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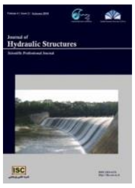

Application of MODIS land surface temperature in snow climatology studies, Case Study: Central Alborz Basins.

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Abstract

The snow budget in mountainous river basins reacts sensitively to temperature fluctuations. Therefore, the desired temperature increase due to climate change could significantly affect the snow budget in the future. These effects could lead to significant changes in the hydrological regime of river basins such as the Central Alborz basins. The aim of this study is to investigate the application of MODIS land surface temperature (LST) data in studying snow climatology. The analysis included several important snow parameters derived from the snow depletion curves (SDCs). These curves were extracted from cloud-reduced MODIS products of daily snowpack for each river basin studied. Correlations between these snow parameters and the MODIS LST data were then investigated. The results show that several snow parameters variations are significantly correlated with MODIS LST data over past 20 years (2002-2022). Specifically, Maximum Snow Cover (MSC), Maximum Snow Cover Day (MSCD), Snow Melt Ending Day, and Accumulation-Ablation Period (AAP) exhibited substantial correlations with LST, as indicated by the Tau correlation coefficients of -0.74, -0.31, -0.51, and -0.35, respectively, at a confidence level of 90%.The SMED was found to be the most sensitive snow parameter to MODIS LST variations. Strong correlations were observed between SMED and LST across all studied subbasins, with an overall Pearson correlation coefficient of -0.79 and a Tau correlation coefficient of -0.51 for the whole study area. The results of this study show that MODIS LST data successfully explain the dependencies between snow budget and temperature in the Central Alborz basins.

Keywords: Snow cover, MODIS, Land surface temperature, Central Alborz basins.

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1. Introduction

Snow is a critical component of the water cycle in mountainous regions and plays a significant role in various aspects of human and natural systems. Understanding the snow accumulation and melt processes is essential for water resource management, ecosystem conservation and hazard

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mitigation. Remote sensing provides a valuable tool for monitoring snow dynamics and its spatiotemporal variations over large and remote areas. Among various remote sensing instruments, the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard Terra and Aqua satellites has been widely used to estimate land surface temperature (LST) and snow cover extent (SCE) due to its high temporal and spatial resolution [1–5][1–4].

In recent years, the use of satellite-derived LST data has gained significant attention as a proxy for surface air temperature in snow climatology studies. Shamir and Georgakakos [6] investigated the use of MODIS LST product as a proxy for surface air temperature in operational snow models. They utilized the MODIS LST product to derive spatially distributed surface air temperature forcing for the operational snow model. Their findings indicated the potential of using MODIS LST as an index of surface air temperature for snowpack estimation. Pérez-Díaz et al. [7] evaluated the accuracy of MODIS LST compared to in-situ snow surface temperature. Their study revealed slight underestimation of both daytime and nighttime values of MODIS LST compared to in-situ measurements. They also explored the impact of MODIS window size on the estimation of in-situ LST and found that increasing the window size led to an overestimation of LST. In a study comparing MODIS LST data with observed snow skin temperature data, Diaz et al. [8] investigated the correlation between MODIS LST and observed snow skin temperature from the CREST-SAFE station. Their analysis revealed a significant correlation between MODIS LST data and observed snow skin temperature, indicating the potential of using MODIS LST for snow climatology studies. Rawat et al. [9] analyzed MODIS data to assess the coherency between LST and snow coverage in Mana basin of Uttarakhand, India. Their findings indicated a rising trend in maximum and mean surface temperature in all four zones of the basin, along with a slight decline in the percentage of snow cover from 2001 to 2018. Kemper [10] utilized MODIS LST data to detect peak snow water equivalents (SWE) and analyze snow cover in the area of Deadhorse/Prudhoe Bay, Alaska. Their approach integrated MODIS LST, NDSI (Normalized Difference Snow Index) snow cover, and albedo data for downscaling ERA (European Reanalysis) data using an SEB (Surface Energy Balance) scheme. Zhou et al. [11] proposed a method for retrieving snow surface temperature based on MODIS data by modifying the practical split-window algorithm. Their study introduced the concept of NDSI-Ts space for analyzing snow surface temperature and demonstrated the feasibility of retrieving snow surface temperature using MODIS data. André et al. [12] combined passive microwave and thermal infrared data to estimate LST during summer snow-free periods over northern high latitudes. Their approach, based on SSM/I-SSMIS 37 GHz measurements, showed promising results with a mean bias of less than 0.4 K and an RMSE of about 2 K. Wan et al. [13] summarized the accomplishments made by the MODIS LST group at the University of California, Santa Barbara, in developing LST algorithms. Their validation studies demonstrated that MODIS LST accuracy was better than 1°C, and they were preparing for the Beta-3 version of the MODIS LST code. Jia et al. [14] introduced a new global daily blue-sky land surface albedo climatology dataset using 20-year MODIS products. Although this study did not specifically focus on MODIS LST for snow, it highlights the availability of long-term MODIS products for studying land surface characteristics. Dong et al. [15] investigated the link between temperature and MODIS snow cover retrieval inaccuracies in the western United States. They demonstrated a relationship between errors in MODIS snow cover products and temperature, which was well-represented by a cumulative double exponential distribution function. Choudhury et al. [16] analyzed the spatial and temporal fluctuations in snow cover area in the northwest Himalaya region using MODIS Terra daily LST product. Their study examined the response of snow cover to temperature, precipitation and elevational variations over a 20-year period from 2000 to 2019. Zhong et al. [17] used split-window method to retrieve LST in Tibetan Plateau using AVHRR and MODIS data. Although their study did not specifically focus on LST estimation over snow, it demonstrated the application of split-window method for LST retrieval in a challenging terrain. Rani and Mal [18] utilized MODIS data from 2001 to 2019 and found mixed LST trends with intra-regional variations. In this study, the overall warming in the region is attributed to increases in atmospheric water vapor and normalized difference vegetation index, as well as decreases in cloud fraction and snow cover area. Xie et al. [19] utilized MODIS LST data to investigate Antarctic amplification. During their study period from 2001 to 2018, surface temperature variations is estimated and compared with ERA5 data. The results showed that MODIS LST data could successfully capture Antarctic amplification and its seasonal and sub-regional differences.

In summary, these studies demonstrate the potential of using MODIS LST as a proxy for surface air temperature in snowpack estimation. The accuracy of MODIS LST compared to in-situ measurements varies, with slight underestimation observed in some cases. However, there is a significant correlation between MODIS LST and observed snow skin temperature, indicating its potential of LST data for snow climatology studies. Various studies have utilized MODIS LST data to analyze snow cover, snow water equivalents, and spatiotemporal variations in snow cover area. The use of split-window algorithms and integration with other data sources has been explored to improve LST retrieval over snow. Overall, MODIS LST data offers valuable insights for understanding snow dynamics and characteristics in different regions. In this context, this paper aims to explore the application of MODIS LST data to investigate snow climatologic trends in the Central Alborz basins.

2. Study Area and Data

2.1. Study area

The Central Alborz is situated in northern part of Iran, specifically between latitudes 35.2° and 36.8° North and longitudes 50.3° and 53.3° East. It encompasses a total area of 26,845 square kilometers and exhibits an altitude range from sea level to 5,604 meters above sea level (a.s.l.). The Central Alborz is divided into north and south slopes. The climate of the north slope can be described as hot and moist, primarily affected by moisture-laden airflows originating from the Khaza Sea. This slope experiences orographic precipitation and a high persistence of clouds due to its geographical location. The presence of the Alborz mountain range obstructs the flow of clouds, resulting in dry zone on the lee slope. In contrast, the precipitation in the south slope is originated from the Mediterranean air fronts. For instance, the long-term average annual precipitation in Tehran province, located within this area, is approximately 294 millimeters per year. Conversely, the mean annual precipitation in Gilan and Mazandran, situated in the northern side, is approximately 703 and 896 millimeters, respectively [20]. The Central Alborz comprises different river basins that are presented in Table 1 and depicted in Figure 1.

Table 1. The studied basins characteristics

River basin names	Basin Area (Km^2)	Altitude Range (m)	Mean Altitude (m)	Mean Hypsometric Altitude (m)
Whole study area	26845	0 - 5604	2056	2102
Haraz	4064	199 - 5604	2654	2758
FiroozKuh	2535	1458 - 4048	2465	2415
Chaloos	1659	108 - 4275	2040	2039
Mamloo	1771	1241 - 4300	2229	2133
Karaj	844	1710 - 4343	2835	2802
Taleghan	947	1730 - 4394	2673	2645
Sehezar	941	74 - 4761	2178	2312
Lar	733	2532 - 5597	3120	3085
Latian	701	1609 - 4300	2567	2533

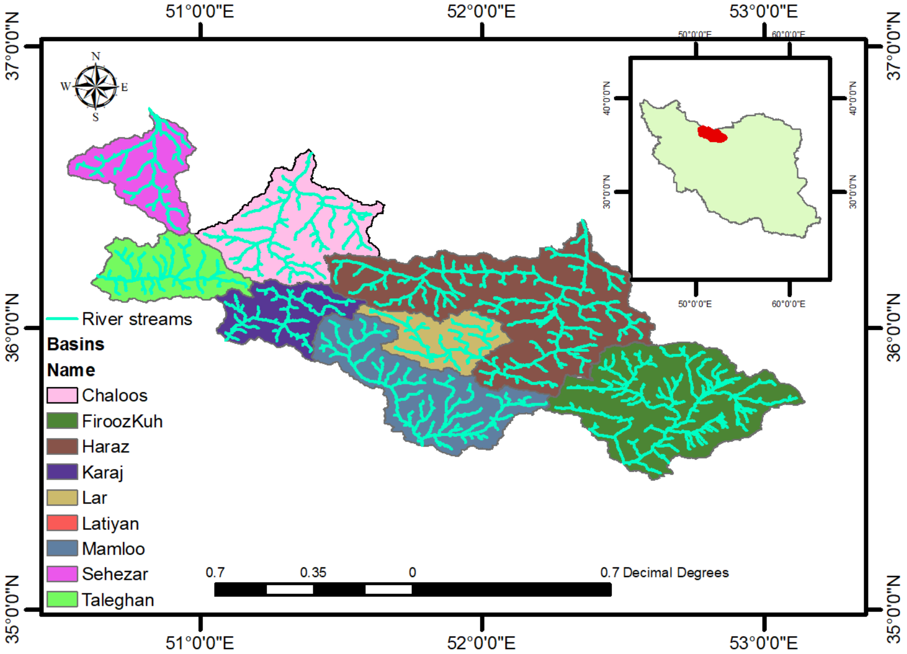


Figure 1. Study area

2.2. MODIS Snow Cover Products

This study focuses on the evaluation of the period from 2002 to 2022, as it aligns with the availability of MODIS SCP and LST data. MOD10A1 and MYD10A1 V06 refer to gridded datasets obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments aboard the Terra and Aqua satellites, respectively. These datasets offer data on snow cover extent at a spatial resolution of 500 meters [21]. They can be accessed through the National Snow and Ice Data Center (NSIDC) and NASA's Earth Observing System Data and Information System (EOSDIS). The latest version of these products, V006, has been enhanced to reduce cloud contamination and improve the accuracy of LST and SCE estimates. MOD10A1 and MYD10A1 V006 are widely used in snow monitoring and climatological studies due to their high temporal and spatial resolution and their ability to capture snow dynamics and climate factors [22].

2.3. MODIS LST

MOD11C3 is a remote sensing product that provides global monthly LST and emissivity data from the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra satellite [23]. This data set is widely used in various fields, including snow climatology. In this paper, we use MOD11C3 data to investigate the snow cover patterns in the central Alborz Basin. The high-quality LST data with a spatial resolution of 1 km provided by MOD11C3 allows us to monitor the thermal behavior of the snowpack, which is crucial for understanding snowpack dynamics and its interactions with the atmosphere. A total of 156 images in study period are downloaded via “Reverb” website. LSTs are preprocessed to obtain basin wide temperatures at Celsius unit. The LSTs digital numbers (DNs) in 16 bit are converted into Celsius and then gridded and averaged on every basin. An example of used MOD11C3 products is shown in Figure 2.

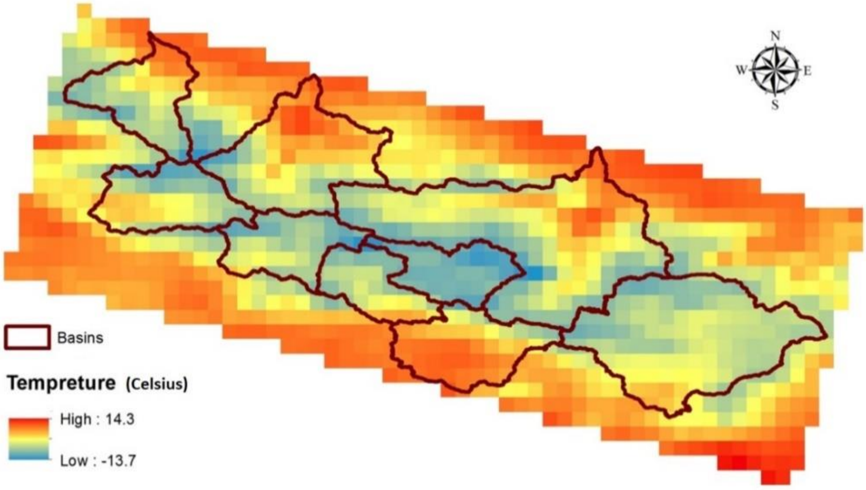


Figure 2. MOD11C3 product for January 2008

3. Methodology

3.1. Cloud removal algorithm

In this study, the sequential cloud removal algorithm proposed by Dariane et al. [24] is used. In this algorithm a dynamic sequence of different cloud removal methods including Terra and Aqua SCPs combination, time window filling, snow and land lines and using surrounding pixels’ methods is used to reduce the cloud contamination as much as possible. The performance and accuracy of this algorithm in reducing cloud cover over study area is given in Table 2 and **Figure *3***. These results illustrate a significant reduction in cloud coverage, with values consistently below 10% throughout the year. However, it is worth noting that certain months, such as February, March, and April, exhibit higher levels of cloud contamination, exceeding 50%. Despite this, the validation results indicate that the reduction in cloud coverage has a minimal impact on the accuracy of snow cover classification, with an overall accuracy variation of less than 5% annually. Monthly analyses of validation accuracies reveal that December exhibits the lowest accuracy at 88%, while July to September demonstrate the highest accuracy levels.

Table 2. Cloud removal algorithm accuracy and performance in study area

		Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Annual
Accuracy (%)		98	93	88	89	92	93	94	95	99	100	100	100	95
Cloud coverage (%)	Raw SCPs	26.8	44.2	45.7	41.6	59.2	60.5	51.2	41.5	21.7	19.3	17.1	14.9	37.0
	Cloud reduced SCPs	1.2	3.4	2.4	1.2	6.1	6.9	4.8	0.9	0.4	0.4	0.4	0.2	2.4

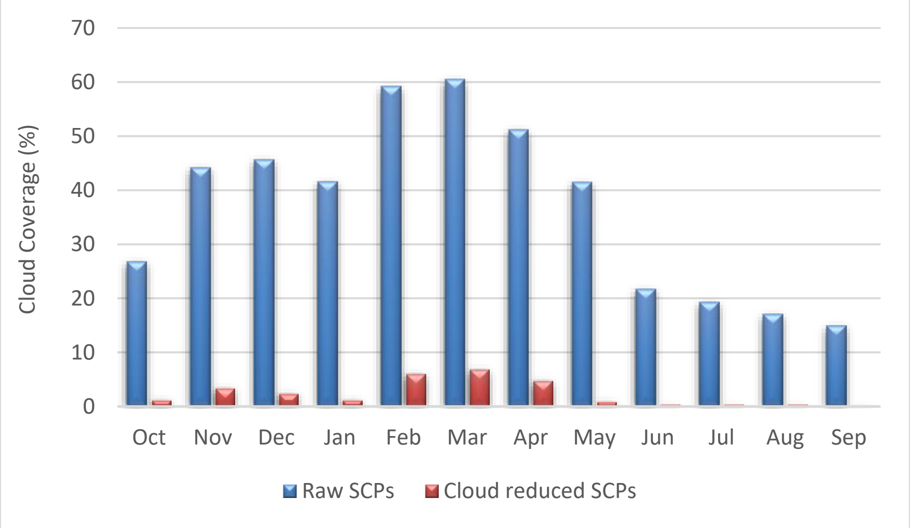


Figure 3. Cloud coverage before and after cloud removal

3.2. Snow Climatologic Indexes

To explore the snow cover climatology using MODIS Snow Cover Products (SCPs), it is necessary to establish specific indices. In this investigation, we employed the snow cover indices proposed by Dariane et al. [24], which will now be briefly introduced.

To define these indices, snow depletion curves (SDCs) were derived for each of the studied basins. SDCs were constructed by drawing the time series of snow covered area fraction in each river basin. Accordingly, for each basin, a total of 20 SDCs were generated, corresponding to each year. To mitigate the effects of short-term snow cover fluctuations, a five-day moving average was applied to the SDCs. **Figure *4*** provides an illustrative example of an SDC, accompanied by the following explanation.

- Snowmelt Ending Day (SMED): This marks the termination of snow storage within the basin. SMED is influenced by the amount of snow accumulated in cold season and the air temperature in the snowmelt season. It is defined as the number the day when the SCE falls below 5%.
- Snow Accumulation Onset Day (SAOD): This is the day when snow accumulation begins. The occurrence of SAOD can be delayed due to factors such as reduced precipitation or elevated air temperatures during the preceding days. SAOD is defined as the day when the SCE ascends to 5% and stays above this threshold for at least 10 days ahead.
- Accumulation-Ablation Period (AAP): This period spans from snow accumulation onset day to snowmelt ending day and characterizes the duration of snow accumulation and subsequent melting.

- Maximum Snow Cover Day (MSCD): This refers to the specific day when the snow cover reaches to its maximum value.

- Maximum snow cover (MSC): This index represents the peak of observed snow coverage fraction.

- Snow Melting Period (SMP): It encompasses the time from the occurrence of maximum snow coverage fraction to the day that it drops below 5%. This duration provides insights into the complete depletion of stored snow within the basin.

- Snow Accumulating Period (SAP): This denotes the duration from onset of snow accumulation to the point of highest snow coverage fraction.

- Snow Accumulating Slope (SAS): This index quantifies the slope of snow accumulating in the river basin. It is calculated as the ratio of MSC to SAP, representing the slope of the rising limb in the SDC.

- Snow Melting Slope (SMS): Same as SAS, this index characterizes the rate of snow melting, corresponding to the slope of the falling limb in the SDC. It is calculated as the ratio of MSC to SMP.

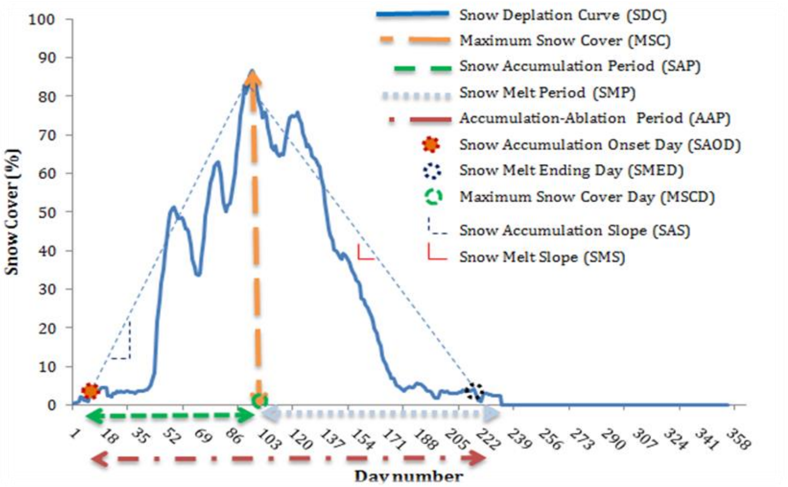


Figure 4. Utilized snow climatological indices

3.3. Analysis of Snow Cover Indexes and LST dependencies

Pearson’s r and Kendall’s tau are used to measure the non-monotonic and monotonic correlation with the LST and snow cover indices, respectively. Pearson's correlation coefficient (r) and Kendall's tau (τ) are statistical measures used to quantify the strength and direction of the relationship between two variables. Pearson's r measures the linear correlation between two variables, with values ranging from -1 to +1, where -1 indicates a perfect negative correlation, 0 indicates no correlation and +1 indicates a perfect positive correlation [25]. Kendall's tau, on the other hand, measures the rank correlation between two variables, i.e. the extent to which the ranking of the values in one variable matches the ranking of the values in the other variable [26]. The values of Kendall's tau are between -1 and +1 and are interpreted similarly to Pearson's r. Both measures are widely used in various fields, including climate science, ecology and economics, to analyze the relationship between different variables. The equations for Pearson's r and Kendall's Tau are as follows:

Pearson's r:

$$r = \frac{(n\Sigma xy - \Sigma x\Sigma y)}{\sqrt{(n\Sigma x^2 - (\Sigma x)^2)(n\Sigma y^2 - (\Sigma y)^2)}}$$

Where n is sample size and x_i and y_i are the individual sample points.
Kendall's Tau:

$$\tau = \frac{(n_c - n_d)}{\sqrt{(n_0 - n_1)(n_0 - n_2)}}$$

where n_c is the number of concordant pairs, n_d is the number of discordant pairs, n_0 is the total number of pairs, and n_1 and n_2 are the number of tied values in the first and second variables, respectively.

Furthermore, in order to assess the significance levels, p-values are calculated using the t-student test. The t-Student test for linear trend analysis is a common statistical method used in scientific research to assess the presence of a linear trend in a data set over time [27]. With this test, researchers can check whether there is a significant linear relationship between the independent variable (time) and the dependent variable.

In the t-Student test for linear trend analysis, the formula for calculating the t-value is as follows:

$$t = (b - 0) / SE(b)$$

In this formula, "b" stands for the estimated slope coefficient of the linear trend and SE(b) refers to the standard error of the slope coefficient. The t-value is then compared with the critical values of the t-distribution to determine the statistical significance of the linear trend.

4. Results and Discussions

To measure the strength of the relationship between snow cover and temperature variations, Pearson’s r and Kendall’s tau are calculated for the pairs of derived indices and monthly LSTs in the corresponding time periods. Corresponding periods refer to the months that are important for the formation of the indices. For example, the maximum snow cover corresponds to the temperature between fall and mid- winter. We considered the monthly averaged LST from November to February as corresponding to MSC, SAP, SAS, MSCD and SAOD. Similarly, the average temperature from March to June is assumed to correlate with SMP, SMS and SMED. In addition, the monthly average temperature from December to June is assumed for the accumulation-ablation period (AAP). Table 3 and

Table *4* show the calculated Pearson’s R and Kendall’s tau correlation coefficients in the different basins, respectively.

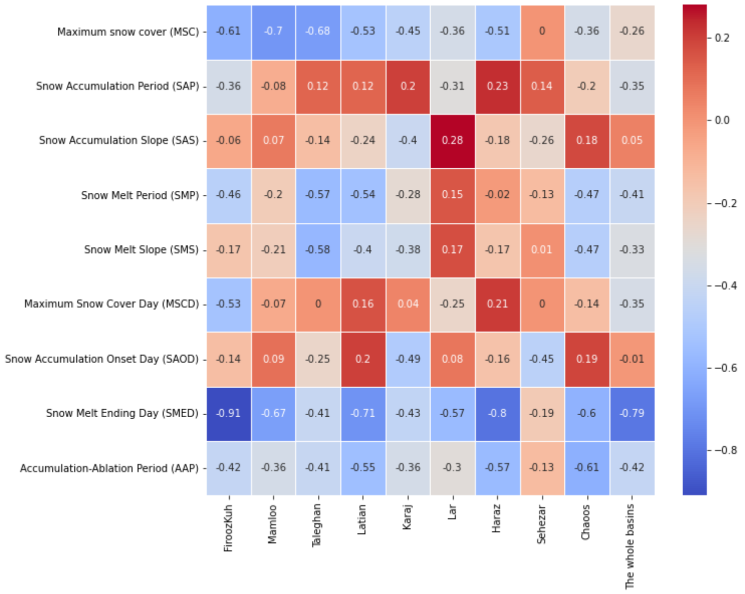
Table 3. Pearson's R correlations between derived indexes and land surface temperature (*: Significant at 90% level)

Basins	FiroozKuh	Mamloo	Taleghan	Latian	Karaj	Lar	Haraz	Sehezar	Chaloos	The whole basins
Maximum snow cover (MSC)	-0.61*	-0.70*	-0.68*	-0.53*	-0.45*	-0.36*	-0.51*	0	-0.36*	-0.26
Snow Accumulation Period (SAP)	-0.36	-0.08	0.12	0.12	0.2	-0.31	0.23	0.14	-0.2	-0.35
Snow Accumulation Slope (SAS)	-0.06	0.07	-0.14	-0.24	-0.4	0.28	-0.18	-0.26	0.18	0.05
Snow Melt Period (SMP)	-0.46*	-0.2	-0.57*	-0.54*	-0.28	0.15	-0.02	-0.13	-0.47*	-0.41
Snow Melt Slope (SMS)	-0.17	-0.21	-0.58*	-0.4	-0.38	0.17	-0.17	0.01	-0.47*	-0.33
Maximum Snow Cover Day (MSCD)	-0.53*	-0.07	0	0.16	0.04	-0.25	0.21	0	-0.14	-0.35
Snow Accumulation Onset Day (SAOD)	-0.14	0.09	-0.25	0.2	-0.49*	0.08	-0.16	-0.45*	0.19	-0.01
Snow Melt Ending Day (SMED)	-0.91*	-0.67*	-0.41*	-0.71*	-0.43*	-0.57*	-0.8*	-0.19	-0.6*	-0.79*
Accumulation-Ablation Period (AAP)	-0.42	-0.36	-0.41	-0.55*	-0.36	-0.3	-0.57*	-0.13	-0.61*	-0.42*

Table 4. Kendall's tau correlations between derived indexes and land surface temperature (*: Significant at 90% level)

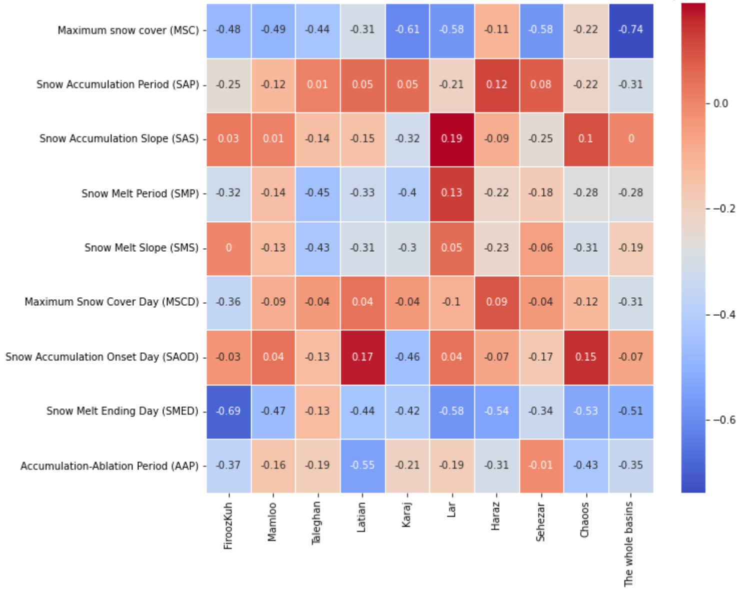
Basins	FiroozKuh	Mamloo	Taleghan	Latian	Karaj	Lar	Haraz	Sehezar	Chaloos	The whole basins
Maximum snow cover (MSC)	-0.48*	-0.49*	-0.44*	-0.31	-0.61*	-0.58*	-0.11	-0.58*	-0.22	-0.74*
Snow Accumulation Period (SAP)	-0.25	-0.12	0.01	0.05	0.05	-0.21	0.12	0.08	-0.22	-0.31
Snow Accumulation Slope (SAS)	0.03	0.01	-0.14	-0.15	-0.32	0.19	-0.09	-0.25	0.1	0
Snow Melt Period (SMP)	-0.32*	-0.14	-0.45*	-0.33	-0.4*	0.13	-0.22	-0.18	-0.28	-0.28
Snow Melt Slope (SMS)	0	-0.13	-0.43*	-0.31	-0.3	0.05	-0.23	-0.06	-0.31	-0.19
Maximum Snow Cover Day (MSCD)	-0.36*	-0.09	-0.04	0.04	-0.04	-0.1	0.09	-0.04	-0.12	-0.31*
Snow Accumulation Onset Day (SAOD)	-0.03	0.04	-0.13	0.17	-0.46*	0.04	-0.07	-0.17	0.15	-0.07
Snow Melt Ending Day (SMED)	-0.69*	-0.47*	-0.13	-0.44*	-0.42*	-0.58*	-0.54*	-0.34*	-0.53*	-0.51*
Accumulation-Ablation Period (AAP)	-0.37*	-0.16	-0.19	-0.55*	-0.21	-0.19	-0.31	-0.01	-0.43*	-0.35*

In addition, **Figure *5*** and **Figure *6*** show the heat map of correlation between LST and snow indexes in different basins.



	FiroozKuh	Mamloo	Taleghan	Latian	Karaj	Lar	Haraz	Sehezar	Chaoos	The whole basins
Maximum snow cover (MSC)	-0.61	-0.7	-0.68	-0.53	-0.45	-0.36	-0.51	0	-0.36	-0.26
Snow Accumulation Period (SAP)	-0.36	-0.08	0.12	0.12	0.2	-0.31	0.23	0.14	-0.2	-0.35
Snow Accumulation Slope (SAS)	-0.06	0.07	-0.14	-0.24	-0.4	0.28	-0.18	-0.26	0.18	0.05
Snow Melt Period (SMP)	-0.46	-0.2	-0.57	-0.54	-0.28	0.15	-0.02	-0.13	-0.47	-0.41
Snow Melt Slope (SMS)	-0.17	-0.21	-0.58	-0.4	-0.38	0.17	-0.17	0.01	-0.47	-0.33
Maximum Snow Cover Day (MSCD)	-0.53	-0.07	0	0.16	0.04	-0.25	0.21	0	-0.14	-0.35
Snow Accumulation Onset Day (SAOD)	-0.14	0.09	-0.25	0.2	-0.49	0.08	-0.16	-0.45	0.19	-0.01
Snow Melt Ending Day (SMED)	-0.91	-0.67	-0.41	-0.71	-0.43	-0.57	-0.8	-0.19	-0.6	-0.79
Accumulation-Ablation Period (AAP)	-0.42	-0.36	-0.41	-0.55	-0.36	-0.3	-0.57	-0.13	-0.61	-0.42

Figure 5. Pearson's r correlation between Snow cover indices and LST in studied basins



	FiroozKuh	Mamloo	Taleghan	Latian	Karaj	Lar	Haraz	Sehezar	Chaoos	The whole basins
Maximum snow cover (MSC)	-0.48	-0.49	-0.44	-0.31	-0.61	-0.58	-0.11	-0.58	-0.22	-0.74
Snow Accumulation Period (SAP)	-0.25	-0.12	0.01	0.05	0.05	-0.21	0.12	0.08	-0.22	-0.31
Snow Accumulation Slope (SAS)	0.03	0.01	-0.14	-0.15	-0.32	0.19	-0.09	-0.25	0.1	0
Snow Melt Period (SMP)	-0.32	-0.14	-0.45	-0.33	-0.4	0.13	-0.22	-0.18	-0.28	-0.28
Snow Melt Slope (SMS)	0	-0.13	-0.43	-0.31	-0.3	0.05	-0.23	-0.06	-0.31	-0.19
Maximum Snow Cover Day (MSCD)	-0.36	-0.09	-0.04	0.04	-0.04	-0.1	0.09	-0.04	-0.12	-0.31
Snow Accumulation Onset Day (SAOD)	-0.03	0.04	-0.13	0.17	-0.46	0.04	-0.07	-0.17	0.15	-0.07
Snow Melt Ending Day (SMED)	-0.69	-0.47	-0.13	-0.44	-0.42	-0.58	-0.54	-0.34	-0.53	-0.51
Accumulation-Ablation Period (AAP)	-0.37	-0.16	-0.19	-0.55	-0.21	-0.19	-0.31	-0.01	-0.43	-0.35

Figure 6. Kendall's tau correlation between Snow cover indices and LST in studied basins

The results revealed significant relationships between MODIS LST and the snow parameters in the Central Alborz basins. The correlation coefficients and Kendall's Tau values were calculated to quantify the strength and direction of the relationships.

Maximum Snow Cover (MSC):

The MSC showed negative correlations with MODIS LST in almost all basins, indicating that higher LST values were associated with reduced snow cover. The correlations were statistically significant for FiroozKuh, Mamloo, Taleghan, Latian, Karaj, and Chaloos basins. This suggests that higher temperatures measured by MODIS LST are associated with decreased snow cover in these basins.

Snow Accumulation Period (SAP):

The SAP exhibited weak positive correlations with MODIS LST, indicating a slight increase in snow accumulation during periods of higher LST values. However, these correlations were generally not statistically significant.

Snow Accumulation Slope (SAS):

The SAS showed mixed results, with some basins displaying positive correlations and others showing negative correlations. The correlations were generally weak and not statistically significant.

Snow Melt Period (SMP):

The SMP displayed negative correlations with MODIS LST, indicating that higher LST values coincided with earlier snowmelt. The correlations were statistically significant for FiroozKuh, Mamloo, Taleghan, Karaj, and Chaoos basins.

Snow Melt Slope (SMS):

Similar to SMP, SMS also exhibited negative correlations with MODIS LST, suggesting that higher LST values were associated with steeper snowmelt slopes. The correlations were statistically significant for FiroozKuh, Mamloo, Taleghan, Karaj, and Chaloos basins. However, in other basins, no significant correlation was found between SMS and LST. These findings suggest that the influence of SMS on LST patterns may be influenced by local topographic and environmental factors, highlighting the complex nature of the interactions between snowmelt dynamics and temperature variations. Further research is needed to explore the underlying mechanisms and potential spatial variability in the relationship between SMS and LST across the study area.

Maximum Snow Cover Day (MSCD):

The MSCD showed negative correlations with MODIS LST, indicating that higher LST values were associated with earlier dates of maximum snow cover. The correlations were statistically significant for FiroozKuh, Mamloo, and Haraz basins.

Snow Accumulation Onset Day (SAOD):

The SAOD displayed mixed results, with some basins showing positive correlations and others showing negative correlations. However, these correlations were generally weak and not statistically significant.

Snow Melt Ending Day (SMED):

The SMED exhibited strong negative correlations with MODIS LST in most basins, indicating that higher LST values were associated with earlier dates of snowmelt completion. The correlations were statistically significant for all basins except Lar and Sehezar.

Accumulation-Ablation Period (AAP):

The AAP showed negative correlations with MODIS LST, suggesting that higher LST values were associated with shorter accumulation-ablation periods. The correlations were statistically significant for most basins, indicating a consistent relationship between LST and the duration of the accumulation-ablation period.

Overall, the results indicate the utility of MODIS LST data in snow climatology studies of the Central Alborz basins. The negative correlations observed between LST and snow parameters such as MSC, SMP, SMS, MSCD, SMED, and AAP suggest that higher temperatures measured by MODIS LST are associated with reduced snow cover, earlier snowmelt, steeper snowmelt slopes, and shorter accumulation-ablation periods. These findings contribute to a better understanding of the relationship between temperature and snow dynamics in the study area.

It is important to note that the correlations presented in this study are based on MODIS LST data and may vary depending on the specific characteristics of the study area and the temporal resolution of the data. Additional investigation is required to confirm these results and examine further factors that could impact the correlation between temperature and snow dynamics in the Central Alborz basins.

5. Conclusion

In this study, we investigated the use of MODIS LST data to understand the intricate relationship between temperature and snow dynamics in the Central Alborz basins. Through the analysis of various snow parameters, we discovered significant correlations with MODIS LST, which provided quantitative insights into the impact of temperature on snow cover and melt processes.

Among the snow parameters analyzed, the Snow Melt Ending Day (SMED) emerged as the most sensitive indicator to temperature variations. We observed a robust negative relationship between SMED and MODIS LST in most of the studied catchments, with correlation coefficients ranging from -0.69 to -0.91. These results indicate that higher temperatures, as indicated by the LST data, were associated with an earlier completion of snowmelt. This finding is consistent with the understanding that warmer temperatures accelerate the melting of snow packs, leading to an earlier termination of the snowmelt season.

Furthermore, we found that higher LST values were linked to decreased snow cover, as evidenced by negative correlations between Maximum Snow Cover (MSC) and LST, ranging from -0.61 to -0.70. This relationship is in line with expectations, as increased temperatures promote snowmelt and reduce the duration and extent of snow cover. The negative correlation coefficients indicate that as LST increases, the maximum snow cover decreases, suggesting that temperature plays a crucial role in regulating the snowpack's extent.

Additionally, steeper snowmelt slopes, represented by the Snow Melt Slope (SMS), displayed negative correlations with LST in certain basins. The correlation coefficients for SMS and LST ranged from -0.21 to -0.62. This suggests that higher temperatures are associated with more rapid snowmelt on steeper slopes. The influence of temperature on snowmelt slope can be attributed to the enhanced energy transfer from the atmosphere to the snow surface, which accelerates the melting process on steeper terrain.

Our findings also indicate that higher LST values were associated with earlier dates of maximum snow cover, as demonstrated by negative correlations between Maximum Snow Cover Day (MSCD) and LST in some basins. The correlation coefficients for MSCD and LST ranged from -0.03 to -0.50. This implies that as temperatures rise, the peak snow cover occurs earlier in the season. The timing of peak snow cover is crucial for hydrological processes, as it influences the timing and magnitude of snowmelt runoff and water availability in the basins.

The statistical significance of these correlations underscores the robustness of the relationship between temperature and snow dynamics in the Central Alborz basins. These findings provide valuable insights into the interplay between temperature and snow processes, enhancing our understanding of the region's snow climatology.

These results emphasize the importance of considering SMED as a key indicator of temperature influence on snow dynamics. By understanding the sensitivity of SMED to temperature variability, researchers can gain valuable insight into the timing and duration of snowmelt, which has significant implications for water resource management, hydrologic modeling, and climate change studies in the Central Alborz basins. The strong negative correlations observed between SMED and LST support the notion that temperature is a critical driver of snowmelt timing and the overall duration of the snowmelt season.

However, it is critical to recognize that the correlations and sensitivities observed in this study are specific to the Central Alborz Basin and may not be directly transferable to other regions with different characteristics. The unique topographic, climatic, and vegetation characteristics of the Central Alborz basins contribute to the observed temperature-snow dynamics relationships. Future research should further investigate the influence of factors such as elevation, aspect, and vegetation cover on the temperature-snow relationship to improve our understanding of snow dynamics in different environments.

In conclusion, this study provides valuable insights into the complex interactions between temperature and snow dynamics in the Central Alborz basins. The significant correlations observed between temperature and various snow parameters highlight the role of temperature in shaping snow cover, snowmelt timing, snowmelt slopes, and the duration of snowmelt. These findings contribute to our knowledge of snow climatology and have practical implications for water resource management and hydrological modeling in the region. Further research is needed to expand these findings and explore additional factors that influence temperature-snow relationships in different geographical contexts.

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