Vegetation cover changes and their relationship to climate variation in the source region of the Yellow River, China, 1990–2000

W. Q. GUO*†, T. B. YANG†, J. G. DAI‡, L. SHI† and Z. Y. LU†
†Key Laboratory of Western China’s Environmental Systems (Ministry of Education), Lanzhou University, South Tianshui Rd 222, Lanzhou 730000, China
‡School of Geomatics, Liaoning Technology University, Fuxin 123000, China

(Received 16 July 2006; in final form 31 March 2007)

The change history of vegetation cover and its relations to growing season precipitation (GSP) and average growing season temperature (AGST) in the source region of the Yellow River (SRYR) during 1990–2000 was retrieved based on the 1 km Advanced Very High-Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) data and meteorological records. The results show an overall warming and drying trend of the climate and a common degradation tendency of the ecosystem, with a greening trend in higher rugged regions. The pixel-by-pixel correlations between NDVI and climate factors indicate that a decrease in GSP mainly affects ecosystems with low precipitation and worse vegetation condition, and superimposes on the effects of increasing AGST which further deteriorate the climate background of these ecosystems. However, the positive correlations between AGST and NDVI in some higher/rugged regions suggest that the raising temperature can ameliorate vegetation growth conditions in these areas. Comparison and combination of the results of three change detection algorithms, i.e. post-classification comparison (PCC), principal components analysis (PCA) and a newly developed multi-temporal image difference (MTID) method, show that the integration of different methods can give a more comprehensive understanding of vegetation changes than any single method.

1. Introduction

Great efforts have been made to study vegetation cover and its changes during the last few decades via remote sensing data (e.g. Goward et al. 1985, Townshend and Justice 1986, Tucker 1986, DeFries et al. 1999, Weiss et al. 2001, Pan et al. 2003, Yu et al. 2004). The Advanced Very High Resolution Radiometer (AVHRR) onboard the National Oceanic and Atmospheric Administration (NOAA) series satellites is frequently referred to by researchers, due to its long observation sequence (since the late 1970s), and its daily data-acquisition cycle. The Normalized Difference Vegetation Index (NDVI) derived from AVHRR data is further broadly used as the indicator of vegetation activities in these studies, since it is closely related to the parameters such as photosynthesis, net primary productivity (NPP) and transpiration, etc. (e.g. Running and Nemani 1988, Prince 1991, Ruimy et al. 1994). The NDVI is also the major data source to evaluate the relationships between vegetation cover and climatic factors and has been widely accepted by researchers for the study of the impact of climate change on ecosystem evolutions (e.g. Cihlar et al. 1991, Di

*Corresponding author. Email: guowq_china@hotmail.com

Researchers also studied the Chinese vegetation changes and their relationship to climate variations. A decrease in productivities of vegetations in forest regions and an increase in agricultural regions are revealed by Young and Wang 2001, Liu et al. 2002, Yu et al. 2003, Xiao and Moody 2004, Yu et al. 2004, Piao et al. 2006). Their results also show a potential increase in productivity in parts of Qinghai and Tibet primarily related to increasing precipitation and temperature. The relationship between AVHRR NDVI and eco-climatic parameters in China were studied by Li et al. (2002). Although Li et al. did not give any results of vegetation change, they described a strong correlation between vegetation and growing degree-days (GDD), as well as rainfall, which is particularly significant in grassland (steppe and savanna). Another study that focused on the vegetation responses to variations in climate factors in eastern central Asia (Yu et al. 2004) concluded that the pre-season climate variation can partially explain the changes in typical steppe and desert steppe, however, they found that meadow steppe has no significant relationship to pre-season climate factors in that region.

These studies partly reveal some aspects of Chinese vegetation changes and their relationship to climate variations and introduce schematic scenarios of Chinese ecosystem evolution. However, the coarse spatial resolution (8 km) of the data they used cannot give a precise and reliable account of general changes in vegetation types. Furthermore, the studies on alpine vegetation types, such as alpine meadow and alpine steppe, were rarely reported. Since the Tibetan Plateau is typical of alpine ecosystems and plays a very important role in the Chinese ecological regime, studies on alpine vegetation changes in the Tibetan Plateau and their relationship to climate variations is urgently needed.

High altitude regions, such as Tibetan Plateau, were proven to have experienced a more dramatic climate change than the average global or hemisphere climate change according to a review by Beniston et al. (1997). Other researches on the effects of climate change on the alpine ecosystem also reveal that the changes in climate factors (temperature, precipitation, sunshine duration, etc.) significantly influence vegetations of high altitude mountain regions, mainly characterized by upward migrations of alpine plant species (Grabherr et al. 1994, Miehe 1996, Guisan and Theurillat 2000, Theurillat and Guisan 2001, Fagre et al. 2003).

The source region of the Yellow River (SRYR), which is located at the northeastern part of the Tibetan Plateau, has a vital importance for sustainable development of the northeastern Tibetan Plateau, even of the whole Yellow River drainages. The natural ecosystem of the SRYR is very vulnerable and fairly sensitive to regional climate changes and human exploitation activities. Since the late 1980s, numerous eco-environmental issues have arisen in this region, such as land desertification, grassland degradation, glacier thawing and frequent occurrence of upriver zero-flow events. These problems have caused enormous damage to regional social stability and economic sustainability. However, because of its remote geographical location and inaccessibility, large parts of the SRYR have not yet been investigated. Consequently, studies of ecosystem changes in the SRYR region have been rarely reported.

This study aims to reveal the vegetation cover changes and their relationship to variations in climate factors (growing season precipitation (GSP) and average growing season temperature (AGST)) of the SRYR. The objectives are (i) the detailed vegetation cover change history of the SRYR from 1990 to 2000, (ii) climate
variations of the SRYR during the same period and (iii) the relationship between vegetation cover changes and climatic variations.

2. Study area

The geographical definition of the SRYR in this study follows primarily the traditional hydrological definition, which refers to the upper drainages of Yellow River above the Tangnag hydrometric station (E100°09′, N35°30′) and further incorporates the area between Tangnag and Longyangxia Reservoir. This region covers an area of about 130,523 km², has an average elevation of 4072 m and contains 24 counties which belong to Gansu, Qinghai and Sichuan provinces (see figure 1).

The study area is largely comprised of grassland ranging from desert steppe to meadows influenced by the high altitude and rigorous climate. Forests only cover a very small area (about 1.25% of the total study area, ca 1632.5 km²) with Sabina przewalskii and Picea crassifolia as the dominant species. The widely distributed ligneous plants are shrubs, with constructive species like Salix oritrephe, S. sclerophylla, Dasiphora fruticosa. There are also some human-introduced vegetation types like crop and sand-protection plants, which are primarily distributed at Gonghe basin. Glaciers also cover some areas in the middle mountain ridges but there size is insignificant (see figure 2).

3. Data and methods

3.1 Data

Monthly temperature and precipitation data from 38 weather observation stations for the growing seasons from 1989 to 2001 were used in this study. These weather
stations were selected by their locations relative to our study area, of which 11 sites are located in the study area, and the remaining stations are evenly distributed around the study area (see figure 1).

The NOAA-AVHRR Level-1B data obtained from NOAA Comprehensive Large Array-data Stewardship System (CLASS) were used in this study. The Local Area Coverage (LAC) and High Resolution Picture Transmission (HRPT) data, which have a nominal 1.1 km spatial resolution, were selected as the main source to derive vegetation information. The AVHRR dataset used in this study comprises the years from 1990 to 2000 (except 1993 and 1994), and commonly includes daily AVHRR data for July and August of each year, which generally have best vegetation throughout the whole growing season. The years of 1993 and 1994 were excluded because the cloud-free data is unavailable for the months of July and August in the last two years. Cloud-free and small view angle data (≤30°) were then chosen or subset from these data for further processing.

Field investigations were carried out during the period 20 July to 10 August 2005. A large amount of field observations and samples were collected to form the ground truth database. The routes are designed based on the consideration of crossing all kinds of vegetation cover types and all grades of elevation (see figure 3). The sampling zones were evenly distributed along the routes, comprising all kinds of vegetation cover types and were accurately positioned by using global positioning system (GPS). A digital elevation model (DEM) was generated from 1 : 250 000 topographic maps and resampled into an 1100 m × 1100 m grid (figure 3).
Data preprocessing

The AGST and GSP records of 38 weather stations for the period between 1990–2000 (excluding years 1993 and 1994) were interpolated into 1.1 km raster images using SKlm (Simple Kriging with varying local means) methods (Goovaerts 2000), which was tested to be the best spatial interpolate algorithm for the study area among GIDS (Gradient-plus-Inverse Distance Squared) (Nalder and Wein 1998), statistical, OK (Ordinary Kriging), and Co-Kriging. The local mean in SKlm of AGST and GSP were both evaluated by multi-linear regression to universal transverse Mercator (UTM) coordinates (in kilometres) and elevations. Among the selected four semi-variogram models (spherical, exponential, Gaussian and hole effect model) the hole effect model, used in the simple Kriging algorithm in SKlm, yields the most accurate results for both AGST and GSP data, which was verified by cross-validation.

The AVHRR Level-1B data were first calibrated using post-launch calibration algorithms and coefficients suggested by Rao and Chen (1995, 1996, 1999). Then, interactive geometric correction was performed with references to 1:250,000 topographic map. The atmospheric and angular effects were corrected by 6S code (version 4.1) software (Vermote et al. 1997). Typical atmospheric parameters were used due to the absence of simultaneous measurements: standard mid-latitude summer atmosphere, continental aerosol model, a visibility distance of 25 km and the DEM derived target altitude. Rahman et al.’s (1993a) model was selected to correct the angular effect, with parameters presented by Rahman et al. (1993b).

Topographic effects were also considered and corrected. The model presented by Sandmeier and Itten (1997) was used to correct the effects of rugged terrain on the irradiance reached at targets. The effects of inclining surface on Bidirectional
Reflectance Distribution Function (BRDF) were also corrected by a simple geometric transformation suggested by Schaaf et al. (1994).

A spectral normalization procedure was employed to remove the residual mismatching of data obtained on different dates by different satellites (Hall et al. 1991). The AVHRR imagery of 25 July 2005 was selected as the common reference basis. The NDVI was then calculated and the maximum-value composite (MVC) criterion (Holben 1986) was then used to generate the annual NDVI imagery.

### 3.3 Data analysis

Three different change detection algorithms were employed in this study, i.e. post-classification comparison (PCC), multi-temporal image differencing (MTID) and principal components analysis (PCA).

A stage mean composite was performed before classification with PCC in order to minimize the effects of instant phonological phenomena on NDVI, as well as to reduce the data volume. The data spanning nine years were divided into three stages, namely 1990–1992, 1995–1997 and 1998–2000. A simple NDVI threshold method was used to classify the study region into areas with different vegetation coverage ranks according to correlations between NDVI and biomass. A five-rank criterion, including sparse vegetation (SV), low-coverage vegetation (LV), moderate-coverage vegetation (MV), high-coverage vegetation (HV) and dense vegetation (DV), was employed to depict the different vegetation conditions in the study region. Vegetation classifications for all the stages were performed using the same NDVI scheme that was empirically determined according to the field samples. In addition, the water bodies were masked for all stages and their areas were not included in later analyses.

The MTID algorithm used in this study was mathematically deduced from bi-temporal case, which integrates NDVI between 1990 and 2000 under a shifted basis for NDVI of 2000 (equation (1)). The change intensities were also rendered by summation of the absolute NDVI differences between adjacent years (equation (2)).

\[
T = \sum_{i=1990}^{1999} (D_{2000} - D_i)
\]

\[
I = \sum_{i=1990}^{1999} |D_{i+1} - D_i|
\]

where \(T\) is change tendency, \(I\) is change intensity, \(i\) is calculated year and \(D\) is the NDVI of the corresponding year. A positive \(T\) value represents a dominant change trend towards better vegetation conditions, while a negative value represents degradation tendencies. A high \(I\) value represents a stronger or more frequent change.

Standardized PCA was also employed in this study. Determining the actual meaning of each principal component (PC) with reference to previous researchers is difficult due to the data they used and the objectives of their studies (Eastman and Fulk 1993, Anyamba and Eastman 1996, Young and Wang 2001). However, PCC and MTID methods used in this study can provide helpful information for analysing the actual meaning of each PC.

A pixel-by-pixel correlation analysis between the nine-year composite NDVI data and GSP, as well as AGST, was performed to reveal the relationships between climatic factors and vegetation coverage changes.
4. Results and discussion

4.1 Change processes presented by PCC

The results of PCC are represented in the classification maps in figure 4 and the change matrices in tables 1 and 2. According to these results, vegetation cover in SRYR has dramatically changed. The area of lower vegetation coverage zones universally increased while the area of higher vegetation coverage decreased, with some fluctuations in LV and HV.

From the vegetation classification maps (figure 4), the spatial patterns of vegetation cover changes can be clearly distinguished. The most significantly changed regions are in the counties Maduo, Chengduo and Qumalai, where a large area of HV impressively degraded to MV from stage 1 to stage 2, with some restorations from stage 2 to stage 3. The MV class also degraded across a large area, mainly at northern Qumalai county and northwestern Maduo county. County Xinghai is also a zone of apparent degradations, where the frontiers of DV and HV significantly retreated toward mountain ridges from stage 1 to stage 2, with some advances from stage 2 to stage 3, indicating that stage 3 has better vegetation conditions than stage 2 in this region. However, county Dari shows a different pattern. The degradation area from stage 1 to stage 2 is mainly HV, with slight expansion of DV. But the DV and HV classes were both distinctively degraded from stage 2 to stage 3, indicating that stage 3 presents less favourable vegetation conditions than stage 2. Similar developments were observed at county Zeku and Gande, where the DV continuously degraded into HV, particularly from stage 2 to stage 3, further indicating that stage 3 presents worse vegetation conditions than stage 2.

![Figure 4. Distribution of vegetation classifications of stage 1 (1990–1992) (a); vegetation classifications of stage 2 (1995–1997) (b); vegetation classifications of stage 3 (1998–2000) (c); and vegetation classifications for 2005 (d).](image-url)
The shrinkages of DV, HV and MV were synchronous with the expanding LV and SV classes. This is particularly obvious in the Gonghe basin. The HV and MV classes (representing crops or sand-protection plants in this place) shrink continuously while the SV and LV classes gradually expand. This gives salient evidence for the desertification of Gonghe basin, which was also suggested by Zeng et al. (2003). The LV class in the north of Gyaring Lake and Ngoring Lake also continuously expands, indicating an aridification trend of the local ecosystem, consistent with the conclusions of Wang et al. (2003).

Apparently, the degradation trend is more conspicuous at the northern and western regions of the study area where the topography is relatively lower and flatter. The degradation is less obvious at the middle mountainous region with higher elevation and rugged topography originally covered mainly by DVs. Actually, some parts of the central region show a good tendency of vegetation change. It is very typical at counties Maqu and Jiuzhi, where the DV class is gradually expanding from stage 1 to stage 3.

Further calculations from PCC results show the detailed change process of each vegetation cover type. By assigning each vegetation cover type a unique code, incrementing with higher NDVI value (i.e. one to SV, two to LV and five to DV, etc.), we classified different change patterns into six categories (table 3). The results show that a large part of the study area (66.09%) remains absolutely unchanged and about 10.25% of the area (including up-wave and down-wave change area) can be regarded as almost unchanged. The major part of the remaining area has experienced stable degradation (15.12%) and 8.27% of the area has changed to better conditions.

### Table 1. Vegetation cover changes from stage 1 to stage 2 (km²).

<table>
<thead>
<tr>
<th>Stage 1</th>
<th>Stage 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>SV</td>
<td>844.58</td>
</tr>
<tr>
<td>LV</td>
<td>211.75</td>
</tr>
<tr>
<td>MV</td>
<td>21.78</td>
</tr>
<tr>
<td>HV</td>
<td>1.21</td>
</tr>
<tr>
<td>DV</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>1079.32</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stage 1</th>
<th>Stage 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>SV</td>
<td>831.27</td>
</tr>
<tr>
<td>LV</td>
<td>10275.32</td>
</tr>
<tr>
<td>MV</td>
<td>17567.99</td>
</tr>
<tr>
<td>HV</td>
<td>24220.57</td>
</tr>
<tr>
<td>DV</td>
<td>37937.13</td>
</tr>
<tr>
<td>Total</td>
<td>12056.44</td>
</tr>
</tbody>
</table>

DV, dense vegetation; HV, high-coverage vegetation; LV, low-coverage vegetation; MV, moderate-coverage vegetation; and SV, sparse vegetation.

### Table 2. Vegetation cover changes from stage 2 to stage 3 (km²).

<table>
<thead>
<tr>
<th>Stage 2</th>
<th>Stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>SV</td>
<td>1305.59</td>
</tr>
<tr>
<td>LV</td>
<td>431.97</td>
</tr>
<tr>
<td>MV</td>
<td>14.52</td>
</tr>
<tr>
<td>HV</td>
<td>0</td>
</tr>
<tr>
<td>DV</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>1752.08</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stage 2</th>
<th>Stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>SV</td>
<td>534.82</td>
</tr>
<tr>
<td>LV</td>
<td>11209.44</td>
</tr>
<tr>
<td>MV</td>
<td>3224.65</td>
</tr>
<tr>
<td>HV</td>
<td>33.88</td>
</tr>
<tr>
<td>DV</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>15002.79</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stage 2</th>
<th>Stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>SV</td>
<td>15.73</td>
</tr>
<tr>
<td>LV</td>
<td>1263.24</td>
</tr>
<tr>
<td>MV</td>
<td>5219.94</td>
</tr>
<tr>
<td>HV</td>
<td>21.78</td>
</tr>
<tr>
<td>DV</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>26622.42</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stage 2</th>
<th>Stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>SV</td>
<td>1.21</td>
</tr>
<tr>
<td>LV</td>
<td>43.56</td>
</tr>
<tr>
<td>MV</td>
<td>3431.56</td>
</tr>
<tr>
<td>HV</td>
<td>5576.89</td>
</tr>
<tr>
<td>DV</td>
<td>43945.99</td>
</tr>
<tr>
<td>Total</td>
<td>50742.56</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stage 2</th>
<th>Stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>SV</td>
<td>0</td>
</tr>
<tr>
<td>LV</td>
<td>75.02</td>
</tr>
<tr>
<td>MV</td>
<td>6721.55</td>
</tr>
<tr>
<td>HV</td>
<td>43945.99</td>
</tr>
<tr>
<td>DV</td>
<td>45172.93</td>
</tr>
<tr>
<td>Total</td>
<td>52925.4</td>
</tr>
</tbody>
</table>

DV, dense vegetation; HV, high-coverage vegetation; LV, low-coverage vegetation; MV, moderate-coverage vegetation; and SV, sparse vegetation.
Profile change revealed by MTID and PCA

The change trends as retrieved by MTID (see figure 5(b)) show the dominant change tendencies of ecosystem productivity. It is clear that some areas in the study region have changed to less favourable vegetation conditions, especially in areas of counties Gonghe, Guinan, Xinghai, Zeku, Maqin, Gande, Maduo, and Qumalai. However, some areas in the middle mountainous region have turned to better conditions, such as counties Jiuzhi, Hongyuan, Aba, parts of Maqu and Henan.

In order to better understand the details of the MTID results, we performed a rough threshold classification to stratify the obtained values. In addition, we calculated the average elevation of all pixels in each threshold to outline vertical distributions of each change class. Table 4 shows the detailed classification scheme and outcomes. Suppose that the middle 30% of the study area remains unchanged, a larger part of the remaining area (37.06%) has experienced greening process, while another lesser part (32.92%) has turned into bad vegetation condition. The mean elevations of each change type depict that the major area of deterioration are located at a relatively lower elevation area, whereas areas of greening are mostly confined to high altitude zones. The positive correlations between elevation and change trends also verified this potential relationship (with a correlation coefficient of 0.1941 for total 108,261 samples, significant at a 0.05 level).

The change intensity presented with absolute difference summation for each two consecutive years may describe the stability of change trends as well as the reliability of the change trends analysis. It delineates the change property when co-analysed with change trends. The values of change intensity were also divided into six thresholds that represent different change intensity types (table 4). The results indicate that the main part (60.25%) of the study area has experienced moderate changes and the primary part of the remaining area (31.82%) has experienced slight changes. A small area part comprising intensively changed region (8.04%) denotes that the change trend revealed by MTID is reliable on the major part of the study area, or the change trends are relatively stable.

In the PCA analysis, the first principle component (PC1) represents the largest variations in the original data and more evenly contributed by nine years NDVI. It
displays the characteristic distribution of NDVI in the whole study area, much similar to the average NDVI distribution of this region (see figure 5(c)). The second principle component (PC2) shows less locality-specific properties than PC1. It can be explained by errors introduced by miscalibration, miscorrection and misregistration in the data processing. The remarkable variations of PC2 on loadings of 1990 and 1992 (see figure 6(b)) may largely be caused by platform change in AVHRR data used in this study (NOAA-11 during 1990–1992 and NOAA-14 during 1995–2000). Other fluctuations may have been introduced by miscorrection and misregistration. The spatial distribution of PC3 looks much like the change trends of MTID (see figure 5(b) and 5(d)). It represents the first non-sensor-related variance in original data. The higher positive values of PC3 refer to the increase of NDVI and the higher negative values denote a decrease in NDVI. Regarding PC3 as the NDVI change trend, we did not carry out further discussions on other PCs in this study.

We performed the same operations on PC3 as for MTID, counting the pixel fall within each threshold determined by histogram matching with MTID change trend.
results (see table 5) and calculating the mean elevation of pixels in each threshold. The results are very similar to MTID, but indicate that more areas had changed to more favourable vegetation conditions. The correlation coefficient between elevation and PC3 reaches 0.2653 (significant at 0.01 level), indicating a more explicit relationships between NDVI and elevation.

4.3 Comparisons and combination analysis of MTID, PCA and PCC results

Apparently, the PCC method gives different results from MTID and PCA. The results of PCC show a universal degradation on each vegetation cover type, sketched by the shrinkages of DV and the expansions of SV and MV. The results of MTID
and PCA, however, depict a larger quantity of greening region (about 38\% of total area) than deteriorated area (about 31\% of total area).

The difference between the results of PCC, MTID and PCA can be explained by the various aspects concerned by the three algorithms. The PCC deals with a common vegetation status, which is generated by the average data of three years NDVI. However, the defined NDVI thresholds to classify the vegetation overshadow changes contained in the threshold. In contrast, the PCA and MTID are sensitive to slight differences in NDVI, and take into account any tiny variance in the data series, including the differences contained within vegetation types defined by PCC. This effect partly accounts for the difference between PCC and MTID/PCA.

The specialities of each change detection algorithm in ecosystem or land cover change study can also be outlined by comparisons. The PCC can provide a detailed change process of different vegetation areas, while it discards changes that happen within the thresholds. In contrast, MTID and PCA analyse the entire time series rather than slices of data segments, yielding a more quantified change profile that illustrates the dominant change trend of each pixel, but it may obliterate some important fluctuations in the change process. Nevertheless, the combination of the two complementary catalogues of change detection methods provides an opportunity to comprehensively understand the different aspects of regional vegetation cover change.

A combination analysis was performed on the results of PCC, MTID and PCA in order to reveal the differences between the three methods, and to gain further understanding of vegetation cover change processes. Both change patterns (from PCC) and change trends (from MTID/PCA) of each pixel were considered to represent the difference of the three change detection algorithms. The results show a significant mismatch between PCC and MTID as well as PCC and PCA. However, some inherent correlation can still be found among the results of PCC and MTID/PCA. The combination of stable up/down change patterns and change trends depicts that the major part of stable-up zone (68.7\% of MTID and 50.7\% of PCA) has a greening trend, and a large area of stable-down zone (63.97\% of MTID and 48.5\% of PCA) has a deteriorating trend, exhibiting some inter-relationships between PCC, MTID and PCA.

Another important phenomenon is that both PCA and MTID have recognized a major part of stable pattern area as greening change zone (37.6\% of MTID and 40.88\% of PCA). Among these greening zones that have a stable change pattern, the

<table>
<thead>
<tr>
<th>Change types</th>
<th>Thresholds</th>
<th>Area (km²)</th>
<th>Percentage (%)</th>
<th>Average elevation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intensive degradation</td>
<td>[-0.378, -0.216]</td>
<td>860.31</td>
<td>0.66</td>
<td>3735.88</td>
</tr>
<tr>
<td>Moderate degradation</td>
<td>[-0.216, -0.096]</td>
<td>10919.04</td>
<td>8.34</td>
<td>3781.27</td>
</tr>
<tr>
<td>Slight degradation</td>
<td>[-0.096, -0.024]</td>
<td>28291.01</td>
<td>21.61</td>
<td>3945.79</td>
</tr>
<tr>
<td>No change</td>
<td>[-0.024, 0.024]</td>
<td>39484.72</td>
<td>30.16</td>
<td>4094.36</td>
</tr>
<tr>
<td>Slight greening</td>
<td>[0.024, 0.096]</td>
<td>44924.88</td>
<td>34.31</td>
<td>4180.14</td>
</tr>
<tr>
<td>Moderate greening</td>
<td>[0.096, 0.216]</td>
<td>6267.8</td>
<td>4.79</td>
<td>4255.82</td>
</tr>
<tr>
<td>Intensive greening</td>
<td>[0.216, 0.612]</td>
<td>179.08</td>
<td>0.14</td>
<td>4148.21</td>
</tr>
</tbody>
</table>
DV notably occupies the largest part (54.3% of MTID and 47% of PCA). Since the DV is top-class in this study, any change of DV toward better condition will therefore be discarded by PCC. This may be part of the reason of the mismatch between PCC and MTID/PCA.

There are also some mismatches between MTID and PCA according to the results of combination analysis. The most significant one lies in the difference on change trends recognition of unstable change patterns. With the PCA method, the major part (40.38%) of up-wave change pattern area was recognized as greening area and a relatively larger part (33.54%) of down-wave change pattern area was defined as deterioration area. In contrast, the MTID method gives completely contradicting results in that the major part (47.15%) of up-wave change pattern area degrades while large areas (51%) with down-wave change patterns have a greening trend. As the up-wave change pattern can be regarded as a greening trend and down-wave change pattern should largely have a degradation trend, the MTID result gives a false result on these two change patterns. This depicts the shortages of the MTID method in detecting unstable change trends. On the other hand, within the recognition of stable, stable-up and stable-down patterns, more accurate results consistent with PCC were achieved by using MTID than by using PCA (32.53%, 68.76% and 63.97% of MTID versus 32.17%, 50.7% and 48.5% of PCA), showing the specialty of MTID in the detection of stable change trends.

4.4 Climate variation and its relationship to NDVI changes

Figure 7 shows the change profiles of AGST and GSP that were recorded by ten meteorological stations located in SRYR. Table 6 lists the change trends of AGST and GSP at the ten meteorological stations. It can easily be seen that AGST displays an overall increasing trend, particularly at northern and western parts of the study area (counties Gonghe, Xinghai, Maduo, etc.). AGST in counties Henan and Maqu also increases significantly. GSP shows a less stable tendency and changing dramatically from year to year, but a universal decreasing trend still can be seen, with the most evident decrease occurring at western and central parts of the study area as well as in county Jiuzhi.

Figure 7 also illustrates a notable change of GSP and AGST around 1998. All meteorological stations located within SRYR recorded a drastic rise of AGST in 1998, which is obviously higher than for other years during the period 1989 and 2001. GSP exhibits similar variations. Almost all stations have recorded a relatively higher precipitation in 1998 (or 1999) suggesting that in the year 1998 (or 1999) the growing conditions for vegetation may have been most favourable.

The spatial distribution of NDVI trend that positively correlates to elevations, combined with the overall warming and drying trend of climate denoted by figure 7 and table 6, implies impact of climate change on the regional ecosystem evolution. The continuously rising temperature ameliorates the growing conditions in high elevation zones, where chilly freezing temperature is not favourable for plant survival. In contrast, the growing conditions in lower elevation zones that originally have poor moisture conditions may get worse under rising temperature and lowering precipitation.

This hypothesis is proved by the results of pixel-by-pixel correlation analysis between the NDVI series and GSP (see figure 5(e)), as well AGST (see figure 5(f)) for corresponding years. The results indicate that a larger part of SRYR shows positive correlations between NDVI and GSP. Counties Guinan, Zeku and Tongde have the
most significant correlations between GSP and NDVI. County Jiuzhi and the southwestern part of county Maqu also show a strong positive correlation. The western part of counties Xinghai, Maqin and Gande, the northern Dari and some areas of county Maduo show weaker positive correlations. These positive correlations suggest that the local ecosystem is intensively affected by changes in precipitation. The significant decline of GSP in some of these regions may be partly responsible for the degradations in the local ecosystem.

The negative correlations between NDVI and GSP are distributed mainly in counties Henan, Ruoergai, Hongyuan, Aba, Chengduo, the western Maqin, Gande and the southern Maduo, which are covered mainly by high-coverage vegetations.

Table 6. Change trends of average growing season temperature (AGST) and growing season precipitation (GSP) from 1989 to 2001 recorded by meteorological stations located within the source region of the Yellow River (SRYR).

<table>
<thead>
<tr>
<th>GSP</th>
<th>AGST</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate (mm a⁻¹)</td>
<td>Significance</td>
</tr>
<tr>
<td>Gonghe</td>
<td>-1.17363</td>
</tr>
<tr>
<td>Xinghai</td>
<td>-2.23077</td>
</tr>
<tr>
<td>Maduo</td>
<td>-7.65659</td>
</tr>
<tr>
<td>Maqin</td>
<td>-14.4973</td>
</tr>
<tr>
<td>Dari</td>
<td>-1.43846</td>
</tr>
<tr>
<td>Henan</td>
<td>-2.88571</td>
</tr>
<tr>
<td>Jiuzhi</td>
<td>-9.70659</td>
</tr>
<tr>
<td>Maqu</td>
<td>1.275275</td>
</tr>
<tr>
<td>Ruoergai</td>
<td>-1.34011</td>
</tr>
<tr>
<td>Hongyuan</td>
<td>1.284615</td>
</tr>
</tbody>
</table>

Figure 7. Changes of growing season precipitation (GSP) and average growing season temperature (AGST) recorded by meteorological stations in the source region of the Yellow River (SRYR).
and commonly have abundant precipitations and/or relative flat terrain. The weak negative correlations in these places may indicate that the changes in the local ecosystem are not necessarily induced by variations in precipitation.

The correlations between AGST and NDVI present a different spatial pattern. The most significant positive correlations distributed mainly at the southern and eastern parts of the study area, while the strongest negative correlations primarily spread at the northern regions of the study area. The areas in Gonghe basin, counties Xinghai, Tongde and Henan in particular display positive correlations between NDVI and AGST. The degradations of ecosystems in these places therefore can largely be explained by increase in AGST, which superimposed on the effects of GSP decrease. Some locations in counties Maduo, Gande and Dari, which are also part of the vegetation deterioration zone, show a weaker negative correlation between NDVI and AGST. This indicates that increasing temperature may play a less important role in vegetation degradation in the flat zones at higher elevations. However, the coupled relationships between NDVI and AGST, as well as GSP, may somehow explain the degradations of vegetation in these regions.

The regions in the central part of the study area that lie near the borders of eastern Maqin and northern Gande, also show significant negative correlations between NDVI and AGST. The decreasing trend in NDVI in these locations (see figure 5(b) and 5(d)) may have the same causality similar to Gonghe basin. Other parts of the study area with rugged topography and higher elevation show generally weak to medium positive correlations. This can be explained by the hypothesis presented earlier. The continuously increasing temperature ameliorates the living conditions of some locations with higher elevation and propelled the progressive successions of local ecosystem.

On the remaining parts of the study area with relatively lower elevation and flat terrains, the NDVI and AGST show a locality-dependent correlation. Some areas of counties Maqu and Maqin that are predominantly situated at broad valleys of Yellow River show a positive correlation, which demonstrates the positive effects of rising temperature on the growth conditions partly also influenced by the local terrain. However, some locations in Ruoergai and Hongyuan with sufficient precipitations and flat topography, display similar correlations as Gonghe basin. This may be explained by some detrimental changes to vegetation growth, such as large increases in evapotranspiration caused by rising temperatures.

5. Conclusions

Both the climate factors (AGST and GSP) and vegetation cover (indicated by NDVI) of the SRYR have dramatically changed during the period 1990–2000. An overall warming and drying trend of the local climate has been retrieved by linear regressions of meteorological data observed by 10 weather stations in SRYR, indicating the impacts of global warming on the regional climate.

Three change detection algorithms (PCC, MTID and PCA) were employed in this study to retrieve the change history of vegetation cover. The results show that large areas originally with better vegetation cover degrade to a less favourable condition during this period, while conditions for some other regions are changed more favourable. The degradations have occurred mainly in regions with lower elevation or with relatively higher elevation and flat topography, in contrast with the upgrading vegetation cover transformations which have mainly occurred at mountainous regions with higher elevation.
Vegetation cover changes in the SRYR show very impressive correlations to climatic factors. The positive correlations between NDVI and precipitation occurred mainly at the northern and western parts of the study area, which commonly have low annual precipitations and sparse vegetations. According to this relationship, the decrease in precipitation can therefore partly serve as an explanation to the universal degrading trends in the northern and western parts of the study area. The negative correlations have weaker significances and primarily spread at the regions with higher precipitations and denser vegetations, indicating that the precipitation variations may play a less important role in the changes of the local ecosystem.

The relationship between vegetation cover change and AGST show different spatial patterns. Negative correlations mainly disperse in regions of lower NDVI with relatively flat terrains, while positive correlations are largely seen in mountainous regions with rugged topography and relatively higher elevation, or in the broad river valleys. It can be concluded that the overall increase in temperature is one of the important driving factors that cause the universal degradations of all vegetation cover types in the lower-elevation or flat-topography regions with limited precipitations. However, temperature increases ameliorate the growing condition of vegetation in high mountainous areas and broad river valleys with better moisture availability.

The comparison and combination analysis of the results of the three change detection algorithms also suggests the specifics of PCC, MTID and PCA on detecting changes in vegetation/land cover. The PCC method is advantageous for detecting changes among different classes, however, it is unsuitable for detecting changes that occur within the classes. The MTID and PCA methods are excellent in retrieving the overall change trends, but cannot clearly sketch the detailed change processes or transformations between different classes. Therefore, an integrated use of PCC, MTID and PCA is recommended for analogous studies to overcome the shortages of any one method.

The accuracy of our study is largely limited by the data we used. Owing to coarse spatial resolution and short temporal representation (July and August) of AVHRR data in this paper, and due to sparsely distributed weather stations in and around the study area, a more detailed history of vegetation change is not pursued in this paper. The lack of in situ measurement data of atmospheric status and multi-angular ground reflectance may also bring some uncertainties in the data, although the AVHRR data preprocessing scheme was designed to reduce the sensor-related variations in NDVI to a minimum level. Additionally, anthropogenic factors were not considered in this paper. All of these shortages will be attempted to be overcome in future studies.

Acknowledgement
Financially support for this research was received from the National Natural Science Foundation of China (NSFC) Innovation Team Project (No. 40421001) and from the Excellent Young Teachers Programme of the Ministry of Education (No. 20022031). The 1:1000000 vegetation map of the Tibetan Plateau was vectorized by the Institute of Geographic Sciences and Natural Resource Research (CSA) and provided by Data-Sharing Network of Earth System Science (National Scientific Data Sharing Project of China). We also sincerely thank NOAA CLASS for providing AVHRR data.
References


