Temporal Information Entropy and Its Application in Remote Sensing Monitoring of Spatiotemporal Changes in Vegetation Cover: Postprint

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Date: 2017-11-10T00:00:00+00:00

Abstract

Change detection based on remote sensing imagery represents a current research hotspot, providing decision support for regional ecological conservation, resource management, and development planning. Current remote sensing image change detection predominantly relies on two temporal phases, which inadequately captures the continuous temporal variation characteristics of vegetation. By introducing information theory, this study proposes a method utilizing temporal information entropy to comprehensively characterize long time-series vegetation change features. Taking the Yanhe River Basin as the experimental area and employing MODIS/NDVI data, the temporal information entropy method was applied to calculate vegetation cover change information for the region from 2000 to 2010, thereby elucidating spatiotemporal variation patterns. Results demonstrate that vegetation cover change in the Yanhe River Basin over the past decade has been primarily increasing, representing 80.7% of the basin area; areas with significantly increased vegetation cover constitute 13.9% of the basin area, predominantly distributed in the northeastern and southeastern regions; areas with decreased vegetation cover account for 2.4%, mainly located in the western and northwestern regions; and areas with severely decreased vegetation cover represent 1.1%, primarily distributed in the central and southwestern regions, which constitute priority areas for ecological restoration and management. Compared with regression analysis, the temporal information entropy method can more objectively characterize the continuous change intensity and trends of long time-series vegetation cover, thereby providing a more scientific theoretical basis for regional ecological environment protection and management.

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Full Text

Temporal Information Entropy and Its Application in the Detection of Spatio-temporal Changes in Vegetation Coverage Based on Remote Sensing Images

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Abstract

Change detection based on remote sensing imagery is a prominent research topic that provides decision support for regional ecological conservation, resource management, and development planning. However, current studies predominantly focus on bi-temporal change detection, which cannot adequately reflect the continuous change characteristics of vegetation in the temporal dimension. By introducing information theory, this paper proposes a novel method using temporal information entropy to comprehensively characterize the long-term change features of vegetation. Taking the Yanhe watershed as the study area and using MODIS/NDVI data, we applied the temporal information entropy method to calculate vegetation coverage change information from 2000 to 2010 and identified its spatio-temporal change characteristics. The results showed that vegetation coverage in the Yanhe watershed mostly increased during this period, accounting for 80.7% of the total watershed area. Areas with obvious increase accounted for 13.9% and were mainly distributed in the northeastern and southeastern parts of the watershed. Areas with decreased vegetation coverage accounted for 2.4%, mainly distributed in the western and northwestern regions, while severely decreased areas accounted for 1.1%, primarily located in the central and southwestern parts of the watershed that require focused ecological restoration and management. Compared with regression analysis, the temporal information entropy method can more objectively characterize the continuous change intensity and trend of long-term vegetation coverage, providing a more scientific theoretical basis for regional ecological environment protection and management.

Keywords: remote sensing; change detection; time series data; temporal information entropy; vegetation coverage

1. Introduction

Remote sensing-based change detection of ground objects is a crucial method for evaluating the sustainable development of watershed ecological environments. Although diverse detection methods exist, their accuracy remains a concern. Issues such as land use change, urban development, and ecological environment changes, which affect people' s livelihoods and sustainable human development, can be collectively summarized as ground object change detection problems [1-2]. Remote sensing technology has become the primary technical means for change detection due to its strong timeliness, wide coverage, and repeatable observation capabilities, enabling quantitative monitoring of the location, process, and magnitude of surface changes [3]. Change detection is currently a hot topic in remote sensing application research [4-5].

Remote sensing image change detection involves quantitatively analyzing and determining surface changes from multi-temporal remote sensing data. Scholars have proposed numerous methods from different perspectives. Singh et al. [7] categorized change detection methods into direct comparison and post-classification comparison based on whether images are classified. Rensink [8] classified methods into pixel-level, feature-level, and decision-level based on research object hierarchy. Others have categorized techniques into arithmetic operation, classification comparison, advanced model, visual analysis, and other methods based on mathematical approaches [9]. From the perspective of detection strategy, methods can be divided into bi-temporal change detection and time series change detection [1,10]. The former detects changes between two temporal images, with common methods including image algebra, principal component analysis, change vector analysis, texture feature analysis, Markov random field models, and data fusion. Deng et al. [11] used change vector analysis to detect land use/cover changes in the North China Plain with good results. Tsarouchi et al. [12] applied principal component analysis, while Bruzzone et al. [13] introduced Markov random field models to change detection. Camps-Valls et al. [14] applied data fusion to multi-temporal remote sensing imagery, extracting spatial neighborhood information from two-temporal images and achieving good noise suppression, optimizing detection results.

Time series change detection of long-term vegetation coverage is an important field in ecological research and a hotspot in global change studies. The development of remote sensing technology and information theory has established theoretical and data foundations for time series change detection. With the accumulation of remote sensing data, long-term remote sensing images have completely recorded surface change processes, enabling better reflection of spatio-temporal change patterns [16-17]. Time series change detection can fully extract temporal change information of ground objects and has wide applications in land cover change research, most directly for monitoring surface vegetation changes [18-19].

Common vegetation coverage change detection methods include regression analysis, principal component analysis, Fourier transform, and wavelet transform. Regression analysis, which considers statistical relationships between variables, is currently the most widely used method for long-term vegetation coverage trend studies [20-21]. Its advantage lies in simple calculation, but it requires research objects to follow normal distribution and has poor error avoidance capability for remote sensing image noise [22], making it difficult to objectively reflect change intensity characteristics of long-term vegetation coverage. Principal component analysis, Fourier transform, and wavelet transform enhance change information through image transformation or mathematical processing of time series data, then detect changes from transformed components [23]. While these methods can effectively highlight change information and express macroscopic vegetation coverage change features well, the transformed images lack clear meaning and cannot reflect specific temporal change characteristics [24].

Given the limitations of conventional methods in long-term vegetation coverage change detection, this paper introduces information theory to propose the concept and calculation method of temporal information entropy, hoping to provide new ideas for this research field. Information entropy, originating from physics to reflect the disorder degree of thermodynamic systems, was introduced to communication by Shannon in 1948 and reflects the average uncertainty of information sources [25]. It has been widely applied in ecology, social sciences, and other fields [26-27]. In remote sensing change detection, information entropy has been mostly applied to two-temporal change detection. Li et al. [28] proposed using image object difference entropy to detect two-phase land cover changes, while Ren et al. [29] proposed land use change entropy to extract change information from two-phase images, achieving good results with low requirements for data registration accuracy and resolution. Building on existing research, this paper proposes using temporal information entropy to deeply extract vegetation coverage change information from time series remote sensing images, quantitatively characterizing its temporal change patterns. Using the Yanhe watershed as a test area, we applied this method to objectively reflect the spatio-temporal change characteristics of long-term vegetation coverage, aiming to provide decision support for regional ecological conservation and management.

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2. Study Area

The Yanhe River Basin, located in the hinterland of the Loess Plateau in northern Shaanxi, is a first-level tributary of the Yellow River originating from Tianjawan Township, Jingbian County, Yulin City. It flows from northwest to southeast through Jingbian County, Ansai District, Baota District, and Yanchang County, finally emptying into the Yellow River near Liangshui’ an, Nanhegou Township, Yanchang County. The watershed covers 108°45 –110°28 E, 36°23 – 37°17 N, with a total area of 7,687 km^2 and a main stream length of 286.9 km. The total population is approximately 520,000 (61% agricultural), with a GDP of 38.27 billion yuan [30]. Baota District is a famous red tourism destination, while Ansai District is rich in mineral resources, with petroleum industry as its economic pillar.

The basin has a typical warm temperate continental semi-arid monsoon climate, cold and dry in winter, hot and rainy in summer, with significant temperature gradients from northwest to southeast. Annual precipitation is low and unevenly distributed, averaging 520 mm (range: 475–1,787 mm), with annual temperatures of 8.8–10.2°C. Vegetation coverage shows significant variation from south to north. Given the prominent ecological environmental issues, the Yanhe watershed is a key area for ecological construction in Shaanxi Province. Objectively reflecting its long-term vegetation coverage changes can provide decision-making information for ecological construction and management.

[Figure 1: see original paper] Location of Yanhe watershed

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3. Data Sources

Normalized Difference Vegetation Index (NDVI) is a crucial data source that effectively reflects surface vegetation coverage and is the most widely used parameter for vegetation monitoring from remote sensing satellites [32]. This study used MODIS NDVI data (MOD13Q1 product) from NASA (https://ladsweb.nascom.nasa.gov/data) with 250 m spatial resolution and 16-day temporal resolution. The data are in MODLAND projection with preprocessing including cloud removal and radiometric correction. The study period was 2000–2010.

We used MODIS Reprojection Tools (MRT) for format and projection conversion to WGS84/Albers Equal Area Conic, with nearest-neighbor resampling at 250 m resolution. Maximum Value Composites (MVC) were applied to 16-day data to further eliminate cloud, atmosphere, and solar zenith angle effects [33], obtaining annual maximum NDVI data for the study area.

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4. Methods

4.1 Information Entropy

Information entropy, also called Shannon entropy, is calculated based on discrete random variables using formula (1):

$$H(X) = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i)$$

where x_i represents states or values of random variable X, and $p(x_i)$ are corresponding probabilities.

For continuous random variables, information entropy is not simply the limit of the above formula but is defined as differential entropy [34]:

$$H(X) = -\int_{-\infty}^{+\infty} f(x) \log_2 f(x) dx$$

where $f(x)$ is the probability distribution function.

The key to calculating information entropy is determining the probability density or distribution function. Vasicek et al. [35] proposed estimating entropy directly from observed data without requiring probability density functions, proving the estimator converges in probability to the theoretical value. For ordered sample points $x_1, \ldots, x_n$ (where $x_1 \le x_2 \le \ldots \le x_n$) and positive integer m, the entropy can be expressed as:

$$H(X) = \frac{1}{n} \sum_{i=1}^{n} \log_2 \left(\frac{n}{2m} (x_{i+m} - x_{i-m}) \right)$$

where $x_{i-m} = x_1$ when $i \le m$, and $x_{i+m} = x_n$ when $i \ge n - m$.

Ebrahimi et al. [36] improved this formula with smaller bias and root mean square error:

$$H(X) = \frac{1}{n} \sum_{i=1}^{n} \log_2 \left(\frac{n}{c_i m} (x_{i+m} - x_{i-m}) \right)$$

where $c_i = \begin{cases} 1 + \frac{i-1}{m}, & 1 \le i \le m \\ 2, & m+1 \le i \le n-m \\ 1 + \frac{n-i}{m}, & n-m+1 \le i \le n \end{cases}$

4.2 Temporal Information Entropy

Drawing on information entropy concepts and considering remote sensing data characteristics, this paper proposes temporal information entropy to fully extract vegetation coverage change features in the temporal dimension, characterizing change intensity and trend information for a given period. Temporal information entropy reflects vegetation coverage change intensity characteristics, calculated as:

$$H = \frac{1}{n} \sum_{i=1}^{n} \log_2 \left(\frac{n}{c_i m} \cdot \frac{x_{i+m} - x_{i-m}}{\Delta} \right)$$

where $x_1 \le x_2 \le \ldots \le x_n$ are ordered sample points, with x_i representing the NDVI value of a pixel in year i; m is a positive integer not exceeding $n/2$; and Δ standardizes different data sources for comparable results.

Parameter selection is crucial. Different m values reflect change characteristics at different temporal scales. In this study, vegetation coverage is represented by annual maximum NDVI, so the temporal scale is annual and $m = 1$. Δ represents the standardized basic change unit derived from time series data statistics; in this study, $\Delta = 0.02$.

The H value reflects vegetation coverage change intensity during a period—larger H indicates greater change intensity, while smaller H indicates weaker change. However, since calculation involves sorting remote sensing observations, the result only reflects change intensity, not trend information.

To reflect vegetation coverage change trends, we propose time-series information entropy:

$$H' = \frac{1}{n}\sum_{i=1}^{n} \operatorname{sgn}\left(\frac{x_{i+m} - x_{i-m}}{\Delta}\right) \log_2\left(\frac{n}{c_i m} \cdot \left|\frac{x_{i+m} - x_{i-m}}{\Delta}\right|\right)$$

where sgn is the sign function ($\operatorname{sgn}(\theta) = 1$ if $\theta > 0$, -1 if $\theta < 0$, and 0 if $\theta = 0$). Positive H' indicates increasing vegetation coverage trend, negative indicates decreasing trend, and larger absolute values indicate more significant trends.

These entropy measures can extract vegetation coverage change intensity and trend information from time series. By segmenting the entropy value histograms, we can obtain vegetation coverage change level maps, providing convenient and macroscopic references for regional ecological conservation and management.

4.3 Linear Regression Analysis

Linear regression analysis is commonly used to reflect long-term vegetation coverage changes [21-22]. This study compares newly established temporal information entropy and time-series information entropy with linear regression. Regression analysis uses slope values to express change intensity and trend:

$$\text{slope} = \frac{n \times \sum_{i=1}^{n} i \times \text{NDVI}_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} \text{NDVI}_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where n is the number of monitoring years and NDVI_i is the NDVI value for year i. Larger absolute slope values indicate greater change intensity; positive slopes indicate increasing trends, negative slopes indicate decreasing trends.

4.4 Validation and Comparison

To verify the scientific validity of the proposed method, we compared it with the most commonly used linear regression analysis for long-term vegetation coverage change detection. Taking the Yanhe watershed as the test area, we selected representative sample points based on slope value and determination coefficient

(R^2) distributions from regression analysis, choosing points from areas with flat, increasing, and decreasing trends.

Data of representative sample points

Year	Sample1	Sample2	Sample3	Sample4
2000	0.8269	0.3862	0.4734	0.3373
2001	0.8335	0.4126	0.4276	0.3415
2002	0.8369	0.5188	0.4154	0.3590
2003	0.8423	0.4157	0.4111	0.2956
2004	0.8436	0.5169	0.4246	0.3154
2005	0.8412	0.5072	0.4382	-
2006	0.8387	0.5065	-	-
2007	0.8395	0.6021	-	-
2008	0.8426	0.5687	-	-
2009	0.8433	0.6798	-	-
2010	0.8516	0.5907	-	-

5. Results

5.1 Linear Regression Analysis Results

Linear regression analysis showed that vegetation coverage in the Yanhe watershed generally increased from 2000–2010, with decreasing trends mainly in the central region. The determination coefficient R^2 was used to test slope reliability. Larger R^2 values indicate higher credibility of slope values. The results showed that areas with larger R^2 were mainly in the northern, northeastern, and southeastern parts of the watershed, while areas with smaller R^2 were mainly in the central region, indicating low reliability and inability to objectively reflect vegetation changes.

[Figure 2: see original paper] Distribution of slope values in Yanhe watershed
[Figure 3: see original paper] Distribution of determination coefficient in Yanhe watershed

5.2 Temporal Information Entropy Results

The temporal information entropy method revealed that vegetation coverage change intensity was generally large in the Yanhe watershed during 2000–2010. The watershed is primarily covered by farmland and grassland [30]. Implementation of policies such as "Grain for Green" over the past decade caused substantial overall vegetation changes. The southern and southwestern forested areas showed weaker change intensity and thus smaller entropy values, consistent with actual conditions.

[Figure 4: see original paper] Distribution of temporal information entropy in Yanhe watershed
[Figure 5: see original paper] Distribution of time-series information entropy in Yanhe watershed

Time-series information entropy showed that areas with increasing vegetation coverage were mainly distributed in the northern, northeastern, and southeastern watershed, while decreasing trends occurred mainly in the central, northwestern, and southwestern regions. Conservation efforts should focus on these deteriorating areas to prevent further degradation.

5.3 Algorithm Comparison

Comprehensive comparison based on long-term vegetation coverage change intensity and trend detection demonstrates the objectivity and scientific validity of temporal information entropy. For the sample points:

- **Sample 1**: Data changed very smoothly with a significant decreasing trend. Regression analysis showed a high R^2 (0.6558), indicating reliable slope. Temporal information entropy reflected this change intensity (0.3557), while time-series information entropy showed the decreasing trend (-0.8204).
- **Sample 2**: Data showed an obvious increasing trend with high R^2 (0.7673). Temporal information entropy (3.7075) reflected large change intensity, and time-series information entropy (2.0994) indicated a significant increasing trend.
- **Sample 3**: Although regression slope was the same as Sample 1, change fluctuations differed significantly. Linear regression cannot objectively reflect such temporal characteristics, with extremely low R^2 (0.106) indicating minimal credibility. Temporal information entropy (3.0973) properly characterized the large fluctuations.
- **Sample 4**: Similar to Sample 3 but with small fluctuations, temporal information entropy was only 0.3557, accurately reflecting the change characteristics.

Comparison of the results

Method	Sample1	Sample2	Sample3	Sample4
Linear Regression				
Slope values	0.0015	0.0237	-0.0156	0.0015
Determination coefficient	0.6558	0.7673	0.8015	0.0106

Method	Sample1	Sample2	Sample3	Sample4
Temporal Information Entropy	0.3557	3.7075	3.0973	2.5343
Time-series Information Entropy	-0.8204	2.0994	-1.5576	1.3599

Overall, 46.9% of the watershed had $R^2 < 0.65$, meaning regression slopes for these areas lack reliability. Temporal information entropy effectively characterizes such change patterns, with large entropy values reflecting substantial fluctuations.

By segmenting entropy value histograms, we obtained thresholds: $A = 1.68$ for temporal information entropy (distinguishing basic unchanged areas), $B = 1.96$ and $C = -0.73$ for time-series information entropy (identifying obvious increase and severe decrease). The final classification showed: 80.7% increased (13.9% obviously increased in northeast and southeast), 2.4% decreased (mainly west and northwest), 1.1% severely decreased (central and southwest requiring priority restoration), and 1.9% basically unchanged.

[Figure 6: see original paper] Location of typical observation points
[Figure 7: see original paper] Distribution of vegetation change levels in Yanhe watershed

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6. Conclusion

This study used temporal information entropy to calculate vegetation coverage change information in the Yanhe watershed from 2000–2010, clarifying its spatio-temporal characteristics. Results show overall vegetation improvement, consistent with actual conditions and effective policy implementation. However, central and southwestern vegetation shows deterioration trends requiring conservation attention and restoration efforts.

Compared with regression analysis, temporal information entropy more objectively characterizes long-term vegetation coverage change intensity and trend, providing scientific decision-making references for regional ecological protection and management. The method offers a new approach for vegetation coverage change detection in long-term remote sensing imagery.

This research aims to reveal overall regional vegetation coverage change characteristics within a time period but has not yet addressed influencing mechanisms. Future research should combine temporal information entropy with natural and human factor analysis to reveal driving mechanisms of vegetation coverage spatio-temporal changes.

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Note: Figure translations are in progress. See original paper for figures.