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Increasing global vegetation browning hidden in overall vegetation greening: Insights from time-varying trends

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ABSTRACT

Global vegetation dynamics are of critical importance for understanding changes in ecosystem structure and functioning and their responses to different natural and anthropogenic drivers. Under the background of rapid global warming, it is still unclear whether there were significant changes in the extent and intensity of global vegetation browning during the past three decades. Taking satellite-derived normalized difference vegetation index (NDVI) as the proxy of vegetation growth, we investigated spatiotemporal variances in global vegetation trends during the period 1982–2013 using the ensemble empirical mode decomposition (EEMD) method and two piecewise linear regression models. Our study suggests that increasing global vegetation browning is masked by overall vegetation greening. A > 60% increase in browning area was found during the study period, and the results consistently indicate that the expansion of browning trends has accelerated since 1994. After the late 1990s, browning trends increased in all latitudinal bands in the Northern Hemisphere. This increase was particularly pronounced in the northern mid-low latitudes, where the greening trends stalled or even reversed. Areas with browning trends increased in all land cover types, although the increase processes varied substantially. During 1982–2013, although most vegetated lands exhibited overall greening trends, greening-to-browning reversals occurred on all continents and occupied a much larger area than browning-to-greening reversals. Greening trends prevailed before the turning points, and browning trends largely expanded and enhanced thereafter. The increased browning trends resulted in a slowdown of the increase in global mean NDVI since the early 1990s. Since drought is likely the main cause of the increasing browning trends, global vegetation growth is at risk of reversal from long-term greening to long-term browning in the warmer future.

1. Introduction

Vegetation is a fundamental component of the terrestrial ecosystem that contributes to ecosystem services by regulating the water, carbon and energy cycles (Ballantyne et al., 2017; Feng et al., 2016; Forzieri et al., 2017). In the context of rapid environmental change, vegetation dynamics have received increasing research interest (Fensholt et al., 2012; Myneni et al., 1997; Zhu et al., 2016). Satellite remote sensing provides temporally continuous and spatially explicit observations of the status of terrestrial ecosystems through measures of vegetation indices (VIs). Normalized difference vegetation index (NDVI), defined as the normalized difference of red and near-infrared reflectance (i.e., $(\rho NIR - \rho RED)/(\rho NIR + \rho RED)$, Tucker, 1979), is the most commonly used VI. As vegetation photosynthetic capacity increases, more visible red light is absorbed due to the increased chlorophyll content of leaves and stems, and more near-infrared light is scattered because of the alignment of cell walls. This relationship makes NDVI a good proxy of photosynthetic capability; therefore, NDVI is considered an efficient indicator of vegetation growth status (Tucker and Sellers, 1986). An increase in NDVI (i.e., greening) usually indicates enhanced vegetation growth, and a decrease in NDVI (i.e., browning) usually indicates reduced vegetation growth. Data from the Advanced Very HighResolution Radiometer (AVHRR) cover the period from 1981 to present and provide the only long-term updated global dataset of vegetation greenness (Pinzon and Tucker, 2014). The available archives of more than thirty years of remotely sensed optical observations provide a large amount of

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spatiotemporal data, which show changes in vegetation growth under the variable climate as per-pixel NDVI trajectories.

Satellite observations have indicated that increases in vegetation growth have occurred since the early 1980s; these increases are mainly attributed to the ease of climatic constraints (Fensholt et al., 2012; Nemani et al., 2003; Zhou et al., 2001) and the fertilization effect of elevated CO_2 concentrations (Los, 2013; Piao et al., 2006; Zhu et al., 2016), and they have occurred in a number of regions, including northern extratropical latitudes (Mao et al., 2016; Slayback et al., 2003), India (Wang et al., 2017), Sahel (Dardel et al., 2014), part of Australia (Donohue et al., 2009) and Amazonia (Nemani et al., 2003). In addition, evidences from vegetation inventories (Ciais et al., 2008; Goodale et al., 2002) and ecosystem models (Cheng et al., 2017; Forkel et al., 2016) have also confirmed the increases in vegetation growth. On the other hand, studies have also suggested decreased vegetation growth in many regions, such as northern Eurasia (Piao et al., 2011), the southwestern United States (Zhang et al., 2010), boreal forests in North America (Beck and Goetz, 2011), Inner Asia (Mohammat et al., 2013), and the Congo Basin (Zhou et al., 2014). Intensified drought stress (Zhang et al., 2010; Zhou et al., 2014) and the resulting fire disturbances (Goetz et al., 2005) are considered the main causes of the browning trends. In addition to the diverse natural drivers (Buitenwerf et al., 2015; Gonsamo et al., 2016; Kong et al., 2017), anthropogenic factors such as land abandonment (Horion et al., 2016) and agriculture expansion (Viglizzo et al., 2011) are also identified as causes of the alternations between greening and browning trends. Although there is debate regarding whether global terrestrial net primary productivity and greenness declined in the first decade of the 21st century (Medlyn, 2011; Samanta et al., 2011; Zhang et al., 2017; Zhao and Running, 2010, 2011), large-scale vegetation browning at the regional scale indicates that the vegetation trend in many regions may have reversed from long-term greening. Under the background of continuous global warming and CO_2 enrichment, changes in vegetation growth trends may imply altered climatic mechanisms impacting terrestrial ecosystems.

Correctly characterizing vegetation trends and the inherent shifts are the foundation for understanding the altered climatic impacts on terrestrial ecosystems. Nevertheless, most analyses of vegetation index time series consider only monotonic trends under the assumption that the vegetation trend preserves its change rate throughout the study period. In the context of widespread antecedent greening, potential later browning is at risk of being fully masked when a simple linear model is used to characterize the vegetation trend. Accounting for the nonlinearity of vegetation trends, methods including piecewise linear regression models (Wang et al., 2011), BFAST (breaks for additive seasonal and trend) analysis (Verbesselt et al., 2010), DBEST (detecting breakpoints and estimating segments in trend) analysis (Jamali et al., 2015) and trend estimations on deseasonalized time series (Forkel et al., 2013) have been proposed to gain further insight into vegetation changes. However, these methods are sensitive to short-term fluctuations and abrupt changes (Tian et al., 2015). This characteristic reduces their ability to identify trend changes and turning points in long NDVI time series, which are usually noisy and may contain spurious short-period trends induced by inadequate orbital drift correction and among-instrument calibration. It should be noted that all of these methods have an implicit assumption that the change rate varies abruptly at the turning point. This is the case for several structural changes in ecosystems, such as vegetation changes before and after disturbances (Verbesselt et al., 2010). Nevertheless, in most circumstances, this assumption may be not suitable for changes in long-term vegetation trends because slowly acting climate change and land degradation are more likely to cause gradual changes in vegetation growth (de Jong et al., 2012). One option for identifying gradual and nonlinear changes in a time series is the use of a cubic polynomial fitting model in which abrupt variations in the change rate do not exist (Jamali et al., 2014). However, a cubic polynomial still contains an oscillatory component, which is different from the traditional definition of a long-term trend. On the other hand, a cubic polynomial must select several a priori determined functional forms, and there is no foundation to support the contention that a complex NDVI time series should follow the selected simplistic functional forms (Wu et al., 2007).

Ensemble empirical mode decomposition (EEMD) is an adaptive time-frequency analysis method suitable for complex time series (Wu and Huang, 2009). EEMD iteratively extracts the intrinsic time scales of the secular trends from the series, yielding a finite set of components with decreasing frequencies and a residual trend component. This procedure is clearly different from that of curve fitting methods, in which the functional forms are determined a priori. The extracted secular trend, either monotonic or containing only one extremum, does not follow a predetermined functional form, varies with time and does not exhibit an abrupt variation in the change rate. More importantly, this secular trend is not sensitive to the extension of the time series (Ji et al., 2014), ensuring that the physical interpretations from a specific temporal domain will not change significantly when the time series is lengthened. These intriguing properties enable EEMD secular trends to robustly reveal more underlying physical information on the nonlinear and nonstationary NDVI time series. The effectiveness of EEMD in analysing the interannual dynamics and secular trends in vegetation growth has been demonstrated (Guan, 2014; Hawinkel et al., 2015; Yin et al., 2017).

Previous studies paid much attention to the spatial distribution of long-term greening and browning trends; however, little is known about the temporal variations in these trends. Using EEMD and two piecewise linear regression models, our study provides the first comprehensive analysis of the spatiotemporal evolution process of global vegetation trends during the past three decades. The key questions addressed in this work are 1) How much has the area of browning trends expanded globally? and 2) Where and when have trend reversals occurred?

2. Data and methods

2.1. Data

In this study, we used the third generation NDVI datasets from the Global Inventory Modeling and Mapping Studies (both GIMMS NDVI3g V0 and V1), which are produced semimonthly at a spatial resolution of 1/12°. These datasets are derived from NOAA AVHRR instruments and span from July 1981 to December 2013. Multiple measures have been taken during preprocessing to minimize the errors arising from among-instrument calibration, volcanic eruptions, orbital drift, and atmospheric conditions (Pinzon and Tucker, 2014). GIMMS NDVI3g has the best temporal consistency among existing long-term NDVI datasets (Marshall et al., 2016; Tian et al., 2015) and has been widely used in dynamic vegetation monitoring at regional and global scales (Buitenwerf et al., 2015; Garonna et al., 2016; Kim et al., 2017; Liu et al., 2015; Wang et al., 2017). In this study, monthly NDVI data were generated by the maximum value composite (MVC) method to further reduce the effects of cloud and haze contamination (Holben, 1986). All figures and statistics in the main text are based on GIMMS NDVI3g V0. Grids with an annual mean NDVI < 0.1 were thought to be non-vegetated regions and were masked (de Jong et al., 2013a; Jamali et al., 2014). We did not take a higher threshold because a higher threshold might exclude several Arctic regions and arid zones with sparse vegetation cover (Anyamba and Tucker, 2005; Raynolds et al., 2006). Water bodies, bare land and snow/ice were also removed according to land cover maps. To minimize the errors caused by seasonal snow cover and large solar zenith angles, our analysis used the monthly average of the ‘growing season’ data. For each grid, the ‘growing season’ was defined as the months with a mean surface air temperature ≥ 0 °C according to the climatology during 1982–2013. This definition of the growing season has been widely used in previous global studies (Mao et al.,