds. However, the extraction of snowline altitude at the end of the melting season should also focus on distinguishing non-seasonal snow from clean-surface glaciers, which can be achieved by utilizing their different characteristics in the near-infrared band according to the near-infrared image histogram classification. Particularly with the emergence of Sentinel-1 SAR, the distinction between glaciers and snow has become more feasible.

The snowline altitude extraction method in this study is only suitable for regional (or basin) scale snowline altitude extraction. If pixel-scale spatiotemporal differences in snowline altitude are to be analyzed (such as the influence of aspect, slope, and other micro-topographic factors), pixel-scale snowline altitude extraction methods should be employed.

4.2 Spatial Differentiation of Snowline Altitude at End of Melting Season

This study found that the snowline altitude at the end of the melting season in the study area showed an upward trend over the past 30 years, which is consistent with research conclusions that the mass balance of the Tianshan Mountains is in a negative balance state. From the annual snowline altitude at the end of the melting season in the study area, the Qiongwusankush River Basin generally has the highest snowline altitude at the end of the melting season, significantly higher than the other three basins, while the Akeyazi River Basin has the lowest snowline altitude at the end of the melting season. The main reasons for this distribution characteristic are: the Qiongwusankush River Basin is located on the southern slope of the Tianshan Mountains, which is a sunny slope receiving more solar radiation, resulting in relatively higher temperatures compared to the northern slope. Additionally, the overall terrain of this basin is relatively high, affected by mountain elevation, so the snowline altitude in this area is the highest. The Akeyazi River Basin is located on the northern slope of the Tianshan Mountains, affected by water vapor from the Atlantic Ocean and Arctic Ocean, with relatively abundant precipitation, less solar radiation, and relatively lower temperatures, resulting in the lowest snowline altitude at the end of the melting season in the Akeyazi River Basin.

4.3 Impact of Climate Change on Snowline Altitude at End of Melting Season

As a climatic indicator, snowline altitude is influenced by climate factors and also reflects climate change. Existing studies have shown that under the influence of global warming, glacier areas continue to shrink and snowline altitudes continue to rise, which is consistent with this study. This study found that summer temperature is the main factor affecting the change in snowline altitude at the end of the melting season. Previous studies on snowline altitude at the end of the melting season or glacier equilibrium line changes in high mountain areas have reached similar conclusions. For example, Tang et al. used MODIS data to monitor snowline altitude on the Tibetan Plateau and found that snowline altitude at the end of the melting season in the Asian high mountain region showed an overall upward trend from 2001 to 2019, particularly evident in the Tianshan Mountains and Himalayan regions, with summer temperature being the main influencing factor. Chen et al. found that summer temperature is the dominant climatic factor affecting changes in glacier equilibrium line altitude. This study, based on Landsat data and supported by the Google Earth Engine platform, extracted long time series of snowline altitude data and also found that summer temperature is the dominant factor. The powerful storage and computing capabilities of the Google Earth Engine platform have significantly improved the efficiency of remote sensing extraction of snowline altitude, providing strong computational resources for long-term, large-scale remote sensing monitoring of snowline altitude.

5 Conclusions

Based on the Google Earth Engine cloud computing platform and Landsat satellite data, this study developed a remote sensing extraction model for regional snowline altitude at the end of the melting season, extracted long time series of snowline altitude data at the end of the melting season from 1991 to 2021, and analyzed the spatiotemporal variation characteristics of snowline altitude and its relationship with temperature and precipitation in four basins of the Tianshan Mountains. The main conclusions are as follows:

(1) The snowline altitude at the end of the melting season extracted by the model has high consistency with the "minimized" snow cover extent extracted by Sentinel-2 at the end of the melting season, with an average overall accuracy of 91.6% and an average Kappa coefficient of 0.90. This extraction model can accurately extract regional snowline altitude at the end of the melting season within basins and can be effectively applied to basin-scale, long time series remote sensing monitoring of snowline altitude.

(2) From 1991 to 2021, the snowline altitude at the end of the melting season in the study area showed significant interannual fluctuations but an overall upward trend. The rising rate of snowline altitude at the end of the melting season was slowest in the Akeyazi River Basin ($2.8\ \mathrm{m \cdot a^{-1}}$) and fastest in the Manas River Basin ($6.4\ \mathrm{m \cdot a^{-1}}$).

(3) The snowline altitude at the end of the melting season in the study area is mainly affected by temperature, showing a significant positive correlation with summer temperature and a weak negative correlation with precipitation. When summer temperature increases (decreases) by 1 °C, the snowline altitude at the end of the melting season in the basin increases (decreases) by approximately 50.7–82.9 m. When annual precipitation increases (decreases) by 100 mm, the snowline altitude at the end of the melting season in the basin decreases (increases) by approximately 23.8–36.4 m.

References

[1] Licker M D. Dictionary of Earth Science[M]. New York: McGraw Hill, 2003.

[2] Mengel J, Short D, North G. Seasonal snowline instability in an energy balance model[J]. Climate Dynamics, 1988, 2(3): 127-131.

[3] Baum S K, Crowley T J. Seasonal snowline instability in a climate model with realistic geography: Application to carboniferous (300 MA) glaciation[J]. Geophysical Research Letters, 1991, 18(9): 1719-1722.

[4] Xie Zichu, Liu Chaohai. Leading Principles of Glaciology[M]. Shanghai: Shanghai Popular Science Press, 2010.

[5] Qin Dahe, Yao Tandong, Ding Yongjian. Glossary of Cryospheric Science[M]. Beijing: China Meteorological Press, 2014.

[6] Pandey P, Kulkarni A V, Venkataraman G. Remote sensing study of snowline altitude at the end of melting season, Chandra Bhaga basin, Himachal Pradesh, 1980-2007[J]. Geocarto International, 2013, 28(4): 311-322.

[7] Flint R F. Glacial and Quaternary geology[M]. New York: John Wiley Press, 1971.

[8] Rabatel A, Bermejo A, Loarte E, et al. Can the snowline be used as an indicator of the equilibrium line and mass balance for glaciers in the outer tropics?[J]. Journal of Glaciology, 2012, 58(212): 1027-1036.

[9] Guo Zhongming, Gu Zhujun, Wu Hongbo, et al. Research progress of glacier snowline altitude[J]. Remote Sensing Technology and Application, 2016, 31(4): 645-652.

[10] Shea J, Menounos B, Moore R, et al. An approach to derive regional snow lines and glacier mass change from MODIS imagery, western North America[J]. The Cryosphere, 2013, 7(2): 667-680.

[11] Barandun M, Huss M, Usubaliev R, et al. Multi-decadal mass balance series of three Kyrgyz glaciers inferred from modelling constrained with repeated snow line observations[J]. The Cryosphere, 2018, 12(6): 1899-1919.

[12] McFadden E, Ramage J, Rodbell D. Landsat TM and ETM+ derived snowline altitudes in the Cordillera Huayhuash and Cordillera Raura, Peru, 1986-2005[J]. The Cryosphere, 2011, 5(2): 419-430.

[13] Zhang Qibing, Kang Shichang, Zhang Guoshuai, et al. Changes of snow line altitude for glaciers on western Nyainqentanglha range observed by remote sensing[J]. Scientia Geographica Sinica, 2016, 36(12): 1937-1944.

[14] Che Tao, Li Xin, Li Xinwu, et al. Developing cryospheric remote sensing, promoting scientific programme of Earth' s Three Poles[J]. Bulletin of Chinese Academy of Sciences, 2020, 35(4): 484-493.

[15] Notarnicola C. Hotspots of snow cover changes in global mountain regions over 2000-2018[J]. Remote Sensing of Environment, 2020, 243: 111781.

[16] Verbyla D, Hegel T, Nolin A W, et al. Remote sensing of 2000-2016 alpine spring snowline elevation in dall sheep mountain ranges of Alaska and Western Canada[J]. Remote Sensing, 2017, 9(11): 1157.

[17] Spiess M, Huintjes E, Schneider C. Comparison of modelled and remote sensing derived daily snow line altitudes at Ulugh Muztagh, northern Tibetan Plateau[J]. Journal of Mountain Science, 2016, 13(4): 593-613.

[18] Krají P, Holko L, Perdigão R A, et al. Estimation of regional snowline elevation (RSLE) from MODIS images for seasonally snow covered mountain basins[J]. Journal of Hydrology, 2014, 519: 1769-1778.

[19] Tang Z, Wang J, Li H, et al. Extraction and assessment of snowline altitude over the Tibetan plateau using MODIS fractional snow cover data (2001 to 2013)[J]. Journal of Applied Remote Sensing, 2014, 8(1): 084689.

[20] Tang Z, Wang X, Deng G, et al. Spatiotemporal variation of snowline altitude at the end of melting season across high mountain Asia, using MODIS snow cover product[J]. Advances in Space Research, 2020, 66(11): 2629-2645.

[21] Girona Mata M, Miles E S, Ragettli S, et al. High resolution snowline delineation from Landsat imagery to infer snow cover controls in a Himalayan catchment[J]. Water Resources Research, 2019, 55(8): 6754-6772.

[22] Hu Z, Dietz A, Kuenzer C. The potential of retrieving snow line dynamics from Landsat during the end of the ablation seasons between 1982 and 2017 in European mountains[J]. International Journal of Applied Earth Observation and Geoinformation, 2019, 78: 138-148.

[23] Guo Z, Wang N, Wu H, et al. Variations in firn line altitude and firn zone area on Qiyi Glacier, Qilian Mountains, over the period of 1990 to 2011[J]. Arctic, Antarctic, and Alpine Research, 2015, 47(2): 293-300.

[24] Chen An'an, Chen Wei, Wu Hongbo, et al. The variations of firn line altitude on the Binglinchuan Glacier, Ulugh Muztagh during 2000-2013[J]. Journal of Glaciology and Geocryology, 2014, 36(5): 1069-1078.

[25] Wang Ninglian. Grey relational analysis of the leading climatic factor influencing the changes of the equilibrium line[J]. Journal of Glaciology and Geocryology, 1995, 17(1): 8-15.

[26] Fu Dongjie, Xiao Han, Su Fenzhen, et al. Remote sensing cloud computing platform development and earth science application[J]. National Remote Sensing Bulletin, 2021, 25(1): 220-230.

[27] Liu Chang, Li Zhen, Zhang Ping, et al. Evaluation of MODIS snow products in southwestern Xinjiang using the Google Earth Engine[J]. Remote Sensing Technology and Application, 2018, 33(4): 584-592.

[28] Crumley R L, Palomaki R T, Nolin A W, et al. Snow cloud metrics: snow information for everyone[J]. Remote Sensing, 2020, 12(20): 3345.

[29] Sorg A, Bolch T, Stoffel M, et al. Climate change impacts on glaciers and runoff in Tien Shan (Central Asia)[J]. Nature Climate Change, 2012, 2(10): 725-731.

[30] Xu M, Kang S, Wu H, et al. Detection of spatiotemporal variability of air temperature and precipitation based on long-term meteorological station observations over Tianshan Mountains, Central Asia[J]. Atmospheric research, 2018, 203: 141-163.

[31] Chen Yaning, Li Zhi, Fang Gonghuan, et al. Impact of climate change on water resources in the Tianshan Mountains, Central Asia[J]. Acta Geographica Sinica, 2017, 72(1): 18-26.

[32] Li P, Li Z, Muller J P, et al. A new quality validation of global digital elevation models freely available in China[J]. Survey Review, 2016, 48(351): 409-420.

[33] Hall D K, Riggs G A, Salomonson V V. Development of methods for mapping global snow cover using moderate resolution imaging spectroradiometer data[J]. Remote Sensing of Environment, 1995, 54(2): 127-140.

[34] Zhang H, Zhang F, Zhang G, et al. Enhanced scaling effects significantly lower the ability of MODIS normalized difference snow index to estimate fractional and binary snow cover on the Tibetan Plateau[J]. Journal of Hydrology, 2021, 592: 125795.

[35] Xiao P, Li C, Zhu L, et al. Multitemporal ensemble learning for snow cover extraction from high spatial resolution images in mountain areas[J]. International Journal of Remote Sensing, 2020, 41(5): 1668-1691.

[36] Negi H S, Kulkarni A, Semwal B. Estimation of snow cover distribution in Beas basin, Indian Himalaya using satellite data and ground measurements[J]. Journal of Earth System Science, 2009, 118(5): 525-538.

[37] Wang X, Chen S, Wang J. An adaptive snow identification algorithm in the forests of northeast China[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2020, 13: 5211-5222.

[38] Wang X, Wang J, Che T, et al. Snow cover mapping for complex mountainous forested environments based on a multi-index technique[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2018, 11(5): 1433-1441.

[39] Liu C, Li Z, Zhang P, et al. Variability of the snowline altitude in the eastern Tibetan Plateau from 1995 to 2016 using Google Earth Engine[J]. Journal of Applied Remote Sensing, 2021, 15(4): 044601.

[40] Li X, Wang N, Wu Y. Automated glacier snow line altitude calculation method using Landsat series images in the Google Earth Engine platform[J].

Remote Sensing, 2022, 14(10): 2377.

[41] Deng G, Tang Z, Hu G, et al. Spatiotemporal dynamics of snowline altitude and their responses to climate change in the Tienshan Mountains, Central Asia, during 2001-2019[J]. Sustainability, 2021, 13(7): 3992.

[42] Wang Shengjie, Zhang Mingjun, Li Zhongqin, et al. Response of glacier area variation to climate change in Chinese Tianshan Mountains in the past 50 years[J]. Acta Geographica Sinica, 2011, 66(1): 38-46.

[43] Zhang Liancheng, Hu Liequn, Li Shuai, et al. GIS-based analysis on the snowline distributional characteristics of South and North slopes of Tianshan Mountain and their influencing factors[J]. Research of Soil and Water Conservation, 2015, 22(3): 259-263.

[44] Dai Xingang, Li Weijing, Ma Zhuguo, et al. Water vapor source shift of Xinjiang region during the recent twenty years[J]. Progress in Natural Science, 2007, 17(5): 569-575.

[45] Wayand N E, Marsh C B, Shea J M, et al. Globally scalable alpine snow metrics[J]. Remote Sensing of Environment, 2018, 213: 61-72.

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