remote sensing

Article

Assessing Forest Landscape Stability through Automatic Identification of Landscape Pattern Evolution in Shanxi Province of China

Bowen Hou [1], Caiyong Wei [1,2], Xiangnan Liu [1,*], Yuanyuan Meng [3] and Xiaoyue Li [1]

[1] School of Information Engineering, China University of Geosciences, Beijing 100083, China
[2] High Resolution Satellite Remote Sensing Application Department, Ningxia Institute of Remote Sensing Survey, Yinchuan 750021, China
[3] Key Laboratory for Earth Surface Processes, Institute of Ecology, College of Urban and Environmental Sciences, Peking University, Beijing 100871, China
* Correspondence: liuxn@cugb.edu.cn; Tel.: +86-10-8232-3056

Abstract: The evolution of forest landscape patterns can reveal the landscape stability of forest dynamics undergoing complex ecological processes. Analysis of forest landscape dynamics in regions under ecological restoration can evaluate the impact of large-scale afforestation on habitat quality and provide a scientific basis for achieving sustainable eco-environment development. In this study, a method for assessing forest landscape stability by characterizing changes in forest landscape patterns was proposed. Toeplitz inverse covariance-based clustering (TICC) was used to automatically identify landscape pattern evolution by investigating the synergistic changes of two landscape indices—forest cover area (CA) and patch density (PD)—and to extract the short-term processes—degradation, restoration, and stable—that took place between 1987 and 2021. Four long-term evolution modes, no change, increase, decrease, and wave, based on the temporal distribution of short-term change processes, were also defined to assess landscape stability. Our results showed that (i) the forest's short-term change processes have various forms. The restoration subsequence was the largest and accounted for 46% of the total subsequence and existed in 75% of the landscape units. The time distribution of these three change processes showed that more landscape units have begun to transition into a stable state. (ii) The long-term change modes showed an aggregation distribution law and indicated that 57% of the landscape units were stable and 6.7% were unstable. Therefore, our study can provide a new perspective for the dynamic analysis of landscape patterns and offer insights for formulating better ecological restoration strategies.

Keywords: landscape stability; forest landscape pattern; forest landscape evolution; TICC algorithm

Citation: Hou, B.; Wei, C.; Liu, X.; Meng, Y.; Li, X. Assessing Forest Landscape Stability through Automatic Identification of Landscape Pattern Evolution in Shanxi Province of China. *Remote Sens.* **2023**, *15*, 545. https://doi.org/10.3390/rs15030545

Academic Editors: Vilém Pechanec and Jan Brus

Received: 15 December 2022
Revised: 7 January 2023
Accepted: 14 January 2023
Published: 17 January 2023

1. Introduction

Ecosystem stability plays a prominent role in ecological safety and service [1]. A stable forest landscape incurs low management costs and shows sustainable development, which is also the purpose of ecological restoration [2,3]. An ecological restoration project implemented by the Chinese government on the Loess Plateau substantially changed the forest landscape in the area [4]. The increase in forest coverage as a result of ecological restoration projects has effectively improved ecological quality in China [5]. Nevertheless, it was found that the Loess Plateau has afforestation areas with excessive recovery as well as those with inefficient recovery [6], which have led to a decline in the ecological quality of the region. The uncertain stability of the forest ecosystem can cause blind ecological restoration. Therefore, it is necessary to evaluate the stability of the forest landscape to maintain the achievements of the project for sustainable future management.

Landscape stability refers to the ability of a landscape to maintain its own state for a period of time and to recover quickly after being disturbed [7]. Different ecological processes have multiple impacts on forest landscapes [8,9]. The assessment of landscape stability is carried out by analyzing the active change processes in the landscape [10]. Satellite remote-sensing time series has the advantage of procuring long-term and large-scale data and is widely used for monitoring the changes in a landscape [11,12]. The normal remote-sensing assessment of landscape stability is a pixel-based index time-series analysis. It usually extracts the dynamic characteristics of the forest in the process of disturbance and restoration through continuous spatiotemporal monitoring and constructs indicators such as resilience and resistance to quantify these processes to assess stability from multiple perspectives [13–15]. For example, von Keyserlingk et al. quantified the recovery rate after disturbance from the NDVI time series using a change-detection algorithm and clarified the impact of grazing and drought on ecosystem stability [16]. As forest change often affects regions, pixel-based methods neglect spatial contextual information by considering only the temporal features [13]. Therefore, it is necessary to consider the spatial structural characteristics of forests while evaluating ecological processes to assess the ecosystem's stability.

Landscape pattern refers to the spatial structure and configuration of the landscape. The landscape pattern index can be used to analyze the characteristics of a forest landscape from the perspectives of fragmentation, coverage, and diversity. Some studies analyzed landscape stability by constructing biodiversity indices and calculating landscape indices. Xu et al. constructed a landscape ecological risk index to assess landscape stability from two perspectives of landscape loss and ecological sensitivity [17]. However, forest landscapes undergoing afforestation are highly heterogeneous. The dynamics of these forest landscapes have unpredictable effects on landscape stability. Therefore, it is necessary to assess landscape stability by analyzing the dynamics of landscape indices.

The dynamics of landscape indices reflect diverse ecological processes [18]. Some studies assess landscape stability by monitoring the dynamics of landscape indicators and analyzing the impact of various ecological processes on forest landscapes. Hermosilla et al. characterized the recovery of vegetation spatial patterns in Canadian forests after various disturbances by analyzing the changes that occurred in multiple landscape indices [19]. Zhang et al. provided a method for mangrove conservation in China using landscape indices related to fragmentation, shape, and coverage [20]. Previous studies typically assumed a uniform landscape transformation for the entire time series [21–24]. However, there are often high-frequency and complex ecological processes over a long-term observation. Extracting the intermediate change process can consider the impact of different ecological processes on landscape stability [25]. An equal interval and a fixed time window are the normal strategies that are used for describing landscape pattern changes over long time periods [26–28]. Wang et al. quantified the impact of afforestation on forest landscape patterns by delineating time periods into 5-year intervals to assess the effectiveness of ecological restoration [29]. Zhang et al. extracted frequent change patterns to analyze forest landscape stability at 1-year intervals [30]. However, the forest change process is heterogenous, which means that the change process in even the same type of forest is of inconsistent duration [31–34]. The fixed time window analysis ignores the spatiotemporal correlation of the change process and is susceptible to random noise [35]. Therefore, it is necessary to develop a method for dynamic landscape analysis that can automatically extract segmented temporal indicators derived from a subset of time series to assess landscape stability.

The development of a sequenced time series analysis makes it possible to mine the heterogeneous subset of time series. The heterogeneous subsequence often represents the continuous behavior of the object in a certain period of time. Considering the continuous transformation of space and time of the object is of great significance for extracting the characteristics of the time series object [36]. Toeplitz inverse covariance-based clustering (TICC), an algorithm that discovers repetitive patterns contained in multivariable time series [37], has been applied to behavior recognition, transportation, and finance fields. Each cluster in the TICC is defined by a Markov random field (MRF), characterizing the interdependencies between the different series features. This unique iterative updated algorithm ensures that the typical heterogeneous subset of time series can be found.

In this study, a new method that can evaluate landscape stability by automatically extracting high-frequency and complex landscape change processes was proposed. There were two objectives of our study: (1) to extract the spatiotemporal dynamics of the degradation and restoration processes in continuously changing landscape patterns based on TICC, and (2) to develop an automatic and continuous landscape stability assessment by defining long-term evolution modes based on degradation and restoration processes.

2. Materials and Methods

2.1. Study Area

The Shanxi Province is located between 34°34′–40°44′N latitude and 110°14′–114°33′E longitude and covers a total area of 156,700 square kilometers. Mountains and hills account for 80% of this area, which has complex and diverse landform types in the typical semi-arid loess hilly region. On its east lies a massive mountain, formed by the Taihang Mountains as the main vein. On the west is the Loess Plateau, with the Luliang Mountain as its main trunk, and in the middle lies the Fenhe river basin (Figure 1). The overall terrain is low in the middle and high on both sides. Shanxi has a typical temperate continental monsoon climate, with annual precipitation between 358 and 621 mm and average temperatures of 4.2–14.2 °C. Shanxi is rich in coal resources, and the development of mining areas has had a serious impact on the local ecosystem. It has resulted in substantial forest degradation, making the fragile ecological situation of the Loess Plateau even more uncertain [38,39]. Due to the increasingly severe ecological problems in the area, China has implemented large-scale vegetation construction projects, resulting in a significant increase in forest coverage (http://zrzyt.shanxi.gov.cn/ (accessed on 14 February 2022)). During more than 30 years of development, Shanxi's forest landscape has undergone tremendous changes.

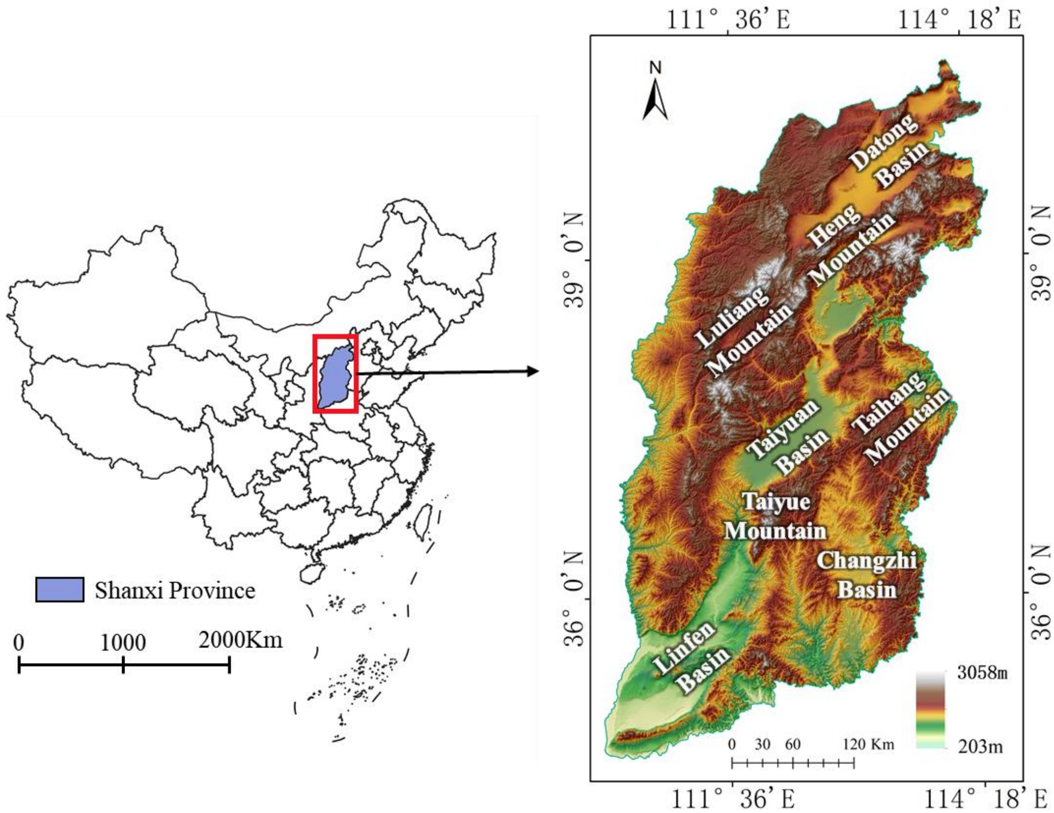

Figure 1. Location of the study area based on a digital elevation model (DEM).

2.2. Methodology

The framework of the research method used in this study is shown in Figure 2. First, the annual Landsat images for Shanxi from 1987 to 2021 were obtained through the Google Earth Engine (GEE) platform, and a random forest classifier was used to classify the land-use type to obtain the annual distribution map of the forest. According to the forest distribution map, the forest cover area (CA) and patch density (PD) in each landscape unit was calculated. Second, subsequences with information on the synergistic changes in the landscape indices were extracted based on TICC. Ordinary least squares (OLS) regression was used to analyze the changing trends of the two landscape indices in subsequences to define the ecological processes in landscape change. Finally, four long-term evolution modes were identified using the temporal distribution of subsequent. Based on the spatiotemporal distribution characteristics of the evolution modes, landscape stability in this study region was assessed.

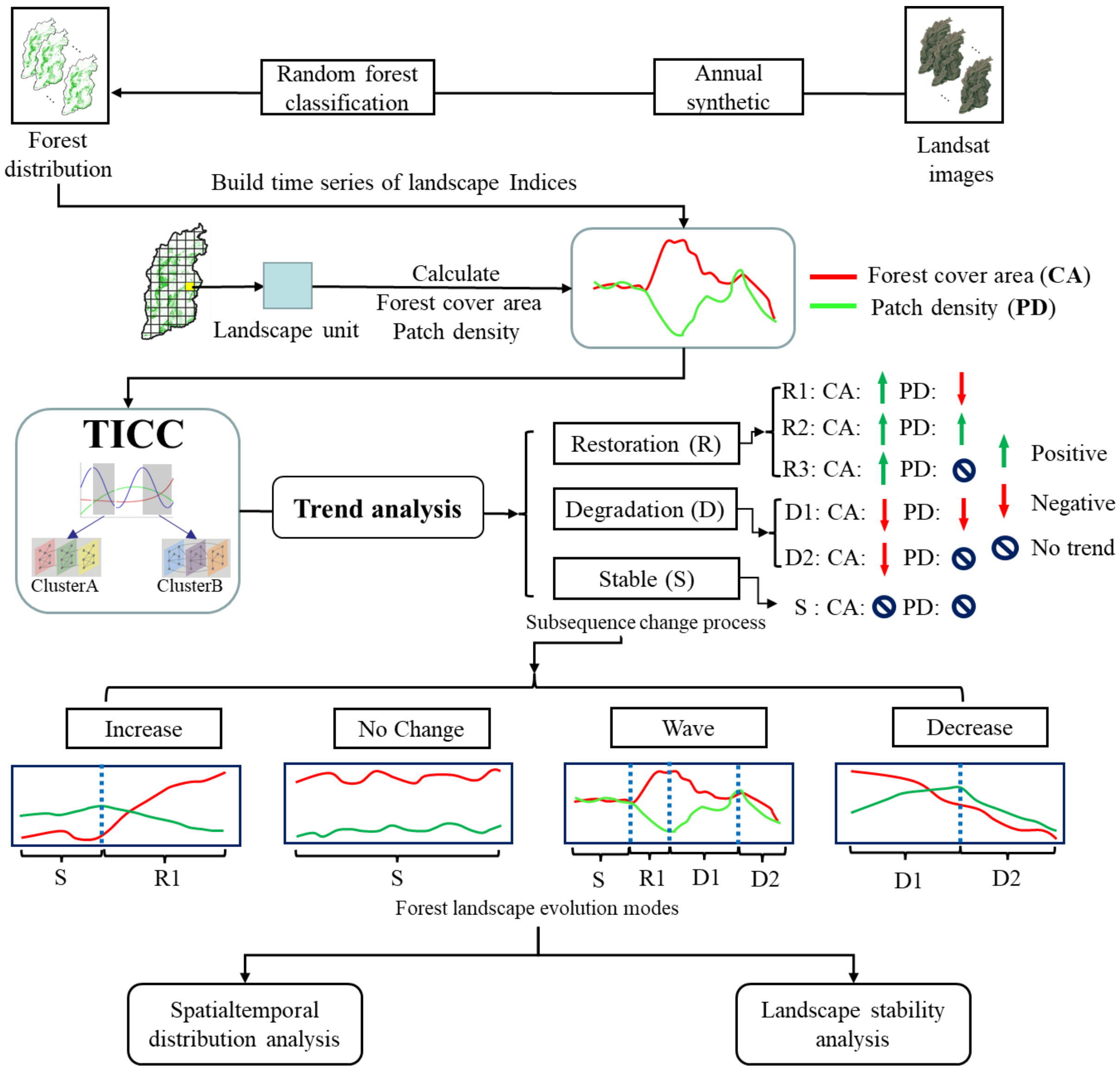

Figure 2. Schematic representation of the research method used in this study.

2.2.1. Data Preparation

Based on the GEE platform, terrain-corrected and radiation-corrected Landsat data from 1987 to 2021 were obtained for the study area. The post-2003 Landsat-5 TM data largely made up for the missing data resulting from the failure of Landsat-7 SLC. Therefore, this study used the Landsat-5 TM data from 1987 to 2000 and 2003 to 2012, the Landsat-7 ETM+ data from 2001 to 2002, and the Landsat-8 OLI data from 2013 to 2021. Due to the final forest classification mapping, to reduce the impact of forest phenology, the image-collection time was limited from June to September each year. At the same time, poor observations were replaced with better observations obtained in other months by referencing the QA band of the image to complete the collection of better images for the year. The median value is not affected by the maximum and minimum values [11] and can represent the general level of the entire data. To further avoid the impact of poor observations, the median value of the annual image set was used to synthesize the annual images, and the annual Landsat time series images from 1987 to 2021 were obtained.

Forest distribution maps form the basis of forest landscape research. In this study, GEE's random forest classifier was used to classify the land-use types in the study area into six categories based on the annual Landsat images: forest, water, cultivated land, construction land, grassland, and unused land. Here, the forest is considered to be a land area with a canopy density of >30%. The input features of the random forest classifier consisted of all bands of the Landsat image, and at least 1000 sample points (including no less than 500 forest samples) were selected from each year for land cover classification. Finally, the land cover classification for 1987–2021 was obtained. In the study area, 700 sample points were randomly generated for each year to verify the accuracy of the classification results, and the overall accuracy and Kappa Coefficient were generated by constructing a confusion matrix for accuracy evaluation.

2.2.2. Calculation of the Forest Landscape Index

Under the influence of ecological restoration projects and human activities, forest coverage and fragmentation in semi-arid areas have undergone tremendous changes [40,41]. According to the definition of ecological land degradation and restoration forwarded by Feng et al., the synergistic changes in forest coverage and fragmentation can indicate the degradation and restoration processes of landscape patterns [42]. Therefore, this study calculated two landscape indices—CA and PD—to analyze the ecological process. Their formulas and ecological significance are shown in Table 1.

Table 1. Formulas for the representative landscape indices and their ecological significance.

Index	Formula	Units	Ecological Significance
Forest cover area (CA)	$CA = F(\frac{1}{10{,}000})$ F:total forest area in landscape units (m^2)	ha	Forest area is the basis for maintaining forest ecosystem activities. The loss of forest represents the loss of biological habitat, which translates into reduced stability. The trend in CA is also an important basis for distinguishing different ecological processes.
Patch density (PD)	$PD = \frac{N}{A}$ N: number of patches in landscape units A: area of landscape units (1 km^2)	number (1 km^2)	PD can reflect forest fragmentation, which is the most direct manifestation of forest landscape structural changes and is an important indicator to measure the activity of ecological processes. The increase in fragmentation often represents a decrease in stability.

The classic way to calculate the landscape index is to divide the study area into regular grids. Each grid is regarded as a landscape unit, and the landscape index is calculated one by one. By referring to the existing research, a 1×1 km grid was used as the landscape unit size, which could effectively capture local details of landscape dynamics and identify the temporal heterogeneity of the landscape in the time series analysis [43]. Since forest pattern evolution takes time, it is important to determine at the outset which landscape units must be observed to study the pattern of change. This study observed 119,668 landscape units, including forests, in 1987 as the initial landscape units and calculated the landscape indices year by year. The calculation process was performed using the Fragstats v4.2 software.

2.2.3. Segmenting Time Series Based on TICC

TICC is a model-based multivariate time series clustering method. It can find regular structures in multidimensional time series data, discover complex synergistic changes among multiple time series features, then segment and classify time series data with adaptive lengths to obtain interpretable change processes. It deals with a set of multidimensional time series of length T (Equation (1)). However, TICC clusters subsequences of length w instead of each time point. The subsequences are divided by the original time series, called $X_t = [x_{t-w+1}, x_{t-w+2}, \ldots, x_t]$. Moreover, a new sequence, $X = [X_1, X_2, X_3, \ldots, X_T]$, is obtained. Each X_T in the new sequence has a one-to-one correspondence with the x_t of the original sequence. TICC analyzes X_T and assigns the cluster type to the corresponding time point x_t, and then obtains the repetition pattern of the original time series.

$$X_{orig} = [x_1, x_2, x_3, \ldots, x_T] \tag{1}$$

TICC uses an inverse covariance matrix θ to describe the subsequences and clusters. The elements in different positions of the matrix represent the correlation between two time series features at different times, which can provide an interpretable representation for the clustering results. TICC updates the cluster parameters based on the alternating direction method of multipliers (ADMM). TICC assigns a cluster through a dynamic programming algorithm. The details of the algorithms refer to the work by Hallac et al. [37].

Determining the optimal number of clusters for the TICC algorithm requires several evaluation metrics. In this study, the Bayesian information criterion (BIC) and the Davies Bouldin index (DBI) were used to select the number of clusters [37]. According to the minimum value of BIC and DBI, a set of timing segmentation results can be obtained.

2.2.4. Extracting Short-Term Change Process

It was necessary to further analyze the results of TICC to determine forest restoration and degradation. The results of TICC showed the change processes with temporal heterogeneity, which implied that the length of each type of change process varied. This study averaged the subsequences of the same length for each cluster, and the OLS method was employed to obtain the trend of two indices to represent the trend of the cluster. A positive slope (K) indicated a positive trend; otherwise, the trend was negative [44]. Furthermore, the F-test was used to determine the significance of the linear trends ($F > F_a$, $p > a$, $a = 0.05$). A significance level of 0.05 was used to reject the null hypothesis, which stated that there was no significant trend in the series. As shown in Table 2, each cluster could be defined as a degradation-restoring stable one by analyzing the trends of the two indices. According to the description of ecological land and ecological restoration in the Opinions on the Delineation and Strict Observance of the Red Line of Ecological Protection (http://www.gov.cn/zhengce/2017-02/07/content_5166291.htm (accessed on 23 August 2022)) and the report of Feng et al. [42] and Li et al. [45], this study defined the ecological process that reflects the increase in integrity, stability and connectivity of the ecosystem as restoration, and the opposite process as degradation. The results of TICC showed that each landscape unit contained at least one subsequence change process. The cumulative times of different change processes in each landscape unit were counted to determine the spatial distribution of the restoration, degradation, and stable change processes. Moreover, the duration and start time of the change processes were obtained to determine the temporal distribution.

Table 2. Definitions of the change processes based on CA and PD trends.

Change Process	Trend		Ecological Significance
	CA	PD	
Degradation	Negative	No trend	The decrease in the area of forest patches does not change the overall fragmentation, and the patches disappear from locations on the edges or inside of existing patches. Patch changes correspond to the change process of shrinkage and perforation.
Degradation	Negative	Negative	Decreased area of forest patches leads to decreased overall fragmentation. Patch changes correspond to the change process of attrition.
Degradation	Negative	Positive	Decrease in patch area fragments forest patches, leading to an increase in overall fragmentation. Patch changes correspond to the change process of division.
Degradation	No trend	Positive	Although the patch area is stable, the degree of fragmentation increases and the integrity of the forest landscape decreases, which is considered degradation.
Restoration	Positive	No trend	Increase in patch area does not affect overall fragmentation; the increase in patch area is located at the edge or inside of the patches. Patch changes correspond to the change processes of expansion and infilling.
Restoration	Positive	Positive	An increase in the number of patches leads to an increase in forest area and fragmentation. Patch changes correspond to the change process of outlying.
Restoration	Positive	Negative	Increase in the patch area reduces overall fragmentation. This is the process of landscape connectivity.
Restoration	No trend	Negative	Patch area is stable, and the decrease in fragmentation implies that the integrity of the forest landscape has increased, which is considered restoration.
Stable	No trend	No trend	Both the area and the fragmentation remain stable.

2.2.5. Assessing Landscape Stability

According to the subsequence change processes, four forest landscape evolution modes were defined (as shown in Table 3). Based on the characteristics of these evolution modes, the landscape stability was evaluated from two aspects: its ability to maintain its own state and its ability to recover after being disturbed.

Table 3. Definition of long-term evolution based on degradation, restoration, and stable processes.

Long-Term Evolution Mode	Description	Stability Measurement
No Change mode	There are no restoration or degradation processes in long-term evolution. Forest landscape pattern does not change.	Stable
Decrease mode	There are at least one or more degradation processes but no restoration process in long-term evolution.	Unstable
Increase mode	There are at least one or more restoration processes but no degradation processes in long-term evolution.	Stable
Wave mode	There are both degradation and restoration processes in long-term evolution. For example, forest landscape patterns may first degrade, then recover to stable.	Cumulative time switching frequency restoration time

No change mode implies that a forest can remain stable all the time, which indicates strong resistance. Furthermore, persistent forest patches have higher ecological value and resilience [46–48]. The increase mode shows forest gain and defragmentation. Lower fragmentation and higher coverage indicate a higher ecosystem resilience [49]. There are no degradation processes in increase mode, which indicates strong resistance. Landscape units with these two evolution modes have strong stability.

Decrease mode shows forest loss and fragmentation, which indicates declining ecosystem resilience. Landscape units with decreased mode are unstable as they cannot resist disturbance and cannot recover to a stable state.

The stability of the wave mode cannot be directly determined because of the diversity and uncertainty of the duration of the change processes. In order to assess the landscape stability of the units with wave mode, four metrics were calculated. The process of degradation and restoration can reflect changes in landscape stability. Therefore, the cumulative time of forest degradation and restoration was calculated to evaluate its stability. The shorter the cumulative time of degradation, the longer the cumulative time of restoration, and the more stable the landscape is. The switching frequency of degradation and restoration can indicate the forest's vulnerability and resistance [15]. The lower the frequency, the more stable the landscape is. This study also analyzed whether the forest could be recovered to a stable state after degradation to judge the resilience of the forest landscape. The less time it takes to restore the landscape to stability, the more stable it is.

3. Results

3.1. Characteristics of Subsequence in Landscape Dynamic

DBI and BIC were used to test the effects of TICC, and the number of clusters ranged from 6 to 12. Based on the minimum values of DBI and BIC for different cluster numbers, the optimal cluster number was determined to be 9 (Table 4).

Table 4. Performance of various validity indices in different cluster numbers.

Index	Number of Clusters						
	6	**7**	**8**	**9**	**10**	**11**	**12**
BIC (10^8)	5.791	5.966	6.131	5.804	7.163	7.474	8.017
DBI	1.72	1.92	1.94	1.60	2.03	2.00	2.28

With the performance of CA and PD in each cluster, this study found four restoration, two degradation, and three stable processes (Figure 3 and Table 5). The distribution of the landscape indices has been counted for each cluster of TICC to analyze the subsequence change process.

Table 5. Statistics of forest change processes.

Cluster	CA (ha)				PD (Patch Number/1 Km^2)				Change Process
	Mean	**Change Rate**	**St.dv**	**Trend**	**Mean**	**Change Rate**	**St.dv**	**Trend**	
1	14.1	0.59	6.7	Positive	18.2	−0.40	5.9	Negative	Restoration
2	14.2	0.64	6.0	Positive	31.8	1.66	10.5	Positive	Restoration
3	27.2	0.44	7.0	Positive	27.7	0.37	7.2	Positive	Restoration
4	42.9	0.38	8.0	Positive	19.4	−0.02	5.4	No trend	Restoration
5	11.1	−0.54	5.1	Negative	7.9	−0.23	5.1	Negative	Degradation
6	15.7	−0.75	2.9	Negative	16.7	0.57	7.1	Positive	Degradation
7	63.2	0.06	9.2	No trend	9.5	−0.05	3.8	No trend	Stable
8	42.7	0.12	15.3	No trend	13.4	0.08	5.1	No trend	Stable
9	85.7	0.04	7.7	No trend	3.6	−0.07	2.0	No trend	Stable

A forest landscape in the restoration process will have a high degree of fragmentation and varying degrees of forest cover area. There were three types of restoration processes: Cluster 4 represented forest patch expansion, Clusters 2 and 3 represented forest restoration based on the increase in forest patches, and Cluster 1 showed defragmentation.

This study found two degradation processes, Cluster 5 represented shrinking forest degradation, and Cluster 6 represented forest patch split. Low coverage, fragmentation, and variance show that the degradation process is mainly distributed in the landscape units with low coverage.

The characteristics of the stable process showed that forest landscapes with high coverage and low fragmentation remain stable. The CA's variance in Cluster 8 was higher than that in any other clusters, which suggests that some low-coverage landscape units can also remain stable.

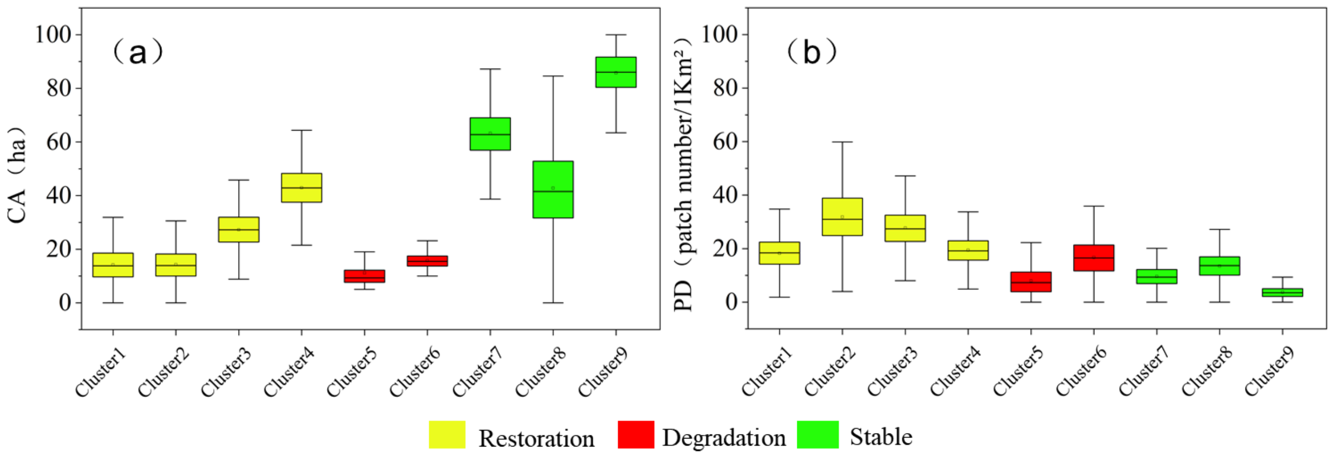

Figure 3. Distribution of forest landscape indices in different clusters: (**a**) forest cover area (CA) and (**b**) patch density (PD).

3.2. Spatiotemporal Distribution of the Forest Change Processes

This study found a total of 275181 subsequences, of which 26% were stable, 46% were restoration, and 28% were degradation. Landscape units with restoration, stable, and degradation processes accounted for 75%, 42%, and 47%, respectively. Landscape units with restoration processes were widely distributed in the study region, as shown in Figure 4a, and 26.5% of landscape units had a cumulative restoration time of more than 30 years (Figure 4c). The duration of all restoration subsequences was counted, as shown in Figure 4b. The percentages of restoration subsequences for the two time periods (5–10 years and 10–15 years) were large, accounting for 26.7% and 21.3%, respectively. Restoration subsequences of more than 30 years accounted for 16.7%. There were fewer areas where the cumulative restoration time was less than 10 years, but more subsequences with a duration of fewer than 10 years, which shows that the restoration is mainly short-term and occurs several times in the landscape units.

As shown in Figure 5a, landscape units with a cumulative degradation time of more than 30 years were mainly distributed in the central Fenhe river basin, Taiyuan Basin, and west of the Luliang Mountains and accounted for 17.6% of the total area (Figure 5c). The distribution of the degradation subsequences in each time period was relatively uniform, as shown in Figure 5b. Most of the degradation lasted less than 10 years, accounting for 53.1%. The cumulative time and duration of degradation showed that the degradation process was mainly short-term, most landscape units contained multiple degradations, and the long-term degradation distribution was relatively concentrated.

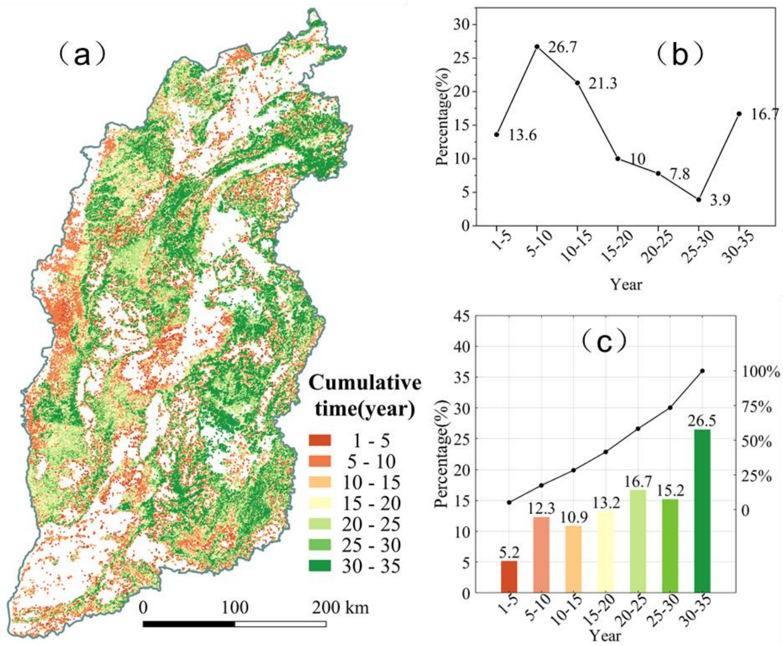

Figure 4. The spatial and temporal distribution of the change processes: (**a**) spatial distribution of restoration; (**b**) the statistics of duration of restoration subsequences; (**c**) the statistics of cumulative time of restoration.

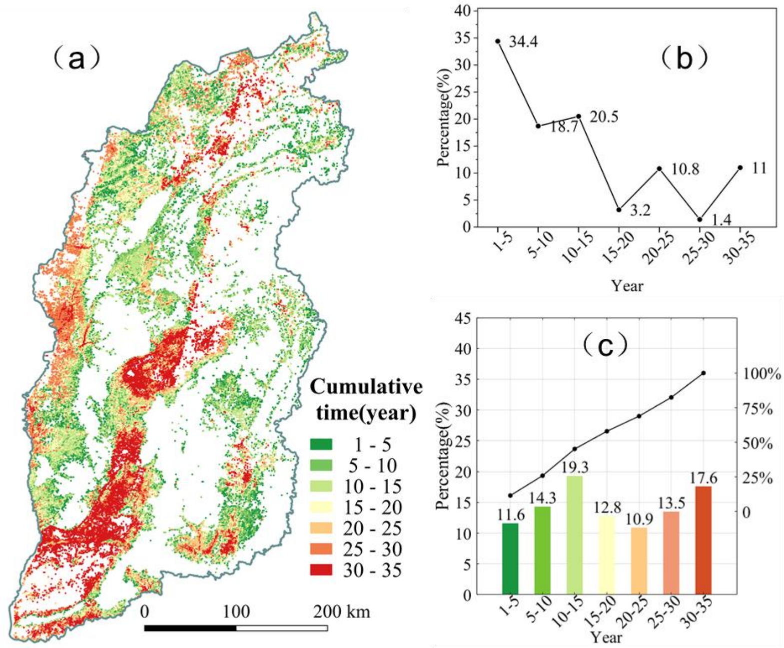

Figure 5. The spatial and temporal distribution of change processes: (**a**) spatial distribution of degradation; (**b**) the statistics of duration of degradation subsequences; (**c**) the statistics of cumulative time of degradation.

As shown in Figure 6a, the distribution of the landscape units with stable processes was concentrated in the mountain area, and the areas that had cumulative stable times of more than 30 years accounted for 38.2% (Figure 6c). The duration of stable subsequences was mainly distributed in <10 years and >30 years, accounting for 50.3% and 30.1%, respectively (Figure 6b).

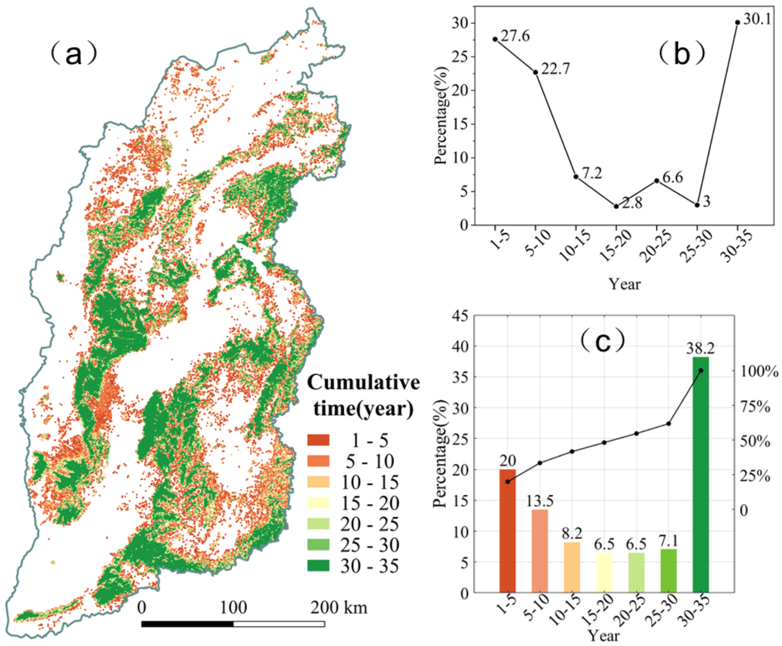

Figure 6. The spatial and temporal distribution of change processes: (**a**) spatial distribution of stable; (**b**) the statistics of duration of stable subsequences; (**c**) the statistics of cumulative time of stable.

This study counted all start times for the three change processes (Figure 7). The initial time period (1987–1995) showed an exceptionally high percentage of experiencing the beginning of degradation (21.9%) and a low percentage of the beginning of stability (13.4%). Over time, the beginning of degradation appears less and less; only 0.4% of the degradation processes began in the last time period (2015–2021). During the 2000–2005 time period, the beginning of restoration started to increase and reached a peak (10%) in the period 2005–2010. From the 2005 to 2010 time period, the beginning of the stable process kept increasing until the last time period (2.4%).

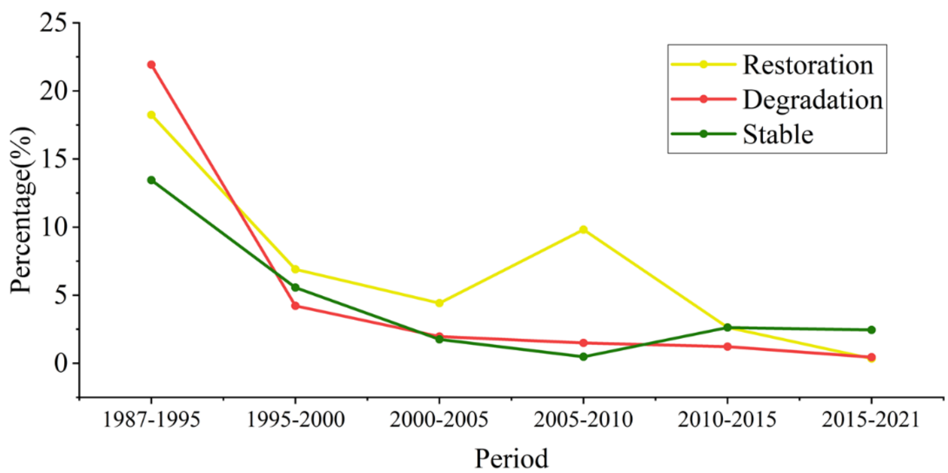

Figure 7. Percentage of area exhibiting the beginning of the change processes.

3.3. Characteristics of Landscape Stability

Four forest landscape evolution modes were summarized through the spatiotemporal distribution of degradation, restoration, and stable processes. This study evaluated the landscape stability based on the characteristics of these four evolution modes. Notably, all landscape units with decreased mode were degraded over 30 years. These forest landscapes with decreasing mode were severely degraded and unstable. Fortunately, they had the smallest share at 6.7% and were mainly distributed in the Taiyuan Basin and in the middle of the Fenhe river basin (Figure 8e).

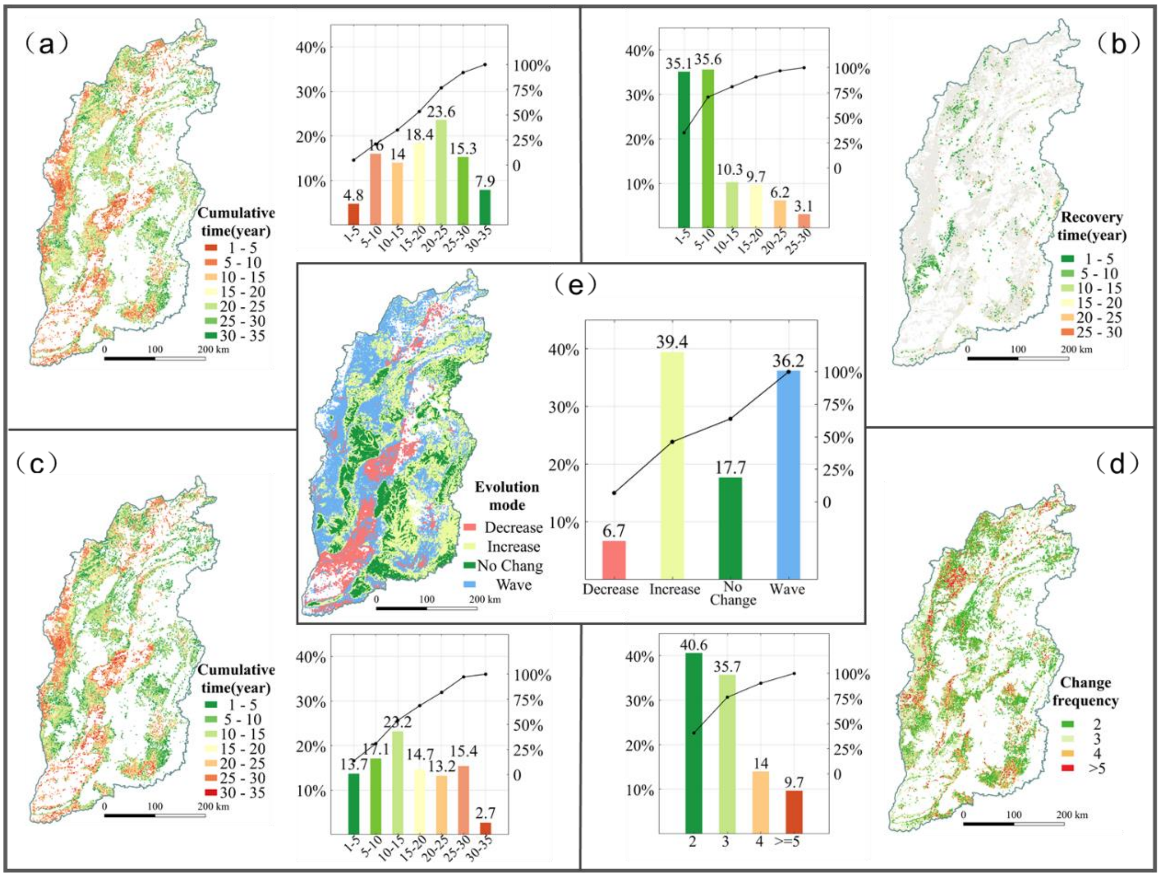

Figure 8. Spatial distribution of evolution modes and landscape stability evaluation index for wave mode: (**a**–**d**) landscape stability evaluation index for wave mode and (**e**) spatial distribution of evolution mode.

The no change mode and increasing mode showed that the ecological habitat could maintain the continuous growth and defragmentation of the area or a stable state and had strong stability and anti-interference ability. As shown in Figure 8e, landscape units in no change mode accounted for 17.7%, and those in increasing mode accounted for the highest proportion at 39.4%. In general, more than half of the region was stable (57.1%).

Several evaluation metrics are calculated to determine the stability of landscape units with wave mode (Figure 8a–d). Figure 8e shows the change frequency of different processes, and the area with a change frequency of fewer than three times accounts for 76.3%. In most regions, the cumulative time of restoration and degradation were trade-offs (Figure 8a,c), which implies that the duration of maintaining stable processes was short in most regions. Only a small part of forest landscape units could be restored to a stable state, and 70.7% of them were restored within 10 years (Figure 8b). Severely degraded areas are located in Datong Basin, the northwest of Shanxi, the hilly loess area in the west, and the southern Taiyue Mountains. Those areas with long cumulative times of degradation and high frequencies of change indicate that the forest landscape would deteriorate after a short period of restoration. Furthermore, Figure 8d shows the resilience of the forest landscape. Those areas were difficult to restore to a stable state and were unable to maintain a recovery state. The high-frequency change areas were located in the north, south, and west of Luliang Mountain. Furthermore, some areas could be restored to a stable state and displayed strong resilience, but they were easily disturbed.

3.4. Landscape Stability Assessment of Representative Regions

The spatial distribution of landscape stability is an important reference for ecological restoration on the Loess Plateau. This study analyzed the spatial distribution of landscape stability in several typical regions (Figure 9). This is important to formulate ecological restoration strategies in line with regional development.

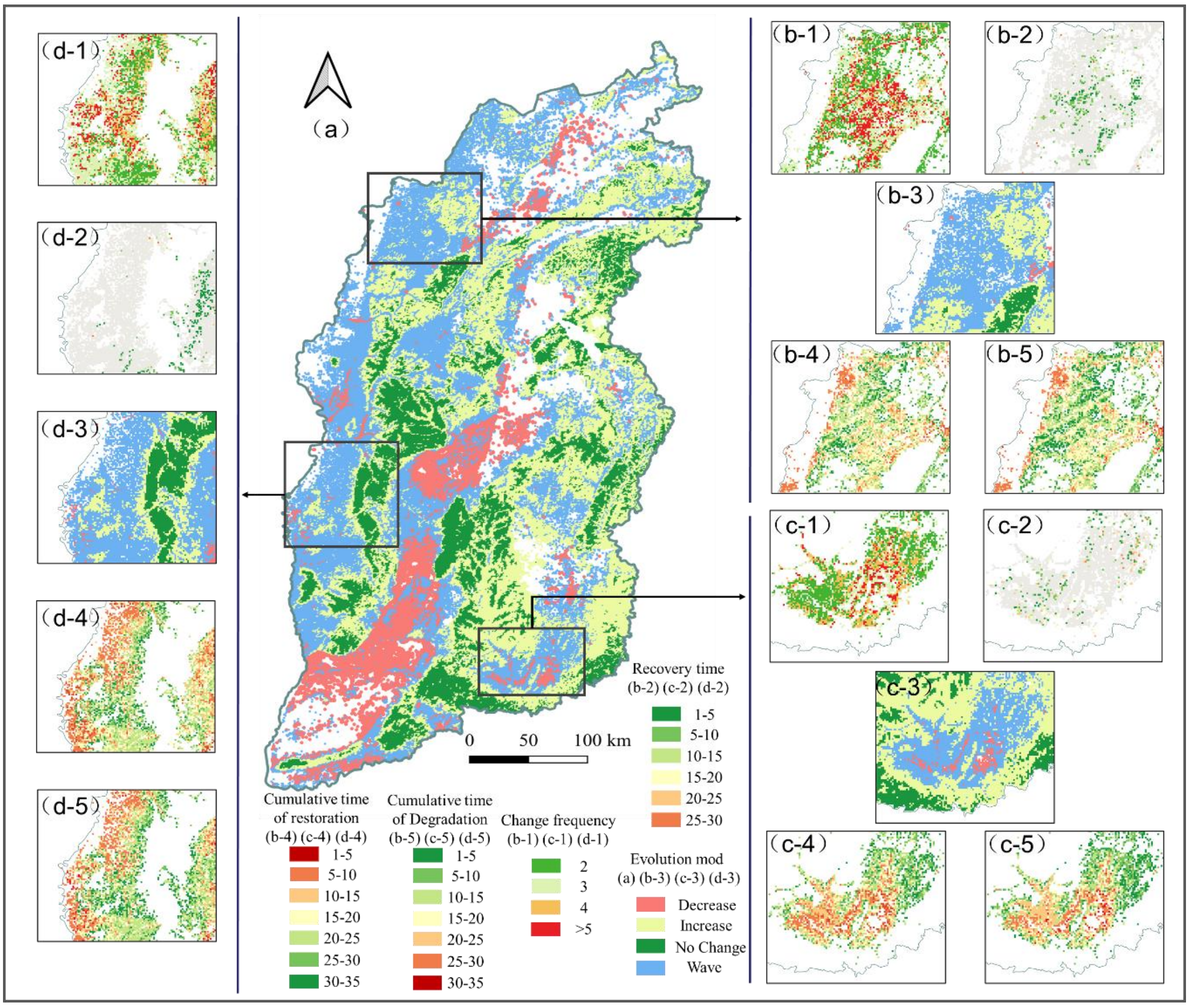

Figure 9. Typical regional forest landscape stability: (**a**) spatial distribution of evolution mode; (**b**) spatial distribution of evolution modes and landscape stability evaluation index for wave mode in Northwest Shanxi; (**c**) spatial distribution of evolution modes and landscape stability evaluation index for wave mode in Northwest Shanxi; (**d**) spatial distribution of evolution modes and landscape stability evaluation index for wave mode in the west of the Luliang Mountains.

Figure 9b shows the spatial distribution of forest landscape stability in Northwest Shanxi. The forest landscape evolution mode in this area is dominated by wave mode. Figure 9b-4,b-5 show that the most severely degraded area is located in the northwest. The degree of degradation in the central and southern is low, and some areas can be restored to a stable state (Figure 9b-2), which shows that ecological restoration has achieved certain results. However, these areas change frequently (Figure 9b-1), and most of the changes are more than five times, suggesting the ecological environment in this area is fragile and land desertification is serious. This shows that the ecological environment in Northwest Shanxi needs continuous attention.

Figure 9c shows the spatial distribution of forest landscape stability in the Jincheng Basin. The distribution of forest landscape evolution patterns in this area presents a ring shape, which indicates that the stability of the forest landscape gradually increases from the center to the edge. Figure 9c-4,c-5 show that the most severely degraded areas are located in the middle of the basin, and these areas have a high frequency of change and cannot return to a stable state (Figure 9c-1,c-2), with poor landscape stability. Although the western of the basin also experiences long-term degradation, the frequency of change is low, and some areas could return to a stable state. The degree of degradation is low in the north of the basin.

Figure 9d shows the spatial distribution of forest landscape stability in the west of the Luliang Mountains. This area is a typical loess hilly area with a fragile ecological environment. The forest landscape evolution mode in this area is dominated by wave mode. Figure 9d-4,d-5 show that the degree of degradation in this area gradually increases from east to west. Most areas have a high frequency of change, and it is difficult to return them to a stable state (Figure 9d-1,d-2). Notably, although there are also areas with severe degradation and a high frequency of change in the east of the Luliang Mountains, these areas were able to return to a stable state. The difference between the east and west sides of Luliang Mountain further illustrates the ecological fragility of the Loess Plateau.

4. Discussion

In this study, a method for assessing landscape stability by characterizing forest landscape change processes based on TICC was proposed. TICC can consider the temporal correlation of landscape changes, which allows us to automatically segment the time series of multiple landscape indices and extract the intermediate change process of the landscape. Detailed information such as start time, features, and durations of different change processes could be automatically derived without the requirement of setting parameters. Four long-term evolution modes were defined—decrease, increase, no change, and wave—based on the distribution of change processes. These four evolution modes can evaluate landscape stability and provide a reference for the formulation of ecological restoration strategies.

Under different ecological processes, forest landscape indices show various distributions and trends [19]. Statistical characteristics and trends of the change process allowed us to analyze the spatiotemporal characteristics of the degradation, restoration, and stable processes of the Shanxi forest landscape. The three forms of the stable process indicated that the stable process mainly occurred in relatively complete forest landscapes that could maintain long-term stability, which was consistent with the research of Li et al. [50]. Various forms of degradation and restoration processes may be related to different driving factors; for example, as shown in Table 5, the fragmentation of cluster 2 increased rapidly, as did the forest area, which may have been caused by the restoration of afforestation projects. Our descriptions of changes in landscape patterns were based on multiple landscape indices and helped to improve our understanding of forest degradation, restoration, and stable processes.

The cumulative time of the three change processes in a landscape unit can clarify the degree of forest degradation and restoration in different regions. It has been shown that altitude is an important factor that affects forest evolution [51]. High altitude hinders forest fragmentation, and forests tend to maintain their own stability. It was found that the areas that can maintain long-term stability are distributed in the interior of the mountainous area. The areas that were seriously degraded were distributed in the main basins of Shanxi. It is worth noting that the hilly loess area to the west of Luliang Mountain was also severely degraded. This area is relatively high in altitude, but it is a typical coal-producing, hilly loess area and underwent more serious degradation.

Wang et al. pointed out the impact of ecological restoration projects on forest landscape patterns [29]. These restoration processes found in this study were related to the Natural Forest Conservation Project and the Grain for Green Project. The start times of the three change processes allowed us to further explore the impact of ecological restoration projects on forest landscapes. The Natural Forest Conservation Project was implemented in 1998, and the Grain for Green Project in 2000. A considerable part of the restoration process started in 2000–2005, and more and more stable landscapes appeared after 2005, which indicates that ecological restoration achieved certain benefits.

Restoration and stable processes have a positive impact on landscape stability, while the degradation process represents a decline in landscape stability. The long-term evolution mode defined by these three ecological processes represents the composite ecological processes and the impact of different ecological processes on landscape stability. This ensures that landscape stability can be analyzed from the perspective of details and holistically, which enables a better understanding of landscape stability. In Shanxi, 57.1% of the forest landscape units were stable, 6.7% were severely unstable, and the proportion of severely degraded landscape units (accumulated degradation time of more than 30 years) in the wave mode was relatively low, which indicated that Shanxi's forest landscape was generally stable but with areas of potential degradation. The restoration process in the wave mode differed from that in the increase mode. The structure and composition of the initial community formed during the post-degradation restoration process are unstable [3], which is why most landscape units in wave mode fail to return to a stable state. There were high-frequency change areas in the wave mode, most of which were distributed in the northern part of Luliang Mountain. These are the intersections of the ecologically fragile area and the sandstorm hazard area in northwest Shanxi [52]. The natural environment is harsh, and vegetation restoration is difficult.

This study proposed a method to evaluate landscape stability by automatically extracting and analyzing the dynamics of forest landscape patterns with high-frequency and complex ecological processes. However, there were limitations in our landscape stability assessment that should be addressed in future studies:

(1) Classification accuracy affected the landscape index calculation in landscape patterns. The results of landscape evolution modes based on this classification could be recognized as long as the annual classification accuracy was accepted since the recognition of landscape stability assessment is based on the change processes that have occurred in the landscape indices from the land cover maps.
(2) A variety of driving factors and their interactions will affect ecological land degradation-restoration [53], and it is necessary to combine driving factors to understand the mechanism of forest landscape evolution. In the future, multiple time series can be constructed that consider different driving factors (such as drought, fire, and deforestation) to determine the relationship between forest landscape dynamics and driving factors.
(3) The landscape change process defined in this study was not universal but based on prior knowledge and actual conditions in the study area. Such criteria may not apply to other land-use types [54–59]. Hence, future research must use deep-learning algorithms to detect change processes more intelligently to extract landscape evolution modes of various land-use types.

5. Conclusions

In this study, a method was proposed to evaluate landscape stability by analyzing the coordinated changes of multiple landscape indices to automatically extract the change processes occurring in the forest landscape. It takes into account the continuity of landscape changes through the TICC algorithm and automatically extracts the intermediate change processes, including degradation, restoration, and stability. Long-term evolution modes defined by these change processes can be used to quantify landscape stability.

The degradation and restoration of forest landscapes in Shanxi had various forms. The restoration process occurred in landscape units with high fragmentation and multiple coverages, and the duration was mainly short-term <10 years), accounting for 40.3%. The degradation process occurred in low-cover landscape units, and the duration was mainly short-term (<10 years), accounting for 50.3%. The stable process occurred in landscape units with high coverage and low fragmentation, and the duration was mainly short-term (<10 years) and long-term (>30 years), accounting for 30.1% and 50.3%, respectively. The time distribution showed that there were fewer degradations and more stable processes over time, which indicated that the forest landscape in Shanxi was tending toward a stable state.

More than half of the stable landscape units (57.6%) were distributed in the interior of the mountains. Severely degraded areas accounted for 6.7% and were mainly distributed in basins. Landscape units with wave modes accounted for 36.2%, most of which cannot return to stability. There also exist frequently changing landscape units, which still require attention.

Author Contributions: Conceptualization, X.L. (Xiangnan Liu) and B.H.; methodology, B.H.; validation, B.H. and Y.M.; writing—original draft preparation, B.H.; writing—review and editing, Y.M. and X.L. (Xiaoyue Li); visualization, B.H. and X.L. (Xiaoyue Li); supervision, X.L. (Xiangnan Liu); project administration, X.L. (Xiangnan Liu); funding acquisition, X.L. (Xiangnan Liu) and C.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Flexible Introduction Team of Ningxia Hui Autonomous Region (Grant No. 2020RXTDLX03); Remote Sensing Monitoring and Evaluation of Ecological Status in Ningxia (Grant No. NXCZ20220203).

Data Availability Statement: Not applicable.

Acknowledgments: The Landsat Level-2 data were downloaded from the Google Earth Engine platform. We thank the broad Google Earth Engine community for their help and comments. We would like to thank the anonymous reviewers and the editor for their constructive.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Kang, W.; Liu, S.; Chen, X.; Feng, K.; Guo, Z.; Wang, T. Evaluation of ecosystem stability against climate changes via satellite data in the eastern sandy area of northern China. *J. Environ. Manag.* **2022**, *308*, 114596. [CrossRef]
2. Sun, J.; Li, G.; Zhang, Y.; Qin, W.; Wang, M. Identification of priority areas for afforestation in the Loess Plateau region of China. *Ecol. Indic.* **2022**, *140*, 108998. [CrossRef]
3. Cao, S.; Chen, L.; Yu, X. Impact of China's Grain for Green Project on the landscape of vulnerable arid and semi-arid agricultural regions: A case study in northern Shaanxi Province. *J. Appl. Ecol.* **2009**, *46*, 536–543. [CrossRef]
4. Chen, Y.; Wang, K.; Lin, Y.; Shi, W.; Song, Y.; He, X. Balancing green and grain trade. *Nat. Geosci.* **2015**, *8*, 739–741. [CrossRef]
5. Xu, X.; Zhang, D. Evaluating the effect of ecological policies from the pattern change of persistent green patches–A case study of Yan'an in China's Loess Plateau. *Ecol. Inform.* **2021**, *63*, 101305. [CrossRef]
6. Cao, S.; Chen, L.; Shankman, D.; Wang, C.; Wang, X.; Zhang, H. Excessive reliance on afforestation in China's arid and semi-arid regions: Lessons in ecological restoration. *Earth-Science Rev.* **2011**, *104*, 240–245. [CrossRef]
7. Turner, M.G.; Romme, W.H.; Gardner, R.H.; O'Neill, R.V.; Kratz, T.K. A revised concept of landscape equilibrium: Disturbance and stability on scaled landscapes. *Landsc. Ecol.* **1993**, *8*, 213–227. [CrossRef]
8. Amrutha, K.; Danumah, J.H.; Nikhil, S.; Saha, S.; Rajaneesh, A.; Mammen, P.C.; Ajin, R.S.; Kuriakose, S.L. Demarcation of Forest Fire Risk Zones in Silent Valley National Park and the Effectiveness of Forest Management Regime. *J. Geovisualization Spat. Anal.* **2022**, *6*, 8. [CrossRef]
9. Raji, S.A.; Odunuga, S.; Fasona, M. Spatially Explicit Scenario Analysis of Habitat Quality in a Tropical Semi-arid Zone: Case Study of the Sokoto–Rima Basin. *J. Geovisualization Spat. Anal.* **2022**, *6*, 11. [CrossRef]
10. Wu, J. Landscape sustainability science: Ecosystem services and human well-being in changing landscapes. *Landsc. Ecol.* **2013**, *28*, 999–1023. [CrossRef]
11. Bai, B.; Tan, Y.; Guo, D.; Xu, B. Dynamic Monitoring of Forest Land in Fuling District Based on Multi-Source Time Series Remote Sensing Images. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 36. [CrossRef]
12. Harris, A.; Carr, A.; Dash, J. Remote sensing of vegetation cover dynamics and resilience across southern Africa. *Int. J. Appl. Earth Obs. Geoinf.* **2013**, *28*, 131–139. [CrossRef]
13. Liu, M.; Liu, X.; Wu, L.; Tang, Y.; Li, Y.; Zhang, Y.; Ye, L.; Zhang, B. Establishing forest resilience indicators in the hilly red soil region of southern China from vegetation greenness and landscape metrics using dense Landsat time series. *Ecol. Indic.* **2020**, *121*, 106985. [CrossRef]
14. Duveneck, M.J.; Scheller, R.M. Measuring and managing resistance and resilience under climate change in northern Great Lake forests (USA). *Landsc. Ecol.* **2015**, *31*, 669–686. [CrossRef]

15. Ma, J.; Zhang, C.; Guo, H.; Chen, W.; Yun, W.; Gao, L.; Wang, H. Analyzing Ecological Vulnerability and Vegetation Phenology Response Using NDVI Time Series Data and the BFAST Algorithm. *Remote. Sens.* **2020**, *12*, 3371. [CrossRef]
16. von Keyserlingk, J.; de Hoop, M.; Mayor, A.; Dekker, S.; Rietkerk, M.; Foerster, S. Resilience of vegetation to drought: Studying the effect of grazing in a Mediterranean rangeland using satellite time series. *Remote. Sens. Environ.* **2021**, *255*, 112270. [CrossRef]
17. Xu, W.; Wang, J.; Zhang, M.; Li, S. Construction of landscape ecological network based on landscape ecological risk assessment in a large-scale opencast coal mine area. *J. Clean. Prod.* **2020**, *286*, 125523. [CrossRef]
18. Hu, W.; Wang, G. Advances in Research of Landscape Patterns and Ecological Processes of Wetland. *Prog. Geogr.* **2007**, *22*, 969–975.
19. Hermosilla, T.; Wulder, M.; White, J.; Coops, N.C.; Pickell, P.D.; Bolton, D.K. Impact of time on interpretations of forest fragmentation: Three-decades of fragmentation dynamics over Canada. *Remote. Sens. Environ.* **2018**, *222*, 65–77. [CrossRef]
20. Zhang, J.; Yang, X.; Wang, Z.; Zhang, T.; Liu, X. Remote Sensing Based Spatial-Temporal Monitoring of the Changes in Coastline Mangrove Forests in China over the Last 40 Years. *Remote. Sens.* **2021**, *13*, 1986. [CrossRef]
21. Kennedy, R.E.; Yang, Z.; Cohen, W.B. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr—Temporal segmentation algorithms. *Remote Sens. Environ.* **2010**, *114*, 2897–2910. [CrossRef]
22. Huang, C.; Goward, S.N.; Masek, J.G.; Thomas, N.; Zhu, Z.; Vogelmann, J.E. An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks. *Remote Sens. Environ.* **2010**, *114*, 183–198. [CrossRef]
23. Lhermitte, S.; Verbesselt, J.; Verstraeten, W.; Coppin, P. A comparison of time series similarity measures for classification and change detection of ecosystem dynamics. *Remote. Sens. Environ.* **2011**, *115*, 3129–3152. [CrossRef]
24. Verbesselt, J.; Hyndman, R.; Newnham, G.; Culvenor, D. Detecting trend and seasonal changes in satellite image time series. *Remote Sens. Environ.* **2010**, *114*, 106–115. [CrossRef]
25. Prokopová, M.; Salvati, L.; Egidi, G.; Cudlín, O.; Včeláková, R.; Plch, R.; Cudlín, P. Envisioning Present and Future Land-Use Change under Varying Ecological Regimes and Their Influence on Landscape Stability. *Sustainability* **2019**, *11*, 4654. [CrossRef]
26. Lele, N.; Nagendra, H.; Southworth, J. Accessibility, Demography and Protection: Drivers of Forest Stability and Change at Multiple Scales in the Cauvery Basin, India. *Remote. Sens.* **2010**, *2*, 306–332. [CrossRef]
27. Zhang, X.; Wang, G.; Xue, B.; Zhang, M.; Tan, Z. Dynamic landscapes and the driving forces in the Yellow River Delta wetland region in the past four decades. *Sci. Total. Environ.* **2021**, *787*, 147644. [CrossRef] [PubMed]
28. Jaeger, J.A.G. Landscape division, splitting index, and effective mesh size: New measures of landscape fragmentation. *Landsc. Ecol.* **2000**, *15*, 115–130. [CrossRef]
29. Wang, Y.; Brandt, M.; Zhao, M.; Xing, K.; Wang, L.; Tong, X.; Xue, F.; Kang, M.; Jiang, Y.; Fensholt, R. Do afforestation projects increase core forests? Evidence from the Chinese Loess Plateau. *Ecol. Indic.* **2020**, *117*, 106558. [CrossRef]
30. Zhang, Y.; Liu, X.; Yang, Q.; Liu, Z.; Li, Y. Extracting Frequent Sequential Patterns of Forest Landscape Dynamics in Fenhe River Basin, Northern China, from Landsat Time Series to Evaluate Landscape Stability. *Remote. Sens.* **2021**, *13*, 3963. [CrossRef]
31. Chazdon, R.L.; Brancalion, P.H.S.; Laestadius, L.; Bennett-Curry, A.; Buckingham, K.; Kumar, C.; Moll-Rocek, J.; Vieira, I.C.G.; Wilson, S.J. When is a forest a forest? Forest concepts and definitions in the era of forest and landscape restoration. *AMBIO* **2016**, *45*, 538–550. [CrossRef] [PubMed]
32. Qiu, B.; Chen, G.; Tang, Z.; Lu, D.; Wang, Z.; Chen, C. Assessing the Three-North Shelter Forest Program in China by a novel framework for characterizing vegetation changes. *ISPRS J. Photogramm. Remote Sens.* **2017**, *133*, 75–88. [CrossRef]
33. Liu, S.; Gong, P. Change of surface cover greenness in China between 2000 and 2010. *Chin. Sci. Bull.* **2012**, *57*, 2835–2845. [CrossRef]
34. Li, Y.; Cao, Z.; Long, H.; Liu, Y.; Li, W. Dynamic analysis of ecological environment combined with land cover and NDVI changes and implications for sustainable urban–rural development: The case of Mu Us Sandy Land, China. *J. Clean. Prod.* **2017**, *142*, 697–715. [CrossRef]
35. Forzieri, G.; Dakos, V.; McDowell, N.G.; Ramdane, A.; Cescatti, A. Emerging signals of declining forest resilience under climate change. *Nature* **2022**, *608*, 534–539. [CrossRef]
36. Jian, M.; Wang, J.; Yu, H.; Wang, G.-G. Integrating object proposal with attention networks for video saliency detection. *Inf. Sci.* **2021**, *576*, 819–830. [CrossRef]
37. Hallac, D.; Vare, S.; Boyd, S.; Leskovec, J. Toeplitz Inverse Covariance-Based Clustering of Multivariate Time Series Data. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Halifax, NS, Canada, 13–17 August 2017; pp. 215–223.
38. Miao, Z.; Marrs, R. Ecological restoration and land reclamation in open-cast mines in Shanxi Province, China. *J. Environ. Manag.* **2000**, *59*, 205–215. [CrossRef]
39. Yan, D.; Bai, Z.; Liu, X. Heavy-Metal Pollution Characteristics and Influencing Factors in Agricultural Soils: Evidence from Shuozhou City, Shanxi Province, China. *Sustainability* **2020**, *12*, 1907. [CrossRef]
40. Gu, L.; Gong, Z.; Du, Y. Evolution characteristics and simulation prediction of forest and grass landscape fragmentation based on the "Grain for Green" projects on the Loess Plateau, P.R. China. *Ecol. Indic.* **2021**, *131*, 108240. [CrossRef]
41. Li, S.; Liang, W.; Fu, B.; Lü, Y.; Fu, S.; Wang, S.; Su, H. Vegetation changes in recent large-scale ecological restoration projects and subsequent impact on water resources in China's Loess Plateau. *Sci. Total. Environ.* **2016**, *569–570*, 1032–1039. [CrossRef]
42. Feng, R.; Wang, F.; Wang, K. Spatial-temporal patterns and influencing factors of ecological land degradation-restoration in Guangdong-Hong Kong-Macao Greater Bay Area. *Sci. Total. Environ.* **2021**, *794*, 148671. [CrossRef] [PubMed]

43. Wulder, M.A.; White, J.C.; Han, T.; Coops, N.C.; Cardille, J.A.; Holland, T.; Grills, D. Monitoring Canada's forests. Part 2: National forest fragmentation and pattern. *Can. J. Remote. Sens.* **2008**, *34*, 563–584. [CrossRef]
44. Zhao, Y.; He, C.; Zhang, Q. Monitoring vegetation dynamics by coupling linear trend analysis with change vector analysis: A case study in the Xilingol steppe in northern China. *Int. J. Remote. Sens.* **2011**, *33*, 287–308. [CrossRef]
45. Li, F.; Cheng, C.; Yang, R. A review of ecosystem restoration: Progress and prospects of domestic and abroad. *Biodivers. Sci.* **2022**, *30*, 22519. [CrossRef]
46. Zhou, G.; Liu, S.; Li, Z.; Zhang, D.; Tang, X.; Zhou, C.; Yan, J.; Mo, J. Old-Growth Forests Can Accumulate Carbon in Soils. *Science* **2006**, *314*, 1417. [CrossRef] [PubMed]
47. Barlow, J.; Gardner, T.A.; Araujo, I.S.; Ávila-Pires, T.C.; Bonaldo, A.B.; Costa, J.E.; Esposito, M.C.; Ferreira, L.V.; Hawes, J.; Hernandez, M.I.M.; et al. Quantifying the biodiversity value of tropical primary, secondary, and plantation forests. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 18555–18560. [CrossRef] [PubMed]
48. Wingfield, M.J.; Brockerhoff, E.G.; Wingfield, B.D.; Slippers, B. Planted forest health: The need for a global strategy. *Science* **2015**, *349*, 832–836. [CrossRef]
49. McGarigal, K.; McComb, W.C. Relationships Between Landscape Structure and Breeding Birds in the Oregon Coast Range. *Ecol. Monogr.* **1995**, *65*, 235–260. [CrossRef]
50. Li, Y.; Liu, M.; Liu, X.; Yang, W.; Wang, W. Characterising three decades of evolution of forest spatial pattern in a major coal-energy province in northern China using annual Landsat time series. *Int. J. Appl. Earth Obs. Geoinf.* **2020**, *95*, 102254. [CrossRef]
51. Oikonomakis, N.; Ganatsas, P. Land cover changes and forest succession trends in a site of Natura 2000 network (Elatia forest), in northern Greece. *For. Ecol. Manag.* **2012**, *285*, 153–163. [CrossRef]
52. Zhao, Y. Research of Regionalism by Ecological Fragility Based on Condition of Soil Erosion in Shanxi Province. *J. Soil. Water Conserv.* **2003**, *17*, 71–74. [CrossRef]
53. Sun, B.; Li, Z.; Gao, W.; Zhang, Y.; Gao, Z.; Song, Z.; Qin, P.; Tian, X. Identification and assessment of the factors driving vegetation degradation/regeneration in drylands using synthetic high spatiotemporal remote sensing Data—A case study in Zhenglanqi, Inner Mongolia, China. *Ecol. Indic.* **2019**, *107*, 105614. [CrossRef]
54. Tian, L.; Liu, X.; Liu, M.; Wu, L. State-and-Evolution Detection Models: A Framework for Continuously Monitoring Landscape Pattern Change. *IEEE Trans. Geosci. Remote. Sens.* **2021**, *60*, 1–14. [CrossRef]
55. Coops, N.C.; Gillanders, S.N.; Wulder, M.A.; Gergel, S.E.; Nelson, T.; Goodwin, N.R. Assessing changes in forest fragmentation following infestation using time series Landsat imagery. *For. Ecol. Manag.* **2010**, *259*, 2355–2365. [CrossRef]
56. Cui, H.; Liu, M.; Chen, C. Ecological Restoration Strategies for the Topography of Loess Plateau Based on Adaptive Ecological Sensitivity Evaluation: A Case Study in Lanzhou, China. *Sustainability* **2022**, *14*, 2858. [CrossRef]
57. Chen, L.; Sun, R.; Lu, Y. A conceptual model for a process-oriented landscape pattern analysis. *Sci. China Earth Sci.* **2019**, *62*, 2050–2057. [CrossRef]
58. Chowdhury, S.; Peddle, D.R.; Wulder, M.A.; Heckbert, S.; Shipman, T.C.; Chao, D.K. Estimation of land-use/land-cover changes associated with energy footprints and other disturbance agents in the Upper Peace Region of Alberta Canada from 1985 to 2015 using Landsat data. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *94*, 102224. [CrossRef]
59. Cardille, J.; Turner, M.; Clayton, M.; Gergel, S.; Price, S. METALAND: Characterizing Spatial Patterns and Statistical Context of Landscape Metrics. *Bioscience* **2005**, *55*, 983–988. [CrossRef]