Inter-seasonal Non-uniform Time-lag Responses of Terrestrial Vegetation to Asymmetric Warming: Auto-blocking and Parallel Processing Mechanism (ABPP)

You-yue WEN, Jian YANG* and Kui LING
South China Institute of Environmental Science, Ministry of Environmental Protection, No. 18 Ruihe RD., Guangzhou 510535, P.R. China
*Corresponding author

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Abstract. In this study, an auto-blocking and parallel processing mechanism (ABPP) was raised to deal with long-term, high spatio-temporal resolution materials at macro scale. ABPP was then used to quantify the inter-seasonal non-uniform time-lag responses of terrestrial vegetation to asymmetric warming at globe from 1982-2014, a phenomenon poorly studied by predecessors. Results showed that ABPP enabled heavy burden works to be done successfully and the time was cut from 51 hours and 56 minutes to 12 hours and 57 minutes. Using ABPP, we showed that warming in nighttime (NW) and daytime warming (DW) have significant time-lag effects on vegetation growth that exhibit spatial heterogeneities; the time-lag effects of DW vs. NW on vegetation growth are not equally distributed across space. This study proposed a new approach in eco-environmental research field and could expand our knowledge of the responses of terrestrial vegetation to asymmetric warming.

Introduction
Disentangling the true relationships between terrestrial ecosystems and external factors is a burden but meaningful work, which generally involves dealing with a mass of data and results in long-time consume and heavy resource intensity. As a consequence, many researchers choose settle for second best: reducing the spatio-temporal resolution of input data, cutting the study time span, confining the research region or choosing less relevant parameters (Anderegg et al., 2015) (Wan et al., 2009) (Wang et al., 2017) (Piao et al., 2015). While such opportunistic practice may fade the authenticity of these studies in revealing the true relationships of terrestrial ecosystems variations and affecting factors of real world greatly. Therefore, it’s of great importance and urgency to find out an approach so as to enable this work being executed more swimmingly.

Climate warming exhibits asymmetric patterns over a diel cycle, with the trend of nighttime warming (NW) exceeds that of daytime warming (DW) (IPCC, 2014; Zhou et al., 2009), which is expected to significantly affect terrestrial vegetation growth (Peng et al., 2013). To date, many studies have documented the complex asymmetric interactions of DW and/or NW on terrestrial vegetation growth (Peng et al., 2013; Su et al., 2015; Tan et al., 2014; Xia et al., 2014) (Anderegg et al., 2015) (Wan et al., 2009) (Wang et al., 2017) (Piao et al., 2015), but they primarily focused on the simultaneous interactions with the time-lag effects of DW and/or NW on vegetation growth being ignored. The time-lag effects have a great significance on plant growth and terrestrial ecosystem balance (Sherry et al 2008; Vicente-Serrano et al 2013; Wiegand et al 2004). Besides, ascertaining the time-lag effects of ambient temperatures on vegetation growth and understanding their mechanisms is important for environment management (Braswell et al 1997; Mulder et al 2016; Sherry et al 2008; Zhang et al 2015), as we can take full measures, in advance, to respond to the anomalous temperature behavior so as to minimize possible accompanying losses. Therefore, under the background of increasing asymmetric warming (IPCC, 2014; Zhou et al., 2009), it’s of great importance and urgency
to assess the time-lag effects of DW and NW on terrestrial vegetation growth, and knowledge of time lags allows us to better understand the interactions between climate warming and vegetation growth.

However, accessing the time-lag effects of asymmetric warming on vegetation growth at global scale requires preparation of long-term vegetation data and relevant climatic materials (i.e., time-series data of average air temperature, maximum air temperature, minimum air temperature, precipitation and solar radiation) (Peng et al., 2013), which tends to make this seemingly simple work not that easy. Therefore, a short-time-cost and low-resource-requiring method was appealed in quantifying the time-lag impacts of asymmetric warming on vegetation growth and further disclosing the mechanisms underlying this phenomenon.

In this study, to reduce the time cost and resource requirement, we first designed an auto-blocking and parallel processing mechanism (ABPP). We used the monthly normalized difference vegetation index (NDVI) to represent the variations in vegetation growth and the monthly maximum air temperature (Tmax) and minimum air temperature (Tmin) to represent the condition of DW and NW. Partial correlation and time-lag analyses were applied to compute the time-lag effects with the help of ABPP.

Methods and Materials

Methods

The Auto-blocking and Parallel Processing Mechanism. Given the large data and heavy storage requirement, we designed ABPP to automatically detected the memory errors, and the data in each block was intelligently allocated to one unoccupied parallel pool. ABPP was applied to drive the statistical methods used to calculate the lagged time of asymmetric warming exhibiting on vegetation growth.

Partial Correlation and Time-lag Analyses. Partial correlation is a statistical measure of the direction and strength of a linear relationship between an independent variable and a dependent one (X, Y), while eliminating the disturbed impacts from one or more covariates (Z = [Z₁, Z₂, ..., Zₙ]). Here, we applied partial correlation analyses to acquire the correlations between NDVI and Tmax (or Tmin) (Peng S. et al 2013) as in Eq. (1).

\[
R_{X,Y|Z} = \frac{R_{XY} - R_{XZ} \cdot R_{YZ}}{\sqrt{(1-R_{XZ}^2)} \cdot (1-R_{YZ}^2)}
\]  

(1)
where X, Y and Z refer to NDVI, Tmax (or Tmin) and [Tmin, PRCP, SR] (or [Tmax, PRCP, SR]); the $R_{X,Y|Z}$ represents the PR between X and Y while controlling for the covariates $(Z = [Z_1, Z_2, ..., Z_n])$; and the $R_{XY}$, $R_{YZ}$ and $R_{XZ}$ are the regular correlation coefficients among X, Y and Z.

We performed time-lag effects analyses to obtain the hysteretic impacts of DW and/or NW on NDVI. We firstly assumed that certain lagged intervals ($0 \leq k \leq 3$ months) are exhibited in the effects of DW and/or NW on vegetation changes (Wu et al 2015); then, at each supposed time lag, we obtained the accompanying PR ($PR_0, PR_1, PR_2$ and $PR_3$) between Tmax/Tmin and NDVI; finally, the PR ($PR_k$, $0 \leq k \leq 3$) when it reached its maximum determination coefficient ($PR_k^2$), was taken as the optimal PR (OPR, Eq. (2)) between Tmax/Tmin and NDVI, and the $k$ was considered to be the optimal time lag (OTL, Eq. (3)) for NDVI responses to Tmax/Tmin.

$$\text{OPR} = PR_k, \text{when } PR_k^2 = \text{Maximum}\{PR_0^2, PR_1^2, PR_2^2, PR_3^2\} \quad (0 \leq k \leq i \leq 3) \quad (2)$$

$$\text{OTL} = k, \text{when } PR_k^2 = \text{Maximum}\{PR_0^2, PR_1^2, PR_2^2, PR_3^2\} \quad (0 \leq k \leq i \leq 3) \quad (3)$$

Materials
The 3rd generation NDVI, version of the 1st (NDVI.3g.v1), from Jan. 1982 to Dec. 2014 was used in the present study. NDVI.3g.v1 was produced by the Global Inventory Monitoring and Modeling Studies (GIMMS) program and provided with following attributes: a spatial resolution of 1/12 deg. and a 15-day interval (Tucker et al 2005). The maximum value composite (MVC) method was applied on the original NDVI time series to construct monthly NDVI datasets.

Five climatic datasets including the monthly average temperature (Tavg), Tmax, Tmin, total precipitation (PRCP) and total downward shortwave solar radiation data (SW) from Jan. 1982 to Dec. 2014 were used. All of them possess the attributes of monthly temporal resolution and 0.5° spatial resolution and were resampled into 1/12 deg. to keep the spatial resolution consistency with NDVI. The Tavg, Tmax, Tmin and PRCP were provided by the Climatic Research Unit (CRU, TS3.24) (Harris et al 2014). The SW was originated from Princeton Global Forcings, version 2 (PGF.v2) (Sheffield et al 2006).

Results

Time Reduced by Auto-Blocking and Parallel Processing Mechanism
Six parameters were used in this study, and each parameter spanned from Jan. 1982 to Dec. 2014 at a month scale. Therefore, there were 2376 gridded files covering the global land, and the total memory requirement was 68.91G. By using ABPP, the total time spent on obtaining the time lags was cut from 51 hours and 56 minutes to 12 hours and 57 minutes.

Time Lags of NDVI Responses to Asymmetric Warming
Overall, the average lagged time of the NDVI responses to Tmin ($1.68 \pm 1.05$ months) were near 0.23 months longer than the responses to Tmax ($1.45 \pm 0.96$ months). According to Fig. 2 a-b, the inter-seasonal NDVI variations have short time-lag responses to both Tmax and Tmin over the mid-high northern latitudes (> 45°N); in contrast, the NDVI in semi-arid and arid regions, such as the deserts in Australia and the Deccan Plateau, responds to asymmetric warming with a distinctly long protracted duration. Fig. 2 d-e demonstrates that only small proportions of the global land area show no time lag in the responses of NDVI to Tmax (16.44%) and Tmin (17.04%); furthermore, the pixels that are covered by a 3-month protracted duration account for a larger percentage in the NDVI responses to Tmin (27.14%) than to Tmax (17.56%). According to Fig. 2c and f, the regions with longer lagged time in NDVI responses to Tmax than to Tmin account for up to 31.00% of the total areas, which is approximately 18.57% larger than the reverse situation; these results suggest that there
are a considerable amount of vegetation pixels (43.44%) that are characterized by unequal lagged time in NDVI responses to Tmax vs. Tmin.

Figure 2. Spatial distributions of lagged time of NDVI responses to a) Tmax and b) Tmin and c) the OTL difference of the results in a) to those in b) from 1982 to 2014. The inset bar charts of d)-f) show the frequency distributions of the grids with different lagged values in corresponding maps. The negative values in c) represent the NDVI response to Tmax that exhibits shorter time lags than to Tmin, whereas the positive values denote the NDVI response to Tmax that exhibits longer time lag than to Tmin, and the zeros represent the NDVI response to Tmax and Tmin with equal lag time. White areas represent places with no data or with no significant correlations (p > 0.5).
Summary

In summary, we investigated the non-uniform, inter-seasonal time-lag effects of terrestrial vegetation responses to asymmetrical warming from 1982 to 2014 with the help of ABPP. It highly encourages ecologists to use the ABPP when dealing with large amount of data. We showed that the inter-seasonal growth of terrestrial vegetation responds to DW and NW with an overall average time lag of 1.68 ± 1.05 months and 1.45 ± 0.96 months, respectively; these time lags are distributed heterogeneously across space, with smaller values distributing over temperature-limited regions and greater values over other places, particularly the arid regions; considerable amounts (43.44%) of vegetation pixels have unequal time lags in responding to DW than to NW; the average time lags for different vegetation types mostly range between ~1-2 months, with longer lagged time resulted from NW than from DW.

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