Regional vegetation dynamics and its response to climate change—a case study in the Tao River Basin in Northwestern China

Changbin Li1,5, Jiaguo Qi2,5, Linshan Yang1, Shuaibing Wang1, Wenjin Yang1, Gaofeng Zhu1, Songbing Zou3 and Feng Zhang4

1 Key Laboratory of Western China’s Environmental Systems (Ministry of Education), Lanzhou University, Lanzhou, Gansu 730000, People’s Republic of China
2 Zhejiang University, Hangzhou, Zhejiang 310058, People’s Republic of China
3 Cold and Arid Regions Environment and Engineering Research Institute, Chinese Academy of Sciences, Lanzhou, Gansu 730000, People’s Republic of China
4 Key Laboratory of Arid and Grassland Agro-Ecology (Ministry of Education), Lanzhou University, Lanzhou, Gansu 730000, People’s Republic of China
5 Center for Global Change and Earth Observations, Michigan State University, East Lansing, MI 48823, USA

E-mail: licb@lzu.edu.cn

Received 9 March 2014, revised 28 October 2014
Accepted for publication 29 October 2014
Published 2 December 2014

Abstract
The 30-year normalized-difference vegetation index (NDVI) time series from AVHRR/MODIS satellite sensors was used in this study to assess the regional vegetation dynamic changes in the Tao River Basin, which cuts across the Eastern Tibetan Plateau (ETP) and the Southwestern Loess Plateau (SLP). First, principal component and correlation analyses were carried out to determine the key climatic variables driving ecological change in the region. Then, regression models were tested to correlate NDVI with the selected climatic variables to determine their predictive power. Finally, Sen’s slope method was used to determine how terrestrial vegetation has responded to regional climate change in the region. The results indicated an average winter season NDVI value of 0.14 in the ETP but only 0.04 in the SLP. Primarily driven by increasing temperature, vegetation growth has generally been enhanced since 1981; spring NDVI increased by 0.03 every 10 years in the ETP and 0.02 in the SLP. Further, results from trend analyses suggest vegetation growth in the ETP shifted to earlier-start and earlier-end dates, however in the SLP, the growing season has been extended with an earlier-start and later-end date. The precipitation threshold for vegetation germination, measured by the cumulative spring rainfall, was found to be 44 mm for both the ETP and SLP.

Keywords: vegetation dynamics, climate change, remote sensing, Tao River Basin

1. Introduction
Climate and vegetation dynamics are tightly coupled: regional climate affects land surface processes over a range of scales with unprecedented speed (IPCC 2007, Zhao et al 2011), while vegetation, in turn, affects climate through feedbacks via photosynthesis and evapotranspiration, changes in albedo and biogenic volatile organic compound emissions (Henderson-Sellers 1993, Fang et al 2003, Meng et al 2011, Faubert et al 2012, Wang and Dickinson 2012, Henden et al 2013). For example, studies reported that vegetation growth at high latitudes in some Northern hemisphere regions has increased from 1981 to the 1990s due to climate change (e.g., Nemani et al 2005), and changes in vegetation leaf area index have lead to shifts in temperature and precipitation patterns (Ge
However, these feedback mechanisms are complex, varying greatly from location to location and over time (Turner et al. 2003, Pettorelli et al. 2005, Nie et al. 2012) because the response of terrestrial vegetation to climatic factors such as air temperature and precipitation is spatially and temporally heterogeneous (Cury 1980, Lambin et al. 2001, Tucker et al. 2005). To account for this heterogeneity and to fully understand the response of ecosystems to climate change (Ni 2011, Guo and Zhang 2013, Li et al. 2013), it is necessary to conduct location specific case studies for different geographic regions (Fan and Zhang 2010, Horion et al. 2013) so that spatially explicit conclusions can be drawn.

Remote sensing provides a vital tool to capture the temporal dynamics of vegetation change in response to climate shifts, at spatial resolutions fine enough to capture the spatial heterogeneity. Frequent satellite data products, for example, can provide the basis for studying time-series of ecological parameters related to vegetation dynamics (Bradley et al. 2007, Gu et al. 2009, Jacquin et al. 2010, Beck et al. 2011). Among the many available remote-sensing data products, the normalized-difference vegetation index (NDVI) has been frequently used in vegetation dynamics studies, as this index is highly correlated with the leaf area index, photosynthetic capacity, biomass, dry matter accumulation, and net primary productivity (Wang et al. 2010, Cartus et al. 2011, Raynolds et al. 2012). Therefore, NDVI data are frequently used to assess spatio-temporal changes in regional vegetation dynamics (Kang et al. 2011, Zhang et al. 2011) in response to changes in regional climate.

In this study, we used advanced very high resolution radiometer (AVHRR) and moderate resolution imaging spectroradiometer (MODIS) NDVI data, along with yearly and monthly net radiation, air temperature, and precipitation data to examine the feedback mechanisms between climate and vegetation. To capture the spatial heterogeneity of vegetation responses to a changing climate, we selected the Tao River Basin (TRB) in Northwest China, with a gradient in both climate and vegetation, to study the feedback mechanisms between spatially heterogeneous vegetation and climate regimes. The objective of this study is to better understand the spatial variability of vegetation responses to regional climate change.

2. Study area

The TRB covers a total area of 25,527 km² between 101°36′E and 104°20′E, and 34°06′N and 36°01′N (figure 1) and includes portions of the Eastern Tibetan Plateau (ETP) and Southwestern Loess Plateau (SLP). In the ETP, forests dominate mountains and grasslands mainly cover open valleys, whereas in the SLP, the vegetation are primarily grasslands at low coverage. The region averaged annual mean air temperature increases from 1 °C in the ETP at elevations ranging from 4560 to 2800 m asl (above sea level), to 9 °C in the SLP at elevations ranging from 2800 to 1730 m asl. The annual mean precipitation decreases from 600 mm in the West to 300 mm in the East (Yang et al. 2014). In addition, the annual net radiation is higher in the ETP because of its higher elevation. In short, from upstream in the West to downstream in the East, the dominant climate varies from an alpine cold humid and sub-humid climate to a temperate semi-arid climate, while the terrestrial vegetation ranges from alpine grasslands in the upstream regions to forest and arid grasslands in the middle and downstream regions.

From 1980s to 2000s, the dominant land cover and land use (grasslands, forests, rainfed cultivated lands and little urban areas) changed insignificantly with less than 1% in total area of the watershed. Further, based on limited statistical data from the ‘grain for green’ project survey, it was concluded that total land use conversion during this period of time was less than 0.5%, suggesting human-related land use change is insignificant (Li et al. 2014). Land use change during our study period (1981–2000), including grazing intensity and expansion of irrigated agriculture is insignificant in the TRB. The grazing ban policy was implemented in early 1970s with traditional wire fences, and since then there has been no change. Irrigated agriculture, based on our survey and an existing Land Use Map of China (produced by the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 2000), does not appear to exist in the region. Therefore, at the TRB-basin scale, changes in land use have had little impact on regional scale vegetation vigor, during our study period from 1981 to 2010.

Preliminary remote sensing analyses in this study indicated an increasing trend in NDVI in the ETP and SLP regions, suggesting that total vegetative cover increased significantly, especially in the spring seasons, NDVI has increased by 34% and 29% for the ETP and SLP regions, respectively, since the 1980s beyond a reasonable level expected due to human impact alone. Therefore, we hypothesize that climate is the likely dominant driver of vegetation change in the study area. The objectives of this study are to determine whether or not climate is the dominant driver of vegetation change, and if so, what are the specific climate variables that are most effective for predicting vegetation change.

3. Methodologies

3.1. NDVI data cross-calibration

In this study, the NDVI products derived from AVHRR (8 km resolution) and MODIS (1 km resolution) were acquired for the period from 1981 to 2006 and from 2001 to 2010, respectively. We obtained the largest annual NDVI value for each pixel in the region using the maximum-value composite (MVC) method, and resampled all the MODIS data to an 8 km resolution to correspond to the AVHRR data resolution (Holben 1986, Yang et al. 1988).

We recognized there exist some discrepancies between the AVHRR and MODIS datasets, and there is a need for cross calibration (Gitelson and Kaufman 1998, Tucker et al. 2005, Fensholt et al. 2009). Gitelson and Kaufman
used spectral characteristics to fuse the two datasets, while Brown et al. (2008) attempted to use neural network as data fusion tool. These analyses on the data consistency fusion techniques focus on high spatial resolution imagery such as MODIS and Landsat/MISR/ASTER (Stefanov and Netzband 2005, Naud et al. 2007, Vermote et al. 2007, Roy et al. 2008, Hilker et al. 2009, Li et al. 2013, Walker et al. 2014). For much coarser spatial resolution datasets such as AVHRR (GIMMS) and MODIS or AVHRR and SPOT, given that they are often acquired during different time periods (e.g. AVHRR/GIMMS was acquired during 1981–2006 while MODIS is 2001–present), consistency assessment is often carried out by correlating corresponding pixels of overlapping time period (e.g. Song et al. 2010). This method would avoid any issues associated with spectral and spatial calibrations of each sensor and, therefore, was adopted in this study. We used the subset of two datasets acquired during the overlapping time period from 2001 to 2006 and a linear regression method to assimilate the two time series so that they have the same mean values during the overlapping dates. The regression equation for the assimilation was found to be:

$$\text{NDVI}_{\text{MODIS}} = 0.6757 \times \text{NDVI}_{\text{AVHRR}} + 0.111.$$  

We further checked the consistency of the two NDVI series after assimilation (figure 2). The correlation coefficient between the two series was 0.77 ($P < 0.01$). The absolute error of NDVI was less than 0.1 and the relative error was less than 20% for 87.1% of the pixels. Thus, there was high consistency between the AVHRR and MODIS NDVI values after the cross calibration, and it was therefore reasonable to use the assimilation approach to analyze the regional vegetation dynamics for the entire 30 year-period from 1981 to 2010.

### 3.2. Climate data

The climatic data used in this study included net radiation ($R_n$, MJ m$^{-2}$), maximum, minimum and mean monthly air temperatures ($^\circ$C) ($T_{\text{mean}}, T_{\text{max}}, T_{\text{min}}$), cumulative monthly air temperatures above 0, 3, 5, and 10 $^\circ$C (CT$_0$, CT$_3$, CT$_5$, and CT$_{10}$, respectively), and cumulative precipitation (mm) in the present year (CP$_0$), and since December (CP$_1$) and November (CP$_2$) of the previous year until the month when the NDVI value was recorded. Combining the climate data with the assimilated monthly average NDVI data, we constructed a monthly climate and vegetation time-series. The climate data
were interpolated from weather stations in the TRB (figure 1) using a krigging method, and were subsequently used for zonal statistics analyses. For seasonal analyses we further divided the annual data into four seasons: winter (December–February), spring (March–May), summer (June–August), and autumn (September–November). This allowed us to examine vegetation responses to climate in different seasons.

3.3. Trend analysis

Trend analysis is an active subject for variability determination of natural time series such as climate, hydrology and vegetation (Hamed 2008, Zhao et al 2008). In this study, we conducted trend analysis to better understand the interactive nature between climate and vegetation dynamics. Numerous trend analysis methods have been developed (e.g., Henebry and Betancourt 2010, Ma et al 2011, Ye et al 2013) and three frequently used methods tested in this study are the Mann–Kendall test (Mann 1945, Kendall 1955), least-squares linear regression, and Sen’s slope trend test (Sen 1968, Nayak et al 2010, Yin et al 2011). Among these methods, the Mann–Kendall test was found to be the best for detecting significant trends, but not their magnitude, whereas least-squares linear regression and Sen’s slope trend test were better for determining the magnitude of the slope. The Mann–Kendall test was found to be less sensitive to extreme values in the data series, whereas least-squares linear regression was affected by both extreme values and autocorrelation within the data series. Sen’s slope trend test was able to eliminate the impact of missing data or anomalous trends by using the median of the series of slopes as the judgmental foundation (Zhang et al 2002, Stow et al 2004). In this study, we compared all three methods and selected Sen’s slope to detect and characterize trends in the vegetation dynamics and climate parameters in the TRB.

3.4. Principal-components analysis (PCA)

We investigated 11 climatic factors that potentially affect vegetation dynamics in the study area. PCA revealed the relative contribution of these factors or groups of factors to vegetation dynamics, as measured by changes in NDVI. We used the eigenvalue and cumulative contribution of the principal components to classify the standardized driving factors into different categories. We standardized the climatic factors that affected the vegetation dynamics using the following equation:

$$X_j = (X_{j obs} - \bar{X}_j)/\sigma_j; \quad (1)$$

where $X_j$ is the standardized value of the $j$th driving factor; $X_{j obs}$ is the observed value of the $j$th driving factor; $\bar{X}_j$ is the arithmetic mean of the $j$th driving factor; $\sigma_j$ is the standard deviation of the $j$th driving factor; and $j \in (1, n)$, where $n$ represents the number of driving factors.

Based on orthogonal transformation, the $n$ standardized driving factors can be converted into $m$ principal components:

$$\begin{align*}
F_1 &= a_{11}X_1 + a_{12}X_2 + \cdots a_{1n}X_n, \\
F_2 &= a_{21}X_1 + a_{22}X_2 + \cdots a_{2n}X_n, \\
&\quad \cdots, \\
F_m &= a_{m1}X_1 + a_{m2}X_2 + \cdots a_{mn}X_n,
\end{align*} \quad (2)$$

where $F_m$ is the standardized equivalent value of principal component $m$ estimated by the driving factors $X_m$; $a_{mn}$ is the score coefficient for the components and is equal to the principal component load matrix divided by the corresponding eigenvalue. It reflects the impact of a climate factor on the principal component. The principal component load matrix requires mutual independence among the variables as much as possible, and must converge after several iterations of orthogonal transformation to minimize the number of variables for the highest load component. The resulting estimated load matrix reflects the relevance of the variables and principal components. The higher the value of the rotated principal component matrix, the greater the impact of the driving factors on this principal component, and the more easily a change in this principal component will cause changes in the vegetation.

3.5. Correlation analysis

We ranked the climatic factors according to their contributions in the PCA. Since some climatic factors may be correlated, we used correlation analysis to test for a linear relationship between any two variables. We divided the absolute value of the correlation coefficients (Pearson’s $r$) into a weak correlation ($0 < |r| \leq 0.3$), a low correlation ($0.3 < |r| \leq 0.5$), a moderate correlation ($0.5 < |r| \leq 0.8$), and a strong correlation ($0.8 < |r| \leq 1$).
We then used the *t*-test to look for significant correlations between driving factors:

\[ t = \left( \frac{r_{xy}}{\sqrt{1 - r_{xy}^2}} \right) \times \sqrt{N - 2} , \]

where \( r_{xy} \) is the correlation coefficient between \( x \) and \( y \), and \( N \) is the sample size. The critical value \( t_{\alpha/2} \) at different significance levels can be found in standard tables for the distribution of this parameter. If \( t > t_{\alpha/2} \), the correlation is significant. Combining the PCA and correlation analysis, the climatic factors with high correlations were rejected and the key climatic factors with low correlations were retained to avoid auto correlation. For example, both radiation and temperature contributed strongly to dynamic vegetation change (table 1), but they are highly correlated (table 2) through the PCA analysis and correlation. Therefore, because the radiation parameter had a weaker contribution to the total variance, the temperature parameter was retained as the climate variable for further analyses.

### 3.6. Exploration of regressive modules

Based on the results of the correlation analysis, we explored possible regressive modules for the remaining key parameters to determine the relationships of vegetation dynamics with regional climate change. NDVI was the dependent variable and the key climate factors were the independent variables:

\[ \text{NDVI} = \left( \sum b_i C_i \right) + \epsilon, \]

where \( b_i \) is the regression coefficient for key climatic factor \( C_i \) of factor set \( i \), and \( \epsilon \) is an error term. The regression equation can be then used to examine how vegetation responds to changes in climate.

### Table 1. Rotated principal-components matrix to examine the effects of the climatic factors on NDVI dynamics.

| Climatic factors | Eastern Tibetan Plateau | Southwestern Loess Plateau |
|------------------|-------------------------|---------------------------|
|                  | First       | Second      | First       | Second      |
| \( R_n \)        | 0.89        | -0.34       | 0.92        | -0.31       |
| \( T_{\text{mean}} \) | 0.98        | 0.04        | 0.99        | 0.02        |
| \( T_{\text{max}} \) | 0.96        | 0.01        | 0.97        | -0.01       |
| \( T_{\text{min}} \) | 0.98        | 0.07        | 0.98        | 0.07        |
| \( C_{T0} \)     | 0.99        | 0.03        | 1.00        | 0.00        |
| \( C_{T3} \)     | 0.99        | 0.02        | 1.00        | 0.00        |
| \( C_{T5} \)     | 0.98        | 0.02        | 0.99        | 0.00        |
| \( C_{T10} \)    | 0.93        | 0.02        | 0.97        | 0.00        |
| \( C_{P0} \)     | 0.17        | 0.98        | 0.14        | 0.99        |
| \( C_{P1} \)     | 0.00        | 1.00        | -0.02       | 1.00        |
| \( C_{P2} \)     | -0.15       | 0.98        | -0.17       | 0.98        |

4. Results and discussion

#### 4.1. Trend analyses

The decadal trends and the magnitudes of the effects of the key climatic factors estimated by means of least-squares linear regression, Sen’s slope trend test, and the Mann–Kendall test score are presented in figure 3. To facilitate visual comparison, the scales of the climate parameters were adjusted by multiplying the precipitation values by 0.1, the mean annual air temperatures by 10, NDVI values by 200, and net radiation by 0.1 as shown in figure 3. The least-squares linear regression and Sen’s slope trend test showed similar magnitudes of trends for the climatic factors and NDVI. The three statistical results showed considerable consistency in the trends, indicating a high level of confidence in the trends for vegetation and climate change. Because of its ability to account for extreme values, we chose Sen’s slope trend test to estimate the yearly and monthly trends and the magnitudes of vegetation and climate variation.

#### 4.2. Correlations between vegetation dynamics and climatic factors

4.2.1. PCA results. The PCA analysis revealed two principal components whose eigenvalues were greater than 1 in the ETP region and the SLP region, with cumulative contributions that explained 96.0% and 97.3% of the total variance, respectively, in the two regions. Table 1 shows the rotated principal-components matrix for the climatic factors in each region. The higher the value in this matrix, the greater the impact of the driving factor on this principal component.
and the more easily a change in this principal component can cause changes in vegetation.

The results shown in table 1 suggested that net radiation, air temperature, and cumulative air temperature were the most important driving factors for the first principal component in both regions. Thus, the first principal component explained the impact of solar radiation and air temperatures on vegetation dynamics. In contrast, the precipitation factors were most important for the second principal component, which therefore explained the impact of moisture availability on vegetation dynamics.

4.2.2. Correlation analyses. Table 2 summarizes the correlations among the monthly climatic factors and NDVI in both regions. There were strong correlations among most of the climatic factors, especially among the air temperatures, with correlation coefficients close to or greater than 0.9. There were also strong correlations among the cumulative precipitation factors, but these factors showed weak correlations with the other climatic factors in both regions.

Based on the results of the correlation analysis, the air temperature factors were all significantly correlated with NDVI and the cumulative precipitation was weakly or non-significantly correlated with NDVI. In section 4.3.3, we will discuss the key factors revealed by this analysis and their effect on NDVI.

4.2.3. NDVI responses to climate factors. From the 11 factors that we initially selected, the PCA and correlation analysis showed that net radiation and air temperature had a stronger contribution to vegetation dynamics than precipitation factors in the TRB. Based on these analyses, we divided the factors that affected vegetation dynamics into two parts: (1) the air temperature and net radiation factors and (2) the precipitation factors. We explored possible regressive modules to determine the response of NDVI to these two groups of factors.

The regression results showed that the air temperature and net radiation factors predicted NDVI very well, whereas the cumulative precipitation did not. However, the sine of the cumulative precipitation predicted NDVI well in both regions, particularly for CP1. Based on the degree of independence of the parameters (correlation analysis) and the results of the regressive module exploration, we chose $T_{\text{mean}}$ and CP1 as the independent parameters to predict NDVI and obtained the following:

For the ETP:

$$\text{NDVI} = 0.013T_{\text{mean}} - 0.08 \sin (CP1^{0.3}) + 0.35.$$  \hfill (5)

For the SLP:

$$\text{NDVI} = 0.008T_{\text{mean}} - 0.11 \sin (CP1^{0.3}) + 0.23.$$  \hfill (6)

To calibrate these equations, we used data from the assimilated NDVI data series from 1981 to 2000; to validate the equations, we used data from 2001 to 2010. Figure 4 shows the scatterplots for the calibration and validation in the two regions.

The correlation coefficients for the regressive module were greater than 0.85 for both the calibration and validation periods in the two regions (figure 4). This indicates that the accuracy of the regression equations was high. We used the Nash coefficient to estimate the stability of the two models: for the ETP, the coefficient was 0.77 for calibration and 0.88 for validation; for the SLP, these values were 0.86 and 0.87, respectively. This means that both regression equations were stable and that they can represent the relationship between vegetation dynamics and climatic factors in both regions of the TRB.

4.2.4. Response of vegetation dynamics to regional climate change. Based on the regression equations, we examined

|        | $R_0$ | $T_{\text{mean}}$ | $T_{\text{max}}$ | $T_{\text{min}}$ | $CT_1$ | $CT_2$ | $CT_3$ | $CT_{10}$ | $CP_0$ | $CP_1$ | $CP_2$ | NDVI |
|--------|-------|-------------------|------------------|------------------|--------|--------|--------|----------|--------|--------|--------|-------|
|        | 1.00  | 0.91              | 0.91             | 0.87             | 0.91   | 0.90   | 0.87   | -0.17     | -0.32  | -0.44  | 0.78   |
| $T_{\text{mean}}$ | 0.88  | 1.00              | 0.99             | 0.98             | 0.98   | 0.97   | 0.93   | 0.16      | 0.00   | ns     | -15    | 0.88  |
| $T_{\text{max}}$ | 0.88  | 0.99              | 1.00             | 0.95             | 0.96   | 0.95   | 0.89   | 0.13      | -0.03  | ns     | -17    | 0.84  |
| $T_{\text{min}}$ | 0.85  | 0.98              | 0.96             | 1.00             | 0.97   | 0.96   | 0.92   | 0.21      | 0.05   | ns     | -10    | 0.89  |
| $CT_1$ | 0.86  | 0.96              | 0.94             | 0.96             | 1.00   | 1.00   | 0.97   | 0.15      | -0.02  | ns     | -17    | 0.92  |
| $CT_2$ | 0.85  | 0.96              | 0.93             | 0.95             | 1.00   | 1.00   | 0.97   | 0.14      | -0.02  | ns     | -17    | 0.92  |
| $CT_{10}$ | 0.84  | 0.94              | 0.91             | 0.94             | 1.00   | 1.00   | 0.98   | 0.14      | -0.02  | ns     | -17    | 0.92  |
| $CP_0$ | 0.77  | 0.86              | 0.83             | 0.87             | 0.95   | 0.96   | 0.97   | 1.00      | 0.14   | -0.03  | ns     | 0.93  |
| $CP_1$ | -0.18 | 0.21              | 0.18             | 0.24             | 0.19   | 0.19   | 0.17   | 1.00      | 0.98   | ns     | 0.29   |
| $CP_2$ | -0.33 | 0.04 ns           | 0.02 ns          | 0.07 ns          | 0.02 ns| 0.02 ns| 0.02 ns| 0.02 ns    | 0.98   | 1.00   | 0.98   | 0.13  |
| NDVI   | 0.66  | 0.86              | 0.82             | 0.88             | 0.92   | 0.92   | 0.91   | 0.42      | 0.27   | 0.11 ns| 1.00   |

ns- not significant; all other values are significant at $P < 0.05$. 

Table 2. Analysis of the correlations ($r$) between climatic factors in the Eastern Tibetan Plateau (shaded area below the diagonal) and the Southwestern Loess Plateau (unshaded area above the diagonal).
vegetation dynamics as a function of air temperature and precipitation. The results (figure 5) suggest that air temperature was more important to vegetation dynamics in the ETP than in the SLP. This is understandable because the vegetation in cold regions is typically more sensitive to air temperature than the vegetation in warmer regions. Precipitation was more important in the SLP than in the ETP, which is also reasonable because the vegetation in dry regions is more sensitive to precipitation than in humid regions. During the cold season, the low cumulative precipitation in the beginning of the year and the high cumulative precipitation at the end of the year led to a positive value for \( \sin(CP1) \), but a negative value for the corresponding coefficient. The negative value reflects the low NDVI during the early growing season and defoliation of the vegetation late in the year. During the warm season, the moisture and thermal conditions are favorable for vegetation growth, so NDVI in both regions was higher than it was during the cold season. Because evergreen needle-leaved forest grows in the ETP, the lowest NDVI during the cold season is about 0.14, versus 0.04 in the SLP, where there are few evergreen species. These values represent the lowest NDVI levels in the two regions. Due to the combined effects of high air temperatures and cumulative precipitation, NDVI in both regions was highest in July or August. The red solid circles in figure 5 show that under the same moisture and thermal conditions, NDVI was higher in the ETP because of the high background NDVI value due to the presence of evergreen forest. The white arrows represent the approximate direction of the NDVI change between seasons, and the length of the arrows represents the magnitude of the change. In general, the vegetation cover was higher in the ETP, and the annual NDVI change was gentler.

4.3. Spatio-temporal vegetation dynamics and climatic factors

4.3.1. Temporal patterns of vegetation and climate change

The changes in NDVI and the two key climatic parameters were well synchronized during the past 30 years. The air temperature and NDVI both increased while the precipitation decreased in the two regions. However, at time scales of seasons or months, the characteristics of the variation were different.

The seasonal trends for NDVI, \( T_{\text{mean}} \) and \( CP1 \) from 1981 to 2010 are summarized in table 3. As indicated by the slopes, there was no vegetation change in winter or summer in both regions. In the ETP, NDVI increased during the spring and decreased during the autumn. This indicates that the growing season may be starting earlier and ending earlier. In the SLP,
NDVI increased in both the spring and the autumn, suggesting that the growing season is starting earlier and ending later. These trends are not necessarily directly related to the length of the growing season, but may instead be based on the background of increasing temperatures in all seasons. However, the trend of decreasing precipitation in all seasons may lead to long-term problems with moisture availability that reduce the effects of rising temperatures on vegetation growth. Determining the start and end of the growing season is beyond the scope of this study, but would be an interesting topic for future research.

4.3.2. Spatial patterns of vegetation dynamics. Using the period from 2001 to 2010 as an example, we can see that NDVI increased in some areas of the ETP and decreased in others. Overall, NDVI increased slightly during this period in this region. In the SLP, NDVI generally increased during the study period (figure 6). This increase may be related to the ‘Grain for Green’ program, which was implemented in 1999 (Li et al 2010, Lü et al 2012) to return slope agricultural lands to natural grasslands. Under this program, farmers and livestock herders were encouraged to stop farming or herding their animals on ecologically fragile lands in exchange for government compensation, leading to vegetation recovery in some degraded ecosystems. The decrease in the area of farmland in the TRB under this program has been small (less than 0.5% of the basin’s area), and has been concentrated in dry arable regions mainly with rain-fed agriculture. The effect of land cover changes and human activities is therefore expected to be small, and the vegetation dynamics at a decadal scale are likely to be mainly affected by climate change. Based on the relationships between the decadal vegetation change (NDVI) and the two climatic parameters ($T_{\text{mean}}$ and $CP_1$), there appears to be a fairly loose correspondence between them. In addition, the trends in the changes of air temperature, precipitation, and NDVI, and the magnitudes of the changes, differ from decade to decade.

4.3.3. Potential drivers for vegetation dynamics. Based on the relationships between vegetation growth and the moisture and thermal conditions that are reflected in the regression

Table 3. Trends in NDVI, the mean monthly air temperature ($T_{\text{mean}}$), and cumulative precipitation ($CP_1$) from 1981 to 2010 in the Tao River Basin.

| Season | Eastern Tibetan Plateau | Southwestern Loess Plateau |
|--------|-------------------------|---------------------------|
|        | NDVI | $T_{\text{mean}}$ (°C) | $CP_1$ (mm) | NDVI | $T_{\text{mean}}$ (°C) | $CP_1$ (mm) |
| Winter | 0.00 ns | 0.69 | −3.85 ns | 0.00 ns | 0.63 | −4.94 ns |
| Spring | 0.03 | 0.58 | −2.79 ns | 0.02 | 0.56 | −1.54 ns |
| Summer | 0.00 ns | 0.47 | −11.25 ns | 0.00 ns | 0.50 | −3.35 ns |
| Autumn | −0.02 ns | 0.46 | −13.05 ns | 0.01 | 0.30 | −14.31 ns |
| Annual | 0.01 ns | 0.55 | −7.73 ns | 0.01 | 0.50 | −6.04 ns |

Note: ns—not significant; all other values are significant at $P<0.1$. 

Figure 6. Spatial distribution of Sen’s slope in MODIS-derived NDVI variation (right) and its corresponding significance level (left) of the Tao River Basin from 2001 to 2010 for the Eastern Tibetan Plateau (ETP) and the Southwestern Loess Plateau (SLP).
equations we constructed for each region (equations (5) and (6)), NDVI appears to be positively linearly related to air temperature in both regions, but negatively related to the sine of cumulative precipitation. The coefficients of air temperature and precipitation have the same sign in the equations for both regions.

Numbers and arrow lines in the top of figure 7 describe the average ranges of climatic values for the growing season (autumn included in the summer ranges) in the two regions in the TRB. In the ETP, the coefficient for air temperature is higher than that in the SLP, indicating that vegetation dynamics are more sensitive to air temperature in this region. The higher precipitation coefficient in the SLP indicates that the vegetation in this arid region is significantly affected by precipitation. Because precipitation has decreased in all seasons in both regions since 1981, the increase in NDVI during this period can be attributed entirely to the increasing air temperature. Particularly during the spring, NDVI increased rapidly (by 0.03 and 0.02 per 10 years in the ETP and the SLP, respectively). The annual increase in NDVI has been 0.01 per 10 years in both regions since 1981 under different backgrounds of regional climate change (table 3).

It is noted that using vegetation indicators to assess subtle change of vegetation over large area is challenging as it relies on, e.g., NDVI’s sensitivity to vegetation signals and insensitivity to external environmental noises such as atmospheric and soil variations. Given the data availability and the time period of interest in this area, NDVI remains the only choice and its subtle increase (decadal mean value of 0.03) appears to be questionable. However, if we examine its relative change, then the decadal 0.03 is substantial. Annual variation of NDVI, along with corresponding temperature and precipitation is shown in figure 8 for both ETP and SLP sub regions, to allow a visual examination of the annual NDVI changes.

4.3.4. Threshold of spring precipitation for vegetation growth. The black solid dot on the left diagram in figure 7 is the cumulative spring precipitation threshold (44 mm in this case) required for NDVI to increase (changes of NDVI ≥ 0). This value represents a reasonable precipitation requirement to support spring vegetation growth. If the amount of precipitation is below this threshold, vegetation growth will be poor due to a lack of sufficient soil moisture. There appears to be little difference in the thresholds for ETP and SLP regions. The background NDVI in winter is especially low in the SLP and thus this threshold is particularly meaningful assessing vegetation dynamics in the region.

The concept of precipitation threshold (44 mm in this study) is important in climate change research, particularly in ecosystem assessment and water resource management in these semi-humid and semi-arid regions. Note that the 44 mm threshold in figure 7 is the threshold beyond which NDVI starts to change (increase in this case), an indicator of onset of vegetation growth. It should also be noted that vegetation growth (onset) is determined by many environmental variables, including climate, snow melting, ground water, soil and topography. The combination of these key factors influences vegetation germination and growth rate in general, but in the study region snowfall in the winter seems to play a dominant role in the following spring growth. In the study area, previous work (Wang et al 2014) indicated frequent droughts in the winter, therefore spring rainfall becomes critical to vegetation growth in the region, in addition to temperature.

It is further noted that ETP and SLP regions have unique climates and are expected to have different precipitation thresholds to trigger spring growth (ΔNDVI > 0). However, the reality is that the two regions were found to have approximately the same (44 mm) precipitation thresholds.

5. Conclusions

In this paper, we assimilated the AVHRR and MODIS NDVI time-series to produce a comprehensive NDVI time-series for the TRB. We identified the key climatic factors that affected the vegetation dynamics (measured by changes in NDVI)
throughout the region by means of PCA and correlation analysis, and conducted the exploration of regressive modules to determine the relationships between NDVI and these factors. Several conclusions can be drawn from this study:

First, we were able to successfully assimilate the AVHRR and MODIS NDVI series, as indicated by the small error for pixels during the same period and the high stability of the regression for the two NDVI series, allowing us to create continuous data from 1981 to 2010 for three decades of trend analysis of vegetation dynamics.

Second, the vegetation and climate trend analyses revealed by least-squares linear regression, Sen’s slope trend test, and the Mann–Kendall test were generally consistent, suggesting that all three methods can be used to analyze hydrometeorological and NDVI trends in our study area.

Third, based on the PCA and correlation analysis, we identified the mean air temperature and cumulative monthly precipitation since December of the previous year as the key climatic parameters influencing vegetation dynamics in the study area. Regression of NDVI against these climate parameters provided useful clues indicating that climatic variables can predict NDVI in the ETP and the SLP with acceptable accuracy in the TRB.

Fourth, the dominant climatic factor responsible for the vegetation dynamics differed between the two parts of the TRB. In the colder ETP, air temperature had the strongest effect on vegetation dynamics, whereas precipitation was most important in the drier SLP.

Fifth, Sen’s slope trend test showed that NDVI has generally been increasing throughout the TRB since 1981, largely as a result of increasing temperatures, despite a declining precipitation trend. The rate of increase in spring NDVI was higher in the ETP sub-region than in the SLP, with values of 0.03 and 0.02 per 10 years, respectively. The results suggest that the vegetation growing season in the ETP is starting earlier and ending earlier, while that in the SLP, the growing season is starting earlier and ending later.

Finally, the NDVI regression equations that we constructed suggest that the threshold of cumulative spring precipitation for vegetation germination is 44 mm. If spring precipitation is below this threshold, there will be a significant negative impact on vegetation growth.

Acknowledgments

This study was supported by the following grants: the NSFC Project (41001014), the Doctoral Program of Higher Education Research Fund (20110211110011), the NASA LCLUC project (NNX08AH50G) at Michigan State University, and...
the Fundamental Research Funds for the Central Universities (Izujbky-2014-118). The authors are grateful to Geoffrey Hart for his assistance and Jenni Gronseth for her editorial assistance.

References

Beck H E, McVicar T R, van Dijk A I, Schellekens J, de Jeu R A and Bruinzeel L A 2011 Global evaluation of four AVHRR–NDVI data sets: intercomparison and assessment against Landsat imagery Remote Sens. Environ. 115 2547–63
Bradley B A, Jacob R W, Hermane J F and Mustard J F 2007 A curve fitting procedure to derive inter-annual phenologies from time series of noisy satellite NDVI data Remote Sens. Environ. 106 137–45
Brown M E, Lary D J, Vrieling A, Stathakis D and Musa H 2008 Neural networks as a tool for constructing continuous NDVI time series from AVHRR and MODIS Int. J. Remote Sens. 29 7141–58
Cartus O, Santoro M, Schmullius C and Li Z Y 2011 Large area temporal variation in areal extent and configuration accuracy for the MODIS NDVI product Remote Sens. Environ. 115 931–43
Curran P J 1980 Multispectral remote sensing of vegetation amount Prog. Phys. Geog. 4 319–41
Fan J and Zhang X 2010 Study on the vegetation dynamic change using long time series of remote sensing data Proc. of SPIE 7824, Remote Sensing for Agriculture, Ecosystems, and Hydrology 12th Int. Society for Optics and Photonics ed C M U Neale and A Maltese 2010 782415
Fang J Y, Piao S L, Wang Q and Ma W H 2003 Vegetation activity component of a global climate model: a preliminary assessment Clim. Change 4 337–77
Henebry G M and Betancourt J L 2010 Toward a US National Phenological Assessment: Third USA National Phenology Network (USA-NPN) and Research Coordination Network (RCN) Annual Meeting Eos, Transactions American Geophysical Union Milwaukee, Wisconsin 5–9 October 2009 91 3
Hilker T, Wulder M A, Coops N C, Setz N, White J C, Gao F, Masek J G and Stenhouse G 2009 Generation of dense time series synthetic Landsat data through data blending with MODIS using a spatial and temporal adaptive reflectance fusion model article Remote Sens. Environ. 113 1988–99
Holben B N 1986 Characteristics of maximum-value composite images from temporal AVHRR data Int. J. Remote Sens. 7 1417–34
Horion S, Cornet Y, Erpicum M and Tychon B 2013 Studying interactions between climate variability and vegetation dynamic using a phenology based approach Int J. Appl. Earth Obs. 20 20–32
IPCC 2007 Summary for policymakers. Climate change: the physical science basis Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change ed S Solomon, D Qin, M Manning, Z Chen, M Marquis et al (Cambridge: Cambridge University Press)
Jacquin A, Sheeren D and Lacombe J P 2010 Vegetation cover degradation assessment in Madagascar savanna based on trend analysis of MODIS NDVI time series Int. J. Appl. Earth Obs. 12 S3–10
Kang Y, Li Z C, Tian H, Liu R, Shi X K, Zhang J H and Wen J 2011 Trend of vegetation evaluation and its responses to climate change over the source region of the Yellow River Clim. Environ. Res. 16 505–12 (in Chinese)
Kendall M G 1955 Rank Correlation Methods (London: Griffin)
Lambin E F et al 2001 The causes of land-use and land-cover change: moving beyond the myths Glob. Environ. Change 11 261–9
Li C, Qi J, Feng Z, Yin R, Guo B, Zhang F and Zou S 2010 Quantifying the effect of ecological restoration on soil erosion in China’s Loess Plateau region: an application of the MMF approach Environ. Manage. 45 476–87
Li C B, Yang L S, Wang S B and Yang W J 2014 Land use and land cover change in Tao River Basin and its driving forces Sci. Geographica Sin. 34 848–55 (in Chinese)
Li Z, Huffman T, McConkey B and Townley-Smith L 2013 Monitoring and modeling spatial and temporal patterns of grassland dynamics using time-series MODIS NDVI with climate and stocking data Remote Sens. Environ. 138 232–44
Li Y et al 2012 A policy-driven large scale ecological restoration: quantifying ecosystem services changes in the loess plateau of China PLoS One 7 e31782
Ma Y, Feng S Y, Zhan H, Liu X, Su D, Kang S and Song X 2011 Water infiltration in layered soils with air entrapment: modified Green–Ampt Model and experimental validation J. Hydrol. Eng. 16 628–38
Mann H B 1945 Nonparametric tests against trend Econometrica 1 345–59
Meng M, Ni J and Zong M J 2011 Impacts of changes in climate variability on regional vegetation in China: NDVI-based analysis from 1982 to 2000 Ecol. Res. 26 421–8
Naud C M, Baum B A, Pavoloni M, Heidinger A, Frey R and Zhang H 2007 Comparison of MISR and MODIS cloud-top heights in the presence of cloud overlap Remote Sens. Environ. 107 290–10
Nayak A, Marks D, Chandler D G and Seyfried M 2010 Long-term snow, climate, and streamflow trends at the reynolds creek experimental watershed, Owyhee Mountains, Idaho, United States Water Resour. Res. 46 W06519
Nemani R R, Keeling C D, Hashimoto H, Jolly W M, Piper S C, Tucker C J, Myneni R B and Running S W 2005 Climate-driven increases in global terrestrial net primary production from 1982 to 1999 Science 300 1560–3
Ni J 2011 Impacts of climate change on Chinese ecosystems: key vulnerable regions and potential thresholds Reg. Environ. Change 11 49–64
Nie Q, Xu J H, Ji M, Cao L, Yang Y and Hong Y 2012 The vegetation coverage dynamic coupling with climatic factors in Northeast China transect Environ. Manage. 50 405–17
Pettorelli N, Vik J O, Mysterud A, Gaillard J M, Tucker C J and Stenseth N C 2005 Using the satellite-derived NDVI to assess ecological responses to environmental change Trends Ecol. Evol. 20 503–10
Pu B and Dickinson R E 2013 Hydrological changes in the climate system from leaf responses to increasing CO2 Clim. Dyn. 2013 1–19
Raynolds M K, Walker D A, Epstein H E, Pinzon J E and Tucker C J 2012 A new estimate of tundra-biome phytomass from trans-Arctic field data and AVHRR NDVI Remote Sens. Lett. 3 403–11
Roy D P, Ju J, Lewis P, Schaaf C, Gao F, Hansen M and Lindquist E 2008 Multi-temporal MODIS–Landsat data fusion for relative radiometric normalization, gap filling, and prediction of Landsat data Remote Sens. Environ. 112 3112–30
Sen P K 1968 Estimates of the regression coefficient based on Kendall’s tau J. Am. Stat. Assoc. 63 1379–89
Song Y, Ma M G and Frank V 2010 Comparison and conversion of AVHRR GIMMS and SPOT VEGETATION NDVI data in China Int. J. Remote Sens. 31 2377–92
Stefanov W L and Netzband M 2005 Assessment of ASTER land cover and MODIS NDVI data at multiple scales for ecological characterization of an arid urban center Remote Sens. Environ. 99 31–43
Stow D A et al 2004 Remote sensing of vegetation and land-cover change in Arctic Tundra ecosystems Remote Sens. Environ. 89 281–308
Tucker C J, Pinzon J E, Brown M E, Slayback D A, Pak E W, Mahoney R, Vermote E F and El Saleous N 2005 An extended AVHRR 8 km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data Int. J. Remote Sens. 26 4485–98
Turner W, Spector S, Gardiner N, Fladeland M, Sterling E and Steininger M 2003 Remote sensing for biodiversity science and conservation Trends Ecol. Evol. 18 306–14
Vermote E F, Roger J C, Sinyuk A, Saleous N and Dubovik O 2007 Fusion of MODIS–MISR aerosol inversion for estimation of aerosol absorption Remote Sens. Environ. 107 81–9
Walker J J, de Beurs K M and Wynne R H 2014 Dryland vegetation phenology across an elevation gradient in Arizona, USA, investigated with fused MODIS and Landsat data Remote Sens. Environ. 144 85–97
Wang K and Dickinson R E 2012 A review of global terrestrial evapotranspiration: observation, modeling, climatology, and climatic variability Rev. Geophys. 50 1–54
Wang S B, Li C B, Yang L S, Yang W J and Fan X P 2014 Drought assessment based on comparison between standardized precipitation index and Z-index in Taoho River Basin Arid Zone Res. (in press)
Wang Y, Xia W T, Liang T G and Wang C 2010 Spatial and temporal dynamic changes of net primary product based on MODIS vegetation index in Gannan grassland Acta Prataculturae Sin. 19 201–10 (in Chinese)
Yang L S, Li C B, Wang S B and Yang W J 2014 Sensitive analysis of potential evapotranspiration to key climatic factors in Taoho River Basin Trans. Chin. Soc. Agric. Eng. 30 102–9 (in Chinese with English abstract)
Yang Q Y, Zhang B P and Zheng D 1988 On the boundary of the Loess Plateau J. Nat. Resour. 3 9–15 (in Chinese)
Ye J S, Reynolds J F, Sun G J and Li F M 2013 Impacts of increased variability in precipitation and air temperature on net primary productivity of the Tibetan Plateau: a modeling analysis Clim. Change 119 321–32
Yin H, Li Z G, Wang Y. L and Cai F 2011 Assessment of desertification using time series analysis of hyper-temporal vegetation indicator in Inner Mongolia Acta Geographica Sin. 66 653–61 (in Chinese)
Zhang G L, Xu X L, Zhou C P, Zhang H B and Ou Y H 2011 Responses of vegetation changes to climatic variations in HulunBuir grassland in past 30 years Acta Geographica Sin. 66 47–58 (in Chinese)
Zhang Y L, Li B Y and Zheng D 2002 A discussion on the boundary and area of the Tibetan Plateau in China Geogr. Res. 21 1–8 (in Chinese)
Zhao D S, Wu S H, Yin Y and Yin Z Y 2011 Vegetation distribution on Tibetan Plateau under climate change scenario Reg. Environ. Change 11 905–15
Zhao F F, Xu Z X, Huang J X and Li J Y 2008 Monotonic trend and abrupt changes for major climate variables in the headwater catchment of the Yellow River basin Hydrol. Process. 22 4587–99