Monotonic Vegetation Trend Detection Based on Ensemble Empirical Mode Decomposition in Ningxia, China

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Abstract. China and its local governments have made a variety of efforts in vegetation protection and restoration to ensure sustainability especially in the area threatened by severe desertification, such as Ningxia. Studying the vegetation trend and the underlying driving factors is integral to the assessment of the effect of those efforts. This paper applied Ensemble Empirical Mode Decomposition (EEMD) in combination with Mann-Kendall (M-K) significance test to detect the monotonic trend of vegetation in Ningxia based on the 16-day MODIS NDVI time series spanning the period from 2006 to 2015. The result showed that the vegetation in Ningxia exhibited an upward trend in general. The area with upward and downward trend accounted for 80.94% and 14.87%, respectively, and the area without significant change accounted for 4.46%. A rapid increase was found in the central part of the Loess Plateau, whereas a non-increase occurred in the urban expansion area. The possible major driving factors for the detected trend include the implementation of the “Grain for Green” program and urbanization.

1. Introduction

The vegetation in terrestrial ecosystem plays an important role in the global cycle of material and energy and is becoming more and more crucial to the sustainability in the context of global climate change and intensifying human activities. Vegetation loss and degradation may cause a series of problems such as desertification and soil erosion [1,2], and eventually threaten local livelihood. Vegetation protection and restoration is therefore carried out, and its effect can be assessed by analysis of detected vegetation trend.

Vegetation trend change is thought to be associated with land degradation [3,4], and can be broken further up into three types: gradual, abrupt and null (i.e. no change takes place). For vegetation trends, the last one is rare. Within a few decades, it is generally believed that abrupt vegetation change may be caused by short-term processes such as fires, harvests, disasters, or rainfall events, snow cover reductions, whereas gradual vegetation change over a longer period of time reflects the adaptation of vegetation to global changes, including oceanic oscillations and persistent climate change, such as reduced interannual rainfall or increased atmospheric CO₂ concentrations. In fact, gradual vegetation change may be caused by continuous local efforts in ecological restoration, as in Ningxia, China.

Ningxia is situated in the upper and middle reaches of the Yellow River, northwestern China, and covers an area of approximately 66,400 km², extending from 104°17′ E to 109°39′ E, and from...
35°14′ N to 39°14′ N. It is a transitional zone between desert and the Loess Plateau and has a temperate continental arid and semi-arid climate. There are three major deserts surrounding it and desertification is a challenging threat there. Several decades of efforts have been made therefore to protect and restore vegetation for desertification combatting, including the implementation of the Grain for Green Program. That program is the largest ecological restoration project in central and western China initiated by the Chinese Central Government in 1999. It was reported that the desertification there has been significantly alleviated. Therefore, many scholars are of great interest to understand it from the perspective of vegetation cover change in this area.

The normalized difference vegetation index (NDVI) is currently widely used to estimate vegetation cover, biomass and leaf area index and thus its trends can be used as a proxy for greening or browning [5]. In recent decades, several scholars have used NDVI data to conduct in-depth research on the trend of vegetation cover change [6-8]. Their results showed that the growth of vegetation is closely related to not only climate factors but also human activities [9].

However, the NDVI time series has strong seasonality. When it is used for trend analysis, either its seasonality must be removed. Any auto-correlation within the dataset will violate some model assumptions, so linear regression needs to be used with caution at without temporal integration [10]. Zhao investigated the patterns of spatiotemporal variation of vegetation coverage using the methods of linear regression, Mann-Kendall (M-K), correlation analysis and Hurst in the LP during 2000-2014 [11].

This paper studied monotonic trends of the vegetation in Ningxia with the assumption that those trends preserve their increasing or decreasing throughout the time-series. Instead of linear regression analysis, the paper used Ensemble Empirical Mode Decomposition (EEMD) method to extract the trend component of NDVI time series, in combination with M-K significance test to detect monotonic change trend, which is integral to the sustainability of regional socioeconomic development and ecological restoration planning.

2. Data and Methods

2.1. Data and Preprocessing

The NDVI time series in this study was obtained from MOD13A2 product data of the Moderate-resolution imaging spectroradiometer (MODIS) during the period from January 2006 to December 2015. The product downloaded from website http://ladsweb.nascom.nasa.gov/data/search.html, 1km spatial resolution and 16day NDVI MVC Product. The MOD13A2 products are converted format from HDF to TIFF and re-projected by MODIS Reprojection Tools (MRT). Due to cloud contamination, atmospheric variations or multidirectional effects, MOD13A2 product still contain a lot of residual noises and outliers by Maximum Value Compo site processed. These residual noises outliers hinder further analysis and have a risk to produce erroneous results, and be eliminated by further preprocessed. The optimum-length Savitzky-Golay filter was selected for preprocessing to reconstruct high-quality NDVI time-series by approaching the upper NDVI envelope via an iteration process [12].

2.2. Ensemble Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) was proposed as a time-frequency signal analysis method by Huang et al. in 1998 [13]. It can decompose time-frequency signal into a finite number of Intrinsic Mode Function (IMF) according to the characteristics of the data signal itself. The decomposed IMF components contain local characteristic signals of different time scales of the original signal, which is especially suitable for the analysis of nonlinear and non-stationary signals [14]. The EMD of the one-dimensional signal $x(t)$ can be expressed as Eq. (1):

$$x(t) = \sum_{i=1}^{n} \text{imf}_i(t) + r_n(t)$$

where $\text{imf}_i(t)$ is $i$th IMF, and $r_n(t)$ is residual function, after $n$ IMFs are extracted. Figure 1 shows the results of a 10-year NDVI time series decomposed using EMD at a certain point in southern China.
The frequency from the component $imf_1$ to $imf_6$ decreased gradually, and $res$ represents the residual, which is a monotonic function and indicated an average trend. It can be seen in Figure 1 that NDVI value decreased approximately linearly from 2006 to 2015.

**Figure 1.** The IMF components of the decomposition of the original input signal in the top panel using EMD. The $imf_1$ to $imf_6$ represent decomposed six IMF component, and $res$ represents the residual.

EMD has been widely used for signal processing owing to its advantages over many other decomposition methods [15]. A major drawback of the EMD is the frequent occurrence of mode mixing. Mode mixing means that a single IMF consists of multiple signals of different scales, or a similar scale signal in different IMF components. Mode mixing is often a consequence of signal intermittency. The intermittency could not only cause serious aliasing in the time–frequency distribution, but also make the physical meaning of individual IMF unclear.

To overcome the scale separation problem, the Ensemble EMD (EEMD) method is proposed [15]. It defines the true IMF component as the average of the experimental set, consisting of the signal plus a finite amount of white noise. Each of the noise-added decompositions consists of the signal and the added white noise. The added white noise is treated as the possible random noise that would be encountered in the measurement process. Under such conditions, the $i$th “artificial” observation will be

$$x_i(t) = x(t) + w_i(t)$$

Where $w_i(t)$ denotes the $i$th added white noise. This EEMD proposed here has utilized many important statistical characteristics of white noise. Since the white noise added in each test was different in separate trials, it was canceled out in the ensemble mean of enough tests. The ensemble mean is treated as the final decomposed signal. Figure 2 shows the IMF components of the decomposition using EEMD at a same point. In Figure 2, NDVI value decreased slowly from 2006 to 2008, and decreased relatively rapidly between 2009 and 2012, and remains almost unchanged from 2013 to 2015, and until 2016, there was a slow increase.
Figure 2. The IMF components of the decomposition of the original input signal in the top panel using EEMD. In the EEMD, an ensemble member of 100 is used, and the added white noise in each ensemble member has a standard deviation of 0.4.

2.3. M-K Significance Test

The M-K test was performed to determine whether the NDVI value change was significant or not. The M-K test, originally proposed by Mann and Kendall, was used to detect long-term trends and mutations in precipitation. In time series trend analysis, M-K test is continuously used to analyze temperature, water quality, precipitation and runoff time series trend [16]. The M-K test is not interfered by outliers, nor does it need to follow a certain data distribution, and is thus suitable for abnormally distributed data.

In the M-K test, let a time series data \((x_1, x_2, ..., x_n)\) be \(n\) independent, random variables with the identical distribution, test statistic \(S\) can be calculated by Eq. (3):

\[
S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i)
\]  

(3)

where \(\text{sgn}(\theta)\) is symbolic function. When \(n > 10\), \(S\) is an approximately normal distribution with a mean of 0, variance is \(\text{var}(S) = n(n-1)/(2n+5)/18\), standard normal system variables \(Z_{MK}\) are calculated by Eq.(4):

\[
Z_{MK} = \begin{cases} 
(S - 1)\sqrt{\text{var}(S)}, & S > 0 \\
0, & S = 0 \\
(S + 1)\sqrt{\text{var}(S)}, & S < 0 
\end{cases}
\]

(4)

In the bilateral trend test, at the \(\alpha\) significant level, if \(|Z_{MK}| > Z_{1-\alpha/2}\), that means, at the \(\alpha\) significant level, the time series data has a significant upward or downward trend, otherwise the time series data has no trend. For statistics \(Z_{MK}\), when it is greater than 0, it is an upward trend, and otherwise a downward trend. When the significance level is \(\alpha\), the confidence level is \((1-\alpha)\) 100%. In this study, the confidence level was set to 95% confidence as required, which corresponded to \(Z_{MK} = 1.96\).
Since this study focused mainly on detecting the underlying trend of monotonicity, trend test for the residual amount, that is, using M-K significant test to tell that whether the trend is significantly monotonous increasing, monotonous decreasing, or no significant change.

3. Results and Discussions

Figure 3 illustrated the result of increasing trend and decreasing trend distribution for NDVI data in Ningxia using EEMD and M-K significant test.

In figure 3, the NDVI value of Ningxia presented an increasing trend. Vegetation in the southern part of Ningxia showed an increasing trend, and the vegetation in the north showed a decreasing trend, while in the northern and western parts, the vegetation changed little.

The area with increasing and decreasing trends accounted for 79.43% and 11.39%, respectively, and the area of without significant change and unchanged accounting for 7.36% and 1.82%. This is consistent with the news that the forest coverage rate in Ningxia increased from 8.4% to 12.63% between 2000 and 2015 in Ningxia Daily. It should be said that the growth trend of NDVI in Ningxia is closely related to the implementation of the Grain for Green program.

Figure 4 is the results of adding urban residential locations in Figure 3, those locations are indicated by the star point. It is observed from figure 4 that there is a significant trend of vegetation reduction in Yinchuan, the capital of the northern region of Ningxia and the surrounding residents of several neighboring cities and counties. We think it is probably related to urban expansion and economic development. In the northwest of Ningxia is the eastern foot of the Helan Mountains, the decreasing trend of vegetation is related to less precipitation. Vegetation conditions have improved significantly, and the area of coverage has increased significantly in the southern mountainous of Ningxia and Yanchi Country. This is due to the closure of mountain grazing, forestation and
ecological environment construction began in Ningxia in the early part of this century. The Hongsibao District in central Ningxia is the largest concentration area of ecological poverty alleviation and immigration in China. Its expansion has caused a significant decreasing trend of vegetation in the area.

4. Conclusions

This paper presented vegetation increasing or decreasing trends of Ningxia over a period of ten years using EEMD combined with M-K significant test. The results showed that during the year from 2006 to 2015, the vegetation of Ningxia exhibited a significant increasing trend, with the vegetation of minority areas showed decreasing trend. Increasing and decreasing trend accounting for 79.43% and 11.39%, respectively, and area without significant change and unchanged accounting for 7.36% and 1.82%. The vegetation increasing trend is consistent with the news that the forest coverage rate in Ningxia increased from 8.4% to 12.63% between 2000 and 2015 in Ningxia Daily. After analysis, drawn the following conclusions:

(1) The vegetation in Ningxia showed an increasing trend in 2006-2015, mainly due to Grazing prohibition policy and Grain for Green Program.

(2) The amount of precipitation Ningxia is also related to the response of the vegetation coverage. If there is more rainfall, the vegetation trend will increase, and vice versa.

(3) Human activities had dual influences on vegetation coverage. On the one hand, the ecological restoration project played an important role in the rapid increase of vegetation cover in the central part. On the other hand, the expansion of urban areas has accelerated the degradation of vegetation.

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