Changes in grassland cover and in its spatial heterogeneity indicate degradation on the Qinghai-Tibetan Plateau

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Abstract: Arid grassland ecosystems undergo degradation because of increasing environmental and human pressures. Degraded grasslands show vegetation cover reduction and soil-patch development, leading to grassland fragmentation and changes in spatial heterogeneity. Understanding grassland degradation that involves soil-patch development remains a challenge over large areas with limited accessibility such as the Qinghai-Tibetan Plateau. We hypothesized that vegetation cover, its spatial heterogeneity and changes thereof over time retrieved from satellite data can indicate grassland development and degradation levels. To test the hypothesis, we studied these indicators from 2000 to 2016 and related them to previously described degradation levels on the eastern Qinghai-Tibetan Plateau (QTP) in 2004. We further use these indicators to map the new grassland development and degradation levels in 2016. We found that lower vegetation cover does not always indicate a more severe degradation; instead, higher spatial heterogeneity is a better correlate of degradation. Combined temporal changes in grassland cover and its spatial heterogeneity are related to the literature-defined degradation levels. We found that grassland areas on the eastern QTP have moved into new degradation stages from 2000 to 2016 using changes in grassland cover and its spatial heterogeneity as indicators. The normalized difference vegetation index (NDVI) as a proxy for grassland cover declined over time in the literature-defined degraded areas but increased in the desert areas from 2000 to 2016. Spatial heterogeneity generally increased across different degradation levels from 2000 to 2016; however, this increase was less pronounced in severely degraded and slightly deserted areas. Our newly defined degradation levels in 2016 included degradation, desertification, and improving levels. Across our study area, 63% of all areas were classified as degraded and 2% were at risk of desertification. The remaining areas (35%) classified as improving and re-growing occurred in higher-elevation or previously severely degraded grassland. Our study demonstrates that a combination of changes in grassland cover and in its spatial heterogeneity can indicate grassland degradation levels and serve as an early-warning signal for desertification threats.

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A B S T R A C T

Arid grassland ecosystems undergo degradation because of increasing environmental and human pressures. Degraded grasslands show vegetation cover reduction and soil-patch development, leading to grassland fragmentation and changes in spatial heterogeneity. Understanding grassland degradation that involves soil-patch development remains a challenge over large areas with limited accessibility such as the Qinghai-Tibetan Plateau. We hypothesized that vegetation cover, its spatial heterogeneity and changes thereof over time retrieved from satellite data can indicate grassland development and degradation levels. To test the hypothesis, we studied these indicators from 2000 to 2016 and related them to previously described degradation levels on the eastern Qinghai-Tibetan Plateau (QTP) in 2004. We further use these indicators to map the new grassland development and degradation levels in 2016.

We found that lower vegetation cover does not always indicate a more severe degradation; instead, higher spatial heterogeneity is a better correlate of degradation. Combined temporal changes in grassland cover and its spatial heterogeneity are related to the literature-defined degradation levels. We found that grassland areas on the eastern QTP have moved into new degradation stages from 2000 to 2016 using changes in grassland cover and its spatial heterogeneity as indicators. The normalized difference vegetation index (NDVI) as a proxy for grassland cover declined over time in the literature-defined degraded areas but increased in the desert areas from 2000 to 2016. Spatial heterogeneity generally increased across different degradation levels from 2000 to 2016; however, this increase was less pronounced in severely degraded and slightly deserted areas. Our newly defined degradation levels in 2016 included degradation, desertification, and improving levels. Across our study area, 63% of all areas were classified as degraded and 2% were at risk of desertification. The remaining areas (35%) classified as improving and re-growing occurred in higher-elevation or previously severely degraded grassland. Our study demonstrates that a combination of changes in grassland cover and in its spatial heterogeneity can indicate grassland degradation levels and serve as an early-warning signal for desertification threats.

1. Introduction

Human activities and climate change are causing ecosystem degradation, especially in arid ecosystems where degradation has affected the livelihood of a large part of the world's population (Berdugo et al., 2017; Kéfi et al., 2007). Arid-ecosystem degradation is commonly characterized by vegetation fragmentation interspersed with small bare-soil patches at the early stage of degradation and eventually large bare soil-patch development that potentially leads to desertification with increasing environmental and human pressures (Bestelmeyer et al., 2013; Kéfi et al., 2007). Vegetation fragmentation and bare soil-patch development result in changes in vegetation cover and spatial heterogeneity, which have been used as indicators of arid-ecosystem degradation (Kéfi et al., 2014, 2007; Lin et al., 2010; Maestre and Escudero, 2009; Rietkerk et al., 2004) and serve as early-warning signals of desertification in drylands (Berdugo et al., 2017; Lin et al., 2010; Maestre and Escudero, 2009; Rietkerk et al., 2004).

Grassland ecosystems on the Qinghai-Tibetan Plateau (QTP) have been degraded. The natural grassland was first encroached by non-edible and poisonous invasive species (Cai et al., 2015; Chen et al., 2017; Liu et al., 2008; Wang et al., 2015), and followed by grassland cover reduction and bare-soil patches development, the latter eventually turning into larger areas of bare soil called "black soil patches" (Liu et al., 2008; Qin et al., 2019). The development of bare-soil patches causes spatially discontinuous grassland cover and therefore brings about changes in spatial heterogeneity like in other arid ecosystems.

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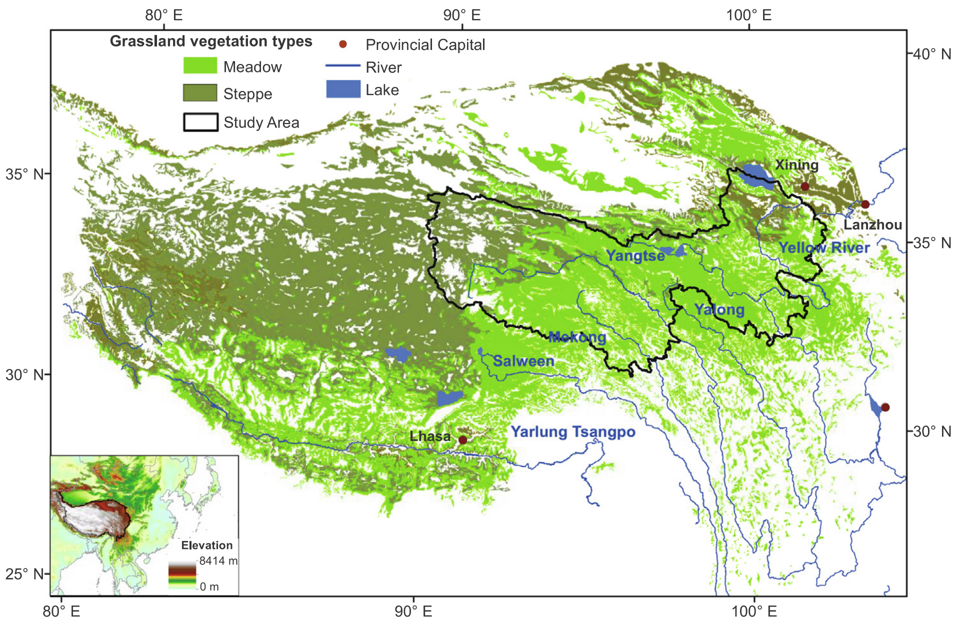

Fig. 1. Map of the Qinghai-Tibetan Plateau indicating main grassland vegetation types and major rivers and lakes. Our study area of the "Three-River Headwaters" region in the eastern part of QTP is indicated by the black outline. Inset indicates elevation data of the extended area based on the NASA Shuttle Radar Topographic Mission (SRTMVersion 4) (Farr et al., 2007).

Severe degradation occurred at the "Three-River Headwaters" region (Li et al., 2018b) on the eastern QTP, where degraded grasslands with "black soil patches" are the very common (Li et al., 2014b). This region was selected as our study area as it is the source region of three of Asia's major rivers, Yangtze, Yellow River and Mekong, and therefore ecologically very important (Fig. 1). Grassland degradation in this area results in soil erosion, rangeland productivity reduction (Dong et al., 2013) and hydrological disturbances (Harris, 2010), threatening the livelihoods of a large part of the population, especially people living in downstream areas depending on freshwater coming from the QTP (Lehnert et al., 2014; Liang et al., 2013).

For the above reasons, monitoring grassland degradation stages on the QTP especially at the "Three-River Headwaters" region is important for developing and implementing conservation strategies. Previous researchers have studied soil organic matter, species composition, vegetation cover and numbers of small-mammals to identify grassland degradation levels via field observations (Wang et al., 2010a, 2010b; Guo and Wang, 2013; Feng et al., 2005). However, these field studies focused on small areas and short time periods, therefore providing limited insights in grassland degradation on a larger and long-term scale. However, such insight is important because grassland degradation is a slow and gradual process and widely spread on the QTP. As we show in this paper, large-scale and long-term assessment in this area can be achieved using remote sensing data (Kennedy, 1989; Li et al., 2014a; Purevdorj et al., 1998; Tucker, 1979).

Vegetation cover and changes therein have been considered as indicators of degradation levels by interpreting satellite images from different years (Fassnacht et al., 2015; Li et al., 2014b; Liu et al., 2008). Both positive (Zhang et al., 2014; Zhong et al., 2010) and negative trends have been reported in past decades (Song et al., 2009; Wang et al., 2011). However, so far no attention has been paid to spatial heterogeneity related to soil and vegetation patches on the QTP, although such heterogeneity has been identified as a relevant indicator for evaluating degradation in other arid ecosystems (Kéfi et al., 2007).

In this study, we aim to develop indicators that can be used to quantify the spatial variation of grassland degradation and development status. We first test whether the combination of changes in grassland cover and spatial heterogeneity derived from remote sensing data are informative indicators for mapping grassland degradation and development stages on the QTP. We justify these two indicators by studying how changes in vegetation cover and spatial heterogeneity from 2000 to 2016 are related to published degradation levels in 2004 at the "Three-River Headwaters" region on the eastern QTP. Second, we use the new indicators of changes in vegetation cover and in its spatial heterogeneity to derive new degradation levels for 2016.

2. Data

Grassland cover and its spatial heterogeneity can be derived from satellite data of the Normalized Difference Vegetation Index (NDVI) for large spatial extents. We used the Moderate Resolution Imaging Spectroradiometer (MODIS) Bidirectional Reflectance Distribution Function (BRDF) Adjusted Reflectance (MCD43A4) product from 2000 to 2016 (Schaaf et al., 2002).

The advantage of using this product is that it has good quality because it has removed view-angle effects and minimized cloud and aerosol contaminations (Xulu et al., 2018). The product is available every 16 days and has a spatial resolution of 500 m.

Road network data from OpenStreetMap (Haklay and Weber, 2008) and river network data extracted from hydrological data (HydroSHEDS: Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales) (Lehner et al., 2008) were used to mask higher spatial heterogeneity value caused by roads and rivers. Elevation and slope data obtained from the National Aeronautics and Space Administration (NASA) Shuttle Radar Topographic Mission (SRTM) Version 4 (Farr et al., 2007) were used to analyze how spatial heterogeneity was related to topography. We accessed and processed the above satellite data in the Google Earth Engine Platform (Gorelick et al., 2017).

A grassland degradation-level dataset covering the study area for 2004 (Fig. S1) (Liu et al., 2008) was used to justify that changes in grassland cover and spatial heterogeneity can indicate different degradation levels. This dataset covers the whole study area, which provides more efficient samples to study how two indicators have changed in different degradation groups than studies providing data only for particular sites (Wang et al., 2010a, 2010b; Guo and Wang, 2013; Feng et al., 2005). Grassland cover and vegetation-patch size were used for generating the 2004 grassland degradation-level dataset along with field photos, topography maps, land-use maps and vegetation-type maps (Liu et al., 2008). The authors classified grassland into (1) areas without degradation, (2) areas with grassland fragmentation, (3) desertification/salinization, (4) cover decline, (5) drying swamp and (6) areas with improving grassland. Each degradation category had been subdivided into the three intensity levels slight, medium and severe. In this study, we focus on the first three categories (no degradation, grassland fragmentation, and desertification/salinization) which are characteristic for soil-patch development and therefore relevant to assess grassland degradation using spatial heterogeneity. The above three groups all together accounted for a representative 90% of the study area. We refer to these three categories as (1) non-degraded, (2) degraded and (3) desertified areas. Together with three intensity levels of slight, medium, and severe in the degraded and desertified categories, we further refer to these categories as seven degradation levels (Fig. 6).

3. Methods

3.1. Grassland spatial heterogeneity

Grassland cover and its spatial heterogeneity can be measured from satellite data for large spatial extents. The NDVI spectral index was introduced to map vegetation cover (Kennedy, 1989; Li et al., 2014a; Purevdorj et al., 1998; Tucker, 1979). NDVI is a well-developed and easily available product from MODIS and widely used for monitoring grassland cover on the QTP (Gao et al., 2010; Zhang et al., 2013), therefore being a better candidate than other vegetation indices such as soil-adjusted (SAVI), modified soil-adjusted (MSAVI) and transformed soil-adjusted vegetation indices (TSAVI) (Purevdorj et al., 1998) that are not widely available.

In this study, we assessed grassland spatial heterogeneity in terms of the spatial distribution of vegetation and bare-soil patches. On the QTP such patches vary in size ranging from less than one meter to above one kilometer (Fig. 2) depending on topography, soil properties and vegetation types (Chen et al., 2017). We measured spatial heterogeneity of vegetation cover within a 3×3-pixel moving window of 1500×1500 m area. Considering the bare-soil patch size and grid size of satellite images, measuring spatial heterogeneity within this window size is reasonable for detecting grassland heterogeneity for our purpose of large-scale degradation mapping. The corresponding 3×3-pixel moving window provides nine NDVI samples with a grid size of 500 m, which is statistically sufficient to calculate the coefficient of variation. This window size selection further allows capturing the locality of the spatial heterogeneity as the output of spatial heterogeneity becomes spatially smoother with the increasing window size. The coefficient of variation (CV) of NDVI within the selected moving window was calculated to quantify the spatial heterogeneity that we use as a leading indicator of ecosystem heterogeneity (Carpenter and Brock, 2006) and spatial variance (Kéfi et al., 2014). High spatial heterogeneity around rivers and roads may not indicate degradation as commonly understood but represent more heterogeneous land-cover types. We identified these using buffers of river and road networks and excluded them when calculating the CV of NDVI. In the end, all land-cover types other than grasslands were masked out.

3.2. Temporal changes in NDVI and in its spatial heterogeneity

The median NDVI and its CV within 3×3-pixel moving windows during the growing season (June–September) were calculated for each year from 2000 to 2016. We applied linear regression which is a common method (de Jong et al., 2011; Piao et al., 2005) to study long-term changes in vegetation cover. To analyze and visualize differences of NDVI and spatial heterogeneity among degradation categories identified in the literature, we calculated their means and plotted their distributions. Both significant values of changes in NDVI and its spatial heterogeneity were extracted for the above analysis (Fig. S2).

3.3. Combining temporal changes in NDVI and its spatial heterogeneity to map new degradation levels for 2016

Our study is based on the hypothesis that the combination of changes in NDVI and its spatial heterogeneity can be used to identify grassland degradation levels. This hypothesis is based on the fact that bare-soil patches have developed in the degraded grassland on the QTP. The bare-soil patches can be observed both in the field and from satellite images (Fig. 2 (b, e-f)). The development of bare-soil patches results in the increase of spatial heterogeneity from intact to degraded grassland (Fig. 2 (a-b)) but the reduction of spatial heterogeneity in severely degraded grassland or in the stage of desertification (Fig. 2 (f)). However, the grassland cover does not always decline with degradation level because exotic species have invaded grasslands in the degraded regions on the QTP. The invasive species increase vegetation cover but indicate degradation because the species are unpalatable for livestock or even toxic (Fig. 2 (c-d)). In the following sections, we introduce our hypothesis in detail.

a. Increases in NDVI and decreases in spatial heterogeneity combined represent improving conditions

Because NDVI represents vegetation photosynthesis and has been widely used as a proxy of vegetation cover (Kennedy, 1989; Li et al., 2014a; Purevdorj et al., 1998; Tucker, 1979), significant increases of NDVI in the long-term indicate increasing vegetation cover. The healthy and intact grasslands on the QTP are characteristic of a homogeneous landscape (Fig. 2 (a)), showing a spatially consistent vegetation greenness and NDVI from the satellite data, representing low spatial heterogeneity. Therefore, increases in NDVI and decreases in spatial heterogeneity indicate that grasslands become more productive and homogeneous, suggesting improving conditions (Fig. 2 (a)).

b. Increases in NDVI and spatial heterogeneity combined represent re-growing conditions or slight degradation

Combined increases in NDVI and spatial heterogeneity may indicate two different cases. In desert or sparsely-vegetated regions, where average NDVI is lower than 0.2 (Piao et al., 2011; Zhang et al., 2013), increases in NDVI show that the landscape likely turns from non-vegetative to low vegetative status, where NDVI increases but shows spatial variation, leading to increased spatial heterogeneity (Fig. S3). Thus, in the sparsely or non-vegetated areas we interpret an increase in NDVI and in spatial heterogeneity as regrowth of vegetation.

In the vegetated areas ($NDVI > 0.2$) with slight degradation, invasive species commonly colonized grasslands (Fig. 2 (c-d)). The invasive species are characteristic of higher plant cover compared with the native species *Kobresia pygmaea* (Milton and Siegfried, 1994; Wang et al., 2015) (Fig. 2 (c-d)), contributing to an increase of vegetation greenness. At this stage, vegetation patches (Li et al., 2014b) with exotic species are interspersed with soil patches, leading to increasing spatial heterogeneity. Therefore, in vegetated areas we interpret increases in NDVI combined with increases in its spatial heterogeneity as a sign of initial or slight degradation.

c. Decreases in NDVI and increases in spatial heterogeneity combined represent medium degradation

In degraded and already fragmented grassland, the bare-soil patches continue to increase in number and size with increasing environmental and grazing pressures, which further increases the spatial heterogeneity and reduces the vegetation cover, and therefore results in negative NDVI trends. Therefore, decreases in NDVI and increases in spatial heterogeneity indicate a medium level of degradation (Fig. 2 (b, e)).

d. Decreases in NDVI and decreases in spatial heterogeneity combined represent severe degradation or desertification

Vegetation-patch sizes decrease and bare-soil patches become larger and connected as degradation becomes more severe (Fig. 2 (f)); this is reflected in reduced vegetation cover and spatial heterogeneity. In the sparsely vegetated area where vegetation cover is relatively low ($NDVI < 0.2$), combined decreases in NDVI and spatial heterogeneity indicate that vegetation shifts from a patchy stage to bare soil, i.e. the stage of desertification (Milton and Siegfried, 1994; Rietkerk et al., 2004).

To summarize, changes in vegetation cover and its spatial heterogeneity are not linearly correlated with degradation level, and a combination of changes in these two variables allows for a richer analysis of grassland development and therefore can better indicate different

Fig. 2. Example images of grassland showing the changes in vegetation cover and spatial heterogeneity, development of soil patches and invasive species at different degradation levels. a). Picture of healthy grassland on the northeastern QTP in July 2015 showing the typically homogeneous landscape. b) Pictures of degraded grassland with invasive species at Naqu on 8 August 2016 and c): Pictures of degraded grassland with invasive species at Minxian county on the eastern QTP in 2008 (Yan et al., 2014). d). Picture of degraded grassland with bare-soil patches at Zekog, Zequ county in July 2015. e). Picture of severely degraded grassland showing vegetation-patch sizes decrease and bare-soil patches become larger and connected at Wudaoliang, Qinghai province in August 2016. f): Satellite image of fragmented grassland representing spatially heterogeneous grassland landscape over a larger scale in Madoi county (Sentinel-2 image ID: 20160819T040552_20160819T093629). This image was extracted from the Google Earth Engine platform. The above pictures are original from this study except for picture (c) which was extracted from the study (Yan et al., 2014).

degradation stages. Examples of healthy grasslands, degraded grasslands with invasive species and bare-soil patches at different scales are displayed in Fig. 2. We summarize the above characteristics of grassland development and degradation stages with the decision tree shown in Fig. 3. Here we further use this decision tree for assigning areas with particular NDVI and CV trends to the six new degradation levels introduced in this study. Because less than 0.01% of the total area showed no detectable changes in NDVI and its spatial heterogeneity from 2000 to 2016, these areas defined as non-degraded grassland were not considered when classifying new degradation levels.

4. Results

4.1. Linking grassland cover and spatial heterogeneity to degradation levels

We mapped spatial heterogeneity of grassland cover represented by the CV of NDVI within a 3 × 3-pixel moving window in an area of 1500 × 1500 m (Fig. 4). Lower spatial heterogeneity was found in the eastern meadow-dominated region, higher spatial heterogeneity in the northwestern steppe-dominated and mountainous regions (Fig. 1 and Fig. 4). Spatial heterogeneity increased with slope and was lowest at medium elevations of 3000–4500 m (Fig. 5 (a)).

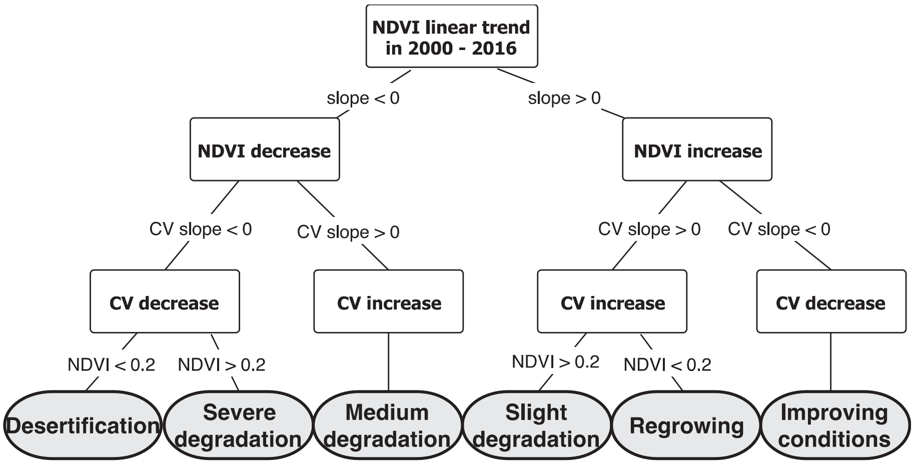

Fig. 3. Flowchart for defining new degradation levels in 2016 based on linear trends of NDVI and its spatial heterogeneity (measured as CV of NDVI in 3 × 3-pixel moving windows of 1500 × 1500 m). For further details see Section 3.3 and the discussion in Section 5.2. Note that non-degraded grassland is not included in this decision tree.

We analyzed differences in NDVI and its spatial heterogeneity for the different degradation levels defined in Liu et al. (2008) (Fig. 6). We found the mean NDVI is lower in non-degraded compared with degraded areas, and higher in degraded and severely desertified areas (Fig. 6 (a)). This shows that the mean NDVI was not sufficient to order areas into a monotonic sequence of degradation levels. Adding the CV of NDVI, we found higher spatial heterogeneity in more severely fragmented and deserted areas (Fig. 6 (b)). However, it did not show a linear trend with the increased literature-derived degradation levels from non-degradation to severe degradation and desertification.

4.2. Temporal changes in NDVI and spatial heterogeneity among different degradation levels

NDVI temporal trends over 2000–2016 varied spatially (Fig. 7 (a)) over the study area, being negative in the central and southern regions (Fig. 7) and positive in the northeastern region of the study area. Spatial heterogeneity showed mainly increasing trends from 2000 to 2016 (Fig. 7 (b)), with an exception in the northeastern region, where it decreased in areas with increasing mean NDVI values (overlapping green areas in Fig. 7 (a) and (b)). Less than 0.01% of the total area showed no detectable changes in NDVI and its spatial heterogeneity from 2000 to 2016. These areas were not considered when classifying new degradation levels. Examples of time-series analyses of change trends of NDVI and CV from 2000 to 2016 are shown in the supplementary material (Figs. S4, S5).

We analyzed changes in NDVI and its spatial heterogeneity in different degradation levels as defined in 2004 by Liu et al. (2008). Trends of NDVI and its spatial heterogeneity largely varied between but also within the degradation levels. In non-degraded areas that accounted for 75.3% of the study region, both decreasing and increasing NDVI trends were found, while spatial heterogeneity mostly increased (Fig. 8). In fragmented-grassland areas that covered 10.3% of the entire study region, the NDVI mainly decreased and spatial heterogeneity mainly increased. In desertification areas, both the NDVI and its spatial heterogeneity generally increased (Fig. 8). Overall, the vegetation cover represented by NDVI showed decreasing trends from 2000 to 2016 in slightly- to medium-fragmented areas, which contrasted with the increasing trends in desertification areas. The spatial heterogeneity generally increased over time and this increase was weakest in severely degraded areas and early stages of desertification, i.e. slightly deserted areas (Fig. 8).

The temporal trends of NDVI and its spatial heterogeneity were found to be elevation-dependent (Fig. 9). The NDVI decreased at

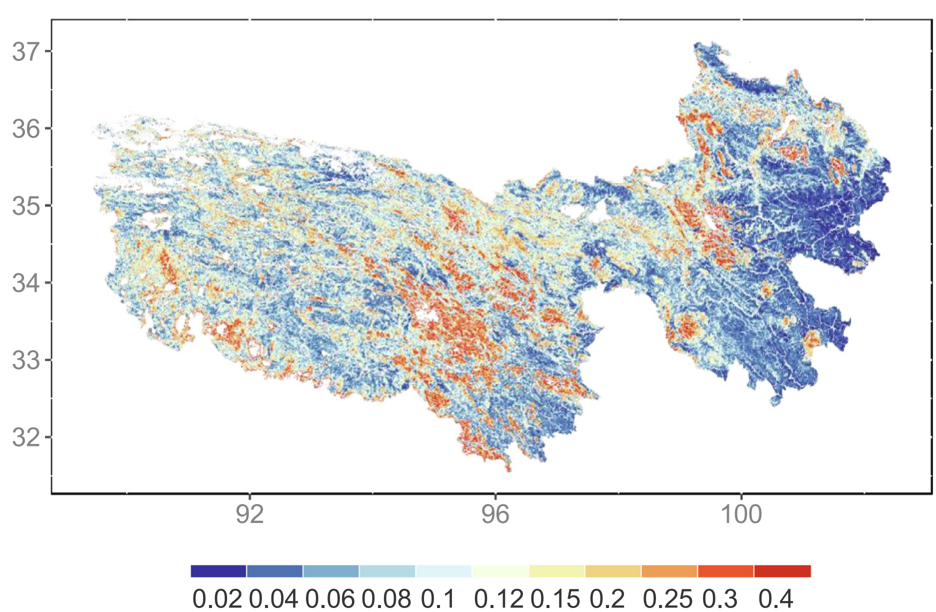

Fig. 4. Spatial heterogeneity of grassland at the "Three-River Headwaters" region on the eastern QTP in 2016. Spatial heterogeneity was calculated as the CV of NDVI within a 3 × 3-pixel moving window (with the median NDVI value for the growing season from June to September).

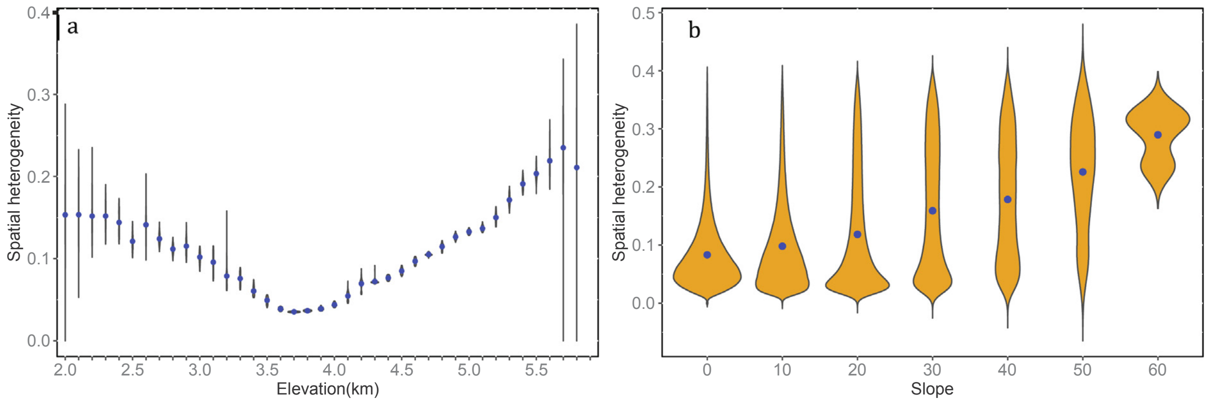

Fig. 5. Distribution and mean (blue dots) of spatial heterogeneity of grassland cover along elevation (a) and slope (b) gradients in 2016. Spatial heterogeneity was calculated as the CV of NDVI within a 3 × 3-pixel moving window.

intermediate elevations and increased in lower and higher elevations (Fig. 9a). The spatial heterogeneity increased in most elevation zones except for areas above 5500 m (Fig. 9b). When correlating the NDVI trends with its spatial heterogeneity trends, we found an overall negative correlation between them. Areas with decreasing NDVI trends mostly showed increasing CV trends, but areas with increasing NDVI trends occurred with both decreasing and increasing CV trends, meaning that vegetation cover reduction tends to intensify spatial heterogeneity, however, increases in vegetation cover can lead to either a more homogeneous or more heterogeneous landscape (Fig. S6).

4.3. *Combining temporal changes in NDVI and spatial heterogeneity to map new degradation levels for 2016*

NDVI and its spatial heterogeneity had changed in most of the study area over 2000–2016, spatial heterogeneity mostly increased from 2000 to 2016 and NDVI showed both increasing and decreasing trends. These changes indicated that grassland areas may have moved into new

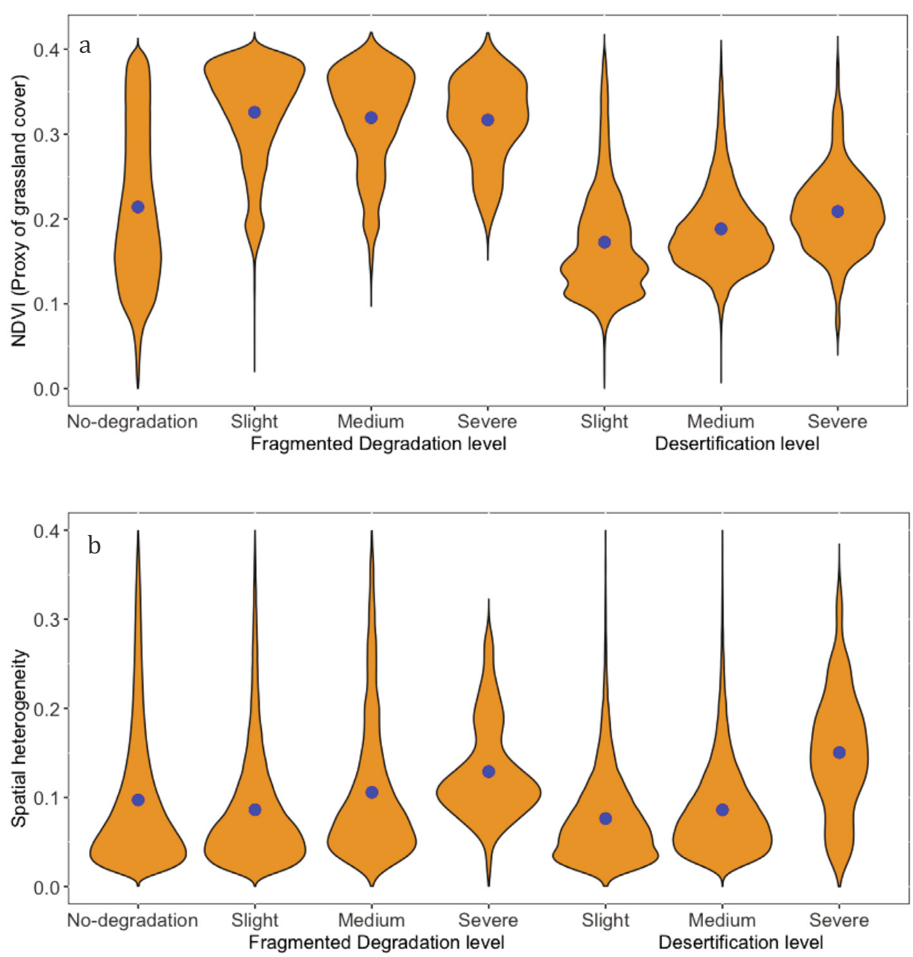

Fig. 6. Grassland cover (NDVI) (a) and its spatial heterogeneity (CV of NDVI) (b) in 2004 along increasing degradation levels from non-degraded to degraded and desertification levels as defined in Liu et al. (2008). Violin bars show the distribution of NDVI and CV, blue dots show the mean of NDVI and CV.

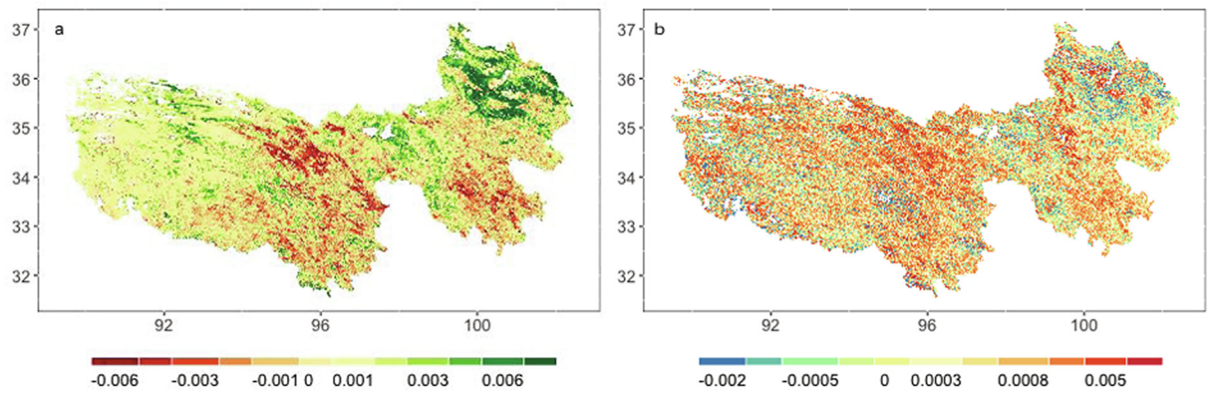

Fig. 7. Linear temporal changes (including significant and non-significant ones) in NDVI (a) and its spatial heterogeneity (b) from 2000 to 2016. The changes with only significant values can be found in the supplementary Fig. S2.

degradation stages over the time interval. We used these changes to define degradation levels and mapped them for 2016 (Fig. 10). Compared with the earlier study of Liu et al. (2008), who classified 75% of the total study area as non-degraded grasslands, we found that these non-degraded grasslands have been degraded to different levels. We use the combination of increasing NDVI and increasing spatial heterogeneity as an indicator of slight degradation and the combination of decreasing NDVI and increasing spatial heterogeneity as an indicator of medium degradation (see Fig. 3 and Section 3.3). According to our degradation classification framework, we found that 21% of the total study area became slightly degraded and 34% and 8% became medium degraded and severely degraded, respectively. These degraded areas mainly occur in meadow-dominated regions (Fig. 1 and Fig. 10). Increasing NDVI and decreasing spatial-heterogeneity trends showed that grasslands had become more productive and less fragmented, indicating improving conditions across 24% of the total study area. In the sparsely vegetated areas where NDVI was less than 0.2, increases in NDVI and spatial heterogeneity indicated re-growing conditions and these

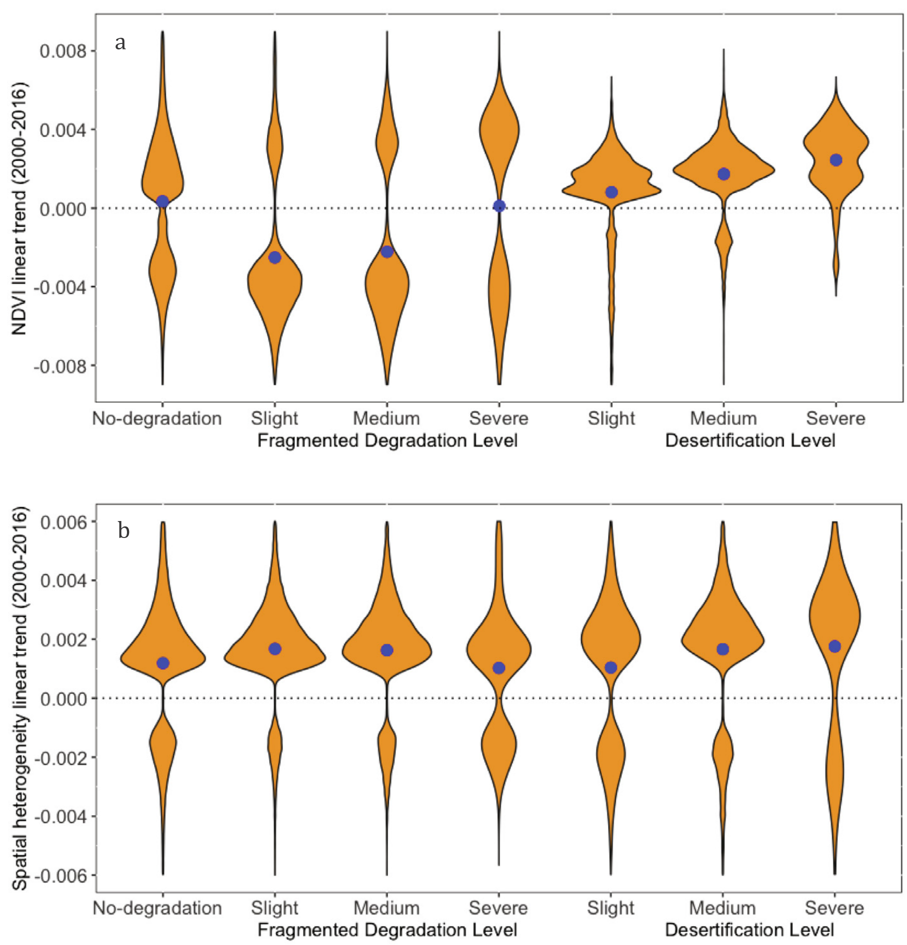

Fig. 8. Significant (*P* less than 0.05) linear temporal trends in means (a) and CVs (spatial heterogeneity) (b) of NDVI from 2000 to 2016 along increasing degradation levels from non-degraded to fragmented and desertification levels defined in Liu et al. (2008). Violin bars show the distribution of NDVI and CV linear trends, blue dots show their mean values.

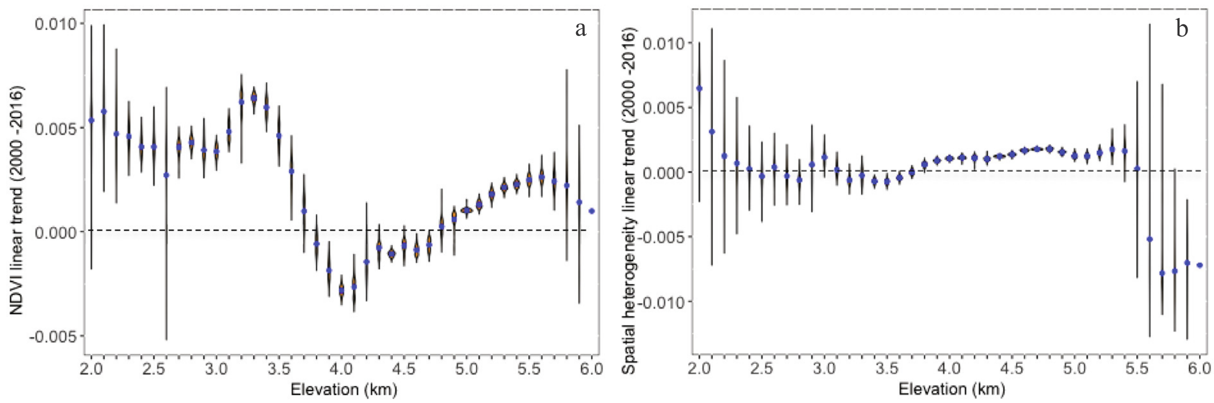

Fig. 9. Average of significant NDVI trends (a) and trends in spatial heterogeneity (CV of NDVI) (b) along the elevation gradient.

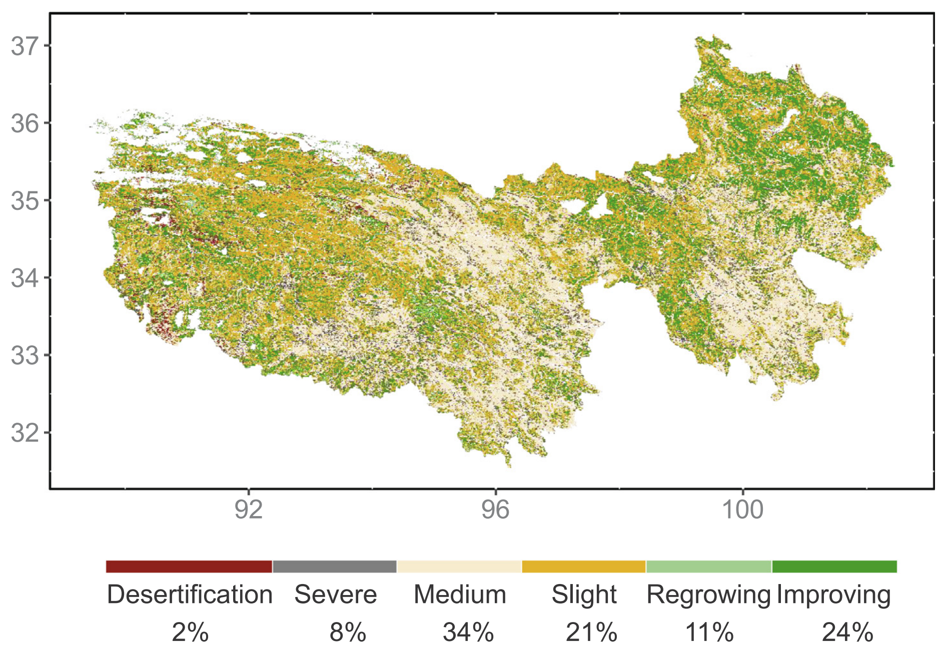

Fig. 10. Spatial distribution of grassland-development ("re-growing", "improving") and degradation ("slight", "medium", "severe", "desertification") levels identified with the classification system presented in Fig. 3.

occurred across 11% of the total study area (Fig. 10). On the western part of the study area, on the other hand, decreases in NDVI and its spatial heterogeneity indicated that vegetation shifted from a patchy stage to bare soil (2% of our study area), indicating being at the risk of desertification.

5. Discussion

5.1. Heterogeneity in grassland cover as a degradation indicator

Degraded arid ecosystems show self-organized vegetation patches and soil patches; and thus the pattern and size of vegetation patches in drylands have previously been identified as a warning signal for potential catastrophic ecosystem shifts (Barbier et al., 2006; Kéfi et al., 2007; Rietkerk et al., 2004). Likewise, degraded grasslands on the QTP have been characterized by mosaics of soil patches and vegetation patches (Cai et al., 2015; Chen et al., 2017; Liu et al., 2008; Wang et al., 2015). Previous studies have measured vegetation patch size to characterize ecosystem degradation (Kröpfl et al., 2013; Sheffer et al., 2013), which is an accurate way to understand ecosystem status over a small area. However, the same measures would not be efficient and sustainable on an extensive geographic area such as the QTP. Remote sensing offers the possibility to monitor the development of soil patches over large areas and on a long-term scale. In this study, we quantify soil patches in degraded grasslands using the spatial heterogeneity defined by the coefficient of variation of the vegetation index NDVI within 1500 × 1500 m neighborhoods consisting of nine 500 × 500 m pixels.

We found that lower vegetation cover does not always suggest more severe degradation of grassland because vegetation cover could actually be higher in some degraded areas than in non-degraded areas. Considering that low vegetation cover is a characteristic of grassland ecosystems on the QTP, we argue that vegetation cover at one single time is not a representative indicator of grassland degradation level. Our new findings point to the limitations of previous degradation assessments based mainly on vegetation cover (e.g. Li et al., 2014b).

We found that in areas identified as severely degraded in a reference study from 2004 (Liu et al., 2008), the spatial heterogeneity of vegetation cover was generally high (Fig. 6 (b)), suggesting that spatial heterogeneity of vegetation cover could be a good candidate to indicate degradation on the QTP. Larger bare-soil patches increase in size and number with environmental pressure like wind erosion, which enhances desertification risks (Dong et al., 2009). Such degradation and desertification processes are more obvious in steeper areas where soil erosion is higher and spatial heterogeneity is also higher (see Fig. 5(b) and Fig. S7).

Considering the various scales of soil patches that occurred on the QTP (Fig. 2), the size of soil patches that can be detected depends on the spatial resolution of satellite data and the neighborhood (moving window in this study) over which spatial heterogeneity is calculated. Satellite data with high or coarse spatial resolution can be used to define spatial heterogeneity related to soil patches. To test the impacts of spatial resolution and moving window size on the spatial heterogeneity, we compared spatial heterogeneity quantified at a spatial scale of 500 m with spatial heterogeneity at 30 m (Landsat 8 satellite data), using a moving window size of 3 × 3 pixels for both scales. As expected, the outputs of spatial heterogeneity differed between the two scales, however, we found that the general pattern was comparable between two (see Fig. S8). Higher spatial-resolution satellite data (i.e. Landsat dataset (30 m) and Sentinel-2 dataset (10–20 m)) can be used to map spatial heterogeneity on the QTP, but are limited to monitor changes in spatial heterogeneity because of lower temporal resolutions than the MODIS dataset.

Spatial heterogeneity monitored at a lower resolution (500 m) might involve different processes from those monitored at a higher resolution (30 m). For example, high spatial heterogeneity and bare-soil patches caused by burrowing activities of small mammal (Chen et al., 2017; Wei et al., 2007) are more likely to be detected at 30 m scale rather than at 500 m scale. Spatial heterogeneity defined at 500 m in this study possibly indicates a response to increased resource scarcity (Lejeune et al., 2002) under climate change such as rising temperature and precipitation decline on the QTP (Lehnert et al., 2016). The soil patchiness further results in ecosystem degradation by reducing vegetation productivity (Zhang et al., 2019) and altering carbon emission process (Qin et al., 2019).

5.2. Combining temporal changes in NDVI and spatial heterogeneity to map new degradation levels for 2016

We found that vegetation cover reduction mostly results in grassland fragmentation but increases in vegetation cover lead to changes in spatial heterogeneity in two directions: either a spatially more homogeneous or a spatially more heterogeneous landscape (Fig. S6). Changes in spatial heterogeneity and vegetation cover form a unique combination among groups with different degradation levels (Fig. 8). Our study showed that a combination of changes in vegetation cover and its spatial heterogeneity could better indicate grassland degradation levels than vegetation covers alone. Previous studies have indicated grassland degradation based on negative NDVI trends and grassland improvements based on positive trends (Wang et al., 2016b). According to only changes in NDVI, these and other authors concluded that vegetation that accounts for 61.2% of the QTP had been recovering (Wang et al., 2016b, Fan et al., 2010; Xu et al., 2011). In contrast, we found that a large fraction of the study area with increasing NDVI also shows increases in spatial heterogeneity. One of the plausible interpretation is that invasive species (Zeng et al., 2013) have been colonizing degraded grassland. Previous studies have found that sedges were gradually replaced by forbs in the slightly degraded grasslands (Zhang et al., 2019) because forbs take up low soil nitrogen more efficiently (Zhang et al., 2020). These invasive forb species are generally taller and have larger leaf area than indigenous species (Fig. 2 (c-d). Therefore, the occurrence of forb species increases the vegetation cover and NDVI, leading to increases in spatial heterogeneity. Here we caution that increases in vegetation cover can be a sign of degradation (Liu et al., 2015) when considering the case of invasive species (Fig. 2 (c-d)). We, therefore, suggest that in vegetated areas the increase of spatial heterogeneity is an indicator of the early stage of degradation — even if the NDVI shows increasing trends.

On the QTP, around 26% of the alpine grasslands have been degraded by encroachment with invasive species (Wen et al., 2013). A wide distribution of forb-dominant degraded grassland on the QTP (Ren et al., 2013) (see Fig. 2) makes it possible to monitor these grasslands with invasive species using long-term satellite data, though the individual invasive species cannot be easily detected from the satellite data with a spatial resolution of 500 m used in this study. We found that 21% of the whole study area both vegetation cover and its spatial heterogeneity have been increasing (see Fig. S6 and Fig. 10), which indicates that these areas potentially contained fragmented grassland being colonized by invasive species. Field studies on species composition, vegetation cover and soil properties (Liu et al., 2018; Zeng et al., 2013) will be needed for further verification. Field spectrometric measurement of species composition (Fava et al., 2010) will further help to map degraded grassland dominated by invasive species (Liu et al., 2015).

The changes in grassland cover and spatial heterogeneity from 2000 to 2016 suggest that grasslands have turned into new development and degradation stages. In the slightly and medium-degraded areas in 2004 (Liu et al., 2008), we found that NDVI mostly decreased and spatial heterogeneity increased from 2000 to 2016 (Fig. 8), showing that the grasslands have been fragmented and more soil patches have developed, therefore indicating more severe degradation. With the increasing environmental and grazing pressures, the severely degraded and sparsely vegetated areas are now under risk of desertification, making recovery over short time-scales unlikely (Kéfi et al., 2007). Therefore, our new indicators can serve as early warning indicators of severe grassland degradations and desertification. However, areas that were classified as desertified in 2004 showed an increasing NDVI and spatial heterogeneity trend over time (Fig. 8), suggesting that grassland was re-growing there. This condition was the most apparent in the medium and severely desertified areas.

We found that degraded grasslands were more dominant at elevations of 3500–4500 m, indicated by increasing spatial heterogeneity and decreasing vegetation cover from 2000 to 2016, which is consistent with a previous study that found more severe degradation at this elevation (Wang et al., 2015). In areas above 5000 m altitude, we found that NDVI increased and spatial heterogeneity decreased over time, suggesting an improvement of grasslands. A recent study also found increased vegetation cover at high altitudes in the Himalayas using Landsat satellite data and the strongest trend appeared between 5000 m and 5500 m altitude (Anderson et al., 2020).

Our results suggest that the grasslands on the eastern part of the QTP have undergone degradation during the study period. The degradation levels vary depending on climate, soils and management practices (Wang et al., 2018). Climate change, rodent damage and human factors such as overstocking, population increases and land-use change have been discussed as causes of grassland degradation (Harris, 2010; Lehnert et al., 2016; Miehe et al., 2019). Specifically, climate variability of rising air temperature combined with declining precipitation could be an explanation of vegetation cover decline on the QTP (Lehnert et al., 2016), except at the highest altitudes where vegetation may move upwards due to global warming (see Fig. S3) (Dolezal et al., 2016). Increasing human disturbance via road and township development and grassland privatization (Li et al., 2018a) resulted in grassland loss, furthermore, overgrazing in the vicinity of human settlements caused vegetation cover reductions (Li et al., 2019). Reduced vegetation cover creates a favorable condition for the invasion of pikas *(Ochotona curzoniae)* therefore causing soil-patch development and grassland degradation (Li et al., 2013). Heavy grazing and intensive activities of pika further encourage the invasion of unpalatable and poisonous plant species (Wen et al., 2013).

Warming and wetter climate along with sustainable stocking density of grazing animals might improve vegetation growth (Huang et al., 2016), especially climate warming facilitating vegetation growth by reducing growth constraints and increasing photosynthetic rates (Peng et al., 2012; Wang et al., 2016a), which might explain the improving conditions indicated by increasing NDVI (Zhang et al., 2014; Zhong et al., 2010) and decreasing spatial heterogeneity. Furthermore, ecosystem restoration projects revegetated severely degraded grasslands, which can be a reason for improving conditions monitored in this study (Cai et al., 2015; Gao et al., 2019). However, many of these are speculative explanations and further research is needed for understanding causes of grassland degradation on the QTP (Cao et al., 2019).

Defining solid criteria for evaluating grassland degradation on the QTP is essential for quantifying the extent of degradation and exploring drivers of grassland degradation (Cao et al., 2019), although widely accepted criteria are challenging to define considering wide ranges of grassland types and climate conditions (White et al., 2000). In this study, we defined the grassland degradation levels based on a sequential degradation process on the QTP, which proceeds from intact grassland to species invasion, grassland fragmentation and cover reduction, development of bare-soil patches and finally to the removal of all vegetation at the desert stage (Liu et al., 2008). Our study characterise this degradation sequential process using indicators of changes in grassland cover and spatial heterogeneity. However, only these two indicators can not tell a complete picture of grassland degradation. On the QTP, varying standards and indicators have been used to define degradation at different spatial scales, resulting in uncertainties about the real situation and trends of grassland degradation (Liu et al., 2018; Miehe et al., 2019). Currently, all indicators used for classifying grassland degradation are either only based on field observations (Wang et al., 2010a, 2010b; Guo and Wang, 2013; Feng et al., 2005) or only satellite-data analysis (Fassnacht et al., 2015; Li et al., 2014b; Liu et al., 2008, Zhang et al., 2014; Zhong et al., 2010). We propose that combined indicators based on field measurements on soil properties, species composition and satellite analysis are important to upscale field measurements to large areas for a complete view of grassland degradation on the QTP. We found that combined changes in NDVI and its spatial heterogeneity offer a better indicator for assessing grassland degradation than only using vegetation cover. The proposed indicators allow researchers to assess grassland degradation at various scales both at field level and from satellite observations. They therefore serve as indicators for evaluating grassland degradation on the QTP. The indicators may also be applicable to other arid ecosystems where the development of bare-soil patches has also widely been observed (Aguiar and Sala, 1999; Bestelmeyer et al., 2013; Kéfi et al., 2007).

6. Conclusion and outlook

We studied whether vegetation cover, spatial heterogeneity and their changes can be used to define grassland degradation levels on the eastern QTP. We found that a combination of changes in vegetation cover and in its spatial heterogeneity during 2000–2016 could indicate previously defined degradation levels (Liu et al., 2008). Grassland cover and its spatial heterogeneity have changed in most of the study area, indicating that grassland areas have moved into new degradation stages over the studied time interval.

Areas classified as degraded in 2004 generally became more degraded, as suggested by the reduction of vegetation cover and increases in the number of bare-soil patches. However, areas classified as desertified in 2004 showed signs of recovery or re-growth, as suggested by increasing vegetation cover and increasing spatial heterogeneity. Based on these observations, we define new degradation levels for the QTP grasslands in 2016. Our results suggest that large parts of the total study area (63%) have undergone degradation during the study period, and 2% of the western part of the study areas are now at risk of desertification. Nevertheless, 24% and 11% of the total study area have been improving or recovering, respectively, and these areas are concentrated at high elevation or in severely degraded grassland.

However, grassland degradation is a complicated process that not only involves changes in vegetation cover and spatial heterogeneity but also changes in soil properties and species composition, among other factors (Zhang et al., 2018). The proposed new indicators of changes in vegetation cover and spatial heterogeneity can be estimated with both field and satellite observations, which is important for upscaling field observations to a larger scale to have a comprehensive picture of grassland degradation on the QTP. Combining the remote sensing indicators with field-based indicators on plant community and soil characteristics might be the future direction for evaluating grassland degradation levels and developing efficient mitigation strategies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.106641.

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