

Article

Response of the Normalized Difference Vegetation Index (NDVI) to Snow Cover Changes on the Qinghai–Tibet Plateau

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Abstract: The eco-hydrological process related to vegetation on the Qinghai–Tibet Plateau is special, and the impact of snow cover on the growth of vegetation is unique and important. In this study, we analyzed the multi-year variations in the normalized difference vegetation index (NDVI) and snow cover on the Qinghai–Tibet Plateau from spatial and temporal perspectives and determined the relationship between the changes in the NDVI and snow cover. Results showed that in the last 40 years, the rate of change in the snow depth on the plateau was -0.016 mm/a, and the NDVI changed by 0.0005 /a. The correlations ($|R|$ values) between the different factors and the NDVI followed the order of precipitation (0.77) > snow depth (0.76) > temperature (0.67) > solar radiation (0.21). The responses of the NDVI to changes in meteorological elements were synchronous, whereas the opposite was found for the snow cover. The snow cover had more significant impacts on vegetation at higher elevations. The NDVI had a lag of about 2 months from the onset of the snow cover, and heavy snow events had negative impacts on the NDVI for more than 3 years. Our findings will facilitate studies of ecological vulnerability and the predictions of changes in vegetation on the plateau.

Keywords: snow depth; NDVI; correlation; time lag; Qinghai–Tibet Plateau



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1. Introduction

Plants are major components of terrestrial ecosystems [1], and they play important roles in mitigating climate change as well as regulating regional ecosystem functions and the carbon balance [2]. Vegetation is an integrated “indicator” of ecological changes influenced by biotic and abiotic factors under climate change, where typical phenological characteristics include greening and yellowing [3]. Snow cover is one of the most active natural landscapes on the earth’s surface and the most important component of the cryosphere [4]. Snow cover has significant effects on atmospheric circulation, land surface hydrological processes, and regional water balance due to its high albedo, low thermal conductivity, and snowmelt effect, and snow cover is highly sensitive to climate change [5]. The effect of snow cover on vegetation is mediated by a complex series of coupled elements, e.g., low snow cover in the cold season will lead to the snow melting quickly when the warm season arrives, which can advance the vegetation growth period and increase the productivity of vegetation, whereas advancement of the snowmelt period will enhance the evapotranspiration of soil water to decrease the productivity of vegetation if insufficient precipitation occurs [6].

Due to its unique environment, the Qinghai–Tibet Plateau (QTP) has become a biodiversity reserve and ecological security barrier in China and globally. In recent years, under ongoing global warming, the plateau has become an ecologically fragile zone due to its high sensitivity to climate change, which significantly impacts the lives of local residents and the ecosystem. The ecological problems that affect the plateau are also significant for

studies of the global ecological issues caused by climate change. Therefore, the ecological and environmental issues that affect the QTP are attracting increasing attention. In general, it is considered that temperature and precipitation are the main climatic factors that affect the growth of vegetation [7], and studies have shown that the changes in vegetation on the QTP have prominent regional characteristics. The dominant factor that affects changes in vegetation in the semi-humid and semi-arid zones is the temperature, but the influence of precipitation on the changes in vegetation is significantly greater in the partially arid region than in the semi-humid and semi-arid zone [8].

The snow cover was low from the mid-1960s until the mid-1970s, but the snow cover on the plateau generally tended to increase from the late 1980s until the late 1990s, with a significant increase in the annual amplitude [9]. From the late 1990s until the present, the snow cover has tended to decrease significantly [10]. The impact of snow on vegetation is becoming increasingly evident due to the marked changes in the snow cover on the plateau. However, the mechanism that allows snow cover to affect vegetation on the QTP is complex, and various factors are involved [11]. First, altitude is an important limiting factor for vegetation growth, and studies have shown [12] that the negative correlation between snow and vegetation is more significant when the altitude is higher. Secondly, the indirect effects of snow–vegetation interactions also need to be considered. Snow melting can effectively recharge the soil and increase the soil moisture, which in turn affects vegetation [13]. Thirdly, with the unusual increase in the plateau temperature, the snow melting rate accelerates, and the factors of direct effects in the eco-hydrological processes have changed, which will comprehensively affect the indirect effects of snow on vegetation.

Several previous studies have investigated the relationship between snow and vegetation [14–17], as well as the effects of dynamic changes in snow and vegetation [6] on the QTP, but it is still unclear how various factors might affect snow and vegetation on the Plateau. In particular, few studies have investigated the positive and negative feedback between changes in vegetation and snow cover in different plateau areas and the factors (such as temperature, precipitation, solar radiation, soil moisture, etc.) involved. Therefore, in this study, we used month-by-month temperature, precipitation, solar radiation, and snow depth data for 40 years from 1981 to 2020 and week-by-week NDVI high-resolution plateau-wide raster data for the same period. We wrote a code using MATLAB v2019a, R v4.3.1 and Python v3.8.5 to process the data in batch calculations. Then, we analyzed the multi-year spatial and temporal trends in snow depth and NDVI. In addition, we analyzed the characteristics of snow cover in the eco-hydrological process related to vegetation and clarified the spatial heterogeneity of the effects of changes in snow on the plateau on vegetation at different times.

Moreover, Pearson's correlation coefficients were calculated to test for seasonal lags and identify the extent of spatial variations in the seasonal responses of the NDVI to snow cover changes. Based on our findings, we suggest further research to help understand the lagged response to other meteorological factors in the snow–vegetation system and the related mechanisms. These studies will help to clarify the direct and indirect effects of changes in snow on the eco-hydrological processes related to vegetation on the plateau, as well as the magnitude of these effects and the feedback mechanism involved, which will be important for understanding the ecological changes on the plateau and adaptability to climate change, thereby helping to ensure the ecological barrier and ecological security role of the QTP.

2. Materials and Methods

2.1. Study Area

The average elevation of the QTP is the highest of any plateau throughout the world, and it is the most extensive plateau in China (Figure 1). The QTP is known as the “roof of the world” and the “third pole” [18]. The plateau has an average elevation of about 4320 m, with a total area of 3,083,400 km² [19], average annual temperature of -6°C to 20°C , annual precipitation of 50–2000 mm, and solar radiation of $0.8561\text{--}0.7954\text{ MJ cm}^{-1}\text{ a}^{-1}$, which is the

highest total solar radiation value in China [20]. Due to its high altitude, low temperatures, and widespread snow, glaciers, and permafrost, the QTP is the main snow distribution area in the low and mid-latitude zones of China [4]. Snowfall starts from September to October, and the obvious snow accumulation period is from October to April [21]. The QTP region is rich in various vegetation types, where the main grassland types are alpine meadows, alpine grasslands, and sparse grasslands, but climate change in recent years has led to great uncertainty about the fragile ecosystem on the plateau [22]. In the QTP, the impact of human activities on vegetation is significantly weaker than the effects brought about by climate change, and there are notable regional differences [23,24]. Consequently, in this study, the factor of human activities is disregarded. Therefore, studying the responses in terms of the phenology of vegetation to climate change on the QTP, especially the response to snowpack changes, is important for understanding the vulnerability of the ecosystem as well as the global stability of the ecosystem.

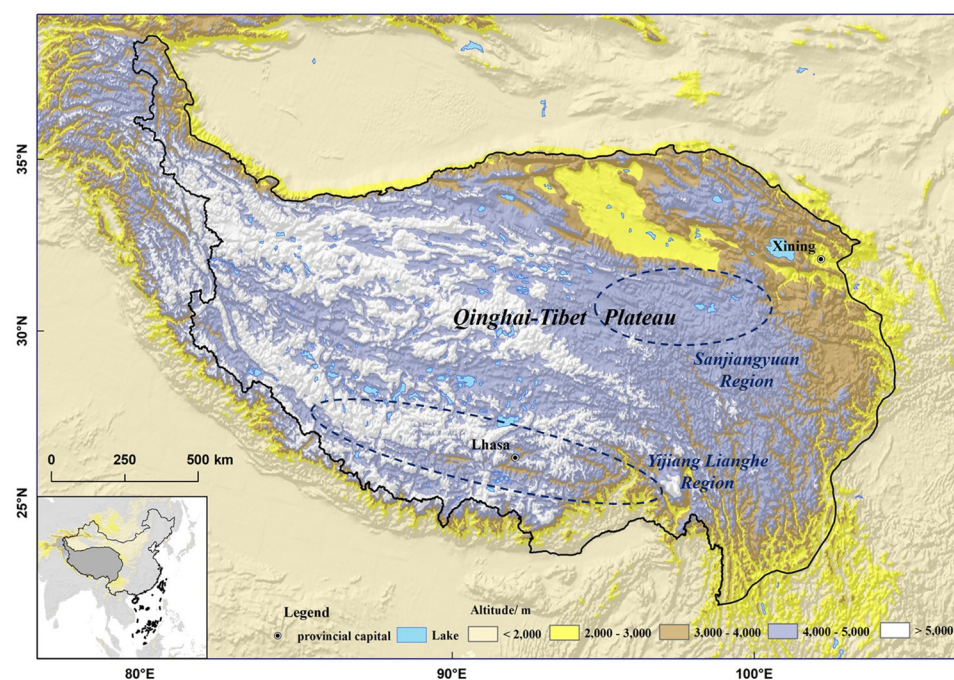


Figure 1. Extent (within China), elevation and location of the Qinghai–Tibet Plateau in China.

2.2. Data Sources and Pre-Processing

The primary data used in this study included raster grids for temperature, precipitation [25], solar radiation [26], NDVI, and snow depth [27] over 40 years from 1981 to 2020 on the QTP, as well as vector outlines for the boundary of the QTP. Raster grids for interpolation were lacking in some years. The snow depth raster grids used for calculating correlations after unifying the spatial resolution with NDVI raster grids, as well as the specific data sources and descriptions, are shown in Table 1.

Table 1. Data sources.

Data Name	Source	Time Range	Time Resolution	Spatial Resolution	Note
Snow depth (snd)	TPDC China Snow Depth Long Time Series Dataset (http://data.tpdac.ac.cn , accessed on 30 August 2022)	1981–2020	Daily	0.25° (about 20 km)	Cropped from China-wide data (missing data for Qinghai–Tibet South)
NDVI	GIMMS NDVI3g	1981–2020	Half-monthly	0.03° (about 4 km)	Cropped from world scale, data are monthly max NDVI, converted by Julian calendar
Temperatures (tem)	TPDC China 1 km resolution monthly average temperature dataset (1901–2020) (http://data.tpdac.ac.cn , accessed on 10 April 2023)	1981–2020	Monthly	0.0083° (about 1 km)	Cropped from China-wide data
Precipitation (pre)	TPDC China 1 km resolution monthly precipitation dataset (1901–2020) (http://data.tpdac.ac.cn , accessed on 10 April 2023)	1981–2020	Monthly	0.0083° (about 1 km)	Cropped from China-wide data
Solar radiation (rad)	High-resolution (10 km) surface solar radiation dataset for regional fused insolation hours in China (1983–2017) (http://data.tpdac.ac.cn , accessed on 10 April 2023)	1983–2017	Monthly	0.083° (about 10 km)	The data are corrected by the actual data from the meteorological stations and cropped from China-wide data
QTP border (vector)	Integration dataset of Tibet Plateau boundary (http://data.tpdac.ac.cn , accessed on 10 October 2020)	2019	—	—	Use of parts within China
Vegetation map for QTP	A new vegetation map for QTP by integrated classification from multi-source data products (2020) (http://data.tpdac.ac.cn , accessed on 15 March 2023)	2020	—	0.0083° (about 1 km)	—

After downloading, the data were reviewed and screened to select raster data with an appropriate spatio-temporal resolution and to handle cases of missing and incorrect data. Most of the data ranges covered China, but the NDVI data covered the whole world, so the data had to be cropped according to the vector range for the QTP. The code was written in Python v3.8.5 to crop the study area because the data volume was excessively large. Finally, to meet the research needs in terms of temporal resolution, codes were written in MATLAB v2019a to calculate the multi-year annual average, seasonal average, and monthly average snow depth, as well as the annual maximum, seasonal maximum, and monthly maximum NDVI, and multi-year annual average and monthly average temperature, precipitation, and solar radiation for lagging analysis. All data were sampled at a spatial resolution of 0.083° (~10 km) for correlation analysis.

As shown in Figure 2, In this study, we mainly analyzed according to the following three steps. (1) MATLAB v2019a was used to calculate the multi-year mean snow depth and NDVI values, as well as the one-dimensional regression trends in snow and vegetation over a long time series of 40 years, and explored the correlations and differences in the spatial and temporal changes in snow cover and NDVI. (2) Pearson's correlation coefficients were calculated to determine the temporal correlations between multi-year mean snow cover and NDVI, meteorological elements and the changes in NDVI. We spatially analyzed the changes in snow cover and NDVI according to Pearson's correlation coefficients. (3) Using the lag analysis method, we calculated the temporal lag and spatial distribution of the seasonal lag. We also investigated the long-term lag effect on NDVI under abnormal increases in the snow depth caused by heavy snow events.

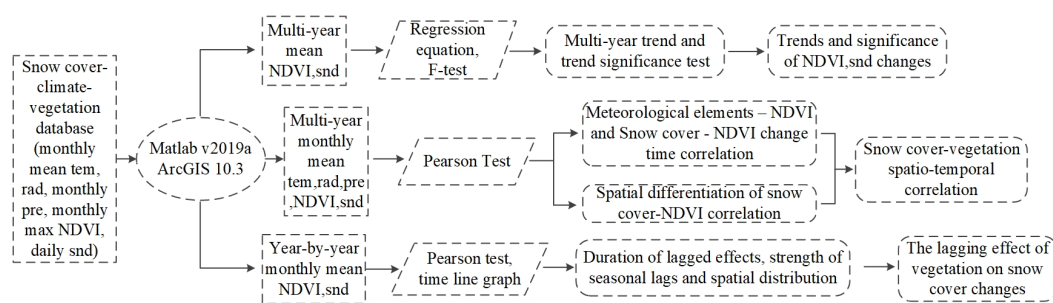


Figure 2. Experimental protocol.

2.3. Research Methodology

Trends in the data were analyzed to assess the spatio-temporal changes. For long-time-scale raster grids, the trends in the unit image elements over time can be calculated by using the one-dimensional linear regression method [28]. In this study, we calculated the slope of each image element in the raster grids for the snow cover and NDVI parameters in the study area (i.e., the inter-annual rate of variation in each parameter) using MATLAB v2019a code. The spatial distribution of the inter-annual variation in each parameter in the study area was obtained from 1981 to 2020 using the following equation:

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

where i is the year number, m is the length of the time series, and X_i is the value of each parameter in the i -th year. $Slope > 0$ indicates an increasing trend, and $Slope < 0$ indicates a decreasing trend. The significance of changes in slope was tested using the F-test, where we considered whether the trend was significant at the 95% confidence level, i.e., the trend was not significant when $p \geq 0.05$, whereas the trend was significant when $p < 0.05$.

Pearson's correlation coefficients were calculated for correlation analysis between the snow cover phenology and climatic and vegetation factors [14]. Pearson's correlation coefficient measures the closeness of the correlation between two series by the product of their deviations from the respective means. It has the advantages of a simple and intuitive

calculation method, and the correlation coefficient is a standardized dimensionless value that is comparable between different studies. Suppose that we have series X and series Y :

$$\begin{cases} X = \{X(k)|k = 1, 2, \dots, n\} \\ Y = \{Y(k)|k = 1, 2, \dots, n\} \end{cases} \quad (2)$$

where k denotes the sampling points in sequence X and sequence Y , and n is the total number of sampling points in sequences X and Y , then the Pearson's correlation coefficient r between sequence X and sequence Y is calculated as:

$$r = \frac{\sum_{i=1}^m (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^m (X_i - \bar{X})^2} \cdot \sqrt{\sum_{i=1}^m (Y_i - \bar{Y})^2}} \quad (3)$$

where r is the correlation coefficient between X and Y , X_i is the snow depth parameter in the year i ; Y_i is the annual precipitation, annual average temperature, annual average solar radiation, or NDVI in year i ; $\bar{X}$ is the average multi-year snow depth; $\bar{Y}$ is the average precipitation, annual average temperature, annual average solar radiation, or NDVI; and m is the number of years in the monitoring period. $r > 0$ denotes a positive correlation between the two variables, $r < 0$ denotes a negative correlation, $|r| \leq 0.2$ denotes an insignificant correlation, and $|r| > 0.2$ denotes a significant correlation between the two variables.

The response of vegetation to climate does not always occur in real time, and thus a time lag effect may be evident in the response of vegetation to changes in climate [29]. In this study, based on Pearson's correlation test and the actual situation on the QTP, we designed a test to clarify the lagged effect of snow on vegetation. The effects of the snow depths were calculated in winter (December–February in the following year), spring (March–May), and the plateau cold season (September–March in the following year) on the spring maximum NDVI and summer maximum NDVI (the warm season maximum NDVI was equal to the summer maximum NDVI). Based on these results, we determined the correlations between winter snow cover and the NDVI in the following spring, spring snow cover and summer NDVI, and cold season snow cover and warm season NDVI to characterize the lagged effect of snow cover on vegetation, as shown in Figure 3.

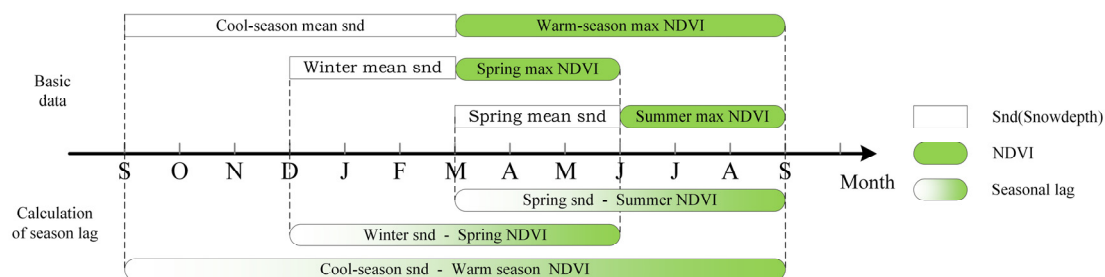


Figure 3. Lagging evaluation method.

A distributed lag regression model [30] was applied to quantify the lag time of the effects of snow and climatic factors on vegetation, and the first-order autoregressive term was used in the distributed model:

$$X_m = \rho + \varphi * X_{m-1} + \sum_{i=0}^{i=k} \mu_i * Y_{m-i} + \tau_t \quad (4)$$

where X_m and X_{m-1} represents the NDVI values at time m and $m-1$, Y_{t-i} represents the value of the climatic factor (snow depth, precipitation, temperature and solar radiation) at time $m-1$. The unit of time m was measured in months, and the duration of study for various elements spans 40 a (with solar radiation being studied for 35 a). The data was organized on an annual basis; hence, the range of m was from 1 to 480 (for the study of

solar radiation, the range was from 1 to 420). ρ and τ_m are the intercept and random error, respectively, φ and μ_i are the coefficients, k is the lag time (monthly). Following the relevant studies [21], we used the Akaike information criterion (AIC) to select the optimal lag order and defined the maximum value of k as 3. We evaluated the optimal lag length for 0–3, and found the best fit value as the optimal lag length for the vegetation response to the factor. The calculation in this study was implemented by using the R package [31].

3. Results

3.1. Analysis of Spatial and Temporal Changes in Snow Cover and NDVI

3.1.1. Variations in Snow Depth

As shown in Figure 4, the variations in the snow depth over the entire plateau surface during 1981–2020 exhibited small but significant fluctuations with a multi-year rate of change of -0.016 mm/a. The sharpest fluctuations occurred between the 1980s and 1990s, with the highest snow depth in 1986, followed by a clear decreasing trend. From the 1990s to the mid-2010s, the fluctuations were smaller, but a clear decrease was observed, although a significant increase occurred in 1995 until a peak was reached around 1998, before a subsequent decrease. After 2016, another significant increase was observed, and this continued until 2020. Spatially, the areas with decreasing trends in the multi-year snow depth accounted for 56.5% of the entire plateau area during the study period, with significant decreasing trends in the Karakorum Mountains, western Kunlun Mountains, Nyenchen Tanglha Mountain, Tanggula Mountains, and Zongwulong Mountains, where the slope of the one-dimensional regression was -0.05 and above. The snow depths in the central, eastern, and southwestern areas of the plateau exhibited an increasing trend, including the areas surrounding the plateau surface. Significant increases were found in some areas of the central “Sanjiangyuan” region (The source of the Yangtze River, Yellow River and Lancang River), but the overall area was relatively small at only 10.9%. The multi-year snow depth in the highlands was more significant but with a decreasing trend.

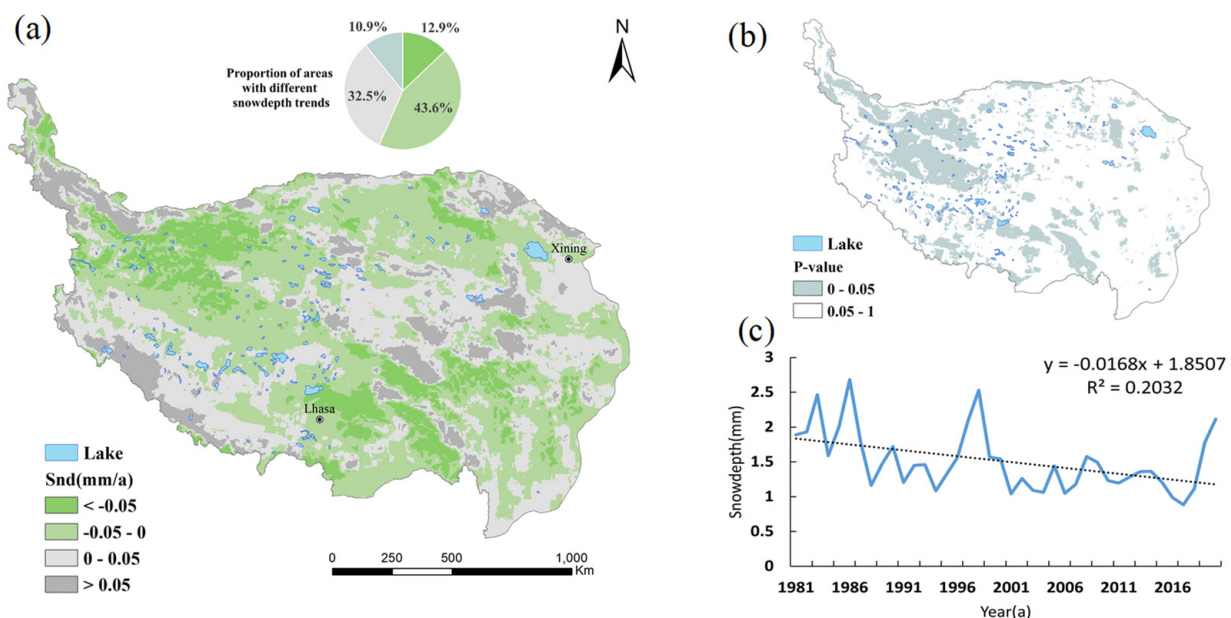


Figure 4. Multi-year spatial and temporal variation of snow depth on the QTP: (a) spatial distribution of trend changes; (b) significance of trend; (c) time series of changes.

3.1.2. Variations in NDVI

As shown in Figure 5, the NDVI on the whole plateau surface exhibited a sizeable non-significant increase, with a multi-year rate of change of 0.0005 /a between 1981 and 2020. In particular, the NDVI exhibited a fluctuating increasing trend between the 1980s

and 2000s, but a significant increase occurred after 2000, where the mean value fluctuated around 0.13 to 0.14, and it remained at this level in subsequent years. The average value increased significantly, but the fluctuations decreased significantly. Spatially, the multi-year NDVI increased by 78.83% over the total area of the whole plateau, but the increasing trend was not significant. Significant increases occurred in western Sichuan, northwestern Yunnan, western Gansu, the “Sanjiangyuan” region, and part of southeastern Tibet, with multi-year rates of change greater than 0.001/a and greater than 0.003/a in some areas, although these areas only accounted for 3.17% of the total, where these changes may have been related to the implementation of grazing bans and other ecological protection policies in these areas. The increases in the NDVI were slower in the western and northern parts of the plateau, where the trend was between 0 and 0.001 per year. These changes occurred in 55.79% of the total area of the plateau, and this was the main trend in the NDVI on the plateau. The rates of increase in the NDVI in the Qaidam Basin, Tanggula Mountains, and some human activities and development areas in the “Yijiang Lianghe” (Brahmaputra, Nianchu, and Lhasa Rivers) basin were less than 0.

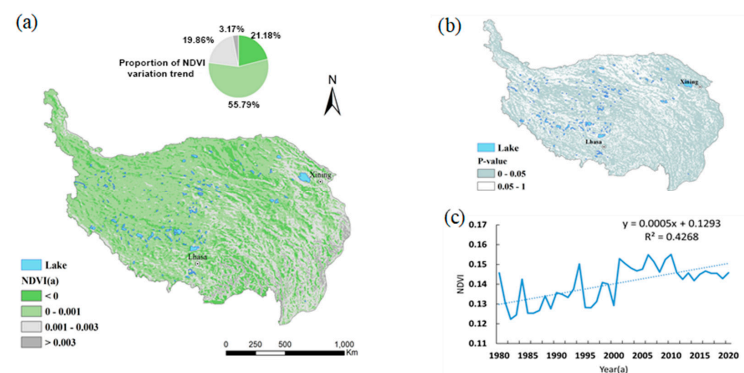


Figure 5. Multi-year spatial and temporal variation of NDVI on the QTP: (a) spatial distribution of trend changes; (b) trend significance; (c) time series of changes.

3.2. Analysis of Temporal Correlation between Snow Cover and NDVI

3.2.1. Temporal Correlation between Snow Cover and Changes in NDVI

The intra-annual trends in the snow depth and NDVI are shown in Figure 6. The snow depth gradually decreased as the NDVI increased from April to August, when the NDVI reached its peak for the year in the period with the most vigorous growth of vegetation, and the amount of accumulated snow was the lowest during the year. Subsequently, the snow depth gradually started to increase as the NDVI decreased. In addition, we observed a lag in the occurrence of the minimum NDVI compared with the period when the deepest snow cover occurred. The intra-annual correlation between each meteorological element and the NDVI was the opposite of that between the snow cover and NDVI. The trends in the meteorological elements were similar to the changes in the NDVI, where the response of the NDVI to precipitation agreed well with the occurrence of peaks and troughs in the precipitation. There was also a significant lag in the response to solar radiation. Pearson’s correlation coefficients were calculated to quantify the effects of each meteorological element on the NDVI for each data set. In particular, the snow cover and NDVI had a significant negative correlation ($R = -0.76$), and the correlations between the temperature, precipitation, and solar radiation with the NDVI were $R = 0.67$, 0.77 , and 0.21 , respectively. The correlations between the temperature and precipitation with the NDVI were significant and negative, and the correlation between the solar radiation and NDVI was not significant and negative. The absolute R values indicated the significance of the correlations. The significance of the four elements on the NDVI was shown in the following order: precipitation > snow depth > temperature > solar radiation. The difference between the effects of precipitation and snow depth ($|R|$) was small. It should be noted that the correlation indicated by the results of the Pearson correlation test just represented

a mathematical significance. These initial findings suggested that the temporal correlation between plateau snow cover and precipitation with changes in NDVI is highly significant. Temporally, the changes in the snow cover on the plateau were the opposite of the changes in the NDVI. The changes in the NDVI were synchronized with the changes in other elements. The opposite changes in the snow cover and its participation in vegetation eco-hydrological processes were directly related to the effects of snow cover on the phenology of vegetation on the plateau. The snow cover increased during the cold season, and vegetation died due to the lower temperature. The snowpack melted into water in the warm season, which had a positive effect on the growth of vegetation.

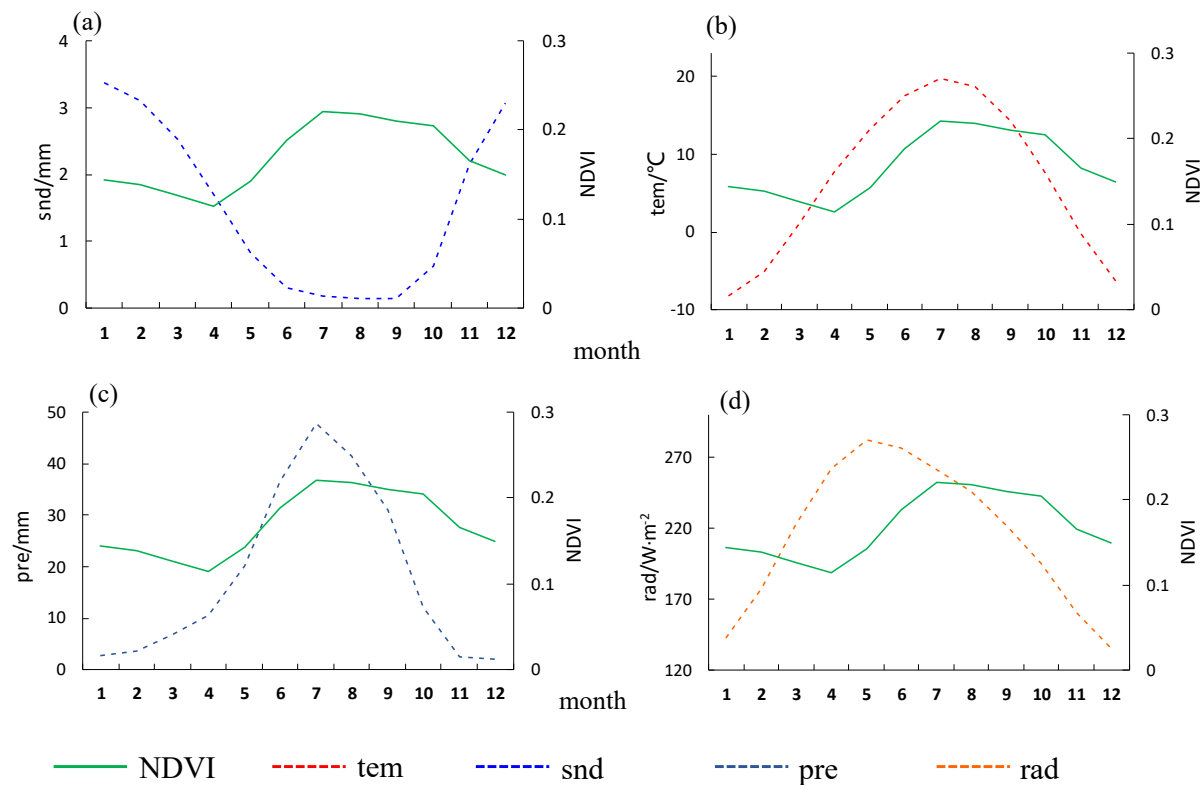


Figure 6. Multi-year average intra-annual trends and relationships of meteorological elements and NDVI on the QTP: (a) snow depth–NDVI; (b) mean temperature–NDVI; (c) precipitation–NDVI; (d) solar radiation–NDVI.

3.2.2. Lagged Response Time Analysis

Based on the results of the time correlation calculation, we found that the response of vegetation to snow cover change has a certain time lag rule. Due to snowmelt's impact on hydrology and subsequently vegetation, there is an intermediate link (the soil mediated the exchange of materials and energy between the two systems), and thus, the impact of snow on the vegetation eco-hydrological process lagged. Time series analysis coupled with the distributed lag regression model [30] was employed to quantify the lag length of NDVI response to snow depth. As the maximum snow depth corresponds to the minimum NDVI value, the lag effect was calculated accordingly. To facilitate cross-comparison, the results were processed, as depicted in Figure 7 and Table 2. During the study period, significant negative correlations were found between the month-by-month snow depth and NDVI when the snow depth increased (or decreased) and when the NDVI decreased (or increased), and the extreme values of each occurred in opposite periods. In particular, the maximum snow depth generally occurred in January (but February in some years) during winter when the temperature was lowest, and the NDVI reached its lowest value in March, and thus there was a negative correlation and a significant lag of nearly 2 months. The lowest snow depth occurred in August–September when the NDVI was at its maximum during the year.

The snow cover and NDVI were significantly negatively correlated but without significant lags during this period (the utilization of multi-year monthly scale snow accumulation and NDVI raster data in this study may account for the inability to capture a lagged response time of less than one month). The average multi-year lag time of snow–NDVI is 1.02 (SD is 0.95), and the adjusted determination coefficient of the distribution regression lag model is low, that is, the fit degree is poor. The significant lag in the correlation between snow cover and the NDVI during the winter and spring, as well as the insignificant lag during the summer, were related to the environmental effects of snow and other meteorological factors on the NDVI during these periods.

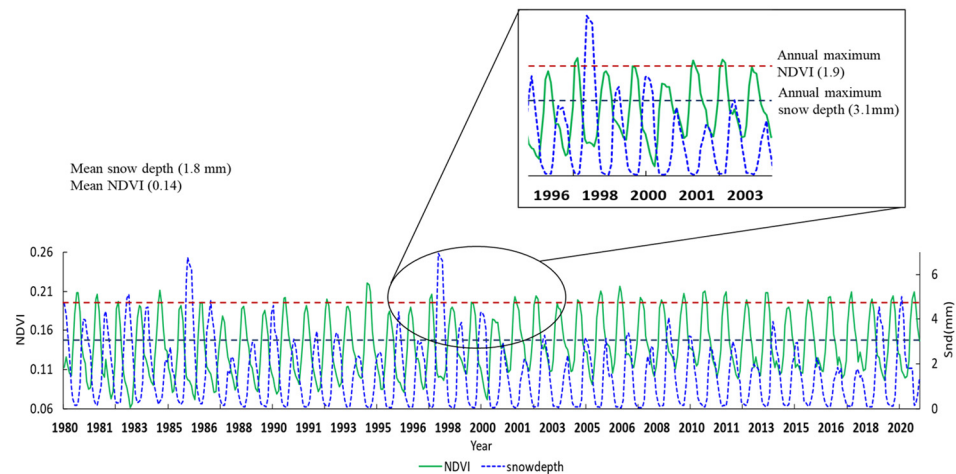


Figure 7. Snow cover and NDVI year-by-year monthly average distribution.

Table 2. Lag length (months) of the NDVI to SND (snow depth).

NDVI	SND		
	Mean	SD	R ²
	1.02	0.95	0.56

We also considered the occurrence of heavy snowfall events on the plateau, which led to anomalously high increases in the snow depth because their effects on vegetation could have lagged for longer and even lasted for more than a year. As shown in Figure 7, after a heavy snowfall event in December 1985, the average snow depth across the plateau reached 6.7 mm, which was significantly higher than the annual maximum value of 3.1 mm. The average annual NDVI values in 1985, 1986, and 1987 were only 0.12, which was significantly lower than the average value of 0.14. The negative effect of the 1985 snowfall event on the NDVI continued until 1987, after which the NDVI rebounded. The deepest snow depth of 6.9 mm on the plateau in the whole study period was recorded in 1997. This heavy snowfall event led to maximum NDVI values of 0.18, 0.19, and 0.17 in 1998, 1999, and 2000, respectively, which were significantly lower than the annual maximum value of 1.9. Thus, the impact of this heavy snowfall event lasted for more than 3 years, and the abnormal increase in snow significantly affected the NDVI for more than two years.

3.3. Analysis of Spatial Correlation between Snow Cover and NDVI

3.3.1. Spatial Differentiation of Snow Cover–NDVI Correlation Features

In this study, only the correlation between the average annual NDVI values of vegetation during the growing season (April to October from 1981 to 2020) and the corresponding snow depth in the same period was calculated, excluding the influence of opposing phenological patterns between snow and vegetation on the spatial Pearson correlation test results. Our research limited its examination to relationships between snow cover and

NDVI accounting for the appropriate temporal lag and emphasizes the eco-hydrological connection between the two variables.

The results are shown in Figure 8. Over the whole plateau, the correlation between snow cover and NDVI was generally significant and negative. Significant positive correlations were found only in the northern QTP, Qaidam basin, Qinghai Lake basin, Hehuang valley, southern Tibet valley, “Yi Jiang Liang He” basin, and part of the southern part of the Hengduan Mountains, but the proportion of the plateau covered by these areas was generally small. Significant negative correlations were found in the western Himalayas and Kunlun Mountains, southern Qilian Mountains, Qinghai Plateau, Tanggula Mountains, and a large area in the northern part of the Transverse Ranges. The areas with positive correlations were relatively flat and low-elevation areas. By contrast, the areas with negative correlations were concentrated in the relatively high-elevation mountainous plateau areas.

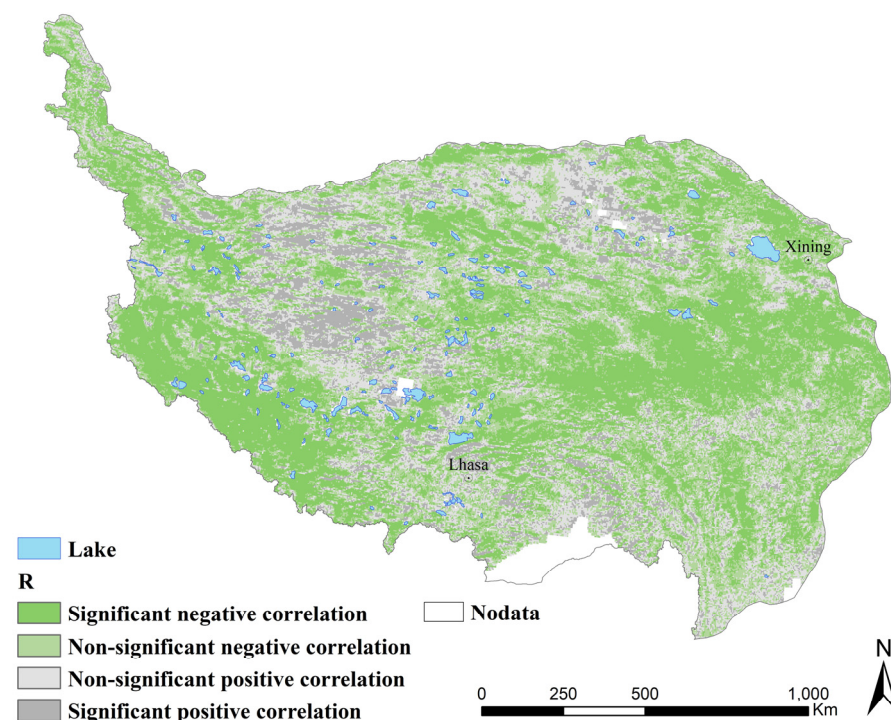


Figure 8. Geographical differences in snow depth–NDVI correlation.

Thus, we analyzed the correlations between snow cover and NDVI in areas at different altitudes, and the results are shown in Table 3. The result showed that the correlation between snow cover and vegetation was related to changes in elevation. In particular, in the basin and valley areas with elevations <3000 m, most of the areas had negative snow cover–vegetation correlations, i.e., 54.45%, where most areas had insignificant positive correlations. Among the areas at 3000–4000 m, the proportion of the areas with significant negative correlations increased significantly. Among the areas at 4000–5000 m, the proportion of the areas with significant negative correlations increased, and they accounted for the majority, whereas the proportion of the areas with positive correlations decreased significantly. The areas with negative correlations accounted for nearly 77% of the alpine plateau areas at >5000 m, and the areas with significant negative correlations increased further, whereas the areas with significant positive correlations comprised the lowest proportion, with less than 5%. Thus, the negative correlation between vegetation and snow depth was more pronounced when the altitude was higher and vice versa.

Table 3. Significant area shares in relation to elevation (statistics for different elevation subdivisions).

Altitude/m	Significant Negative Correlation (%)	Non-Significant Negative Correlation (%)	Non-Significant Positive Correlation (%)	Significant Positive Correlation (%)
<3000	14.25	31.30	36.01	18.44
3000–4000	31.33	37.91	23.43	7.32
4000–5000	41.80	30.91	18.13	9.16
>5000	48.86	28.03	18.36	4.74

The opposite changes occurred in the snow cover and phenology of vegetation because the snow cover increased as the temperature decreased, which reduced the soil temperature and led to the death of vegetation, whereas increased temperatures decreased the snow cover and increased the soil temperature to melt the snow and replenish the soil moisture to allow the vegetation to grow and develop. As a consequence, the snow cover and vegetation were negatively correlated, and each was correlated with the altitude according to the differences in temperature. Thus, we found that vegetation was more significantly affected by the snow cover in high-altitude areas.

3.3.2. Spatial Differentiation of Correlation for Different Vegetation Types

The QTP has a rich diversity of vegetation types, which show different patterns of NDVI changes in recent years [32]. Hence, the correlation between vegetation and snow changes based on NDVI also varies depending on the vegetation types. In this paper, we used the latest distribution map of basic vegetation types on the plateau [33] to examine the spatial distribution and NDVI–snow depth correlation of the main vegetation types, namely grassland, forest (subdivided into evergreen coniferous forest, coniferous and broad-leaved mixed forest and evergreen broad-leaved forest), alpine vegetation and desert. The results are presented in the figure. Firstly, Figure 9 illustrates the spatial distribution of principal grassland vegetation types on the QTP. Compared with the NDVI–snow depth correlation depicted in Figure 9b, a substantial alignment is observed with areas exhibiting a significant negative correlation. Notably, the grassland at the southern slopes of the Qilian Mountains, Qinghai Plateau, Kunlun Mountain, Himalayas, and the Hengduan Mountain ranges highly overlap with the distribution of significantly negative correlation. In essence, most of the high-altitude grassland areas on the plateau demonstrate a marked negative correlation between NDVI and snow depth.

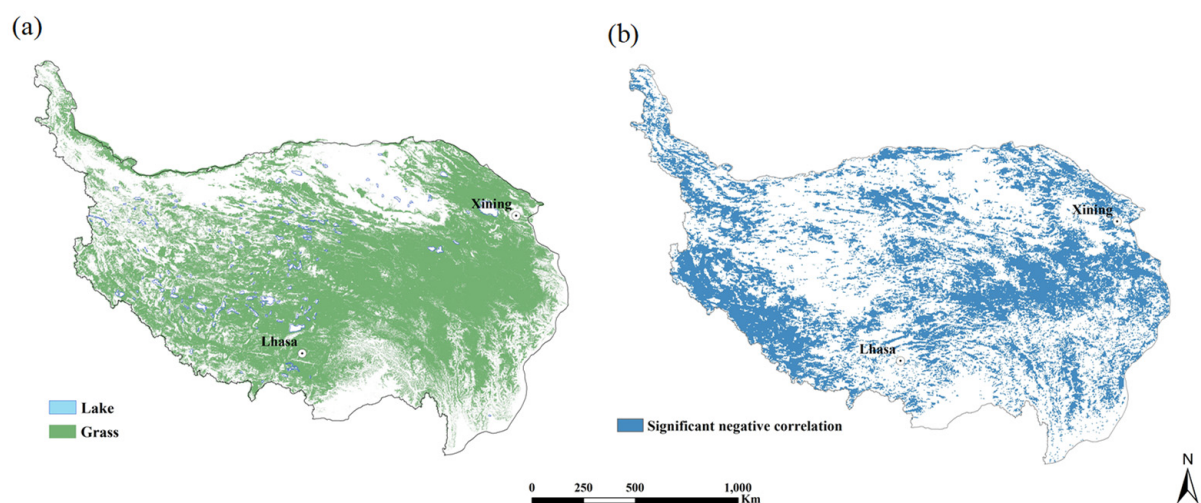
**Figure 9.** Spatial relationship between grassland and snow cover vegetation on the QTP: (a) spatial distribution of grassland; (b) spatial distribution of significant negative correlation.

Figure 10 compares the spatial distribution of forest and desert grassland vegetation types with the positive NDVI–snow depth correlation distribution. A considerable congruence is observed between the two distributions across the plateau, particularly in the desert grassland areas in the Qaidam Basin, the southern slopes of the Kunlun Mountains and the northern plateau, where the snow–NDVI relationship exhibits a marked positive correlation, and statistically significant. The “Yijiang Lianghe” basin and the Hengduan Mountain region in Tibet are characteristic forested areas on the plateau (Figure 10a); the positive correlation distribution in Figure 10b resembles them. In other words, the areas with desert grassland and forest vegetation types on the QTP tend to show a positive and significant correlation between NDVI and snow depth variations.

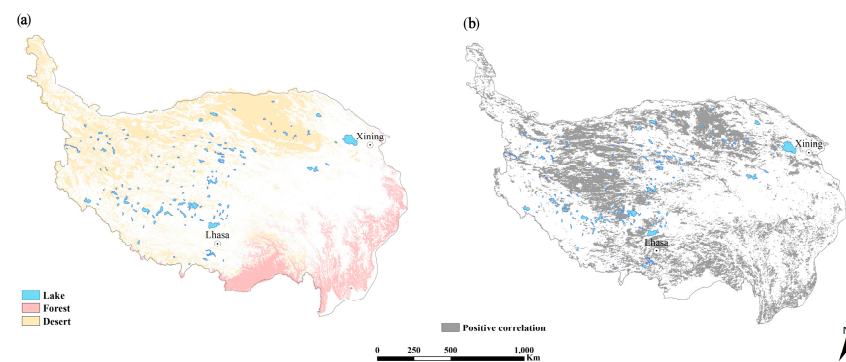


Figure 10. Spatial relationship between forest desert and snow cover vegetation on the QTP: (a) spatial distribution of forest and desert steppe; (b) spatial distribution of significant negative correlation.

3.3.3. Spatial Variation in Seasonal Lag Response

Obviously, the lag effect also has spatial characteristics. The lagged seasonal effects of snow cover on vegetation and its spatial distribution were examined based on the correlations between the snow in spring and NDVI in summer, snow in winter and NDVI in spring, and snow in the cold season and NDVI in the warm season for 40 years from 1981 to 2020. Figure 11a shows the correlations between the snow in winter and NDVI in the following spring. The correlations were mainly positive between the snow cover in winter and NDVI in the following spring over the whole plateau, where the positive correlations were significant in the northern QTP, some parts of the Qinghai Plateau, and “Yijiang lianghe” region. Few areas had significant negative correlations. Figure 11b shows the correlations between the snow cover in the spring and NDVI in the summer, which indicated that positive correlations were found in most parts of the plateau. The correlations between the snow cover in spring and NDVI in summer were weaker compared with those between the snow cover in winter and NDVI in the subsequent spring. The distribution also changed, with positive correlations in the central, southern, and northern Qaidam Basin, and Hengduan Mountains. The positive correlations were significant in the central Himalayan region, central QTP, and Qaidam Basin. Negative correlations were found between the snow cover in spring and NDVI in summer in the higher elevation mountainous regions of the Gangdis and Kunlun Mountains, and the three river source regions of the Qinghai Plateau in the west. The correlations were less significant in all regions, except for the “Sanjiangyuan” region, central QTP, and western Himalayas, thereby indicating that the effect of snow in the spring on the NDVI in the summer was weaker compared with the effect of snow in the winter on the NDVI in the following spring, i.e., the lag was not strong.

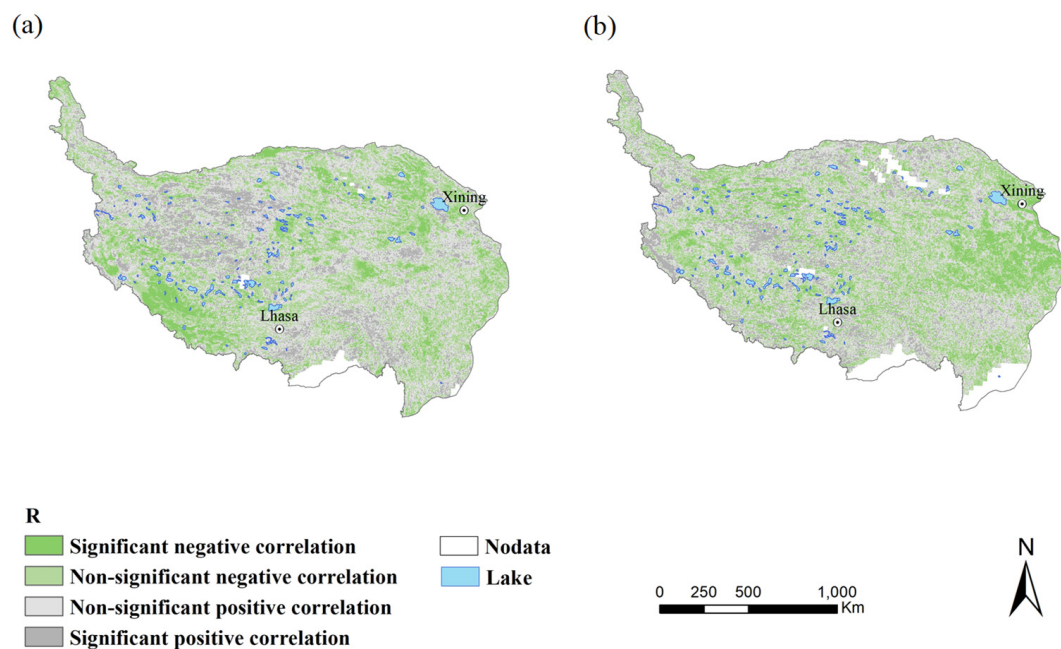


Figure 11. Seasonal snow cover and NDVI correlation: (a) winter snow cover—following spring NDVI; (b) spring snow cover—summer NDVI.

Based on previous studies [34] and the actual snow cover on the plateau, we selected six months from October to March as the cold season and April to September as the warm season. The snow depths in the cold season from 1981 to 2020 were selected to determine their correlations with the NDVI in the warm season, and the results are shown in Figure 12. The snow cover in the cold season generally had positive correlations with the NDVI in the warm season in most of the northern part of the plateau. In contrast, negative correlations were mainly found in southern Tibet and western Sichuan, and a significant negative correlation along the Gangdisha-Tanggula-Hengduan mountain line. The lag effect was more significant in areas with significant correlations between the snow cover and NDVI. According to the correlations between the snow depth in the cold season and NDVI in the warm season, more obvious lags were found in northern and southern Tibet, northern Qinghai, Xinjiang, and Gansu. In contrast, the lags were less significant in the Ali plateau, Qinghai plateau, and northern Sichuan regions. In general, the snow cover during the cold season significantly affected the NDVI during the warm season in most areas of the plateau.

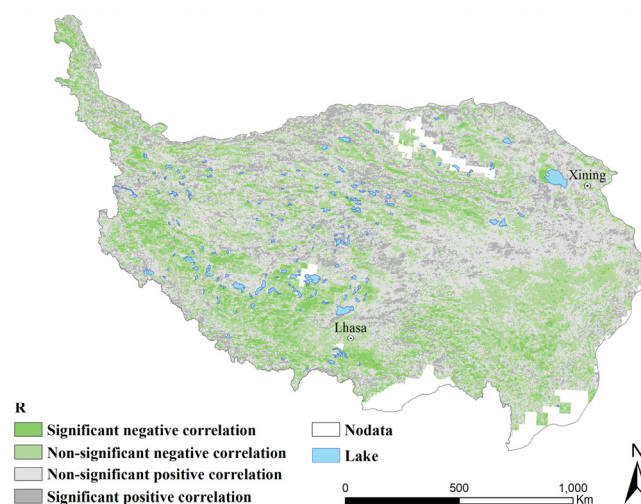


Figure 12. Cold season snow cover—warm season NDVI correlation.

4. Discussion

4.1. Lagged Response of NDVI to Other Meteorological Elements and Its Relationship with Snow Cover

The lagged effects of other meteorological elements on the NDVI may also have influenced the lagged response of snow cover, so we explored the correlations between the lagged effects of precipitation, temperature, and solar radiation on the NDVI. The lagged effects of precipitation on the NDVI are shown in Figure 13a. From a temporal perspective, the multi-year monthly precipitation and NDVI were strongly correlated, and the intra-annual fluctuations in the monthly mean time series corresponded well with the peak and trough values (maximum and minimum values). The maximum NDVI values occurred simultaneously with the precipitation values in 1991, 1993, and 1998. The minimum precipitation values generally occurred at the end of the year, whereas the minimum NDVI values often occurred in the following spring with a lag of about one season (3–4 months), which was related to the effect of cold season snowfall on vegetation in the highlands. The temporal correlation with temperature was very similar to the relationship between the precipitation and NDVI, as shown in Figure 13b. The temperature and NDVI throughout the year were positively correlated in terms of the occurrence of the high and low values. In particular, the highest NDVI values occurred in August and September each year, which corresponded to the highest temperatures in July. Thus, there was a lag of approximately 1 month between the maximum monthly NDVI and the maximum monthly mean temperature and a slightly longer lag of 2–3 months between the minimum values. The relationship between the year-by-year monthly mean solar radiation distribution and NDVI is shown in Figure 13c. The intra-annual temporal trends in the solar radiation and NDVI were the same, with the lowest solar radiation in December and the lowest NDVI in early spring, i.e., there was a seasonal lag. The highest value occurred in July, and the highest NDVI value also occurred with a lag of 1 to 2 months.

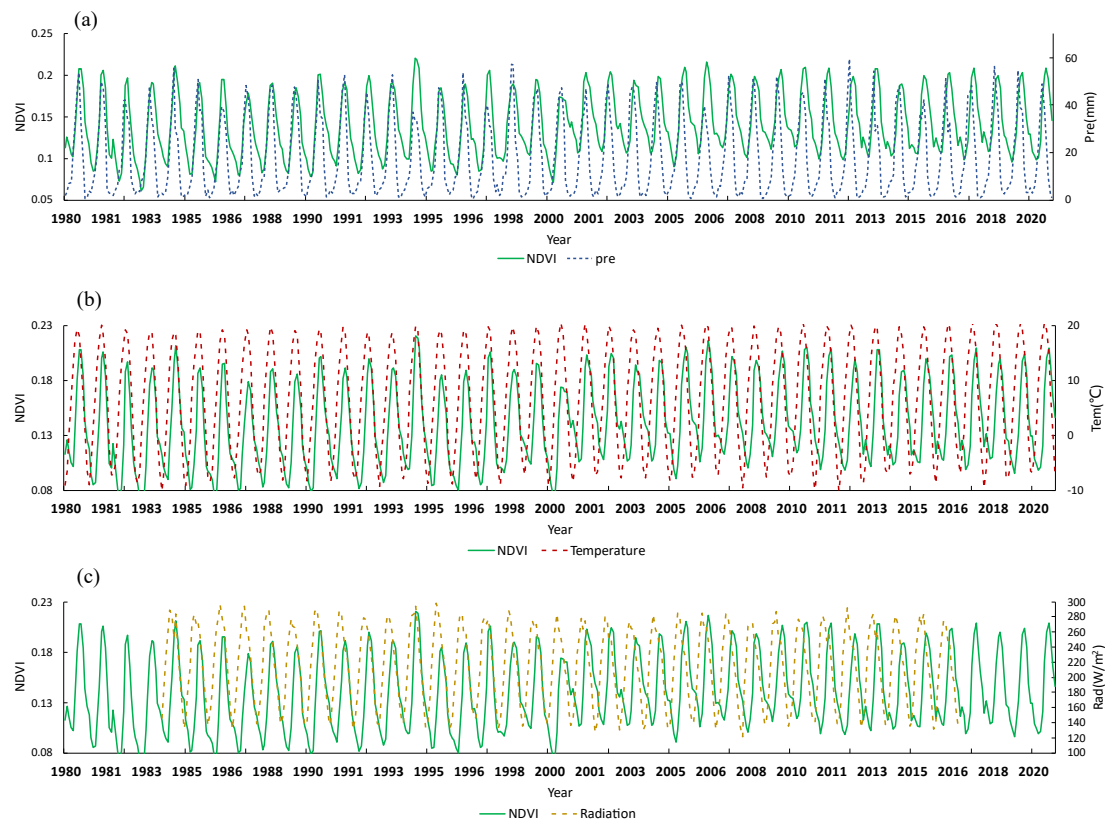


Figure 13. Monthly mean distribution of meteorological elements—NDVI: (a) NDVI-pre; (b) NDVI-Tem; (c) NDVI-Rad.

Compared with the lagged responses of the NDVI to other meteorological elements, the response time to snow cover was significantly shorter, i.e., the effect of snow cover changes on the NDVI was more rapid, but the effect was closely related to changes in meteorological elements, such as temperature, precipitation, and solar radiation. The relationships between the climate, snow cover, and vegetation are complex, but the effects of other climatic elements were not fully considered in this study. In particular, the influence of summer precipitation was not considered when assessing the correlation between the snow cover in spring and NDVI in the summer in the seasonal lag study, and thus, the cause of the lagged response and specific effects requires further study.

Finally, we employ the distributed lag regression model to estimate the lagged response length of NDVI to precipitation, temperature, and solar radiation and compare this data with the depth of snow cover and NDVI. As presented in Table 4. The lag time varies significantly among different factors, with the mean values of the vegetation growth response to precipitation, temperature, and solar radiation being 1.13 (SD = 1.00), 1.52 (SD = 0.93) and 2.60 (SD = 0.62) months, respectively. However, we also observe that the adjusted R^2 of the distributed lag regression model is low, which could be attributed to the large heterogeneity of the atmospheric environment on the plateau, leading to a poor overall fit. Thus, the results should be interpreted with caution, and the future research direction is to delineate the study area by climate type and conduct a more nuanced analysis of the lagged effect.

Table 4. Lag length (months) of the NDVI to SND (snow depth), PRE (precipitation), TEM (temperature), and RAD (solar radiation).

	Mean	PRE SD	R ²	Mean	TMP SD	R ²	Mean	RAD SD	R ²
NDVI	1.13	1.00	0.2	1.52	0.93	0.42	2.60	0.62	0.12

4.2. Investigation of the Mechanism Responsible for the Effect of Snow Cover on Vegetation

Snowpack affects vegetation in two ways: on the one hand, it affects soil temperature, which is the temperature effect; on the other hand, it affects soil moisture, which is the water effect. These two effects affect vegetation phenology, which ultimately affects NDVI or GPP (Gross Primary Productivity). At the same time, there are many parameters of snowpack that are affected not only by snow depth but also by snow area, snow phenology, and snow water equivalent [35]. The relationship between snow cover and vegetation is complex, and snow cover often acts on vegetation through intermediate links to influence the phenology of vegetation; thus, the effect of snow cover is indirect. Generally speaking, snow cover affects vegetation by influencing other variables, such as soil temperature, soil moisture, and surface temperature, thereby affecting the phenology of vegetation [13]. In order to clarify the positive and negative feedback relationships between the snow cover and vegetation on the QTP in a systematic manner, we explored the mechanism that allows snow cover to influence vegetation. Based on the results obtained by correlation analysis and lag analysis, we can clarify the main factors that allow snow to affect the phenology of vegetation on the plateau and determine the relationships between factors with direct and indirect effects. We can also quantitatively analyze the specific effects of the snow/soil temperature and humidity/ground temperature on the vegetation rejuvenation period. A structural equation model will be constructed to explore the relationship between the phenology of vegetation in response to changes in snow cover. Thus, it will be possible to further clarify the factors that might determine the effects of snow cover on vegetation on the QTP, particularly the phenology of vegetation, to better understand the relationship between snow cover and vegetation. This will provide data references and support scientific decision-making directions for exploring environmental changes on the QTP under climate change scenarios, as well as for the future development of plateau animal husbandry and the protection and restoration of the ecosystem.

Meanwhile, the data and methods employed in this study may also have potential limitations. For instance, the change in snow cover in this study refers to snow depth, which is the primary characteristic and indicator of snow cover, but it is not the sole element reflecting snow conditions. Snow area, snow onset date, snow end date, and snow duration can all serve as supplementary indicators for further detailed research. Additionally, this study uses NDVI as an indicator of vegetation growth, but it can be substituted with NPP (Net Primary Productivity) or the green-up period of vegetation. Establishing a correlation study based on dates, such as the correlation between the snow end date and the green-up period of vegetation, could also provide a better explanation for the effects of snow cover on vegetation.

5. Conclusions

In this study, we examined the correlations between changes in snow cover and the NDVI and investigated the response of the NDVI to snow cover changes on the QTP. Our main conclusions can be summarized as follows: The snow depth on the whole plateau exhibited significant small fluctuations, where the multi-year rate of change was -0.016 mm/a. The NDVI did not increase significantly over a large area, and the multi-year rate of change was 0.0005 /a. The changes in snow cover were negatively correlated with the changes in NDVI over time, and other meteorological factors also had correlations, where the Pearson correlations significance followed the order of precipitation > snow depth > temperature > solar radiation. The overall spatial correlations between the snow cover and NDVI had pronounced regional characteristics; the impact of snow cover on vegetation was more significant in high-altitude areas. The maximum snow depth corresponded to the lowest NDVI value with a lag of about 2 months, and abnormally deep snow cover caused by heavy snowfall events had negative impacts on the NDVI for more than 3 years. Compared with the effects of snow in winter on the NDVI in spring, the lagged effect of snow in spring on the NDVI in summer was weaker. The lagging effect was significant inter-annually, but not intra-annually, and extreme weather exacerbated the inter-annual lagging effect. The hysteresis effect was inter-annual but not intra-annual, and extreme weather exacerbated the inter-annual hysteresis effect. These findings have implications for animal husbandry and ecological protection in the QTP region. Future work in this area will contribute to the sustainable development of plateau animal husbandry and ecological protection.

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Data Availability Statement: All observational datasets and model simulations used in this study are publicly available. Snow depth data are available from the TPDC China Snow Depth Long-Time Series Dataset at <http://data.tpdac.cn/zh-hans/data/df40346a-0202-4ed2-bb07-b65dfcda9368/> (accessed on 30 August 2022). NDVI data are available from NOAA GIMMS NDVI3g at <https://www.star.nesdis.noaa.gov/pub/corp/scsb/wguo/data/> (accessed on 5 September 2022). Temperatures data are available from TPDC China 1km resolution monthly average temperature dataset (1901–2020) at <http://poles.tpdac.cn/zh-hans/data/71ab4677-b66c-4fd1-a004-b2a541c4d5bf/> (accessed on 10 April 2023). Precipitation data are available from TPDC China 1 km resolution monthly precipitation dataset (1901–2020) at <http://www.tpdac.cn/zh-hans/data/faae7605-a0f2-4d18-b28f-5cee413766a2/> (accessed on 10 April 2023). Solar radiation data are available from a high-resolution (10 km) surface solar radiation dataset for regional fused insolation hours in China (1983–2017) at <http://www.tpdac.cn/zh-hans/data/a82849b0-9af5-457d-8968-4471dd845f2e/> (accessed on 10 April 2023). Qinghai–Tibet plateau border data are available from the Integration

dataset of Tibet Plateau boundary at <http://data.tpdc.ac.cn/zh-hans/data/61701a2b-31e5-41bf-b0a3-607c2a9bd3b3/> (accessed on 10 October 2020).

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