Water availability surpasses warmth in controlling global vegetation trends in recent decade: revealed by satellite time series

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Keywords: terrestrial vegetation trends, time-varying trend, NDVI, climatic drivers, climate change

Supplementary material for this article is available online

Abstract

A better understanding of the dominant climatic drivers that control vegetation trends across regions and biomes is essential for assessing ecosystem dynamics and land-climate interactions in a warming world. Temperature (TMP) has long been considered as dominant control in global vegetation trends, and growing evidence suggests that water availability plays an increasingly important role in determining trends in vegetation growth over many biomes. However, a detailed spatial-temporal evolution of the vegetation trends and the climatic drivers that effect vegetation trends are not well known. In this study, using a time-varying trend (extracted by the ensemble empirical mode decomposition) of climate and satellite-derived normalized difference vegetation index (as a proxy for vegetation productivity) from 1981 to 2015, we find that the trends in vegetation greening and terrestrial carbon uptake reversed, beginning in the early 2000s, largely driven by the recent drying trend. The relative importance of climatic controls on vegetation productivity trend is estimated using a principal component analysis procedure, and the results demonstrate a global shift in the dominant driver of vegetation trends from TMP to precipitation, and point to intensified water limitation to vegetation growth as warming continues. The findings provide empirical evidence of the spatial-temporal evolution of different climatic drivers behind trends in vegetation productivity.

1. Introduction

Vegetation greening plays a key role in mitigating anthropogenic climate warming by slowing down the accumulation of atmospheric carbon dioxide (CO₂) through an increased land carbon sink (Beer et al 2010, Ballantyne et al 2012). Satellite-derived vegetation indices enable quantification of global vegetation productivity changes (Piao et al 2019), and indicate heterogeneous regional trends with an overall greening trend (Myneni et al 1997, Zhou et al 2001, Jia et al 2003, Wang et al 2018) and an increased browning trend (slowdown or reversal of greening) in recent years (Zhou et al 2014, Brandt et al 2018, Pan et al 2018, Yuan et al 2019). However, a detailed spatial-temporal pattern of variation in vegetation trends and contributions of regional ecosystems to the global trend are not well known.

The trends in vegetation productivity are driven by climate, environmental, and land management factors (Piao et al 2019). The drivers of environment and land management are more straightforward, greening is often contributed by CO₂ fertilization and nitrogen deposition (Zhu et al 2016), intensified agricultural management and afforestation (Chen et al 2019). Whereas, deforestation and disturbances induce browning vegetation (Bi et al 2013, Tagesson et al 2020). However, vegetation responses to climate trends are complex and vary greatly in space and time (Nemani et al 2003, Ahlström et al 2015). Warming substantially increases vegetation growth by alleviating temperature (TMP) constraints, lengthening
the growth season, and enhancing photosynthesis in Tibetan Plateau, boreal, and Arctic regions (Myneni et al 1997, Lucht et al 2002, Xu et al 2013). However, the positive effect of warming on vegetation growth has weakened in recent years (Piao et al 2014, 2017). Warmer summers could decrease plant productivity in extratropics (Angert et al 2005). Alternatively, increasing solar radiation enhances vegetation growth in tropical forests (Nemani et al 2003) and a drying trend significantly decreases vegetation growth (Saatchi et al 2013, Zhou et al 2014). In water-limited ecosystems, changes in precipitation (PRE) dominates trends in vegetation, which shows wetting-driven greening and drying-driven browning (Poulter et al 2014, Ahlström et al 2015, Liu et al 2015, Brandt et al 2018).

The trend in the global climate has experienced noticeable transformations: warming hiatus (slow-down of warming rate) (Trenberth 2015), brightening and subsequent dimming (increase and decrease of surface incoming solar radiation) (Wild 2012), and alterations from wetting to drying in recent years (Trenberth et al 2013). A key question is how the climatic drivers that effect trends in vegetation productivity have evolved over time. Although many trend analyses in the literature have been based on linear fittings, recent works have highlighted that trends in climate and vegetation are nonlinear and are spatially and temporally heterogeneous (Jong et al 2012, Ji et al 2014, Huang et al 2018, Pan et al 2018, Myers-Smith et al 2020). Therefore, this study uses a time-varying trend extracted by the ensemble empirical mode decomposition (EEMD) method to diagnose the spatial-temporal evolution of the climatic drivers and their effects on vegetation trends (Wu and Huang 2009).

This study presents an approach to identify how the climatic drivers effect trends in vegetation productivity and how this has evolved in space and time from 1981 to 2015. We first extract the time-varying trend of climate (TMP, PRE, and radiation), satellite-derived vegetation greenness, atmospheric CO₂ growth rate, and global land carbon sink using the EEMD. We further partition the contributions of regional trends to the global vegetation trends. Finally, we assess the detailed spatial-temporal evolution of the climatic drivers on the decadals trends in vegetation productivity using a principal component analysis (PCA) procedure.

2. Data and methods

2.1. Land cover data
The Terra and Aqua combined moderate resolution imaging spectroradiometer land cover climate modelling grid Version 6 (MCD12C1 v006) data provides International Geosphere Biosphere Programme land cover types (0.05° × 0.05°; https://lpdaac.usgs.gov/) (Friedl et al 2010), and data in 2001 (the approximate middle year of the study) was used to define global biomes (see details in figure S1 (available online at stacks.iop.org/ERL/16/074028/mmedia)). The satellite derived global vegetation continuous fields dataset, consisting of percentages of tree canopy cover, short vegetation cover and bare ground cover, was employed to detect the land-use and land cover changes (Song et al 2018).

2.2. Climate data
Gridded land surface monthly climate datasets were used, including the Climate Research Unit dataset (CRU TS4.03, gridding from ground observations (0.5° × 0.5°); http://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.03) (Harris et al 2014) mean air TMP and PRE total, and mean radiation (SSRDs, surface solar radiation downwards) of ERA5 reanalysis (0.25° × 0.25°) (https://cds.climate.copernicus.eu/cdsapp#!/dataset/10.24381/cds.f17050d7?tab=form) (Hersbach et al 2019). The SSRD values were neighboringly averaged from 0.25° to 0.5°. The monthly climatology and anomalies of all three climate variables were further calculated from July 1981 to December 2015.

2.3. Satellite normalized difference vegetation index (NDVI) measurements
NDVI is a remotely sensed vegetation index widely used as an indicator of vegetation productivity (Myneni et al 1997, Nemani et al 2003, Piao et al 2014). The Global Inventory Monitoring and Modelling System NDVI third generation (GIMMS NDVI₃g) dataset derived from multiple advanced very high resolution radiometer (AVHRR) instruments was used (https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/) (Pinzon and Tucker 2014). The bimonthly NDVI₃g provides the longest consistent non-stationary AVHRR NDVI observations at spatial resolution of 8 km (0.083°) from July 1981 to December 2015. It is currently the most appropriate choice and the most widely used AVHRR NDVI dataset for long-term vegetation trend analysis (Tian et al 2015, Myers-Smith et al 2020).

The bimonthly NDVI₃g data with good quality (flag 0) were extracted to obtain monthly values using the maximum value composite approach, and the monthly values were further aggregated to 0.5°, the same as that of climate variables. Finally, the monthly climatology and anomalies of NDVI were calculated from July 1981 to December 2015 for both spatial resolutions of 0.083° and 0.5°, and pixels of no-data were further filled with the monthly climatology to ensure the continuity of NDVI anomalies time series.

2.4. Atmospheric CO₂ concentration and global land carbon sink
The measurements of monthly mean Mauna Loa atmospheric CO₂ concentration were used
The time-varying trend was extracted using the EEMD method, a noise-assisted, adaptive, and temporal local analysis method (Wu and Huang 2009). The noise amplitude of 0.2 standard deviation and ensemble number of 1000 were used as suggested. The EEMD approach was performed pixel by pixel for gridded climate (0.5° × 0.5°) and vegetation productivity anomalies (0.5° × 0.5° and 0.083° × 0.083°). The time-varying trend, which excludes the signal disturbances of short-term variability, facilitates a better understanding of the spatially and temporally non-uniform trend. In detail, time series of climate variables and vegetation productivity anomalies from 1981 to 2015 were decomposed into eight components (EEMD 1–8). The sum of last two components (EEMD 7 and EEMD 8; green line) represents the nonlinear and non-stationary trend, and the time-varying trend (blue line) was calculated as TrendEEMD = EEMD 7 + 8 (198107) (figure S2). Therefore, values of the time-varying trend start from zero and indicate the accumulated change since July 1981 (Ji et al 2014). Furthermore, in order to effectively eliminate the impact of increased CO2 emissions on the trend of the atmospheric CO2 growth rate, firstly the secular trend of the atmospheric CO2 growth rate from 1981 to 2015 and from 1959 to 2015 were extracted separately, then the time-varying trend of CO2 growth rate was calculated as the secular trend differences (in monthly time steps). The same processes were performed to eliminate the impact of accumulated CO2 concentration in atmosphere on the land carbon sink trend (in yearly time steps) (figure S3). Here, the time-varying trend at a given time indicates the relative alteration in trend over the 35 years (1981–2015) compared to the long-term baseline from 1959 to 2015.

The area-weighted time-varying trend was further calculated by multiplying trend value by its weighting factor, while weighting factor of the reference pixel located at the equator was defined as one, and weighting factors of other pixels were derived as their area percentage compared to the reference pixel. Contribution of a pixel to the global vegetation productivity trend was calculated using the method introduced by Ahlström et al (2015) based on times series of area-weighted time-varying trend. Pixels with high positive values control the global trend, in contrast pixels with negative values dampen the global trend.

### 2.6. Estimating climatic drivers on trend in vegetation productivity

The relative importance of climatic controls on vegetation productivity trend (climatic driver, characterized as climate weight) was estimated using a principal component regression (PCR) procedure to each valid pixel (48 456), modifying from method proposed by Seddon et al (2016). The time-varying trend time series were normalized to standardized anomalies (a) based on the monthly values (x), climatology means (m), and the standard deviations (s) of each variable respectively:

\[
a = \frac{x - m}{s}
\]

Then, in order to remove the co-linearity between TMP, radiation, and PRE, a PCA procedure was adopted. We further performed multiple linear regression analysis between vegetation productivity and principal components. Finally, for those principal components who had significant relationship with vegetation productivity (p < 0.05), we multiplied their regression coefficients and the PCA loading scores of each variable and summed these scores (hereafter, climate weights) (figure S4(a)).

We performed the PCR analysis with a moving time window of 10 year/decade trend in decadal timescale is most commonly quantified from satellite-derived vegetation analyses (Zhou et al 2014, Myers-Smith et al 2020), deriving 295 raster layers (0.5° × 0.5°) of climate weights for each climate variable. In order to make changes of climate weights comparable through time, data of each variable were standardized based on the mean and standard deviation of the whole time period, and the standardized anomalies were then used to perform the PCR procedure. All pixel values of climate weights (48456 × 295 × 3) were sorted into percentiles (0%–100%), and climate variables with higher absolute value play more important role in controlling trend of vegetation productivity (figure S4(b)).

### 2.7. Linear trend analysis and spatial median filter

Linear trends of vegetation productivity and land cover changes values were calculated by using the nonparametric Mann–Kendall test, which is robust in trend detection and insensitive to outliers (Song et al 2018, Chen et al 2019). A p-value of 0.05 was used to test the significance. In order to get a better visual clarity of the results in space, a median filter (5 × 5) was applied to eliminate the spatially sporadic noisy data in figures.
3. Results and discussion

3.1. Recent reversal of vegetation greening and carbon uptake

The time-varying trends with different ending time help to understand the development of the long-term trend of vegetation productivity, and help to compare to previous studies over different time period. Globally, the vegetation shows an overall long-term greening trend and an evident reversal circa 2000 regardless of changes in the ending time (figure 1(a)). Before 2000, the greening rate is almost homogeneous and constant for all trends derived from different ending times. Since 2000, the greening rate stalls or increases slightly with an ending time of 2011, coinciding with the previously reported long-term vegetation greening and the extraordinary terrestrial carbon sink (Poulter et al 2014, Ahlström et al 2015, Zhu et al 2016). However, the greening gradually reverses to a browning trend (less green than peak greening) when data in years of 2012–2015 is included (Pan et al 2018, Yuan et al 2019), and the browning trend obviously weakens the accumulated greening especially with ending time of 2014 and 2015. Meanwhile, the reversal of the greening trend is consistent with the recent strong drying trend (figure 1(b)).

Value of the time-varying trend of atmospheric CO\(_2\) growth rate is mainly negative (blue line in figure 1(a)), suggesting an increased land and ocean carbon sink in recent years (1981–2015) compared to the long-term baseline (1959–2015). The decrease of atmospheric CO\(_2\) growth rate before 2000 indicates gradually enhanced carbon sink, and the following increase after 2000 indicates progressive slowdown of the enhanced carbon sink (figure 1(a)); coinciding with reversal of land carbon sink and vegetation productivity from increase to decrease (wine and purple line in figure 1(a)). The logical inverse correspondences between trend of satellite-derived vegetation productivity/modeled land carbon sink and ground-observed CO\(_2\) growth rate, suggest a relapse in the long-term trend in the terrestrial carbon sink capacity, which may be driven by the recent drying trend. Heterogeneous changes of vegetation trends

3.2. Heterogeneous changes of vegetation trends

The time-varying trend enables interpretation of relative increases or decreases at any given time, facilitating detection of the spatial-temporal patterns of greening or browning, warming or cooling, brightening or dimming, and wetting or drying (figure 2). During the study period, vegetations are ever greener than the beginning over 87.8% of the land surface (figure 3), and most of the vegetated area shows greening trend in the end of the study period (figures 2(a) and S5). It shows a continuously increased trend in vegetation productivity over 12.5% of land surface, and grasslands (30.5%), croplands (19.1%), tundra (13%), and savannas (13%) dominate the monotonic greening (figure 3). Prior 2000, greening trends dominate the vegetation change; however, the overall greening is then gradually offset by the enhanced browning in magnitude and in area (figure 2(a)). Thus, the increased browning trend and greening heterogeneity has amplified in recent years (Pan et al 2018, Myers-Smith et al 2020).
Figure 2. Latitudinal patterns of zonally averaged time-varying trend for vegetation productivity (a), TMP (b), radiation (c), and PRE (d) anomalies. Statistics were calculated for every half degree by latitude.

Figure 3. Spatial patterns in trend type for vegetation productivity. The map is based on data (0.083° × 0.083°) with a median filter (5 × 5), and the statistics (percentage area of each type in the parenthesis) are based on the original data.
Arctic tundra gradually greens and reaches its peak after 2000 (figure 2(a)), associated with the continuous warming driven alleviation of TMP constraints (figure 2(b)), longer growing season, photosynthesis enhancement and shrubs expansion (Lucht et al 2002, Piao et al 2019, Wang et al 2020a). After the peak greening, despite the amplified warming driven by the strong positive ice-TMP feedbacks (Screen and Simmonds 2010); the greening reverses to browning around 2002 in the north and 2010 in the south, shifting concurrently with accelerated radiation dimming earlier in the north and later in the south (figure 2(c)), where radiation co-limits vegetation growth (Nemani et al 2003, Beer et al 2010). Over the study period, noticeable greening firstly take place in the croplands, grasslands, and boreal forests occupied middle latitudes of the Northern Hemisphere (45° N–60° N), and reach their peak circa 2000, much earlier compared to other regions (figure 2(a)). But the subsequent warming hiatus (figure 2(b)) and water deficit (figure 2(d)) gradually weakens the greening magnitude (Angert et al 2005, Piao et al 2011, Buermann et al 2014).

The strongest and long-lasting zonally averaged greening occurs in the region of 5° N–15° N, dominated by northern sub-Saharan Africa with homogeneous greening (figure 5), also known as the Sahel regreening. The unique greening is related to two aspects, the severe droughts of the 1970s and early 1980s causing a low baseline for vegetation productivity; and the apparent revival of PRE from later 1980s onward, pronouncedly boosting vegetation growth in this extremely thirsty water-limited ecosystem (figures 2(a) and (d)) (Hickler et al 2005, Dardel et al 2014, Kaptue et al 2015).

In contrast, latitudinal bands of 3° N–20° S (tropical forests and savannas in Africa and South America) and 40° S–45° S (shrublands in Chile and Argentina) shows significant vegetation browning (negative values of the time-varying trend) after 2011 (figure 2), corresponding to the synchronous intensification of water deficit stress associated with extraordinary drying and intensified warming trend driven by the prolonged 2014–2016 El Niño conditions (Saatchi et al 2013, Zhou et al 2014, Brandt et al 2018).

Understanding these patterns is vitally important owing to the key role of tropical forests, savannas, and shrublands in the trend of the global land carbon sink (Ahlström et al 2015, Liu et al 2015), and a reduction in the trend of the global land carbon sink has already been observed (figure 1(a)). The vegetation productivity of savannas and shrublands could increase quickly in response to a wet climate (Liu et al 2015, Piao et al 2019). However, the productivity of tropical forests may recover slowly even though PRE returned to normal or wet conditions (Saatchi et al 2013, Wigneron et al 2020), thus the severe drying trend would have a persistent adverse impact on carbon uptake of tropical ecosystems.

Figure 4 shows the contributions of region to global vegetation productivity trend. The northern sub-Saharan Africa, India, eastern China, southeastern North America, Europe, and southern Russia govern the global vegetation trend (figure 4(a)). In contrast, regions with strong negative contribution centered around 15° S (figure 4(b)), have the opposite trend shape (figure 3), which weaken the overall greening trend. Noteworthy, croplands (23.5%) and grasslands (23.5%) dominate global greening trends from 1981 to 2015, followed by tundra (13.4%), savannas (12.8%), and boreal forests (12.3%) (figure 4(c)). Demonstrating importance of the Northern Hemisphere (88.6%) in controlling global vegetation trend, where both the climate change and anthropogenic management boost vegetation growth (Chen et al 2019, Piao et al 2019).

3.3. Weakening TMP but strengthening PRE control
For temporal changes in each climatic driver, the evolutionary pattern of TMP is more homogeneous and evident than for radiation and PRE (figures 5(a)–(c)). In the first several years, the Northern Hemisphere shows an increased control by TMP. However, the role of TMP decreases in the southern
Figure 5. Latitudinal evolution of climatic drivers of the decadal vegetation productivity trend. (a)–(c), The spatial patterns of climatic driver changes from the first decade over time, and the increased/decreased importance is indicated as blue/red color. (d)–(f), The spatial-temporal relative importance of climatic control between climate variables. (d), PRE dominance (blue), and TMP dominance (red); (e), radiation dominance (blue), and TMP dominance (red); (f), PRE dominance (blue), and radiation dominance (red). Time is on the horizontal axis, indicating the central month of the decadal moving time window (for example, July 1986 represents the first decade of time period from July 1981 to June 1991).
hemisphere. An obvious reduction in TMP control occurs since 1996 globally, and showing stronger values in tropics (figure 5(a)). The decreasing role of TMP can also be supported by a weakening coupling between vegetation productivity and TMP (Piao et al. 2014, 2017). In contrast, due to spatial heterogeneity and a dynamic temporal evolution in climatic driver of radiation and PRE (figures 5(b)–(c)), the compensatory effects among regions lead to significantly less change in global magnitude (about 20%) compared to TMP (figures 6(a)–(c)).

Among climatic drivers (figures 5(d)–(f)), TMP is the most important factor driving vegetation trends north of 14° S (except for 7° N–15° N) in the first two decades. In contrast, PRE predominantly controls the vegetation trends south of 15° S throughout the study period, and it gradually exceeds the role of TMP circa 2000 globally, showing the greatest climatic dominance after 2006 (figure 6). In addition, radiation dominates trends of the Arctic vegetation in recent years (>65° N). Hence, we find a weakening control of TMP but strengthening control of PRE on vegetation trends from 1981 to 2015 (figures 5, 6, and S6), demonstrating a shift in climatic dominance from TMP to PRE globally over time.

The shift of climatic dominance is closely related to the vegetation responses to regional climate change. The tropical forests show the highest decline in TMP dominance and the greatest increase in the role of PRE in controlling vegetation trends (figures 6(a) and (c)), leading to the largest contrast (PRE minus TMP) with 2.6 times the global average in magnitude (figure 6(d)). Before 1998, enhanced plant growth occurs as expected in the radiation-limited tropical forests when radiation increases greatly (Nemani et al. 2003), and the role of radiation increases. However, strong greening does not appear during the robust brightening period after 2000, and the role of radiation declines substantially (figure 6(b)). The role of PRE increases throughout the study period especially when accelerated warming trend induces strong browning trends (figure 6(c)) (Saatchi et al. 2013, Zhou et al. 2014, Brandt et al. 2018), and it surpasses role of TMP and radiation circa 2004 (figure 6(e)). Moreover, reduced canopy photosynthesis is intensified by warming-related heat stress during water deficit, and air TMP already exceeds the optimal TMPs of tropical ecosystems (Huang et al. 2019).

In contrast to tropical ecosystems, air TMPs of the Arctic tundra and boreal forest ecosystems are often below optimal TMPs for ecosystems (Huang et al. 2019). One may expect that strong warming would continuously boost vegetation growth over the warming amplified Arctic. However, the dominance of TMP as a climatic driver weakened substantially, which may relate to the increased cloud-cover limiting radiation reaching the surface in the Arctic, the warming hiatus and drying, and reduced sensitivity of vegetation to warming in boreal regions (Buermann et al. 2014, Piao et al. 2014, 2017). Note that TMP is still the most important factor driving vegetation trends in boreal forests. PRE dominates the vegetation trends of shrublands and savannas, consistent with the primary limitation of water availability (Poulter et al. 2014, Liu et al. 2015). TMP control increases obviously during quick warming, and it evidently decreases under the warming hiatus for croplands and grasslands.
3.4. Uncertainty in climatic control on trend in vegetation productivity

The GIMMS NDVI_{3g} dataset is produced from multiple AVHRR sensors (AVHRR/2, from 1981 to 2000; AVHRR/3, from 2000 on) on board different satellites. The AVHRR/2 and AVHRR/3 have different sensor design, and the AVHRR/3 tend to shift more negative NDVI values than the AVHRR/2 (Pinzon and Tucker 2014). GIMMS NDVI_{3g} dataset has performed multiple process to minimize the effects of sensor shift and degradation on data continuity and compatibility, and it is the most appropriate choice available for long-term vegetation trend analysis up to date (Tian et al 2015, Myers-Smith et al 2020).

Although the effects of sensor degradation and shift have been improved in the GIMMS NDVI_{3g} dataset, but they cannot be fully eliminated (Pinzon and Tucker 2014, Pan et al 2018). The greening slowdown or browning occurs since 2000s, and the time is close to switch of AVHRR/2 and AVHRR/3. It seems that the sensor shift and degradation play a part in the recent vegetation browning, and their roles need to be further explored by comparing with more datasets in future work.

The EEMD decomposition emphasizes the adaptiveness and temporal locality of the data (Wu and Huang 2009). The time-varying trends of NDVI anomaly with ending time of 2014 and 2015 are very close to each other (figure 1(a)). The severe El Nino event in 2015–2016 induces a browner trend in 2015 compared to that in 2014, but it cannot change the browning tendency since 2000, which already be reflected through time series analyses from 1981 to 2014. Suggesting that the El Nino event reinforces the browning trend in 2015, and the exclusion of NDVI data of 2015 would not change the long-term vegetation trend. On the other hand, the time-varying trends provide continuous trend characteristics along time, and the changes of climatic drivers are derived from a 10 year moving window; hence the results will not change when the last years’ data are masked.

The satellite observed vegetation trend is a synthetic result of plant responses to climate change, environment (CO$_2$ fertilization, nitrogen deposition, disturbances), and land management (agricultural management, afforestation, deforestation) (Piao et al 2019). The CO$_2$ fertilization effect is one of the major drivers of vegetation greening, and it explains most of the greening trend in the tropics, whereas climate change results in greening in the high latitudes and the Tibetan Plateau from 1982 to 2009 (Zhu et al 2016). Ideally, the effects of other factor, including the CO$_2$ fertilization effect, besides climate change on vegetation trend should be removed before the analyses. However, it is nearly impossible to derive a pure climate induced vegetation change signal from satellite observation, although contributions of different drivers on long-term vegetation greening can be estimated based on simulations (Zhu et al 2016).

In general, climate plays a fundamental role in driving changes in vegetation productivity globally (Nemani et al 2003, Ahlström et al 2015, Yuan et al 2019). Meanwhile, regional vegetation trends may be dominated by the CO$_2$ fertilization effect, land management, afforestation, or deforestation (Chen et al 2019, Tagesson et al 2020).

The evolution of climatic drivers in this study reflects their relative changes in climate importance from 1981 to 2015, the effects of environment and land management may have impacts on the magnitude of the climatic driver evolution rather than direction. Firstly, CO$_2$ fertilization, nitrogen deposition, agricultural management, and afforestation often enhance vegetation greening, while deforestation, disturbances, and climate extremes events lead to browning. These factors act as climate variables which enhances/reduces plant growth, and they may reinforce the role in which climate variables control vegetation trends. Secondly, their effects (positive or negative) are consistent over time and are more regionally specific (Zhu et al 2016, Piao et al 2019).

Thirdly, the impact of extreme climate events on vegetation productivity are part of climatic controls. Disturbances like fire and insect outbreak are generally triggered and enhanced by warmer and dryer climate (Abatzoglou and Williams 2016, Deutsch et al 2018), and these effects can be interpreted as indirect effects of climate variables that lead to vegetation browning.

For example, the CO$_2$ fertilization effect drives vegetation greening, enhancing the role of climate variables that increase vegetation growth. Meanwhile, and it would not induce vegetation browning; although CO$_2$ fertilization effect can partly offset the climate driven vegetation browning, but if vegetation browning happens, the climate governs the vegetation trend. Therefore, the CO$_2$ fertilization effect would not change the evolution direction of climatic driver. Furthermore, the CO$_2$ fertilization effect on vegetation productivity has decreased recently due to increasing constraints of foliar nutrient concentrations and water availability (Wang et al 2020b), supporting the enhanced climatic driver of water availability in controlling vegetation trends in recent years.

Land-use and land cover change is also one major driving factor of vegetation changes. Over the past 34 years, about half of land surface experiences significant land changes based on satellite observations (figure S7), and 30% of land change is associated with direct human activities, including agricultural expansion and management, tropical deforestation, and reforestation in the Northern Hemisphere (Song et al 2018). The climatic driver over these regions may have higher uncertainty. Moreover, exclusion of the highly uncertain croplands from the analysis would not change the final global results (figure 6). Furthermore, the climatic driver evolutions are robust over
most of the land, particularly over regions with natural vegetation.

One major advancement of this study is using the PCA to directly obtain the spatial-temporal evolution patterns of climatic driver to trends in vegetation productivity based on the time-varying trends. In previous studies, the sensitivity of vegetation response to climate is estimated based on interannual variability (detrended time series), and the results are further employed to constrain the decadal responses of plants to climate (Piao et al. 2014, 2017, Seddon et al. 2016). Consequently, results based on data of time-varying trend and interannual variability may have differences, and need to be further verified.

3.5. Implications of climatic control under climate change

Air TMP increases as greenhouse gas concentrations rise (Trenberth 2015), and warming will further enhance vegetation growth in the northern high latitudes but with a weakening effect or decreasing control than before (Piao et al. 2014, 2017). In a warmer climate, water loss from evapotranspiration increases and more water is needed to maintain balance due to the growing evaporative demand. However, the increase of land PRE under global warming is not homogeneous and highly uncertain (Wu et al. 2013), and most regions with increased PRE cannot keep pace with the growing evaporative demand (Sherwood and Fu 2014), leading to overall background climate drying (aridity) and dryland expansion (Huang et al. 2015). Furthermore, warming will likely intensify climate extremes (heatwave, drought) and disturbances (fire, insect outbreak) particularly during periods of decreasing PRE (Trenberth et al. 2013, Abatzoglou and Williams 2016, Deutsch et al. 2018). Therefore, the warming related intensification of heat and water stress will further enhance the PRE control on vegetation in major biomes in a warmer and dryer world. Additionally, the enhanced plant water use efficiency driven by increased atmospheric CO₂ concentration would partly offset the negative impacts of water stress on vegetation growth under climate change (Mathias and Thomas 2021).

4. Conclusions

This study comprehensively assesses the spatial and temporal evolution of the time-varying trends in climate and satellite derived vegetation productivity from 1981 to 2015. The trends in vegetation productivity are heterogeneous in space and time, and shows increased browning trend and amplified greening heterogeneity along time. The evident reversal of trend in vegetation greening circa 2000 suggests a relapse in the long-term trend in the carbon uptake capacity of terrestrial ecosystems. We provide empirical evidence of the evolution of climatic drivers on trends in vegetation productivity. It shows a shift in the global climatic controls on the trends in vegetation productivity from TMP to PRE. These findings indicate that future terrestrial vegetation productivity and the carbon cycle may become more sensitive to changes in PRE under global warming. Meanwhile, our understanding of the evolution of climatic drivers, mechanisms, and feedbacks, are still limited, and further work is needed to better understand the regional ecosystem responses to the evolving climatic patterns under current and future climate change.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

This work was jointly supported by the Strategic Priority Research Program of the Chinese Academy of Sciences (Grant No. XDA19030401) and the National Natural Science Foundation of China (Grant No. 41590853).

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10
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