Agricultural and Forest Meteorology 256–257 (2018) 10–21

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Spatial heterogeneity of the relationship between vegetation dynamics and climate change and their driving forces at multiple time scales in Southwest China

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ARTICLE INFO

Keywords:
Multiple time scale analysis
Vegetation dynamics
Climate change
Human activities
Spatial heterogeneity

ABSTRACT

Under global climate change, relationship between vegetation dynamics and climate change is vital for vegetation conservation and restoration in fragile ecological system. However, the relationships at multiple time scales are unclear. Based on the Ensemble empirical mode decomposition method (EEMD), we revealed the spatial heterogeneity of vegetation dynamics and its relationship with climate change at multiple time scales in Southwest China during 1982–2015. Vegetation dynamics can be divided into 3-, 6-, 14-, and 32-year time scale oscillations with an increasing trend. Hereinto, the 3-year time scale and the increasing trend are dominant. In Guangxi and north of Guizhou provinces, vegetation dynamics was dominated by the long-term trend, whereas in the other areas it was dominated by the 3-year time scale. With increasing time scale, the impact of climate change became more pronounced. The relationship between vegetation dynamics and temperature in growing season was determined by elevation and vegetation type at the 3- and 6-year time scales, but only by vegetation type over the long-term trend. The relationship between vegetation dynamics and precipitation was driven by karst landform and vegetation type at the 3-year time scale, by precipitation amount at the 6-year time scale, and by karst landform and elevation over the long-term trend. Based on multivariate regression analysis with multiple time scale analysis, climate change had a good and significant interpretation on vegetation dynamics in 54.1% of the study area. Specifically, in Guangxi and north of Guizhou provinces, the impact of climate change on vegetation dynamics was greater than that of human activities. Our findings showed that multiple time scale analysis might facilitate a better understanding of the mechanisms of vegetation dynamics, and provide scientific knowledge on vegetation restoration and conservation in fragile ecosystems.

1. Introduction

Global warming and the associated increase in precipitation variability are major threats to terrestrial ecosystems (Jiménez et al., 2011; Craine et al., 2012; Miao et al., 2015). Vegetation is one of the most essential components of terrestrial ecosystems, due to its beneficial impacts on the terrestrial carbon balance and the climate system (Piao et al., 2011; Peng et al., 2012; Du et al., 2015; Hou et al., 2015; Tong et al., 2016a). Monitoring vegetation dynamics and its relationship with climate change is considered highly important for global change research and ecological environment conservation, since vegetation might be vulnerable and highly sensitive to climate change and external disturbances (Krishnaswamy et al., 2014; Sun et al., 2015; Tong et al., 2016a; Xie et al., 2016; Xu et al., 2016). The Normal Difference Vegetation Index (NDVI), which is strongly correlated with vegetation coverage, growth conditions, biomass and photosynthesis intensity, is widely used to monitor vegetation dynamics (Du et al., 2015; Sun et al., 2015; Tong et al., 2016b; Zhang et al., 2016a; Zewdie et al., 2017). A growing number of studies have used NDVI data to explore the relationship between vegetation and climate change (Wang et al., 2008; Yang et al., 2012; Sun et al., 2015; Tong et al., 2016b; Zewdie et al., 2017). However, most of them focused on single time scales using traditional time series analysis such as (partial) correlation analysis and linear regression models (Wang et al., 2008; Krishnaswamy et al., 2014; Du et al., 2015; Wang et al., 2015; Hou et al., 2015; Xie et al., 2016). The relationship between vegetation and climate variables is scale-

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https://doi.org/10.1016/j.agrformet.2018.02.015
Received 27 June 2017; Received in revised form 11 February 2018; Accepted 14 February 2018

dependent (Hawinkel et al., 2015; Liu and Menzel, 2016). Single time scale analysis cannot comprehensively reveal the response of vegetation to climate change, and may ignore some important information on other time scales. Recently, several studies focused on the relationships at multiple time scales (i.e. monthly, seasonally and annually, Wang et al., 2008; Yang et al., 2012; Tong et al., 2016b; Kong et al., 2017). However, these studies were mainly based on direct comparisons of different time series at different time scales, under linear and stationary assumptions (Hawinkel et al., 2015; Yin et al., 2016). In fact, the time series of NDVI and climatic variables, whatever monthly, seasonally or annually, are generally non-stationary and contain different frequency components, such as long- and short-term fluctuations (He et al., 2012; Verma and Dutta, 2012; Liu and Menzel, 2016; Yin et al., 2016). Therefore, a linear and stationary assumption is not optimal for exploring the relationship between vegetation and climate change. It is necessary to choose a suitable method to divide those non-stationary time series into variations at multiple time scales. Moreover, most studies focused on intra-annual time scales, and only few focused on inter-annual scales and long-term trends. The latter are considered to be crucial in understanding and predicting the response of ecosystems to an increasingly changing climate (Hawinkel et al., 2015). Therefore, it is essential to investigate the relationships between vegetation and climate change at multiple time scales, including annual, inter-annual, and inter-decadal scales, and long-term trends.

In addition to climate change, human activities are also the main driving forces of vegetation dynamics (Sun et al., 2015; Huang et al., 2016). With population expansion and economic development, human activities, such as urbanization, ecological management and restoration, overgrazing, and cropping, cause increasing influences on vegetation changes(Qu et al., 2015). To develop sustainable ways to cope with the consequences of climate change and economic development in fragile ecosystem, it is necessary to explore the relative importance of climate change and human activities on vegetation dynamics (Huang et al., 2016). A growing number of studies are thus differentiating between human-induced and climate-driven vegetation changes (Sun et al., 2015; Qu et al., 2015; Huang et al., 2016; Jiang et al., 2017; Li et al., 2017). The contributions of climate change and human activities are found to vary with spatial location, vegetation type, elevation, and time period (Wang et al., 2015; Huang et al., 2016; Jiang et al., 2017; Li et al., 2017). However, most studies quantify the relative role stemming from climatic variables at one single time scale under linear assumption. Ignoring the influences of climate change on vegetation dynamics at multiple time scale will underestimate the influences. Thus, multiple time scale analysis is necessary for assessing the relative importance of climate change and human activities.

The Ensemble Empirical Mode Decomposition (EEMD) method, which is advanced by Wu and Huang (2009), is thought to be a suitable time series processing tool to reveal the relationship between climate and vegetation at multiple time scales (Hawinkel et al., 2015; Yin et al., 2016). EEMD is an extension of the Empirical Mode Decomposition (EMD) methods (Huang et al., 1998). EEMD together with EMD can divide the non-stationary time series into a finite set of components with decreasing frequency and a residual trend component (Huang et al. 1998; Hawinkel et al., 2015). These are widely used in signal and image processing, climatic diagnosis, and hydrology (Wu and Huang, 2009; Hawinkel et al., 2015; Liu et al., 2016a; Chen et al., 2017). Recently, more studies have applied EEMD to remote sense data (Verma and Dutta, 2012; Hawinkel et al., 2015; Liu and Menzel, 2016; Yin et al., 2016; Wen et al., 2017). Although some identified the relationships between vegetation and climate variables at multiple time scales (Hawinkel et al., 2015; Liu and Menzel, 2016), they were not based on pixel scale, but rather in regional scale, which ignores spatial heterogeneity. The relationship has apparent spatial heterogeneity which are driven by different forces (Wang et al., 2008; Hou et al., 2015; Huang et al., 2016; Rishmawi et al., 2016; Tong et al., 2016a; Yin et al., 2016). Thus, multiple time scale analyses should be performed at the pixel scale to reveal the spatial heterogeneity of the relationships.

Southwest China is the most continuous karst region in China, with a high population pressure and underdeveloped economy (Wang et al., 2008; Li et al., 2016; Zhang et al., 2016b). It is one of the most fragile regions with low environmental capacity and poor self-recovery capability, and thus vulnerable to climate change (Peng et al., 2011; Jiang et al., 2014; Zhang et al., 2016b). Studying the relationship between vegetation dynamics and climate change in Southwest China may provide scientific knowledge for the protection of vegetation services and restoration of fragile ecological environments (Wang et al., 2008; Hou et al., 2015). Previous studies have already suggested this issue in this region (Wang et al., 2008; Hou et al., 2015; Tong et al., 2016a). However, the relationship at multiple time scales have not been studied yet.

In this paper, vegetation dynamics and climate change at multiple time scales were extracted using the EEMD method. Their relationships at multiple time scales were further explored to provide scientific knowledge for vegetation conservation and restoration in fragile ecosystems. For this, we aimed to: (1) Determine which time scale is dominantly responsible for vegetation dynamics. (2) Assess the spatial heterogeneity of the relationships between vegetation dynamics and climate change at different time scales and their driving forces. (3) Evaluate the relative importance of climate change and human activities on vegetation dynamics.

2. Materials and methods

2.1. Study area

Southwest China (97°38′E-112°10′E, 21°6′N -29°16′N), including Yunnan, Guizhou and Guangxi provinces, is located in the subtropical/tropical climate zone with annual precipitation > 1100 mm and average temperature > 20 °C (Fig. 1). The study area is dominated by karst landform and comprises about 384,343.38 km^2, occupying 48.32% of the total area of the three provinces.

2.2. Data sources

2.2.1. Normalized difference vegetation index (NDVI) dataset

The AVHRR NDVI3g (third generation, Pinzon and Tucker, 2014) dataset constructed by the Global Inventory Modelling and Mapping Studies (GIMMS) project for the period 1982–2015 was used in this study. This dataset, with the spatial resolution of 8 km and 15-day interval, has been widely used to monitor vegetation dynamics and reveal the relationship to climatic factors, due to its superior performance relative to prior versions and its capability for providing the longest time-series record from the early 1980s (Huang et al., 2016). The maximum-value composite (MVC) method was used to choose the higher value of bimonthly NDVI to obtain the monthly NDVI (Holben, 1986). To reflect the vegetation more appropriately, the NDVI products were averaged over the entire growing season from April to October to get growing-season NDVI (GSN).

2.2.2. Meteorology, DEM, karst and vegetation data

Monthly precipitation and temperature data during the period of 1957–2015 were collected by a network of approximately 120 weather stations provided by Climatic Data Center, National Meteorological Information Center, China Meteorological Administration (http://cdc.cma.gov.cn/). The growing-season summed precipitation (GSP) and growing-season mean temperature (GST) were then calculated here as the two main influencing climatic factors since they had a strong relationship with GSN. Based on DEM data (derived from United states geological Survey), these data were interpolated to continuous surface data with an 8 km spatial resolution to match NDVI dataset using thin-plate-smoothing spline-fitting techniques (Hutchinson, 1995) in ANUSPLIN 4.4 (http://fennerschool.anu.edu.au/research/products/