Object-based change detection for vegetation disturbance and recovery using Landsat time series

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ABSTRACT
Accurate characterization of historical trends in vegetation change at the landscape scale is necessary for resource management and ecological assessment. Vegetation disturbance and recovery are coherent spatial and temporal processes. Pixel-based change detection methods often struggle to provide reliable estimates of change events because they neglect spatial contextual information and are affected by salt-and-pepper noise. To address such problems, we propose a new approach, “object-based change detection in disturbance and recovery” (Object-LT), which introduces object-based image analysis (OBIA) into the current framework of LandTrendr algorithm. We then applied this approach to detect vegetation changes during 2000–2020 in the ecologically fragile region of Guyuan, Ning Xia, China. Accuracy assessment indicated that Object-LT could accurately identify disturbance and recovery trends in vegetation with overall accuracies of 90.05% and 87.50%, respectively. Compare with pixel-based LandTrendr algorithm, Object-LT significantly improved user’s accuracy and removed salt-and-pepper noise. Spatial-temporal maps of vegetation change showed that the recovery area was 571.27 km² while the disturbed area was 297.65 km², accounting for 5.44% and 2.83% of the study area, respectively. This indicates a general vegetation recovery trend in the study area. Object-LT allowed for an accurate and comprehensive characterization of vegetation change over large areas, which contributes to a better understanding of change processes of vegetation landscape over time.

Introduction
Vegetation dynamics caused by environmental stresses and anthropogenic activities are accelerating and require continuous long-term monitoring (Lewińska et al. 2020; Chu et al. 2019). In ecology, disturbance is a common natural phenomenon that substantially affects the dynamics of vegetation and plant populations (Laska 2001). Vegetation disturbance general includes anthropogenic disturbance and natural disturbance, and disturbance are mainly manifested as changes caused by deforestation, forest fires, deforestation, pests and diseases, and forest tending and management policies (Yang 2015; Frolking et al. 2009; Ramírez-Marcial, González-Espinosa, and Williams-Linera 2001). Forest deforestation and degradation reduce the quantity and quality of forest vegetation cover and alter the spatial structure of landscapes through the ecological process (Gao et al. 2020; Panta, Kim, and Joshi 2009). During the past decades, linked to global climate change and increasing economic activities, forest degradation has become one of the most serious ecological problems in China, especially in ecologically vulnerable arid and semi-arid regions (Wang et al. 2013; Pan et al. 2022) To reduce deforestation and promote forest gain, the Chinese government have implemented many ecological programs since 1990s. For example, the Grain to Green Program (GGP), the largest ecological restoration project in western and central China, converting croplands on steep slopes and degraded croplands to forests or grasslands (Li et al. 2019). While, the Natural Forest Conservation Program (NFCP) aims to protect forests by prohibiting commercial logging of natural forests and restoring forests. However, the ecological effects of these programs remain ambiguous, and there is a lack of consistent long-term data on vegetation disturbance and recovery (Yin et al. 2018). Timely and accurate
characterization of vegetation change is required to provide references for resource management and the assessment of ecological actions.

The development of satellite sensor technology and remote sensing techniques have shown great potential for monitoring vegetation changes owing to their high efficiency, wide spatial coverage, and long time series (Liu et al. 2017; Chu et al. 2019; Long et al. 2021). Previous studies utilized images before and after a change event and then separated ecologically relevant changes from phenology or background noise by comparing the differences between the two dates to a threshold (Huang et al. 2019b; Lv et al. 2018; Xiao et al. 2019). However, bi-temporal change detection methods do not fully tap the interrelationships among multi-temporal images and may not be able to separate noise from subtle or long-duration changes in cover conditions (Zhu 2017).

Time series (TS) analysis of remote sensing images is an effective method for quantitatively analyzing and determining the characteristics and processes of land surface changes (Muro et al. 2018). Over the past several years, amounts of TS change detection algorithms have been proposed and utilized to vegetation change detection, including the vegetation change tracker (VCT; Zhao, Huang, and Zhu 2015), Landsat-based detection of trends in disturbance and recovery (LandTrendr; Kennedy, Yang, and Cohen 2010b), breaks for additive season and trend monitor (BFAST Monitor; DeVries et al. 2015), and continuous change detection and classification (Zhu et al. 2017). These change detection algorithms differ substantially in terms of user’s complexity, stability, flexibility, and accessibility, and target different populations. The CCDC algorithm can not only accurately detected the change time, but also the land cover type before and after the change. However, CCDC requires high temporal frequency of images, and is less helpful for detecting the changes in areas with inter-annual variations. The BFAST algorithm can detect both inter-annual and seasonal changes; however, it is not clear how to detect the recovery process after disturbance and repeated disturbance events. LandTrendr is an algorithm with many tunable parameters and several processing filter parameters (Kennedy, Yang, and Cohen 2010b); it can capture both short- and long-term trends in vegetation. When tuned for a given system, LandTrendr achieves high accuracy. It has been incorporated to the Google Earth Engine (GEE) cloud platform to improve the computing efficiency (Cohen et al. 2018). Several studies have been conducted to detect vegetation changes using the LandTrendr algorithm. For example, Long et al. (2021) analyzed the general trends and potential factors of vegetation change using the LandTrendr algorithm. Yang et al. (2015) assessed the ability of the LandTrendr algorithm and Landsat TS to detect vegetation changes and characterize long-term dynamics in mining areas. However, this algorithm does not consider the behavior of spatially-adjacent areas (Kennedy, Yang, and Cohen 2010a), and usually detected many pseudo-changes with small disturbances.

Historically, most algorithms have treated pixels independently when detecting changes. However, per-pixel-based methods neglect spatial contextual information by considering only the temporal features, which leads to a large amount of salt-and-pepper noise and spatially discontinuous mapping. Object-based image analysis (OBIA) refers to a category of remote sensing image analysis approaches that is used to study geographic entities; or phenomena based on image objects instead of pixels (Blaschke 2010). Image objects generally consist of similar neighboring pixels that have a common meaning, such as a field with the same crop or a plot of forest with the same species. Image objects contain more comprehensive information such as geometric features and spatial context than individual pixels. In addition, the results of OBIA tend to match the visual sense of humans (Blaschke 2010), and this is useful in mapping application. (Yu et al. 2006) evaluates the ability of OBIA for detailed vegetation classification in northern California and demonstrated that the OBIA method can overcome the problem of salt-and-pepper effects. Over the past decades, OBIA has been successfully applied to many areas such as mapping tree species diversity (Schäfer et al. 2016), paddy fields (Su 2017), and planning for landscape restoration (Marignani, 2008). Furthermore, OBIA has been used to map land cover change in different systems and with different techniques (Desclee, Bogaert, and Defourney 2006; Stumpf et al. 2011; Wang et al. 2018; Tan et al. 2019; Liu, Yang, and Lunga 2021). However, most of these studies focused on land cover change using bi-temporal images, and there is still a lack of OBIA studies applied to satellite-based time-series
analysis. Therefore, the combination of OBIA and TS analysis should be further explored.

In contrast to pixel-based change detection, image segmentation is a key step in OBIA. Image segmentation is the division of satellite images into spatially continuous and homogeneous regions (Flanders, Hall-Beyer, and Pereverzoff 2003). A segmentation algorithm is expected to divide the image into relatively homogeneous and semantically significant groups of pixels. Object-based change detection generally segment multi-date image synchronously to obtain image objects consistent in size, shape, and location over time (Hussain et al. 2013). For example, Conchedda, Durieux, and Mayaux (2008) and Stow et al. (2008) used multi-date composite images in both the classification phases and segmentation to map vegetation change objects. Duveiller et al. (2008) applied clustering to multi-date objects to analyze deforestation in Africa.

To explore the benefits of OBIA in satellite-based time-series analysis, we developed a new approach based on the LandTrendr algorithm, named “object-based change detection of trends in disturbance and recovery” (Object-LT). Object-LT introduces image segmentation into the current framework of LandTrendr, with the aim of improving detection accuracy and enabling an object-based mapping approach of trends in disturbance and recovery for long-term vegetation change. We tested Object-LT in the ecologically fragile region of Guyuan to explore vegetation dynamics during 2000–2020 and compared its performance with that of the pixel-based LandTrendr algorithm.

**Study area and data**

**Study area**

Guyuan City (26°0705″N–27°2824″N, 110°3216″E–113°1632″E), China, covers an area of 10,500 km² and located in the south of the Ningxia Hui Autonomous Region (Figure 1). It belongs to a continental climate, with an average annual temperature of 6.7°C–8.8°C and an average annual precipitation of 397–631 mm (Sun, Li, and Li 2020). Precipitation decreases from southeast to northwest. The southern part of the region is dominated by deciduous woodlands and grasslands in mountainous areas, whereas croplands dominate in the north. Lying in northwest China, which has an arid climate, vegetation in this area is highly sensitive to human activities such as grazing, deforestation and wasteland reclamation (Meng et al. 2022; Li et al. 2015).

![Figure 1. Study area maps. (a) General location in China; (b) Location within Ningxia; (c) Elevation map and restoration areas of Guyuan.](image-url)
some ecological projects have been implemented in this area to improve ecological conditions and alleviate desertification since 1990s (Li et al. 2013).

Data preparation

The data used in this study included Landsat imagery, land-cover data, and field survey data (Table 1). Land cover data in Guyuan for the year 2000 and 2020 were obtained from http://www.globallandcover.com (Jun, Ban, and Li 2014), used for parameter setting and sample selection. As shown in Figure 1, the field survey data marked some restoration areas where ecological projects have been implemented. The data were obtained from Ningxia Institute of Remote Sensing Survey to provide reference for parameter settings and accuracy assessment.

GEE is a platform which host a multi-petabyte catalog of satellite imagery and provide massive computations capabilities (Gorelick et al. 2017; Mahdianpari et al. 2020). All available TM/ETM+/OLI Level-2 Surface Reflectance data from Landsat 5, 7, 8 between 2000 and 2020 on GEE platform were used to construct the TS; atmospheric and geometrical corrections was already applied to these data (You et al. 2020). Landsat Collection consists of three categories: tier 1, tier 2, and real time. We used data only from Tier 1 because they met the formal quality criteria and were thus most suitable for TS analysis (Liu et al. 2019). We filtered the image collections according to the extent of the study area (WRS-2 Path/Row 121/40 and 122/40). Long-term and consistent satellite data were needed to monitor inter-annual changes in vegetation, and so satellite images were acquired between June 1 to September 30, each year, which covered the growing season of vegetation in this area. As Landsat OLI has a higher radiation resolution (12 bits) than TM/ETM+, statistical harmonic function between the spectral values of the OLI and TM/ETM + sensors was used to normalize the data (Venkatappa et al. 2019). In addition, the Fmask algorithm was used to identify and mask clouds in the image (Zhu et al. 2018). Finally, 21 annual composite images were created using the median reflectance values of the collection.

Table 1 Datasets used in the study

Methodology

As shown in Figure 2 the study involved four main steps. (1) First, we preprocessed Landsat images to construct annual composite images during 2000–2020. (2) Then, we performed image segmentation on the multi-date image to obtain contiguous objects in time-space. (3) Subsequently, we constructed object-level TS by computing the median value of pixels in each object. (4) Finally, we performed object-level change detection analysis based on the LandTrendr algorithm. The detailed procedure of this approach is described below. The

![Figure 2. Workflow of the proposed object-based change detection of trends in disturbance and recovery (Object-LT) using Landsat.](image-url)
image preprocessing and analysis for this study were primarily implemented through the GEE cloud platform, which enables efficient computationally intensive tasks.

**Image segmentation based on TS similarity**

Prior to TS construction and change detection, objects with greater homogeneity must be extracted from a series of remote sensing images. In this study, multi-date image segmentation was based on TS similarity using the G-means algorithm. G-means is an unsupervised clustering algorithm based on the k-means method, which solves the problem of setting the number of clusters in the clustering process (Hamerly et al. 2004). In practice, it is difficult to set appropriate cluster numbers for unsupervised clustering algorithms. Especially, in multi-date image segmentation using clustering algorithms, the appropriate number for image segmentation cannot be determined in advance. Therefore, G-means is suitable for multi-date image segmentation because there is no need to set the cluster number. The algorithm assumes that the data subsets obey the statistical test of Gaussian distribution and iteratively runs the k-means clustering algorithm to test the number of clusters k until all the data subsets satisfy the Gaussian distribution, and it is considered that a suitable number of clusters has been found (Haraty, Dimishkieh, and Masud 2015). In addition, G-means requires only one intuitive parameter (the standard statistical significance level $\alpha$, which was taken as 0.005 in this study), which is convenient for practical applications. Therefore, we selected the G-means algorithm for image segmentation.

The annual composite images collected from 2000 to 2020 were used for segmentation. Each image uses four bands: RED, GREEN, BLUE, and near infrared (NIR). The images of all time phases were stacked chronologically to generate a new image of 84 bands. Then, we clustered pixels inside the multi-date image using G-means algorithms and performed post-processing operations to obtain objects with similar TS. The G-means algorithms was implemented by GEE and pyclustering library (Novikov 2019).

In our study, image segmentation is independent of change detection and simply provides the basic unit of analysis for change detection. So, we do not care about the specific class of each pixel, but whether neighboring pixels with similar TS are merged into the same object. For instance, neither of them affects the result of image segmentation when two distant pixels are misclassified into the same or different classes. The results will be affected only when neighboring pixels are misclassified. On the one hand, clustering all pixels in the entire image at once usually consumes considerable computing resources. On the other hand, pixels with similar TS usually appear in adjacent areas. Therefore, we partition the entire image into several blocks by a spatial grid and cluster pixels in each image block independently. In this way, we can not only reduce the computational effort, but also constrain the incorrect clustering results within one block. In the study, the entire image was divided into image blocks with a size of 600 x 600 pixels, and then the G-means clustering algorithm was performed on each image block individually. Finally, the clustering results for each block were obtained.

As the boundaries of image blocks can lead to discontinuous objects, post-processing is required to remove speckle noise and discontinuous objects near block boundaries after clustering. The process consists of five steps: (1) First, we grouped pixels of the same class together according to the 8-neighborhood rule to obtain connected patches. (2) Then, we used spatial filtering to merge patches smaller than five pixels into larger surrounding patches. (3) All patches were converted from raster to vector polygons, and the median value of pixels for 84 raster bands within each polygon was counted as attributes of them. (4) Overlaying patches with partition grid lines, and filtering polygons that intersected with grid lines with a tolerance of 10 meters, to obtain the polygons near the partition boundary. Then, we clustered them based on attributes of polygons using the G-means algorithm. (5) According to the secondary clustering results, these adjacent homogeneous polygons were merged and relabeling to obtain the final segmentation results. Figure 3 shows a fraction of the image segmentation results, and the baselayer of this map is a Landsat 8 image acquired in 7 September 2020.

**TS construction based on object characteristics**

The normalized difference vegetation index (NDVI) is the most commonly used indicator for characterizing vegetation status (Liu et al; Huete 1995; Epiphanio et al. 1995; Miura, Huete, and Yoshioka 2006). It has been widely used to access the effect
and dynamics of environmental change on vegetation distribution. It can not only reflect the growth status of surface vegetation, but also the degree of land degradation (Li, Yang, and Zhang 2021). Therefore, we selected NDVI as the indicator to detect vegetation change. The NDVI index can be calculated as follows:

\[
NDVI = \frac{NIR - R}{NIR + R}
\]

(1)

where NIR represents reflectance of the near-infrared band, and R represents reflectance of the red band (Huete et al. 1994).

Objects generated by image segmentation were composed of several pixels with highly similar TS, appearing as a band of similarly behaving trajectories. A parcel converted from a shrub land to construction land is illustrated in Figure 4. Here, a TS of pixels within the parcel has been described as a band of trajectories. We found that the TS of all pixels within an object show a similar trend. Most current OBIA methods use the mean value of pixels within an object as features (Marignani et al. 2008; Marshak, Simard, and Denbina 2019). However, the average value is easily affected by abnormal pixels or noise within the object, and usually fails to reflect the actual
characteristics of ground objects. The median can better reflect the characteristics of most pixels in an object, is more representative, and has a stronger anti-interference ability (García, Funes, and Silva 2018). Therefore, we used the median value of pixels within an object to construct the NDVI TS of objects.

**Object-LT**

The LandTrendr spectral-temporal segmentation algorithm proposed by (Kennedy, Yang, and Cohen 2010a) is useful for change detection in TS of moderate-resolution satellite imagery (primarily Landsat). The input to the algorithm is a TS of spectral indices or bands. The operation process mainly includes four steps: trajectory extraction, potential segmentation point determination, time series trajectory fitting, and model optimization (Kennedy et al. 2018). In general, the LandTrendr algorithm treats pixels independently when detecting changes, and the TS of single pixels are taken as input. Unlike the LandTrendr algorithm, we fed the NDVI TS of each object into the LandTrendr algorithm to detect the disturbance and recovery of vegetation at the object scale. Then, variation features such as the change magnitude, change time, duration, and other information of the segment were obtained according to the time and spectral values of the segment nodes. Object-LT identifies disturbance and recovery events from the TS using these features.

The LandTrendr algorithm must set a threshold for the magnitude of the change to filter out small spectral changes (Kennedy, Yang, and Cohen 2010b). If the threshold is too small, real changes cannot be distinguished from background noise, and normal fluctuations in the ecosystem will be identified as disturbance or recovery, resulting in false detection. If the threshold is too large, real changes cannot be identified, resulting in missed detection. Therefore, 50 disturbance and recovery samples were selected from the study area. We then analyzed the Landsat spectral trajectories and fitting lines (Figure 5) of these samples and determined the change threshold by the minimum amplitude of the disturbance and recovery. Finally, we set NDVI declines over 0.27 as disturbance, and NDVI increases over 0.29 as recovery. As some conversion processes from bare land or built-up land to water bodies may be incorrectly identified as disturbances, we set the NDVI value before disturbance to > 0.3 (Griffiths 2015). The vegetation recovery

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**Figure 5.** Samples of vegetation disturbance and recovery. Transformation process of (a) forest land to construction land, (b) grassland to construction land, (c) cultivated land to forest land, and (d) grassland to forest land.
process usually takes a long time (Ye et al. 2021), and short-term NDVI growth is often caused by noise or normal ecosystem fluctuations; therefore, we set the recovery time to > 2 years.

Validation

The validation of change detection was based on an independent point sample obtained through stratified random sampling (Cochran 1977; Card 1982; Campbell et al. 2022). Samples were generated by overlaying land-cover data for 2000 and 2020 and randomly sampling for different conversion types, including: 100 disturbance samples generated in areas converted from vegetation (including grassland, shrub, and woodland) to other land cover types, 100 recovery samples generated in grassland-to-forest and bare land-to-grass areas, and 100 unchanged samples generated in areas where the land cover type was vegetation and unaltered. Finally, we determined the changed/unchanged samples by viewing Landsat imagery, high-resolution imagery available on Google Earth, and NDVI TS. By comparing the sample labels with the detection results, we constructed a confusion matrix and calculated parameters such as the overall accuracy, user’s and producer’s accuracy (Foody 2002). As some recovery samples were also disturbed, we compared the disturbance and recovery samples with the unchanged samples separately, instead of comparing the three samples together.

Results

Accuracy assessment

The confusion matrix for the change detection results indicated that Object-LT created a reliable map of the disturbance and recovery (Table 2). The overall accuracy of the disturbance was slightly higher than that of the recovery. The user’s accuracy for disturbance and recovery were both over 90%, and were especially high for the disturbance class, which indicates that the algorithm can effectively remove noise in the detection results. With producer’s accuracy of 86.00% and 82.00% for the disturbance and recovery classes, respectively, the assessment suggests relatively high omission errors compared with commission errors. The overall accuracy of recovery is lower than that of disturbance, suggesting Object-LT is less effective for recovery than for disturbance.

Table 2. Confusion matrix of the change detection assessment.

The accuracy of LandTrendr was evaluated using the method described in Section 3.4, and then compared with that of our method. As shown in Table 3, the user’s accuracy and overall accuracy of Object-LT in the disturbance class were higher than those of the LandTrendr algorithm, whereas the producer’s accuracy was slightly lower. Object-LT is less effective than LandTrendr for recovery detection. The overall accuracy and producer’s accuracy of recovery were slightly lower than those of LandTrendr, whereas the user’s accuracy was higher. Compared with LandTrendr, the user’s accuracy of Object-LT in the disturbance and recovery classes is higher.

Table 3. Detection accuracies of LandTrendr and Object-LT.

Disturbance and recovery map

The detection results were visualized as a gradient according to the years of occurrence, representing the spatial and temporal distribution of vegetation change from 2000 to 2020. Figure 6 and Figure 7 shows the disturbance and recovery areas, respectively. During 2000–2020, the disturbed area was approximately 297 km², while the recovering area reached approximately 571.27 km², which is much higher than the disturbed area, indicating a general recovery trend of vegetation in Guyuan. The disturbance and recovery areas are extensive but not uniformly distributed in time and space. Change is a distinctly nonrandom process. Disturbance is primarily distributed in western and northern areas of Guyuan, whereas the recovery is primarily distributed in eastern and southern areas. We selected several areas (Figure 6, L1 and L2; Figure 7, L1 and L2; Scale of all close-up windows is 1:30,000) to illustrate the spatial pattern of disturbance and recovery and to present the characteristics of Object-LT in mapping them.

Figure 8 shows the total annual area of disturbance and recovery from 2000 to 2020 in Guyuan. The areas of disturbance and recovery showed an opposite variation trend, i.e. the restored area is higher when the disturbed area is lower. And the restored area was more extensive than the disturbed area in most years. The highest disturbed area was observed in 2020. And
the area of disturbance was higher during the period 2014–2016. The restored area showed significant fluctuations during the study period, peaking in 2010 and 2012. In addition, it is worth noting that the first and the last year’s area of recovery and disturbance are significantly higher than the adjacent years.
Comparison of object-LT and LandTrendr

Pixel-based methods tend to detect the same change process as different results, which is caused by the natural heterogeneity of vegetation and the amplification of small differences when fitting the TS. Object-LT takes objects as the basic unit of analysis, and thus guaranteed internal consistency of the detection results. Figure 9 shows the case of vegetation disturbance for the conversion of grassland to construction land in 2012. The trend of the NDVI TS at the object scale was obvious, and the fitting line correctly captured the change process, which is consistent with the change process shown in the Landsat image. However, the TS at the pixel scale (e.g. p1, p2, and p3 in the target object) struggled to capture the real change process when fitting lines, resulting in missed or false detection. For example, pixel p1 captured the change process, but the variation in the fitted trajectory segment was too small, resulting in missed detection; the TS of pixel p2 was incorrectly segmented, which led to the wrong time point of the detected change; and the TS of pixel p3 was incorrectly fitted as a straight segment. The results show that Object-LT improved the anti-noise performance of LandTrendr, and more easily captured the changing process for fitting, making it more robust.

In addition, we selected a typical area (36°0047” N–36°0311”N, 106°2524”E–106°1756”E) in Guyuan and mapped the disturbed areas identified using LandTrendr and Object-LT. This area contains extensive land converted from cropland or grassland to construction land. The disturbed areas identified by pixel-based LandTrendr are fragmented, and there is extensive salt and pepper noise in the map. The detection results of Object-LT have clear boundaries, the distribution of disturbance years is more concentrated, and the connected area is larger than that in the LandTrendr results. This indicates that the spatial aggregation of object-based change detection results was stronger, and the problem of salt-and-pepper noise was well solved. At the same time, the detection results for most pixels were consistent with the object at the same location, and the spatial and temporal pattern of vegetation disturbance identified by LandTrendr was consistent with that of Object-LT.

Discussion

Characteristics of object-LT

In this study, we combined OBIA with the LandTrendr algorithm. The resulting model, Object-LT, could effectively detect vegetation disturbance and recovery in the study area. Compared with the pixel-based LandTrendr algorithm, Object-LT has a higher overall accuracy for disturbance and user’s accuracy for disturbance and recovery.

Cohen et al. (2018) compared seven different Landsat time series algorithms and found that LandTrendr have a lower user’s accuracy and a higher producer’s accuracy than VCT, CCDC, and other algorithms, indicating a larger improvement space in the user’s accuracy of the LandTrendr algorithm. Object-LT significantly improved user’s accuracy by removing noise and false changes. As mentioned in section 4.3, some pixels in the patch.

Figure 8. Total annual area of vegetation disturbance and recovery during 2000 to 2020 in Guyuan.
fail to be detected by LandTrendr due to amplification of small differences when fitting the TS. Object-LT improved the anti-noise performance of LandTrendr by considering the behavior of spatially-adjacent areas. However, the accuracy assessment showed that Object-LT have a lower producer’s accuracy than LandTrendr. It could be attributed to the fact that image segmentation incorporates isolated changing pixels into the surrounding larger patches, and thus, ignores small change areas. Meanwhile, the TS of changed patches may be affected by noise from unchanged pixels or abnormal pixels, resulting in missed detection. So, Object-LT may be less effective for small-sized disturbances such as selective logging because they are easily confused with noise. The TS of objects is obtained by counting the median value of pixels in each object. The changes are detected by Object-LT when changed pixels within an object are predominant; whereas, changes will be missed when unchanged pixels dominate.

Compared with LandTrendr, Object-LT has a high overall accuracy for disturbance and a low overall accuracy for recovery. This is associated with poor producer’s accuracy for recovery. Generally, vegetation recovery is harder to detect because it is a slower process that does not show dramatic changes such as fires, windstorms, and deforestation (Frolking et al. 2009). Therefore, LandTrendr tends to split the TS into several segments and fails to capture recovery trends. Whereas, Object-LT detects changes on objects rather than pixels, potentially worsening the problem. For example, some recovery pixels can be detected individually will be omitted in objects. Therefore, Object-LT is less effective than LandTrendr when the trend of TS is not obvious. Furthermore, with Object-LT, it might be possible to set a lower magnitude threshold to improve accuracy.
In some cases, not all pixels within the same object share the same change process, and they may not change at the same time. However, we can identify the change process based on the detection results of most pixels within the object. The results of single-pixel analysis tend to replace a single large event with many small ones, reducing the usefulness of the map for monitoring and environmental modeling (Hughes et al.). Object-LT ties pixels with a similar TS prior to change detection and detects changes on objects rather than pixels, enabling for the identification of spatially consistent change events in heterogeneous vegetation and removal of salt-and-pepper noise. This enables more accurate identification of vegetation changes caused by human factors, such as deforestation and afforestation, and the detection results are more consistent with the actual spatial extent of change. The change maps of Object-LT are convenient for comparison with human disturbance and ecological restoration projects, which is meaningful for ecological assessment.

**Spatiotemporal patterns of disturbance and recovery**

Our study consistently mapped vegetation changes at annual intervals, thereby highlighting the spatial and temporal characteristics of disturbance and recovery in Guyuan. Our results show that the restored area was significantly higher than disturbed area in Guyuan during the study period, showing a general recovery trend of vegetation. This is in line with findings from previous studies, which indicate that northwest China is experiencing greening (Chen et al. 2019).

We found that both the disturbed and restored area in the first and last year are significantly higher than the adjacent years. LandTrendr usually have a poor detection for first and last year due to the lack of data before and after the study period (Kennedy, Yang, and Cohen 2010a). Therefore, the detection results of first and last year had a lower confidence than other years. Although the restored area was much higher than disturbed area, the restored area seems to be lower in years when the disturbed area was relatively high. This suggested that they may be driven by the same factors. Considering the arid climate of the study area, this pattern may be related to precipitation factors. For example, the area of vegetation disturbance was higher during 2014–2016, which coincided with a dry climate period in this region. However, the lack of long-term consistent precipitation data prevented us from exploring and verifying it further.

The spatial distribution of both vegetation disturbance and recovery varies substantially. Vegetation disturbance was primarily distributed in western and northern regions, while recovery was primarily distributed in eastern and southern regions, which might reflect factors such as topography, population, and policies. The western and northern regions of Guyuan face greater environmental pressure owing to extensive cultivated land and dense population, and this is reflected in the more extensively disturbed areas; the eastern and southern regions of Guyuan have steeper terrain slopes and vegetation dominated by forests and grasslands. The GGP policy encourages forest regeneration on steep terrain, and some grasslands are prohibited from grazing (Uchida, Xu, and Rozelle 2005). Also, the climate in the southern region of the study area is more humid because of the topography. Therefore, vegetation recovery in the southern mountainous area of Guyuan was relatively high. Overall, vegetation changes in the region show a recovery trend, but whether this change is driven by environmental policies or caused by topographic and climate change remains unclear. Further vegetation change monitoring, such as using the Landsat archive for mapping, is needed to better understand the role of ecological restoration and environmental policy on long-term vegetation dynamics.

**Limitations and future work**

The accuracy of Object-LT depends partly on the quality of the image segmentation. The accuracy assessment results (producer’s accuracies of disturbance and recovery of 86.00% and 82%, respectively) show that both disturbance and recovery had lower producer’s accuracies. It could be associated with under-segmentation error, which resulted in too few segments. In the future, we should improve the image segmentation algorithm to reduce the under-segmentation error. In addition, a voting mechanism introduced to detect changes at the pixel scale and integrate the results to the object scale could avoid missed detections due to image segmentation to some extent.
NDVI become saturated at high amounts of green biomass (Tesfaye et al. 2020), resulting in the inability to detect changes effectively in high vegetation coverage areas. In addition to the reasons (vegetation recovery is generally harder to detect) we mentioned before, the saturation of NDVI could be an important reason for lower producer’s accuracy. Therefore, in our next work, we will explore the sensitivity of different indicators to the vegetation recovery process and improve the detection accuracy of vegetation recovery.

In summary, despite the advantages of Object-LT, its practical and widespread application should be further investigated. In particular, (1) the quality of the multi-temporal image segmentation should be evaluated and improved, especially for under-segmentation error and 2) the saturation problem of NDVI in areas with dense vegetation cover should be addressed.

**Conclusions**

In this research, we proposed a novel change detection approach based on LandTrendr algorithm using the TS at the object level instead of the pixel level. We applied our approach, named Object-LT, to monitor vegetation changes in Guyuan during 2000–2020. The results indicate that the disturbance and recovery of vegetation could be accurately captured. Compared with the LandTrendr algorithm, Object-LT effectively reduced salt-and-pepper noise, which is a typical problem in pixel-based methods, and significantly improved the user’s accuracy. Object-LT is a useful and practical approach that can provide high-quality assessment of vegetation dynamics. Our method enables the identification of long-term and spatially consistent change events in heterogeneous vegetation. It offers a tool for researchers and managers to better understand environmental change, and provides a reference for the formulation and implementation of ecological policies.

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**Disclosure statement**

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**Data availability statement**

The detection results of this study are available in GitHub at https://github.com/XUXIAK/Object-LT.

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