ПРОБЛЕМЫ ЭКОЛОГИИ И РАЦИОНАЛЬНОГО ПРИРОДОПОЛЬЗОВАНИЯ. БИОТЕХНОЛОГИИ
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Assessing the Ecological Health of Hexi Corridor's Forest Ecosystem Using RSEI Time Series

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Abstract. ***Introduction.*** This study provides an in-depth analysis of the forest Remote Sensing Ecological Index (RSEI) time series data in the Hexi Corridor area from 2000 to 2023, employing nonlinear curve fitting to uncover the changing trends and characteristics of the region's forest ecosystems. *Research Aim.* Harnessing the characteristics of nonlinear curves, specific transformative periods and points within the series are identified, facilitating refined predictions for forest ecological trends. By combining the generalized additive model (GAM) to extract the different impact relationships between altitude and RSEI in different forest ecological regions, and the IncMSE analysis of the random forest model, the differences between altitude and forest type on forest ecosystems in different forest ecological regions were found Influence. *Result.* Forests at higher altitudes exhibit greater ecological stability and elevated RSEI values, suggesting improved environmental quality. Natural forests, characterized by their rich biodiversity and complex structures, consistently display the highest RSEI values across various ecological zones, highlighting their pivotal role in maintaining ecological balance and delivering ecosystem services. In contrast, artificial forests, primarily situated at lower altitudes and often near human activities, show linear and stable temporal patterns with lower RSEI values. *Conclusion.* Significant temporal fluctuations of RSEI were identified, particularly in the years 2002, 2010, and 2017, with a noticeable trend of decreasing fluctuation periods over time, likely reflecting the impact of recent forest conservation and restoration efforts. This study uniquely combines curve analysis with ecological indices to provide a comprehensive framework for understanding and predicting changes in forest ecosystems, offering crucial insights for future conservation and management strategies, especially in the Hexi Corridor.

Keywords: Forest ecosystem; RSEI; Generalized Additive Model (GAM); Random Forest; IncMSE Analysis; Temporal Analysis; Hexi Corridor

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Introduction

Forest ecosystems, as one of the most important biological communities on Earth, play an irreplaceable role in maintaining biodiversity, regulating the climate, and the carbon cycle [1]. With the intensification of global changes, forest ecosystems are facing unprecedented threats, such as forest degradation [2], forest fire disturbances [3], and loss of biodiversity [4], all of which urgently require in-depth research and effective monitoring by the scientific community. The Hexi Corridor is located in northwest China and is a typical ecologically fragile arid and semi-arid region [5]. Due to its special geographical and climatic conditions, it is crucial to the forest ecosystem of the Hexi Corridor. Remote sensing technology, especially the acquisition and analysis of multi-temporal remote sensing data, offers a unique and effective means to monitor forest cover changes on a global and regional scale. By analysing the time series of remote sensing data, tracking, and assessing the long-term trends in forest ecosystems [6], it is crucial for understanding the characteristics of changes in forest ecosystems and formulating forest management strategies.

The advancement of remote sensing technology has facilitated the development and application of various remote sensing ecological indices, such as the Normalized Difference Vegetation Index (NDVI) [7], the Enhanced Vegetation Index (EVI) [8], and the Remote Sensing Ecological Index (RSEI) used in this study [9]. These indices provide powerful tools for assessing the health status and ecological functions of forests and vegetation. They offer a quantitative means to evaluate and understand the dynamic changes in forest ecosystems by integrating the photosynthetic capacity and biomass level of vegetation.

As time series analysis methods become widely applied in ecological research, time series fitting techniques have become crucial for understanding forest and vegetation dynamics. Linear regression methods used for time series trend analysis can reveal inter-annual changes in forest cover [10], while incorporating seasonal changes through methods like LandTrendr [11] and BFAST [12] can identify short-term disturbances within these trends. Nonlinear fitting methods using polynomial fits [13] offer a more accurate description and analysis of nonlinear changes in vegetation time series data, revealing deeper mechanisms of vegetation changes and the impact of environmental factors [14].

Despite the extensive application of linear and polynomial regression methods in remote sensing time series analysis of forests, these approaches often show limitations when dealing with the complexity of ecological data. Linear models may not adequately capture the complex nonlinear relationships between environmental factors and forest ecosystems [15], and although polynomial models provide some capacity for nonlinear processing, they can be overly simplistic when dealing with high-dimensional interactions [16]. In contrast, Generalized Additive Models (GAM) [17] not only allow each predictor to maintain different nonlinear relationships [18] but also adapt flexibly to data structures through smoothing functions, making them particularly suitable for analyzing complex dynamics in environmental and ecological variables within time series [19]. Furthermore, GAMs can effectively test the impact of each smoothing term to ensure the model is both flexible and avoids overfitting [18]. Meanwhile, the Random Forest model, by constructing multiple decision trees and outputting variable importance scores through Incremental Mean Square Error (IncMSE) analysis [20], provides a powerful tool for identifying and verifying which environmental factors significantly impact forest health [21]. Compared to a single decision tree model, Random Forests enhance prediction accuracy and generalization capabilities due to their ensemble learning nature [22].

The aim of this research was to explore the temporal changes in the forest ecosystems of the Hexi Corridor from 2000 to 2023, using remote sensing data time series analysis with RSEI as a key indicator of forest ecological health. Curve fitting divides the RSEI time series transformation curve into three linear models and six curve models, and identifies the time points of abrupt changes in the forest ecosystem based on the curve models. Combining elevation and forest type, Generalized Additive Models are used to study the relationship between elevation and different forest ecological regions, while Random Forest models employ Incremental Mean Square Error (IncMSE) analysis to assess the impact of elevation and forest type on forest RSEI across different ecological regions.

Research area

The Hexi Corridor is located in the northwest part of Gansu Province, China, with geographic coordinates ranging from 101°08′E to 103°50′E and 36°45′N to 39°27′N. This region covers an area of approximately 78,000 km^2 and serves as an important passage connecting the Chinese mainland with its northwest frontier, as well as being one of the core sections of the ancient Silk Road [23]. Situated at the southern edge of the Qilian Mountain range, the terrain of the Hexi Corridor gradually descends from south to north, creating a unique topography and ecosystem (Fig. 1). Climatically, the Hexi Corridor features a typical temperate continental arid climate, characterized by dryness, scarce precipitation, and abundant sunshine [24]. The annual average temperature is about 7,7 °C, while the annual precipitation varies depending on the location, generally showing a decreasing trend from east to west and from south to north, with annual average precipitation ranging from 50 to 400 millimeters. A significant seasonal precipitation pattern is observed, with about 90 % of the rainfall concentrated between May and October. In terms of forest resources, the forest coverage rate in the Hexi Corridor is relatively low, mainly concentrated in the mountainous areas and oasis regions near rivers. The Qilian Mountains are the main forest distribution area in this region, where the forests are primarily composed of Qinghai spruce (*Picea crassifolia*), Sea-buckthorn (*Hippophae rhamnoides*), forming a unique alpine forest ecosystem [25].

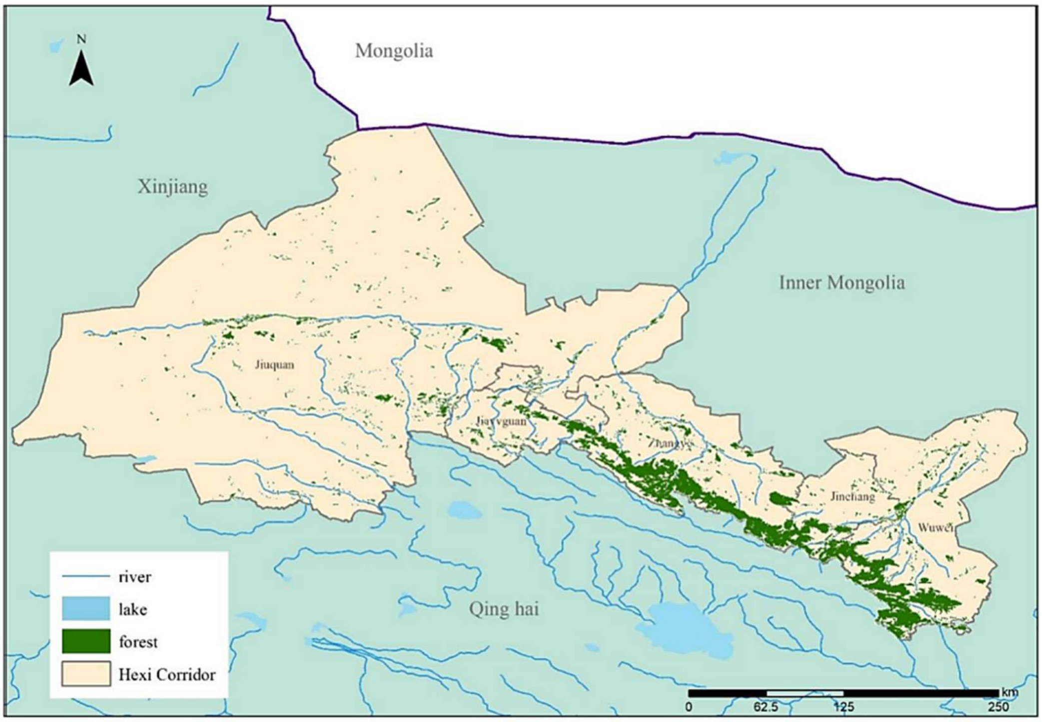

Fig. 1. Location of forest areas in Hexi Corridor
Рис. 1. Расположение лесных массивов в коридоре Хэси

Data and methods

In this study, we examine the changes in forest ecosystems within the Hexi Corridor area by utilizing the RSEI [26] time series from 2000 to 2023. The remote sensing imagery employed in our analysis is sourced from the Google Earth Engine (GEE) platform, which offers Landsat imagery provided by the United States Geological Survey (USGS). The imagery covers Landsat 5 from 2000 to 2011, Landsat 7 for 2012, and Landsat 8 from 2013 to 2023. The choice of the June to October period for image acquisition is based on the alignment with the peak growth of forest vegetation, ensuring the best possible representation of vegetation health. Over 24 years, a total of 5064 images were acquired, averaging 211 images per year.

Prior to analysis, extensive preprocessing of the imagery was performed on the GEE platform [27]. This involved the removal of cloud cover and the masking of water bodies, snow, glaciers, and barren lands to ensure the dataset's continuity and reliability. The RSEI for forested areas was computed annually using the Landsat images, and linear interpolation was applied to fill in any missing values within the RSEI time series on a per-pixel basis. The RSEI calculation [28] incorporates the following components:

$$RSEI = f(Greenneess, Wetness, Dryness, Heat). \quad (1)$$

Greenness: Represented by the Normalised Difference Vegetation Index (NDVI); Wetness: Derived from the moisture component in the tasseled cap transformation; Dryness: Gauged by the Normalised Difference Impervious Surface Index (NDISI), which incorporates both the Index-based Built-up Index (IBI) and the soil index (SI); Heat: Indicated by the land surface temperature (LST).

The analysis posits that external events impacting forests during the study period can trigger rapid ecological shifts, manifested as either improvements or deteriorations, which then stabilize after initial fluctuations, as argued by Falk et al. [29]. This research enhances traditional linear trend analysis by incorporating three additional time-series curve fitting models based on the S-curve archetype: exponential, logarithmic, and logistic. These models characterize states of initial stability followed by change (exponential), change followed by stability (logarithmic), and a return to stability after change (logistic), thereby capturing key ecological transition points with nuance. Fig. 2 presents the comprehensive steps of the research flowchart.

Furthermore, the analysis categorizes the overall direction of RSEI changes – increasing or decreasing – based on the slope of the time series, with a threshold of 0,05 set to define a linearly stable state. This methodology delineates nine distinct time-series fitting models: linear decreasing, linear increasing, linear stable, exponential increasing, exponential decreasing, logarithmic decreasing, logarithmic increasing, logistic decreasing, and logistic increasing (Fig. 3). Through this sophisticated modeling approach, the study meticulously simulates the temporal dynamics of forest ecosystems, providing a refined understanding of ecological trends over the observed period.

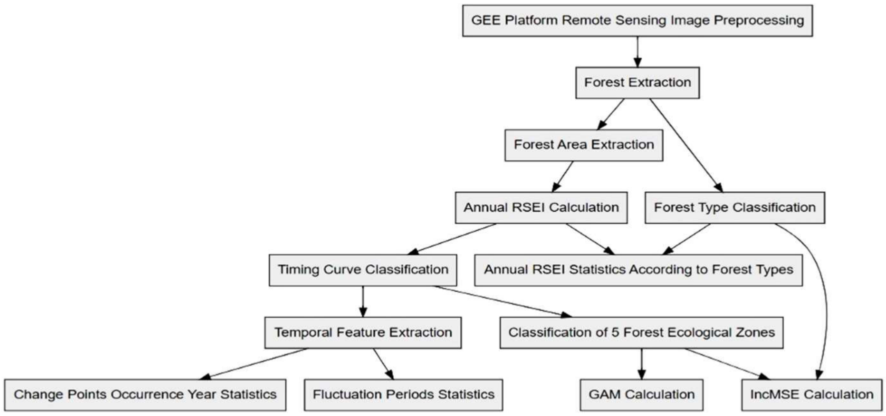

Fig. 2. Experimental flow chart
Рис. 2. Схема эксперимента

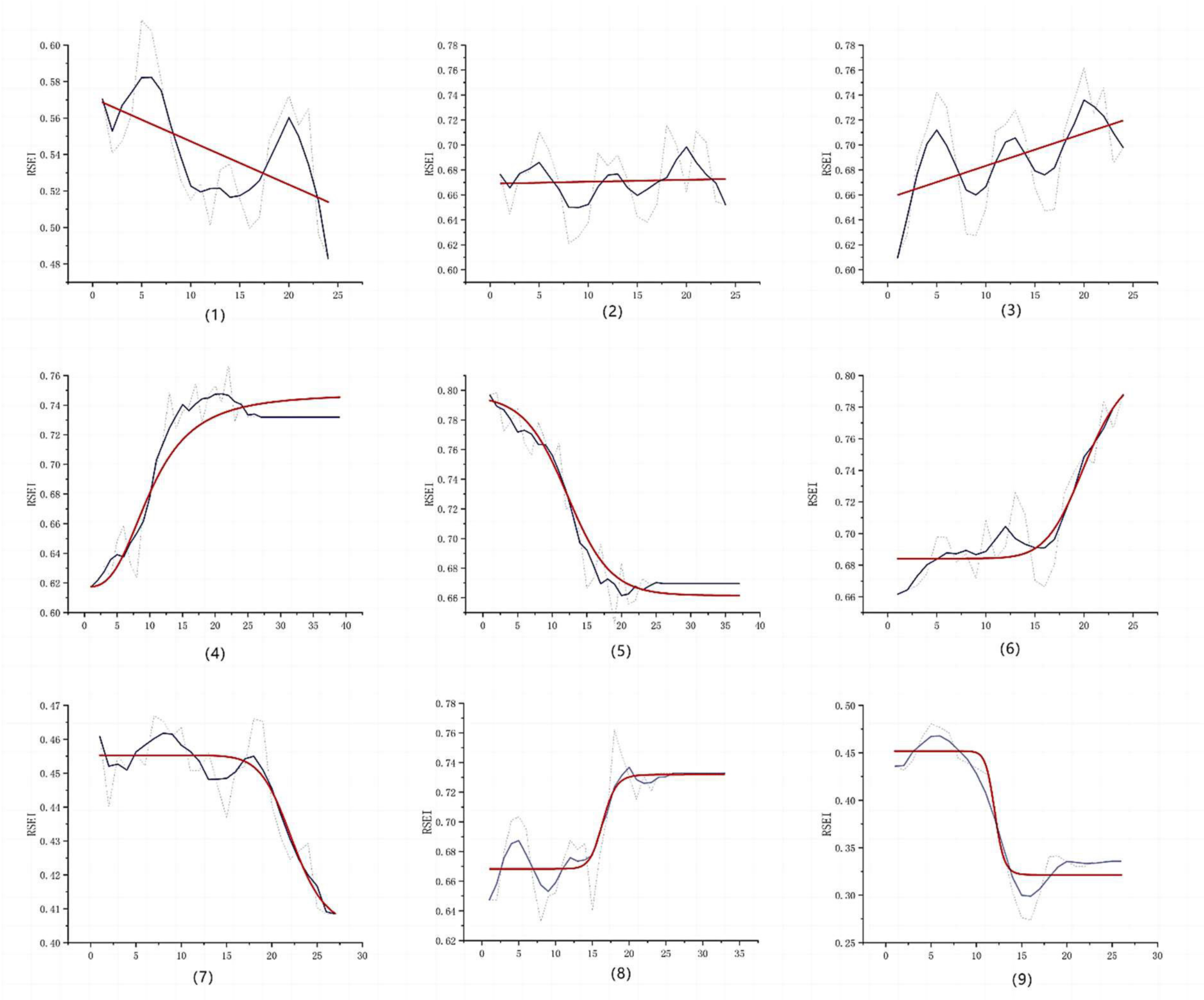

Fig. 3. Timing curves: (1) linear decreasing; (2) linear stable; (3) linear increasing; (4) logarithmic increasing; (5) logarithmic decreasing; (6) exponential increasing; (7) exponential decreasing; (8) logistic increasing; (9) logistic decreasing

Рис. 3. Кривые: (1) линейного снижения; (2) линейной стабильности; (3) линейного роста; (4) логарифмического роста; (5) логарифмического снижения; (6) экспоненциального роста; (7) экспоненциального снижения; (8) логистического роста;(9) логистического снижения

In this study, we utilized two sophisticated approaches, the Generalized Additive Models (GAM) [30] and Random Forest (RF) [31], to investigate the dynamics of the RSEI and its interaction with environmental factors. The application of these two models aims to analyze and predict changes in RSEI from different perspectives and identify key environmental factors driving these changes.

Generalized Additive Models (GAM) are flexible statistical models with considerable degrees of freedom, suitable for studying the nonlinear regression effects of data. They represent a form of non-parametric smoothing regression within the framework of multivariate regression models. In GAM, it is assumed that the dependent variable Y follows a normal distribution, and the relationship between the independent variables X and the dependent variable Y's conditional mean can be succinctly expressed as follows [32]:

$$E(Y \mid X) = \alpha + f_1(X_1) + f_2(X_2) + \\ + \ldots + f_p(X_p) + \varepsilon, \quad (2)$$

here, $E(Y \mid X)$ denotes the expected value of Y given the set of independent variables X, α is the intercept, and $f_1, f_2, \ldots, f_p$ are smooth functions of the independent variables $X_1, X_2, \ldots, X_p$, respectively, and ε is an error term.

Firstly, the introduction of GAM leverages its flexibility as a regression model to explore the nonlinear relationships between the RSEI and altitude. GAM models the relationship between response variables and explanatory variables through nonlinear smoothing functions, effectively capturing and revealing the complex nonlinear dynamics between variables. Within the framework of this study, to explore and elucidate the complex nonlinear relationships between the Forest RSEI and environmental factors, GAM was chosen as a key analytical tool. Evolving from GLM, GAM introduces nonlinear smoothing functions [33], enabling the model to flexibly capture and reveal the dynamic nonlinear relationships between response and explanatory variables.

In order to further analyze and predict changes in the Forest RSEI and its response to environmental factors, we employed the RF model, particularly utilizing Incremental Mean Squared Error (IncMSE) [34] analysis to evaluate the importance of key environmental factors influencing RSEI changes. IncMSE analysis is a method to assess the importance of feature variables in Random Forest models, based on the core assumption that if a feature significantly contributes to the model's predictive ability, randomly altering the values of that feature in the dataset will significantly increase the model's prediction error [35]. Therefore, IncMSE analysis evaluates the impact of randomly shuffling each environmental factor's values on the model's predictive performance, thereby determining the most influential environmental factors on RSEI.

IncMSE analysis begins by calculating the model's prediction error (Mean Squared Error) on the original data, then performs the following steps for each feature: selects a feature and randomly shuffles its values across all samples in the dataset, keeping the values of other features constant. The model's prediction error is recalculated on this new dataset with the shuffled feature values [36]. The prediction error after shuffling the feature values is compared to the original prediction error, and the error increment, IncMSE, is calculated. A higher IncMSE [20] for a feature indicates a greater contribution to the model's predictive ability, thus considered more important.

Through the combined use of GAM and RF models, this study comprehensively explores the relationship between RSEI and environmental factors, deepening the understanding of changes in forest ecosystems. We classified linearly stable time series as the RSEI stable zone, logarithmic increasing and logistic increasing as the high RSEI stable zone, logarithmic decreasing and logistic decreasing as the low RSEI stable zone, linearly decreasing as the RSEI decreasing zone, and exponential increasing and linearly increasing as the RSEI increasing zone. We employed the GAM to explore the impact of altitude on annual mean RSEI, aiming to reveal the complex relationship between altitude and RSEI within different ecological zones. By introducing altitude as a key explanatory variable and the annual mean RSEI as the response variable, we constructed models for five ecological zones. The model uses a Gaussian link function to accommodate the continuous nature of RSEI and fully capture its nonlinear relationship with altitude. GAM reveals the nonlinear relationships and key turning points between environmental factors and RSEI, while the RF model and IncMSE analysis pinpoint which environmental factors are most crucial to RSEI changes, providing a scientific basis for forest ecology protection and management. This integrated methodology not only enhances insights into the forest ecosystem's response to environmental changes but also offers practical tools for devising effective conservation strategies and management measures.

Results

In this study, we first extracted forest areas in the Hexi Corridor region and classified them as natural forests, shrublands, mixed forests, and plantations according to their forest types. To assess the ecological health and dynamics of these forests over time, we computed the annual RSEI for each forest area from the year 2000 through to 2023. Each year's PCI value was greater than 80, ensuring the reliability of the annual RSEI values. Our findings, as depicted in Figure 3, indicate that the average annual RSEI values were initially high, exhibiting relatively stable fluctuations with a discernible upward trend. Notably, the RSEI reached its peak in the year 2019, suggesting a period of enhanced ecological conditions within the forest ecosystems of the Hexi Corridor.

Based on the pre-established time-series assessment model employed in the experiment, the RSEI time series for each pixel was analyzed, resulting in eight distinct temporal patterns: exponential growth, linear decline, linear growth, linear stability, logarithmic decline, logarithmic growth, logistic decline, and logistic growth (see Fig. 4). Contrary to anticipated outcomes, no instances of exponential decrease were identified, suggesting that there are no areas within the study region where the forest RSEI has transitioned from a stable state to a continuous downward trajectory. The observed patterns of growth, in particular, exhibited a more nuanced classification than a simple linear trend, with areas of both growth, and decline showing a variety of complex temporal dynamics.

For different time-series curves under forest types: exponential increasing, linear decreasing, linear increasing, linear stable, logarithmic decreasing, logarithmic increasing, logistic decreasing, and logistic increasing. These further classified into 4 forest types – natural forest, shrubland, mixed forest, and plantation forest. For each category, we compute the area, average RSEI, and mean elevation in Table. Except for planted forests, the majority of forests were in a linearly stable state, with areas of RSEI growth exceeding those of RSEI decline. Combined with Fig. 5 we can see the average annual RSEI values for different curves showed significant differences in altitude, and there were also distinct differences between the average annual RSEI and altitude among different forest types under the same curve.

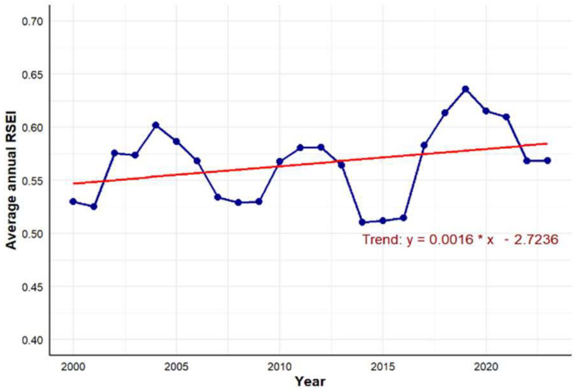

Fig. 4. Average annual RSEI statistics from 2000 to 2023
Рис. 4. Статистика среднегодовых значений индекса RSEI с 2000 по 2023 гг.

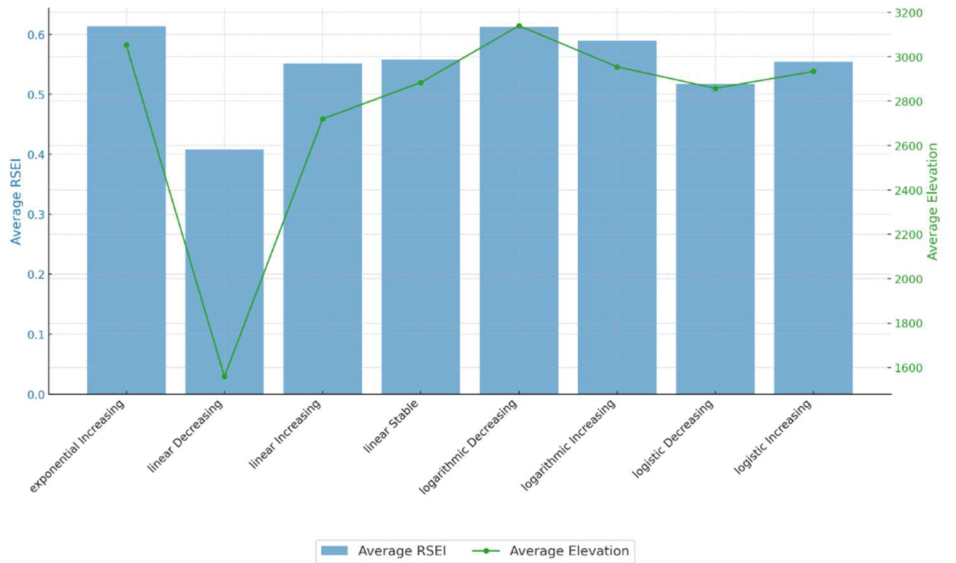

Fig. 5. Average RSEI and average altitude under different curve areas
Рис. 5. Средние значения индекса RSEI и средние значения высоты над уровнем моря под разными участками кривой

Timing curves according to the forest types
Кривые в соответствии с типом леса

Timing Curve	Forest type	Area, km^2	RSEI	Elevation (meter)
Exponential Increasing	Natural Forest	269	0,6399	3039
	Shrubland	571	0,6195	3160
	Mixed Forest	350	0,5898	2940
	Plantation Forest	13	0,4052	1809
Linear Decreasing	Natural Forest	0,21	0,3695	1567
	Shrubland	0,62	0,3653	2709
	Mixed Forest	10	0,4103	1487
	Plantation Forest	0,62	0,4203	1537
Linear Increasing	Natural Forest	13	0,6221	3093
	Shrubland	50	0,5141	2498
	Mixed Forest	44	0,5759	2894
	Plantation Forest	1,24	0,3784	1540
Linear Stable	Natural Forest	1556	0,6187	3005
	Shrubland	3257	0,5523	2983
	Mixed Forest	1570	0,5198	2631
	Plantation Forest	100	0,3882	1721
Logarithmic Decreasing	Natural Forest	6	0,6297	3060
	Shrubland	22	0,6211	3228
	Mixed Forest	16	0,5935	3051
Logarithmic Increasing	Natural Forest	37	0,6221	2963
	Shrubland	31	0,5921	3159
	Mixed Forest	40	0,5551	2788
	Plantation Forest	0,41	0,5393	3040
Logistic Decreasing	Natural Forest	23	0,5863	3036
	Shrubland	30	0,4969	2998
	Mixed Forest	12	0,4448	2253
	Plantation Forest	1	0,4114	1581
Logistic Increasing	Natural Forest	124	0,6267	3115
	Shrubland	146	0,5467	3141
	Mixed Forest	68	0,445	2238
	Plantation Forest	4	0,3865	1468

The relationship between tree species and altitude demonstrated the adaptability of different forest types to geographical locations and environmental conditions. Natural forests and shrublands tend to grow in higher altitude areas, which are usually more pristine and less affected by human activities, while mixed forests have a broader altitude distribution, showing adaptability under different environmental conditions from low to high altitudes. Planted forests are primarily concentrated in lower altitude areas, possibly related to their planting purposes and the need for management convenience. These relationships between tree species and altitude reflect the complex interactions of forest ecosystems under different environmental pressures and the impact of human activities on forest distribution and forest type selection. Natural forests and shrublands typically display higher environmental quality indicators, while planted forests have lower indicators, maintaining these patterns across different temporal changes. In some cases, mixed forests also show higher RSEI values, especially in linear increasing.

According to Fig. 4, the Exponential increasing category demonstrated the highest average RSEI values at 0,613, with an average forest altitude of 3,054 meters. Other time-series curve types also showed similar trends, indicating a strong correlation between high RSEI values and high altitudes. Forests in high-altitude areas are generally less disturbed by human activities, likely harbouring more pristine and intact ecosystems, which contributes to maintaining high environmental quality.

Forests in the linear decreasing trend area had the lowest average RSEI value of 0,408, with an average altitude of 1,559 meters, which is relatively low. Lower altitude areas are more susceptible to human activities such as agriculture, urban expansion, and industrial activities, which may lead to biodiversity loss and ecosystem service degradation, thus lowering the quality of the forest ecological environment. Based on the characteristics of the curves, we first extracted the significant change points in forest RSEI time series within the study period for three types of temporal curves: exponential increasing, logarithmic increasing, and logarithmic decreasing (Fig. 6). Density indicates the frequency of RSEI time series change points in that year. We found that the time of significant change points is concentrated between 2015 and 2020, especially the exponential increase is particularly significant. The time points for exponential increasing indicate the years when forest RSEI transitions from stable to rapidly increasing. Logarithmic increasing shows forest RSEI transitioning from rapid increase to stability. Logarithmic decreasing represents forest RSEI shifting from rapid decline to stability. As illustrated in Fig. 6, the frequency of these time points shows three peaks in the years 2002, 2010, and in 2017, with the highest frequency occurring in 2017, especially for exponential increasing, where the quantity of this curve type significantly surpasses the other two.

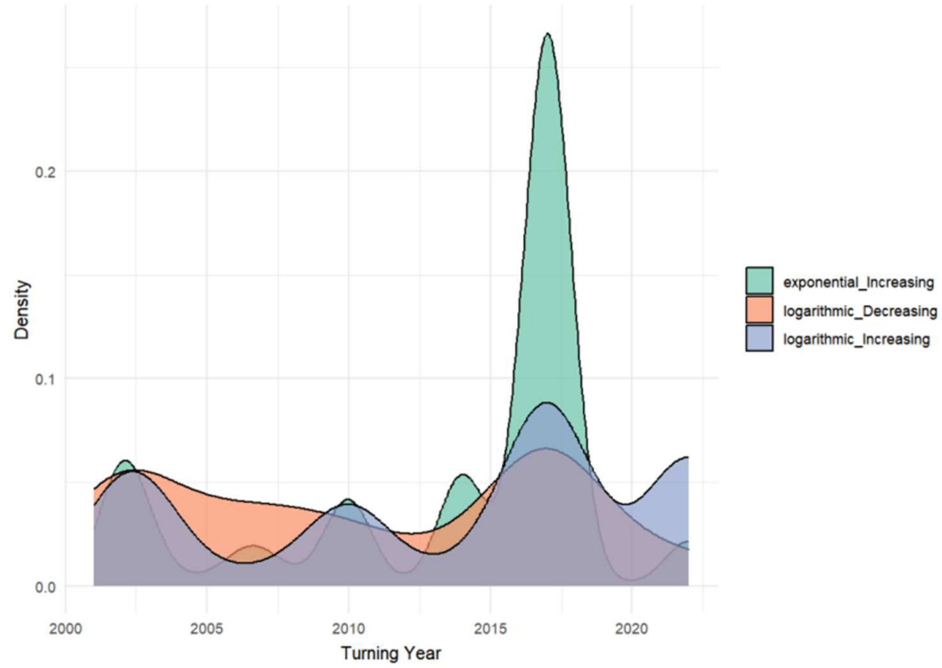

Fig. 6. Density statistics chart of exponential increasing, logarithmic increasing, and logarithmic decreasing change points occurrence years

Рис. 6. График статистики плотности точек изменения при экспоненциальном росте, логарифмическом росте и логарифмическом убывании по годам возникновения

Similarly, the change points for logistic curves, which depict periods of fluctuation from stability back to stability, were extracted. As shown in Fig. 7, fluctuating periods are present throughout the entire study period, but the specific times of fluctuations and their durations vary. The start times are primarily clustered around 2001 and 2014, while the end times concentrate around 2004 and 2018. In 2013, the most common duration of fluctuation was 4 years, with fluctuation periods mainly ranging from 1 to 5 years.

Although all experienced a process from stability to fluctuation and back to stability, the time of fluctuation varies. Based on the concentration of start and end times at the extremes of the study period and the fact that most changes occurred within five years, we can hypothesise that the fluctuation intervals in the entire study period are mainly concentrated in two phases: 2000–2005 and 2013–2023. The analysis of all change periods (Fig. 8) indicates that the early phase of the study experienced longer durations of fluctuation, while the later phase had shorter durations, with a peak in 2013. This suggests a trend of shortening fluctuation periods over time, indicating that the forest RSEI in these areas can recover to stability more quickly in later periods.

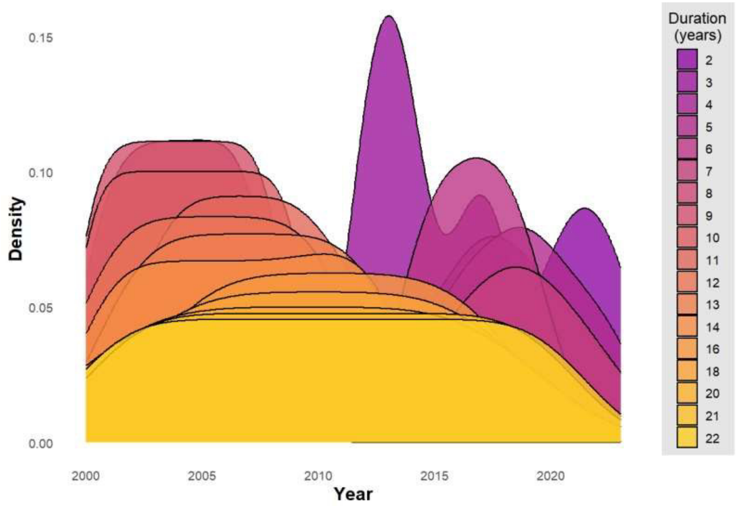

Fig 7. Fluctuation periods of RSEI Logistic curve
Рис. 7. Периоды колебаний логистической кривой индекса RSEI

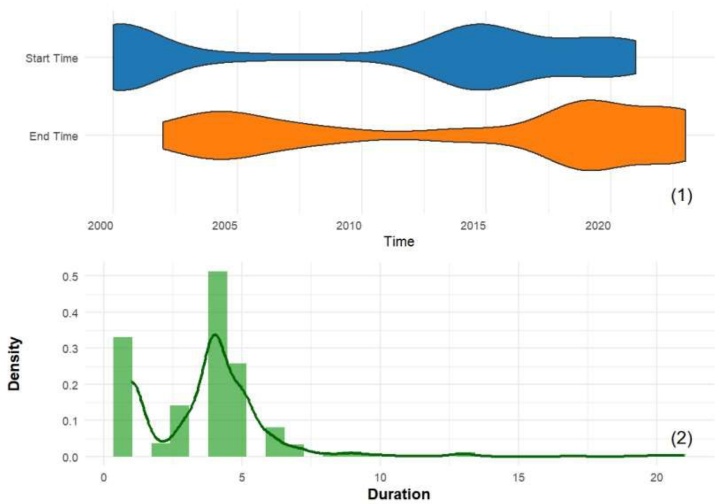

Fig. 8. (1) Logic curve fluctuation start time and end time statistics; (2) Logic curve fluctuation duration statistics
Рис. 8. (1) Статистика времени начала и окончания периодов колебаний логистической кривой; (2) статистика длительности колебаний логистической кривой

Using the GAM analysis, response curves for RSEI with altitude across different ecological zones were calculated (Fig. 9). The analysis revealed a significant nonlinear relationship between altitude and annual mean RSEI. This indicates that, in the majority of ecological zones, as altitude increases, forest RSEI correspondingly rises, reflecting better ecological quality and environmental stability. Notably, aside from the unique pattern exhibited by the ecological decreasing zone, the other four ecological zones show a tendency for RSEI changes to stabilize when altitude exceeds 3,000 meters, demonstrating adaptability to high-altitude environments.

Further analysis identified a clear turning point at around 2,000 meters in altitude across these four ecological zones, indicating this altitude as a key threshold affecting forest ecological stability. Meanwhile, at altitudes around 4,000 meters, the trend of RSEI improvement slows down or even slightly declines in the high RSEI stable zone and low RSEI stable zone compared to the stable zone, suggesting that ecosystem stability might be challenged under extreme high-altitude conditions.

In-depth analysis using the RF model across different ecological zones identified altitude as a universally important predictor, particularly in the RSEI stable and RSEI increasing zones, as evidenced by the Incremental Mean Square Error (IncMSE) values of altitude changes (Fig. 10). Especially in the RSEI stable and RSEI increasing zones, higher IncMSE values underscore the significant role of altitude variations on forest RSEI, indicating that forest ecological quality in these areas may improve with increasing altitude. Concurrently, there was a notable decrease in the IncMSE value of altitude within the RSEI decreasing zone.

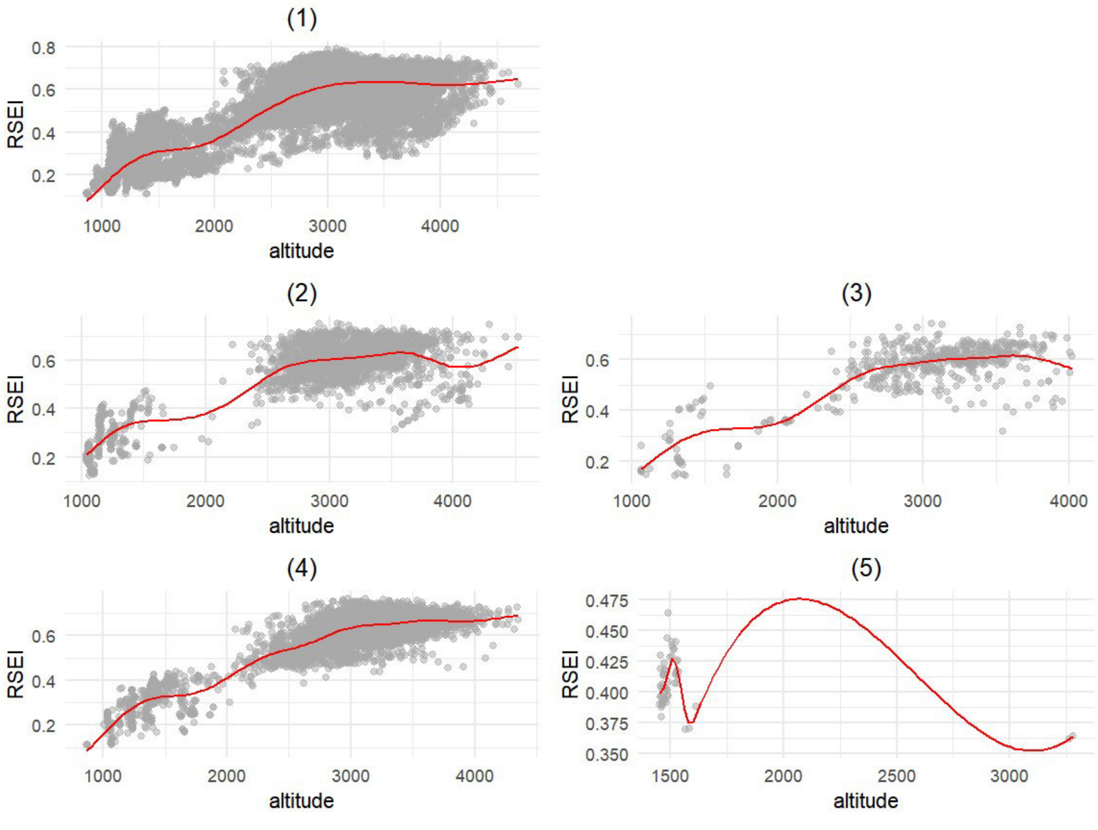

Fig. 9. Altitude's influence curve in different zone: (1) RSEI Stable Zone; (2) High RSEI Stable Zone; (3) Low RSEI Stable Zone; (4) RSEI Decreasing Zone; (5) RSEI Increasing Zone

Рис. 9. Кривая влияния высоты над уровнем моря в разных зонах: (1) зона стабильного индекса RSEI; (2) зона стабильно высокого индекса RSEI;(3) зона стабильно низкого индекса RSEI; (4) зона снижения индекса RSEI; (5) зона роста индекса RSEI

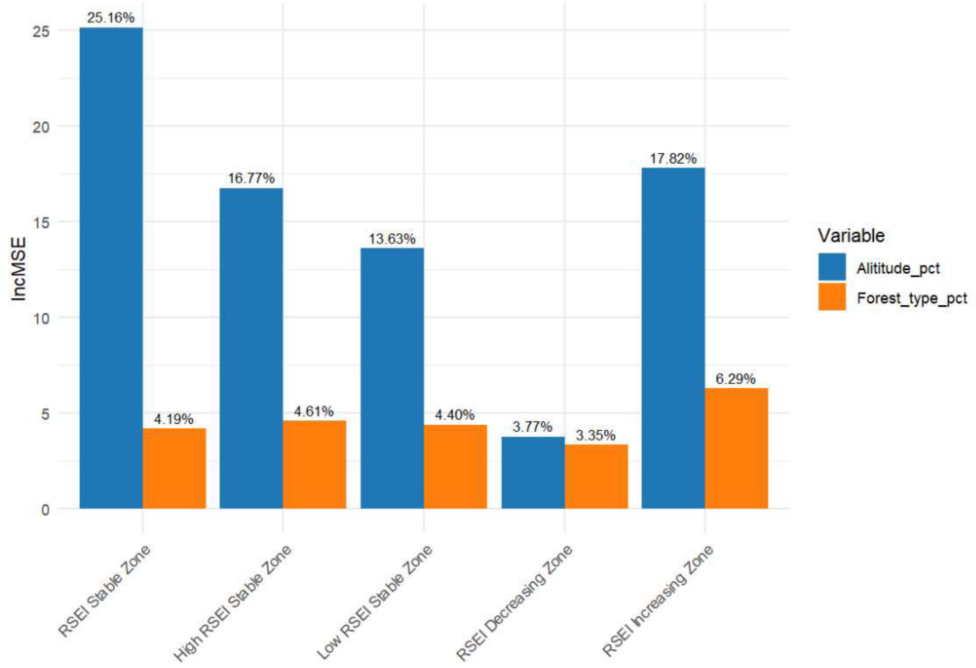

Fig. 10. A comparison of how altitude affects RSEI
Рис. 10. Сравнение влияния высоты над уровнем моря на индекс RSEI

In the RSEI stable zone, the IncMSE value for altitude is the highest, suggesting a close connection between the terrain features and climatic conditions of these areas and altitude changes. The environmental gradient caused by altitude changes may be a significant factor affecting forest ecosystems. In both the high RSEI stable zone and the low RSEI stable zone, the impact of forest types is similar, but altitude has a more substantial influence on the high RSEI stability zone. The characteristic of the RSEI decreasing zone is that IncMSE values of all the factors are relatively low, indicating that ecological degradation might not be solely caused by altitude or forest types but could result from the combined effects of multiple complex factors such as human activities, climate, and fires. In the RSEI increasing zone, both altitude and forest types have relatively high IncMSE values, suggesting that these natural factors play a positive role in improving or restoring forest ecology, potentially related to ecological restoration measures or natural regeneration processes.

Discussion

Compared to traditional linear trend studies of time series, research employing curve trends allows for a more detailed and comprehensive analysis of temporal change patterns [37]. These studies not only identify the trends of change but also extract specific points and periods of transformation within the time series through the characteristics of the curves, thereby facilitating more convenient predictions for the forest ecosystem. By utilizing various curve types, the temporal changes of RSEI can be more accurately modeled, allowing for the identification of specific change points and periods. In the Hexi Corridor region, some studies have already utilized time-series RSEI analysis for small-scale areas [13, 14]. Building on this foundation, our study further supplements the analysis of RSEI changes under different forest types. By employing the GAM and the Increment of IncMSE methods, we not only validate existing research conclusions but also explore the complex nonlinear relationships and variable importance between RSEI, forest types, and altitude in this region.

Natural forests typically have high biodiversity and complex ecosystem structures, contributing to ecological balance and offering a wealth of ecosystem services [38]. These factors may lead to higher RSEI values in natural forest areas, primarily located at higher altitudes with minimal human impact, reflecting better environmental quality and ecological stability. The self-recovery ability and adaptability of natural forests to environmental changes also help maintain their RSEI values. Shrublands usually play a supportive and transitional role within ecosystems, providing habitats and protecting the ground surface, thereby reducing erosion [39]. The RSEI values of shrublands vary by location, showing significant differences at different altitudes, generally ranking just below natural forests. This depends on their role in specific ecosystems and surrounding environmental conditions. Mixed forests are distributed at altitudes lower than natural forests and shrublands but higher than artificial forests. The complex structure of mixed forests offers a variety of ecological niches, encompassing all types of temporal changes. Their RSEI values are lower than those of natural forests and shrublands but higher than those of artificial forests. Artificial forests typically exhibit a linearly stable temporal pattern, often lacking the diversity and complexity of natural forests [40], with relatively lower RSEI values. Located at lower altitudes, often near human activity areas, artificial forests maintain a low stable RSEI under human intervention.

The differences in the distribution of various forest types may reflect the different species' response capabilities to environmental changes and their distribution characteristics under various geographical and ecological conditions [41]. The widespread distribution of natural forests and shrublands demonstrates their strong adaptability to environmental changes, while the characteristics of artificial forests conform to their limitations under artificially intervening environmental conditions. Mixed forests combine the features of both natural forests, shrublands, and artificial forests.

There is a certain correlation between high RSEI values and high altitudes, aligning with the analysis conclusions of the Generalized Additive Model for five regions. This indicates that as altitude increases, its impact on RSEI also grows. High-altitude forests, being less disturbed by human activities, may have higher environmental quality. Conversely, lower RSEI values often occur in lower-altitude areas, likely due to more frequent human activities such as agriculture, urban expansion, and industrial activities [42]. Therefore, altitude may be an important factor affecting forest environmental quality, with high-altitude forests possibly having higher RSEI values due to their relative isolation and ecosystem integrity. These findings highlight the characteristics of forests in the Hexi Corridor region, emphasizing the importance of protecting high-altitude forests for maintaining biodiversity and ecosystem services, while also pointing out the challenges of forest protection and management in low-altitude areas.

The study identified fluctuations in the region's forests in 2002, 2010, and particularly in 2017. Periods of rapid ecological fluctuation occurred between 2000–2005 and 2013–2023. Furthermore, a trend of shortened fluctuation periods over time was observed, likely related to forest protection and restoration projects implemented in recent years. These measures have promoted the stability and recovery of the forest ecosystem. Future research could further analyze the causes of ecological changes in forests based on these specific time points.

The extraction results from the logistic function's band intervals indicate a trend of gradually shorter durations of fluctuation over the years, indicating that the forest ecosystem in the region might be developing in a better direction, able to return to a stable state more quickly. This could be attributed to forest engineering projects implemented since 2000 in the high-altitude areas of the Qilian Mountains, such as the "Three-North Shelterbelt Project (Phases IV and V)" and the "Natural Forest Protection Project," among others. The focused periods of fluctuation in 2000–2005 and 2013–2023 suggest further investigation into the causes of fluctuation during these periods, aiming at more targeted protection of the forest ecosystem in the region.

Conclusions

This study analyzes the RSEI time-series data of forest areas in the Hexi Corridor region from 2000 to 2023, employing various curve-fitting techniques to more accurately analyze the changing trends of the forest ecosystem. Compared to traditional linear trend studies, the application of curve trends allows for a more detailed and comprehensive examination of the changes within the time series. Not only do they reveal the trends of change, but they also extract specific points and periods of transformation through the characteristics of the curves, facilitating more convenient predictions for the forest ecosystem.

The study reveals that different temporal fitting curves delineate five characteristic regions and analyze the impact of altitude and forest type on forest RSEI within these regions. A significant correlation between forest RSEI values, altitude, and forest type has been found, with RSEI values of different forest types exhibiting unique temporal characteristics and changing trends. The forest ecosystem in the Hexi Corridor region remains stable overall, with altitude being an important environmental factor significantly affecting forest RSEI values. Forests in high-altitude areas typically exhibit higher RSEI values and better ecological stability due to less human disturbance. Natural forests possess higher RSEI values and stability compared to other forest types.

These findings are significant for guiding forest conservation and management strategies in the Hexi Corridor and broader regions, especially in terms of protecting high-altitude forests and restoring forests in low-altitude areas. By utilizing the unique mathematical properties of curves, changes and periods undetectable by traditional linear trends are identified, thus providing a more complete analysis of the changes in the forest ecosystem.

Future research could further analyze the causes of ecological changes at these specific time points to better guide practical protection and management measures. Continued exploration of the effectiveness of forest conservation and restoration projects, and assessment of the response and adaptation strategies of different forest types to environmental changes, will better inform practical conservation and management actions.

REFERENCES / СПИСОК ИСТОЧНИКОВ

1. Mori A., Lertzman K., Gustafsson L. Biodiversity and ecosystem services in forest ecosystems: a research agenda for applied forest ecology. *Journal of Applied Ecology*. 2017;54(1):12–27. DOI: 10.1111/1365-2664.12669

2. Mitchell A., Rosenqvist A., Mora B. Current remote sensing approaches to monitoring forest degradation in support of countries measurement, reporting and verification (MRV) systems for REDD+. *Carbon Balance and Management.* 2017;12(1):9. DOI: 10.1186/s13021-017-0078-9

3. Kurbanov E., Vorobev O., Lezhnin S., et al. Remote sensing of forest burnt area, burn severity, and post-fire recovery: A review. *Remote Sensing*. 2022;14(19):4714. DOI: 10.3390/rs14194714

4. Brockerhoff E. G., Barbaro L., Castagneyrol B., et al. Forest biodiversity, ecosystem functioning and the provision of ecosystem services. *Biodiversity and Conservation*. 2017;26(13):3005–3035. DOI: 10.1007/s10531-017-1453-2

5. Wei W., Liu C., Liu Ch., et al. Spatiotemporal analysis of ecological vulnerability in arid region: A case study of Hexi corridor, northwest China. *Human and Ecological Risk Assessment: An International Journal*. 2022;28(5–6):564–593. DOI: 10.1080/10807039.2022.2081834

6. Park T., Ganguly S., Tømmervik H., et al. Changes in growing season duration and productivity of northern vegetation inferred from long-term remote sensing data. *Environmental Research Letters*. 2016;11(8):084001. DOI: 10.1088/1748-9326/11/8/084001

7. Zhu X., Liu D. Improving forest aboveground biomass estimation using seasonal Landsat NDVI time-series. *ISPRS Journal of Photogrammetry and Remote Sensing*. 2015;102:222–231. DOI: 10.1016/j.isprsjprs.2014.08.014

8. Setiawan Y., Yoshino K., Prasetyo L. Characterizing the dynamics change of vegetation cover on tropical forestlands using 250 m multi-temporal MODIS EVI. *International Journal of Applied Earth Observation and Geoinformation.* 2014;26:132–144. DOI: 10.1016/j.jag.2013.06.008

9. Zheng Z., Wu Z., Chen Y., et al. Instability of remote sensing based ecological index (RSEI)

and its improvement for time series analysis. *Science of the Total Environment.* 2022;814:15259. DOI: 10.1016/j.scitotenv.2021.152595

10. Forkel M., Carvalhais N., Verbesselt J., et al. Trend change detection in NDVI time series: Effects of inter-annual variability and methodology. *Remote Sensing*. 2013;5(5):2113–2144. DOI: 10.3390/rs5052113

11. Cohen W., Yang Z., Healey S., et al. A LandTrendr multispectral ensemble for forest disturbance detection. *Remote Sensing of Environment*. 2018;205:131–140. DOI: 10.1016/j.rse.2017.11.015

12. Wu L., Li Z., Liu X., et al. Multi-type forest change detection using BFAST and monthly Landsat time series for monitoring spatiotemporal dynamics of forests in subtropical wetland. *Remote Sensing*. 2020;12(2):341. DOI: 10.3390/rs12020341

13. Wang J., Xie Y., Wang X., et al. Detecting Patterns of Vegetation Gradual Changes (2001–2017) in Shiyang River Basin, Based on a Novel Framework. *Remote Sensing*. 2019;11(21):2475. DOI: 10.3390/rs11212475

14. Wang Y., Kurbanov E., Vorobiev O. Time series analyses of forest cover change according to elevation gradient in Gansu province of China. *Current problems in remote sensing of the earth from space*. 2022;19(5):176–192. DOI: 10.21046/2070-7401-2022-19-5-176-189 (In Rus).

15. Sileshi G. W. A critical review of forest biomass estimation models, common mistakes and corrective measures. *Forest Ecology and Management*. 2014;329:237–254. DOI: 10.1016/j.foreco.2014.06.026

16. Lambert J., Drenou C., Denux J. P., et al. Monitoring forest decline through remote sensing time series analysis. *GIScience & Remote Sensing*. 2013;50(4):437–457. DOI: 10.1080/15481603.2013.820070

17. Naik P., Dalponte M., Bruzzone L. Prediction of forest aboveground biomass using multitemporal multispectral remote sensing data. *Remote Sensing.* 2021;13(7):1282. DOI: 10.3390/rs13071282

18. Wellington M. J., Lawes R., Kuhnert P. A framework for modelling spatio-temporal trends in crop production using generalised additive models. *Computers and Electronics in Agriculture*. 2023;212:108111. DOI: 10.1016/j.compag.2023.108111

19. Wernicke J., Körner M., Möller R., et al. The potential of generalized additive modelling for the prediction of radial growth of Norway spruce from Central Germany. *Dendrochronologia*. 2020;63:125743. DOI: 10.1016/j.dendro.2020.125743

20. Mallinis G., Chrysafis I., Korakis G., et al. A random forest modelling procedure for a multi-sensor assessment of tree species diversity. *Remote Sensing*. 2020;12(7):1210. DOI: 10.3390/rs12071210

21. Chen S., Yao S. Evaluation of forestry ecological efficiency: A spatiotemporal empirical study based on China's Provinces. *Forests*. 2021;12(2):142. DOI: 10.3390/f12020142

22. Main-Knorn M., Moisen G. G., Healey S. P., et al. Evaluating the remote sensing and inventory-based estimation of biomass in the Western Carpathians. *Remote Sensing*. 2011;3(7):1427–1446. DOI: 10.3390/rs3071427

23. Yang L., Shi Z., Zhang S., Lee H. Climate change, geopolitics, and human settlements in the Hexi Corridor over the last 5,000 years. *Acta Geologica Sinica-English Edition*. 2020;94(3):612–623. DOI: 10.1111/1755-6724.14529

24. Jiang Y., Du W., Chen J., et al. Climatic and Topographical Effects on the Spatiotemporal Variations of Vegetation in Hexi Corridor, Northwestern China. *Diversity.* 2022;14(5):370. DOI: 10.3390/d14050370

25. Yang W., Wang Y., Webb A., et al. Influence of climatic and geographic factors on the spatial distribution of Qinghai spruce forests in the dryland Qilian Mountains of Northwest China. *Science of the Total Environment.* 2018;612:1007–1017. DOI: 10.1016/j.scitotenv.2017.08.180

26. Xu H., Wang Y., Guan H., et al. Detecting ecological changes with a remote sensing based ecological index (RSEI) produced time series and change vector analysis. *Remote Sensing*. 2019;11(20):2345. DOI: 10.3390/rs11202345

27. Zhang H., Song J., Li M., et al. Eco-environmental quality assessment and cause analysis of Qilian Mountain National Park based on GEE. *Chinese Journal of Ecology*. 2021;40(6):1883–1894. DOI: 10.13292/j.1000-4890.202106.034

28. Xv H., Wang M., Shi T., et al. Prediction of ecological effects of potential population and impervious surface increases using a remote sensing based ecological index (RSEI). *Ecological indicators*. 2018;93:730-740. DOI: 10.1016/j.ecolind.2018.05.055

29. Falk D., van Mantgem P., Keeley J., et al. Mechanisms of forest resilience. *Forest Ecology and Management.* 2022;512:120129. DOI: 10.1016/j.foreco.2022.120129

30. Opsomer J. D., Breidt F. J., Moisen G. G., et al. Model-assisted estimation of forest resources with generalized additive models. *Journal of the American Statistical Association*. 2007;102(478):400–409. DOI: 10.1198/016214506000001491

31. Loozen Y., Rebel K. T., de Jong S. M., et al. Mapping canopy nitrogen in European forests using remote sensing and environmental variables with the random forests method. *Remote Sensing of Environment.* 2020;247:111933. DOI: 10.1016/j.rse.2020.111933

32. Huang Q., Peng L., Huang K., et al. Generalized additive model reveals nonlinear trade-offs/synergies between relationships of ecosystem services for mountainous areas of Southwest China. *Remote Sensing*. 2022;14(12):2733. DOI: 10.3390/rs14122733

33. Gruba P., Socha J. Exploring the effects of dominant forest tree species, soil texture, altitude, and pHH2O on soil carbon stocks using generalized additive models. *Forest Ecology and Management*. 2019;447:105–114. DOI: 10.1016/j.foreco.2019.05.061

34. Ma X., Zhang J., Wang P., et al. Estimating the nonlinear response of landscape patterns to ecological resilience using a random forest algorithm: Evidence from the Yangtze River Delta. *Ecological Indicators.* 2023;153:110409. DOI: 10.1016/j.ecolind.2023.110409

35. Ye T., Zhao N., Yang X., et al. Improved population mapping for China using remotely sensed and points-of-interest data within a random forests model. *Science of the Total Environment*. 2019;658:936–946. DOI: 10.1016/j.scitotenv.2018.12.276

36. Esteban J., McRoberts R., Fernández-Landa A., et al. Estimating forest volume and biomass and their changes using random forests and remotely sensed data. *Remote Sensing*. 2019;11(16):1944. DOI: 10.3390/rs11161944

37. Ghorbanian A., Mohammadzadeh A., Jamali S. Linear and Non-Linear Vegetation Trend Analysis throughout Iran Using Two Decades of MODIS NDVI Imagery. *Remote Sensing*. 2022;14(15):3683. DOI: 10.3390/rs14153683

38. Nichol J. E., Abbas S. Evaluating Plantation Forest vs. Natural Forest Regeneration for Biodiversity Enhancement in Hong Kong. *Forests*. 2021;12(5):593. DOI: 10.3390/f12050593

39. Mengist W., Soromessa T. Assessment of forest ecosystem service research trends and methodological approaches at global level: a meta-analysis. *Environmental Systems Research*. 2019;8:22. DOI: 10.1186/s40068-019-0150-4

40. Pretzsch H., Zenner E. Toward managing mixed-species stands: from parametrization to prescription. *Forest Ecosystems*. 2017;4:19. DOI: 10.1186/s40663-017-0105-z

41. Xu W., Zhou P., González-Rodríguez M.Á., et al. Changes in Relationship between Forest Biomass Productivity and Biodiversity of Different Type Subtropical Forests in Southern China // Forests. 2024;15(3):410. DOI: 10.3390/f15030410

42. Jin A., Xiong K., Hu J., et al. Remote Sensing Ecological Quality and Its Response to the Rocky Desertification in the World Heritage Karst Sites. *Land*. 2024;13(4):410. DOI: 10.3390/land13040410

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Оценка экологического состояния лесных экосистем коридора Хэси с использованием временных рядов индекса RSEI

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Аннотация. ***Введение.*** В исследовании проведён глубокий анализ данных временных рядов экологического индекса дистанционного зондирования (англ. Remote Sensing Ecological Index, RSEI) лесов на территории коридора Хэси (Ганьсуский коридор, КНР) с 2000 по 2023 гг. с использованием нелинейной аппроксимации кривых для выявления тенденций изменения и характеристик лесных экосистем региона. *Цель исследования* – осуществить оценку и прогнозирование экологических тенденций состояния лесов при использовании временных рядов спутниковых данных и нелинейных зависимостей. Необходимо проанализировать взаимосвязь между высотой над уровнем моря и типом лесов исследуемого региона, а также влияние этих параметров на экологическое состояние лесов на основе объединения обобщённой аддитивной модели (англ. Generalized Additive Model, GAM) с анализом IncMSE модели случайного леса (англ. Random Forest, RF). *Результаты* указывают на значительную корреляцию между значениями RSEI леса и высотой над уровнем моря. Леса на больших высотах демонстрируют лучшую экологическую стабильность и более высокие значения RSEI, что свидетельствует о более высоком качестве окружающей среды. Естественные леса, характеризующиеся богатым биоразнообразием и сложной структурой, неизменно показывают самые высокие значения RSEI в различных экологических зонах, что подчёркивает их ключевую роль в поддержании экологического баланса и предоставлении экосистемных услуг. В то же время искусственные леса, расположенные преимущественно на более низких высотах и часто вблизи деятельности человека, характеризуются линейными и стабильными временными закономерностями с более низкими значениями индекса RSEI. *Заключение.* Выявлены значительные временные колебания индекса RSEI, особенно в 2002, 2010 и 2017 гг., с заметной тенденцией к уменьшению периодов колебаний с течением времени, что, вероятно, отражает влияние предпринятых в последнее время усилий по сохранению и восстановлению лесов в КНР. Настоящее исследование оригинально сочетает анализ нелинейных моделей с использованием экологических индексов с целью обеспечить комплексную основу для понимания и прогнозирования изменений в лесных экосистемах и предоставить важнейшую аналитическую информацию для выработки будущих стратегий сохранения и управления, прежде всего в районе коридора Хэси.

Ключевые слова: лесная экосистема; RSEI; обобщённая аддитивная модель (GAM); случайный лес; анализ IncMSE; временной анализ; коридор Хэси

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