## Response to Reviewer 1

#### **General comments**

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At the moment, this paper feels like a model evaluation paper. There are a lot of results here and it would be nice to see the key results promoted a bit more. Then I would like to see separate results and discussion sections. At the moment, it is a bit mixed up. After the model description section (section 2), I would like section 3 to be the results section, section 4 to be the discussion section and section 5 to be the conclusions section.

R: We appreciate Reviewer #1's carefully reading and insightful comments and suggestions. We have made revisions according to the reviewer's comments/suggestions. They really help us to substantially improve the paper. Please find our responses below for each comment. Please note that the reviewer's comments/suggestions are in black, while responses are in blue. The page and line numbers in the response are regarding to the clean version "manuscript.pdf".

The purpose of this paper is to investigate the effects of climate regime shift during the 1980s on ecosystem trends, by comparing the contribution of three primary drivers (i.e. atmospheric CO<sub>2</sub>, global warming, and climate variability) on vegetation cover fraction, LAI and GPP trends, during the periods before and after the 1980s. Studies on this subject show that the contributions of each drivers are model dependent (Beer et al, 2010; Zhu et al, 2016; Huntzinger et al, 2017). Although SSiB and TRIFFID are both well-evaluated models, the coupled version SSiB4/TRIFFID is used for the first time in this study. It is necessary, therefore, to include an evaluation step before its application.

20 We deemphasize the model evaluation section with fewer paragraphs in our revision. Figure 4 (presenting the vegetation cover fraction) is moved to the appendix. Figure 6 and Figure 7 is modified to show the difference between simulated and satellite-derived LAI and GPP, separately.

The results and discussion sections are separated in the revised manuscript. Key results are emphasized during the discussion and also in the conclusion section.

- 25 Meanwhile, the structure is adjusted in the revised manuscript as following:
  - 1. Introduction

2.1 Model description 2.2 Experimental design 2.3 Data 5 2.3.1 Initial condition for equilibrium simulation 2.3.2 Meteorological forcing data 2.3.3 Observation-based data 3. Results 3.1 Vegetation initial condition 10 3.1.1 Quasi-equilibrium simulation 3.1.2 Effect of large-scale disturbance 3.2 Evaluation of simulated vegetation distribution, LAI and GPP 3.2.1 Vegetation spatial distribution 3.2.2 Leaf area index 15 3.2.3 Gross primary product 3.3 Simulated vegetation temporal variability Vegetation temporal variability during 1982-2007 and its comparison to observationbased data 3.3.2 Three major types of vegetation trend change since the 1950s 20 3.4 Attribution of three environmental drivers on ecosystem trends 3.4.1 Global overview of three simulated environmental drivers' effects on the ecosystem trends 3.4.2 Dominant factor in influencing trend reversal from negative to positive in West Africa and East Asia Dominant factor in influencing trend reversal from positive to negative in western 25 3.4.3 North America Dominant factor in influencing the enhanced positive trend in rainforest, boreal 3.4.4 forest, subarctic, and Tibetan Plateau 2

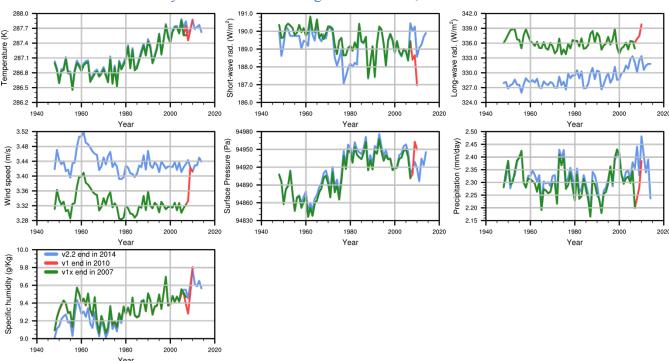
2. Model description, experimental design and data

#### 4. Discussion

#### 5. Conclusion

The Princeton meteorological dataset is used to drive the SSiB4/TRIFFID model. There is data available from 1948-2010. Why have you not performed the model experiments for this time period?

R: We have downloaded three versions of Princeton meteorological dataset with the ending year of 2007 (v1x), 2010 (v1) and 2014 (v2.2), respectively. v1 had merged the data v1x plus the data from 2008-2010. However, when we compared the two versions (i.e. v1x and v1), we found that although v1x and v1 are generally consistent before 2007, there was an abrupt shift in some variables (such as wind speed) after 2007 (See Response Figure 2). To ensure the consistence and minimize the uncertainties associated with the meteorological forcing data, we decided to stop the simulation at 2007. The v2 data, which starts to be available in later 2016, is quite different from the v1 data (Response Figure 1, blue line) for a number of variables. Since by that date we had finished most of our work, and since these few additional years should make no great difference, we have stuck with the v1x data.



5 Response Figure 1. Comparison between different version of Princeton meteorological datasets over global land (-180° W,180° E, -60° S, 75° N)

#### **Specific comments**

Page 1

#### Abstract

Change the abstract from 3 paragraphs to 1.

5 R: It has been merged to 1 paragraph in the revised manuscript.

Lines 18-20: You state that more than 40% of the global land area has shown significant trends in LAI and GPP since the 1950s. Is this for the period 1958-2007 or from the 1958-1980s? When you mean positive trends, I assume that is an increase in LAI and GPP and the opposite for negative trends? It is better to explicitly state this.

10 R: Approximately 40% of the global land area shows significant trends in LAI and GPP is for the period 1957-2007. We have clarified it in the revised manuscript (page 2 line 10).

Yes, the positive trends imply an increase in LAI and GPP and opposite for negative trends. This has been clarified in the revised manuscript (page 2 line 10).

Lines 22-27: The last paragraph goes straight into which environmental driver affects LAI and GPP the most. Add a line to place the results in context.

R: We have made a number of modifications so that the manuscript flows better (page 2 line 15).

Page 2

#### Introduction

Line 3: Remove e.g. when adding references to the end of statements. "...at global and regional scales (e.g. Garcia et al., 2014)" should be "...at global and regional scales (Garcia et al., 2014)". This happens throughout the manuscript. Please remove all occurrences.

R: Removed in the revised manuscript as suggested (page 3 line 4 and other occurrences).

Line 4: Change "...by altering fluxes exchanges, energy balance, carbon cycle, etc." to "...by altering the exchange of carbon, water and energy between the atmosphere and land surface".

25 R: Done in page 3 line 5.

Line 5: Put references in chronological order. Do this throughout the manuscript.

R: Done in page 3 lines 5-6 and other occurrences.

Lines 5-6: Add a reference for this.

R: References have been added in page 3 lines 7-8.

Line 8: Change the definition of LAI from "defined as the one-side leaf area in a unit area" to "defined as the one-sided leaf area per unit ground area"

R: Thanks, Corrected in the revised manuscript in page 3 lines 10-11. Thanks.

5 Line 10: Increasing rate of what? Do you mean a strengthening of the land C sink?

R: Yes. It is a strengthening of the land carbon sink. We have explained this better in the revised manuscript in page 3 line 13.

Line 26: Put the word atmospheric before CO<sub>2</sub>.

R: Added atmospheric before CO<sub>2</sub> in page 4 line 4 and all other occurrences.

10 Line 27: I would say simulate rather than predict since you are not performing model runs into the future.

R: Changes have been made in page 4 line 4 and other occurrences.

Line 28: What are the associated surface characteristics? Give one or two examples (e.g. roughness length, albedo).

15 R: Roughness length, albedo, PFT distribution, LAI and etc. are the characteristics that we intended to express here. This has been clarified in the revised manuscript in page 4 line 4.

Lines 30-31: I would like a reference at the end of this statement. Instead of using the phrase "since the later 1980s", use "towards the end of the 1980s" or "since the second half of the 1980s".

R: Changed to "towards the end of the 1980s". A reference has been added. Please find in page 4 lines 20 10-11.

Page 3

Lines 8-9: Add some references at the end of this sentence.

R: References have been added in the revised manuscript in page 4 line 23.

Lines 9-10: Give an example of some other external forcing.

25 R: For instance, wind speed and sea surface pressure. This has been added to the revised manuscript in page 4 line 25.

Line 15: Change "by applying a dynamic global vegetation model" to "by using the SSiB4/TRIFFID (Simplified Simple Biosphere model version 4/Top-down Representation of Interactive Foliage and Flora Including Dynamics) DGVM...". Just use the abbreviation from now on.

R: Changes have been made in the manuscript according to this suggestion (page 5 lines 3-5).

5 Lines 19-24: Remove these lines and add your research questions here.

R: Lines were removed. The research questions in this paper are: 1) how do the vegetation trends change before and after the 1980s? 2) What is the effect of climate regime shifts during the 1980s on the vegetation trend change? These questions have been added to the manuscript in page 5 lines 8-10.

#### 2 Model description, observational datasets, and experimental design

Move section 2.4 (Experimental design) to just after the model description section.

The structure of this section should be:

- 2.1 Model description
- 2.2 Experimental design
- 2.3 Data
- 15 2.3.1 Meteorological forcing data
  - 2.3.2 Observation-based data

R: We have modified the structure of this section based on the reviewer suggestion.

Line 25: Change 2.1 title to "Model description".

R: Done (page 5 line 12).

20 Line 26: Change "...is a biophysically based model incorporating estimates fluxes of radiation..." to "...is a biophysically based model which simulates fluxes of radiation...".

R: Done (page 5 lines 13-15).

Lines 29-32: Change this sentence to "The TRIFFID DGVM (Cox, 2001) was coupled to SSiB version 4 (Xue et al., 2006) to calculate vegetation dynamics, including relevant land-surface characteristics of vegetation cover and structure."

R: Done (page 5 lines 16-18).

Page 4

Line 2: Delete "Some parameters were also updated in this process".

R: Deleted.

10

Lines 2-7: I don't think you need this here. Please add a description of how GPP and LAI are calculated in SSiB4.

R: Lines have been removed from the revised manuscript, and the following sentences on how GPP and LAI calculation in SSiB4/TRIFFID are added in page 5 lines 21-26.

"SSiB4 estimates net plant photosynthesis assimilation rate, autotrophic respiration and other surface conditions such as canopy temperature and soil moisture for TRIFFID. TRIFFID updates the coverage of a PFT based on the net carbon available to it and the competition with other PFTs, which is controlled by the Lotka-Volterra equations. Vegetation is descripted by leaf, wood, and root with associating carbon pools. Leaf phenology is simulated as a function of canopy temperature and soil moisture."

#### 2.2 Meteorological forcing data

In this section, please add more information regarding the Princeton dataset. How was it created? Where did you download it from?

15 R: We have modified this paragraph to including the data source and how it was created. Please find it in page 7 lines 14-22.

Line 11: "modelling" instead of "modeling".

R: Done in page 7 line 14.

Lines 13-14: Add units.

20 R: Done in page 7 lines 19-21.

#### 2.3 Observation-based data

Can you make a section called Data? Add a brief paragraph detailing what datasets were used as input (meteorological, vegetation, soil) to SSiB4/TRIFFID and those used to evaluate the model. Then add the Meteorological forcing data and Observation-based data sections as subsections.

R: We have rearranged the data information and made a section called Data (section 2.3), which includes three subsections: 2.3.1 Initial condition for equilibrium simulation (covering the vegetation map and soil used as input in the quasi-equilibrium simulation); 2.3.2 Meteorological forcing data (covering the Princeton global meteorological dataset used as forcing data for quasi-equilibrium and

- real-forcing simulations); 2.3.3 Observation-based data (covering GLC2000 and MODIS for vegetation distribution evaluation, GIMMS and GLASS LAI data for LAI evaluation and FLUXNET-GPP for GPP evaluation). The following has been added to summarize the datasets used as input and those used to evaluate the model (page 7 lines 2-6).
- 5 "A SSiB vegetation and soil map is used as the preliminary initial condition for the quasi-equilibrium simulation. A 3-hourly meteorological forcing data from 1948 through 2007 (Sheffield et al., 2006) is used for this study. The observation-based LAI and GPP products (Zhu et al., 2013; Xiao et al., 2014; Jung et al., 2009) are used to validate and calibrate the model to produce proper vegetation spatial distribution and temporal variability."
- 10 Line 17: Is this the land cover map used by the model or is it used to evaluate the model after spin-up? Where did you download it from? Did you have to do any processing of the land cover map for the study? What is the native resolution of the database?
  - R: The global land cover map was used to evaluation the model results driven by 1948-2007 meteorological forcing data. It was download from
- http://forobs.jrc.ec.europa.eu/products/glc2000/glc2000.php. This dataset consists of a global map with one legend, as well as regional maps with separate legends containing more detailed classification for certain regions. We used the 1000 m resolution reginal products to generate land cover fraction map by counting the percentage of each PFT in a 1-degree grid. Then the regional fraction maps were merged to obtain a global land cover fraction map. Furthermore, a land cover map for dominant type at 1-degree
- 20 resolution was generated based on the vegetation type having the largest coverage in a 1-degree grid box. The paragraph introducing vegetation cover data has been rewritten in page 7 lines 24-26 and page 8 lines 1-15.
  - Line 19: Please explain what S1 is? "SPROT" should be "SPOT".
- R: "S1" stands for SPOT-VEGETATION standard product S1: daily maximum of NDVI composite of spectral reflectance at the top-of-canopy. We have modified this sentence to "The Global Land Cover (GLC) database for the year 2000 (Bartholome et al., 2002) used the data from Satellite Poul l'Observation de la Terre at the spatial resolution about 1 km" in page 7 lines 25-26 and page 8 line 1.

Line 23: What do you mean by dominance in the GLC2000 dominance map? Is this a map in which the PFT that has the most coverage in each grid box is the dominant PFT? Line 25: Provide a brief explanation of the differences between the GLC2000 and MODIS land cover map?

R: As mentioned in response to the previous question "Did you have to do any processing of the land cover map for the study?", the high resolution (1000 m) vegetation type product was converted to vegetation fraction map by counting the percentage of each PFT in a 1-degree grid. Then the dominant vegetation map (at 1-degree resolution) was generated, by assigning the type with maxim fraction cover in each grid of the fraction map.

GLC2000 and MODIS are derived from different sensors on-board different satellite and in different classification system. GLC2000 is based on the daily data from VEGETATION sensor on-board Satellite Poul l'Observation de la Terre (SPOT) 4, while MODIS land cover map is based on the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra-1 satellite. MODIS produces the vegetation every year which another product only has GLC2000 and GLC 2014. We feel GLC data may have better quality control.

15 Line 26: Do you mean assess and not access?

R: Thanks. This typo has been corrected in page 8 line 16.

Lines 27-28: Where did you download GIMMS, GLASS and MODIS LAI datasets from? Can you provide a couple of sentences on the differences between these LAI datasets? Did you have to do any processing of the LAI data?

R: The Global Inventory Modeling and Mapping Studies (GIMMS) LAI (refer to LAI3g, the third generation) was downloaded from <a href="https://ecocast.arc.nasa.gov/data/pub/gimms/">https://ecocast.arc.nasa.gov/data/pub/gimms/</a>. A neural network algorithm was trained to using the AVHRR GIMMS NDVI3g (covering the period July 1981 to December 2011) and best-quality Terra MOIDS LAI (covering the period 2000 to 2009) for the overlapping period 2000-2009. Then the trained neural network algorithm was used to generate corresponding LAI dataset at 15-day temporal resolution and 1/12-degree spatial resolution for the period from July 1981 to December 2011.

The Global Land Surface Satellite (GLASS) LAI was download from <a href="http://www.bnu-datacenter.com/">http://www.bnu-datacenter.com/</a>. The GLASS LAI was generated from AVHRR reflectance (1982-1999) and MODIS

reflectance (2000-2012). The GLASS LAI provides observations at 8-day temporal resolution and 1 km spatial resolution for the period from 1982 to 2012.

The MODIS LAI includes products derived from Terra and Aqua platform and product derived from the combination of the two platforms. The MODIS products are at 8-day temporal resolution and 500 m spatial resolution.

GIMMS LAI and GLASS LAI are used to evaluate the spatial distribution and temporal variability of model simulation. We didn't use MODIS LAI for the comparison directly. GIMMS LAI and GLASS LAI products are averaged to monthly mean, and then regridded to 1-degree spatial resolution.

Above information is included in the revised manuscript in page 8 lines 16-28 and page 9 lines 1-3.

Page 5 Lines 1-2: Change from "...remapped to 1-degree spatial resolution and a monthly temporal interval." to "...regridded to 1-degree spatial and monthly temporal resolution."

R: We changed it to "resampled" in page 9 line 3.

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Lines 3-4: This sentence would be better written as "SSiB4/TRIFFID GPP was evaluated using the upscaled FLUXNET GPP (hereafter referred to as FLUXNET-MTE) (Jung et al., 2009; Jung et al., 2011)." Also where did you download the data from? Provide more information on how the dataset was created.

R: The sentence is re-written and additional information is provided (page 9 lines 4-10). The FLUXNET-MTE GPP was downloaded from <a href="https://www.bgc-jena.mpg.de/geodb/projects/Data.php">https://www.bgc-jena.mpg.de/geodb/projects/Data.php</a>. The FLUXNET observations of carbon dioxide flux were upscaled to the global scale using the machine learning technique, model tree ensembles (MTE), which was trained to predict site- level GPP based on remote sensing indices, climate and meteorological data, and information on land use. This data set provides global monthly mean GPP at 0.5-degree spatial resolution for the period from 1982 to 2011.

Line 7: Change "MTE-GPP data was remapped to 1-degree spatial and a monthly temporal resolution." to "FLUXNET-MTE GPP was regridded to 1-degree spatial and monthly temporal resolution.".

R: This sentience has been written in page 9 line 10.

The FLUXNET-MTE GPP was regridded to 1-degree spatial resolution.

Lines 9-10: Change this sentence to "In this study, SSiB4/TRIFFID was used to simulate the global vegetation distribution and assess the sensitivity of ecosystem trends to climate and eCO2."

R: Done in page 6 lines 5-6.

Line 10: Remove "For this purpose". "performed" instead of "conducted"

5 R: Done in page 6 line 6.

Lines 13-14: Remove the sentence "Meanwhile, the effect of largescale disturbance (LSD) on restricting tree expansion to savanna areas was investigated." Put this in the results/discussion sections.

R: Moved to the results/discussion sections.

Line 17: Remove "firstly". What are the multiple biotic variables?

R: "firstly" is removed. The multiple biotic variables stand for vegetation coverage, LAI and GPP. It has been replaced by "vegetation coverage, LAI and GPP" in the revised manuscript in page 6 line 14.

Pages 6-14

#### 3 Vegetation initial conditions

This section should now be your results section. Each subsection should have the questions as the heading, so the reader does not have to go back to the introduction again. In each subsection, have a sentence that summarizes the main finding. This makes it easier for the reader to understand the key findings.

I suggest the following. Obviously, you should add your own question after each subsection number. I have only added what I think the section should be about.

- 20 3 Results
  - 3.1 Evaluating the quasi-equilibrium simulation. Comparison to land cover map. Effect of large-scale disturbance.
  - 3.2 Evaluating GPP/LAI.
  - 3.3 Assessment of vegetation temporal variability.
- 25 3.4 External forcing effects on ecosystem trends.
  - R: The structure of results section has been modified accordingly in the revised manuscript.
  - 3 Results
  - 3.1 Vegetation initial condition

- 3.2 Model evaluation of simulated vegetation distribution, LAI and GPP
- 3.3 Simulated vegetation temporal variability and trend changes
- 3.4 Attribution of three environmental drivers on ecosystem trends

We added a sentence as the beginning of each subsection to point out the main content in this section.

5 The discussion section (section 4) should have 4 subsections, each discussing the corresponding results from section 3. The Conclusions section will be section 5.

R: The discussions currently in Section 3 have been moved to the discussion section.

Page 6

#### 3.1 Quasi-equilibrium simulation

10 Lines 3-16: The first 2 paragraphs could be moved to the discussion section.

R: Thanks for your suggestion. We have carefully read and compared before and after we move the first 2 paragraphs to the discussion section. We feel it is better to keep those paragraphs so the readers can easily follow this section, and the flow is better.

Lines 17-25: Move this paragraph to the beginning of this section.

15 R: Please see the answer for above question.

Line 11: Do you mean allocation instead of reallocation? Line 12: Don't start a sentence with "Figure X shows...". Make a statement regarding the result and reference the figure in brackets at the end of the sentence. Do this throughout the manuscript.

R: Yes, it is "allocation". This has been corrected in the revised manuscript in page 10 line 1.

20 Thanks for pointing out, we have gone through manuscript to reduce use of this phrase.

Line 23: Delete the phrase "That being said".

R: Deleted.

Page 7 Lines 3-5: Delete the sentence "Detailed comparison of the simulated...".

R: Deleted.

25 Line 27: You could reference Figure 4 here.

R: We generated a figure includes vegetated area comparison in Supplement figure 1. It is cited in page 11 line 13.

Page 8 Line 28: Re-write this sentence as "The spatial correlation coefficient between model and FLUXNET-MTE GPP is 0.93 (P<0.05) (Figure 7)".

R: Modified as suggested in page 12 line 24.

Line 30: The standard way to quote global GPP values is in PgC/yr. Remove 1135 gC/m2/yr.

5 R: Modified in page 12 line 26 and page 13 lines 1-2.

Line 32: Lack of N-limitation.

R: Corrected in page 13 line 3.

Page 9 Line 8: Change "for the model validation" to "for model evaluation".

R: Changed in page 13 line 15.

10 Page 10 Line 6: I don't think you need Figure 9 as it is referenced only once. You could add a reference at the end of the sentence instead.

R: Done.

Lines 6-7: State the temperatures as Celsius instead.

R: The paragraph has been removed in the revised manuscript.

15 Lines 18-19: Remove the information regarding the stipples (dots) on Figure 10 as it is already included in the caption.

R: Done

Lines 24-25: Reference a figure at the end of this sentence.

R: This sentence refers to Figure 10 (Figure 7 in the revised manuscript). It is added in the revised manuscript in page 14 line 17.

Page 11 Can you include a few sentences on how elevated CO2 affects GPP/LAI in the model as part of the discussion?

R: Yes. SSiB uses Collatz et al model to calculate photosynthesis process (Zhan et al, 2003) which is given the following equations:

$$A_n = \frac{g_b}{1.4} \frac{C_a - C_s}{p}$$

$$GPP = A_n + R_d$$

where  $A_n$  is the net CO<sub>2</sub> assimilation,  $g_b$  is stomatal conductance to latent and sensible heat transfer,  $C_a$  is the atmospheric CO<sub>2</sub> concentration,  $C_s$  is the CO<sub>2</sub> concentration at leaf surface, p is the air pressure, and is  $R_d$  the dark respiration rate of the canopy. Based on above equations, increase in  $C_a$  leads to a larger  $A_n$ , then a larger GPP.

Vegetation in TRIFFID is presented as leaf, root, and wood carbon, and for each a corresponding carbon pool is updated the based on the net carbon available to it and the competition with other PFTs, which is controlled by Lotka-Volterra equations. LAI is calculated based on the leaf carbon pool and leaf phenology. Larger GPP leads more carbon goes in to the vegetation carbon pool in leaf, root and wood, then larger LAI.

A summary of these explanations has been added to the discussion section in page 20 lines 15-22.

Page 12 Lines 6-8: Remove these lines.

R: Removed.

Page 14

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#### 15 6. Conclusion

I would like to see some more discussion in the Conclusions section. It is a bit short. Of the three sensitivity experiments, please state which one is the most important and why?

R: This is a valid point, we agree that the conclusion concerning driver contributions is a bit short. We have included additional discussion in the revised manuscript.

20 Line 9: Change "to the climate variability" to "to climate variability".

R: Changed in page 21 line 16.

Lines 10-11: Delete the phrase "The results show". Use "We have shown that the SSiB4/TRIFFID model can simulate the vegetation distribution and temporal variability for the X time period."

R: Done in page 21 lines 18-19.

25 Lines 28-30: Is there a University service for making the data available rather than a google drive account? Can you obtain a doi for the data? Also can you specify what data you have made available?

R: We have uploaded the available data to a University server and will indicate the available data in "data availability" section (page 21 lines 16-17). We will request a doi from your journal for the data when we submit the revision.

Figure 2 Can you use different colors for the lines as they are difficult to distinguish? Figure 4 I don't think you need this figure. Can you remove?

R: We have redrawn Figure 2 with different colors to make it clearer. Figure 4 has been moved to the appendix.

Figure 5 Can you include the MODIS dataset since you mention it on Page 4, line 24?

R: We have added figure to show the comparison of vegetated area in simulation, GLC and MODIS in supplement.

Figure 6 Please plot the differences (model - obs) instead.

R: This figure has been replaced.

Figure 7 Plot the difference instead.

R: We have redrawn this figure to show the difference.

15 Figure 8 You haven't said what the black line is? Is this SSiB4/TRIFFID?

R: Yes, it is SSiB4/TRIFFID. It has been added to the revised manuscript.

Change first line of caption to "Comparison of standardized LAI anomalies between simulation and observations for 9 sub-regions."

R: Done.

### Response to Reviewer 2

#### **Main comments**

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First, I fail to see what is new here compare to previously published studies: the current study uses only one model which does not seem to perform better than the TRENDY models used in Zhu et al. (2016) according to the results p. 8 l. 24-27 and p. 9 l. 22-25. As referee #1 mentions, this paper reads like a model evaluation and new scientific insights should be brought forward. If version 5 outperforms version 4 as mentioned p. 8 l. 25-27, the authors should consider using it instead.

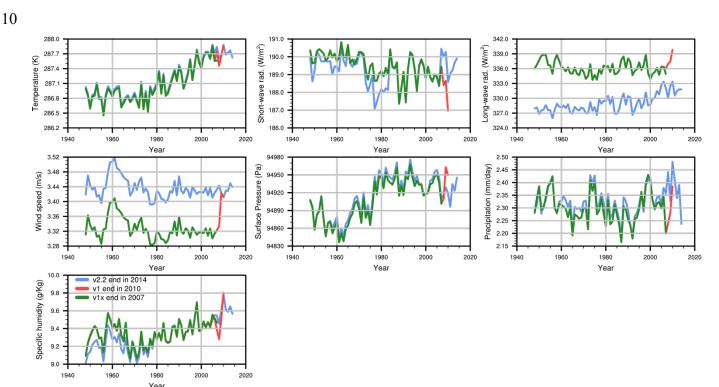
R: There are a number of new features of our study. Firstly, it uses a new model, SSiB4/TRIFFID, which was not included in the TRENDY model inter-comparison. SSiB5/TRIFFID (as described on p. 8 l. 25-27) is a significantly updated version of SSiB4/TRIFFID. It is a new model which has not completed its testing. It will become publicly available next year. We have taken the sentence out in the text to avoid the confusion.

Secondly, and most importantly, our study focusses specifically on the impact of the climate regime shift during the 1980s. Previous DGVM studies (including TRENDY models used in Zhu et al, 2016), which investigated the effect of climate change on vegetation, only focused on the period after the 1980s. In our study, the contribution of the primary drivers on the ecosystem trends for each regime is identified. We estimate large-scale trends in terms of carbon fixation (GPP), vegetation growth (LAI), and expansion (vegetation fraction) rather than focus only on one aspect such as LAI trends in (Zhu et al, 2016).

Model inter-comparison exercises are excellent ways to assess common features of different model projections, and to estimate uncertainties. However, analysis of the responses to given climate anomalies is more effectively carried-out through detailed analysis of a single model, and this is precisely what we undertake in this paper. We have added text to the paper to make these innovative aspects of our study clearer.

Second, why is the study limited to the years 1958-2007? Considering the increasing availability of EO since 2007, extending the study period to nowadays would help address the "global vegetation variability" using satellite data as the title and the introduction (p. 3 l. 17).

R: We have downloaded three versions of Princeton meteorological dataset with the ending year of 2007 (v1x), 2010 (v1) and 2014 (v2.2), respectively. v1 had merged the data v1x plus the data from 2008-2010. However, when we compared the two versions (i.e. v1x and v1), we found that although v1x and v1 are generally consistent before 2007, however, there was an abrupt shift in some variables (such as wind speed) after 2007 (See Response Figure 2). To ensure the consistence and minimize the uncertainties could be involved by the meteorological forcing data, we decided to stop the simulation at 2007. The v2 data, which starts to be available in later 2016, is quite different from the v1 data (Response Figure 1, blue line) for a number of variables. Since by the time we have finished most of our work, we have kept with on the v1x data.



Response Figure 2. Comparison between different version of Princeton meteorological datasets over global land (-1800 W,1800 E, -600 S, 750 N)

15 Third, there is a lack of consistency between p-values reported, see for example p.9 l. 23 which points to possible cherry-picking from the authors.

R: Thanks for pointing out this. A consistent p-value of 0.05 is be used in the revised manuscript.

#### **Minor comments**

- p. 2 l. 6 Can you support this statement with a reference?
- R: References (Myneni et al., 1997; Piao et al., 2011, 2015; Ichii et al., 2013; Los 2013; Zhu et al., 2016) are added to the revised manuscript in page 3 lines 7-8.
- 5 p. 21. 9 Leaf area "per unit of ground" area
  - R: Corrected to "per unit ground area" according to Referee 1, Referee 2, and book "Plant Factory" Chapter 9: Photosynthesis and respiration (page 3 lines 10-11).
  - p. 21. 25 Consider citing Zhu et al. 2013 as an example of dataset covering the period 1980 to present R: The citation was added in page 4 line 2.
- 10 p. 21. 30 Please cite articles that support this 'general consensus'
  - R: Ichii et al 2013; Piao et al 2015; Zhu et al 2016, 2017 have been added in the revised manuscript in page 4 lines 10-11.
  - p. 3 l. 15 See my main comment about the study period
  - R: Please see the response for the second main comment.
- 15 p. 31. 18 'apportioned' is perhaps more correct than 'attributed'
  - R: In this study, the experiments were designed to identify and quantify the contribution of three external forcings on the ecosystem trends. These drivers are the cause of these ecosystem trends. As a matter of course, previous studies on this subject also used the term "attribution", for instance Ichii et al 2013; Piao et al 2015; Zhu et al 2016, 2017. We feel the word "attribute" may be more familiar to
- 20 readers.
  - p. 4 l. 19 Please define SPOT (Satellite Pour l'Observation de la Terre), indicate what type of sensor VEGETATION is and a what resolution these data were available.
  - R: We have added a definition of SPOT in the revised manuscript. The VEGETATION sensor has four spectral bands.. The spectral bands are blue (437–480 nm), red (615–700 nm), near-infrared (772–892
- 25 nm) and short-wave infrared (1600–1692 nm). This paragraph has been rewritten in the revised manuscript in page 7 lines 24-26 and page 8 lines 1-7.
  - p. 4 l. 26 To my knowledge GIMMS is also derived from AVHHR data.

R: Yes. The GIMMS LAI was generated using the overlapping AVHRR GIMMS NDVI3g data and best-quality MODIS LAI, then generating the full temporal coverage GIMMS LAI3g data using AVHRR GIMMS NDVI3g. The GIMMS LAI provides observation at 15-day temporal resolution and 1/12-degree spatial resolution for the period from July 1981 to December 2014. Proper modification was added in the revised manuscript in page 8 lines 16-28 and page 9 lines 1-3.

p. 5 l. 3-7 As the study aims to use satellite data, why not using MODIS GPP/NPP (or GIMMS-based NPP from Kolby-Smith et al. 2016).

R: This is a good suggestion. The observation-based datasets are used in this paper to evaluate the model simulation whenever the reference data available. The MODIS data set starts from 2000. The period is too short for this study. In fact, comparing the two observation-based GPP datasets (MODIS and FLUXNET MTE GPP), Anav et al. (2015) found they are in similar range of the global average and inter-annul variability, as well as in similar spatial pattern. FLUXNET-MTE is found to be more climate representativeness. Moreover, model simulations presented in Anav et al (2015) show higher spatial and temporal correlations against FLUXNET-MTE GPP than that against MODIS GPP.

15 p. 5 l. 20 onwards Can you summarize the experiments in a table?

R: A table is added in the revised manuscript.

p. 6 l. 8 Transient simulations are usually performed from a steady-state obtained under past conditions. Using the average conditions of the period 1948-2007 may reduce the model's sensitivity to the warming that occurred during that period. It would have been better to use the first ~10 years of driving

20 data for this procedure.

R: Thank you, this is a good idea. We decided to use the average conditions of the period 1948-2007 in the quasi-equilibrium simulation was based on the practical consideration. Many experiments have been conducted to test the model performance under different meteorological condition. For instance, using the first year (1948) meteorological forcing, and the first 10/20 years' average. We obtain the best and the most stable results when the model was driven by average of the whole period 1948-2007, and also excluded the first 10-year results as spin-up period in the analysis.

p. 6 l. 15: Is this checked at pixel level, or only globally? Have you checked whether fluxes and initial stocks were at equilibrium? see e.g. Exbrayat et al. (2014) for the importance of initial stocks on transient simulations.

R: It is checked at reginal scale. We have checked the quasi-equilibrium status at different regions across the world, with particular attention on the transition areas between major climate zones. Per referee's concern, we draw the spatial distribution of absolutely relative changes of the last 10-year simulation for each PFT, which is defined as

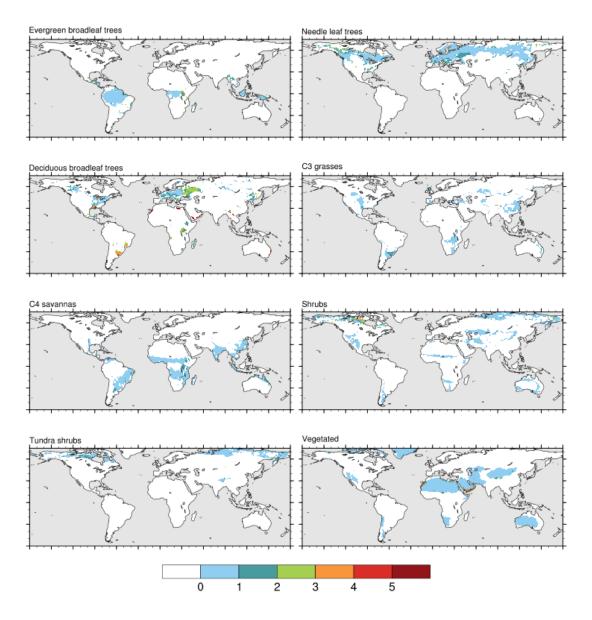
$$average\left(\left|\frac{fraction-mean\_fraction}{mean\_fraction}*100\%\right|
ight),$$

where mean fraction is the averaged from the last 10-year simulation, please see Response Figure 3.

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As defined in the manuscript, the quasi-equilibrium status is reached when the fraction change is less than 2% of the mean vegetation fraction. Therefore, only fraction time series are shown here. We also checked other variables such as LAI and GPP at the equilibrium simulation, and both reach the quasi-equilibrium status. SSiB4/TRIFFID is a water, carbon and energy balanced model. When several key variables involved in water, carbon and energy cycle reach a steady-state systematically, other variables should follow. In the current version of SSiB4/TRIFFID, soil organic carbon mentioned in Exbrayat et al (2014) is a diagnostic variable as a result of plant litter and soil microbial process; no feedback to vegetation growth.



Response Figure 3. Mean absolutely relative change of the last 10-year simulation in quasi-equilibrium simulation for each PFT p. 6 l. 22-25 Are these sentences referring to the model or GLC?

R: It was referring to the comparison between simulation and GLC. This sentence has been removed in the revised manuscript.

p. 7 l. 1 This part is very specific to the model used here. Readers who are not familiar with TRIFFID need a bit of context to understand how the LSD coefficient is used, and the impact of increasing its value ten-fold.

R: This is a valid point. LSD ( $\gamma_{\nu}$ ) is a parameter in TRIFFID descripting the rate of vegetation loss (units: yr<sup>-1</sup>) caused by large scale disturbance such as fire, flooding and insect outbreaks. The change in plant functional type (PFT) fraction ( $\nu$ ) is controlled by the PFT competition (the first term of the right-hand side of the equation) and the disturbance (the 2<sup>nd</sup> term).

$$C_v \frac{dv}{dt} = \lambda \Pi v \left\{ 1 - \sum_j c_{ij} v_j \right\} - \gamma_v v C_v,$$

where v is the vegetation fraction for each PFT, Cv is the carbon content in the plant,  $\gamma_v$  is the largeo scale disturbance which results in vegetated area loss at the prescribe rate. It was set to  $0.004/\text{yr}^{-1}$  for trees and  $0.100/\text{yr}^{-1}$  for grasses. Those values were chosen largely by model calibration in offline tests. We increased LSD in the tree and grass mixed areas as the consideration of more fire occurrences in those areas. We add some explanation in page 10 lines 15-25. We are developing the fire module to more realistically simulate that disturbance in the future.

15 p. 7 l. 21 You can also cite Poulter et al. (2014)

R: Done in page 19 line 22. Thanks.

p. 8 l. 19 Please clarify whether you are referring to global average LAI.

R: This sentence is regarding the LAI spatial distribution. The spatial correlation coefficients comparing observations are presented for both global and North Hemisphere.

p. 8 l. 25-27 This statement raises an important question: why do you use model version 4 when you know that model version 5 outperforms it?

R: As response to the main common 1, the SSiB5/TRIFFID mentioned in p. 8 l. 25-27 is an updated version of current SSiB4/TRIFFID. It is still under development. SSiB4/TRIFFID works well for the current study. We have removed this sentence in the revision.

p. 9 l. 22-23 Please consider rewording... correlations of 0.35 cannot be described as matching the reference data closely.

- R: Thanks for pointing out. We have modified this sentence and only indicate it is a significant correlation in the revised manuscript in page 14 lines 1-2.
- p. 10119 Once again p-value...
- R: Correction is made in the revised manuscript with consist p-value of 0.05.
- 5 p. 14 l. 29 I have not been able to access the data using this link, please check.
  - R: We have uploaded the data to a University server.

# Global vegetation variability and its response to elevated CO<sub>2</sub>, global warming, and climate variability - A study using the offline SSiB4/TRIFFID model and satellite data

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**Abstract.** The climate regime shift during the 1980s had a substantial impact on the terrestrial ecosystems and vegetation at different scales. However, the mechanisms driving vegetation changes, before and after the shift, remain unclear. In this study, we used a biophysical-dynamic vegetation model to estimate large-scale trends in terms of carbon fixation, vegetation growth and expansion during the period 1958-2007, and to attribute these changes to environmental drivers including elevated atmospheric CO<sub>2</sub> concentration (hereafter eCO<sub>2</sub>), global warming, and climate variability (hereafter CV). Simulated Leaf Area Index (LAI) and Gross Primary Product (GPP) were evaluated against observation-based data. Significant spatial correlations are found (correlations>0.87), along with regionally varying temporal correlations of 0.34-0.80 for LAI and 0.45-0.83 for GPP. More than 40% of the global land area shows significant positive (increase) or negative (decrease) trends in LAI and GPP during 1958-2007. Regions over globe show different characteristics in terms of ecosystem trends before and after since the 1980s. While 1950s: 11.7% and 19.3% of land has consistently positive LAI and GPP trends, respectively, since 1958; while 17.1% and 20.1% of land, saw LAI and GPP trends, respectively, reverse during the 1980s. Vegetation fraction cover (FRAC) trends, representing vegetation expansion/shrinking, are found at the edges of semi-arid areas and polar areas. Environmental drivers affect the change in ecosystem trend over different regions. Overall, eCO<sub>2</sub> consistently contributes to positive LAI and GPP trends in the tropics. Global warming is shown to mostly affectsed LAI, with positive effects in high latitudes and negative effects in subtropical semi-arid areas. CV is found to dominate the variability of FRAC, LAI, and GPP in the semi-humid and semi-arid areas. The eCO<sub>2</sub> and global warming effects increased after the 1980s, while the CV effect reversed during the 1980s. In addition, plant competition is shown to have played an important role in determining which driver dominated the regional trends. This paper presents a new insight into ecosystem variability and changes in the varying climate since the 1950s.

**Keywords**: Ecosystem variability, dynamic vegetation model<u>ling</u>, elevated CO<sub>2</sub>, global warming, climate change and variability, TRIFFID, SSiB

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#### 1 Introduction

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Climate variability and change, including global warming, and elevated atmospheric CO<sub>2</sub> concentrations (referred to as eCO<sub>2</sub> in this paper), have profound impacts on the terrestrial biosphere at global and regional scales (e.g. Garcia et al., 2014); while the terrestrial biosphere, in turn, affects the global climate by altering the fluxes exchanges of carbon, water and, energy between the atmosphere and land surface (Cox et al., 2000; Xue et al., 2004, 2010; Friedlingstein et al., 2006; Ma et al., 2013). balance, carbon cycle, etc. (e.g. Cox et al., 2000; Xue et al., 2004; Xue et al., 2010; Ma et al., 2013; Friedlingstein et al., 2006). Important trends in terrestrial ecosystem carbon fixation, growth, and expansion in the past 60 years have been detected (Myneni et al., 1997; Piao et al., 2011, 2015; Ichii et al., 2013; Los 2013; Zhu et al., 2016). For instance, general earth greening has been discovered by 10 analyszing satellite-derived Normalized Difference Vegetation Index (NDVI) (Myneni et al., 1997; Piao et al., 2011; Ichii et al., 2013; Los 2013)(Myneni et al., 1997; Ichii et al., 2013; Los, 2013; Piao et al., 2011) and Leaf Area Index (LAI, defined as the one-side leaf area per groundin a unit area) products (Piao et al., 2011, 2015; Zhu et al., 2016). (Piao et al., 2011; Piao et al., 2015; Zhu et al., 2016). The 15 Earth's terrestrial vegetation has acted as an important carbon sink in the past 60 years (Ballantyne et al., 2012; Le Quéré et al., 2013), with a significantly increasing strengthening carbon sink rate, about 0.06 PgC/yr<sup>-2</sup>, after the 1980s (Sitch et al., 2015), revealing growth in plant productivity (Nemani et al., 2003; Anav et al., 2015). In the meantime, vegetation fractional coverage (hereafter FRAC) has been changing, including some large-scale increases in total vegetation cover (e.g. Piao et al., 2005; Donohue et al., 2009; McDowell et al., 2015), and shifts in the spatial distributions of plants species, such as 20 woody plants encroachment in the savanna area (Stevens et al., 2017) and shrubification in the tundra biome (Epstein et al., 2012; Mod and Luoto, 2016).

Many studies have attributed these large-scale ecosystem trends to climatic drivers and eCO<sub>2</sub> after applying statistical methods to satellite-based observations or the results from process-based land surface models (e.g. Myneni et al., 1997; Liu et al., 2006; Ichii et al., 2013; Mao et al., 2013; Piao et al., 2015; Schimel et al., 2015; Sitch et al., 2015; Devaraju et al., 2016; Zhu et al., 2016; Smith et al., 2016). Statistical regression and cross-correlation have been applied to attribute the recent biosphere changes to precipitation, temperature, and solar radiation variability (e.g. Zeng et al., 2013; Myers-Smith et al.,

2015). Results from these studies indicated that northern mid- to high- latitude NDVI anomalies were positively correlated with temperature, and positively associated with precipitation in temperate to tropical semi-arid and arid regions (Zeng et al., 2013). However, statistical methods rarely isolate the drivers' contribution to the inter-annual or decadal variability of the terrestrial ecosystem (e.g. Ahlbeck, 2002; Piao et al., 2015). Moreover, the satellite products only cover the period after 1980 (Zhu et al., 2013).

Process-based land surface models overcome these limitations and are also able to include atmospheric CO<sub>2</sub> as an external driver. Dynamic Global Vegetation Models (DGVMs) simulated predict vegetation cover changes in response to changes in climate and atmospheric CO<sub>2</sub>, and update associated surface characteristics such as PFT distribution and LAI (Claussen and Gayler, 1997; Smith et al., 2001; Bonan et al., 2002; Sitch et al., 2003; Woodward and Lomas, 2004; Krinner et al., 2005; Zeng et al., 2005; Zaehle and Friend, 2010; Lawrence et al., 2011; Zhang et al., 2015). By applying DGVMs in a model intercomparison project (called TRENDY), a general consensus has been reached that eCO<sub>2</sub> explains the greater part of the increasing trend of LAI and GPP since the later 1980s towards the end of the 1980s (Schimel et al., 2015; Sitch et al., 2015; Zhu et al., 2016). Air temperature, precipitation, land use and land cover change, and nitrogen decomposition, also play roles in the changing terrestrial biosphere (e.g. Cramer et al., 2001; Schimel et al., 2015; Zhu et al., 2016). However, DGVMs should be applied with caution. The Coupled Model Intercomparison Project Phase 5 (CMIP5) reported that most DGVMs overestimated LAI in comparison to Global Inventory Monitoring and Modeling System (GIMMS) data (Murray-Tortarolo et al., 2013; Zhu et al., 2013). In addition, large discrepancies between models were found when predicting ecosystem variability and trends (Piao et al., 2013; Zhu et al., 2017). Unsurprisingly, the dominant factors obtained from different models are often significantly different (Beer et al., 2010; Huntzinger et al., 2017). Furthermore, DGVM simulations were sensitive to meteorological forcing data (Slevin et al., 2017; Wu et al., 2017). Therefore, a comprehensive evaluation of large-scale terrestrial ecosystem vegetation trends and potential drivers is crucial for improved DGVM application.

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Most ecosystem trend detection and attribution studies have focused on the period after the 1980s when satellite data has been available (Myneni et al., 1997; Schimel et al., 2015; Zhu et al., 2015).

However, a climate regime shift, identified by abrupt shifts in temperature, precipitation, and other climate variables (e.g. wind speed and sea surface pressure) external forcing, was observed during the 1980s (e.g. Gong and Ho, 2002; Lo and Hsu, 2010; Reid et al., 2016). The responses of vegetation to these climate shifts have not yet been comprehensively investigated, especially at the level of individual Plant Function Types (PFTs).

In this study, we investigate the effect of eCO<sub>2</sub> and climate drivers including global warming and climate variability (i.e., meteorological forcing excluding global warming, referred to as "CV") on the trends of FRAC, LAI, and GPP during the period 1958-2007 by using the SSiB4/TRIFFID applying a dynamic global vegetation model (Simplified Simple Biosphere model version 4/Top-down Representation of Interactive Foliage and Flora Including Dynamics) DGVM SSiB4/TRIFFID, (Xue et al., 1991; Cox, 2001; Zhan et al., 2003; Zhang et al., 2015; Harper et al., 2016) at both grid and PFT levels, and using satellite products whenever they are available. Changes in the ecosystem trends are attributed to changes in eCO<sub>2</sub> and climate effects, focusing particularly on the climate regime shift during the 1980s. The key focuses of this paper are on 1) how the vegetation trends change before and after the 1980s; and 2) What is the effect of climate regime shifts during the 1980s on the vegetation trend before/after the 1980s. The model and data description are presented in section 2. In section 3, we show results of a quasi-equilibrium simulation, which is used to produce the initial condition for the subsequent long term simulation. In section 4, the model performance in reproducing the spatial distribution and temporal evolution of vegetation variables are evaluated using satellite products. Finally, the paper delineates the linear trend of FRAC, LAI, and GPP before/after the 1980s and quantifies the contribution of different environmental drivers.

# 2. Model description, experimental design and data observational datasets, and experimental design

#### 2.1 Model description Brief description of SSiB4/TRIFFID

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25 The Simplified Simple Biosphere model (SSiB) is a biophysically based model which simulates incorporating estimates fluxes of radiation, momentum, sensible heat, and latent heat, as well as runoff, soil moisture, and surface temperature (Xue et al., 1991). A photosynthesis model (Collatz et

al., 1991, 1992)(Collatz et al., 1991;Collatz et al., 1992) has been implemented into SSiB to calculate carbon assimilation, forming SSiB2 (Zhan et al., 2003). The TRIFFID DGVM (Cox, 2001) Top-down Representation of Interactive Foliage and Flora Including Dynamics (TRIFFID) (Cox, 2001; Harper et al., 2016) was subsequently coupled towith SSiB version 4 (Xue et al., 2006) to calculate vegetation dynamics, including relevant land-surface characteristics of vegetation cover and structure. Zhang et al. (2015) (Xue et al., 2006), called SSiB4/TRIFFID. Zhang et al. (2015) updated the competition dominance hierarchy from tree-shrub-grass (i.e., trees dominate shrubs and grasses, and shrubs dominate grasses) to tree-grass-shrub, but still allowed shrubs and grasses to compete for sunshine and space. Some parameters were also updated in this process. In a North American study (Zhang et al., 2015) SSiB4/TRIFFID reproduced the main ecysystem features of North America. Based on the North 10 America experiments, we further distinguished deciduous/evergreen broadleaf trees as they form the land cover in different latitudes and have distinctly different phenological features. The absence of deciduous trees in SSiB4/TRIFFID caused an unrealistic lower summer LAI in the nertheatern U.S. (Zhang et al., 2015). SSiB4 estimates net plant photosynthesis assimilation rate, autotrophic respiration and other surface conditions such as canopy temperature and soil moisture for TRIFFID. TRIFFID 15 updates the coverage of a PFT based on the net carbon available to it and the competition with other PFTs, which is controlled by the Lotka-Volterra equations. Vegetation is descripted by leaf, wood, and root with associating carbon pools. Leaf phenology is simulated as a function of canopy temperature and soil moisture. In addition, tundra was separated from the original single shrub category in order to better reflect the arctic biomes. Evergreen and deciduous broadleaf trees are also separated as different 20 PFTs. To date, SSiB4/TRIFFID therefore includes 7 PFTs: 1) Evergreen broadleaf trees, 2) Deciduous broadleaf trees, 3) Needle leaf broadleaf trees, 4) C3 grasses, 5) C4 plants, 6) Shrubs, and 7) Tundra.

#### 2.2 Meteorological forcing data

The Princeton global meteorological dataset for land surface modeling (Sheffield et al., 2006) was used to drive SSiB4/TRIFFID for the period of 1948-2007 at 1° x 1° spatial resolution and 3-hourly temporal interval. This dataset, including surface air temperature, pressure, specific humidity, wind speed, downward short-wave radiation flux, downward long-wave radiation flux, and precipitation, is

constructed by combining a suite of global observation-based datasets with the National Centers for Environmental Prediction/National Center for Atmospheric Research reanalysis data.

#### 2.3 Observation-based data

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The global land cover map products from the Global Land Cover (GLC) database for the year 2000 is produced by an international partnership of about 30 research groups coordinated by the European Commission's Joint Research Centre (Bartholome et al., 2002). It is based on daily S1 data from the VEGETATION sensor on-board SPROT 4 acquired between 1<sup>st</sup> November 1999 and 31<sup>st</sup> December 2000. This dataset provides a global map with one consistent legend, as well as regional maps with separate legends containing more detail for certain regions. For instance, tundra is not included in the 21-category global legend but is included in the regional product for Northern Eurasia (Bartalev et al., 2003). In this study, we generated a GLC2000 dominance map for land cover validation according to the regional maps and the corresponding legends. Other than GLC2000, we also employed the Moderate Resolution Imaging Spectroradiometer (MODIS) land cover data product (MCD12Q1) as a reference (Friedl et al., 2010).

To access the climatology, variation, and trends of simulated LAI, two widely used LAI products were used as references in this study: the Global Inventory Modeling and Mapping Studies (GIMMS) LAI and the Global LAnd Surface Satellite (GLASS) LAI. GIMMS-LAI is based on the third generation of Normalized Difference Vegetation Index (NDVI3g) from the GIMMS group and an Artificial Neural Network model (Zhu et al., 2013). GIMMS-LAI provides a 1/12 degree resolution, 15-day composites, and spans the period July 1981 to December 2011. GLASS-LAI is generated from Advanced Very High Resolution Radiometer (AVHRR) (from 1982 to 1999 with 0.05 degree resolution) and MODIS (from 2000 to 2012 with 1 km resolution) time series reflectance data using general regression neural networks (Xiao et al., 2014). GIMMS and GLASS-LAI, and the meteorological forcing data for overlap period 1982 to 2007, were remapped to 1-degree spatial resolution and a monthly temporal interval.

The Model Tree Ensemble (MTE) GPP product (Jung et al., 2009; Jung et al., 2011) was used as the reference to evaluate the GPP simulation. MTE is based-on a machine learning technique in which

the model is trained to predict the carbon fluxes at FLUXNET sites driven by observed meteorological data, land cover data, and the remotely-sensed fraction of absorbed photosynthetic active radiation (Jung et al., 2009). Then the trained model is then applied at grid scale driven by gridded forcing data. MTE-GPP data was remapped to 1-degree spatial and a monthly temporal resolution.

#### 5 2.24 Experimental design

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In this study, SSiB4/TRIFFID was <u>usedapplied</u> to <u>simulateproduce</u> the global vegetation distribution and assess the sensitivity of ecosystem trends to climate and eCO<sub>2</sub>. For this purpose, <u>T</u>two sets of simulations were <u>performedeonducted</u>: 1) a 100-year quasi-equilibrium simulation driven by climatological forcing, and 2) sensitivity simulations driven by real-forcing from 1948-2007 (<u>TableFigure 1</u>). In the first set, SSiB4/TRIFFID was driven with the climatological forcing and 1948 CO<sub>2</sub> concentration to reach a steady state, which was used as the initial condition in the second set of simulations. <u>Meanwhile</u>, the effect of large-scale disturbance (LSD) on restricting tree expansion to savanna areas was investigated.

Using the quasi-equilibrium simulation results as the initial condition, the historical meteorological forcing and yearly updated <u>atmospheric CO</u><sub>2</sub> concentration were used to drive SSiB4/TRIFFID from 1948 through 2007. In this control simulation, we <u>firstly</u> evaluated the model performance in reproducing the climatology and variability of <u>vegetation coverage</u>, <u>LAI and GPP multiple biotic variables</u> in comparison with multiple observation-based datasets. The long-term trends were diagnosed before and after the climate regime shift of the 1980s. Furthermore, three sets of experiments were conducted to quantify the effects of <u>environmental external</u> drivers (climate and CO<sub>2</sub>) and vegetation competition on the ecosystem trends. These experiments were designed as following:

- 1. Fixed-CO<sub>2</sub>: The model was driven by the same meteorological forcing as the control experiment, but CO<sub>2</sub> concentration was fixed at the level of 1948 (310.33 ppm). The difference between control experiment and Fixed-CO<sub>2</sub> indicates the eCO<sub>2</sub> effect.
- 25 2. Detrend-Temp: The mean warming trend over each 10 degrees of latitude, from 1948 to 2007, was subtracted in this experiment. Then the detrended temperature along with other

- meteorological forcing and annually varying CO<sub>2</sub> concentration were used to drive the model. Subtraction of Detrend-Temp from the control experiment isolates the effect of global warming.
- 3. Climate Variability: Subtraction of both Fixed-CO<sub>2</sub> and Detrend-Temp from the control experiment was regarded as representing the effect of CV.

#### 5 **2.3 Data**

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A SSiB vegetation and soil map is used as the preliminary initial condition for the quasi-equilibrium simulation. A 3-hourly meteorological forcing data from 1948 through 2007 (Sheffield et al., 2006) is used for this study. The observation-based LAI and GPP products (Zhu et al., 2013; Xiao et al., 2014; Jung et al., 2009) are used to validate and calibrate the model to produce proper vegetation spatial distribution and temporal variability.

#### 2.3.1 Initial condition for equilibrium simulation

There are different ways to initialize the surface condition for the quasi-equilibrium simulation. Based on our previous study (Zhang et al., 2015), we set up the initial condition using the SSiB vegetation map and SSiB vegetation table, which are based on ground survey and satellite-derived information (Dorman and Sellers, 1989; Xue et al., 2004b; Zhang et al., 2015) with 100% occupation at each grid point for the dominant PFT and zero for other PFTs.

#### 2.3.2 Meteorological forcing data

The Princeton global meteorological dataset version 1 for land surface modelling (Sheffield et a., 2006) is used to drive SSiB4/TRIFFID for the period of 1948-2007. This dataset is constructed by combining a suite of global observation-based datasets with the National Centers for Environmental Prediction—National Center for Atmospheric Research (NCEP—NCAR) reanalysis starting from 1948 (http://hydrology.princeton.edu/data/pgf/). The spatial resolution is 1° x 1° and temporal interval is 3-hourly. This dataset, including surface air temperature (K), pressure (Pa), specific humidity (g/kg), wind speed (m/s), downward short-wave radiation flux (W/m²), downward long-wave radiation flux (W/m²),

and precipitation (mm/day). Its 60-year mean climatology with three-hour interval from January 1 through December 31 was generated to drive quasi-equilibrium simulation.

#### 2.3.3 Observation-based data

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Two satellite-derived global land cover maps are used to evaluate the vegetation distribution in both quasi-equilibrium and real-forcing simulations. The Global Land Cover (GLC) database for the year 2000 (Bartholome et al., 2002) is used that was derived from Satellite Poul l'Observation de la Terre at the spatial resolution about 1 km. This dataset provides a global map with one consistent legend, as well as regional maps with separate legends containing more detail for certain regions. For instance, tundra is not included in the global legend but is included in the regional product for Northern Eurasia (Bartalev 10 et al.. 2003). The regional land cover maps (download http://forobs.jrc.ec.europa.eu/products/glc2000/glc2000.php) are used to calculate the land cover fraction by counting the percentage of each PFT in a 1-degree grid, then are merged to form a global land cover fraction map. Other than GLC2000, the Land Cover Type Climate Modelling Grid (CMG) product (MCD12C1), which is derived using the same algorithm that produces the V051 Global 500 m Land Cover Type product (MCD12Q1) from the observation input of Terra and Aqua on board the 15 Moderate Resolution Imaging Spectroradiometer (MODIS), is also used as a reference (Friedl et al., 2010). The MODIS-MCD12C1 product provides land cover fraction at the spatial resolution of 0.05°, which then converted to 1-degree resolution. The SSiB4/TRIFFID only includes primary land cover types, while both GLC2000 and MODIS IGBP have more sublevel classes. For easy comparison of the 20 distribution of dominant vegetation types with different products, we hierarchically combine the GLC2000 and the MODIS IGBP classifications to the SSiB4/TRIFFID PFTs.

To assess the climatology, variation, and trends of simulated LAI, two widely used LAI products were used as references in this study: the Global Inventory Modelling and Mapping Studies (GIMMS) LAI (refer to LAI3g, the third generation, Zhu et al., 2013) was downloaded from <a href="https://ecocast.arc.nasa.gov/data/pub/gimms">https://ecocast.arc.nasa.gov/data/pub/gimms</a>. A neural network algorithm was trained to using the AVHRR GIMMS NDVI3g (covering the period July 1981 to December 2011) and best-quality Terra MOIDS LAI (covering the period 2000 to 2009) for the overlapping period 2000-2009. Then the trained neural network algorithm was used to generate corresponding LAI dataset at 15-day temporal resolution

and 1/12-degree spatial resolution for the period from July 1981 to December 2011. The Global Land Surface Satellite (GLASS) LAI was downloaded from http://www.bnu-datacenter.com. The GLASS LAI was generated from AVHRR reflectance (1982-1999) and MODIS reflectance (2000-2012) (Xiao et al., 2014). The GLASS LAI provides observations at 8-day temporal resolution and 1 km spatial resolution for the period from 1982 to 2012. Both datasets have general consistence in LAI spatial distribution, however, GIMMS shows 25% of the vegetated areas are greening during the 1982 to 2009, whereas 50% in GLASS LAI (Zhu et al., 2016). GIMMS and GLASS LAI, and the meteorological forcing data for overlap period 1982 to 2007, were resampled to 1-degree spatial resolution and a monthly temporal interval.

SSiB4/TRIFFID GPP was evaluated using the FLUXNET-MTE GPP, which was downloaded from https://www.bgc-jena.mpg.de/geodb/projects/Data.php. The FLUXNET-MTE GPP was upscaled from FLUXNET observations of carbon dioxide flux to the global scale using the machine learning technique, model tree ensembles (MTE). This method was trained to predict site-level GPP based on remote sensing indices, climate and meteorological data, and information on land use (Jung et al., 2009).

This data set provides global monthly mean GPP at 0.5-degree spatial resolution for the period from 1982 to 2011. The FLUXNET-MTE GPP was resampled to 1-degree spatial and monthly temporal resolution.

#### 3. Results

#### 3.1 Vegetation initial conditions

The DGVM's initial conditions for long-term simulations is obtained from a quasi-equilibrium solution in a long term simulation using the climatological forcing as presented in Section 2.3.2. The effect of Large-scale disturbance (LSD) on regulating tree fraction over the savanna areas is also investigated. The parameter for LSD is tuned to generate a reasonable tree cover distribution there.

#### 3.1.1 Quasi-equilibrium simulation

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DGVMs typically requires initial conditions for a number of state variables. as an initial condition pertaining to a particular meteorological forcing. DGVMs normally takecommonly takes 50-1000 years' simulation under specified meteorological forcing to reach this steady-state (e.g. Bonan and Levis, 2006; Zeng et al., 2008). Since our purpose was only to generate the initial condition for the decadal simulations, we applied a shortcut to reach the quasi-equilibrium coexistence of PFTs under the climatological forcing. We started the model from a SSiB 1-degree dominant vegetation map (Xue et al., 2004), with 100% occupation of the dominant PFT and zero for other PFTs at each grid point. The 1948-2007 averaged meteorological forcing along with 1948 CO<sub>2</sub> concentration was used to drive the SSiB4/TRIFFID for 100 years.

SSiB4/TRIFFID is a water, energy, and carbon balanced model. Plants expansion, and biotic properties such as vegetation height and LAI are constrained by carbon reallocation. FRAC links the carbon accumulation within plants and intra-species competition via a system of the Lotka-Volterra equations (Cox, 2001). Figure 2 shows the temporal evolution of FRAC during the quasi-equilibrium simulation over four general climate zones. In the early first ten years of the simulation, most PFTs' FRACs change rapidly, but then take decades to reach a steady state (Figure 1). To qualify the steady state, we define quasi-equilibrium status as occurring when the rate of change of vegetation fraction is less than 2% of the mean vegetation fraction, over the last ten years of simulation. The result shows 100-year spin-up time is sufficient for our model.

Overall, in the tropical areas (23.5°S~23.5°N), C4 plants and evergreen broadleaf trees are of mixed dominance and coexistent with C3 grasses, shrubs, and deciduous broadleaf trees. The subtropical areas (23.5°~35° in both hemispheres) are dominated by C3 grasses, C4 plants, and shrubs with similar occupation for each (~18%), whereas 40% of the subtropical areas are occupied by bare land. Needle leaf trees, C3 grasses, shrubs, and deciduous broadleaf trees are mix dominant the temperate zones (35°~66.5°, particularly in North Hemispheres). Over the polar areas (66.5°~90° in both hemispheres), shrubs and tundra are of mixed dominance (**Figure 12**). We recognize that these broad zones each incorporate many different PFTs that are not represented in our model. That being said, the broad distributions are very close to those based on the climatology of the global ecosystem

simulated by the SSiB4/TRIFFID using the meteorological forcing from 1958-2007, which will be discussed in detail in Section 4.1.1

#### 3.1.2 Effect of large-scale disturbance

large-scale disturbance such as fire, and insect outbreaks alter physical structure and/or arrangement of biotic elements with great effect. TRIFFID introduce only a global uniform and PFT depended parameter to represent the rate of vegetation loss caused by LSD (units: yr<sup>-1</sup>). The Our preliminary quasi-equilibrium run shows that under this approach, trees extended the absence of fire disturbance in SSiB4/TRIFFID causes trees' extension into the South American and African savanna areas (Figure 2a3a), where the climate acting alone would seem to favour tree growth (Bond et al., 2005). However, disturbance alters the physical structure or arrangement of biotic elements quickly and with great effect. mMajor ecological disturbances such as fire, flooding, and insect outbreaks vary spatially and temporally (Giglio et al., 2006). . TRIFFID prescribes the large-scale disturbance (LSD) coefficient as a uniform value for every PFT globally according to model calibration (Cox, 2001). We raised the LSD coefficient (largely representing fire at this scale) from 0.004 to 0.04 (yr<sup>-1</sup>) for tree PFTs that coexist with C3 grasses and C4 plants. With the updated setting, the SSiB4/TRIFFID produced reasonable dominant tree coverage over the tropical rainforest areas (Figure 2b3b) in comparison with the GLC2000 dataset (Figure 2c). The global PFT distributions in the equilibrium run are close to the results using the real meteorological forcing. Detailed comparison of the simulated global vegetation spatial distribution with the contemporary satellite based datasets is discussed in Section 4, in which the model was driven by the 1948-2007 meteorological forcing.

3.2 Model evaluation of simulated vegetation distribution, LAI and GPP

#### 4. Simulation results using the 1948-2007 meteorological forcing

Based on <u>Using initial conditions derived from</u> the equilibrium run—as <u>initial condition</u> for both biotic and abiotic variables such as FRAC, LAI, vegetation height, soil moisture, and temperature, the model is then driven with the historical meteorological forcing and yearly updating <u>atmospheric</u> CO<sub>2</sub> concentration from 1948 to 2007. <u>DGVMs have shown diverse performance in reproducing the spatial</u>

distribution and temporal variability of the ecosystems (Murray-Tortarolo et al., 2013;Piao et al., 2013;Anav et al., 2015;Zhu et al., 2017), which resulted in large discrepancies between models in identifying the attributed dominant drivers of changes (Beer et al., 2010;Huntzinger et al., 2017). It is therefore important to validate the model performance first before use for attribution studies. In this section, the global (hereafter referring to the regions of 180°W to 180°E, 60°S to 75°N) distributions of the simulated FRAC, LAI, and GPP are compared to the observation-based datasets to ensure SSiB4/TRIFFID generates reasonable spatial pattern and temporal variability of those variables, which provides a base for further assessment of the impact of external drivers on some surface variables. LAI and GPP inter-annual variabilities are also evaluated over several regions, showing large ecosystem variability and changes.

### 4.1 Assessment of the simulated vegetation spatial distribution

It is a challenge for DGVMs to reproduce PFT coexistence, particularly for the smaller PFTs in the semi-humid to semi-arid areas as they are fragile and sensitive to climate and vulnerable to competition (Fu et al., 2006). For instance, Zeng et al. (2008) introduced a specific sub-model to grow the trees and grasses firstly, then shrubs in unoccupied spaces. However, recent studies suggest that the interannual variability of the global terrestrial carbon sink is dominated by semi-arid ecosystems (Ahlstrom et al., 2015). The SSiB4/TRIFFID allows smaller stature PFTs to co-exist (Cox, 2001; Zhang et al., 2015).

## 3.2.1 Vegetation spatial distribution 4.1.1 Global Vegetation distribution

Satellite-derived products are used to assess the model-simulated mean FRAC averaged over the last ten-year (Figure 2). The spatial distribution of the dominant PFT is closely related to large-scale the climate (MacDonald, 2002). Figure 4 shows the FRAC for each PFT from the control experiment averaged over the last ten years of the run (1998-2007). Overall, the model simulated vegetated land cover of 79.6% of the global land surface, less than GLC2000 estimation, 80.8% and higher than the MODIS estimation, 79.3% (Figure S1). There is no human activity included in the model simulation, as such an agricultural category is not included. Therefore, in the following vegetation coverage

comparison with the GLC products, Simulated PFT coverage in the grid boxes with agriculture is reduced by multiplying based on the GLC agriculture fraction. On this basis, the total simulated tree cover (the sum of evergreen broadleaf trees, deciduous broadleaf trees, and needle leaf trees) is 28.8%, close to 29.8% in GLC2000. The evergreen broadleaf trees in the Amazon, Central Africa, and Southeast Asia, deciduous broadleaf trees in southeast North America, and needle leaf trees in the highmid latitudes of North America and Eurasia are reasonably predicted. The SSiB4/TRIFFID simulates<del>predicted</del> 12.7% C3 grass occupation, which is slightly higher than 11.9% in the GLC2000, with reasonably simulation in the mid-latitudes in both hemispheres such as the central U.S., Eurasian Steppes, South America, South and East Africa, and East Australia. The model simulates 10.1% natural C4 plants, compared to 7.9% in the GLC2000. The discrepancy could be partially attributed to the absence of C4 plants in some GLC2000 regional maps (such as Southeast Asia). The global GLC2000 map is assembled from these regional maps. In fact, a satellite-based physiological model simulation predicted estimated 13.9% of C4 plants coverage with no agriculture category (Still et al., 2003). In the SSiB4/TRIFFID prediction without excluding agricultural land, the C4 plants cover 13.5%, close to Still et al's estimation. C4 plants are primarily located in South American and African savanna areas, the Indian Subcontinent, Southeast Asia, the southeastern U.S., and northern Australia. The model simulates<del>predicted</del> 15.9% shrubs and tundra occupation, which is close to 16.7% in the GLC2000, with shrubs primarily located in the semi-arid areas in both hemispheres and the pan-arctic area, while tundra is located in the pan-arctic area and Tibetan Plateau (Figure 3 and also see vegetation fractional distribution in Figure S2).

### 3.2.24.1.2 Leaf area index and Gross Primary productivity

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This section discusses the spatial and temporal correlations between the simulations and observations and compares with other model results. -Since other published studies on this subject have not excluded agricultural areas when evaluating LAI and GPP simulation, to make our results comparable with others, the agricultural areas are not subtracted. In fact Moreover, the difference between the results with and without presented in this section and those excluding the exclusion of agriculture area for our results are less than 0.01.

SSiB4/TRIFFID produces a similar global LAI pattern compared to both the GIMMS and GLASS products, confirmed by global spatial correlation coefficients of 0.86 (GIMMS, p<0.05) and 0.87 (GLASS, p<0.05), and above 0.74 (P<0.05) against both observations over the Northern Hemisphere (**Figure 46**). Previous studies reported spatial correlation coefficients between models and GIMSS-LAI over the globe/Northern Hemisphere in the range of 0.44-0.77/0.21-0.61 (Murray-Tortarolo et al., 2013; Mahowald et al., 2015). The latter study reported that in general DGVMs tended to overestimate global average LAI by 0.69±0.44 units calculated based on the table in Mahowald et al. (2015). [recalculated from (Mahowald et al., 2015)]. The SSiB4/TRIFFID produces ~0.95 units higher global averaged LAI than the satellite-derived data. The absence of nitrogen limitation in the model could contribute to the overestimation and the latest development of SSiB5/TRIFFID with a global nitrogen model seems promising.

## 3.2.3 Gross primary product

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The spatial correlation coefficient between model our simulation of GPP and FLUXNET-the MTE GPP dataset is 0.93 (P<0.05) (Figure 75). Anav et al. (2015) reported less than 0.8 correlation against FLUXNET-MTE\_-GPP for multi-model comparison. Over the globe, SSiB4/TRIFFID simulatespredicted 1135 gC/m²/yr (or 151 PgC/yr<sub>2</sub>), greater than the FLUXNET-MTE average of 920 gC/m²/yr (or 122 PgC/yr<sub>2</sub>). However, our simulation was still withinin the range of 130-169 PgC/yr reported by Anav et al. (2015) and 111-151 PgC/yr reported by Piao et al. (2013). for 10 offline models. In addition, to our model's deficiencies (such as lack of on N-limitation), the lack of CO<sub>2</sub> fertilization during the MTE model training may have contributed to an underestimation in the FLUXNET-MTE\_GPP.

## 4.2 Assessment of the simulated 3.3 Simulated vegetation temporal variability

- 3.3.1 Vegetation temporal variability during 1982-2007 and its comparison to observation-based data
- Model performance in predicting temporal variability has been less evaluated in previous studies on ecosystem trend detection and attribution (Ichii et al., 2013; Piao et al., 2013; Zhang et al., 2015).

However, performance in predicting estimating LAI and GPP trends and variability has been found to vary among models (Murray-Tortarolo et al., 2013; Piao et al., 2013; Anav et al., 2015; Zhu et al., 2017). To better assess model performance in this regard, we selected 13 sub-regions associated with different regional climate and land cover conditions (Table 21). Although the MTE excludes CO<sub>2</sub> fertilization during its model training, FLUXNET-MTE\_-GPP still incorporates variability at different scales associated with climate variability and is widely used by the community for the model validation evaluation. Both annual LAI and GPP correlation coefficients are calculated over the period of 1982-2007.

Globally, the correlations for annual mean LAI between the SSiB4/TRIFFID and the satellitebased products are 0.58 (P<0.05) for GIMMS and 0.64 (P<0.05) for GLASS. The correlation for annual GPP is 0.59 (P<0.05) between the SSiB4/TRIFFID and FLUXNET-MTE GPP. Piao et al. (2013) had reported less than 0.4 correlation by for GPP from 10 offline models. This improvement may be due to SSiB4/TRIFFID better capturing the interannual variability in semi-arid areas which dominate interannual variability (Ahlstrom et al., 2015). For instanceRegionally, LAI correlations over West Africa are 0.79 (P<0.05) with GIMMS and 0.77 (P<0.05) with GLASS (Figure 68), and GPP 15 correlation is 0.80 (P<0.05) with FLUXNET-MTE GPP in that region. For the other semi-arid areas in western North America, South American savanna areas, and East Africa, the simulated LAI significantly matches at least one of the two reference datasets with correlation in the range of 0.46-0.58 (P<0.05). The simulated GPP correlations with FLUXNET-MTE GPP are in the range of 0.63-0.70 (P<0.05). The LAI over the forested areas are better correlated to GLASS LAI, while GPP are only 20 significantly corrected to FLUXNET-MTE GPP over the boreal forests. Over the cold regions (subarctic and Tibetan Plateau), the SSiB4/TRIFFID matches the reference data in a varying range of 0.46-0.74 (P<0.05) for LAI and 0.49-0.72 (P<0.05) for GPP.MTE were in the range of 0.63-0.70 (P<0.05).

For the forested areas, simulated LAI and GPP were both well correlated with reference data over the Northern Hemisphere boreal forests, whereas only LAI had significant correlation over the rainforest areas. The inconsistency over the rainforests indicated that the missing CO<sub>2</sub>-fertilization in MTE-GPP could be a predominant limitation to GPP in those areas. Over the cold regions (subarctic

and Tibetan Plateau), SSiB4/TRIFFID matched the reference data closely with the significant correlations ranging 0.35-0.74 (P<0.1) for LAI and 0.49-0.72 (P<0.05) for GPP. It should be pointed out that although there is general consistency between the satellite-based LAI products, large relative uncertainties were identified (Jiang et al., 2017).

As shown in Figure 8, there were Ddistinct decadal variabilities are identified in most subregions. For instance, trends reversal sign in West Africa (from negative to positive) and western North America (from positive to negative) during the 1980s (Figure 6). Areas with enhancement in trends slopes, such as the subarctic after the 1980s climate regime shift in the 1980s, will be discussed in detail in the next section.

Summary, statistics are listed in Table 2. Generally, SSiB4/TRIFFID simulatespresented reasonable predictions of terrestrial ecosystem climatology and variability compared to the observation-based datasets (Table 2). Compared to other DGVMs, SSiB4/TRIFFID shows above average performance in reproducing the spatial distribution, but with certain bias in absolute numbers. In particular, SSiB4/TRIFFID captures the ecosystem temporal variabilities over different regions across the world, which provides a good basis for pursuing the ecosystem trends detection and attribution study presented in the next section.

### 3.3.2 Three major types of vegetation trend change since the 1950s

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### 5. Detection and attribution of decadal trend change during the 1980s

There are a number of studies showing abrupt environmental change during the 1980s (e.g. Hare and Mantua, 2000; Lo and Hsu, 2010; Reid et al., 2016). Since the 1950s, global land surface temperature has risen with the rate of increase accelerating after the 1980s (**Figure 9**). The mean land surface temperature during the three decades of the 1950s, 1980s, and 2000s was 286.84 K, 286.97 K, and 287.65 K, respectively. Global precipitation had shown distinct decadal variability. It decreased from 2.34 mm/day in the 1950s to 2.28 mm/day in the 1980s, then recovered to 2.33 mm/day in the 2000s. In the meantime, the atmospheric CO<sub>2</sub>-concentration steadily increased from 313.44 ppm in the 1950s to 373.67 ppm in the 2000s. In this section, we will discuss how the changing climate and eCO<sub>2</sub> affected

the large-scale vegetation. The sensitivity experiments described in section 2.1 were conducted to quantify the contributions of eCO<sub>2</sub>, global warming, and CV on the trends of FRAC, LAI, and GPP at global and regional scales and on PFT variation and competition. The first ten-years of each simulation (1948-1957) were excluded from the analysis as this served as the spin up period.

### 5 5.1 Three major types of trend change since the 1950s

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The climate regime including temperature and precipitation shifted abruptly during the 1980s, inevitably giving rise to changing in ecosystem trends in many parts of the world. Here we compare trends of FRAC, LAI, and GPP over two periods: 1958-1982 and 1982-2007. The model performance for the second period, for which satellite observations are available, is evaluated in Section 3.3.14. Spatial patterns of the trends are shown in **Figure 7.10**, in which the dots indicate the grid points with a p-value less than 0.1 according to a Mann-Kendal test (Mann, 1945; Kendall, 1955).

At the global scale, significant vegetation trends are only found in the simulations after the 1980s. During this period, FRAC increases at the rate of 0.032/yr. LAI has a positive trend of 0.0029/yr, which matches very well to GIMMS' results (0.0029/yr). GPP has a positive trend of 2.22 gC/m²/yr², within the range of 1.60-4.69 gC/m²/yr² for GPP over similar periods (e.g. Anav et al., 2015; Yue et al., 2015). In contrast to LAI and GPP, there are relatively few areas with a significant simulated FRAC trend (Figure 7).

For the global land surface, over 40.2% has a significant LAI trend since 1958 through 2007, and over 48.1% has a significant GPP trend (Figure 7). In response to the climate regime shift during the 1980s, the terrestrial ecosystem has three major trend changes in different parts of the world after the 1980s (Table 43). 1) There is trend sign reversal from negative to positive in the East Asian monsoon area, West Africa, Central Asia, and Eastern US, over 14.2% (LAI) and 11.4% (GPP) of the land surface. In particular, West Africa experiences the largest vegetation deterioration in the world before the 1980s, associated with LAI and GPP reductions of 0.0258/yr and 18.54 gC/m²/yr², respectively - approximately 10 times the trends of the global average. After the 1980s, recovery is simulated at the rate of 0.0137/yr and 8.02 gC/m²/yr² for LAI and GPP, respectively. 2) Trend sign reversal from positive to negative is found in western North America, South America savanna and East

Africa, which accounted for 2.9% (LAI) and 2.7% (GPP) of the land surface. 3) There are consistent positive trends <u>but</u> substantially enhanced by at least 50% of prior period trends after the 1980s, which are found in Equatorial rainforest areas, boreal forest areas, South Africa, North Australia, subarctic areas, and the Tibetan Plateau, representing over 11.7% (LAI) and 19.3% (GPP) of the land surface. There are also areas with consistent positive trends but no substantial change during the entire period or other types of trend change over much smaller areas. The first three major trend changes as described above will be discussed in the following sections.

### 3.4 Attribution of three environmental drivers on ecosystem trends

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# 3.4.15.2 Global overview of three simulated environmental drivers' external forcing effects on the ecosystem trends

Sensitivity experiments were conducted to isolate the contributions of elevated atmospheric CO<sub>2</sub> concentration, global warming, and climate variability. The differences between the control experiment and Fixed-CO<sub>2</sub> shows that eCO<sub>2</sub> stimulated vegetation growth mainly in the Equatorial areas and eastern North America, Western Europe, and Eastern China in the mid-latitudes. Substantially enhanced positive trends are found after the 1980s for both LAI and GPP over those areas (**Figure 811**). eCO<sub>2</sub> promoted rainforest LAI increase only after the 1980s; however, its effect on GPP appeared during the entire period. GPP is directly linked to CO<sub>2</sub> through the photosynthesis process, while LAI, in addition to the photosynthesis process, is also affected by respiration and carbon reallocation in plants, which are influenced by both climate and eCO<sub>2</sub> (O'Sullivan O et al., 2017).

The differences between the control experiment and Detrend-Temp shows that global warming has minor effects on the trends of LAI and GPP before the 1980s (**Figure 912**). After the 1980s, the rapidly enhanced warming contributes positive LAI trends at high latitudes, while the GPP change seems less substantial. Meanwhile, there are negative trends due to heat stress in low latitudes, particularly in the semi-arid regions such as South American savanna, East Africa, and central Asia.

The differences between the control experiment and Fixed-CO<sub>2</sub> and Detrend-Temp show the CV effect, which has complex influences on the ecosystem. The CV in this study includes contribution of changes in surface pressure, precipitation, surface wind speed, downward longwave and shortwave

radiations, surface humidity, along with temperature that excludes the <u>global warming</u> trend. Precipitation is however found to play a dominant role. The correlation coefficients between the annual mean CV effect on LAI and GPP and annual mean precipitation at the grid points with significant CV effect are greater than 0.60 (P<0.05). Overall, the CV effect alone can explain the total FRAC trends in the control experiment (**Figure 103**).

Before the 1980s, CV causes LAI decrease in East Asian monsoon areas, eastern North America, West Africa, Western Europe, Central Asia, Siberia, and eastern Australia. The GPP also decreases in these areas except for eastern North America, Western Europe, and Siberia. In contrast, the CV effect before the 1980s leads LAI and GPP increase in the Tibetan Plateau and South Asia, western North America, South American savanna areas, East and South Africa, and northern Australia. Due to the climate regime shift, CV has produced the opposite sign to the trends of LAI and GPP in East Asian monsoon areas, Central Asia, West Africa, North America, South American savanna areas, and East Africa. In some areas, such as South Africa and northern Australia, persistent precipitation increase/decrease leads to sustained positive/negative trends from the 1950s.

Overall, after the 1980s, the effects of eCO<sub>2</sub> and global warming have been generally enhanced; but the CV effect has exhibited distinctly different regional features before/after the 1980s over many regions in the world. The enhanced or opposite contribution of the primary driver and the changes in their relative importance on the ecosystem trends occur during the 1980s, result in different ecosystem responses in many regions across the world.

# 20 5.3 Assessments of synthesized effects of the three external forcings in influencing the regional ecosystem trends

The discussion in this section is based on **Tables 3** and **4** and **Figure 14**. Only the significant changes listed in the tables are discussed and the following text is restricted to a subset of world regions. West Africa and East Asia; western North America, and rainforest, boreal forest, subarctic and Tibetan

25 Plateau.

# **5.3.1** <u>3.4.2</u> Dominant factor in influencing trend reversal from negative to positive in West Africa and East Asia

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CV is found to be the dominant driver of the ecosystem trends in West Africa, explaining most of the LAI and GPP trends and trend changes (Figure 11a). Before the 1980s, CV causes C4 plants' LAI, GPP, and FRAC over the region to decrease, followed by shrubs, whereas eCO<sub>2</sub> caused C3 grasses' LAI and GPP to slightly increase. Global warming shows little effect during the entire period from 1958-2007. The ecosystem trends in West Africa reverses from decrease<del>reversed</del> to increase when the precipitation trend changes to increase after the 1980s, with the major increase in C3 grasses and shrubs over the region. A previous study using satellite data also showed recent West Africa greening is highly correlated to the precipitation increase (e.g. Herrmann et al., 2005). The response to eCO<sub>2</sub> of a particular PFT not only depends on its own physiological and morphological characteristics, but is also determined by the interactions that arise with the other PFTs, which are competing for the same resources. eCO<sub>2</sub> plays a role in increasing C3 grasses coverage since the 1950s. However, the PFT competition outcomes reduce the C4 plant coverage over the region, mainly after the 1980s when eCO<sub>2</sub> has a large impact. As such, the change in regional FRAC overall within West Africa is not significant and has been compromised by positive and negative contributions of the individual PFTs after the 1980s. However, our results show that the boundary between Sahara and Sahel has experienced significant variation since the 1950s. Based on the observed precipitation data and the precipitation/NDVI correlation, Thomas and Nigam (2018) suggest a Sahara Desert expansion since the 1950s. Our results are in an agreement at large with the Thomas and Nigam's study (2018) but also with substantial differences. A comprehensive discussion on this issue is out of scope of this paper and will be addressed in a separate paper.

Regional average trends reverse in the East Asian monsoon area because CV and eCO<sub>2</sub> dominate LAI and GPP trends, before and after the 1980s, respectively. Their combined effects cause trend reversal in the East Asian monsoon areas. CV contributes decreasing trends of LAI and GPP before the 1980s, but with minor effects after the 1980s. While The eCO<sub>2</sub> dominates the PFT LAI and GPP trends since the 1950s, which caused significant increase in C3 grasses and trees but significant decrease in C4 plants (Figure 11b).14). Field experiments reported that the differential growth and

competitiveness responses of C3 and C4 plants to eCO<sub>2</sub> is complex and under debate (Lee, 2011;Miri et al., 2012;Leakey et al., 2009). Our simulations suggest that there is a potential increase C3 grasses long-term competitive ability at regional scale. Meanwhile, enhanced global warming after the 1980s stimulates C4 plant growth, but this effect is compromised by its detrimental effect on C3 grasses after the 1980s. \_Furthermore, CV contributed decreasing trends of LAI and GPP before the 1980s, but with minor effects after the 1980s. Overall, CV and eCO<sub>2</sub> relative contribution change during the 1980s dominate the negative toand positive trends shift in this area-before and after the 1980s, respectively.

# 3.4.35.3.2 Dominant factor in influencing trend reversal from positive to negative in western North America

The eCO<sub>2</sub> effect persistently causes LAI, GPP, and FRAC increase since the 1950s, while global warming reduced both LAI and GPP only after the 1980s. However, CV dominated the LAI and GPP trends and trends reversal in western North America by causing the dominant PFTs (C3 grasses and shrubs) to increase/decrease before/after the 1980s (Figure 11c14 and Table 54). The CV effect on FRAC change is more complex due to its different effects on LAI and GPP and FRAC expansion in C3 and shrub PFTs after the 1980s: (Figure 14) both C3 and shrubs expand with LAI and GPP decrease. This discrepancy suggests that expansion might be coupled with carbon fixation less than with growth in the model. We conjecture that CV may promote vegetation expansion into some areas that are largely un-vegetated, but this requires further investigation.

# 3.4.45.3.3 Dominant factor in influencing the enhanced positive trend in rainforest, boreal forest, subarctic, and Tibetan Plateau

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eCO<sub>2</sub> and CV have persistent positive impacts on <u>tropical</u> rainforest growth in terms of LAI and GPP since the 1950s (**Figure 11d14**). eCO<sub>2</sub> dominates the LAI and GPP trends in both periods except for the LAI positive trend before the 1980s, which is dominated by CV. LAI trend enhancement after the 1980s is associated with increased CO<sub>2</sub> fertilization, while GPP trend enhancement is attributed to increase in both eCO<sub>2</sub> and CV effects (**Table 4**). The importance of CO<sub>2</sub> and CV impacts on the rainforests is confirmed by previous analyses on the trends of LAI and NDVI (e.g. Hilker et al., 2014; Zhu et al., 2016).

eCO<sub>2</sub> and global warming increase LAI and GPP in North American boreal forest areas since the 1950s and cause significant positive trends over the Eurasian boreal forest area after the 1980s (Figure 11eTable 4). However, due to CV-induced negative effects on tree LAI, no significant trend is found in regional average LAI in boreal areas before the 1980s (Figure 14). The LAI and GPP trend enhancement in the boreal forest areas can be attributed to the enhanced eCO<sub>2</sub> and global warming effects, accompanied by reduced CV negative effects after the 1980s.

North American subarctic areas have enhanced LAI and GPP positive trends after the 1980s, which were caused by the increase in eCO<sub>2</sub> and CV positive effects, while all. All three environmental drivers have external foreings had effects on LAI and GPP positive trends in the Eurasian subarctic (Figure 11f14 and Table 4). Meanwhile, remarkable FRAC changes are found since the 1950s. Our simulation suggests that global warming continually favorited shrub invasion into tundra biomes, except in the Eurasian subarctic before the 1980s (Figure 14). After the 1980s, this shrubification is enhanced due to increase in the warming effect. In contrast, eCO<sub>2</sub> has promoted tundra expansion and shrub decline over subarctic areas since the 1950s, which mitigates the shrubification. Meanwhile, CV plays a role to help tree and C3 grass expansion into subarctic areas, and also alters the shrub and tundra competition. Observations had supported our conclusion that shrub expansion into tundra ecosystems was linked to climate change (e.g. Myers-Smith et al., 2015), particularly to global warming (e.g. Tape et al., 2006; Elmendorf et al., 2012) and precipitation (e.g. Martin et al., 2017).

Over the Tibetan Plateau (Figure 11g), CV dominates the positive LAI and GPP trends since the 1950s, excepted in the case of the GPP increase before the 1980s which is dominated by eCO<sub>2</sub>. The positive trend enhancements for LAI and GPP after the 1980s are caused by the impact of both eCO<sub>2</sub> and CV. Furthermore, our simulation also suggests that CV favours C3 grasses but harms tundra biome expansion. However, eCO<sub>2</sub> has the opposite effects on those PFTs, in contrast to the CV's.

#### 4. Discussion

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The spatial distribution of the dominant PFT is closely related to large-scale climate (MacDonald, 2002) and DGVMs are designed to reproduce the observed ecosystem/climate relationship. There are diverse performances in reproducing the spatial distribution and temporal

variability of the ecosystems (Murray-Tortarolo et al., 2013; Piao et al., 2013; Anav et al., 2015; Zhu et al., 2017), which resulted in large discrepancies between models in identifying attributed dominant drivers of changes (Beer et al., 2010; Huntzinger et al., 2017). It is therefore important to validate the model performance in reproducing the observed ecosystem variability and spatial distribution first before using DGVMs for attribution studies. As a matter of fact, it is challenge for DGVMs to reproduce PFT coexistence, particularly for the smaller PFTs in semi-humid and semi-arid areas as they are fragile and sensitive to climate and vulnerable to competition (Fu et al., 2006). Because of that difficulty, Zeng et al. (2008) had to introduce a specific sub-model to grow temperate shrubs in the spaces unoccupied by trees and grasses. The SSiB4/TRIFFID allows smaller fractions of PFTs to co
10 exist with full competition with other PFTs (Cox, 2001). After modifying the competition coefficients in the Lotka-Volterra equation (Zhang et al., 2015) and updating large-scale disturbance parameters, it produces reasonable global distribution of temperate shrubs and high-latitudes tundra (Figure 3). During the validation process, some parameters in the SSiB4/TRIFFID have also been calibrated (Zhang et al., 2015).

With all these efforts, the SSiB4/TRIFFID produced LAI and GPP show higher temporal correlation with observation compared to the start-of-art offline models in the TRENDY intercomparison project (Piao et al., 2013; Sitch et al., 2015; Zhu et al., 2016). The improvement may mainly be due to better capturing of the interannual variability by the SSiB4/TRIFFID in semi-arid areas, which has been considered as dominating global interannual variability (Poulter et al., 2014; Ahlstrom et al., 2015). Meanwhile, both simulated LAI and GPP are also well correlated with reference data over the Northern Hemisphere boreal forests. Our evaluation is based on satellite-based products, which are the only sources providing global distribution at long term. Although these products showed a general consistency among them, large relative uncertainties were identified over some regions (Jiang et al., 2017), which contribute to large discrepancy of interannual correlations when the simulated LAI compared to GIMMS and GLASS LAIs (Figure 6). It should be pointed out that the GPP simulation over the rainforests exhibit inconsistency with the FLUXNET-MTE GPP. We consider that the missing CO<sub>2</sub> fertilization in FLUXNET-MTE GPP could be a predominant limitation to its GPP there. By and

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large, the SSiB4/TRIFID's performance suggest this model is proper to be applied for the attribution study.

The SSiB4/TRIFFID simulates increased LAI and GPP after the 1980s (**Figure 8**), which is confirmed by observation and the TRENDY models' simulation (Anav et al., 2013 for GPP; Piao et al., 2013 and Zhu et al., 2016 for LAI). These increases are considered to responding to elevated atmospheric CO<sub>2</sub> concentrations and warming surface temperature in high-latitudes (Zhu et al., 2016). Some areas with decrease LAI and GPP are due to decrease in precipitation and/or increase in stress due to warming temperature in low-latitudes (Anav et al., 2013; Zhu et al., 2016). Our study, however, further estimate large-scale trends in all three aspects, i.e. carbon fixation (GPP), vegetation growth

10 (LAI), as well as expansion, rather than focus only on one aspect, such as LAI trend in Zhu et al. (2016). Our results also reveal different LAI and GPP response to the environmental changes (**Figure 8-10**), indicating LAI and GPP are involved in different process as discussed in O'Sullivan O et al. (2017). The results suggest that GPP is more directly linked to atmospheric CO<sub>2</sub> (**Figure 8**).

In SSiB4/TRIFFID, net CO<sub>2</sub> assimilation is proportional to the gradient of atmosphere and leaf

CO<sub>2</sub> concentration (Zhan et al., 2013, also see supplement). Hence the elevated atmospheric CO<sub>2</sub>
concentration leads to increase in GPP. While LAI in TRIFFID is related to carbon allocation and
competition between PFTs. As such, LAI is not only affected by the atmospheric carbon concentration,
but also other processes, such as phenological processes and the percentage collocated carbon for
growth. Therefore, GPP is more sensitive to the change in atmospheric carbon concentration compared
to LAI. Integrated analysis and observation with multiple variables, such as LAI and GPP, are required
to improve the understanding of vegetation biochemical process and climate effect on ecosystem
changes.

The competition between PFTs within a grid box contributes to the ecosystem trend discussed above. Our analysis with grid point has shown intensive interactions between PFTs. For instance, shrubs are found to expand into tundra ecosystems (**Figure 11f**), which is linked to climate change (Myers-Smith et al., 2015), particularly to global warming (Tape et al., 2006; Elmendorf et al., 2012) and precipitation (Martin et al., 2017). The response to eCO<sub>2</sub> of a particular PFT not only depends on its own physiological and morphological characteristics, but is also determined by the interactions that

arise with other PFTs, competing for the same resources (**Figure 11a**). Field experiments reported that the differential growth and competitiveness responses of C3 and C4 plants to eCO<sub>2</sub> is complex and under debate (Leakey et al., 2009; Lee 2011; Miri et al., 2012). In this paper, we have discussed the competition between C3 and C4, and its contribution to the trend change. It seems under the elevated atmospheric CO<sub>2</sub> concentration scenario C3 grasses show enhanced competitive ability over C4 plant at regional scale (**Figure 11b**). Different responses of the co-exist PFTs to the climate regime shift either enhance or mitigate the environmental drivers' contribution at grid averaged scale.

Furthermore, our results show that the boundary between Sahara and Sahel has experienced significant variation since the 1950s. Based on the observed precipitation data and the precipitation/NDVI correlation, Thomas and Nigam (2018) suggested a Sahara Desert expansion since the 1950s. Our results are in an agreement at large with the Thomas and Nigam's study (2018) but also with substantial differences in the rate at two different climate regimes. A comprehensive discussion on this issue is out of scope of this paper and will be addressed in a separate paper.

### 56. Conclusion

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This work employs a biophysical-dynamic vegetation model (SSiB4/TRIFFID) to explore the responses of the terrestrial ecosystem to the climate variability, global warming, and elevated atmospheric CO<sub>2</sub> concentration during 1948-2007. The SSiB4/TRIFFID is evaluated by available satellite data in simulating the land surface carbon fixation, and plant growth and competition. We have shown that the The results show SSiB4/TRIFFID model can simulate captures the vegetation distribution (spatial correlation larger than 0.87) and temporal variability (regional varying significant temporal correlations of 0.34-0.80 for the period of 1982-2007 LAI and 0.45-0.83 for GPP). A series of sensitivity experiments are then conducted to detect the ecosystem trends and attribute the trends to elevated atmospheric CO<sub>2</sub> concentration (eCO<sub>2</sub>), global warming, and climate variability (CV).

In general, eCO<sub>2</sub>-stimulates vegetation growth mainly in the Equatorial areas, and eastern North America, Western Europe, and Eastern China in the mid-latitudes. The rapidly enhanced global warming after the 1980s contributes positive LAI trends at high latitude, while the GPP change seems

less substantial; meanwhile, there were negative trends due to the heat stress in low latitudes. CV dominates the variability of FRAC, LAI and GPP in the semi-humid and semi-arid areas.

The effects of the external drivers on the ecosystem trends manifest distinct spatial and temporal characteristics. For the global land surface, over 40.2% has a significant LAI trend and over 48.1% had a significant GPP trend since the 1958 through 2007.1950s. In responding to the climate regime shift during the 1980s, the terrestrial ecosystem has three major changes in different parts of the world after the 1980s. Over 14.2% (LAI) and 11.4% (GPP) of the land surface, primarily located in East Asian monsoon area, West Africa, Central Asia, and Eastern US, had trend sign reversal from negative to positive. In contrast, trend reversal from positive to negative is found in western North America, South America savanna and East Africa, which accounted for 2.9% (LAI) and 2.7% (GPP) of the land surface. Meanwhile, there are consistent positive trends substantially enhanced in Equatorial rainforest areas, boreal forest areas, South Africa, North Australia, subarctic areas, and the Tibetan Plateau, representing over 11.7% (LAI) and 19.3% (GPP) of the land surface, respectively.

In general, the major types of trend change are attributed to the changes in relative contributions of environmental drivers, and, consequently, the changes in the dominate driver; or changes in the dominant driver's "direction" in its effect (enhancing or suppression) on ecosystem. The eCO<sub>2</sub> stimulates vegetation growth through fertilization effects mainly in the Equatorial areas, as well as eastern North America, Western Europe, and Eastern China in the mid-latitudes. The rapidly enhanced global warming after the 1980s contributes positive LAI trends at high latitude, while the GPP change seems less substantial. Meanwhile, there are negative trends in LAI and GPP due to the heat stress in low latitudes. CV dominates the variability of FRAC, LAI and GPP in the semi-humid and semi-arid areas. The overall effects on the ecosystem are the integrated contribution of all environmental drivers.

### Data availability

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The data for this paper are available at https://drive.google.com/file/d/1CGlO-x-

25 gSXTH8UNB\_KWoH\_Y53fK-fcBZ/view?usp=sharingSSiB4/TRIFFID simulated vegetation fraction,

LAI and GPP are available at https://ucla.box.com/v/ssib4-offline

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### **Competing interests**

The authors declare that they have no conflict of interest.

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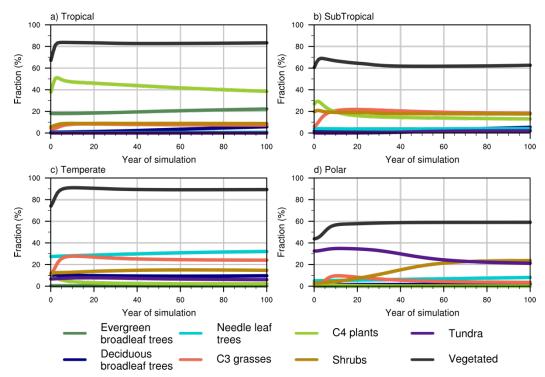
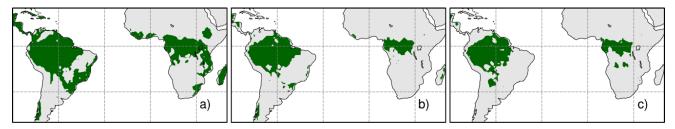


Figure 1-2. Fractional coverage of each plant functional type in typical climate zones in the equilibrium experiment



 $Figure \underline{\textbf{2-3}}. \ Tree \ dominated \ areas \ of \ a) \ unchanged \ large-scale \ disturbance \ experiment, \ b) \ parameter \ updated \ experiment \ and \ c) \ GLC2000$ 

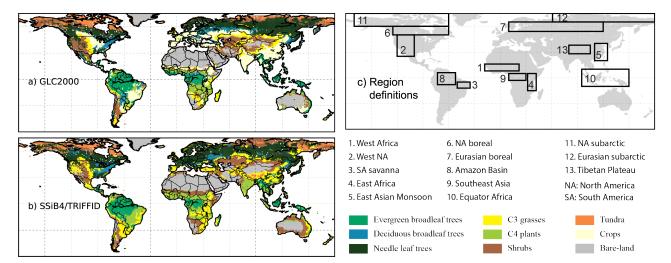


Figure 3-4. Dominant vegetation type comparison between a) GLC2000 and b) SSiB4/TRIFFID, and c) Region definitions.

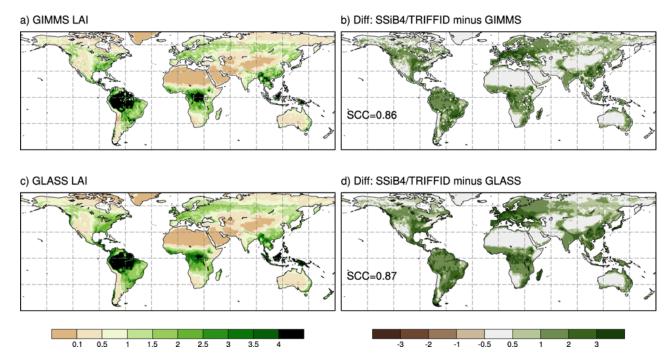
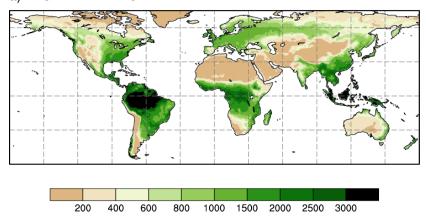


Figure 4-6. 1982-2007 average leaf area index comparison for a) GIMMS LAI, cb) GLASS LAI, and difference between c) SSiB4/TRIFFID and b) GIMMS and d) GLASS. simulated LAI. SCC indicates the spatial correlation coefficient between model simulation and satellite-derived datasets.

## a) FLUXNET-MTE GPP



### b) Diff: SSiB4/TRIFFID minus FLUXNET-MTE

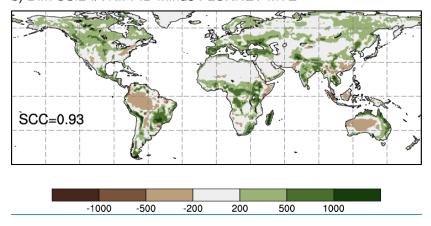


Figure 5-7. 1982-2007 average gross primary product comparison for a) <u>FLUXNET-MTE GPP</u>, and b) <u>different between SSiB4/TRIFFID and FLUXNET-MTE simulated GPP</u>. SCC indicates the spatial correlation coefficient.

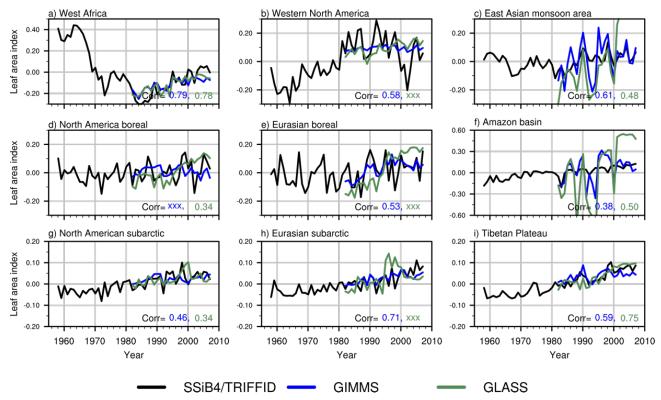


Figure 6-8. Comparison of standardized LAI anomalies between simulation and observations for 9 sub-regions. Corr indicates the interannual correlation coefficient simulated (in black) LAI against the GIMMS (in blue) and the GLASS (in green). Only significant values (P<0.1) are shown, whereas non-significant values are masked by xxx

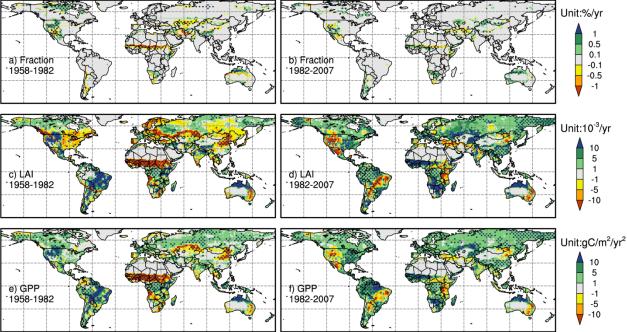


Figure 7-10. Trends (shaded) of a) and b) Fractional coverage (units: %/yr), c) and d) LAI (units:  $10^{-3}/yr$ ), e) and f) GPP (units:  $gC/m^2/yr^2$ ). The left three panels are for 1958-1982 and the right three panels are for 1982-2007. The dots indicate the areas with significance level at P< 0.051 (Mann-Kendall test).

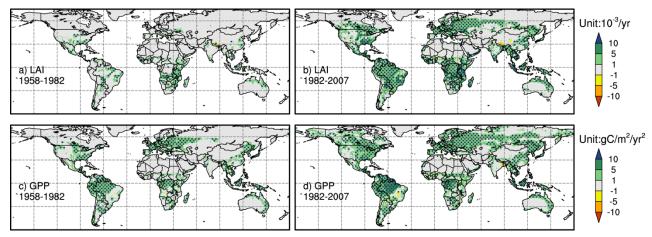


Figure 8 11. CO<sub>2</sub> effect on the trends (shaded) of a) and b) LAI (units:  $10^{-3/}$ yr), and c) and d) GPP (units:  $gC/m^2/yr^2$ ). The left two panels are for 1958-1982 and the right two panels are for 1982-2007. The dots indicate the areas with significance level at P<0.1 (Mann-Kendall test).

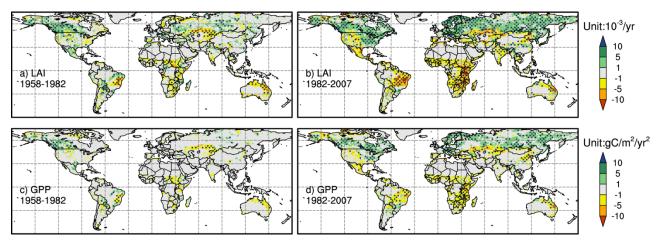


Figure 9-12. Same as Figure 811, but for warming effect.

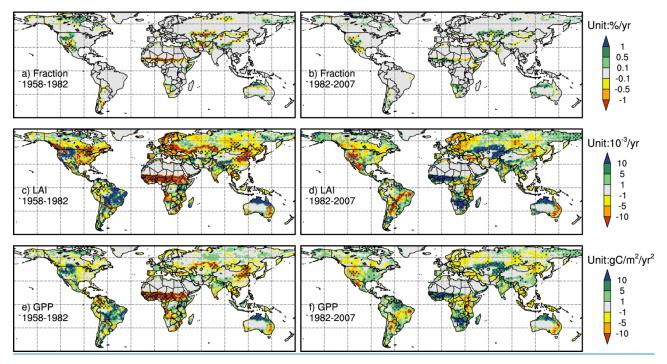


Figure 10 1. Same as Figure 811, but for climate viability effect and also including the effects on fractional coverage (units: %/yr)

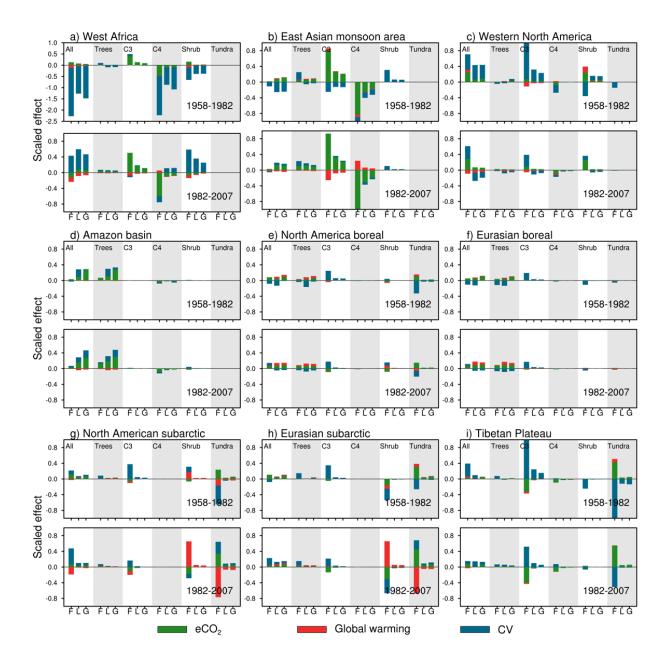


Figure 1411. Contribution of each factor on FRAC (denoted as "F"), LAI (denoted as "L"), and GPP (denoted as "G") trend over sub-regions. The upper panel in each figure is for trends during 1951-1982 and the lower panel is for trends during 1982-2007. The effects of eCO<sub>2</sub>, global warming and CV are shown in green, red, and blue bars, separately. Each column shows the effects on all PFTs (All), trees, C3 grass (C3), C4 plant (C4), shrub, and tundra, separately. The numbers for FRAC, LAI, and GPP are normalized by dividing the standard deviation of global average in the control experiment.

Table 1. Experimental design

Equilibrium simulation	<b>Description</b>	Real-forcing simulation	<b>Description</b>
<b>Control experiment</b>	Fixed CO <sub>2</sub> concentration at 1948 level and driven by climatological forcing for 100 years	<b>Control experiment</b>	Transient CO <sub>2</sub> concentration and meteorological forcing for the period of 1948- 2007
Parameter updated experiment	Adjusting large scale disturbance for trees	Fixed-CO <sub>2</sub>	The same as Control experiment except for fixed CO <sub>2</sub> concentration at 1948 level
		<b>Detrend-Temp</b>	The same as Control experiment except for no global warming trend

Table 12. Location for study areas

Regions	Sub-regions	Location
Arid and Semi-Arid	West Africa	8°N~16°N, 18°W~22°E
Areas	Western North America	25°N~50°N, 120°W~100°W
	South American savanna	12°S~5°S, 50°W~35°W
	East Africa	15°S~5°N, 32°E~42°E
Monsoon Area	East Asian monsoon area	20°N~40°N, 110°E~125°E
Northern Hemisphere	North America boreal	50°N~60°N, 125°W~60°W
boreal areas	Eurasian boreal	54°N~65°N, 10°E~120°E
<b>Equator areas</b>	Amazon basin	8°S~6°N, 73°W~52°W
	Southeast Asia	10°S~10°N, 95°E~150°E
	Equator Africa	3°S~5°N, 10°E~30°E
Subarctic areas	North American subarctic	60°N~75°N, 170°W~60°W
	Eurasian subarctic	65°N~75N, 60°E~180°E
Tibetan Plateau	Tibetan Plateau	28°N~38°N, 80°E~105°E

Table 3-2. Statistics for the comparison between SSiB4/TRIFFID simulated and observation-based LAI and GPP

		LAI Mean			LAI T	CC	GPP N	GPP		
		(m <sup>2</sup> /m <sup>2</sup> ) GIMM GLAS SSiB4/			~~ . ~	~~ · ~	(gC/m²/yr)		TCC	
Regions	<b>Sub-regions</b>					GLAS	MTE	SSiB4/		
		S	S	TRIFFI D	S	S		TRIFFI D	L	
Arid and	West Africa	0.92	0.86	1.75	0.80**	0.79**	759.97	970.82	0.80**	
Semi- Arid	Western North America	0.57	0.46	1.27	0.58**		404.65	520.91	0.70**	
Areas	South American savanna	1.85	1.82	3.27	0.57**	0.54**	1615.2 8	1823.22	0.65**	
	East Africa	1.49	1.38	2.95	0.46**		1188.6 7	1487.25	0.63**	
Monsoon Area	East Asian monsoon area	1.59	1.31	3.58	0.61**	0.48**	1402.4 4	1503.18	0.51**	
	North America	0.80	0.91	1.94		0.34*	544.45	867.94	0.83**	
Hemisphe										
re boreal areas	Eurasian boreal	1.15	1.26	2.46	0.52**		857.16	1036.47	0.70**	
<b>Equator</b> areas	Amazon basin	4.18	4.28	6.15	0.38*	0.50**	2992.2 9	2820.73		
	Southeast Asia	4.00	3.16	4.82		0.38*	2792.9 5	2628.02		
	Equator Africa	3.86	3.48	6.09	0.36*	0.70**	2535.6	2833.9		
Subarctic areas	North American subarctic	0.37	0.38	0.78	0.46**	0.35*	256.46	438.18	0.72**	
	Eurasian subarctic	0.35	0.44	0.92	0.71**		345.82	539.41	0.64**	
Tibetan Plateau	Tibetan Plateau	0.52	0.43	1.29	0.58**	0.74**	323.12	546.2	0.49**	

Note: \* indicates the p<0.1 and \*\* indicates the p<0.05

Table 4-3. Linear trend of vegetation FRAC, LAI and GPP changes during P1 (1958-1982) and P2 (1982-2007) in sub-regions (1)

Regions	Var.	Total		Trees		C3 g	grass C4 plant		Shrub		Tundra		
		P1	P2	P1	P2	P1		P1	P2	P1	P2	P1	P2
West Africa	FRAC	-4.14				0.96	0.99	-4.33	-1.71	-0.96	1.1		
	LAI	-2.58	1.37			0.28	0.43	-1.9		-0.79	0.8		
	<b>GPP</b>	-18.54	8.02	-0.84	0.86	0.92	1.9	-14.09		-4.53	4.49		
East Asian	FRAC			0.51	0.56	1.19	1.72	-2.49	-2.6	0.63			
Monsoon	LAI	-0.34	0.43		0.44	0.34	0.76	-0.9	-0.83				
area	GPP	-1.61	2.39	0.84	2.17	1.06	3.51	-4.35	-3.73	0.84	0.44		
Western	FRAC	1.34	1.38			2.18	0.83	-0.48	-0.38		0.96		
North	LAI	0.96	-0.58			0.65	-0.23			0.34			
America	GPP	5.66	-2.73	1.02	-0.74	2.76	-1.12		-0.42	1.95			
Amazon	FRAC				0.37								
basin	LAI	0.57	0.66	0.61	0.74								
	GPP	3.49	8.7	4.08	8.93			-0.67	-0.39				
North	FRAC		0.36			0.4						-0.34	
American	LAI		0.25										
boreal	GPP	1.77	2.2	1.17	1.41	0.64							0.33
Eurasian	FRAC		0.29			0.37	0.37						
boreal	LAI		0.33		0.23								
		1.58	2.17	1.42	1.61	0.35	0.58						
North	FRAC	0.35	0.69	0.16	0.18	0.51				0.46	0.88	-0.76	-0.29
American	LAI		0.23										
subarctic	GPP	1.33	1.47	0.43	0.35	0.34				0.32	0.59		0.5
Eurasian	FRAC		0.59	0.29	0.39	0.58	0.20			-1.02			
subarctic	LAI		0.35										
	GPP	1.42	2.97	0.52	0.85	0.36					0.56	0.69	1.31
Tibetan	FRAC	0.83	0.32			4.51				-0.44		-3.26	
Plateau	LAI	0.2	0.39			0.48							
	GPP	0.68	2.61		0.78	1.9	0.98					-1.14	0.93

<sup>(1)</sup> Only significant values (P<0.1 in Mann-Kendall test) are shown, positive trends are in bold. Numbers are scaled by multiplying 10 for FRAC and 1000 for LAI.

Table  $\underline{5}$ -4. Climate drivers and eCO<sub>2</sub> effect on the trends of FRAC, LAI and GPP during P1 (1958-1982) and P2 (1982-2007) in sub-regions regarding to their regional average  $^{(1)(2)}$ 

Regions	Var.	Total		Elevated CO <sub>2</sub> Global			Climate		
J				concentration		warming		variab	ility
		P1	P2	P1	P2	P1	P2	P1	P2
West Africa	FRAC	-0.51						-0.51	0.14
	LAI	-1.47	0.78	0.10	0.12	-0.05	-0.13	-1.52	0.80
	GPP	-1.91	0.83	0.07	0.12	-0.05	-0.13	-1.94	0.83
East Asian	FRAC								
Monsoon area	LAI	-0.10	0.12	0.05	0.10			-0.16	
	GPP	-0.11	0.16	0.10	0.16		-0.06	-0.21	0.06
Western	<b>FRAC</b>	0.18	0.18	0.07	0.10			0.09	0.12
North	LAI	0.75	-0.45	0.11	0.14		-0.14	0.64	-0.46
America	GPP	1.09	-0.52	0.22	0.23		-0.19	0.88	-0.56
<b>Amazon basin</b>	FRAC								
	LAI	0.09	0.11	0.03	0.07			0.06	0.06
	GPP	0.12	0.31	0.13	0.19				0.14
North	FRAC		0.04						
American	LAI		0.13	0.05	0.10	0.06	0.10	-0.14	-0.07
boreal	<b>GPP</b>	0.20	0.25	0.14	0.20	0.08	0.14		-0.08
Eurasian	FRAC		0.03						
boreal	LAI		0.13		0.10		0.10	-0.11	-0.06
	<b>GPP</b>	0.15	0.21	0.13	0.18		0.11		-0.09
North	FRAC	0.05	0.09				-0.06		0.13
American	LAI		0.30	0.07	0.10			0.09	0.25
subarctic	<b>GPP</b>	0.30	0.34	0.17	0.24		-0.12	0.12	0.22
Eurasian	FRAC		0.06						0.05
subarctic	LAI		0.39	0.07	0.10		0.11		0.18
	GPP	0.26	0.55	0.17	0.25	0.06	0.13		0.18
Tibetan	FRAC	0.12	0.04					0.10	
Plateau	LAI	0.16	0.31					0.17	0.28
	GPP	0.13	0.48	0.12	0.21				0.26

percentage trend for FRAC:  $Trend_{FRAC}/(grid\ total\ vegetated\ FRAC)*100\%$  percentage trend for LAI and GPP:  $Trend_{var}/(grid\ averaged)*100\%$ , where var stands for LAI or GPP. Units for all three variables are %/yr Only significant values (P<0.05 in Mann-Kendall test) are shown, positive trends are in bold