Nearly Half of Global Vegetated Area Experienced Inconsistent Vegetation Growth in Terms of Greenness, Cover, and Productivity

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Abstract The considerable interest in detecting global vegetation changes based on satellite observations is increasing. However, studies rely on single indices to explore the driving mechanisms of the greening trend might exacerbate uncertainties of global ecosystem change. Thus, vegetation growth dynamics from various biophysical properties required to be monitored comprehensively. In this study, a consistent framework for evaluating vegetation growth trends was developed based on five widely used satellite-derived products of MODIS Collection 6; the consistency in vegetation growth was mapped; and the factors that affected the consistency of vegetation growth were explored. The results showed that, during 2000–2015, 45.6% of global vegetated area experienced inconsistent trends in vegetation greenness, cover, and productivity, especially in evergreen broadleaf forests, grasslands, open shrublands, woody savannas and croplands. Only 5.4% of global vegetated area exhibited simultaneous trends in greenness, cover, and productivity, and the inconsistent areas were expanding in the study period. Contradictory vegetation changes were mainly reflected in the opposite trends of vegetation greenness and productivity in evergreen broadleaf forests. Moreover, the inconsistency change was mainly manifested in the greenness-dominated vegetation enhancement, without enhanced productivity. The increment difference between NPP and GPP also showed respiration losses greatly offset the effect of vegetation greenness or cover on productivity. This study provides integrated insights for understanding the inconsistency of vegetation structural and functional changes in the context of global greening.

Plain Language Summary Terrestrial vegetation dynamics are extremely important to global environmental change and have consequences for the functioning of the Earth system and provisioning of ecosystem services. Recent greening of the global terrestrial ecosystems suggested an increasing trend in vegetation growth. However, different vegetation properties that were described by indices have not been comprehensively compared. In this study, a consistent framework for evaluating vegetation growth trends was developed based on five widely used satellite-derived vegetation indices; the consistency in vegetation growth was mapped; and the factors that affected the consistency of vegetation growth were explored. We found that during 2000–2015, nearly half of global vegetated area experienced inconsistent trends in vegetation greenness, cover, and productivity, especially in evergreen broadleaf forests. The vegetation inconsistent change was manifested in the greenness-dominated vegetation enhancement, but the productivity did not enhance. Relationship between vegetation cover and productivity was higher than that between vegetation greenness and productivity. It was also found that respiration losses greatly offset the effect of vegetation greenness or cover on productivity. This study provides integrated insights into vegetation growth trends, interpreting inconsistency of vegetation structural and functional changes in the context of global greening.

1. Introduction

Vegetation growth dynamics, which are changes of vegetation structure and function, play an important role in the exchange of carbon, water, momentum, and energy between the land and atmosphere and are regarded as indicators of the natural responses and feedbacks of global climate change and human activities (Forzieri et al., 2017; Piao et al., 2019). In recent years, continuous satellite-based monitoring has detected vegetation greening at global scale. Terrestrial vegetation growth activities have been
significantly increased (Fensholt et al., 2012; Huang et al., 2018); consequently, quantifying changes in the structure and function of vegetation growth has elicited considerable interests.

Vegetation greening can enhance productivity by increasing the absorption of photosynthetically active radiation (Piao et al., 2019), but this increasing does not necessarily indicate that greening can directly improve ecosystem functions. For example, Zhang et al. (2019) used a remote sensing data-driven model to show that compared with the global greening rate, the increase of terrestrial gross carbon sequestration was much weaker, due to the variable contributions to gross primary production (GPP) among different land use types. The spatial distribution and temporal changes of the net primary production (NPP) and GPP also showed different patterns and trends in different ecosystems (Zhang et al., 2009). Additionally, there are uncertainties in model-dependent research about vegetation changes (Ryu et al., 2019). Affected by different assumptions and parameter settings, Earth system model estimations often diverge widely from satellite monitoring (Smith et al., 2016).

Satellite technology has enabled large-scale and continuous monitoring of vegetation dynamics (Myneni et al., 1997; Panigada et al., 2019; Piao et al., 2015, 2019). Based on remote sensing data, various vegetation indices (VIs) have been developed. Although these indices have different ecological meanings, most of them characterize greenness, cover, and productivity in vegetation growth. Specifically, greenness can be characterized by the spectral VIs, whereas vegetation cover is assessed by the areal extent of vegetation and leaf area. Productivity can be represented by GPP and NPP, which are the key indicators to detect the carbon cycle of ecosystem and atmosphere. In details, GPP determines the initial energy to enter the ecosystem, and NPP equals to GPP minus respiration-based consumption. Both GPP and NPP are important reference factors in the detection of ecosystem carbon cycle process (Field et al., 1995) and can be used to quantify the health status of the ecosystem (Zhang et al., 2014).

Furthermore, detections of vegetation growth enhancement versus degradation also have given contrasting views on greenness or cover changes. For example, Chen et al. (2019) used leaf area index (LAI) to determine that more than one third of the world’s land area was greening and less than 5% was browning, while Pan et al. (2018) found that the overall vegetation greening estimates based on the normalized difference VI (NDVI) masked the increased browning that occurs in larger areas compared with Chen et al. (2019). The global enhanced VI (EVI) evaluation by Zhang et al. (2017) showed that the area of vegetation greening was larger than that indicated by NDVI. All in all, the diversity of indices, research periods, and trend definitions made the current cognition of global vegetation growth dynamics since 2000 widely divergent, leading to great uncertainties in global vegetation change estimations (Piao et al., 2019). To comprehensively and synthetically understand global vegetation growth dynamics, timely, consistent, and robust evaluations of the spatial patterns and temporal trends of various properties of vegetation growth are urgently required.

In this study, five widely used satellite-derived VIs were applied to assess 2000–2015 global vegetation growth trends. In details, NDVI and EVI were used to characterize vegetation greenness, with LAI representing vegetation cover and NPP and GPP for vegetation productivity. The objectives of this study were to define and evaluate the possibility of global vegetation growth change, to map the consistency of global vegetation greenness, cover, and productivity trends as indicated by various indices, and to explore the factors influencing the consistency of vegetation growth trends.

### 2. Materials and Methods

#### 2.1. Data

MODerate resolution Imaging Spectroradiometer (MODIS) Terra data products from Collection 6 satellite were used for analysis of NDVI, EVI, LAI, NPP, and GPP. All data were obtained from the online database of the National Aeronautics and Space Administration’s (NASA) Land Process Distributed Activity Archive Center at the U.S. Geological Survey’s Center for Earth Resources Observation and Science (https://lpdaac.usgs.gov). In details, NDVI and EVI, which characterized the abundance and activity of green vegetation, were obtained from the MODIS Terra MOD13C2 product; the indices had a temporal resolution of 1 month and were projected on a 0.05° geographic climate modeling grid (CMG) (Didan, 2015). The monthly NDVI and EVI data were extracted and converted to annual values. If the monthly VI value was <0.1, it was treated as null value and the area it represented was excluded from the study area during the analysis. LAI, which
characterized the unilateral leaf area of broadleaf species and half of the total surface area of coniferous species, was obtained from the MODIS Terra MOD15A2H product; these data had a global coverage at an 8-day frequency and a spatial resolution of 500 m (Myneni et al., 2015). The maximum value composite (MVC) method was adopted to aggregate the LAI 8-day data into monthly intervals. This method could largely remove the contaminations of cloud and atmospheric noises (Holben, 1986; Huete et al., 2002). The LAI of all months in the year was averaged to get the annual LAI. Annual NPP and GPP data were derived from MOD17A2H and MOD17A3H products, respectively, based on the results of Zhao et al. (2005). All area-related statistics were spatially aggregated to generate data for the 0.05° CMG using the nearest-neighbor resampling method. They were projected to Mollweide equal area and were set to a common extent. All data calculations were accomplished using MATLAB 2018b (MathWorks, Natick, MA, USA), and cartographic analysis was accomplished using ArcGIS 10.4 (ESRI, Redmond, WA, USA).

To distinguish the enhancement or degradation characteristics of different vegetation types, International Geosphere-Biosphere Program (IGBP) global vegetation classification scheme of 2007 (in the MODIS Terra MCD12C1 product) was used, which included 11 natural vegetation categories, three mosaic land categories, and three non-vegetated land categories (Friedl & Sulla-Menashe, 2015).

2.2. Calculation of Vegetation Growth Trend

The non-parametric Mann-Kendall test was used to determine whether the increasing or decreasing trend was significant for each grid (Mann, 1945; Salmi et al., 2002). The significant level of confidence was p < 0.05, corresponding to a Z value of ±1.96. According to a given time series \(X_t = (x_1, x_2, ..., x_n)\), the calculation formula of the Mann-Kendall test statistic \(S\) is defined by Equation 1:

\[
S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i)
\]

in which \(n\) refers to the number of data in the time series and the sgn function is defined by Equation 2.

\[
\text{sgn}(\theta) = \begin{cases} 
1 & \theta > 0 \\
0 & \theta = 0 \\
-1 & \theta < 0 
\end{cases}
\]

When \(n \geq 8\), the statistic \(S\) is approximately normally distributed (Blain, 2013; Kendall, 1975; Mann, 1945). The standardized test statistic (\(Z\)) is defined by Equation 3:

\[
Z = \begin{cases} 
\frac{S - 1}{\sqrt{\sigma^2}} & S > 0 \\
0 & S = 0 \\
\frac{S + 1}{\sqrt{\sigma^2}} & S < 0 
\end{cases}
\]

where the variance \(\sigma^2\) is calculated by Equation 4:

\[
\sigma^2 = \frac{n(n-1)(2n+5)}{18}
\]

The Theil-Sen median slope was used to estimate the linear trend of the VI annual time series for each grid (Sen, 1968; Theil, 1950). The trend slope \(\beta\) was estimated using Equation 5:

\[
\beta = \text{Median} \left( \frac{x_k - x_j}{k-j} \right), \forall j > k
\]

where “Median” is the median value of all the slopes.

2.3. Definition of Vegetation Growth Change Possibility

At the \(p = 0.05\) significance level, vegetation growth trends were divided into three categories: significantly increased (+), significantly decreased (−), or no significant change (0). To summarize the results, the total
number of significantly changed VIs was segregated into four categories, which effectively represented the probabilities or likelihoods of vegetation growth trends from 2000 to 2015. In this procedure, when all VIs exhibited significant changes in the same direction (i.e., five “+s” or five “−s”), the trend was defined as enhanced or degraded “very likely”. When three or four VIs exhibited significant changes in the same direction (i.e., three to four “+s” or “−s” and one to two “0s”), the trend was defined as “likely”. When two VIs exhibited significant changes in the same direction (i.e., two “+s” or “−s” and three “0s”), the trend was defined as “probably”. When none or only one of the VIs was significant (i.e., five “0s” or one “+” or “−” with four “0s”), or the calculation result of the significant change level had the opposite situation (i.e., both “+s” and “−s”), the trend was defined as “uncertainly”.

Based on the definition of each VI and the consistency of their changes, NDVI and EVI were used to represent vegetation greenness, with LAI referring to vegetation cover and NPP and GPP measuring vegetation productivity. A significant change in any index was defined as the significant change of the vegetation characteristic represented by the index, if there was no significant change in the opposite direction by the other index representing the same vegetation characteristic. Based on these rules, vegetation growth dynamics were analyzed in terms of greenness, cover, and productivity.

3. Results

3.1. Global Patterns of Vegetation Growth Trends

Spatial distribution of the vegetation growth trends showed a mixture of vegetation enhancement and degradation (Figures 1a, 1d, 1g, 1j, and 1m). VIs have generally increased in eastern and southern Asia, southern Europe, central North America, central Africa, and southeastern South America. Conversely, the indices generally decreased at the junction of Asia and Europe, in northern and southern South America, and in southern Africa. The area over which vegetation growth was enhanced was generally larger than the area with degraded vegetation. Overall, the distribution of vegetation growth trends exhibited to be similar between NDVI and EVI and between NPP and GPP, with distinct difference between vegetation greenness indices and productivity indices. Compared with NPP and GPP, the trend of LAI was more similar to that of NDVI and EVI (Figure S1).

Substantial differences were observed in globally annual averaged vegetation growth trends identified by the five indices (Figures 1b, 1e, 1h, 1k, and 1n). Globally annual average NDVI, EVI, and LAI showed significant increasing trends (p < 0.05), but NPP and GPP showed no significant trends (p > 0.05). The corresponding relationship between the initial state (at the year 2000) and the annual trend was similar for different VIs (Figures 1c, 1f, 1i, 1l, and 1o). In details, NDVI had the highest decreasing trend in regions with the medium NDVI (0.4–0.6), while the regions with the highest degradation trends for EVI and LAI corresponded to the lower values in 2000. The value of the highest decreasing trend of NPP and GPP referred to the higher value in 2000, and their absolute value was higher than those with the highest increasing trend. Different from the highest decreasing trend, the area with low base LAI (2 to 4) corresponded to the greatest increasing trend, while NDVI and EVI projected the highest increasing trends with low base values ranging from 0 to 0.4. NPP and GPP also corresponded to high enhancement trends in the lower base values. The difference in the five indices reflected the inconsistency of significantly changed areas in terms of greenness, cover, and productivity during vegetation growth, indicating divergence among vegetation properties described by these indices.

3.2. Possibility of Global Vegetation Growth Change

The possibility assessment of vegetation growth indicated by the five VIs showed that 21.7% of the global vegetated area experienced enhanced vegetation growth. Areas identified by the indices as enhanced very likely accounted for only 2.1% of the global vegetated area, which were distributed mainly in East and South Asia, central North America, and central Africa. Vegetation growth in 6.4% of the global vegetated area had the potential, that is, very likely, likely, or probably to be degraded, and the area with all the indices decreased was only 0.2% of the global vegetated area, which was concentrated in the north of Caspian Sea. Most (71.9%) of the global vegetated areas exhibited uncertain vegetation growth dynamics, including 49.0% that exhibited no significant change in any of the five indices and 21.0% that exhibited significant change in only one VI. Contradicting trends in changes indicated by the five indices appeared only in 1.9% of the global vegetated area.
Spatially, the temperate zone in the Northern Hemisphere exhibited the largest range of vegetation change (Figure 2b). Regardless of the actual area or the area proportion in each latitude, the vegetation growth enhancement in the Northern Hemisphere was much higher than that in the Southern Hemisphere, while the tropical vegetation of the Southern Hemisphere showed the strongest degradation, together with the midlatitudes of the Northern Hemisphere (Figure S2). Thus, it could be concluded that there was no overall significant effect on vegetation growth trends exerted by latitude-induced caloric influences.

Possibility assessment induced enhanced or degraded areas of vegetation growth were both higher than those relying on a single index (Figure 2c). Among the VIs, NPP identified the highest area of vegetation degradation, accounting for 7.2% of the global vegetated area. Accounting for 18.9% of the global vegetated area, EVI indicated the largest area of significant enhancement, which was closest to the possibility assessment induced area potential to be enhanced. The comparison of areas identified by the five indices showed the gaps between different aspects of vegetation growth, reflecting asynchronous changes in vegetation greenness, cover, and productivity. Thus, the asynchronism in vegetation greenness, cover, and productivity should be highly focused.

Figure 1. Global patterns of vegetation growth trends from 2000 to 2015 as determined using NDVI, EVI, LAI, NPP, and GPP. Panels (a), (d), (g), (j), and (m) show the annual trend of each vegetation index, and black dots indicate areas with significant changes (p < 0.05). Panels (b), (e), (h), (k), and (n) show the globally annual averaged value of each index. Panels (c), (f), (i), (l), and (o) show scatter plots of vegetation indices based on the year 2000 and their corresponding annual trends for all grids. The color bar represents the scattered point density.
The combination of changes in greenness, cover, and productivity of global vegetation showed diversity of vegetation growth dynamics (Figure 3). In total, 45.6% of the global vegetated area experienced inconsistent trends in vegetation greenness, cover, and productivity. Only 4.8% of the global vegetated area exhibited increase in all aspects. It was worth noting that area with increased greenness and both unchanged cover and productivity accounted for 9.7% of the global vegetated area, which was the main characteristic of vegetation growth enhancement. These areas were widely distributed globally, but especially in the middle and high latitudes of the Northern Hemisphere, and also close to areas with enhanced greenness and cover, such

**Figure 2.** Global pattern of vegetation growth trends from 2000 to 2015. Panel (a) shows the possibility of vegetation growth trends quantified by five indices. Panel (b) shows the number of grids in each latitude that experienced each type of change. Panel (c) shows the percentage of global vegetated area that exhibited significantly increasing or decreasing by five indices.

**Figure 3.** Combination of trends in vegetation greenness, cover, and productivity. (a) Spatial distribution. (b) Area proportion exhibiting different change trends. The dash (−) represents a non-significant change, with ↑ and ↓ for a significant increasing or decreasing trend, respectively.
as southeastern China, northern India, and southern Brazil. Another noteworthy vegetation growth enhancement category consisted of areas in which only productivity increased. These areas accounted for 6.9% of the global vegetated area and were concentrated in the Sahelian region and tropical rainforests of central Africa, northwestern North America, and the edge of the Amazon rainforest in central Brazil.

Only 0.6% of the global vegetated area decreased in greenness, cover, and productivity. The main manifestation of vegetation growth degradation was productivity degradation only, accounting for 5.9% of the global vegetated area and mainly distributed at the border of Kazakhstan and Russia in northwestern Asia, Angola and Zambia in southern Africa, and Brazil and Peru in South America. In contrast, 2.9% of the global vegetated areas exhibited only decreased greenness, which were mainly located in northern North America and northeastern South America, and for the category of only decreased cover, its area percentage was as low as 1.2%.

It was worth noting that the opposite trends were also exhibited in vegetation greenness, cover, and productivity in some areas. Although these areas altogether accounted for only 2.0% of the global vegetated area, they were concentrated in specific areas. Overall, the area in which vegetation greenness and productivity differed was the largest (Figure 4a). Areas where vegetation greenness increased and yet productivity declined were the most common and were distributed in the area bordering Uruguay and Brazil (Figure 4b),

Figure 4. Spatial distribution of combination of contradicting trends in vegetation greenness, cover, and productivity (a) and the regions where specific inconsistency occurred (b–e). The dash (‐) represents a non-significant change, with ↑ and ↓ for a significant increasing or decreasing trend, respectively.
southeastern China (Figure 4d), and multiple regions in Russia (Figure 4e). Productivity generally increased in many areas of the Sahel in Africa, but vegetation greenness or cover declined (Figure 4c).

The study period was divided into two sections to observe whether the area of inconsistent vegetation growth was expanding (Figure 5). Compared with the former 8 years, the area of global vegetation enhancement in the latter 8 years had increased by 4%. The vegetation enhancement increasing was mainly in the form of only increasing greenness, and increasing both greenness and cover, with the productivity enhancement unchanged. The area with only increased greenness accounted for 7.7% of the total terrestrial vegetated area in the world from 2008 to 2015, which was nearly twice that of the period from 2000 to 2007, and became the most important way of vegetation enhancement. The degraded vegetation area decreased in the latter 8 years. The area where vegetation greenness, cover, and productivity all remained unchanged also decreased by 2%. Comparing the two sections, it could be concluded that the vegetation growth inconsistency was intensified significantly, which was manifested in the greenness-dominated vegetation enhancement, with non-enhancement of the productivity. Similar results could also be obtained for other segmentation schemes of 16 years, such as 9, 10, 11, and 12 years, highlighting the robustness of the conclusion that the areas with inconsistent vegetation growth were expanding (Figure 5).

### 3.3. Inconsistency of Global Vegetation Growth Trends

To more precisely identify spatial patterns of vegetation growth trends, the trends were examined for vegetation types defined by the IGBP (Figure 6). Enhancement or degradation in different vegetation types showed that there were large areas of specific types of vegetation in which the growth enhancement was highly possible, such as grasslands (GRA), croplands (CRO), and open shrublands (OS). In contrast, evergreen broadleaf forests (EBF) showed more degradation areas. In particular, NDVI and EVI indicated similar significant

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**Figure 5.** Area percentage contrast of inconsistent vegetation growth for various situations at different time periods. The dash (−) represents a non-significant change, with ↑ and ↓ for a significant increasing or decreasing trend, respectively.
change areas in different vegetation types. The degraded areas of EBF, GRA, and CRO that were indicated by NPP and GPP were much larger than that indicated by the other three indices, reflecting the substantial differences in the vegetation growth forms (Figure S3).

As shown in Table 1, the global vegetated area experienced inconsistent trends in vegetation greenness, cover, and productivity, especially in EBF (6.9%), GRA (6.2%), OS (5.8%), WS (5.4%), and CRO (5.2%), which were also the five largest vegetation types (Table 1). In view of area proportion to the total area of the vegetation type, vegetation growth was immensely disparate in different vegetation types (Table S1). Overall, 64.0% of the OS vegetation growth remained unchanged, and growth enhancement was mainly manifested by the increase only in greenness (9.5%) or only in productivity (6.2%), while the degradation mainly behaved as the decrease only in productivity (2.3%). The main vegetation growth manifestations of GRA were similar to those of OS. Only 46.1% of the EBF vegetation growth exhibited no changes in all aspects, and the area of EBF that showed inconsistent trends of vegetation growth was larger than that for other vegetation types. As with OS and GRA, vegetation enhancement in EBF was also mainly manifested by the increase only in greenness (7.4%) or only in productivity (7.3%), while the degradation was mainly dominated by the decline only in productivity (14.5%). CRO, a vegetation type deeply affected by human activities, contributed significantly to global greening (Chen et al., 2019). The manifestations of CRO were more concentrated than for the other three vegetation types. The enhancement of vegetation growth was represented by increased vegetation greenness or cover, which accounted for 24.2% of the CRO. Vegetation degradation of CRO was mainly manifested by only reduced productivity, which accounted for 6.8% of the CRO.

For each combination of vegetation growth, the type of vegetation that mainly reflected the various growth aspects was also different (Table S2). CRO dominated the combination of vegetation growth which had all three aspects enhanced (more than 28.9% of the total area). EBF mainly occupied the areas in which vegetation degradation was accompanied by the decrease in vegetation greenness and cover while productivity remained unchanged. However, EBF areas also exhibited the decline of vegetation productivity and other unchanged conditions, which reflected the diversity of EBF growth. EBF and savannas (SAV) mainly accounted for areas in which vegetation growth was manifested by opposing trends between vegetation productivity and greenness as well as cover.

4. Discussion

4.1. Potential Causes of Vegetation Growth Trends Inconsistency

In the results of the consistency assessment, most of the vegetation changes were categorized as only “probably.” Inconsistencies in these cases could be subject to errors from the sensors (Fang et al., 2019), although the effects of the sensor degradation had been basically eliminated in the MODIS Collection 6 products. On
the one hand, MODIS C6 had bands overcorrection over some sites (Lyapustin et al., 2014). For example, MODIS C6 LAI exhibited the largest global linear trend value from 2003 to 2011 compared to GLASS, GLOBMAP, LAI3g, and TCDR (Jiang et al., 2017). Aside from sensor errors, environmental conditions affected the detection of vegetation growth. The quality of MODIS C6 data in some areas was poor, which was affected by the saturation effect of NDVI in dense vegetation (Goswami et al., 2015). In the tropical or subtropical area, cloud and aerosol contamination also affected the data quality (Samanta et al., 2010).

Therefore, the dynamic estimation of vegetation growth based on remote sensing monitoring still had a certain uncertainty. Moreover, the limitation of the product model would also lead to systematic error. For instance, MODIS NPP and GPP products were reported to be underestimated for a lack of correlation between vapor pressure deficit and soil moisture in light use efficiency model (Stocker et al., 2019). Sensor errors and model selection induced data product deviations were one of the reasons for the inconsistency.

However, sensor errors or model limitations did not affect the comparison between VIs, because the differences between the values of VIs were generally greater than that between distinct products for the same VI given the use of different bands and model included in the indices calculation. For example, the global multiyear averaged NDVI difference between MODIS Terra-C6 and Terra-C5 was 0.003 and the multiyear averaged EVI difference between Terra-C6 and Terra-C5 was 0.004, while multiyear averaged global EVI was much lower than NDVI from both Terra-C5 (0.18) and Terra-C6 (0.19) (Zhang et al., 2017). Among all the

| Table 1 | Area Proportion of Each Type of Vegetation Growth to the Global Vegetated Area |
|---------|-----------------------------------------------------------------------------|
| ENF (%) | 0.10 0.08 0.02 0.01 0.22 0.01 0.73 0.42 0.39 1.03 0.01 1.37 0.33 |
| EBF (%) | ↑↑↑ 0.16 0.27 0.06 0.02 0.99 0.02 0.46 0.63 0.46 0.64 0.01 1.11 0.47 |
| DNF (%) | ↑↑↑ 0.27 0.96 0.15 0.06 1.44 0.02 1.74 1.14 0.58 1.54 0.03 0.92 0.65 |
| DBF (%) | ↑↑↑ 0.08 0.22 0.02 0.01 0.22 0.01 0.66 0.44 0.36 0.64 0.01 0.41 0.24 |
| MF (%)  | ↑↑↑ 0.07 0.12 0.00 0.01 0.09 0.00 0.24 0.19 0.17 0.23 0.00 0.20 0.10 |
| CS (%)  | ↑↑↑ 0.26 0.95 0.02 0.09 0.38 0.01 1.13 0.90 0.15 0.90 0.02 0.39 0.62 |
| OS (%)  | ↑↑↑ 0.17 0.53 0.07 0.04 0.53 0.01 0.55 0.56 0.35 0.56 0.03 0.63 0.43 |
| WS (%)  | ↑↑↑ 1.09 6.00 0.57 0.71 2.76 0.11 11.69 4.99 4.59 7.82 0.33 4.32 3.27 |
| SAV (%) | ↓↓↓ 0.03 0.07 0.00 0.01 0.03 0.00 0.07 0.08 0.10 0.07 0.00 0.07 0.05 |
| GRA (%) | ↑↑↑ 0.06 0.19 0.00 0.02 0.05 0.00 0.05 0.08 0.14 0.04 0.00 0.04 0.08 |
| PW (%)  | ↑↑↑ 0.26 0.65 0.01 0.07 0.23 0.00 0.16 0.38 0.37 0.21 0.02 0.24 0.29 |
| CRO (%) | ↑↑↑ 0.03 0.20 0.01 0.04 0.06 0.00 0.09 0.16 0.16 0.25 0.01 0.28 0.09 |
| NVM (%) | ↑↑↑ 0.00 0.04 0.00 0.02 0.00 0.04 0.03 0.03 0.03 0.04 0.00 0.05 0.03 |

Note: The total global land area is 144.68 million km², of which 103.90 million km² (71.8%) is vegetated area. The area value in this table indicates the proportion of the area in each case to the global vegetated area. The colors and signs have the same meaning as the legends in Figures 3 and 4.

Abbreviations: CRO, croplands; CS, closed shrublands; DBF, deciduous broadleaf forests; DNF, deciduous needleleaf forests; EBF, evergreen broadleaf forests; ENF, evergreen needleleaf forests; GRA, grasslands; MF, mixed forests; NVM, natural vegetation mosaics; OS, open shrublands; PW, permanent wetlands; SAV, savannas; and WS, woody savannahs.
available vegetation products, MODIS products could effectively capture spatial and temporal patterns across various biomes and climatic conditions in GPP and NPP and had been applied globally (Zhao & Running, 2010). Our MODIS-based results revealed the inconsistencies in the temporal trends and spatial patterns of greenness, cover, and productivity of vegetation growth, which aligned with other global studies (Chen et al., 2019; Zhang et al., 2019). These inconsistencies indirectly led to uncertainties in measurements of ecological factors. For example, Hobi et al. (2017) used MODIS products to measure species richness and found that no MODIS vegetation products consistently provided the best model for all regressions, challenging the understanding and assessment of ecosystem changes and thus emphasizing the need for comprehensively analyzing vegetation growth indicators. In this study, annual averaged data and stable trend analysis methods were used to characterize vegetation growth to reduce the potential impact of sensor errors on the results.

This study found that the inconsistencies in vegetation growth mainly existed in EBF, GRA, OS, WS, CRO, MF, and SAV (Figure 6); and these findings could also be inferred from previous studies (Asner et al., 2009; Dong & Sutton, 2015). Vegetation types explained this inconsistency to some extent, because of the different efficiency in using sunlight resulting from differentiated vegetation biophysical and environmental properties (Walthier et al., 2018). For example, farmland had higher photosynthetic capacity than other vegetation types (Huang et al., 2018). In addition to vegetation types, the changes in greenness, cover, and productivity were closely related to climatic conditions and human activities, both of which also affected the consistency of vegetation growth trends. First, climate change played important roles in vegetation growth. Previous research found that from 1980 to 2010, changes in global LAI were mainly driven by CO2 fertilization and were contributed 8% by climate change (Zhu et al., 2016), while the study of global GPP suggested greater contribution (28.6%) of climate change (Chen et al., 2019). Moreover, the impacts of climate change on vegetation greenness varied between regions. In tropical areas, warming could intensify drought, which largely reduced forest photosynthesis, but slightly increased canopy greenness (Yang et al., 2018). For example, according to Hubau et al. (2020), both African and Amazonian tropical forests showed increasing tree growth, but asynchronous carbon sink saturation due to distinct drought induced tree mortality in the latter. In high-latitude or high-altitude regions, growing season warmth significantly increased both vegetation productivity and greenness (Keenan & Riley, 2018). On the other hand, affected by human activities, the greenness (Chen et al., 2019) and peak productivity (Huang et al., 2018) of croplands had been improved, but the annual productivity of some cultivated land declined. Furthermore, the results of mathematical modeling were affected by the growth period of the cultivated crops and some particular vegetation types (Yuan et al., 2015). Although plantations, including timber stands, economic forests, and firewood forests, had rapidly increased the vegetation greenness or cover, productivity might not increase simultaneously, thus resulting in inconsistencies in greenness, cover, and productivity. The inconsistency also depended on the time frame. For example, fruits accounted for 46% of tree NPP and showed large seasonal variations in the subtropical areas, while the changes of GPP were much smaller (Navarro et al., 2008).

4.2. Linkage Among Vegetation Greenness, Cover, and Productivity

The inconsistency of vegetation greenness, cover, and productivity trends may be due to the correlation between changes in different indices. For example, non-green leaves may contribute to photosynthesis during vegetation growth, and photosynthesis of green tissues may end under extreme conditions (Fang et al., 2019); and both of these situations affect the response of greenness indices to vegetation growth and contribute to inconsistent results. Another example is that increasing fertilization leaf growth does not necessarily translate linearly to GPP, because increased leaf growth may also lead to enhanced self-shadowing, which will reduce productivity (Street et al., 2007).

In this study, trend values were converted to change ratios to compare the change rates of annual global vegetation greenness, cover, and productivity (Figure 7). As the increasing rate in LAI increased, GPP and NPP showed a consistent increasing trend. However, the response of productivity to changes in greenness was concentrated in the interval where the increasing rate in greenness was relatively low. When the increasing rate in greenness was high, the increasing rates in GPP and NPP did not change accordingly. In general, changes in vegetation greenness were much slower than changes in the physiological functions of plants, which responded quickly to changes in key biophysical drivers (Yan et al., 2019). This result was also supported by the research of Glenn et al. (2008), emphasizing that vegetation greenness was not
necessarily related to the number of total photosynthetic plants, but only driven by living leaf components. In contrast, photosynthesis and transpiration were mainly carried out at the leaf level, and thus, the consistency between productivity and LAI was better.

The impacts of vegetation greenness and cover on productivity worldwide were further explored (Figure 8). The annual increment of GPP per unit area was the highest when both vegetation greenness and productivity increased, but incremental greenness did not contribute to the increment of NPP. The annual increment of NPP per unit area when both vegetation greenness and productivity increased was significantly smaller than that when only vegetation productivity increased (Table S3). Vegetation cover showed the same responses to the productivity (Table S4). Increased greening and cover may promote more carbon storage during the growing season, but the annual amount of carbon storage cannot increase significantly (Yue et al., 2017). The increase in productivity caused by increased greenness or cover is close to that contributed by other factors, indicating that, from the perspective of annual change, the contribution of greenness and cover to productivity is limited.

Although this study emphasized that different aspects of vegetation growth were mainly not synchronized, it should be noted that there were still synchronized changes in greenness, cover, and productivity, accounting for 5.4% of the global vegetated area. Among these areas, 4.8% were comprehensively enhanced for all aspects of vegetation growth; and this response had critical implications for understanding ecosystem
change under the influence of land management, such as the greening contribution by ecological engineering in China and cropland plantation in India (Chen et al., 2019; Tong et al., 2020). These findings could be used as a reference to support the evaluation of vegetation growth and the impact of land management. Furthermore, the areas with degraded vegetation were mainly distributed in northern Argentina, Angola, and the borders between Russia and Turkey. Despite the small area involved, the total degradation of vegetation caused by deforestation and rapid intensification of agriculture should be raised as a concern globally.

4.3. Limitations and Future Research Directions

It should also be noted that this study had some limitations. First of all, remote sensing sensor displacement, atmospheric and surface noise signals, and model selection (for light use efficiency) could all contribute to uncertainty in VIs (Ryu et al., 2019; Yuan et al., 2015). Although this study emphasized that the impact of absolute error was reduced by using change trends, the source, extent, effects, and countermeasures of the uncertainties should be further explored. Moreover, this study conducted a preliminary analysis of vegetation growth possibilities and inconsistent combinations in view of vegetation greenness, cover, and productivity using the widely used VIs of NDVI, EVI, LAI, GPP, and NPP. However, the mechanisms of the inconsistency need to be further examined, especially for the disparity among different vegetation types. Natural disturbances also affect plant growth, especially in the forests, including fire, drought, biotic agents, storms, and wind-driven events (Anderegg et al., 2020; Silvério et al., 2019). Therefore, further analyses involving the influencing factors are needed to facilitate a full understanding of the mechanism behind the inconsistencies in various aspects of the vegetation growth, so as to provide references for the prediction of future vegetation dynamics under climate change.

5. Conclusions

This study developed a consistent evaluation framework for vegetation growth trends based on five widely used satellite-derived VIs. Through mapping the consistency of global vegetation growth, it was found that from 2000 to 2015, the combination of five indices provided possibility attribute for vegetation growth assessment, and the area of enhanced or degraded vegetation was much smaller than that when these indices were independently applied. In all, trends revealed by different VIs were asynchronous. Only 5.4% of the global vegetated area increased or decreased in all vegetation properties at the same time. Also, 45.6% of the global vegetated area experienced inconsistent trends of vegetation growth in greenness, cover, and productivity, especially in evergreen broadleaf forests (6.9%), grasslands (6.2%), open shrublands (5.8%), woody savannas (5.4%), and croplands (5.2%). Furthermore, the trend synchronicity between vegetation cover and productivity exceeded that between greenness and productivity. Contradicting the relationship for GPP, the global NPP increment due to increased vegetation greenness or cover was significantly lower than when these
two indices did not increase, which highlighted that respiration losses greatly offset the effect of greenness or cover on productivity at global scale. This study provides integrated insights for understanding the inconsistency of vegetation structural and functional changes in the context of global greening.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The Collection 6 MODIS monthly NDVI and EVI (MOD13C2) (https://e4ftl01.cr.usgs.gov/MODV6_Comp_C/MOLT/MOD13C2.006/), the Collection 6 MODIS 8‐day LAI (MOD15A2H) (https://e4ftl01.cr.usgs.gov/MOLT/MOD15A2H.006/), the MODIS GPP (MOD17A2H) and NPP (MOD17A3H) (http://files.ntsg.umt.edu/data/NTSG_Products/MOD17/), and the MODIS Land Cover Type (MCD12C1) (https://e4ftl01.cr.usgs.gov/MOTA/MCD12C1.006/) data can be retrieved online. The data sets used in this analysis are available from their respective sources linked above.

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