The different impacts of the daytime and nighttime land surface temperatures on the alpine grassland phenology

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Abstract. Land surface temperature (LST) is often a direct control on herbaceous plants but has been under-appreciated on the alpine grassland phenology in response to climate change. In the present study, we used satellite data of the Moderate Resolution Imaging Spectroradiometer (MODIS) Normalized Difference Vegetation Index (NDVI) and LST products to study the land surface phenology (LSP) of alpine grasslands in response to LST changes in the Qinghai Lake Basin (QLB), which is on the northeastern Tibetan Plateau. Our results showed that LSP, including the start (SOS), end (EOS), and length (GSL) of the growing season, presented high spatial heterogeneity and had significant correlation with landform elevations. Both averaged SOS and EOS across QLB were advanced from 2001 to 2017, but the greater advancement of SOS compared to that of EOS led to an overall prolonged GSL. Daytime LST (LSTd) and nighttime LST (LSTn) had the contrasting effects on SOS (i.e., SOS can be delayed with the increase in LSTd, while it can be advanced with the increase in LSTn). However, increase in LSTd and LSTn in August had the same advancing effect on EOS. Moreover, LSTd played the dominant role in controlling the grassland phenology. Specifically, an 1°C increase in the LSTd in the non-growing season (i.e., from previous October to April) significantly postponed the SOS by 2.2 d and advanced the EOS by 1.1 d in August. This study highlights the utility and biological relevance of LST in research of grassland phenology and differential impacts of daytime and nighttime LST on grassland phenology.

Key words: land surface phenology; land surface temperature; alpine grassland; Tibetan Plateau.

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INTRODUCTION

Vegetation phenology is a long-studied discipline of ecology, which focuses on the periodic biological events in vegetation growth and their relationship with environmental factors (Richardson et al. 2013, Tang et al. 2016, Chuine and Régnière 2017, Helman 2018). Because the vegetation life cycle is highly sensitive to climate change, phenophases are important biological indicators for understanding how ecosystems are affected by climate changes and how it will change in the future (Wolkovich et al. 2014, Buitenwerf et al. 2015, Johansson et al. 2015). For example, global warming has had demonstrable effects on plant phenology around the world and resulted in a general earlier onset of spring and delayed onset of autumn in most regions of the northern hemisphere since the 1970s (Cleland et al. 2012, Ge et al. 2015, Gill et al. 2015, Körner et al. 2016, Wang et al. 2016, Richardson et al. 2018). Shifts in phenology can also affect land–atmosphere interactions and ecosystem functions such as canopy conductance and albedo and, more broadly, carbon and water cycling and energy fluxes (Calderaru et al. 2013, Richardson...
et al. 2013, Keenan et al. 2014, Zhou et al. 2016, Liu et al. 2017). Therefore, it is crucial to explore the variability and climatic controls of vegetation phenology across multiple scales, in order to improve our understanding of terrestrial ecosystem response to climate change.

It is widely acknowledged that air temperature has a major influence on plant growth (Gill et al. 2015, Liu et al. 2016, Richardson et al. 2018). During the past few decades, sprawling investigations have revealed a deep mechanistic understanding of vegetation phenology variations in response to temperature based on plant physiological processes (Pope et al. 2014, Shi et al. 2014, Martínez-Lüscher et al. 2017, Shi et al. 2017, Lin et al. 2018). For example, earlier studies mainly focused on the spring high temperature, which significantly advances seed germination and leaf unfolding according to higher growing rate in spring (Fujisawa and Kobayashi 2010, Körner et al. 2016, Shi et al. 2017). However, recent research revealed that winter low temperature also plays an important role in plant dormancy and warming in winter may postpone vegetation spring onset due to delayed chilling fulfillment (Luedeling and Gassner 2012, Vitasse et al. 2014, Fu et al. 2015, Martínez-Lüscher et al. 2017). For autumn senescence, higher temperatures in summer and autumn may enhance activities of photosynthetic enzymes and slow down the speed of chlorophyll degradation during autumn leaf senescence (Shi et al. 2014, Liu et al. 2016). On the other hand, temperature-induced drought stress may influence carbon and water processes, which, finally, end up with earlier leaf coloration and leaf fall (Hinckley et al. 1979, Barber et al. 2000, van der Molen et al. 2011, Kang et al. 2018). Moreover, daytime and nighttime air temperatures were recently reported to have different influences on vegetation phenology. For example, satellite-derived green-up date was determined mainly by daytime temperature in the northern hemisphere between 1982 and 2011 (Piao et al. 2015). While others report that nighttime minimum temperature has a dominant effect on vegetation green-up date on the Tibetan Plateau (Shen et al. 2016, Li et al. 2019).

However, the impacts of daytime and nighttime land surface temperature (LST) on vegetation phenology are less investigated, especially for alpine grassland ecosystems due to serious weaknesses in data collections (Yu et al. 2010, Zhang et al. 2013). Given that the dominant species in alpine grasslands are usually herbaceous with short rhizome, it is perhaps more correct to assume that vegetation phenology would be more sensitive to LST in alpine ecosystems (Ernakovich et al. 2014). In detail, it is assumed that phenological shifts of most woody plants are closely related to air temperature variations as they have strong stems and can grow to a considerable height (at least 13 feet) above the ground. By contrast, herbaceous plants usually have no persistent woody stem above ground and are comparatively small and short, which is expected to be more sensitive to even minor changes in LST (Ernakovich et al. 2014). Therefore, it is possible that alpine grassland phenology can be more associated with LST variations. However, previous studies mainly elucidated that LST can be a key indicator for monitoring urban heat island (UHI) and vegetation dynamics, and few studies have investigated the influence of LST on vegetation phenology in alpine ecosystems (Julien and Sobrino 2009, Julien et al. 2011, Clinton and Gong 2013, Phompila et al. 2015). In any case, there remains a lack of information about how alpine grassland responds to LST, and this has led to limits in the precise projection of grassland phenology dynamics.

In the past few decades, the records of satellite-derived vegetation indices (VIs) provide an opportunity to generate ecological indicators (i.e., land surface phenology, LSP) available at regional scales, especially in the Tibetan Plateau where the in situ observations are scarce. In addition, remote sensing data provide geospatial products (i.e., MODIS-LST) that reveal broader patterns of land surface temperature variability and make it possible to investigate temperature impacts on phenological dynamics at large scales (Julien and Sobrino 2009, Clinton and Gong 2013, Guo et al. 2014). It thus provides the potential to bridge the gap between vegetation dynamics and LST variations at regional scales, with analyzing correlations between LSP and LST at the same spatial resolution. Therefore, it might provide basis for uncovering the response mechanism of alpine grassland to climate warming.

Here, the primary objectives of the present study were to explore how LSP of alpine grassland responds to LST changes by using the time
series of MODIS-NDVI data and MODIS-derived daytime and nighttime LST (i.e., LST$_d$ and LST$_n$), conducting at a typical alpine grassland on the northeastern margin of the Tibetan Plateau. The major research contents included the spatiotemporal variation of key phenological metrics such as start, end, and length of the growing season (SOS, EOS, and GSL, respectively) and, more importantly, the relationship between LSP and LST variables at different spatial and temporal scales. The present study will offer scientific basis for the eco-environmental protection in alpine grassland and response on fragile ecosystems to global climate change.

**MATERIALS AND METHODS**

**Study area**

The Qinghai Lake Basin (QLB), located on the northeastern margin of the cold Tibetan Plateau (Fig. 1), is of less human disturbances and abundant grassland resources, making it an ideal place to study the temperature effects on alpine grassland phenology. It is within the range of 36°15′–38°20′ N and 97°50′–101°20′ E, and the average altitude ranges from 3007 m to 5285 m. The climate is defined as a plateau continental climate with an annual mean air temperature of 2°C and an annual mean precipitation of approximately 330 mm based on the long-term record since the 1960s. Annual average LST$_d$ and LST$_n$ are 14.3°C and −8.7°C, respectively. Moreover, both LST$_d$ and LST$_n$ have a large range between minimum and maximum temperatures, but it is always higher around Qinghai Lake and main rivers such as Buha River and Daotang River (Fig. 2). Grassland is a widely distributed vegetation type in the study area and plays an important role in supplying feed for livestock and maintaining ecological stability in alpine ecosystems (Guo et al. 2014, Yang et al. 2018). In addition, alpine meadow and alpine steppe are two main typical grasslands in the QLB, which can be regarded as a fine representation of the alpine grassland ecosystem on the Tibetan Plateau.

**NDVI time-series data and LST data**

In the present study, we selected the MODIS-derived 16-d composite vegetation indices (MOD13A1, V006) of atmospherically corrected maximum values at a 500-m resolution from 2001 to 2017. These data were reprojected to Albers equal area projection and WGS84 datum from the original projection by using the MODIS reprojection tool (MRT). The nearest neighbor resampling approach was employed.

The LST data from Terra MODIS product (MOD11A2, V006, 8-d composite, and 1-km spatial resolution) were used to represent temperature variables in this study, which were downloaded from the NASA website (https://wist.echo.nasa.gov). Then, we extracted the LST$_d$ and LST$_n$ from the remote sensing products, and all LST images are first transformed into the WGS1984 coordinate system based on control points on topographic maps and are then adjusted to the spatial resolution of NDVI images by using the nearest neighbor method for resampling.

**Phenological metric extraction and verification**

By extracting the pixel values in each NDVI image and integrating all images, the pixels of these images with the same row and column number are connected together to form a continuous time-series curve. Although the highest-quality reflectance values have been selected, some poor-quality values may still exist as the sensor is interfered by cloud, atmospheric aerosols, snow, and ice. Therefore, further reconstruction of NDVI time series is required to obtain credible phenological metrics. Here, three methods were tested, which are available in the TIMESAT software: Savitzky-Golay filtering, asymmetric Gaussian, and double logistic (Stanimirova et al. 2019). We applied the asymmetric Gaussian function since it has been reported to better perform in depressing noise in grassland ecosystems (Zhu and Meng 2015).

The extraction of vegetation phenological metrics is critical in monitoring vegetation growth status from a large scale and providing a theoretical basis for evaluating the interaction between climate change and terrestrial ecosystems. We extract the key phenological metrics (i.e., SOS, EOS, and GSL) for each pixel from the smoothed NDVI time series using a relative threshold method (White et al. 1997, Wang et al. 2016), which has been widely adopted in research of satellite-derived phenology. The relative threshold method defines the LSP as the date when fitted curve reaches a specific proportion...
Fig. 1. Map of the Qinghai Lake Basin. The maps show the geographic location of the study area in Tibetan Plateau, China.
The SOS and EOS were determined to be the day of year (DOY) when NDVI\textsubscript{ratio}(t) firstly reaches 0.1 and 0.5, respectively.

The in situ long-term observations of grass phenology from 2003 to 2017 at Tianjun station (99°02' E, 37°08' N) were used to validate...
remotely sensed SOS and EOS. The altitude of the Tianjun Station is 3418 m, and the dominant species at the study site are *Stipa krylovii* Roshev (Gramineae) and *Poa crymophila* (Gramineae).

**Trend analysis**

Simple linear regression analysis was used to simulate the trend of LSP from 2001 to 2017. The following simple linear regression analysis model was applied to the research:

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

(2)

where $n$ is the number of studied years; $LSP_i$ is the DOY of vegetation phenology in year $i$; and slope $> 0$ means the changing tendency of vegetation phenology among $n$ years is delayed, and on the contrary, it is advanced (Wang et al. 2016).

The Mann-Kendall test (Mann 1945, Kendall 1975) and Sen’s slope estimator test (Sen 1968) were also applied to the whole time series to detect the direction and magnitude of LSP and LST trend. These tests have been frequently used to quantify the significance of trends in meteorological time series (Gocic and Trajkovic 2013, Sang et al. 2014, Serinaldi et al. 2018, Wang et al. 2020). Because of their widespread use, we do not describe them in detail and equations are clarified with reference to Gocic and Trajkovic (2013). In the present study, significance levels $\alpha = 0.01$ and $\alpha = 0.05$ were used.

**Correlation analysis of LSP and LST**

The Pearson correlation coefficient is widely used in the sciences as a measure of the degree of linear dependence between two variables. This study uses the Pearson correlation coefficient to measure the linear correlation among the LST and phenophases in order to find the driving forces of vegetation phenology change. The formula of the Pearson correlation is as follows:

$$r_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

(3)

where $r_{xy}$ is the simple correlation coefficient of variables $x$ and $y$; $x_i$ is the phenological metrics of the $i$th year; $y_i$ is the monthly LST$_d$ or LST$_n$ of the $i$th year; $\bar{x}$ is the average phenological metrics for all years; and $\bar{y}$ is the average monthly LST$_d$ or LST$_n$ for all years (Mu et al. 2013).

We first examined the correlation coefficients between monthly LST in nongrowing season (i.e., from previous October to April) and averaged SOS and between monthly LST in growing season (i.e., May to September) and averaged EOS. For months whose correlation coefficients ($r$) were significant ($p < 0.05$), we further explored the spatial patterns of their relationship with phenological metrics across the QLB.

**Temperature sensitivity of LSP**

The temperature sensitivity of alpine grassland LSP was determined as the slope of the linear regression between the time series of SOS/EOS and monthly LST from 2001 to 2017, which illustrated a time shift of the phenophases in response to a unit shift in LST.

**RESULTS**

**Spatial patterns of LSP**

The ground-based green-up date and coloring date were significantly positively correlated with SOS ($r = 0.633$, $p = 0.010$) and EOS ($r = 0.601$, $p = 0.018$), derived from remotely sensed data, respectively (Fig. 3). These results indicate that the satellite-derived records can reveal the LSP variations and can be used to analyze the regional LSP.

Spatial patterns of SOS, EOS, and GSL were represented by their mean values over the study period (2001–2017; Fig. 4). SOS showed a wide dynamical range from DOY 64 to DOY 172. An obvious delayed tendency of SOS extended horizontally from southeast to northwest, which was strongly related to the increasing tendency in elevations. Low-elevation (<3600 m) regions accounted for the largest proportion of early SOS (<DOY 130) but the smallest of late SOS (>DOY 150; Fig. 5). Over the region, 54.0% of the alpine grassland showed spring onset from mid- to late May (DOY 130–150), primarily occurring at mid-elevation areas (28.5%). Regions with late SOS, for example, after DOY 150, were mainly found in alpine desert at northwest of the QLB with an elevation over 4200 m, covering about 18.3% of the QLB.

The spatial distribution of EOS is shown in Fig. 4b. Contrary to the spatial pattern of SOS, EOS showed an obvious advanced tendency horizontally from southeast to northwest, which...
was significantly negatively correlated with elevation. Over the region, low-elevation areas around Qinghai Lake consisted of the most proportion in EOS later than DOY 290 (Fig. 5), and the latest EOS was found around Daotang River. 64.2% of the QLB had EOS ranged from DOY 270 to DOY 290, mainly at mid-elevation regions. High regions at the northwest QLB represented early EOS between DOY 260 and DOY 270, accounting for about 14.1% of QLB.

The GSL showed clear spatial patterns over QLB that it decreased from southeast to northwest (Fig. 4c). The absolute values ranged from 86 to 276 d, and the regions with the GSL shorter than 120 d were mainly found in the northwest high-elevation regions (17.7%; Fig. 5). The GSL longer than 140 d was found around the Qinghai Lake (26.2%), where the SOS was earlier than DOY 140 and the EOS was later than DOY 280 in those low-elevation areas. Overall, the spatial difference in phenological metrics displayed great consistency with topographical features and elevations.

**Spatial and temporal variations of LSP**

From 2001 to 2017, the regionally averaged SOS and EOS were 141 DOY (range: 131–149 DOY) and 279 DOY (range: 272–282 DOY), respectively. The interannual variation in regionally averaged SOS and EOS showed asymmetric advancing trend at a rate of −2.0 and −1.3 d/decade, respectively (Fig. 6). However, it presented obvious spatial differences regionally. For SOS, 72.8% of pixels over the region showed advancing trends, mostly at the central area of the QLB, and in both northern and southern parts of the Qinghai Lake (Fig. 7a). Most of the advancing trends were <2 d/decade, and only 7.1% were significant in northern Qinghai Lake and western Daotang River (Fig. 7b). The other 27.2% of pixels showed delaying SOS, mainly in the northwestern to the Qinghai Lake areas, as well as the eastern Daotang Lake, and 6.7% of pixels delayed over 10 d (Fig. 7a).

At the regional level, 70.0% of pixels showed advancing EOS, mostly <5 d/decade, mainly in the northwestern and central of QLB, as well as the north and south parts around the Qinghai Lake, but only 8.2% were significant in central basin and north part of Qinghai Lake (Fig. 7c, d). The areas with delayed trend in the basin are mainly located in the vicinity of the north bank of Qinghai Lake, the middle and lower reaches of the Buha River and the Daotang River. Regions delayed within 10 d accounted for 28.1% of QLB and EOS in areas where returned farmland to forest on the north to east bank of Qinghai Lake was delayed by about 5 d (Fig. 7c).

The spatial differences in SOS and EOS variations resulted in the obvious discrepancy of GSL changes in QLB. From 2001 to 2017, the averaged GSL of vegetation was extended by 1.2 d, and its

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**Fig. 3.** Correlations between the satellite-derived start of the growing season (SOS) and mean green-up date of grass species at Tianjun station and between the satellite-derived end of the growing season (EOS) and mean coloring date of grass species at Tianjun station.
Fig. 4. Spatial patterns of 17 yr of mean (a) start of the growing season (SOS), (b) end of the growing season (EOS), and (c) the growing season length (GSL) in the study area.
A slight extension trend was due to earlier SOS of the vegetation in QLB. The areas with prolonged GSL are widely distributed in the middle northern part of QLB, the northern and southern part of Qinghai Lake, and the west of the Daotang River (Fig. 7e), accounting for 56.8% of the region. The northern part of Qinghai Lake showed most significant extension ($P < 0.05$),
and GSL of vegetation was extended for more than 10 d owing to the grain vegetation cover from green policy (Fig. 7f). The areas of shortened GSL were concentrated in the middle and western basin, the northwestern side of Qinghai Lake, and the eastern side of the Daotang River. 43.2% of pixels showed shortened GSL, but GSL was shortened by more than 10 d in the northwest alpine desert, the northwestern shore of the Qinghai Lake, and the eastern side of the Daotang River (Fig. 7e).

Fig. 7. Spatial patterns of the start, end, and the length of the growing season (SOS, EOS, GSL) changes for 2001–2017. (a) and (b) represent the trend of SOS and its p values; (c) and (d) represent the trend of EOS and its p values; and (e) and (f) represent the trend of GSL and its p values.

**Relationships between LSP and LST across QLB**

We found mean LST$_d$ in nongrowing season and averaged SOS in QLB were positively correlated, with a correlation coefficient of 0.49 ($P < 0.05$; Table 1). However, negative correlation between mean LST$_n$ in nongrowing season...
and averaged SOS was observed, with a correlation coefficient of $-0.35$ (Table 1). During growing season, only LST$_d$ in August showed significant impact on EOS, with a correlation coefficient of $-0.69$ ($P < 0.01$; Table 2). Therefore, nongrowing season and August were identified as the related periods that were important for alpine grassland phenology.

To quantify the spatial patterns of LSP in response to LST variations, we calculated the correlations between SOS and nongrowing season LST, EOS, and August LST across the QLB. The absolute value of correlation coefficient ($r$) between phenophases and LST$_d$ was compared with that between phenophases and LST$_n$ to examine which factor was more dominant in influencing vegetation phenology. The results revealed that both SOS and EOS were more sensitive to LST$_d$ variations over the QLB. As shown in Fig. 8a, b, LST$_d$ covers more area in which LST$_d$ variations had stronger impact on vegetation phenology compared with that of LST$_n$, with 60.87% in the nongrowing season and 58.57% in August, respectively. This suggested a dominant role of LST$_d$ in controlling the vegetation phenology in QLB. Furthermore, LST$_d$ in the nongrowing season was mainly positively correlated with SOS (56.94%) and LST$_d$ in August was mainly negatively correlated with EOS (48.97%; Fig. 8c, d). This relationship indicated that increase in

### Table 1. Correlations between the start of growing season (SOS) and land surface temperature (LST) during the nongrowing season.

| Month        | LST$_d$ Mean LST (°C) | Pearson’s r | Temperature sensitivity (d/°C) | LST$_n$ Mean LST (°C) | Pearson’s r | Temperature sensitivity (d/°C) |
|--------------|-----------------------|-------------|-------------------------------|-----------------------|-------------|-------------------------------|
| Nongrowing season | 7.58                  | 0.49**      | 2.24                          | −13.75                | −0.35       | −2.65                         |
| October      | 11.67                 | 0.50**      | 0.93                          | −6.03                 | −0.25       | −1.19                         |
| November     | 5.63                  | 0.38        | 1.05                          | −12.55                | 0.04        | 0.12                          |
| December     | 0.02                  | −0.03       | −0.1                          | −17.98                | −0.28       | −1.37                         |
| January      | −0.81                 | 0.29        | 1.06                          | −21.50                | −0.26       | −0.49                         |
| February     | 5.38                  | 0.17        | 0.92                          | −17.96                | 0.06        | 0.34                          |
| March        | 13.63                 | 0.42*       | 0.87                          | −12.51                | −0.04       | −0.18                         |
| April        | 17.52                 | 0.09        | 0.15                          | −7.75                 | −0.43*      | −2.05                         |
| May          | 20.74                 | −0.24       | −0.46                         | −2.89                 | 0.04        | 0.35                          |

*Note:* Correlation and sensitivity without an asterisk are not significant ($P > 0.1$).  
* $P < 0.1$.  
** $P < 0.05$.  
*** $P < 0.01$.

### Table 2. Correlations between the end of growing season (EOS) and land surface temperature (LST) during the growing season.

| Month        | LST$_d$ Mean LST (°C) | Pearson’s r | Temperature sensitivity (d/°C) | LST$_n$ Mean LST (°C) | Pearson’s r | Temperature sensitivity (d/°C) |
|--------------|-----------------------|-------------|-------------------------------|-----------------------|-------------|-------------------------------|
| Growing season | 20.74                 | −0.26       | −0.60                         | 2.32                  | −0.16       | −0.71                         |
| May          | 20.54                 | 0.11        | 0.09                          | −2.10                 | −0.40       | −1.48                         |
| June         | 21.58                 | −0.04       | −0.06                         | 1.79                  | −0.38       | −0.81                         |
| July         | 23.29                 | 0.09        | 0.13                          | 6.33                  | 0.19        | 0.38                          |
| August       | 21.35                 | −0.69***    | −1.09                         | 4.39                  | −0.33       | −1.11                         |
| September    | 16.97                 | −0.41       | −0.61                         | 1.19                  | 0.24        | 0.74                          |

*Note:* Correlation and sensitivity without an asterisk are not significant ($P > 0.1$).  
* $P < 0.1$.  
** $P < 0.05$.  
*** $P < 0.01$.  

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LST<sub>d</sub> in the nongrowing season postponed SOS and increase in LST<sub>d</sub> in August advanced EOS.

**DISCUSSION**

**Spatial and temporal changes in LSP**

Vegetation plays a key role in regulating the process of carbon cycling and energy exchange among soil, water, and atmosphere regionally and globally (Caldararu et al. 2013, Richardson et al. 2013, Tang et al. 2016). The spatial-temporal patterns of vegetation phenology directly reflect the annual and seasonal climate change, and present spatial discrepancy as the hydrothermal conditions varied according to elevations (Fig. 5). In the present study, the spatial pattern of the 17-year averaged LSP showed obvious spatial heterogeneity across QLB (Fig. 4). An obvious delayed trend of SOS and advanced trend of EOS extended horizontally from southeast to northwest along the altitudinal gradient. SOS was significantly negatively correlated with EOS, suggesting an early SOS may generally be accompanied by a late EOS; it thus resulted in great discrepancy in GSL of alpine grassland. For the whole region, the area with GSL longer than 150 d was mainly distributed in south of the Qinghai Lake shore (meadow zone) and central alpine steppe of north of the Qinghai Lake. Steppe around Buha River bank showed longest GSL as the vegetation growth was under the greatest hydrothermal conditions at low altitude. In the western and northern alpine meadow zone, GSL was shorter than 110 d mainly due to relative low temperature in spring and frequently early snow at high altitude; thus, it consequently led to a late SOS, early EOS, and short GSL.

Furthermore, the overall prolonged GSL was attributed to the asymmetric advance of the

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![Diagram](https://example.com/diagram.png)

**Fig. 8.** Spatial distributions of response relationships between LSP and LST. (a) and (b) present the dominant role of LST<sub>d</sub> in controlling the SOS and EOS. (c) and (d) further reveal spatial distributions of negative and positive correlations between LST<sub>d</sub> and SOS/EOS, respectively. The inset bar charts show the percentage of the pixels over the QLB.
vegetation phenology, in particular with a trend that SOS advanced greater than EOS (Fig. 6). More importantly, alpine meadow and steppe zone in north of the Qinghai Lake contributed to the major extended GSL due to the significantly advanced trend of SOS. The results are in agreement with some previous studies, which indicated a general advanced SOS but diverse trend in EOS on the Tibetan Plateau (Yu et al. 2010, Dong et al. 2012, Che et al. 2014). However, previous studies also revealed that the earlier onset of spring phenology under the current warming climate differed in magnitude or even reverse, especially for the delayed spring phenology of alpine grassland (Yu et al. 2010, Dong et al. 2012, Fu et al. 2013). In the present study, we also found a delayed trend in SOS in middle alpine meadow and steppe and northwestern part of QLB, accounting for 27.3% of the study area (Fig. 7a). This is possible because whether vegetation green-up is delayed or advanced will to an extent rely on the trade-off between two opposing effects of warming in winter chilling and spring forcing (Luedeling and Gassner 2012, Vitasse et al. 2014, Fu et al. 2015, Martínez-Lüscher et al. 2017). The delayed trend of SOS, therefore, may be primarily due to a delay in the fulfillment of the chilling requirement caused by higher day LST, which may be stronger than the advancing effect of spring heat accumulation, and consequently postpone SOS in spring. To some extent, the results also reflect the feedback mechanisms of vegetation phenology to global warming in the high-cold mountain area of northern hemisphere.

**Differential effects of LST_{d} and LST_{n} on LSP**

By comparing the overall relationship between LSP and LST_{d} and LST_{n} at different timescales across the QLB (Tables 1, 2), as well as the spatial patterns at pixel scale (Fig. 8), we detected different effects of increased LST_{d} and LST_{n} on SOS variations but a same advancing effect on EOS. For SOS, increased LST_{d} during nongrowing season was positively correlated with SOS only except December ($r = -0.03$), while increased LST_{n} during nongrowing season was negatively correlated with SOS except November ($r = 0.04$) and February ($r = 0.06$). The overall significant positive correlation ($r = 0.49; P < 0.05$) between LST_{d} and SOS and a negative correlation ($r = -0.35; P > 0.05$) between LST_{n} and SOS indicated that increased LST_{d} would postpone SOS, whereas increased LST_{n} would result in an earlier SOS. This contrasting effect resulted in an advancing trend in SOS with a decrease in LST_{d} and an increase in LST_{n} during nongrowing season from 2001 to 2017 (Fig. 9).

It is possible that LST_{d} can go up to a higher level than the optimal temperature threshold of winter chilling, shifting the SOS to occur later by delaying the fulfillment of chilling requirement during nongrowing season (Schwartz and Hanes 2009, Harrington and Gould 2015, Shi et al. 2017). However, increase in LST_{n} during the nongrowing season can favor freezing resistance as the low temperature can reach an extreme level at land surface at night (Vitasse et al. 2014). In addition, a higher LST_{n} could provide more available soil water from snow and ice that is typically constrained by the low soil temperature (Yang et al. 2013, Yi et al. 2013). Once the soil moisture increases, plant roots absorb more water to prepare for the leaf unfolding. However, increase in both LST_{d} and LST_{n} in May, the primary month when the alpine grassland began to growth, had the same advancing effect on SOS due to increased heat accumulations.

However, the effect of LST on EOS tends to be more complex during the growing season. Increased LST_{d} and LST_{n} in growing season were negatively correlated with EOS and significantly for LST_{d} in August, which suggested that increased LST in August advanced alpine grassland EOS (Fig. 9). This result is in agreement with the findings of Che et al. (2014) and Li et al. (2018), who reported a significant negative correlation between the EOS of the Tibetan Plateau and air temperature in August. These might be primarily related to the increase in soil water stress and high rate of respiration (Kang et al. 2018). As the LST gradually rises to the highest level in August, soil water evaporation and plant transpiration increase synchronously and it thus leads to a limited soil moisture for EOS. On the other hand, plants may not be able to effectively utilize the long-term warmer conditions due to the high respiration rate, resulting in faster carbon degradation and earlier leaf senescence (Chen et al. 2016, Kang et al. 2018).
The dominant role of LST_d on LSP

The stronger relationship between LSP and LST_d compared with LST_n across the QLB suggested that alpine grassland was more sensitive to LST_d. Specifically, we found more area with higher absolute value of correlation coefficients between LST_d in nongrowing season and SOS and with higher absolute value of correlation coefficients between LST_d in August and EOS than those of LST_n, accounting for 60.87% (Fig. 8a) and 58.57% (Fig. 8b), respectively. Over the QLB, greater coefficient of variation (CV) was found in LST_d (0.12) than that in LST_n (−0.05) during the nongrowing season, indicating a greater fluctuation in LST_d than LST_n. The SOS was therefore could be more sensitive to the variations of LST_d. For the EOS, very high LST_d (21.35 \pm 1.43\degree C) compared with LST_n (4.29 \pm 0.67\degree C) can be the dominant factor that limited the growth of alpine grassland.

Moreover, most LST_d controlled areas were mainly located in the alpine meadow region of the central QLB and along the Buha River, where vegetation tended to have delayed SOS, advanced EOS, and shortened GSL in response to increases in LST_d. This relationship highlighted the future alpine grassland management to focus on the high LST_d in the phenology dynamics.

CONCLUSION

Our study is important because it provides valuable evidences of how alpine grasslands respond to land surface temperature changes in an alpine ecosystem. By using geospatial products (i.e., MODIS-NDVI and MODIS-LST products), we firstly evaluated the impact of LST on the large-scale phenology by the in situ and satellite observations in a case study of a typical alpine grassland on the Tibetan Plateau. Our results...
suggested that LST was not only a fine indicator of the urban heat island effect on vegetation dynamics, but also an innovative indicator for grassland phenology variations. Moreover, the complex vegetation–environment relations were poorly investigated under larger scale as the mismatch between satellite-based phenology and field meteorological records. MODIS-LST herein provides a consistent and repeatable measure of geospatial temperature that can be analyzed across different temporal and spatial resolutions. By analyzing the temporal trends and spatial patterns of LSP response to temperature variables, we found that LST_d and LST_n had different effects on grassland SOS, which to some extent demonstrated the underlying mechanism that related to the effects of temperature increases during vegetation dormancy. More importantly, both SOS and EOS were strongly controlled by LST_d rather than LST_n, which suggests a more precise temperature indicator for alpine grassland phenology and provides critical information for improving existing phenology models at high altitude.

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