Int J Appl Earth Obs Geoinformation 69 (2018) 56–63

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

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

Global linkages between teleconnection patterns and the terrestrial biosphere

Kyla M. Dahlin[a,*], Toby R. Ault[b]

[a] Michigan State University, Department of Geography, Environment, & Spatial Sciences and Program in Ecology, Evolutionary Biology, & Behavior, United States
[b] Cornell University, Department of Earth and Atmospheric Sciences, United States

ARTICLE INFO

Keywords:
Biosphere-atmosphere interactions
Teleconnections
Leaf area index
Global ecology

ABSTRACT

Interannual variability in the global carbon cycle is largely due to variations in carbon uptake by terrestrial ecosystems, yet linkages between climate variability and variability in the terrestrial carbon cycle are not well understood at the global scale. Using a 30-year satellite record of semi-monthly leaf area index (LAI), we show that four modes of climate variability − El Niño/Southern Oscillation, the North Atlantic Oscillation, the Atlantic Meridional Mode, and the Indian Ocean Dipole Mode − strongly impact interannual vegetation growth patterns, with 68% of the land surface impacted by at least one of these teleconnection patterns, yet the spatial distribution of these impacts is heterogeneous. Considering the patterns' impacts by biome, none has an exclusively positive or negative relationship with LAI. Our findings imply that future changes in the frequency and/or magnitude of teleconnection patterns will lead to diverse changes to the terrestrial biosphere and the global carbon cycle.

1. Introduction

Climate fluctuations affect the terrestrial biosphere across seasonal to multi-decadal timescales (Stenseth et al., 2003), while vegetation on the land surface helps regulate the flow of energy, carbon, and water through the climate system. This biosphere-atmosphere coupling will influence the rate of increases in greenhouse gas concentration in the atmosphere, the pace of climate change, the magnitude and scope of biodiversity loss, and the interconnection between food, water, and energy that is the basis of food security this century (Bonan, 2008; Ogutu and Owen-Smith, 2003). However, the sign and magnitude of atmospheric effects on land surface vegetation remains poorly constrained, partly because biosphere-atmosphere coupling depends strongly on season, biome, and timescale, and biosphere-atmosphere feedbacks can have downstream effects on ecological communities (e.g. Charrette et al., 2006; Maza-Villalobos et al., 2013; Ogutu and Owen-Smith, 2003). Further uncertainty arises from a mismatch of spatial and temporal scales at which meteorological and ecological data are collected. Climate datasets typically span several decades with near global coverage at 10–100 km spatial resolution (Phillips et al., 2014), while long-term ecological monitoring studies often focus on finer spatial grain sizes and smaller spatial extents. Remotely sensed data can be used to bridge these scale gaps because they span more than three decades (AVHRR/MODIS/VIIRS, LandSat), and they are produced at spatial resolutions that fall between meteorological and in-situ ecological monitoring scales. Such products permit us to analyze how variations driven by large-scale climate phenomena affect global vegetation activity via large scale climate fluctuation patterns like hemispheric and global teleconnections.

Teleconnections patterns are persistent atmospheric circulation patterns that span large distances. They are defined statistically (Barnston and Livezey, 1987) and can be used to characterize changes in local and regional "packages of weather" (Stenseth et al., 2003) associated with different states of climate modes. Two well known teleconnection patterns are El Niño-Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO). Connecting vegetation responses to teleconnections patterns is challenging because ecosystems may react to different meteorological variables, like temperature or precipitation, across multiple time lags (McPhaden et al., 2006). For example, a positive wintertime NAO is correlated with earlier, higher than average springtime vegetation growth in Europe (Li et al., 2016). Despite these obstacles, weather events associated with ENSO and the NAO have been tied to changes in ungulate populations in South Africa (Ogutu and Owen-Smith, 2003), butterflies in Borneo (Charrette et al., 2006), forest succession in Mexico (Maza-Villalobos et al., 2013), and more (Stenseth et al., 2003). While many of the studies focused on connections between teleconnection patterns and the biosphere have focused on ENSO, recently some studies have expanded to include other indices at global

* Corresponding author.
E-mail address: kdahlin@msu.edu (K.M. Dahlin).

https://doi.org/10.1016/j.jag.2018.02.017
Received 6 October 2017; Received in revised form 20 February 2018; Accepted 26 February 2018
0303-2434/

scales. For example, Zhu et al., (2017) compared fifteen teleconnection patterns to the output from nine dynamic global vegetation models with standardized forcings. They found that the teleconnections were strongly connected to modelled gross primary productivity (GPP), with most areas strongly linked to ENSO, the Atlantic Meridional Mode, and the Pacific Decadal Oscillation. Gonsamo et al. (2016) compared the 30 year NDVI record (NDVI3 g; Pinzon and Tucker, 2014) to eight teleconnection indices. These authors also compared their set of teleconnection indices to net primary productivity from a coupled Earth system model and found that the model was unable to capture the spatial patterns observed in the data.

Instead of testing a large number of possibly cross-correlated teleconnection patterns (Quadrelli and Wallace, 2004), here we elected to document the impacts of two well-studied global teleconnections patterns—ENSO and NAO − and two infrequently considered climate modes − the Indian Ocean Dipole Mode (IODM) and the Atlantic Meridional Mode (AMM). We compare these four teleconnection patterns to land surface vegetation over a time span of 30 years, using the AVHRR-derived Leaf Area Index (LAI3 g) data set (Zhu et al., 2013). The temporal span of this product allows us to consider global connections between the land surface and the climate system that are not possible with shorter time series or locally focused analyses. These four teleconnection patterns represent spatially distinct climatological patterns from around the globe.

ENSO, perhaps the most well-known climatological pattern to ecologists and natural resource managers, is defined by changes in sea surface temperatures (SSTs) in the tropical Pacific, known as El Niño, which is linked to fluctuations in the distribution of atmospheric mass (called the Southern Oscillation; hence the term “El Niño/Southern Oscillation” or ENSO). These variations in the coupled ocean-atmosphere system set up “ripples” in the troposphere, which in turn affect global circulation patterns downstream. ENSO is associated with drought conditions in areas that are usually wet (i.e. Indonesia, southern Africa, India) and heavy rains in dry regions like the equatorial central Pacific, California, and the U.S. Gulf Coast (Rasmusson and Wallace, 1983). Here we describe ENSO using the Oceanic Niño Index (ONI) for December-January-February (DJF) which is a 3-month mean of sea surface temperature (SST) anomalies in the equatorial Pacific (Niño 3.4 region: 5°N–5°S, 120°–170°W (Huang et al., 2015)). Further increases in greenhouse gas concentrations are expected to lead to changes in the mean state of the Pacific Ocean and therefore possibly lead to more strong El Niño and La Niña years with fewer mild years (Cai et al., 2015).

The NAO is a measure of the difference in atmospheric conditions between the subtropical Atlantic and the Arctic (Stenseth et al., 2003). During its positive phase it has been associated with above average temperatures in the Eastern U.S. and northern Europe and below average temperatures in southern Europe and the Middle East and the reverse in the negative phase. Positive phases of the NAO are also associated with higher precipitation in northern Europe, lower precipitation in southern Europe. Similar to ENSO, a wide range of ecological impacts have been attributed to the NAO (de Beurs and Henebry, 2010, 2008; Vicente-Serrano and Trigo, 2011). Feedbacks between the NAO and future climate projections are complex, however, it is possible that a weakening of the NAO could lead to reduced losses of sea ice and fewer tropical storms (Delworth et al., 2016).

The AMM is a measure of SST anomalies in the tropical Atlantic Ocean where SSTs are warmer than usual in the tropical North Atlantic and cooler than usual in the tropical South Atlantic (Nobre and Shukla, 1996). This change in SSTs in turn impacts the location of the Intertropical Convergence Zone (ITCZ) and can change the timing and magnitude of precipitation events throughout the tropics, particularly in northeastern Brazil and the Sahel (Foltz et al., 2012). Because changes in the AMM influence wind patterns, strong AMM events are also associated with increased hurricane activity (Vimont and Kossin, 2007). Few studies have been done of the direct impacts of the AMM on the terrestrial biosphere, however, recent work has suggested that the AMM may play a role in tropical forest dynamics through a combination of hurricane and drought impacts (Chen et al., 2015).

The IODM (Saji et al., 1999) is a pattern of variability originating in the Indian Ocean, with cool SSTs near Sumatra linked to warm SSTs near East Africa. While somewhat correlated with ENSO (Saji and Yamagata, 2003), the impacts of the IODM appear to be much more focused on the countries surrounding the Indian Ocean − anomalously strong rainfall events in East Africa, central India, and Central/Eastern China are all much more closely tied to the IODM than to ENSO (Marchant et al., 2006; Pervez and Henebry, 2015). Importantly, future predictions for the IODM suggest that while its frequency is unlikely to change, the intensity of events will probably increase in coming decades under the influence of climate change (Cai et al., 2013).

Since these teleconnection patterns can often generate conflicting conditions for optimal plant growth (e.g., cooler temperatures and more rainfall), their expected impact on the biosphere is unclear. Each teleconnection is characterized by both a time series “index” of its amplitude through time, as well as a spatial map of its expression in various meteorological fields used to define it. Here we focus on the temporal indices of each pattern to isolate their influence on the terrestrial biosphere through time, across space, and within the annual cycle.

This paper addresses three questions related to the interactions between teleconnection patterns and the terrestrial biosphere: 1) What fraction of global interannual variation in LAI can be linked to two common and two less well studied teleconnection patterns? 2) How do the spatial patterns of impact vary among the different teleconnections? 3) How can we map these connections while taking account for temporal autocorrelation in the data in a simple and consistent manner?

2. Materials and methods

To assess linkages between the four teleconnection indices and local vegetation, we calculated correlations between each index averaged for December, January, and February (DJF) of a given year and LAI3 g minimum, mean, and maximum values for the subsequent three-month intervals (JFM, FMA, through DJ_2F_2 with J_2F_2 being from the following year). All analyses were performed at 0.25° resolution. We used a Monte Carlo approach to eliminate small patches of possibly spurious correlations, likely to be due to temporal autocorrelation. Finally, we aggregated the global correlation fields (36 per teleconnection pattern) to produce single maps of the strongest overall correlations and their seasonality.

Correlation Analysis. The central goal of this paper was to map the correlations between teleconnection pattern indices and variations in the land surface in a way that is permissive enough to capture small but significant relationships, but simple enough to be generalized and interpreted. All analyses were performed in R (RCoreTeam, 2015) using the raster (Hijmans and van Etten, 2013), rgdal (Bivand et al., 2013), and ncdf4 (Pierce, 2015) packages. All maps were made in ArcGIS 10.2.2. Fig. S1 shows a schematic of the analysis process.

In order to have a long enough time series to perform robust correlations, we used the AVHRR derived leaf area index data set (LAI3 g (Zhu et al., 2013)), which is a global data set of LAI for the complete years of 1982–2011 twice per month at twelfth-degree scale. To simplify data processing and to average over small scale changes in local vegetation, these data were rescaled (averaged) to quarter degree resolution. If a 0.25° grid cell had less than 60% coverage it was removed from further analysis, thus many coastal areas were excluded from analysis. Teleconnection pattern indices were obtained from the U.S. National Oceanic and Atmospheric Administration (NOAA, 2017, 2015a, 2015b, 2015c). To simplify comparisons, we selected the three month December-January-February period (‘DJF’; averaged) of each index to compare to subsequent months’ LAI values. DJF was selected for these indices as it is the 3-month period in the first half of the year with the highest interannual standard deviation in all four indices. Fig.