Temporal and spatial changes in estimated near-surface air temperature lapse rates on Tibetan Plateau

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Lapse rate (LR) of near-surface (2 m) air temperature is essential for determining spatially distributed and gridded air temperature interpolated from in situ observational sites. However, due to the limitation of sparse observational networks, high-resolution LRs are not usually available on regional scales, especially in mountainous regions. The purpose of this study is to estimate LRs for the entire Tibetan Plateau (TP) using observed air temperature and moderate-resolution imaging spectroradiometer (MODIS) night-time land surface temperatures (LSTs) and to analyse the spatio-temporal changes of the estimated LRs. First, diurnal cycles of LRs derived from in situ observations in three subregions of the TP were analysed, which shows that the LRs in the western and northeastern regions were shallow in the cold season and steep in the warm season, whereas the southeastern region exhibited a different pattern. Further comparisons revealed that the LRs for night-time air temperatures better represented the LRs for daily mean air temperatures than the daytime ones, and the night-time MODIS LSTs correlated well with the night-time air temperatures, especially for the MODIS Terra data sets. Therefore, the night-time MODIS LSTs from the Terra data sets were used to estimate high-resolution (10 km) LRs for the daily mean temperatures over the entire TP. Estimated LRs over most areas of the TP were shallower than the commonly used environmental LR (−6.5 K/km). The LRs in the southeastern region were steeper than those in the northeastern region, while steeper LR values occurred in the northwestern region with lower temperatures and less humidity.

KEYWORDS
lapse rates, MODIS land surface temperatures, spatial–temporal variability, Tibetan Plateau

\section{INTRODUCTION}

Air temperature is an important input variable for a variety of spatially distributed hydrological and ecological models. Specifically, it is used to calculate processes such as evapotranspiration, snowmelt, soil decomposition, and plant productivity (Dodson and Marks, 1997). In fact, these processes are sensitive to air temperature, especially in the cryospheric regions where it influences the melting of snow, glaciers, and permafrost. Additionally, exchanges of energy and water fluxes between the earth surface and atmosphere can be affected by air temperature (Li \textit{et al.}, 2013). However, due to the irregular and sparse distribution of observation stations, the continuous and accurate distribution of near-surface air temperature data across large areas is not
available (Chiu et al., 2009; Burt and Holden, 2010). Therefore, quantifying the spatial distribution of temperature, especially in regions with varied topography, is important for recognizing different types of precipitation, accurately modelling runoff and evaporation, and understanding annual variations in snow, glaciers, and permafrost distributions (Minder et al., 2010).

Generally, air temperature decreases along with increasing elevation which is defined as lapse rate (LR) (e.g., Kattel et al., 2013). The global mean LR is often taken as $-6.5 \text{ K/km}$ (Michlmayr et al., 2008; Gao et al., 2012; Immerzeel et al., 2012). The LR is often used to extrapolate point measurements to grids, highlighting the importance and necessity of realistic LRs in the generation of gridded air temperature. However, the use of mean LR values can be problematic because LRs may not accurately represent properties of the real atmosphere throughout all regions, as well as during particular seasons. Moreover, LRs vary at diurnal and seasonal timescales because of changes in sensible heat flux between the free atmosphere and underlying surface (Gardner et al., 2009).

LRs are not only influenced by macro-topography (Yoshino, 1975) but also by complex terrains, such as plateaus, mountainous regions, basins, plains, and so forth. Steeper LRs occur with higher levels of solar radiation (Hu, 1996; Erlick and Ramaswamy, 2003; Harlow et al., 2004). Higher wind speed also steepens LRs, especially at night (even close to dry adiabatic LR, $-9.5 \text{ K/km}$), and moister atmospheres produce shallower LRs (close to moist adiabatic LR, $-4.0 \text{ K/km}$) (Jain et al., 2008; Kirchner et al., 2013). Specifically, previous studies have revealed some basic characteristics of region-averaged LRs throughout the Tibetan Plateau (TP) (Wang et al., 2011; Li et al., 2013; Guo et al., 2016; Wang et al., 2016) and other regions (Du et al., 2017). However, studies on LRs with spatially
continuous distribution and high resolution throughout the TP are still lacking.

Moderate-resolution imaging spectroradiometer (MODIS) land surface temperatures (LSTs) have been widely used to estimate daily air temperatures based on their strong correlation with air temperature. Recent studies have found that the MODIS LST agrees well with observed air temperatures during the night-time due to the lack of the solar radiation (Wang et al., 2008; Zhang et al., 2014). In regions with sparse distributions of in situ stations, remote sensing products can be critical and valuable sources of information (Czajkowski et al., 2000; Benali et al., 2012; Wang et al., 2016; Zhang et al., 2016). Therefore, the purpose of this study is to estimate high-resolution LRs for the entire TP using high-resolution (1 km) satellite LSTs; thus, the spatial characteristics of LRs over the TP can be thoroughly analysed. Moreover, we can also investigate the diurnal and monthly variations of LRs from in situ observations.

The remainder of this study is structured as follows. Section 2 briefly describes the study region, data, and methodology used. Section 3 presents and discusses the results of the LRs’ diurnal and monthly variability derived from in situ observations and spatial distributions of LRs estimated from MODIS LSTs. Finally, conclusions are given in section 4.
**MATERIALS AND METHODS**

#### 2.1 Study region

The study area (25°–40°N, 75°–105°E) includes the entire TP and Qinghai Province, as well as parts of the nearby Yunnan, Sichuan, Gansu, and Xinjiang Provinces of China. The elevation declines from the northwest to the southeast, with a mean elevation of 4,000 m (Figure 1). The TP is the largest plateau in China and the highest in the world. Several large mountains and many rivers lie within this region, including the Himalayan, Kunlun, and Qilian mountains and the Yangtze, Yellow, Mekong, Yarlung Zangbo, and Salween rivers. Because of extremely high elevation, the climate is highly variable throughout the study region which is classified as semi-arid and sub-humid plateau continental, with distinct wet and dry seasons. The southeastern region is typically humid due to the influence of monsoons, while an arid climate dominates most of the northwestern region. The annual mean temperature is typically below the freezing point in the northwestern region, where glaciers and snow cover exist for most of the year. The Indian monsoon brings humid air masses from the south during the summer months, whereas air masses from the north and the west-erlies result in less precipitation during the winter months (Xu et al., 2008; Yang et al., 2010; Immerzeel et al., 2012; Kattel et al., 2013; Zhang et al., 2016).

#### 2.2 Data set

The data sets used in this study include hourly observed in situ air temperatures from 85 observation stations recorded by the China Meteorological Administration (CMA) ($T_{\text{obs}}$), 1-km MODIS (MOD11A1 and MYD11A1) LSTs, and digital elevation models (DEMs). The spatial distribution of the 85 observation stations is shown in Figure 1. Both of the MODIS LST products from Terra and Aqua satellites were used, with a resolution of 1 km (total 3,000 × 1,500 grid cells throughout the TP and its surroundings), to estimate the LRs over the entire TP. The satellite transit times for Terra and Aqua were 1030 and 2230, and 0130 and 1330 LST (local time, UTC + 7), respectively. The data used in this study were from January 1, 2002 to December 31, 2006, except for those from Aqua (satellite sensor as it was launched in May 2002).

Generally speaking, LRs are more reliable when calculated in regions with a greater elevation range. The elevations of the stations in this study vary from 2,132 m (Zhaojue in Sichuan) to 4,800 m (Amdo in Tibet). The distribution of the stations ranges from being relatively dense at low elevations (Figure 1) to quite sparse at higher elevations (only 21 stations exist above 4,000 m). We employed the DEM (from the shuttle radar topography mission (SRTM), http://srtm.usgs.gov) to describe the general topography over and around the TP region, as well as to calculate the temperature LRs.

**TABLE 1** LR (K/km) for daily mean observed air temperature in different seasons in three regions

| Regions    | 1      | 2      | 3      |
|------------|--------|--------|--------|
| Annual mean| −4.15  | −4.02  | −5.06  |
| Warm (5–10)| −4.59  | −4.32  | −4.39  |
| Cold (11–4)| −3.70  | −3.72  | −5.74  |
| Spring (3–5)| −4.83  | −4.60  | −5.70  |
| Summer (6–8)| −4.90  | −4.53  | −4.03  |
| Autumn (9–11)| −3.75  | −3.87  | −4.86  |
| Winter (12–2)| −3.09  | −3.08  | −5.66  |

**FIGURE 4** Average diurnal variation of hourly LRs calculated from observed air temperature during cold (November–April) and warm (May–October) season in three regions [Colour figure can be viewed at wileyonlinelibrary.com]
To identify the spatial differences of air temperatures and their LRs, the whole study region was divided into three subregions to guarantee the homogeneous distribution of stations in each subregion (26 stations in region 1, 32 stations in region 2, and 27 stations in region 3, shown in Figure 1). Furthermore, to reveal more difference, regions 2 and 3 were divided into four smaller subregions (A, B, C, and D) and to have reasonable comparisons and reliable estimations, a similar number of stations and larger elevation difference were considered in this partition.

A linear regression method was adopted to estimate the LR in an area of 10 × 10 km for MODIS data,

\[ Y = aX + b, \]
where $Y$ represents the air or land temperature (K), $X$ is the elevation (km), and $a$ is the LR (K/km). The Student’s $t$ test was used to evaluate the statistical significance of the estimated LRs. Once the $t$ value and degrees of freedom are determined, a $p$ value can be found using a table of values from Student’s $t$ distribution. The $p$ value threshold chosen for statistical significance in this study is at the .05 level. Figure 2 provides the flow chart for this study.

3 | RESULTS AND DISCUSSION

3.1 | Temporal and spatial changes in LRs for $T_{\text{obs}}$

The mean air temperature averaged for the period of 2002–2006 shows similar diurnal variations throughout the three regions, with the largest value at 1400 LST and the smallest one at 0400 or 0500 LST. The magnitude of diurnal temperature variation in region 1 was similar to that in region 2, while region 3 in relatively low elevations shows much higher temperatures than those (around 7 K) in regions 1 and 2.

Figure 3 shows the diurnal variability of LRs over a 12-month period throughout the three regions. The LRs in regions 1 and 2 exhibited similar variability, ranging from $-5.63$ to $-1.79$ K/km in region 1 and from $-5.37$ to $-1.79$ K/km in region 2, while region 3 had the same variability and a different magnitude from $-7.06$ to $-3.12$ K/km. For region 3, it is found that the daily mean LR over the study period ($-5.06$ K/km) is steeper than that at daytime ($-4.88$ K/km for 1030 LST and $-4.62$ K/km for 1330 LST) but shallower than that at night-time ($-5.24$ K/km for 2230 LST and $-5.42$ K/km for 0130 LST). The opposite was found in regions 1 and 2, that is, the daily mean LR is steeper than that at night-time but shallower than that at daytime.

The mean diurnal changes in the cold season (November–April) and warm season (May–October) are shown in Figure 4. The LRs in region 3 in the warm and cold seasons have similar variations, as indicated by a sine function pattern. However, the LRs in regions 1 and 2 display different patterns of variability between warm and cold seasons. In the warm season, the LR values decreased first and then increased to the peak at noon and then decreased, which is opposite to the cold season. In addition, we also compared the LRs for daily mean air temperature in different seasons (Table 1). It was found that the LRs in the warm season were steeper than those in the cold season for regions 1 and 2, while the opposite appeared in region 3 with shallower LRs in warm season and steeper LRs in cold season, indicating that steeper LRs can occur in more humid regions, especially during the cold season.

Because of larger variability of daily LRs, the LRs for monthly-averaged daily temperatures were further compared with the LRs for monthly-averaged night-time (2230 and 0130 LST) temperatures (Figure 5). It was found that the LRs for the daily mean $T_{\text{obs}}$ correlated well with the LRs for night-time $T_{\text{obs}}$ in the three regions, especially for the time 2230 LST, indicated by significant correlation coefficients (.99, .94, and .98 in regions 1–3).

Generally, LRs are steeper (greater decrease in temperature with height) during the day than at night and during warmer months than during colder months (Blandford et al., 2008). This phenomenon can be found in regions 1 and 2. However, LRs were shallower during the day than at night on some winter days, which was also found by Li et al. (2015). It was possibly caused by a small temperature difference between air and ice/snow surface in high-altitude areas. During the daytime, the air temperature was close to, or just exceeded, the ice/snow surface temperature because of strong solar radiation and snowmelt, which can result in shallow LRs or even inversion. At night, the air temperature decreased dramatically and caused steeper LRs. In addition, stronger wind speed can also steepen the LRs at night, but during the day this relationship became weaker (Pepin et al., 1999; Chiu et al., 2014). At the monthly scale, when dry and hot conditions are common, strong surface heating causes the vertical mixing of the atmosphere effectively by...
Convection and leads to steeper LRs in the summer (Pepin et al., 1999; Blandford et al., 2008), such as in regions 1 and 2. Furthermore, steeper LRs are also influenced by high amounts of precipitation (Stahl et al., 2005), which explained why LRs in region 3 were steeper than those in regions 1 and 2. Thus, the impacts of synoptic weather types on LRs vary in both season and location. In addition, Li et al. (2013); 2015 also found a reverse seasonal cycle.

**FIGURE 7** Comparison between daily domain-averaged $T_{\text{terra}}$ and $T_{\text{aqua}}$ in the regions 1–3 for the period 2002–2006 [Colour figure can be viewed at wileyonlinelibrary.com]
over the TP. For region 3, the low air temperature and unsaturated air conditions make winter LRs steeper, while summer LRs are shallower due to the warmer and more humid air conditions resulting from the increased sunshine duration and the plentiful rainfall (Qi et al., 2013; Li et al., 2015).

3.2 | Evaluation of performance in MODIS LSTs

In situ observed air temperatures are not uniformly distributed throughout the TP, whereas the MODIS LSTs are spatially homogeneous. If the MODIS LSTs are more representative of air temperatures, then the MODIS LSTs data can be used to reveal more characteristics of the air temperature, especially when we want to understand the distribution pattern of temperature throughout the whole study region. Because of this, the relationship between air temperatures and night-time MODIS LSTs was explored.

First, we detected the relationship between the observed night-time air temperatures \( T_{\text{obs}} \) and the MODIS LSTs throughout the TP using a linear regression method. The results are shown in Figure 6 and the fitted equations are

\[
T_{\text{obs2230}} \text{LST} = 1.0025^* T_{\text{terra2230LST}} + 2.75, \quad (1)
\]

\[
T_{\text{obs0130}} \text{LST} = 1.0024^* T_{\text{aqua0130LST}} + 3.09. \quad (2)
\]

Both the MODIS LST products displayed largely similar and comparable variabilities with observed air temperature together with high correlation coefficients of .88 and .87 for Terra and Aqua, respectively. However, the MODIS Aqua LSTs showed larger BIAS and RMSE than the MODIS Terra LSTs (3.79 and 3.48 K for BIAS, 5.88 and 5.62 K for RMSE, respectively). Further comparisons were conducted between observations and MODIS LSTs in the three subregions (Figure 7). There were larger BIAS and RMSE in MODIS Aqua LSTs consistently throughout the regions. It was concluded that the night-time Terra LSTs were closer to \( T_{\text{obs2230}} \) and thus can be used to accurately estimate the corresponding air temperatures based on Equation (1). In addition, the spatial distribution of annual-mean temperature difference between in situ values and MODIS LSTs at the 85 stations (Figure 8) explained the underestimation of MODIS LSTs and greater accuracy of Terra LSTs.

In general, LSTs and \( T_{\text{obs}} \) are closer at night due to the lack of the solar radiation effect (Kawashima et al., 2000; Wang et al., 2016), but other factors can also enhance/decrease the difference. In our study, the maximum temperature difference can sometimes reach 30 K in some
stations, which is possibly affected by cloud cover. When the satellite pixel is covered by clouds, the corresponding LST for this pixel cannot represent the real temperature of land surface and instead represents the cloud top (Ackerman et al., 1998; Zhang et al., 2016). As a result, $T_{\text{obs}}$ will be far higher than LSTs. In region 3, this temperature difference is more obvious (Figure 7), possibly due to greater vegetation cover and more vegetation variety in the southeastern TP. The rich vegetation can cause transpirational cooling and larger latent heat fluxes by evapotranspiration (Mildrexler et al., 2015). The more complicated the land surface condition is, the larger the difference between $T_{\text{obs}}$ and LST is. Moreover, the difference between station location (single point) and grid cell (areal mean) can cause more bias. The stations are generally located in relatively flat regions, while LSTs from MODIS represent the grid-averaged values. The observed temperature represents the temperature just in the location of the station, while the MODIS LST represents the average temperature in a pixel (e.g., 1 km$^2$ in our study). When the satellite gridded cells in which the stations are located are covered by water body (lake or river), the corresponding LSTs will be higher than $T_{\text{obs}}$.

### 3.3 Spatial distribution of LR$s$ derived from nighttime MODIS Terra LST$s$

The analysis above reveals that the $T_{\text{terra}}$ data are better able to reproduce the observed temperature, and LR$s$ for the temperature at 2230 LST realistically represents the LR$s$ for daily mean temperature. So the air temperature was first estimated using Equation (1) and then the high-resolution LR$s$ were calculated based on the estimated temperature.

To validate the performance of Equation (1), the estimated temperature ($T_{\text{est2230}}$) were compared with observed temperature ($T_{\text{obs2230}}$) in regions 1–3, shown in Figure 9. The further comparison examined in subregions A–D was also shown in Figure 10. It was found that the BIAS between the observation and estimated temperature were less than 1.3 K (1.27, 0.19, 0.97 K for regions 1–3, respectively, and 0.57, 0.18, 1.06, 0.79 K for regions A–D, respectively). The smallest RMSE is 2.08 K for region...
1 and the largest RMSE is 4.61 K for region D. In summary, the estimated temperature has higher accuracy and is comparable with the observed temperature.

Figure 11 shows the comparison between LRs from the estimated temperature data and LRs from the original T_obs_daily. The LRs for the estimated temperatures (Equation (1)) showed the best performance in region B, with an error of 0.93%. For region A, the LRs from the estimated values were underestimated (an error of 4.37%), while overestimated in regions C (an error of 5.72%) and D (an error of 18.4%). The worst performance was recorded in region D, possibly caused by larger BIAS of estimated temperatures.

The spatial distributions of the estimated LRs for the daily mean temperatures are shown in Figure 12a. The corresponding correlation coefficients and elevation ranges are shown in Figure 12b,c. To guarantee confidence level, the
FIGURE 11 Comparison of LRs calculated from observed and estimated air temperature. The values in the horizontal axis are the number of stations in each subregion. The numbers on the top of the bar are the relative errors.

LR values we chose in Figure 12a was based on the limiting condition that correlation coefficients between temperatures and elevations were lower than −.2 or larger than .2 (p < .05). The LRs showed clear spatial variability and were negative over most of the regions. The LRs in the southeast (about −4.00 K/km) were steeper than those in the northeast (about −2.00 K/km, with many positive and null values), with significant correlation coefficients of approximately −.90. This finding fits well with the results in Figure 3, which can be partly explained by the abundant precipitation of region 3. The detailed spatial distributions of LRs in river basins are displayed in Figure 13. This obvious inhomogeneity of LRs is found in all the river basins in our study, and most of the larger LRs were distributed around the river lines.

Generally, LRs are shallower in humid conditions than in dry ones (Blandford et al., 2008; Minder et al., 2010), but this is not always true (e.g., region 3). This is because humid air has a higher probability of being heated by latent heat released from condensation at higher elevations (Li et al., 2013). Latent heat release depends on atmospheric moisture content (Marshall et al., 2007). As such, we found that there were steeper LR values (close to the global mean value) in the northwestern region where there were lower temperatures and smaller specific humidity (Figure 14). However, there were null or positive values of LRs in the Qaidam Basin, the Tarim Basin, and south of the Himalayas, which is mainly caused by smaller elevation differences.

4 | CONCLUSION

Spatio-temporal variability of LRs of air temperature was analysed over the TP by using in situ observations and MODIS LST. First, the diurnal and monthly variabilities of LRs were investigated over the period 2002–2006 using daily in situ air temperature from the 85 observation stations. Then high-resolution (10 km) LRs were estimated from bias-corrected MODIS LSTs and their spatio-temporal variability was analysed.

Three regions had different diurnal variations in LRs although similar diurnal variations of air temperature existed among them. The mean LRs were −4.15, −4.02, and −5.06 K/km in the three regions (western, northeastern, and southeastern), respectively, consistently lower than the commonly used global mean LR (−6.5 K/km). The result indicates that the extrapolation method, that is, using −6.5 K/km to estimate the upland temperature with lowland observations, would most likely underestimate the temperature at high elevations (Li et al., 2015). The LRs in region 3 had values ranging from −7.06 to −3.12 K/km, greater than those in regions 1 and 2. For the daily scale, the shallowest LRs appeared at different times (mostly at night-time except winter for regions 1 and 2, but during daytime for region 3). For the monthly scale, similar patterns were found between regions 1 and 2 with shallower LRs for the autumn and winter than those in the spring and summer, while the opposite pattern occurred in region 3. All three regions displayed similar patterns in summer, agreeing with previous results (Pepin, 2001; Rolland, 2003; Guo et al., 2016).

Because of the sparse distribution of in situ stations throughout the TP, the spatial distribution of the LRs for daily mean temperatures with a high resolution is not available at present. Our study found that the LRs for the night-time (2230 LST) air temperature correlated well with those for the daily mean air temperature, and the night-time (2230 LST) air temperatures had high correlation with the MODIS LSTs for the same period. Accordingly, high-resolution MODIS Terra LSTs can act as substitutes for estimating LR values throughout the TP.

LRs estimated from bias-corrected MODIS Terra LSTs had obvious spatial variability on the TP. As we expected, most regions of the TP experienced negative values and the values were shallower than the commonly used environmental LR (−6.5 K/km) except for the northwest parts. Furthermore, an inversion phenomenon occurs in the Qaidam Basin, the Tarim Basin, and south of the Himalayas. In addition, this phenomenon also occurs in regions with steep topography, heavy snowfall, and large lakes. Cold-air accumulation at lower elevations and more exposure to warm airflow at higher elevations can cause such inversions in these more complex terrains. Furthermore, positive LR values can also be caused by the influence of aspect (north/south orientation), especially in high-elevation mountains (Tang and Fang, 2006; Miró, 2010). Compared with the northern slope, the southern slope has a higher air temperature and tends to have a temperature inversion during daytime, when covered by snow or ice at higher elevation. Because of strong solar radiation on the southern slope during daytime, significant temperature differences between day and night will lead to large differences in the diurnal
change of LR. While at an annual-mean scale, there is little difference of LR variations between north and south aspect (Wang et al., 2016).

Nevertheless, some issues in this study deserve further consideration. First, there is a larger difference (18.4%) of estimated LRs in the southeastern part of the TP (region 3),
which is possibly attributed to larger differences between the MODIS LSTs and air temperatures. Considering the use of MODIS night-time LSTs, we should pay more attention to cloud cover, because the LRs in sunny days and cloudy days can be quite different. Wang et al. (2016) found that the LRs in cloudy days were usually shallower than those in sunny
days in the Yellow River source basin. Second, the influence of latitude and longitude on the calculation of LRs was not considered. However, large latitudinal and longitudinal ranges will affect regional differences and variability in atmospheric processes, especially at high elevations. Finally, some LR values were missing because of a lack of sufficient elevation and/or LST differences within a 10 × 10 km grid range. When the elevation range is too small, it can make unrealistic LRs. We therefore recommend that more accurate LR estimation methods for the TP should be developed in future studies.

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