Extreme Drought-induced Trend Changes in MODIS EVI Time Series in Yunnan, China

Kaicheng Huang[1], Tao Zhou[1*], Xiang Zhao[2]
[1]State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, 100875, China

[2]College of Global Change and Earth System Science, Beijing Normal University, Beijing, 100875, China

E-mail: tzhou@ bnu.edu.cn

Abstract: Extreme climatic events triggered by global climate change are expected to increase significantly hence research into vegetation response is crucial to evaluate environmental risk. Yunnan province, locating in southwest China, experienced an extreme drought event (from autumn of 2009 to spring of 2010), with the lowest percentage rainfall anomaly and the longest non-rain days in the past 50 years. This study aimed to explore the characteristics and differences in the response to drought of four land cover types in Yunnan province, including forest, grassland, shrub, and cropland during the period 2001–2011. We used remote sensing data, MODIS-derived EVI (Enhanced Vegetation Index) to study the vegetation responses to this extreme drought event. The EVI time series were decomposed into trend, seasonal and remainder components using BFAST (Breaks For Additive Seasonal and Trend) which accounts for seasonality and enables the detection of trend changes within the time series. The preliminary results showed that: (1) BFAST proved to be capable of detecting drought-induced trend changes in EVI time series. (2) Changes in the trend component over time consisted of both gradual and abrupt changes. (3) Different spatial patterns were found for abrupt and gradual changes. (4) Cropland exhibited an abrupt change, due to its sensitivity to severe drought, while the forest seemed least affected by the extreme drought.

Keywords: extreme drought; EVI; time series; trend; vegetation response

1. Introduction

The impact of drought is a gradual process which accumulates as precipitation deficiencies persist over a considerable period of time [1]. Under a warming climate, the frequency of persistent droughts may increase [2-4]. Regional droughts due to extreme climatic events are increasing in frequency and severity, with significant adverse eco-social impacts [5], such that the ecological impacts of climate extremes are of increasing interest [6]. Future droughts projected to occur under warmer temperature conditions as climate change progresses are referred to here as global-change-type droughts, yet quantitative assessments of the triggers and potential extent of drought-induced vegetation die-off remain pivotal uncertainties in assessing climate-change impacts [7].

Monitoring drought at regional to global scales remains challenging; assessing the impact of drought on ecosystems and societies is also a complex task, because the same drought severity may have different consequences in different regions and systems due to the underlying vulnerabilities.

[*] To whom any correspondence should be addressed.

Satellite sensors are well-suited to providing the consistent and frequent measurements over large areas which are appropriate for capturing the effects of many processes that cause disturbances [8]. Detecting changes within time series is the first step towards understanding the governing processes and drivers. Estimating change from remotely sensed data series, however, is not straightforward, since time series contain a combination of seasonal, gradual and abrupt ecosystem changes occurring simultaneously [9,10]. Vegetation stress or mortality can be the result of many factors, including drought-induced water deficit or fluctuations in precipitation [11]. Satellite-based Enhanced Vegetation Index (EVI) can provide near-real-time data over large areas at a relatively high spatial resolution, and has been widely used for vegetation condition monitoring [12].

The extreme drought of 2009/2010 over southwestern China was the driest event (having the lowest percentage rainfall anomaly and the longest run of non-rain days during winter season of October-February) in the past 50 years, and was also the most severe (having the lowest percentage rainfall anomaly during the same period) since 1880 [13]. Therefore, the extreme drought of 2009/2010 is a good case study for better understanding how drought impacts on vegetation.

In this study, we selected monthly MODIS EVI data (500 m spatial resolution) for Yunnan province as an indicator of vegetation responses to the extreme drought. To assess the relative severity of the drought's impact on vegetation, we developed a method to generate a near-real-time remotely sensed Maximum Index (MI). Next, we applied a trend breaks analysis (BFAST) procedure to decompose the EVI time series into three components, specifically the trend, seasonal and residual components, to further our understanding of the long-term trend caused by global warming and of the breakpoints caused by the extreme climate events.

2. Data and Methods

2.1 Study area

The study is focused on Yunnan Province, southwestern China, which has the most complex natural conditions. The frequency of extreme weather events in Yunnan has been increasing with global climate change in recent years, and this area is sensitive and highly vulnerable to climate change [14]. Considerable inter-annual variability of precipitation leads to a high probability of winter drought.

2.2 EVI data

Recently, vegetation indices have proven to be a useful means of indicating drought-related vegetation conditions, due to their near-real-time coverage across the globe at relatively high spatial resolution [12]. We used satellite data to observe whether an extreme drought impacted on the vegetation. EVI from the Terra satellite's Moderate Resolution Imaging Spectroradiometer (MODIS) is a composite of leaf area and chlorophyll content that does not saturate, even over dense forests. A suite of images was used to calculate the EVI during 2001-2011. The EVI is calculated from the individual bands as follows:

$$EVI = 2.5 \times \frac{\rho_{NIR} - \rho_{\mathrm{Red}}}{\rho_{NIR} + (6 \times \rho_{\mathrm{Red}} - 7.5 \times \rho_{Blue}) + 1} \tag{1}$$

where ρ_{NIR}, ρ_{Red} and ρ_{Blue} are the reflectances in the near infra-red (NIR), red and blue channels, respectively; 2.5 is a gain factor, 6 and 7.5 are coefficients designed to correct for aerosol scattering and absorption and 1 is a canopy background adjustment [15]. Two tiles of MODIS images were acquired from January 2001 to December 2011. The MOD13A1 is a 16-day composite product with 500 m spatial resolution. The mosaics were generated using the MODIS reprojection tool software.

2.3 Standardized Precipitation Evapotranspiration Index

To depict the characteristics of the extreme drought of 2009/2010, firstly this study uses two sets of meteorological station data: the monthly precipitation and temperature datasets comprising 32 stations in Yunnan province. The selected record covers the period from January 2001 to December 2011. To measure is the drought severity, this study applies the SPEI (Standardized Precipitation Evapotranspiration Index). SPEI is a new drought index based on precipitation and PET (Potential Evapotranspiration) and combines the sensitivity of PDSI with changes in evaporation demand and the multi-temporal nature of the SPI. Mathematically, the SPEI is similar to the Standardized Precipitation

Index (SPI), but includes the effect of temperature. As the SPEI is based on a water balance, it can be compared to the self-calibrated Palmer Drought Severity Index (sc-PDSI), and is suited to detecting, monitoring and exploring the impacts of global warming on drought conditions [16].

2.4 Break for Additive Season and Trend

BFAST is a method used for detecting trend changes within time series. It integrates the decomposition of time series into trend, seasonal and residual components with methods for detecting and characterizing abrupt changes within the trend and seasonal components [17]. BFAST can be used to analyze different types of satellite image time series and can be applied to other disciplines dealing with seasonal or non-seasonal time series, such as hydrology, climatology and econometrics. The algorithm can be extended to label detected changes with information on the parameters of the fitted piecewise linear models. Seasonal breaks is a function that combines the iterative decomposition of time series into trend, seasonal and residual components with significant break detection in the decomposed components of the time series. The methods are available in the BFAST package for R (R Development Core Team) from CRAN (http://cran.r-project.org/package=bfast). Here we use BFAST to detect the drought-induced vegetation impacts. The general model is of the form:

$$Y_t = T_t + S_t + e_t \qquad t \in \{1 ... n\} \tag{2}$$

where Y_t is the observed EVI value at time t in the time series $\{1 ... n\}$, T_t is the trend component, S_t the seasonal component, and e_t is the residual component which contains the variation that is not explained by T_t and S_t.

3. Results

3.1 Temporal and spatial patterns of the drought

The drought impacts exhibited considerable variability both temporally and spatially. Figure 1 shows the 3-monthly SPEI for the entire Yunnan province. The intensity of the drought reached a maximum in November 2009. A significant decline was observed in 2009, and frequent fluctuations occurred in the drought intensity from 2009 to 2011. The SPEI decreased during the 11-year period and reached a minimum in November 2009.

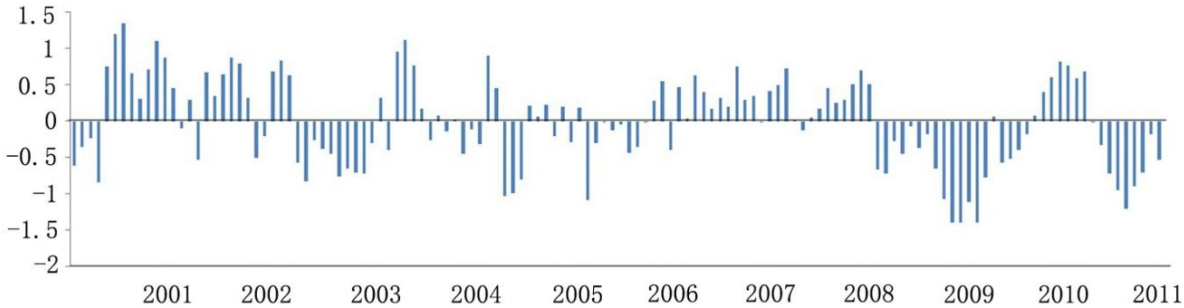

Figure 1. Three-monthly SPEI for the entire Yunnan province

Figure 2 shows the percentage area of Yunnan that experienced abrupt change. A significant increase was observed in 2009, which was almost twice that in 2005, indicating that the drought had negative impacts on vegetation, coincident with the month experiencing the maximum drought intensity, and suggesting that the extreme drought greatly impacted on the vegetation.

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Figure 2. Abrupt change in Yunnan Province

Spatially, as shown in Figure 3, approximately 5.91% of the area (shaded brown) of Yunnan province was found to have experienced abrupt change in 2009 while 2.53% was found to have experienced abrupt change in 2010. The drought was sustained and too severe to allow regeneration.

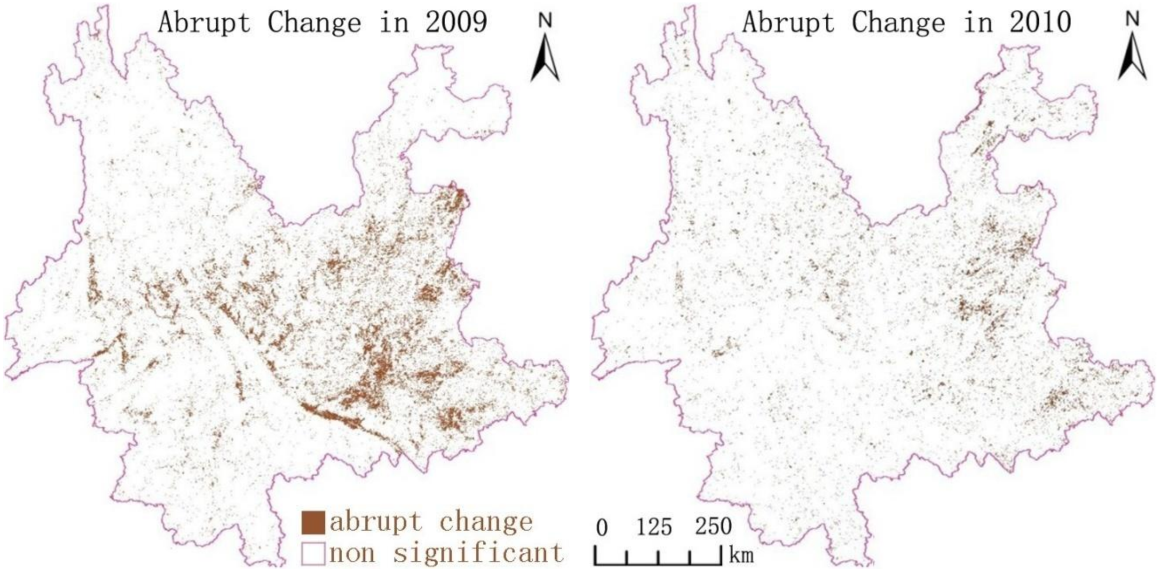

Figure 3. Abrupt change in 2009 and 2010

3.2 EVI trend changes

The application of BFAST to MODIS EVI time series yielded estimates of the time and magnitude of major changes. These results are shown in Figure 4. Cropland was sensitive to the severe drought while the forests were less sensitive, as has been demonstrated in previous research finding the response of vegetation to drought to be modulated by vegetation types, soil properties, climate and land use practices [12,18]. The top panel in Figure 4 shows the EVI data, and the other three panels depict the individual components after decomposition. The seasonal and residual components have zero mean, while the trend component shows the trend in EVI. Due to its sensitivity to severe drought, cropland exhibited an abrupt change when compared to the forests. These observations suggest that forests are less sensitive to the drought, but that forests take longer to recover following an extreme drought event. While the cropland is more sensitive to the drought, it is may be more resilient.

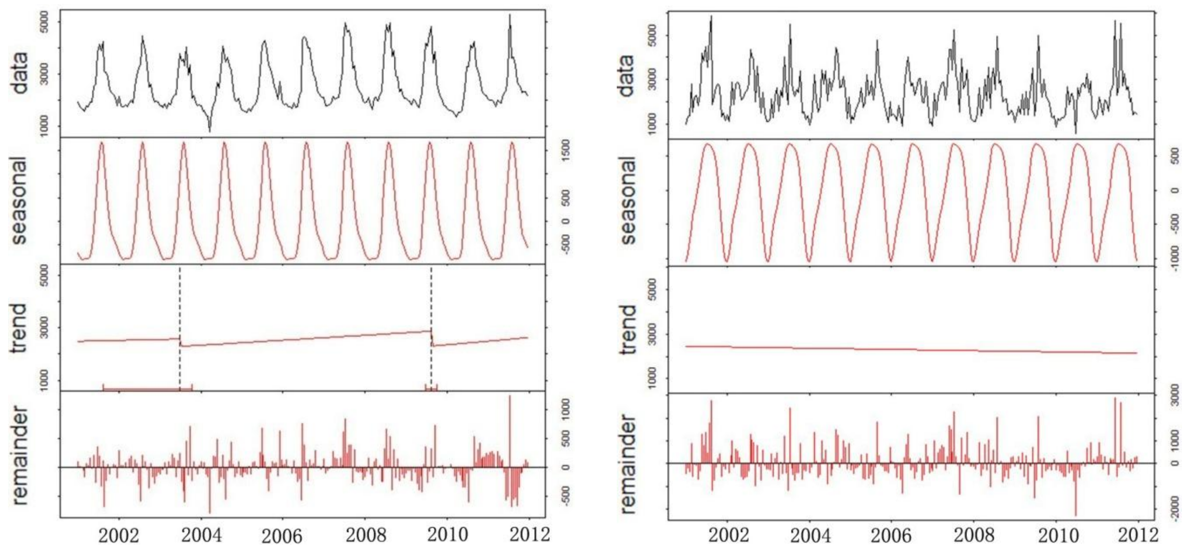

Figure 4. Trend break analysis for cropland and forest in Yunnan province

4. Discussion and conclusion

Spatiotemporal variations of drought in the Yunnan province as revealed by satellite data have been examined in this study. Vegetation was widely affected by the drought, but the impact varied temporally and spatially. We used MODIS-derived EVI data to study how the vegetation reacted to the drought. Although vegetation indices have been widely used for vegetation condition monitoring, the limitation of using vegetation indices should be considered because other factors such as wild fires, insects and deforestation probably result in decreased growth and lower EVI values.

Terrestrial vegetation health is influenced by many cyclical and abrupt events which might cause trends in vegetation health to change [17]. Detecting changes within time series is the first step towards understanding the governing processes and drivers. Here, BFAST was applied to MODIS EVI time series to detect changes in the trend during the extreme drought.

Different spatial patterns were found for drought-induced changes. The BFAST approach presented here proved to be capable of detecting trend changes in EVI time series during the extreme drought. Quantification of recent vegetative change in Yunnan suggests that the vegetation maybe not be able to completely recover by regeneration following prolonged drought.

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References

[1] Lei, Y, Duan, A 2011 *Int. J. Climatol.* **31** 1831-40
[2] Dai, A, Trenberth, K, Qian, T 2004 *J. Hydrometeorol.* **5** 1117–30
[3] IPCC, 2007: Climate Change 2007: synthesis report. Contribution of working groups I
[4] Dai, A 2011 *WIRs. Clim. Change.* **2** 45-65
[5] Mu, Q, Zhao, M, Kimball, John, McDowell, Nathan, Running, Steve 2012 *Bull. Am. Meteorol. Soc.* **94** 83-98
[6] Royer, P, Cobb, N, Clifford, M, Huang, C, Breshears, D, Adams, H, Villegas, J 2011 *J. Ecol.* **99** 714-23
[7] Ma, Z, Peng, C, Zhu, Q, Chen, H, Yu, G, Li, W, Zhou, X, Wang, W et al 2011 *Proc. Natl. Acad. Sci USA.* **109** 2423-27
[8] Jin, S, Sander, S 2005 *Remote. Sens. Environ.* **99** 462−70
[9] Wolfe, R, Roy, D, Vermote, E 1998 *IEEE. T. GeoSCI. Remote.* **36** 1324-38

[10] Verbesselt, J, Zeileis, A, Herold, M 2012 *Remote. Sens. Environ.* **123** 98-108
[11] Yuhas, A, Scuderi, L 2008 *Geogr. Res.* **47** 34-45
[12] Zhang J, Jiang L, Feng Z, Li P 2012 *J. Res. Ecol.* **3** 43-49
[13] Yang, J, Gong, D, Wang, W, Hu, M, Mao, R 2012 *Meteorol. Atmos. Phys.* **115** 173-184
[14] Yan, J, Chen, B, Fang, S, Zhang, H, Fu, D, Xue, Y 2012 *J. Remote. Sens.* **16** 720-737
[15] Huete, A, Justice, C, Liu, H 1994 *Remote. Sens. Env.* **49** 224-234
[16] Serrano, S, Beguería, S, Moreno, L 2009 *J. Climate.* **23** 1696-1718
[17] Jong, R, Verbesselt, J, Schaepan, M, Bruin, S 2011 *Global. Change. Biol.* **18** 642-655
[18] Bhuiyan, C, Singh, R, Kogan, F 2006 *Int. J. Appl. Earth. Obs.* **8** 289-302.