The vertical influence of temperature and precipitation on snow cover variability in the Central Tianshan Mountains, Northwest China

Running head: vertical influence of temperature and precipitation to mountain snow

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Key words: seasonal snow, snow cover variability, temperature, precipitation, threshold altitude, high mountains

Abstract

Seasonal snow cover in mountainous regions will affect local climate and hydrology. In this study, we assessed the role of altitude in determining the relative importance of temperature and precipitation in snow cover variability in the Central Tianshan Mountains. The results show that: (1) In the study area, temperature has a greater influence on snow cover than precipitation in most of time and at most altitudes. (2) In the high-elevation area, there is a threshold altitude of 3900±400 m, below which temperature is negatively while precipitation is positively correlated to snow cover, above which the situation is the opposite. Besides, this threshold altitude decreases from

snow accumulated period to snow stable period and then increases from snowmelt period to snow-free period. (3) Below 2000 m, there is another threshold altitude of 1400±100 m during snow stable period, below (above) which precipitation (temperature) is the main driver of snow cover.

1. Introduction

Seasonal snow cover accumulation and melt can influence runoff, soil moisture, and groundwater (Barnett, Adam, & Lettenmaier, 2005). Understanding snowpack's characteristics and changes is helpful to study climate change and to improve weather forecast accuracy (Brown & Robinson, 2011). Meanwhile, timely information of snowpack accumulation and decay is important for water management, ecosystem processes, and agricultural irrigation (Robinson, Dewey, & Heim, 1993).

To understand the snow cover variation and distribution, it is crucial to know the spatial and temporal behaviors of snowpack as well as the controlling factors. Previous studies have shown that air temperature and precipitation can significantly impact snowpack accumulation and decay (Beniston, 2012; Li et al., 2014). Furthermore, snowpack in mountains has also been shown to link to altitude and topography (Hantel, Ehrendorfer, & Haslinger, 2000; Zheng et al., 2017).

Specifically, the relative influences of temperature and precipitation on mountainous snowpack tend to be different at different altitudes. For this topic, a global study was performed by Hammond, Saavedra, & Haslinger (2018). They took global snow zones into consideration and their results suggested that temperature has greater influence on snow in lower elevation areas while precipitation is more important in high elevations, with mid-elevations displaying a mixture of precipitation and temperature importance. A possible reason was illustrated by Saavedra et al. (2018) by analyzing the relative importance of precipitation and temperature to snowpack with different latitude and elevation in Andes, indicating that precipitation may be more important in dry regions, whereas temperature may be more important in warm regions.

In addition, several local studies demonstrated that there is a threshold elevation in mountains, below which temperature is the main controlling factor for snowpack properties, while above which precipitation plays a dominant role. The threshold altitude is, for example, 1400±200 m in a Swiss mountainous area where the station elevation ranges from 316 m to 2690 m (Morán-Tejeda, López-Moreno, & Beniston, 2013), 1560±120 m in the middle of the Rockie Mountains where the station elevation ranges from 1295 m to 2256 m (Sospedra-Alfonso, Melton, & Merryfield, 2015), and 1580-2181 m in six mountains of the western United States where the station elevation ranges from 1020 m to 3501 m (Scalzittl, Strong, & Kochanski, 2016). All the above local studies showed that temperature has a negative correlation to snowpack while precipitation has a positive correlation. Besides, the influences of temperature and precipitation on snowpack approximately vary linearly with elevation (Sospedra-Alfonso, Melton, & Merryfield, 2015). However, it is noticed that the data of all these local studies are from station records no higher than 3500 m that have a good resolution in time rather than in space. Therefore, it is not clear what relative roles temperature and precipitation play in snow accumulation and decay at high elevation resolution from local viewpoint, especially in the regions with elevation higher than 3500 m.

We will take the mountains in Northwestern China as the study site. Due to the lack of meteorological stations in this area, remote sensing data are often used as study data sets. For example, Bi et al. (2015) used remote sensing data to perform a correlation analysis between snow cover area (SCA) and temperature/precipitation in the Upper Heihe River Basin, where the highest elevation is over 5000 m. They found the threshold elevation to be 3650±150 m, below which temperature is the primary controlling factor on SCA, while above which precipitation is the primary controlling factor. Because of the different snow indices and different data sources, we compared the result of this study (Bi et al., 2015) with others that mentioned above (Morán-Tejeda, López-Moreno, & Beniston, 2013; Sospedra-Alfonso, Melton, & Merryfield, 2015; Scalzittl, Strong, & Kochanski, 2016), and noticed that in Upper Heihe River Basin, instead of constantly positive/negative correlation with precipitation/temperature, the temperature does not keep negative correlation to SCA, and precipitation also has negative correlation to SCA at some elevations. But it is not clear where and when temperature/precipitation will have positive or negative correlation to SCA from the result by Bi et al. (2015).

In this study, we will investigate whether a similar elevation threshold exists in the Central Tianshan Mountains, Northwest China, where the elevation can be higher than 5000 m. If there exists such a threshold we will investigate what it is. Since there are few on-site data in the study area, we will use the remote sensing data for analysis. We will further explore the relative roles that temperature and precipitation play in snow cover accumulation and decay at different elevations in the mountains. The difference about the impact of temperature and precipitation to SCA between the present study and previous studies in relatively lower mountains will be identified.

The study area, data sources, and analysis methods are described in Section 2. The results of the correlation analysis between SCA and precipitation/temperature are presented in Section 3. The discussions and conclusions are provided in Section 4 and Section 5, respectively.

2. Data and Methods

2.1 Study area

The study area is located in the mountainous area of the Manas River basin in the Central Tianshan Mountains, Northwest China, ranging from 43°05′N to 44°10′N and 85°00′E to 86°20′E. The area is about 5156 km², as shown in Figure 1. The monthly mean snow cover ratios calculated from MODIS SCA data from 2001 to 2016 (Zheng et al., 2017) are shown in Figure 2. The calculation method will be presented in the followed Subsection 2.3.2. According to Figure 2, we can know that the seasonal snow cover starts to accumulate from September and becomes stable from December to February. Snow starts to melt from March, followed by the snowless period from June to August. The region has a typical temperate continental arid climate and a wide range of altitudes from 608 m to 5126 m, with a significant difference in vertical climatic zones (Hu, 2004). The snowline altitude is approximately 3900 m in this study area (Hu, 2004). The average annual temperature is 2.5 ℃ – 5 ℃. The average annual precipitation is 200 mm, and summer is the season with the most precipitation in a year (Hu, 2004). In the low and middle elevation areas in winter, the temperature tends to increase when the elevation increases (Zheng et al., 2017). There are no hydrological or meteorological monitoring stations in the mountainous area above 1500 m. Hence, we do not have ground station records for snow and meteorological data in high elevation areas and will use remote sensing data for this study.

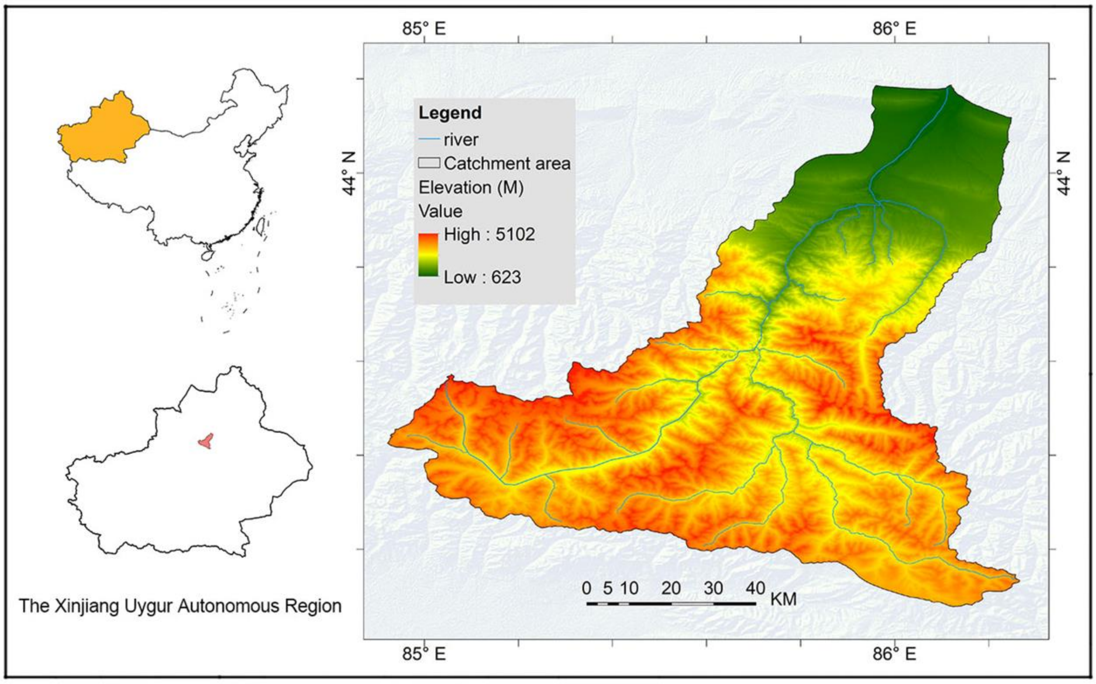

Figure 1. Location of the study area and spatial distribution of elevation.

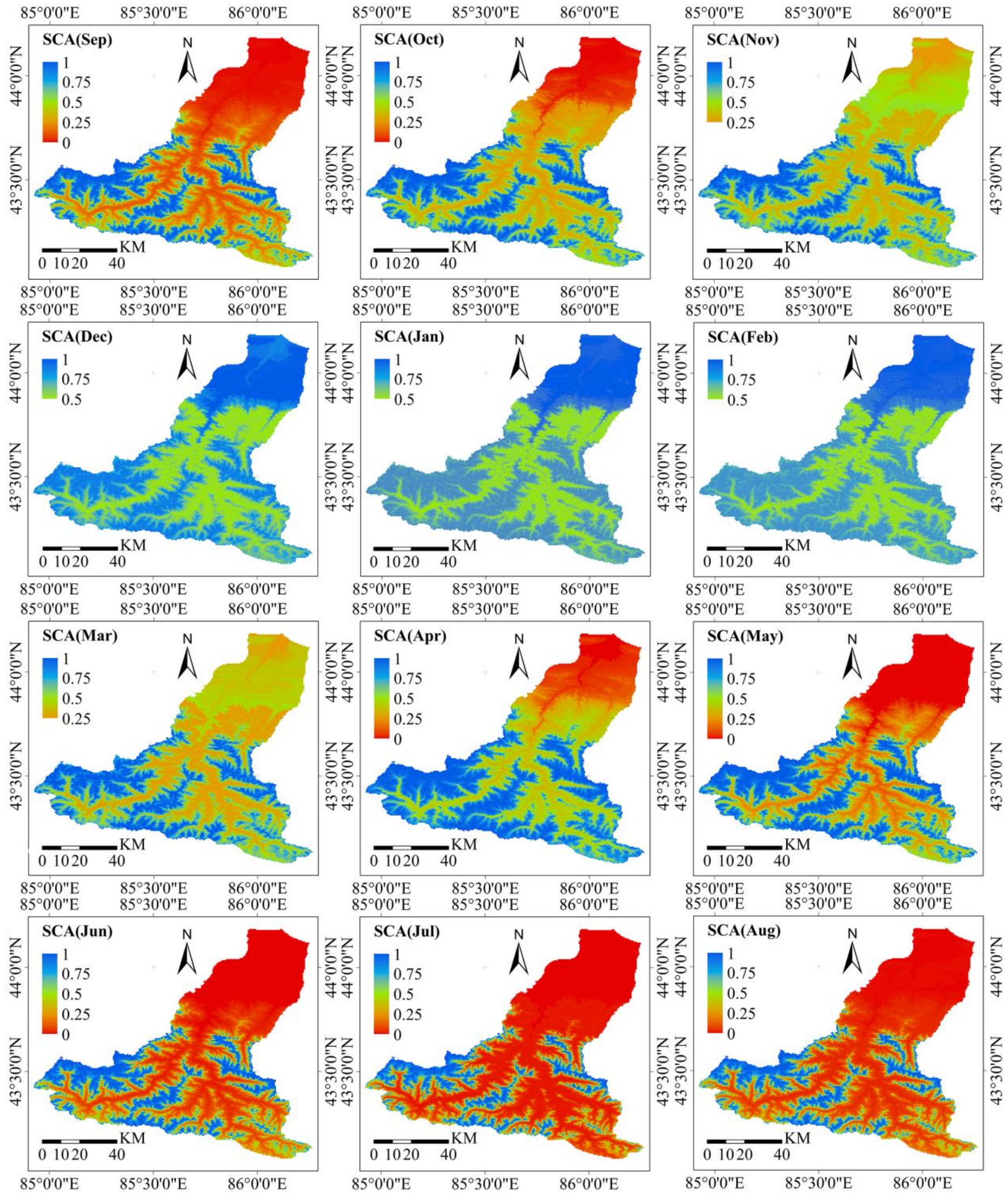

Figure 2. Monthly mean snow cover ratio in the study area.

2.2 Data

2.2.1 SCA data

Both SCA and snow water equivalent (SWE) can be used to characterize snowpack. The spatial resolution of SWE product from passive microwave remote sensing is 25 km (Takala et al., 2011), which would be too coarse for this study site. Hence, we used MODIS SCA data with 500 m resolution to characterize snowpack. Specifically, SCA data are from the MODIS 8-day snow cover product (MOD10A2), which is synthesized from the MODIS daily snow product MOD10A1 by a maximum time synthesis algorithm (Hall, Riggs, & Salomonson,1995). These snow products are available from the National Snow and Ice Data Center (Hall & Riggs, 2007). The accuracy of MODIS snow products has been widely validated in different areas (Zhou, Xie, & Hendrickx, 2005; Liang et al., 2008; Wang, Xie, & Liang, 2008; Raleigh et al., 2013; Marchane et al., 2015). We collected 732 scenes of the MOD10A2 product from January 2001 to December 2016 for this study.

2.2.2 Temperature data

Temperature data are from the MODIS 8-day land surface temperature (LST) product MOD11A2. The spatial resolution is 1 km. The precision of MOD11A2 has been widely assessed in different regions and different time (Bosilovich, 2006; Coll, Wan, & Galve, 2009; Hulley & Hook, 2009), showing that the error can be lower than 1 K in most cases. Zheng et al. (2017) showed that the MOD11A2 is applicable to our study area by comparing with the in situ air temperature data. We collected the MOD11A2 data from January 2001 to December 2016. There are 734 scenes in total.

2.2.3 Precipitation data

Precipitation data used for this study are from Climate Hazards Group Infrared Precipitation with Station data (CHIRPS). The daily CHIRPS products are at the spatial resolution of 0.05° and 0.25°, and the supporting data are available at: http://chg.geog.ucsb.edu/data/chirps/ (Funk et al., 2015). Duan et al. (2016) evaluated eight gridded precipitation products against interpolated rain gauge data at the common 0.25° spatial resolution, showing that CHIRPS comparably ranks as one of the top three best performing products in terms of a suite of statistical metrics. In addition, good performance of CHIRPS was also found in many other regions (Duan et al.,2019). We chose CHIRPS as the precipitation data for this study because of its fine solution (0.05°) and demonstrated good performance. We collected the data from January 1, 2001 to December 31, 2016, one scene per day.

2.2.4 Digital elevation model data

The digital elevation model (DEM) data at the spatial resolution of 90 m from the Shuttle Radar Topography Mission (SRTM) will be used in this study. They are available at http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp.

2.3 Methods

2.3.1 Data processing

Because the data sets are from different sources, we first transformed all the data into the same GCS-WGS-1984 geographical coordinate system. To ensure the same spatial resolution, all the data were resampled to gridded data with cell size of 500 m. The elevation ranges from 623 m to 5102 m in the resampled DEM data. In order to analyze the vertical influence and determine the elevation threshold, the DEM was divided into 41 altitudinal belts at an altitude interval of 100 m. Due to the number of cells for the lowest and the highest altitude belts are very small (< 60 cells), they were merged into their neighboring altitudinal belts. The altitude interval of 100 m was selected based on the total altitude range and the number of cells in each belt, which can reflect the details of the vertical changes and avoid the low number of cells that may cause uncertainties in the successive statistical analysis. The MODIS data and the CHIRPS data were clipped according to the altitudinal belts.

2.3.2 Calculating 8-day average SCA ratio per altitudinal belt

Since the overall areas of different altitudinal belts are different, so is the total snow cover area in the belt. Therefore, we will use the SCA ratio in each belt that is defined as the ratio of SCA to the overall area of the belt. The 8-day average SCA ratio per altitudinal belt SAE^i is calculated as:

$$SAE^i = N_{snow}^i / N^i, \tag{1}$$

where N_{snow}^i and N^i are the number of snow cells and total cells in altitudinal belt i. It is noted that even though the 8-day synthesis algorithm can help reduce the cloud contamination, there are still few cloud pixels in MOD10A2 products (Liang et al., 2008). When calculating SAE^i, the cloud pixels were viewed as snow-free, which may result in a bit underestimation. The monthly mean SCA ratio shown in Figure 2 was calculated as the mean SAE^i value for each month per altitudinal belt.

2.3.3 Calculating 8-day average temperature per altitudinal belt

The MODIS temperature product MOD11A2 includes two data layers: daytime temperature and nighttime temperature, corresponding to the local time of overpasses at 10 o'clock in the morning and 10 o'clock in the evening, respectively. The mean value of daytime and nighttime temperature (D) was firstly calculated. The data values were then transformed to the temperature (T) in degree Celsius as:

$$T = D \times 0.02 - 273.15, \tag{2}$$

Finally, the 8-day area-averaged temperature per altitudinal belt T_m^i was calculated as the average of the cell values in this belt.

2.3.4 Calculating 8-day average precipitation per altitudinal belt

The MODIS SCA and temperature data are one scene per 8-day for a specific site while the CHIRPS data are one scene per day, we transformed the CHIRPS data to one scene per 8-day by summarizing the precipitation of each 8 days. The 8-day average precipitation per altitudinal belt is then calculated as the average of the cells in the belt.

2.3.5 Correlation analysis

Correlation analysis was performed to analyze the relationship between SCA ratio and temperature/precipitation in each altitudinal belt. The Pearson correlation coefficient (R) is calculated as:

$$R = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}, \tag{3}$$

where x represents SCA and y represents temperature or precipitation, n is the number of data elements. We calculated R for each month and each season per altitudinal belt.

Specifically, the set of 8-day average SCA ratio values of each month was regression-analyzed with the set of values of temperature or precipitation in the same month for 16 years. The number of data elements is 48 or 64 corresponding to the case that some months have only 3 scenes, and to the case that the other months have 4 scenes, respectively. Similarly, we also calculated R in each season.

3. Results

The monthly and quarterly correlation analysis results are presented in the order from snow accumulated period (September, October and November), snow stable period (December, January and February), snowmelt period (March, April and May), to snow-free period (June, July and August).

3.1 Impacts on SCA in snow accumulated period

Figure 3 shows the change of the monthly mean SCA ratio, temperature, and precipitation with elevation in the snow accumulated period. The monthly means are further averaged over 16 years and presented in Figure 3(a4), (b4), and (c4). Generally, in this period, snow starts to accumulate from September in the study area as the SCA ratio increases, as shown in Figure 3(a1–a3). With the increase of altitude, the increment of SCA ratio tends to decrease. In November, the SCA ratio over 3900 m is even lower than the previous months (September and October).

The second row from top down shows the variation of temperature with elevation. Figure 3(b1–b3) are the temperature versus elevation for each year and Figure 3(b4) is the yearly mean temperature for September, October, and November versus elevation. Belt-mean temperature in September and October for all years decreases with increasing elevation. However, in November, the temperature increases with increasing elevation until about 2000 m, then decreases with increasing elevation, indicating a temperature inversion has occurred around 2000 m in elevation.

The third row from top down shows the variation of precipitation with elevation. However, precipitation presents a different change pattern with time and altitude. In September, precipitation increases with altitude, where the precipitation in middle and high elevation areas is apparently higher than that in low elevation area, as shown in Figure 3(c1). In October, the maximum precipitation appears in middle elevation area near 2000 m, as shown in Figure 3(c2). Precipitation in November presents an opposite change pattern with that in September, where precipitation gradually decreases with altitude and precipitation in low elevation area is apparently larger than that in middle and high elevation areas, as shown in Figure 3(c3).

The monthly correlation analysis results are presented in Figure 3(d1–d3). The correlation coefficient between SCA and temperature are negatively correlated in low elevation area while positively correlated in high elevation area. However, the correlation coefficient between SCA and precipitation are positive in low elevation area and almost negative in high elevation area except for September. The significance test shows that most of correlation coefficients between SCA and precipitation are not significant except for the low altitude area in October. The two correlation coefficient line intersects approximately in 4300 m (September), 4000 m (October), and 3900 m

(November), which are viewed as the altitude threshold determining the relative impact of temperature and precipitation to SCA.

The quarterly correlation analysis result is presented in Figure 3(d4). Overall in this period, temperature is the main explanatory variability of SCA at each altitudinal belt because of the larger correlation coefficients than precipitation. A special case needed to be noticed is that temperature is positively correlated to SCA in high elevation area over 4000 m. Precipitation only presents significant correlation to SCA in low elevation areas below 2600 m. It has little influence to SCA in higher elevation areas.

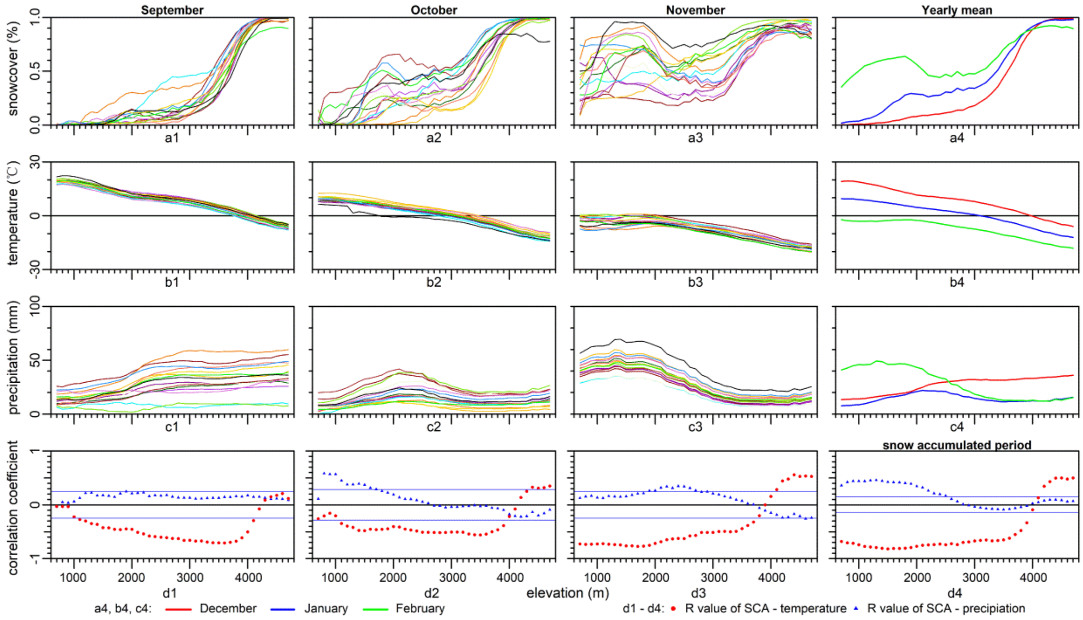

Figure 3. Change of SCA ratio, temperature, precipitation, and the correlation coefficient between SCA and temperature (precipitation) with elevation in snow accumulated period. In a1-a3, b1-b3, and c1-c3, each curve corresponds to the change of monthly means with altitude for a year. In the bottom row, the blue line indicates the correlation coefficient at the significance level of $p<0.05$.

3.2 Impacts on SCA in snow stable period

Figure 4 shows the variation of the belt-mean SCA ratio, temperature, and precipitation with increasing elevation for each month in the snow stable period. Generally, SCA shows a “concave” pattern with altitude, where SCA in middle elevation area is lower than that in low and high elevation areas, as shown in Figure 4(a1–a3). It is noted that SCA in high elevation area is even smaller than that in low elevation area. SCA changes a little with time in this period, as shown in Figure 4(a4). An abnormal case is that SCA in high elevation area declines slightly from December to February. Temperature in this period does not keep decreasing with time and elevation. There is a thermal inversion layer between 800 m and 2000 m, where temperature increases with elevation, as shown in Figure 4(b4). Temperature in January is the lowest while that in February is the highest in this period, indicating that February is close to the end of snow stable period. There is little precipitation in this period at each altitudinal belt, as shown in Figure 4(c1–c4), except that in February, precipitation below 2000 m suddenly increases with two peaks at 900 m and 1400 m, which indicates that the low elevation area is very close to the successive snowmelt period in February.

The correlation coefficients between SCA and temperature (precipitation) at each altitudinal belt for each month in this period are presented in Figure 4(d1–d3). The correlation coefficient between SCA and temperature shows a change pattern of “concave” with elevation, while the correlation between SCA and precipitation shows a “convex” change pattern. In low elevation area, SCA is negatively correlated to precipitation and non-correlated to temperature in most cases. In middle elevation area, SCA is positively related to precipitation while negatively related to temperature. Contrarily in high elevation area, SCA is negatively related to precipitation and positively related to temperature. Therefore, there are two intersection points between the two correlation curves for each month, which means two elevation thresholds in this period. The thresholds are 1300 m, 1500 m, and 1400 m in low elevation area for December, January, and February, respectively, and 4000 m, 3900 m, and 3500 m in high elevation area.

The quarterly correlation analysis result is presented in Figure 4(d4). The curve shape is similar to that for each month. In this period, even though SCA changes a little, it is influenced by both temperature and precipitation. In low and high elevation areas, the impact of precipitation to SCA is more important than temperature, while in middle elevation area, temperature is more important than precipitation.

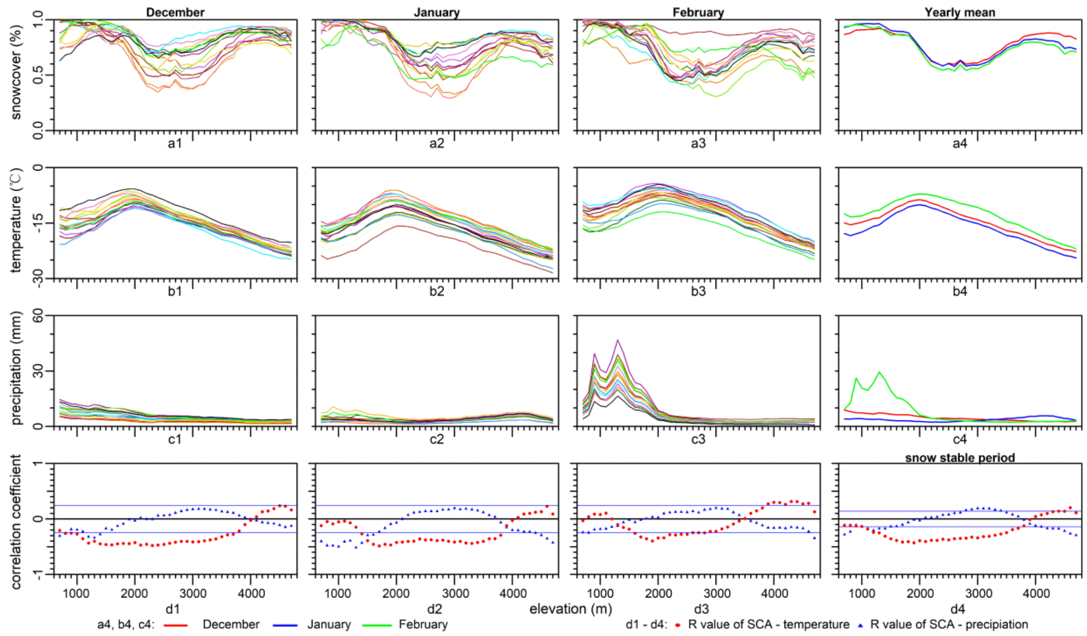

Figure 4. Change of SCA ratio, temperature, precipitation, and the correlation coefficient between SCA and temperature (precipitation) with elevation in snow stable period. In a1-a3, b1-b3, and c1-c3, each curve corresponds to the change of monthly means with altitude for a year. In the bottom row, the blue line indicates the correlation coefficient at the significance level of $p<0.05$.

3.3 Impacts on SCA in snowmelt period

The SCA, temperature, and precipitation of each altitudinal belt for each month in snowmelt period are presented in Figure 4. From March to May, SCA in the low and middle elevation areas are gradually decreased, as shown in Figure 5(a1–a4). The lower the elevation, the higher the SCA declining rate. However, in the high elevation area over 3900 m, SCA changes a little in March and April, and even increases in May. Temperature in this period keeps decreasing with increasing elevation, as shown in Figure 5(b1–b4). Precipitation in this period tends to increase with time, as shown in Figure 5(c1–c4). In March and April, it has two peaks in the middle and high elevation areas, respectively, while in May it keeps increasing with elevation.

The correlation coefficients between SCA and temperature (precipitation) for each month in snowmelt period are presented in Figure 5(d1–d3). SCA is negatively correlated to temperature in low and middle elevation areas while positively correlated to temperature in high elevation areas. Precipitation is negatively, positively, and non-correlated to SCA in low, middle, and high elevation areas, respectively. The two correlation coefficients curves intersect at 3600 m (March), 4000 m (April) and 3900 m (May), respectively.

Through the quarterly correlation analysis result, it is clear to see that temperature is the main impactor of SCA in snowmelt period compared to precipitation, as shown in Figure 5(d4).

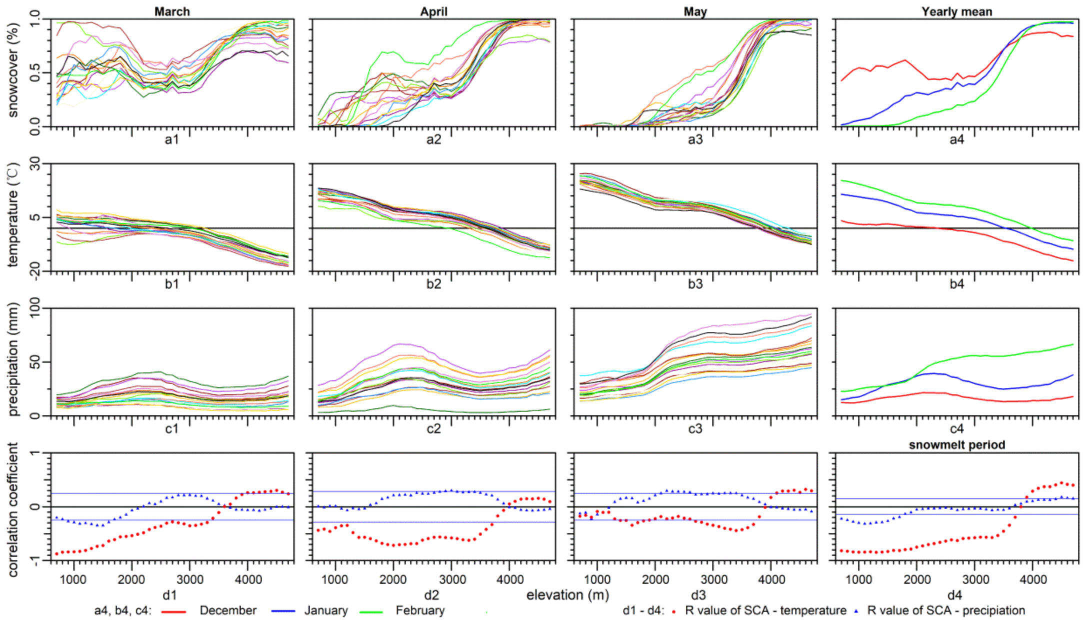

Figure 5. Change of SCA ratio, temperature, precipitation, and the correlation coefficient between SCA and temperature (precipitation) with elevation in snowmelt period. In a1-a3, b1-b3, and c1-c3, each curve corresponds to the change of monthly means with altitude for a year. In the bottom row, the blue line indicates the correlation coefficient at the significance level of $p<0.05$.

3.4 Impacts on SCA in snowless period

The SCA, temperature, and precipitation of each altitudinal belt for each month in snowless period are presented in Figure 6. In this period, SCA changes a little with time. There is almost no snow cover in low and middle areas. SCA is sharply increased from 3000 m and reaches more than 95% above 4200 m, as shown in Figure 6(a1–a4). Temperature and precipitation also have little changes with time in this period, as shown in Figure 6(b1–c4). Temperature keeps decreasing with elevation while precipitation tends to increase with elevation.

The correlation coefficients between SCA and temperature (precipitation) in each altitudinal belts are presented in Figure 6(d1–d3). We only care about the area above 3000 m because it has snow cover. In this period, we can only find the significant negative correlation between SCA and temperature between 3000 m and 4000 m in June and August. The quarterly correlation analysis result also presents a similar indication, as shown in Figure 6(d4). We can find the intersection points of the two correlation curves at 4200 m and 4000 m in June and July, respectively, but no intersection points in August.

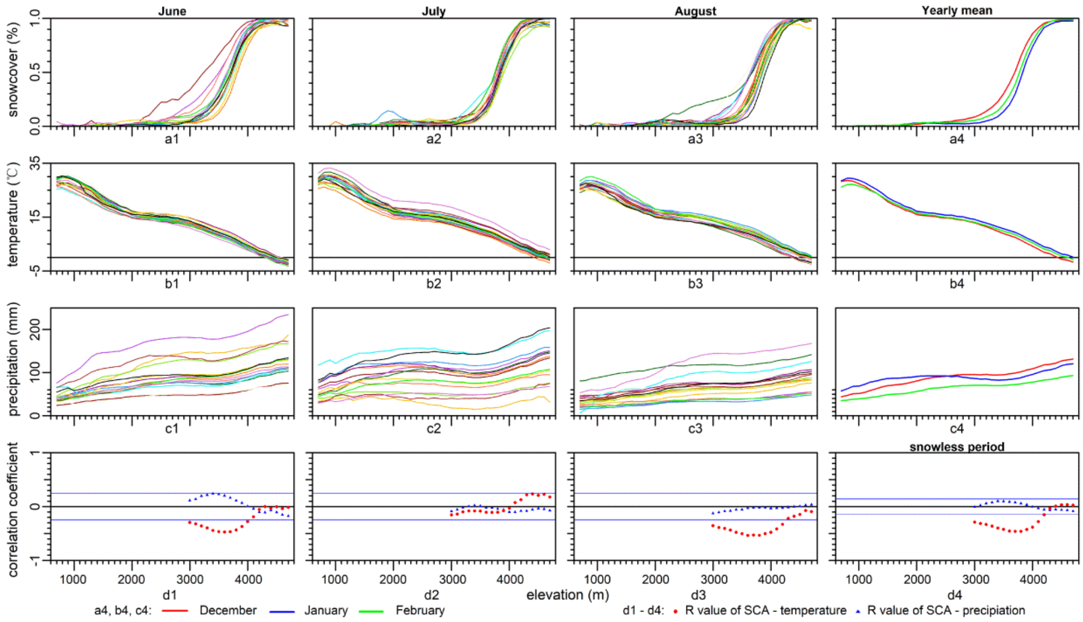

Figure 6. Change of SCA ratio, temperature, precipitation, and the correlation coefficient between SCA and temperature (precipitation) with elevation in snowless period. In a1-a3, b1-b3, and c1-c3, each curve corresponds to the change of monthly means with altitude for a year. In the bottom row, the blue line indicates the correlation coefficient at the significance level of $p<0.05$.

4. Discussion

4.1 Elevation threshold

According to the correlation analysis between SCA and temperature/precipitation, the intersection point of two correlation coefficient curves is viewed as the elevation threshold determining the relative impact of temperature and precipitation on snow. We find such an elevation threshold in this study area at 3900±400 m, below which temperature is negatively correlated to SCA but precipitation is positively correlated, and above which the situation is reversed. This elevation threshold changes with time. It declines from snow accumulated period to snow stable period, and increases from snowmelt period to snow-free period, as shown in Figure 7. The threshold peaks appear at the starting of the snow accumulated period and the snowless period, which are 4300 m and 4200 m, respectively. The lowest threshold is at the end of snow stable period, which is only 3500 m.

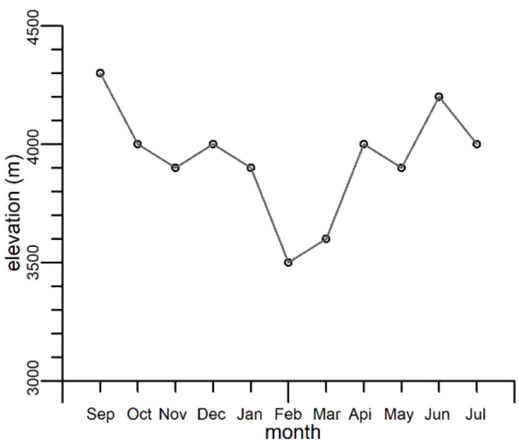

Figure 7. Elevation threshold for determining the relative impact of temperature and precipitation to snow in each month.

Specially, there is another elevation threshold in low altitude area 1400±100 m during snow stable period, which may be caused by the thermal inversion layer. Below this threshold, both temperature and precipitation are negatively corresponded to SCA, but temperature is not the main impact factor for SCA anymore and precipitation has a greater influence on SCA.

Previous studies showed that precipitation drives snowpack above the threshold altitude, while temperature drives snowpack below the threshold altitude (Morán-Tejeda, López-Moreno, & Beniston, 2013; Sospedra-Alfonso, Melton, & Merryfield, 2015; Scalzittl, Strong, & Kochanski, 2016; Bi et al., 2015; Hammond, Saavedra, & Kampf, 2018). However, temperature is generally more important to SCA than precipitation in this study area because the correlation coefficients between temperature and SCA are higher than those between precipitation and SCA at most time and elevations, except for snow stable period where precipitation drives SCA in low altitude area, which may be also caused by temperature because of the thermal inversion layer. Moreover, the correlation analysis results show that precipitation plays an important role in relatively low elevation areas in this study, rather than in relatively high elevation areas as previous studies, e.g., in low elevation area during snow accumulated period (Figure 3(d4)) and in middle elevation areas during snowmelt period (Figure 5(d2-d3)). Since temperature drives SCA at most time and elevations, the threshold altitude in this study serves as a separator of negative and positive correlation for SCA and temperature (precipitation), rather than a separator of main drivers to snowpack as previous studies.

Accordingly, the threshold altitude in our study refers to the abnormal influence of temperature and precipitation to SCA in high elevation area, which is mainly caused by the abnormal SCA change in this area. The abnormal SCA change may be ascribed to snowdrift and sublimation of snow in high elevation area and will be discussed as below.

4.2 Abnormal SCA change in high elevation area

It is abnormal to find that SCA in high elevation area tends to decrease from snow accumulated period to snow stable period while increase during snowmelt period, which is an inverse change of SCA during the snow change procedure. This result is consistent with the study in Tibetan plateau (Tang et al., 2013). Accordingly we find that precipitation has little influence on SCA in high elevation area except for snow stable period, in which precipitation is abnormally negatively correlated to SCA. Temperature is positively correlated to SCA in such area, which is also abnormal. The abnormal SCA change and its correlation to temperature and precipitation in high elevation area could be caused by snowdrift and sublimation of snow. Snowdrift plays a great role at snow redistribution in high altitude area of Central Tianshan Mountains (Wang, Bai, & Chen, 1982; Kane et al., 1991; Li & Hao, 2012). Temperature declines with time during snow accumulated period and snow stable period, which makes snow very dry and easily to be drifted by wind, resulting in decrease of SCA in these periods. However, temperature is gradually increased with time in snowmelt period, which makes snow wetter and difficult to be drifted by wind, resulting in increase of SCA in this period. Because of snowdrift, the lower temperature leads to a greater probability of snowdrift and thus a smaller SCA in high elevation area, which could be the reason why temperature is positively correlated to SCA in such area. In addition, sublimation of snow in dry weather can greatly affect SCA (Qin, Liu, & Li, 2006). During snow accumulated and stable periods, the lower temperature relates to more dry air, resulting in more sublimation of snow and thus a smaller SCA in the high elevation area. As for the abnormal negative correlation between precipitation and SCA in high elevation area in snow stable period, we first note that snowfall in this period is very small. It may be explained by the links between snowfall and temperature. More snowfall may relate to lower temperature, which could lead to more snowdrift and thus lower SCA even though more snow falls onto ground.

4.3 Different snowpack indexes

Moreover, Morán-Tejeda, López-Moreno, and Beniston, (2013), Sospedra-Alfonso, Melton, and Merryfield, (2015) and Scalzittl, Strong, and Kochanski, (2016) showed that the correlation coefficients between precipitation and SWE are always positive, and the correlation coefficients between temperature and SWE are always negative. But our study showed that both temperature and precipitation have negative and positive correlation to SCA. The difference could be caused by following two factors. One is that the elevation of our study area is higher than that of previous studies. For example, in terms of temperature, the correlation coefficients to SCA are negative at most elevations but are positive at high elevation (above 3500 m) in this study. The stations in the studies of Morán-Tejeda, López-Moreno, and Beniston, (2013), Sospedra-Alfonso, Melton, and Merryfield, (2015) and Scalzittl, Strong, and Kochanski, (2016) are all below 3500 m, so that their results could not show the correlation between SWE and temperature in high-elevation area. The other is that SCA is used for correlation analysis in our study while SWE is used in previous studies (Morán-Tejeda, López-Moreno, & Beniston, 2013; Sospedra-Alfonso, Melton, & Merryfield, 2015; Scalzittl, Strong, & Kochanski, 2016). SWE indicates the amount of water contained within the snowpack, so that precipitation will increase the value of SWE and precipitation is thus always positive to SWE. SCA indicates the area of snow cover in a designated area. If the SCA ratio reaches 100%, no more precipitation can improve this value. The difference caused by SCA and SWE deserves further investigation in the future.

4.4 Uncertainties

Because of the lack of station records in the study area, especially those in high elevation area, we adopted remote sensing products to characterize SCA, precipitation, and temperature in the study area. One of the benefits provided by remote sensing data is allowing us to perform analysis of vertical influence on snow cover per altitudinal belt. However, it is unavoidable to bring uncertainties by remote sensing products.

Even though the adopted MODIS 8-day snow cover product (MOD10A2) can reduce the influence of cloud to a certain degree, the cloud still exists, which could result in relatively lower SCA than the true case. In addition, the recognition of forest snow remains a big uncertainty for MOD10A2 (Hall & Riggs, 2007), which brings uncertainty to SCA in the middle elevation area with forest distribution.

The land surface temperature (MOD11A2), rather than air temperature, was used in this study. In addition to worldwide validation, MOD11A2 has already been validated in the low and middle elevation of the study area by comparing with *in situ* air temperature, showing a very good correlation with $R^2 = 0.98$ (Zheng et al., 2017). However, the uncertainty of temperature in high elevation areas is still not clear. Furthermore, unlike air temperature, land surface temperature will be affected by all land surface features, including snow, bare ground, as well as topography. Possibly at high elevations, the snow actually retains a higher temperature than bare areas because of the less sensitivity to day-night temperature variability and higher heat capacity of snow. Accordingly, it may contribute to the abnormal positive correlation between SCA and land surface temperature. To clarify this uncertainty, we made a correlation analysis between SCA and air temperature by using the TerraClimate monthly temperature data (Abatzoglou et al., 2018) from 2001 to 2016; results are shown in Figure 8. The SCA correlation patterns with air temperature and land surface temperature are similar in most months, but quite different in September and December. The difference mainly comes from the middle elevation area from 2000 m to 3000 m, where the correlation coefficients between SCA and air temperature display abnormal positive values. We also found a similar abnormal positive correlation between SCA and air temperature in high elevation area, which partly demonstrated the suitability of using land surface temperature but cannot clarify the uncertainty caused by land surface temperature. If higher-quality air temperature data could be utilized in the future, it will help reduce the uncertainty caused by land surface temperature and better explain the abnormal correlation between SCA and land surface temperature.

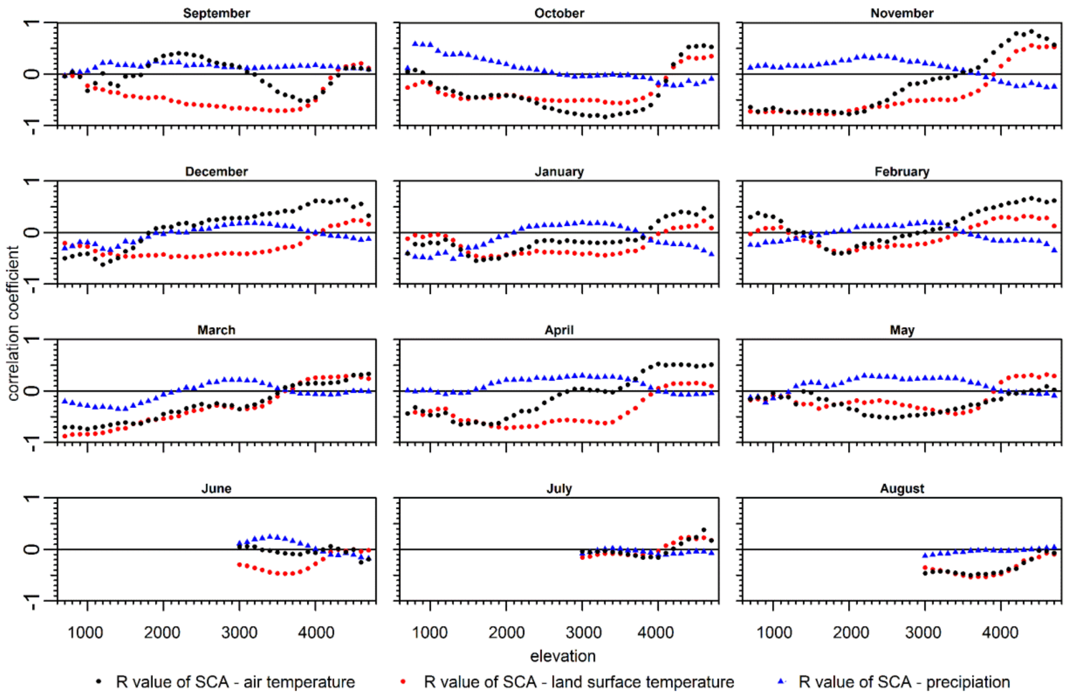

Figure 8. The correlation between SCA and TerraClimate temperature, land surface temperature, and precipitation in each belt of the study area.

CHIRPS precipitation product has been evaluated in other area（Duanet al., 2016; Duan et al., 2019), but the validation was not as wide as that for MODIS snow cover products and temperature products. Since we are not able to verify it in the study area because of the lack of station records, it may bring the most uncertainty for this study. Furthermore, the spatial resolution 0.05° is still too coarse to match with the MODIS data. In the future, new or improved precipitation products with higher spatial resolution and higher accuracy using spatial downscaling and calibration procedures (e.g. Duan and Bastiaanssen, 2013) could help reduce the uncertainty for analyzing influence to snow cover by precipitation.

5. Conclusions

In this study, we used remote sensing data of SCA, temperature, and precipitation to analyze their monthly changes with time and elevation in the Central Tianshan Mountains. The relative impact of temperature and precipitation to SCA was analyzed by Pearson correlation coefficient at different elevations. We found that temperature is more important than precipitation to SCA in this study area at most time and elevations. There is a threshold altitude near 3900 m that separates the negative and positive correlation between temperature (precipitation) and SCA. Below the threshold altitude, temperature is negatively correlated to SCA and precipitation is positively correlated SCA, while above the threshold altitude the correlation becomes opposite. The threshold elevation is dynamic and changes with time. We give a possible explanation to the abnormal SCA change and the correlation to temperature and precipitation by snowdrift and sublimation, as well as the uncertainty caused by using land surface temperature, which needs to be further validated in the future.

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