Effects of permafrost degradation on alpine grassland in a semi-arid basin on the Qinghai–Tibetan Plateau

Shuhua Yi, Zhaoye Zhou, Shilong Ren, Ming Xu, Yu Qin, Shengyun Chen and Baisheng Ye

State Key Laboratory of Cryosphere Sciences, Cold and Arid Regions Environmental and Engineering Research Institute, Chinese Academy of Sciences, 320 Donggang West Road, Lanzhou 730000, People’s Republic of China

E-mail: yis@lzb.ac.cn

Received 29 March 2011
Accepted for publication 2 September 2011
Published 25 October 2011
Online at stacks.iop.org/ERL/6/045403

Abstract

Permafrost on the Qinghai–Tibetan Plateau (QTP) has degraded over the last few decades. Its ecological effects have attracted great concern. Previous studies focused mostly at plot scale, and hypothesized that degradation of permafrost would cause lowering of the water table and drying of shallow soil and then degradation of alpine grassland. However, none has been done to test the hypothesis at basin scale. In this study, for the first time, we investigated the relationships between land surface temperature (LST) and fractional vegetation cover (FVC) in different types of permafrost zone to infer the limiting condition (water or energy) of grassland growth on the source region of Shule River Basin, which is located in the north-eastern edge of the QTP. LST was obtained from MODIS Aqua products at 1 km resolution, while FVC was upscaled from quadrat (50 cm) to the same resolution as LST, using 30 m resolution NDVI data of the Chinese HJ satellite. FVC at quadrat scale was estimated by analyzing pictures taken with a multi-spectral camera. Results showed that (1) retrieval of FVC at quadrat scale using a multi-spectral camera was both more accurate and more efficient than conventional methods and (2) the limiting factor of vegetation growth transitioned from energy in the extreme stable permafrost zone to water in the seasonal frost zone. Our study suggested that alpine grassland would respond differently to permafrost degradation in different types of permafrost zone. Future studies should consider overall effects of permafrost degradation, and avoid the shortcomings of existing studies, which focus too much on the adverse effects.

Keywords: fractional vegetation cover, land surface temperature, permafrost degradation, alpine grassland, Qinghai–Tibetan Plateau

1. Introduction

Permafrost has degraded over the last few decades on the Qinghai–Tibetan Plateau (QTP) (Cheng and Wu 2007, Wu and Zhang 2010); its ecological impacts have received great concerns (Yang et al 2010). It was hypothesized that degradation of permafrost will cause lowering of the ground water table and drying of surface soil, and then degradation of alpine grassland (Jin et al 2009). To test this hypothesis, long-term studies should be performed to monitor the changes of soil environments and vegetation characteristics during the process of permafrost degradation. However, few such monitoring sites exist. An alternative way is to select plots in different areas, which represent different stages of permafrost degradation, and compare the soil environments and vegetation characteristics among them. Results from studies of this type on the QTP supported the above hypothesis (e.g. Wang et al 2008). However, due to difficulties of road accessibility and
Figure 1. Source region of Shule River Basin with different types of permafrost. 1–8 denotes different landscapes where two or three remote sensing plots (30 m × 30 m) were set; each plot has nine quadrats (50 cm × 50 cm) evenly distributed.

logistics, the number of plots studied was very limited, and results were usually affected by local factors, e.g. topography and disturbances.

Remote sensing is an important tool to cover a large study area, and is a good complement to traditional field work. Microwave remote sensing is usually used for retrieving surface soil water content. However, its spatial resolution is too low to study the effects of permafrost degradation on surface soil moisture (e.g. resolutions of SMMR and AMSR are 140 and 50 km at 6.6 and 10.7 GHz, respectively). The relationship between land surface temperature (LST) and normalized difference of vegetation index (NDVI)/fractional vegetation cover (FVC) has been used in surface soil moisture studies using AVHRR datasets (8 km) (Carlson 2007). Therefore, this relationship is potentially useful in studies of the effects of permafrost degradation on surface soil moisture.

FVC is one of the most important and intuitive vegetation characteristics of alpine grassland ecosystems, and is studied extensively at different scales. For relatively low spatial resolution remote sensing applications (e.g. 1 and 8 km in MODIS and AVHRR datasets, respectively), FVC was calculated using the NDVI of a specific pixel, NDVIs of pure vegetation and soil pixels, and was seldom validated (Li et al 2003). For relatively high spatial resolution remote sensing applications (e.g. 30 m in Landsat TM/ETM + datasets), the relationship between FVC and vegetation indices (usually NDVI) at quadrat scale on the ground was first established, then applied to other pixels (Zha et al 2003, Liu et al 2004). Measurements of vegetation indices in situ might happen at different times, and at much smaller spatial scale than that of remote sensing; direct application of the established relationship to remote sensing pixel might be unreasonable. The means of estimating FVC on ground is also problematic. It is usually estimated visually in situ or from pictures taken in situ (Meusburger et al 2010); or using software to classify vegetation from soil, based on RGB (red, green and blue) or IHS (intensity, hue and saturation) characteristics in pictures (Li et al 2005). However, these methods are arbitrary and/or time consuming.

In this study, we aimed to (1) develop an accurate and time-saving method to estimate FVC at quadrat scale, (2) upscale FVC from quadrat scale to 1 km scale, using a 30 m scale satellite remote sensing dataset, and (3) study the characteristics of FVC and LST, and the relationship between FVC and LST on different types of permafrost over a basin on the QTP.

2. Methodology

2.1. Study area and field work

Shule River Basin is located in the western part of Qilian Mountain, which is in the northeast edge of the QTP, China (figure 1). It is mainly controlled by westerly winds, and seldom affected by the Asian monsoon. Mean annual air temperature ranged from −4.0 to −19.4 °C, and mean annual precipitation ranged from 200 to 400 mm over the period of 1960–2010. The study area is in the source regions of Shule River Basin, where alpine meadow and alpine steppe are the dominant vegetation types. The classification of different permafrost types by Cheng and Wang (1982) was used for this study: extreme stable permafrost (mean annual ground temperature (MAGT, at depth of about 15 m) < −5 °C), stable permafrost (−5 °C < MAGT < −3 °C), sub-stable permafrost (−3 °C < MAGT < −1.5 °C), transition permafrost (−1.5 °C < MAGT < −0.5 °C), unstable permafrost (−0.5 °C < MAGT < 0.5 °C), and seasonal frost (MAGT > 0.5 °C). The area fractions are 16%, 18%, 23%, 17%, and 5% for the six frost types, respectively. The field work was carried out during the period 25 July–3 August
2010. We set up two or three plots (30 m × 30 m) in seven landscapes (table 1; none of these selected landscapes was located in the extreme stable or stable permafrost zones due to problems of road accessibility). There were no grazing activities on those landscapes. Slopes of all plots are gentle (less than 4°). In each plot, we set up nine quadrats (50 cm × 50 cm) evenly (figure 1), and took pictures with a conventional camera and a multi-spectral camera vertically at a height of ∼1.4 m above each quadrant. The multi-spectral camera is used in an Agricultural Digital Camera (ADC, Tetracam Inc., Chatsworth, CA, USA), with resolution of 2048 pixels × 1536 pixels. The ADC records three bands, i.e. near infrared, red and green bands of ADC, we set up extra quadrats to the ADC company with ASD measured reflectance values of green (G), red (R) and near infrared (NIR). The ADC company then provided an updated calibration file. The other multi-spectral pictures were then processed using this new calibration file in PixelWrench2 software, which came with the camera, to get TIFF format pictures. NDVI = (NIR − R)/(NIR + R) were further derived. To check the validity of NDVI calculated from multi-spectral pictures, we compared them with the corresponding NDVI derived from measurements with ASD.

We used the threshold method to calculate the FVC of a quadrat based on a multi-spectral picture. For example, if the NDVI of a pixel is greater than a threshold, then this pixel is considered as a vegetation pixel; the ratio between the number of vegetation pixels and number of total pixels is the FVC of a quadrat. To determine the threshold value, we randomly selected 10 of the above-mentioned 50 quadrats. We used ‘true’ FVC as the target value, and calculated the threshold of NDVI for each multi-spectral picture in the following way: (1) providing the initial, maximal and minimal value of a vegetation pixel; (2) iterating through (1) until the difference between calculated FVC and target FVC is less than a specified value (0.1% in this study). We used the average of threshold values from 10 multi-spectral pictures as the threshold. Then we applied it on the multi-spectral pictures of the other 40 quadrats, and compared the calculated FVCs with the ‘true’ FVCs.

2.2. Estimations of FVC at quadrant scale

2.2.1. Estimations based on conventional pictures. We randomly selected 50 quadrats, and had six persons to estimate FVCs from conventional pictures individually. We also had four different persons to derive FVCs based on the classification of the same 50 pictures with WinCAM software (Regent Instruments Inc. Quebec, Canada). We performed one-way ANOVA tests for six visual estimations to evaluate whether there are significant differences among them. Since we did not know the exact value of FVC for a quadrat, we assumed that the average of six visual estimations and four estimations based on WinCAM classification was the ‘true’ FVC of a quadrat. We compared each individual visual estimation and the averages of combinations of any two, three, four and five visual estimations with the ‘true’ FVC. The same tests were done for estimations based on WinCAM classifications. These tests were performed in R.

2.2.2. Calculations based on multi-spectral pictures. We sent five multi-spectral pictures to the ADC company with ASD measured reflectance values of green (G), red (R) and near infrared (NIR). The ADC company then provided an updated calibration file. The other multi-spectral pictures were then processed using this new calibration file in PixelWrench2 software, which came with the camera, to get TIFF format pictures. NDVI = (NIR − R)/(NIR + R) were further derived. To check the validity of NDVI calculated from multi-spectral pictures, we compared them with the corresponding NDVI derived from measurements with ASD.

We used the threshold method to calculate the FVC of a quadrat based on a multi-spectral picture. For example, if the NDVI of a pixel is greater than a threshold, then this pixel is considered as a vegetation pixel; the ratio between the number of vegetation pixels and number of total pixels is the FVC of a quadrat. To determine the threshold value, we randomly selected 10 of the above-mentioned 50 quadrats. We used ‘true’ FVC as the target value, and calculated the threshold of NDVI for each multi-spectral picture in the following way: (1) providing the initial, maximal and minimal value of a threshold; (2) looping through each pixel in the picture; if the NDVI of a pixel is greater than the specified threshold, then this pixel is considered as a vegetation pixel, otherwise a soil pixel; (3) calculating the overall vegetation pixel fraction; if it is greater than a target value, then we set the minimal threshold to be the current threshold, and use the average of the maximal value and the current threshold value as the new threshold; vice versa; (4) iterating through (2) to (3), until the difference between calculated FVC and target FVC is less than a specified value (0.1% in this study). We used the average of threshold values from 10 multi-spectral pictures as the threshold. Then we applied it on the multi-spectral pictures of the other 40 quadrats, and compared the calculated FVCs with the ‘true’ FVCs.

2.3. LSTs and FVCs at 1 km scale

We used eight day composite 1 km MODIS Aqua from 20 July to 27 July directly. We did not calculate FVCs at 1 km scale based on NDVIs of each pixel, of bare soil and of fully vegetated pixels. We upscaled FVCs using HJ-1 A/B (HJ, 30 m resolution) data. HJ is a new generation of small Chinese civilian earth-observing optical
Figure 2. Mean and ± one standard deviation (error bar) of fractional vegetation cover (FVC) of each quadrat: (a) for visual estimations; (b) for estimations from WinCAM classification.

Based on multi-spectral pictures, we calculated the FVCs of all other quadrats. For each plot, we got mean value of FVC from 9 quadrats.

(2) We assumed that the variability of FVCs was small during our field period. We partitioned plots into two categories, one for establishing the relationship between FVCs on the ground and NDVIs of the corresponding pixels on the HJ remote sensing dataset, and the other for validating the relationship (one plot in each landscape).

(3) The plot scale relationship was then applied on the other pixels to retrieve FVCs of the whole study area.

(4) Finally, the 30 m scale FVCs were aggregated to the 1 km scale of MODIS.

Based on the 1 km scale FVCs and LSTs, we compared the FVCs and LSTs among six different permafrost types described earlier using one-way ANOVA in R, and the relationships between FVCs and LSTs.

3. Results

3.1. Estimations based on conventional pictures

A one-way ANOVA (analysis of variance) test for six visual estimations showed that the FVC estimations were significantly different ($p < 0.01$). The maximum and mean of standard deviations of FVC visual estimations of all quadrats among six visual estimations were 33% and 14%, respectively (figure 2(a)). A one-way ANOVA test for four estimations with WinCAM classification showed that the FVC estimations were significantly different ($p < 0.05$). The maximum and mean of standard deviations of FVC visual estimations of all quadrats among four estimations were 25% and 10%, respectively (figure 2(b)). The averages of FVCs from six visual estimations were not significantly different from the averages of FVCs of four estimations from WinCAM classification ($p > 0.05$). Table 2 shows the comparisons of the averages of combinations of estimations based on visual/WinCAM classification and ‘true’ FVCs. For visual estimations, four out of six individual visual estimations, five out of 15 two-person averages, and three out of 20 three-person averages were significantly different from the ‘true’ FVCs ($p < 0.05$). For estimations of FVCs based on WinCAM classification, only one out of four was significantly different from the ‘true’ FVC ($p < 0.02$).

3.2. Estimations based on multi-spectral pictures

The comparisons of NDVI between measurements from multi-spectral pictures and from an ASD Field spec Handheld showed that the Pearson correlation coefficients ($r$) were 0.97, 0.97, and 0.94, for landscapes 1, 7, and 8, respectively ($p < 0.01$, sample sizes were 25, 21, and 24, respectively; figure not shown here).

The threshold for NDVI was 0.45. The FVCs derived using this threshold are presented in figure 3. The $r$ between FVCs estimated with NDVI and the ‘true’ FVCs was 0.85 ($p < 0.01$). FVCs derived were not significantly different from the ‘true’ FVCs ($p > 0.05$); 75% were within one standard deviation of the average of FVCs estimated with conventional pictures, while most of the other 25% were greater than the upper limit.

3.3. FVCs and LSTs of different permafrost zones

The relationship between FVC and NDVI at plot scale can be described by a linear equation (figure 4(a)), comparisons
Figure 4. (a) Relationship between fractional vegetation cover (FVC) and normalized difference vegetation index (NDVI) at plot scale (30 m); the circle was considered as an outlier. (b) Comparisons between calculated FVC (FVC<sub>Cal</sub>) and observed FVC (FVC<sub>Obs</sub>).

between calculated and observed FVCs were reasonably good (figure 4(b)).

The generated FVC of sub-stable permafrost was the greatest, and its average was significantly different from those of stable and transition permafrost ($p < 0.01$, figure 5(a)). The FVC of seasonal frost was the smallest, and its average was significantly different from those of unstable and extreme stable permafrost ($p < 0.01$, figure 5(a)).

LSTs retrieved from MODIS increased from extreme stable permafrost to seasonal permafrost; they had a similar pattern to that of MAGTs (figure 5(b)), which was extrapolated to the whole basin using borehole measurements (Cheng and Wang 1982).

3.4. Relationships between FVC and LST of different permafrost zones

The relationships between FVC and LST changed from positive in the extreme stable and stable permafrost, to relatively weak positive in sub-stable permafrost, and to positive in the transition, unstable permafrost and seasonal frost zones (figure 6).

4. Discussion

4.1. Estimations of FVC at quadrat scale

It usually takes 1–2 min to visually estimate FVC on one conventional picture, and 5–10 min using WinCAM software to classify. While using the threshold method, processing of one multi-spectral picture required less than 1 s. The threshold method is much more efficient. If the averages of all FVC estimations based on conventional pictures were considered as ‘true’ FVCs, there were large differences among different visual estimations. At least three visual estimations were needed to have the mean FVC not significantly different from the ‘true’ value. Similarly, two estimations of FVC were required when using WinCAM classification. FVCs derived from the threshold method using NDVI were not significantly different from the ‘true’ FVCs.

The NDVI threshold we used in this study was 0.45, which is greater than the sum of the average (0.2) and two standard deviations (0.1) of NDVIs of various soils (Montandon and Small 2008). However, we still had higher soil NDVI in those quadrats that FVCs estimated from multi-spectral pictures were higher than ‘true’ FVCs. Most of these quadrats were in landscape 7, which has salinized soil. Using $NDVI = 0.45$ as threshold, these soil pixels were misclassified as vegetation. There was one quadrat which had much lower estimated FVC based on NDVI threshold. In the conventional picture of this quadrat, there were flowers, which were considered as vegetation in visual estimation; however flowers had much lower NDVI values than NDVI threshold, and were considered as non-vegetation.

4.2. FVCs and NDVIs of various scales

Studies have shown that ground based measurements of NDVI were much higher than those from Landsat TM (30 m);
Figure 6. Relationships between land surface temperature (LST; °C) and fractional vegetation cover (FVC) for different permafrost types: (a) extreme stable; (b) stable; (c) sub-stable; (d) transition; (e) unstable; (f) seasonal.

and multi-scale comparisons of vegetation indices using different sensors were not recommended (Cheng 2006, Théau et al 2010). Our results showed that NDVIs from ground measurements were higher than those of corresponding remote sensing datasets. Since the value of NDVI is affected by various factors, including solar zenith angle, and the multi-spectral pictures were not taken at the same time as the overpass of the satellite, we did not establish a relationship between the NDVI of the ground and of the satellite; we assumed that the FVC of the study area would not change during our nine day field work period, and established a relationship between the FVC and the NDVI of the satellite. On the QTP, grassland has maximal above-ground biomass between early July and mid-August (Li and Zhou 1998). In source regions of Shule River Basin, NDVI values from MODIS maximized between late July and early August for most of the years 2000–2010 (figures not shown here). Thus the above-mentioned assumption about FVC is valid.

Due to the harsh environment of the QTP, we cannot set more plots, and thus the number of plots used for establishing the relationship and validating was small. We actually used an unmanned aerial vehicle to take multi-spectral pictures using the same ADC camera in our field work area at a height of about 1 km. Each picture can cover hundreds of 30 m pixels, which can be used for establishing the equation and validating. These pictures need further processing, and are not presented here. This might be a useful tool in the study of alpine grassland on the QTP in the near future.

Alpine grassland types, i.e. alpine meadow, alpine meadow-steppe, and alpine steppe, are different; even for the same grassland type, there are differences among different succession stages. However, it is a common practice to aggregate similar types when a detailed alpine grassland type distribution is not available. It is our next step to survey alpine grassland types in our study area, and develop a specific FVC–NDVI relationship for each type.

4.3. Limiting factors of vegetation growth on different permafrost zones

Relationships between LST and NDVI/FVC were originally used to study soil moisture and evapotranspiration (Sun et al 2008, Tang et al 2010). Sun and Kafatos (2007) and Karneli et al (2010) found that this relationship should be used with caution, because it does not hold in cold regions. In this study, we applied the relationship in studying the limiting factors of vegetation growth in different permafrost types. In the extreme stable permafrost zone, LST was low and FVC was small, vegetation growth was basically limited by energy; in the seasonal frost zone, LST was high and FVC was small, vegetation growth was basically limited by water. In the sub-stable permafrost zone, FVC was the highest and LST was less than that of the seasonal frost zone, and greater than that of the extreme stable zone; the relationship between FVC and LST was neither negative nor positive. This suggested that a
A combination of water and energy was optimal for vegetation growth. Our results showed that 1 km scale MODIS datasets were suitable for studying the effects of permafrost degradation on surface soil wetness and vegetation. The area fractions of extreme stable and stable permafrost areas are 16% and 18%, respectively, where vegetation growth will benefit from increasing air temperature; however, recent studies focus too much on the negative effects of permafrost degradation (Yang et al. 2010). To properly assess the effects of warming on vegetation on the QTP, the extreme stable and stable permafrost areas should not be neglected.

Although our study was performed for alpine grassland on the QTP, the method we propose should be useful for studying effects of permafrost degradation of other cold region ecosystems, e.g. arctic tundra.

5. Conclusions

In this study, we first developed a new method using multi-spectral pictures to estimate FVCs of alpine grassland at quadrat scale. This method is both accurate and time saving. We then upscaled quadrat FVCs to 1 km resolution through 30 m resolution HJ satellite data. Finally, we analyzed the relations between upscaled FVCs and measured LSTs of MODIS in different types of permafrost zone of source regions of Shule River Basin. Results showed that the limiting factor of vegetation growth transitioned from energy in the extreme stable permafrost zone to water in the seasonal frost zone, which suggested that permafrost degradation caused drying of surface soil and degradation of alpine grassland. However, warming of permafrost might also be of benefit to growth of alpine grassland in extreme stable and stable permafrost zones. Existing studies focus too much on the adverse effects of permafrost degradation. To objectively project changes of alpine grassland in a warming climate, future studies should consider both adverse and beneficial effects of permafrost degradation.

Acknowledgments

This study was supported through grants provided to Yi as part of the Major State Basic Research Development Programme of China (973 Programme) (No 2007CB411502), the National Basic Research Program (2010CB951402), and the One Hundred People Plan of the Chinese Academy of Sciences. We would like to thank Drs Huakun Zhou, Gouying Zhou, Guangyang Yue, and Mr Zhilong Zhang for estimating vegetation cover visually or using WinCAM software, and Professor Yu Sheng for providing permafrost data.

References

Carlson T N 2007 An overview of the ‘Triangle Method’ for estimating surface evapotranspiration and soil moisture from satellite imagery Sensor 7 1612–29

Cheng G and Wang S 1982 On the zonation of high altitude permafrost in China J. Glaciol. Geocryol. 4 1–17 (in Chinese with English abstract)

Cheng G and Wu T 2007 Responses of permafrost to climate change and their environmental significance, Qinghai-Tibet Plateau J. Geophys. Res. 113 F02S03

Cheng Q 2006 Multisensor comparisons for validation of MODIS vegetation indices Pedosphere 16 362–70

Jin H J, He R, Cheng G, Wu G, Wang S, Lv L and Chang X L 2009 Changes in frozen ground in the Source Area of the Yellow River on the Qinghai-Tibet Plateau, China, and their eco-environmental impacts Environ. Res. Lett. 4 045206

Karnieli A, Agam N, Pinker R T, Anderson M, Imhoff M L, Gutman G G, Panov N and Goldberg A 2010 Use of NDVI and land surface temperature for drought assessment: merits and limitations J. Clim. 23 619–33

Li X, Chen Y, Shi P and Chen J 2003 Detecting vegetation fractional coverage of typical steppe in Northern China based on multi-scale remotely sensed data Acta Bot. Sin. 45 1146–56

Li X, Chen Y, Yang H and Zhang Y 2005 Improvement, comparison, and application of field measurement methods for grassland vegetation fractional coverage J. Integrat. Plant Biol. 47 1074–83

Li W and Zhou X (ed) 1998 Ecosystems of Qinghai-Xizang (Tibetan) Plateau and Approach for their Sustainable Management, Series of Studies on Qinghai-Xizang (Tibetan) Plateau (Guzhongzhou: Guangdong Science & Technology Press)

Liu Y, Zha Y, Gao J and Ni S 2004 Assessment of grassland degradation near Lake Qinghai, West China, using Landsat TM data and in situ reflectance spectra data Int. J. Remote Sens. 25 4177–89

Meusburger K, Banninger D and Alwelt C 2010 Estimating vegetation parameter for soil erosion assessment in an alpine catchment by means of QuickBird imagery Int. J. Appl. Earth Observ. Geoinformat. 12 201–7

Montandon L M and Small E 2008 The impact of soil reflectance on the quantification of the green vegetation fraction from NDVI Remote Sens. Environ. 112 1835–45

Sun D and Kafatos M 2007 Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America Geophys. Res. Lett. 34 L24406

Sun Z, Wang Q, Matsushita B, Fukushima T, Ouyang Z and Watanabe M 2008 A new method to define the VI-Ts Diagram using subpixel vegetation and soil information: a case study over a semi-arid agricultural region in the North China Plain Sensor 8 6260–79

Tang R, Li Z and Tang B 2010 An application of the Ts-VI triangle method with enhanced edges determination for evapotranspiration estimation from MODIS data in arid and semi-arid regions: implementation and validation Remote Sens. Environ. 114 540–51

Théau J, Sankey T T and Weber K T 2010 Multi-sensor analyses of vegetation indices in a semi-arid environment GISci. Remote Sens. 47 230–75

Wang G, Li Y, Wang Y and Wu Q 2008 Effects of permafrost thawing on vegetation and soil carbon pool losses on the Qinghai-Tibet Plateau, China Geoderma 143 143–52

Wu Q and Zhang T 2010 Changes in active layer thickness over the Qinghai–Tibetan Plateau from 1995 to 2007 J. Geophys. Res. 115 D09107

Yang M, Nelson F E, Shiklomanov N I, Guo D and Wan G 2010 Permafrost degradation and its environmental effects on the Tibetan Plateau: a review of recent research Earth-Sci. Rev. 103 31–44

Zha Y, Gao J, Ni S, Liu Y, Jiang J and Wei Y 2003 A spectral reflectance-based approach to quantification of grassland cover from Landsat TM imagery Remote Sens. Environ. 87 371–5