

# Slow-down of the greening trend in natural vegetation with further rise in atmospheric CO<sub>2</sub>

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## Key Points:

- Satellite observations since the early 1980s show that Earth's greening trend is slowing down and that browning clusters are emerging.
- A collection of model simulations in conjunction with causal theory points at climatic changes as principal driver of vegetation changes.
- Most models underestimate the observed vegetation browning, which could be due to an excessive CO<sub>2</sub> fertilization effect in the models.

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## Abstract

Satellite data reveal widespread changes of Earth's vegetation cover. Regions intensively attended to by humans are mostly greening due to land management. Natural vegetation, on the other hand, is exhibiting patterns of both greening and browning in all continents. Factors linked to anthropogenic carbon emissions, such as CO<sub>2</sub> fertilization, climate change and consequent disturbances, such as fires and droughts, are hypothesized to be key drivers of changes in natural vegetation. A rigorous regional attribution at biome-level that can be scaled into a global picture of what is behind the observed changes is currently lacking. Here we analyze the longest available satellite record of global leaf area index (LAI, 1981-2017) and identify several clusters of significant long-term changes. Using process-based model simulations (Earth system and land surface models), we disentangle the effects of anthropogenic carbon emissions on LAI in a probabilistic setting applying Causal Counterfactual Theory. The analysis prominently indicates the effects of climate change on many biomes – warming in northern ecosystems (greening) and rainfall anomalies in tropical biomes (browning). Our results do not support previously published accounts of dominant global-scale effects of CO<sub>2</sub> fertilization. Altogether, our analysis reveals a slowing down of greening and strengthening of browning trends, particularly in the last two decades. Most models substantially underestimate the emerging vegetation browning, especially in the tropical rainforests. Leaf area loss in these productive ecosystems could be an early indicator of a slow-down in the terrestrial carbon sink. Models need to account for this effect to realize plausible climate projections of the 21<sup>st</sup> century.

## PLAIN LANGUAGE SUMMARY

The satellite-observed greening trend of Earth's land surface is a well documented phenomenon. Our analysis of almost four decades of global leaf area observations reveal a weakening of the greening trend and an expansion of browning regions. Leaf area gain is seen mostly in low

28 density vegetation and the loss in high density tropical forests. These opposing trends imbue  
29 a distinct signature of texture loss in green coverage of natural vegetation. A collection of  
30 factorial model simulations and causal theory identify biome-unique drivers of change linked  
31 to anthropogenic carbon emissions. The effects of climate change are prominently seen in  
32 many biomes, for example, warming in northern ecosystems and rainfall decline/anomalies in  
33 tropical biomes. However, most models do not reproduce the observed vegetation browning,  
34 especially in tropical rainforests. The leaf area loss in these highly productive ecosystems could  
35 be an early indicator of a slow-down in the terrestrial carbon sink.

## 36 1 INTRODUCTION

37 Satellite observations reveal widespread changes in terrestrial vegetation across the entire  
38 globe. The greening and browning trends reflect changes in the abundance of green leaves,  
39 and thus, the rate and amount of photosynthesis. Plants modulate pivotal land-atmosphere  
40 interactions through the process of photosynthesis. Hence, changes in photosynthetic activity  
41 have immediate effects on the land-atmosphere exchange of energy (Forzieri et al., 2017), water  
42 (McPherson, 2007; Ukkola et al., 2016) and carbon (Poulter et al., 2014; Thomas et al., 2016;  
43 Winkler et al., 2019). Several studies have reported that many biomes are largely greening,  
44 from Arctic tundra to subtropical drylands (Myneni et al., 1997; Nemani et al., 2003; Mao et al.,  
45 2016; Zhu et al., 2016; Chen et al., 2019; Winkler et al., 2019). Others have identified regions of  
46 declining trends in leaf area (Goetz et al., 2005; Verbyla, 2011). The drivers underlying these  
47 long-term vegetation changes, however, remain under debate. In the light of nearly forty years  
48 of continuous satellite observations, we reassess the driver attribution of natural vegetation  
49 changes in a new framework of cause-and-effect and challenge previous findings (Zhu et al.,  
50 2016).

51 Anthropogenic vegetation, *i.e.* actively cultivated vegetation, and natural vegetation should  
52 be considered separately due to their distinct origins and properties. A recent study by Chen  
53 et al. (2019) reported that anthropogenic vegetation (35% of the global vegetated area) is  
54 greening due to human land management. The authors identified irrigation, multiple cropping,  
55 and the application of fertilizers and pesticides as the main drivers of leaf area enhancement  
56 (direct drivers). These results challenge the conclusions of a previous study by Zhu et al. (2016)  
57 that attributed the global greening trend mostly to indirect drivers induced by CO<sub>2</sub> emissions,  
58 in particular, the CO<sub>2</sub> fertilization effect (70%).

59 Indirect drivers of vegetation changes usually include CO<sub>2</sub> fertilization and climate change  
60 in the literature, both of which are consequences of rising atmospheric CO<sub>2</sub> concentration.  
61 The term "CO<sub>2</sub> fertilization" includes two effects of increased ambient CO<sub>2</sub> on the physiology  
62 of plants. First, elevated CO<sub>2</sub> in the interior of leaves stimulates carbon assimilation, which  
63 enhances plant productivity and biomass (Leakey et al., 2009; Fatichi et al., 2016). Second,

64 in time leaves adapt to CO<sub>2</sub>-enriched atmosphere by lowering their stomatal conductance.  
65 As a consequence, water loss through transpiration decreases, resulting in increased water-  
66 use efficiency (ratio of carbon assimilation to transpiration rate; Ukkola et al., 2016; Fatichi  
67 et al., 2016). In theory, both effects should result in an expansion of leaf area, especially in  
68 environments where plant growth is constrained by water availability (Ukkola et al., 2016;  
69 Donohue et al., 2009; Donohue et al., 2013).

70 The radiative effect of CO<sub>2</sub> induces climatic changes that can have both harmful or beneficial  
71 effects on the functioning of ecosystems. Temperature-limited biomes are expected to green due  
72 to warming and associated prolongation of the growing season (Park et al., 2016; Winkler et al.,  
73 2019). But long-term drying (Zhou et al., 2014), as well as increased intensity and frequency of  
74 disturbances (Seidl et al., 2017) such as droughts (Bonal et al., 2016) and wildfires (Goetz et al.,  
75 2005; Verbyla, 2011), can induce regional vegetation browning trends. Regional greening and  
76 browning patterns can also be associated with insect outbreaks, local deforestation practices,  
77 regrowing or degrading forests, or nitrogen deposition; however, these drivers are considered  
78 to be of minor importance at the global scale (Zhu et al., 2016).

79 Indirect drivers affect both natural and anthropogenic vegetation unlike direct drivers which  
80 affect anthropogenic vegetation only. Chen et al. (2019) demonstrated that indirect drivers have  
81 either opposing or minor enhancing effects on the leaf area of anthropogenic vegetation. In  
82 general, the greening of anthropogenic vegetation has a negligible effect on the carbon cycle,  
83 because carbon absorbed by agricultural plants almost immediately reenters the atmosphere  
84 due to harvest and consumption. Natural terrestrial ecosystems, however, act as a strong  
85 carbon sink by absorbing about 30% of the anthropogenic CO<sub>2</sub> emissions ( $3.8 \pm 0.8 \text{ Pg C yr}^{-1}$ ;  
86 Quéré et al., 2018) and mitigate man-made climate change (Bonan, 2008; Sitch et al., 2015;  
87 Winkler et al., 2019). Thus, a mechanistic understanding of natural vegetation dynamics under  
88 rising CO<sub>2</sub> is critical and helps to answer one of the key question in current climate research:  
89 *Where does the anthropogenic carbon go* (Marotzke et al., 2017)?

90 This study focuses on the response of natural vegetation under the influence of the two key  
91 indirect drivers, the physiological and radiative effect of rising CO<sub>2</sub>. Throughout this paper  
92 and in accordance with literature, the terms "CO<sub>2</sub> fertilization" and "physiological effect of

93 CO<sub>2</sub>" are used interchangeably, as are "climate change" and "radiative effect of CO<sub>2</sub>". To assess  
94 observed changes in vegetation over climatic time scales, we make use of a 37-year record of  
95 leaf area index (LAI) satellite observations (1982–2017, LAI3g, Section 2.1). The LAI3g product  
96 is based on the Advanced Very High Resolution Radiometer (AVHRR) sensors, for which there  
97 are a number of shortcomings (no on-board calibration, no correction of orbit loss, minimal  
98 correction for atmospheric contamination and limited cloud screening; Section 2.1; Zhu et al.,  
99 2013; Chen et al., 2019). Despite these limitations, the AVHRR record is unique in terms of its  
100 temporal coverage and offers an opportunity to study the evolution of Earth's vegetation while  
101 atmospheric CO<sub>2</sub> concentration increased by 65 ppm (341 to 406 ppm). We define greening  
102 and browning as statistically significant increasing and decreasing trends in LAI, respectively  
103 (Section 2.6). Based on a detailed biome map (Figure S1, Table S1, Section 2.2), we identify  
104 spatial clusters of significant vegetation greening and browning in different natural vegetation  
105 types.

106 We make use of the latest version of the fully-coupled Max Planck Institute Earth system  
107 model in ensemble-mode (MPI-ESM, Section 2.3) and a collection of 13 land surface models  
108 (LSMs) driven with observed climatic conditions (TRENDYv7 ensemble; Section 2.4; Quéré  
109 et al., 2018). As a first step, we analyze historical simulations to examine whether these models  
110 capture the observed behavior of natural vegetation under rising CO<sub>2</sub>. Next, we analyze  
111 factorial simulations to disentangle and quantify the effects of rising CO<sub>2</sub> on LAI changes.  
112 Each factorial experiment consists of all historical forcings except one, which is set to its  
113 pre-industrial level (similar approach in TRENDYv7 simulations, Section 2.4 and 2.6).

114 The conventional approach to detection and attribution in climate science is the method of  
115 optimal fingerprinting, for example as in Zhu et al. (2016). This framework which considers the  
116 observed change to be a linear combination of individual forced signals, is prone to overfitting,  
117 and assumes that linear correlation reflects causation (Hannart and Naveau, 2018). To overcome  
118 these limitations, we propose to use the Causal Counterfactual Theory which has recently been  
119 introduced to climate science (Pearl, 2009; Hannart et al., 2016; Hannart and Naveau, 2018).  
120 The method allows us to test if long-term greening/browning trends can be attributed to the  
121 effects of rising CO<sub>2</sub> in a probabilistic setting combining necessary and sufficient causation  
122 (Section 2.7).

123 This is the first study that addresses vegetation browning as well as greening patterns  
124 across all major biomes, integrated into a global picture. Greening is dominant in terms of  
125 areal fraction, but browning clusters are intensifying, primarily in the tropical forests that are  
126 biodiversity-rich and highly productive. We find that CO<sub>2</sub> fertilization is an important driver  
127 of greening in some biomes, but not dominant globally as suggested previously (Zhu et al.,  
128 2016). The strengthening browning trend identified in our study is most likely linked to the  
129 long-term drying and recurring droughts. Overall, our findings suggest that the emerging  
130 browning clusters in the highly productive ecosystems might be a precursor of a weakening  
131 land carbon sink, which is not yet captured by the current land components of Earth system  
132 models.

## 133 2 MATERIALS AND METHODS

134 2.1 *Satellite observations of LAI: AVHRR LAI3g product*

135 We used an updated version (V1) of the leaf area index dataset (LAI3g; Chen et al., 2019) based  
136 on the methodology developed by Zhu et al. (2013). The data provides global year-round LAI  
137 observations at 15-day (bi-monthly) temporal resolution and  $1/12$  degree spatial resolution.  
138 It spans from July 1981 to December 2017 and is currently the only available record of such  
139 length. The full time series of LAI3gV1 was generated using an artificial neural network and  
140 the latest version (third generation) of the Global Inventory Modeling and Mapping Studies  
141 group (GIMMS) Advanced Very High Resolution Radiometer (AVHRR) normalized difference  
142 vegetation index (NDVI) data (NDVI3g). The latter have been corrected for sensor degradation,  
143 inter-sensor differences, cloud cover, observational geometry effects due to satellite drift,  
144 Rayleigh scattering and stratospheric volcanic aerosols (Pinzon and Tucker, 2014).

145 The LAI3g datasets prior to 2000 were not evaluated due to a lack of required field data  
146 (Zhu et al., 2013; Chen et al., 2019). After 2000, the quality of the LAI3g dataset was assessed  
147 through direct comparisons with ground measurements of LAI and indirectly with other  
148 satellite-data based LAI products, and also through statistical analysis with climatic variables  
149 such as temperature and precipitation variability (Zhu et al., 2013). Various studies used  
150 the predecessor LAI3gV0 and the related dataset of fraction of absorbed photosynthetically  
151 active radiation (fapar; Anav et al., 2013; Forkel et al., 2016; Zhu et al., 2016; Mao et al., 2016;  
152 Mahowald et al., 2016; Piao et al., 2014; Poulter et al., 2014; Keenan et al., 2016) and its successor  
153 LAI3gV1 (Winkler et al., 2019; Chen et al., 2019).

154 Leaf area index is defined as the one-sided green leaf area per unit ground area in broadleaf  
155 canopies and as one-half the green needle surface area in needleleaf canopies in both satellite  
156 observations and models (ESMs and LSMs). It is expressed in units of  $\text{m}^2$  green leaf area per  
157  $\text{m}^2$  ground area. Missing values in the LAI3gV1 dataset are filled using the climatology of  
158 each 16-day composite during 1982-2017. We use the annual averaged LAI of each pixel in this  
159 study.

160 2.2 *Characterization of biomes & clusters of significant change*

161 The land cover product of the MODIS sensors (MCD12C1; MODIS/Terra and Aqua Com-  
162 bined Land Cover Type Climate Modeling Grid (CMG) Yearly Global 0.05 Deg V006, [https://lpdaac.usgs.gov/dataset\\_discovery/modis/modis\\_products\\_table/mcd12c1\\_v006](https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mcd12c1_v006)) is the  
163 primary source underlying the land cover map used in this study (hereafter MODIS land  
164 cover). The classes from the International Geosphere–Biosphere Programme (IGBP) in the  
165 MODIS land cover product are aggregated as follows: Tropical Forests include Evergreen  
166 Broadleaf Forest (EBF), Temperate Forests include Deciduous Broadleaf Forest (DBF) and  
167 Mixed Forest, and Boreal Forests include Evergreen Needleleaf Forest (ENF) and Deciduous  
168 Needleleaf Forest (DNF). Savannas include Woody Savannas and Savannas. Shrublands include  
169 Closed Shrublands and Open Shrublands. Croplands include Croplands and Croplands /  
170 Natural Vegetation Mosaic. The class Others includes Permanent Wetlands, Urban and Built-up  
171 Lands, Permanent Snow and Ice, and Barren. The classes Grasslands and Water Bodies remain  
172 unchanged. The MODIS land cover product provides estimates for the time period from 2001  
173 to 2017 for each pixel. In this study we define a representative biome map based on the most  
174 frequently occurring land cover type throughout the period of 17 years.

176 The MODIS land cover classification does not contain the biome tundra, which is why we  
177 use in addition the land cover product GLDAS2 / Noah version 3.3 that uses a modified IGBP  
178 classification scheme providing the classes Wooded, Mixed or Bare Ground Tundra (<https://ldas.gsfc.nasa.gov/gldas/GLDASvegetation.php>, hereafter GLDAS land cover) (Rodell et  
179 al., 2004). Accordingly, pixels originally of the classes Shrublands, Grasslands, Permanent  
180 Wetlands, or Barren, are converted to Tundra, if classified as Wooded, Mixed or Bare Ground  
181 Tundra in the GLDAS land cover product. The classes Woody Savannas and Savannas span vast  
182 areas across the globe in the MODIS land cover product. We use the GLDAS classification for  
183 these pixels, but only for regions where the MODIS and GLDAS land cover products disagree.  
184 In doing so, we obtain a more accurate global land cover classification. Table S1 describes in  
185 detail how the fusion of the MODIS and GLDAS land cover products is realized.

187 As a last step, we integrate the MODIS tree cover product MOD44B (MODIS/Terra Vegetation  
188 Continuous Fields Yearly L3 Global 250 m SIN Grid V006, [https://lpdaac.usgs.gov/dataset\\_](https://lpdaac.usgs.gov/dataset_)

189 discovery/modis/modis\_products\_table/mod44b\_v006) to account for the underestimation of  
190 forested area in the MODIS land cover product. Areas with tree cover exceeding 10% are  
191 formally defined as forests (MacDicken et al., 2015). Thus, we set non-forest pixels in the  
192 MODIS land cover product above 10% tree cover to Boreal Forest in the high latitudes  $50^{\circ}$   
193 N/S. For tropical forest ( $25^{\circ}$  S –  $25^{\circ}$  N), we increase the threshold to 20% tree cover to allow  
194 for a realistic areal extent of savannas. The pixels in the bands  $25^{\circ}$  N/S –  $50^{\circ}$  N/S remain  
195 unchanged, because the MODIS land cover product already realistically represents the forested  
196 area in these latitudes.

197 Table S1 provides a detailed overview on the conflation of MODIS land cover product,  
198 GLDAS land cover product and the MODIS Tree cover product. The final biome map (originally  
199 resolved at  $0.05^{\circ}$ ) is regridded to the different resolutions of the AVHRR sensor and the models  
200 simulations (MPI-ESM and TRENDYv7) applying a largest area fraction remapping scheme.

201 Based on the observational LAI dataset we define various clusters for greening or browning  
202 in most biomes: North American Tundra (NAm Tundra), Eurasian Tundra (EA Tundra), North  
203 American Boreal Forests (NAm Brl F), Eurasian Boreal Forests (EA Brl F), Temperate Forests  
204 (Tmp F), Tropical Forests (Trp F), Central African Tropical Forests (CAf Trp F), Northern African  
205 Savannas and Grasslands (NAf Sv Gl), Southern African Savannas and Grasslands (SAf Sv  
206 Gl), Cool Grasslands (Cool Gl), and Australian Shrublands (Aus Sl). Some clusters require a  
207 more detailed definition of their geographical location and extent: Southern (Northern) African  
208 Savannas and Grasslands represent these vegetation type south (north) of the equator including  
209 Madagascar. Central African Tropical Forests represent all tropical forests in Africa. Cool  
210 Grasslands refer to grasslands above  $30^{\circ}$  N.

### 211 2.3 *Max-Planck-Institute Earth System Model*

212 MPI-ESM1.2 is the latest version of the state-of-the-art Max Planck Institute Earth System  
213 Model, which participates in the upcoming sixth phase of the Coupled Model Intercomparison  
214 Project (CMIP6; Eyring et al., 2016). Mauritsen et al. (2019) describes thoroughly the model  
215 developments and advancements with respect to its predecessor, the CMIP5 version (Giorgetta  
216 et al., 2013). Here, we use the low resolution (LR) fully coupled carbon/climate configuration

217 (MPI-ESM1.2-LR), which consists of the atmospheric component ECHAM6.3 with 47 vertical  
218 levels and a horizontal resolution of 200 km grid spacing (spectral truncation at T63). The  
219 ocean dynamical model MPIOM is set up on a bi-polar grid with an approximate grid-spacing  
220 of 150 km (GR1.5) and 40 vertical levels. MPI-ESM1.2-LR includes the latest versions of the land  
221 and ocean carbon cycle modules, comprising the ocean biogeochemistry model HAMOCC6  
222 and the land surface scheme JSBACH3.2 (Mauritsen et al., 2019).

223 As opposed to the high-resolution configuration, the LR variant of the MPI-ESM includes all  
224 the important processes relevant for longer time-scale changes of the land surface, such as a  
225 thoroughly equilibrated global carbon cycle, dynamical vegetation changes, interactive nitrogen  
226 cycle, land-use transitions, a process-based fire model (SPITFIRE), and an interactive coupling  
227 of all sub-models. Furthermore, it is possible to run this model configuration to generate 45-85  
228 model years per real-time day with a modern supercomputer (Mauritsen et al., 2019). This  
229 opens up the possibility of conducting a larger number of realizations for each experiment.

230 Specifically, we used the initial CMIP6 release of the MPI-ESM version 1.2.01 (mpiesm-  
231 1.2.01-release, revision number 9234). The final CMIP6 version will include further bug fixes,  
232 which are expected to only slightly influence long-term sensitivities of simulated land surface  
233 processes.

234 We conducted historical simulations (all forcings) and three factorial experiments (all forcings  
235 except one): (a) all historical forcings except the physiological effect of CO<sub>2</sub> (No PE; increasing  
236 CO<sub>2</sub> does not affect the biogeochemical processes), (b) all historical forcings except the radiative  
237 effect of CO<sub>2</sub> (No RE; increasing CO<sub>2</sub> does not affect climate), and (c) all historical forcings  
238 except anthropogenic forcings (No CO<sub>2</sub>). All experiments were performed in ensemble-mode  
239 (6 realizations per experiment) using the latest CMIP6 forcing data (1850–2013). Individual  
240 realizations were initialized from different points in time of a prolongation run of the official  
241 MPI-ESM1.2-LR pre-industrial control simulation. In doing so, we account for the influence  
242 of climatic modes (e.g. El Niño Southern Oscillation) as a source of uncertainty in simulating  
243 long-term changes.

244 The simulated time series were shifted by four years to maximize the overlap with the  
245 observational record of 1982–2017.

246 2.4 *Land surface models: TRENDYv7*

247 Land-surface models (LSMs) or dynamic global vegetation models (DGVMs) simulate key  
248 physical and biological key processes of the land system in interaction with the atmosphere.  
249 LSMs provide a deeper insight into the mechanisms controlling terrestrial energy, hydrological  
250 and carbon cycles, as well as the drivers of phenomena ranging from short-term anomalies  
251 to long-term changes (Sitch et al., 2015; Bastos et al., 2018). Here, we analyze the most  
252 recent TRENDY ensemble (version 7) comprising 13 state-of-the-art LSMs which vary in  
253 their representation of ecosystem processes. All models simulate vegetation growth and  
254 mortality, deforestation and regrowth, vegetation and soil carbon responses to increasing  
255 atmospheric CO<sub>2</sub> levels, climate change and natural variability (Quéré et al., 2018). Some  
256 models simulate an explicit nitrogen cycle (allowing for potential nitrogen limitation) and  
257 account for atmospheric N deposition (Table A1 in Quéré et al., 2018). Most LSMs include  
258 the most important components of land-use and land-use changes, but they are far from  
259 representing all processes resulting from direct human land management (Table A1 in Quéré  
260 et al., 2018). A more detailed description of the TRENDYv7 ensemble, model-specific simulation  
261 setups and references can be found in Quéré et al. (2018, Table A4).

262 We use output from five simulations: all forcings (S<sub>3</sub>), physiological effect of CO<sub>2</sub> only (S<sub>1</sub>),  
263 radiative plus physiological effect of CO<sub>2</sub> (S<sub>2</sub>), land-use changes only (S<sub>4</sub>), and the control run  
264 (S<sub>0</sub>; no forcings: fixed CO<sub>2</sub> concentration of 276.59 ppm and fixed land-use map, loop of mean  
265 climate and variability from 1901–1920). The forcing data consist of observed atmospheric  
266 CO<sub>2</sub> concentrations, observed temporal patterns of temperature, precipitation, and incoming  
267 surface radiation from the CRU-JRA-55 reanalysis (Quéré et al., 2018; Harris et al., 2014), and  
268 human-induced land-cover changes and management from an extensions of the most recent  
269 Land-Use Harmonization (LUH2) dataset (Hurtt et al., 2011; Quéré et al., 2018).

270 In this study, we only analyze output for the period 1982–2017 (matching the observational  
271 record) from models providing spatially gridded data for all five simulations. A few models  
272 provide LAI at the level of plant functional types (PFTs). We calculate the average value of  
273 all LAI values on PFT level multiplied by their land cover fraction for each grid cell. All

274 model outputs were spatially regridded to a common resolution of  $1^\circ$  based on a first-order  
275 conservative remapping scheme (Jones, 1999).

276 The design of factorial simulations in TRENDYv7 and by the MPI-ESM are conceptually  
277 different. The MPI-ESM simulations were conducted using the counterfactual approach, *i.e.*  
278 all forcings are present except the driver of interest. TRENDYv7 provides simulations with  
279 different combinations of drivers as described above. To obtain comparability, we have to make  
280 the assumption that the absence of a specific driver has the same effect, in absolute values, as  
281 its sole presence. Thus, we process the output of the simulations S1, S2, S3 and S4 to obtain the  
282 counterfactual setup as described above for MPI-ESM. This approach neglects possible synergy  
283 effects from simultaneously acting forcings. Also, it has to be noted that these simulations are  
284 only to some extent comparable between the two ensembles. For instance, in the MPI-ESM we  
285 can specifically determine the impact of the radiative effect of CO<sub>2</sub>, whereas TRENDYv7 uses  
286 observed atmospheric fields including changes induced from other drivers, such as non-CO<sub>2</sub>  
287 greenhouse gases.

288 For certain clusters, some models show unreasonable LAI changes and/or extreme inter-  
289 annual variability. To reduce the influence of these extreme models on the overall analysis,  
290 we apply a two-step filtering method for each cluster beforehand. Models are excluded from  
291 the analysis, if they exceed three times the inter-annual variability of observations and/or  
292 show a drastic change (of either sign) of more than 250% between the start and end of the  
293 observational period. Further, we apply a weighting scheme based on the performance of the  
294 all-forcings run for each cluster. We calculate quartic weights based on the distance between  
295 the simulated and observational estimate. These weights are applied when calculating the  
296 multi-model average and standard deviations for the factual and counterfactual runs.

## 297 2.5 Atmospheric CO<sub>2</sub> concentration

298 Global monthly means of atmospheric CO<sub>2</sub> concentration are taken from the GLOBALVIEW-  
299 CO<sub>2</sub> product (for details see <http://dx.doi.org/10.3334/OBSPACK/1002>) provided by the Na-  
300 tional Oceanic and Atmospheric Administration/Earth System Research Laboratory (NOAA/ESRL).

301 2.6 *Processing of the gridded data*

302 Areas of significant change in LAI are estimated using the non-parametric Mann-Kendall  
303 test, which detects monotonic trends in time series. In this study, we set the significance level  
304 to  $p \leq 0.1$ . An alternative statistical test for trend detection (Cox-Stuart test; Sachs, 1997) yields  
305 approximately the same results. The trends are either calculated for time series on the pixel  
306 level or for area-weighted large-scale aggregated time series (e.g. biome level).

307 We define greening (browning) either as a positive (negative) temporal trend, or for better  
308 comparison among models and observations as well as for a better global comparison across  
309 diverse biomes, we express these trends relative to the initial LAI level at the beginning of the  
310 observational record (average state from 1982-1984), denoted as  $\Lambda$  (% decade<sup>-1</sup>).

311 The calculation of yearly net changes in leaf area balances the effects from both statistically  
312 significant browning and greening grid cells. For each cell, we multiply the estimated trends by  
313 the respective grid area. The net change is the sum of all grid cells, where areas of insignificant  
314 change are set to zero.

315 Models fairly accurately reproduce global patterns of vegetation greening, however, the  
316 fraction of browning is considerably underrepresented. Yet, we can only consider pixels with  
317 significant negative trends in LAI, in observations and models alike, and test models with  
318 respect to driver attribution of browning trends. Thus, the attribution of browning trends in  
319 this paper exclusively refers to browning pixels only.

320 Models reveal biases in comparison to observations. To obtain informative results in the  
321 attribution analysis, we process the simulations to match the mean and variance of the  
322 observational time-series. Assuming additive and multiplicative biases in simulations, we  
323 apply the following corrections:

$$b = \frac{\sigma_o}{\sigma_{af}}, \quad (1)$$

$$a = \bar{x}_o + b \times \bar{x}_{af} , \text{ and} \tag{2}$$

$$y_i = a + b * x_i , \tag{3}$$

324

325 where  $\bar{x}_o$  represents the mean value and  $\sigma_o$  the standard deviation of the observational times  
 326 series.  $\bar{x}_{af}$  and  $\sigma_{af}$  are analogous to the all-forcings simulations. All simulated time series  $x_i$  are  
 327 scaled using equation 3, where  $i \in \Omega = \{\text{factual runs, counterfactual runs}\}$ . This processing  
 328 step does not affect the nature of simulated trends.

### 329 2.7 Causal Counterfactual Theory

330 The causal counterfactual approach is anchored in a formal theory of event causation  
 331 developed in computer science (Pearl, 2009; Marotzke, 2019). Recently, a framework for driver  
 332 attribution of long-term trends in the context of climate change has been introduced (Hannart  
 333 et al., 2016; Hannart and Naveau, 2018), and increasingly gains popularity (Marotzke, 2019).  
 334 Through the use of this method we can ascertain the likelihood that a certain external forcing  
 335 has caused an observed change in the Earth system. More precisely, we address the question of  
 336 interest in a probabilistic setting, *i.e.* what is the probability that a given forcing (e.g. radiative  
 337 effect of CO<sub>2</sub>) has caused an observed long-term change in the system (e.g. greening of the  
 338 Arctic).

339 In the following, we highlight the key ideas and relevant concepts of causal theory. A detailed  
 340 description and formal derivations can be found in (Pearl, 2009; Hannart et al., 2016; Hannart  
 341 and Naveau, 2018). We define the cause event ( $C$ ) as "presence of a given forcing" (*i.e.* the  
 342 factual world that occurred) and the complementary event ( $\bar{C}$ ) as "absence of a given forcing"  
 343 (*i.e.* the counterfactual world that would have existed in the absence of a given forcing; Hannart  
 344 and Naveau, 2018). Further, we define the effect event ( $E$ ) as the occurrence of a long-term  
 345 change (here, greening or browning) and the complementary event ( $\bar{E}$ ) as the non-occurrence  
 346 of a long-term change (*i.e.* no persistent vegetation changes). In making use of numerical

347 models, we can conduct factual runs comprising all forcings (*i.e.* historical simulations) as well  
 348 as simulate counterfactual worlds by switching off a forcing of interest (*i.e.* all forcings except  
 349 one). Based on an ensemble of simulations, either in a multi-model and/or multi-realizations  
 350 setup, we derive the so-called factual ( $p_1$ ) and counterfactual probability ( $p_0$ ), which read  
 351  $p_1 = P\{E|\text{do}(C)\}$  and  $p_0 = P\{E|\text{do}(\bar{C})\}$ , respectively (Hannart and Naveau, 2018). More  
 352 precisely,  $p_1$  describes the probability of the event  $E$  in the real world where forcing  $C$  was  
 353 present, whereas  $p_0$  refers to the probability of the event  $E$  in a hypothetical world where  
 354 forcing  $C$  was absent. The notation  $\text{do}(\cdot)$  means that an *experimental intervention* is applied to  
 355 the system to obtain the probabilities (Hannart and Naveau, 2018).

The three distinct facets of causality can be established based on the probabilities  $p_1$  and  $p_0$ :

$$\text{PN} = \max \left\{ 1 - \frac{p_0}{p_1}, 0 \right\}, \quad (4)$$

$$\text{PS} = \max \left\{ 1 - \frac{1 - p_1}{1 - p_0}, 0 \right\}, \text{ and} \quad (5)$$

$$\text{PNS} = \max \{ p_1 - p_0, 0 \}. \quad (6)$$

356 PN refers to the probability of necessary causation, where the occurrence of  $E$  requires that of  
 357  $C$  but may also require other forcings. PS refers to the probability of sufficient causation, where  
 358 the occurrence of  $C$  drives that of  $E$  but may not be required for  $E$  to occur. PNS describes  
 359 the probability of necessary and sufficient causation, where PN and PS both hold (Hannart  
 360 and Naveau, 2018). In other words, PNS may be considered as the probability that combines  
 361 necessity and sufficiency. Thus, the main goal is to establish a high PNS that reflects and  
 362 communicates evidence for the existence of a causal relationship in a simple manner (Hannart  
 363 and Naveau, 2018).

364

365 To obtain PNS, we follow the methodology described in detail in Hannart and Naveau  
 366 (Hannart and Naveau, 2018) and derive cumulative distribution functions (CDF) for the factual  
 367 and counterfactual worlds, denoted  $D_0$  and  $D_1$ , respectively. Assuming a Gaussian distribution,  
 368 PNS follows as

$$\text{PNS} = \max\{D_1(\mu_1, \Sigma) - D_0(\mu_0, \Sigma)\}, \quad (7)$$

369 where  $\mu_1$  and  $\mu_0$  refer to the mean response of all factual and all counterfactual runs,  
 370 respectively.  $\Sigma$  denotes the overall uncertainty and is estimated based on all simulations,  
 371 comprising factual, counterfactual, and centuries-long unforced (pre-industrial) model runs  
 372 (for details see Hannart and Naveau, 2018). Finally, the maximum of PNS determines the  
 373 sought probability of causation (Hannart and Naveau, 2018). We express probabilities using  
 374 the terminology and framework defined by the IPCC (Mastrandrea et al., 2011; Hannart and  
 375 Naveau, 2018).

## 376 3 RESULTS AND DISCUSSION

377 3.1 *Natural vegetation exhibits a net gain of leaf area over the last decades, but the number of browning*  
378 *regions is increasing*

379 More than three and half decades of satellite observations (1982–2017, Section 2.1) reveal  
380 that 40% of the Earth’s natural vegetation shows statistically significant positive trends in LAI  
381 (Mann-Kendall test,  $p < 0.1$ ; Table 1), concurrent with a 65 ppm increase in atmospheric CO<sub>2</sub>.  
382 However, more and more browning clusters are beginning to emerge in all continents (14%;  
383 Table 1). Analyzing earlier versions of three shorter duration (1982–2009) LAI datasets, Zhu  
384 et al. (2016) reported a considerably smaller browning fraction of less than 4% and greening  
385 percentages ranging from 25% to 50% for all vegetation (*i.e.* including agriculturally dominated  
386 regions). The higher browning proportion in the extended record analyzed in this study  
387 indicates an intensification of leaf area loss in recent years.

388 3.2 *Earth’s forests respond diversely throughout the satellite era*

389 A global map of statistically significant trends in LAI (denoted  $\Lambda$ , Section 2.6) for natural  
390 vegetation reveals greening ( $\Lambda > 0$ ) and browning ( $\Lambda < 0$ ) clusters across the globe (Figure 1).  
391 Temperate forests ( $\Lambda > 0$ : 56%) and Eurasian boreal forests ( $\Lambda > 0$ : 53%) exhibit extensive  
392 regions of increasing LAI, and thereby, contribute the largest fraction to the enhancement of  
393 leaf area on the planet (Table 2). The global belt of tropical forests, on the other hand, while  
394 showing a net greening ( $\Lambda > 0$ : 28%), also feature widespread browning areas ( $\Lambda < 0$ : 16%).  
395 In particular, the Central African tropical forests contain large areas of pronounced negative  
396 trends ( $\Lambda < 0$ : 25%). North American boreal forests exhibit the largest fraction of browning  
397 vegetation ( $\Lambda < 0$ : 31%) resulting in an annual net loss of leaf area (Table 1 and 2). The  
398 picture of Earth’s forests is generally in line with results based on other data sources. For  
399 instance, Song et al. (2018) reported a net gain of global forested area, with net loss in the  
400 tropics compensated by a net gain in the extra-tropics.

401 3.3 *As in forests, other biomes also indicate divergent vegetation responses to rising CO<sub>2</sub>*

402 Tundra in North America is primarily greening ( $\Lambda > 0$ : 46% versus  $\Lambda < 0$ : 7%), whereas  
403 in Eurasia, browning is intensifying ( $\Lambda > 0$ : 35% versus  $\Lambda < 0$ : 20%), especially in northern  
404 Scandinavia and on the Taymar Peninsula in Northern Russia. Grasslands in cool arid climates,  
405 mainly comprising the Mongolian and Kazakh Steppe, as well as the Australian shrublands,  
406 stand out as prominent greening clusters ( $\Lambda > 0$ : 40% and 49%, respectively). Although these  
407 biomes show strong positive trends, they are characterized by a low level of LAI. The African  
408 continent, which is still dominated by natural vegetation, reveals a distinct change in leaf area.  
409 A greening band of savannas and grasslands in the northern regions of Sub-Saharan Africa  
410 and a greening cluster in Southern Africa border the browning regions of equatorial Africa  
411 (Figure 1). Overall, the response of LAI to rising CO<sub>2</sub> is somewhat homogeneous for some  
412 biomes (widespread browning of the tropical forests and dominant greening of the temperate  
413 forests), but divergent for others (tundra and boreal forests show a 'North America – Eurasia'  
414 asymmetry, interestingly, in that they show changes of reversed sign; Figure 1).

415 3.4 *Net annual gain of leaf area is declining in natural vegetation*

416 Leaf area loss occurs primarily in densely vegetated biomes (*i.e.* forests), which outweighs  
417 leaf area gain in rather sparsely vegetated regions (e.g. grasslands). For instance, vigorously  
418 greening areas of circumpolar tundra result in a leaf area gain of  $8.74 \times 10^3 \text{ km}^2 \text{ yr}^{-1}$ , which  
419 is almost outbalanced fourfold by a leaf area loss of  $34.31 \times 10^3 \text{ km}^2 \text{ yr}^{-1}$  in the browning  
420 regions of the tropical forests (Table 2). To assess the responses of different biomes to rising  
421 CO<sub>2</sub> in more detail, we iteratively calculate statistically significant LAI trends for different  
422 time windows with advancing initial year (*i.e.* 1982, 1983, ..., 2000), but fixed final year (2017).  
423 Although the estimated trends become less robust with shorter time series, this analysis allows  
424 us to test for weakening or strengthening responses to further rising CO<sub>2</sub>. We see that the  
425 fraction of significantly browning regions is increasing over time, reaching a maximum for  
426 a time window starting in 1995. The greening fraction evolves in the opposite manner. The  
427 estimates are represented as fractions of the total area of significant change, because the latter  
428 inherently decreases as a result of the Mann-Kendall test for shorter time windows. Thus,

429 the average annual net leaf area gain of  $150.51 \times 10^3 \text{ km}^2 \text{ yr}^{-1}$  for the entire observational  
 430 period (1982–2017) decreases with advancing initial year, approaching zero for the period  
 431 1995 to 2017, and rebounding to  $\sim 40 \times 10^3 \text{ km}^2 \text{ yr}^{-1}$  for the period 2000 to 2017 (black  
 432 line in Figure 1 inset). To obtain comparability between different time windows, the net leaf  
 433 area gain estimates were scaled to the total area of significant change derived for 1982–2017  
 434 (unprocessed estimates for period 2000–2017 are listed in Table S2). Chen et al. (2019) reported  
 435 a global greening proportion of  $\sim 33\%$  (AVHRR: 21%; Table S2) and a browning proportion  
 436 of only 5% (AVHRR: 13%; Table S2) analyzing the MODIS record including anthropogenic  
 437 vegetation (2000–2017). On a global scale, LAI trends from MODIS and AVHRR agree over  
 438 61% of the vegetated area (Chen et al., 2019). Disagreement arises primarily in the tropical  
 439 regions (absence of browning in the Central African tropical forests in the MODIS record) and  
 440 in the northern high latitudes (Chen et al., 2019). In a recent study, Yuan et al. (2019) presented  
 441 results comparing various remote sensing datasets of vegetation greenness which are in line  
 442 with AVHRR-based estimates.

### 443 3.5 High LAI regions are browning and low LAI regions are greening

444 The intensification of browning during the second half of the AVHRR observational period  
 445 (2000–2017) results in a reversal of the sign in terms of net leaf area change in some biomes  
 446 (e.g. tropical forests, North American boreal forests, and Eurasian tundra; Table S3). Critically,  
 447 the tropical forests display the sharpest transition from a substantial net gain of  $24.11 \times 10^3$   
 448  $\text{km}^2 \text{ yr}^{-1}$  (Table 2) to a comparably strong net loss of leaf area ( $-18.42 \times 10^3 \text{ km}^2 \text{ yr}^{-1}$ ; Table  
 449 S3). To address the temporal development of positive and negative changes in leaf area in  
 450 more detail, we calculate time series of area-weighted averages of LAI (Figure 2a). We find that  
 451 browning of natural vegetation occurs at a considerably higher level of LAI (on average  $\sim 1.85$ )  
 452 than greening (on average  $\sim 1.32$ ). Throughout the observational period, these two time series  
 453 of opposite trends converge towards a LAI of 1.6 (Figure 2a). This convergence of greening and  
 454 browning is not only evident in terms of their LAI level (Figure 2a), but also in their proportions  
 455 (inset in Figure 1). The time series of anthropogenic vegetation on the other hand, aggregated  
 456 for positive and negative  $\Delta$  separately, are both confined to a comparable low LAI level (on  
 457 average between 1 and 1.25). We next investigate the global LAI distributions of negative

458 and positive changes and their development over time. Comparing distributions of the earlier  
459 (1982–1984) with those of the more recent years (2015–2017) reveals that browning primarily  
460 occurs at a high (5–6) and a medium level of LAI (1–2.5; Figure 2b). Greening, however, is  
461 occurring almost entirely at low levels of LAI between 0–1.5. As a consequence, the global  
462 area-weighted averages of the browning and greening regions are approaching one another  
463 (dashed versus solid vertical lines in Figure 2b), as also depicted by the time series (Figure  
464 2a). Overall, these results suggest a homogenization of Earth’s natural vegetation in terms of  
465 LAI texture with rising CO<sub>2</sub>. This homogenization becomes prominent when we compare the  
466 distributions of negative and positive  $\Delta$  over time using a Q-Q plot (quantile-quantile; Figure  
467 2c). The relationship between the quantiles is skewed to the left at higher LAI (positive  $\Delta$  on  
468  $x$ -axis, negative  $\Delta$  on  $y$ -axis), because browning is prevalent in high LAI regions. Over time, the  
469 quantiles of the greening and browning distributions are approaching the 1-1 line (representing  
470 identical distributions), emphasizing their convergence.

### 471 3.6 *The majority of models reproduce the observed convergence of greening and browning trends*

472 Thus far, we have described the diverse long-term changes of natural vegetation across all  
473 continents and throughout the satellite era. We next investigate the underlying mechanisms  
474 driving these greening and browning trends and use the fully-coupled MPI-ESM and the  
475 TRENDYv7 ensemble of observation-driven LSMs (Section 2.3 and 2.4). First, we ask if  
476 these models capture the observed behavior of natural vegetation under rising CO<sub>2</sub>. MPI-  
477 ESM reproduces the observed browning of high LAI and the greening of low LAI regions,  
478 however, the levels of LAI do not match the observations (Figure S2). Historical simulations of  
479 TRENDYv7 (here 13 models) also show pronounced changes in vegetation, but exhibit a diverse  
480 behavior among the models (results not shown for brevity). Seven LSMs reproduce observed  
481 converging trends of greening and browning, whereas the other six models show divergent  
482 trends. All TRENDYv7 models are driven with identical atmospheric forcing fields, hence, these  
483 six models most likely lack or incorrectly represent key processes of ecosystem functioning. In  
484 general, simulated greening patterns are comparable to observations (Murray-Tortarolo et al.,  
485 2013; Sitch et al., 2015; Mahowald et al., 2016), but browning, especially in the North American  
486 boreal forests, is underestimated (Sitch et al., 2015).

487 3.7 *Models point to the physiological effect of CO<sub>2</sub> as the main driver of greening at the global scale*

488 Hereafter, we use changes in annual average LAI relative to the baseline period 1982–1984  
489 (Section 2.6) for better comparability between biomes, various simulations and the observed  
490 signal. Time series of relative LAI changes from historical simulations (multi-model average for  
491 TRENDYv7 and multi-realizations average for MPI-ESM) are comparable to observations at the  
492 global scale (Figure 3a and 3b; temporal correlations are low due to high internal variability of  
493 the signal).

494 We use the framework of Counterfactual Causal Theory to attribute changes in LAI to a given  
495 driver in a probabilistic setting (Pearl, 2009; Hannart et al., 2016; Hannart and Naveau, 2018).  
496 Based on the all-forcings (also termed factual) and factorial runs (also termed counterfactual),  
497 we derive Probabilities of causation that combines Necessity and Sufficiency of each factor  
498 (PNS). At the global scale, the observed estimate ( $\sim 1.08$  % decade<sup>-1</sup>) and the factual MPI-  
499 ESM estimate ( $\sim 1.14$  % decade<sup>-1</sup>) are comparable, whereas the multi-model average of the  
500 TRENDYv7 ensemble is an overestimate ( $\sim 1.79$  % decade<sup>-1</sup>; Figure 3c). Omitting CO<sub>2</sub>-induced  
501 climate change (no radiative effect of CO<sub>2</sub>, No RE) does not have a strong effect in the MPI-ESM  
502 ( $\sim 1.04$  % decade<sup>-1</sup>), *i.e.* the estimate does not differ considerably from the factual run. The  
503 TRENDYv7 models indicate that the positive trend in LAI can be explained by climate change  
504 to some extent ( $\sim 1.21$  % decade<sup>-1</sup>). However, PNS values are low for the radiative effect of  
505 CO<sub>2</sub> (Figure 3d). The opposite is the case, when the physiological effect of CO<sub>2</sub> (No PE) is  
506 excluded. Both model setups agree that almost no positive trend in LAI is present in a world  
507 without CO<sub>2</sub> fertilization (MPI-ESM:  $\sim 0.18$  % decade<sup>-1</sup>, TRENDYv7:  $\sim 0.08$  % decade<sup>-1</sup>; both  
508 estimates are lower than internal variability of  $\sim 0.49$  % decade<sup>-1</sup>). As a consequence, high  
509 PNS can be established: The physiological effect of CO<sub>2</sub> has in the case of MPI-ESM *likely*  
510 (68%) and in the case of TRENDYv7 *very likely* (91%) caused the positive trend of global LAI in  
511 recent decades (Figure 3d). This result is in line with Zhu et al. (2016) who reported that 70%  
512 of global greening is attributable to CO<sub>2</sub> fertilization. Removing both effects of CO<sub>2</sub> results in  
513 slight negative trends, probably due to land use practices (deforestation; Figure 3c).

514 3.8 *The global signal switches to a minor negative trend in the second half of the observational period*

515 Natural vegetation shows a slight negative trend for the period 2000–2017 ( $\sim -0.4$  % decade<sup>-1</sup>;  
516 Figure 3e). This estimate is within the range of internal variability, and thus, should be  
517 interpreted with caution. Note, that the net change in leaf area is still positive when considering  
518 only significantly changing pixels (inset in Figure 1). Models reproduce this reversal in the  
519 sign when the physiological effect of CO<sub>2</sub> is excluded or with a complete absence of CO<sub>2</sub>  
520 forcing (Figure 3e). Overall, driver attribution at the global scale, as described above, and also  
521 in Zhu et al. (2016), neglects the heterogeneity of natural vegetation and the possibility that  
522 divergent responses of different natural biomes might cancel out. To account for this omission,  
523 we identify eleven clusters of significant change and derive probabilities of causation for each  
524 driver across different vegetation types (Figure 4).

525 3.9 *Temperate forests prosper with rising CO<sub>2</sub> while tropical forests are increasingly under stress*

526 Forests in temperate climates exhibit a strong positive trend in LAI ( $\sim 2.53$  % decade<sup>-1</sup>),  
527 which is also seen in the models, albeit slightly overestimated (MPI-ESM:  $\sim 3.18$  % decade<sup>-1</sup>,  
528 TRENDYv7:  $\sim 2.69$  % decade<sup>-1</sup>; Figure S3). The physiological effect of CO<sub>2</sub> is the main driver  
529 with high PNS (85% for MPI-ESM, 80% for TRENDYv7; Figure 4). The trends are slightly  
530 weakened when only analyzing the second half of the observational period, but the overall  
531 result does not change. Observed warming might have additionally contributed to enhanced  
532 vegetation growth (e.g. growing season extension; Piao et al., 2011; Park et al., 2016), however,  
533 it is not identified as an important driver by models. Most temperate forests are in developed  
534 countries, and thus, have been managed in a sustainable manner for several decades (Currie  
535 and Bergen, 2008). It is conceivable, that some of the positive trends in LAI could be attributed  
536 to forest management or regrowing forests (Pugh et al., 2019), however, this is not captured by  
537 the models (*i.e.* trends are negative when complete CO<sub>2</sub> forcing is absent; Figure S3).

538 The response of tropical forests to rising CO<sub>2</sub> is more complex. The signal over the entire  
539 observational period is slightly positive ( $\sim 0.3$  % decade<sup>-1</sup>), however, it is within the range of  
540 internal variability. Therefore, no robust driver attribution is possible (Figure 4 and Figure S4).  
541 TRENDYv7 models show strongly opposing responses of LAI to the different effects of CO<sub>2</sub>:

542 LAI decreases when the physiological effect is omitted, but increases when the radiative effect  
543 is omitted. MPI-ESM shows qualitatively the same responses, but less pronounced (Figure S4).  
544 For the second half of the satellite record, the observed trend switches sign to a strong negative  
545 trend ( $\sim -1.4$  % decade<sup>-1</sup>). The models reproduce this tendency, but the multi-model average of  
546 the TRENDYv7 ensemble is still positive. During the same time period, the opposing reactions  
547 to CO<sub>2</sub> in the factorial runs are more strongly marked (Figure S4). These results suggest that  
548 browning caused by CO<sub>2</sub>-induced climate change is compensated by greening affiliated with  
549 the CO<sub>2</sub> fertilization effect at the biome level. Based on these findings, we hypothesize that the  
550 physiological effect of CO<sub>2</sub> is strong in models and outbalances the negative effect of climate  
551 change in the tropical forests (Kolby Smith et al., 2016). As a consequence, the all-forcings  
552 simulations fail to reproduce the observed patterns of strengthening vegetation browning in  
553 the tropics (Zhou et al., 2014; Song et al., 2018), for reasons discussed below.

### 554 3.10 *Droughts and intensification of the dry season in the Amazon basin*

555 The Amazonian tropical forests are being frequently afflicted by severe droughts. During  
556 the satellite era most of these droughts were strongly modulated by the El Niño Southern  
557 Oscillation (ENSO). For example, the droughts of 1982-83, 1987 and 1991-92 (Asner and Alencar,  
558 2010; Anderson et al., 2018), 1997 (Williamson et al., 2000), and 2015-16 (Jiménez-Muñoz et al.,  
559 2016). The causes of the droughts in 2005 and 2010, however, were not related to ENSO, but  
560 rather to a warm anomaly in sea surface temperatures in the tropical North Atlantic (Marengo  
561 et al., 2008; Marengo et al., 2011; Xu et al., 2011). Whereas the ENSO-driven droughts peak in  
562 northern hemispheric winter, thus during the wet season, the non-ENSO droughts happened  
563 during the dry season (July – September), when tropical ecosystems are more vulnerable to  
564 negative rainfall anomalies.

565 These intense and frequent droughts have diverse impacts on tropical ecosystems (Bonal  
566 et al., 2016), the most prominent being an increase in wildfires and tree mortality. Recently,  
567 perennial legacy effects have been identified which lead to persistent biomass loss in the  
568 aftermath of severe droughts (Saatchi et al., 2013; Yang et al., 2018). For instance, some regions  
569 were still recovering from the impact of the megadrought of 2005 when the next major drought  
570 began in 2010 (Saatchi et al., 2013). Maeda et al. (2015) found that these extreme events are also

571 capable of disrupting hydrological mechanisms, which can lead to long-lasting changes in the  
572 structure of Amazonian ecosystems. Such droughts and associated wildfires are predicted to  
573 increase in frequency (Cai et al., 2014) and intensity (Fasullo et al., 2018) as a consequence of  
574 the ENSO-related amplification of heat waves, but also due to the projected warming of the  
575 tropical North Atlantic (Munday and Washington, 2019).

576 In addition to these episodic disturbances, long-term changes in climate also affected the  
577 tropical forests in the Amazon region. Rising surface air temperatures have considerably  
578 increased atmospheric water vapor pressure deficit (VPD), which has a negative effect on  
579 vegetation growth (Yuan et al., 2019). Moreover, we find that precipitation has steadily  
580 decreased during the dry season (July – September, Figure S5 and S6) based on the latest  
581 version of the ECMWF reanalysis for the last forty years (ERA5; Dee et al., 2011). This rainfall  
582 deficit and the identified lengthening of the dry season (Fu et al., 2013) exacerbate vegetation  
583 water stress during dry seasons and favor conditions for wildfires. The slight increasing trend  
584 in wet season precipitation (February – April) most likely cannot compensate for the water loss  
585 and its impact during the dry season (Figure S5). Overall, the intensification of the dry season  
586 and the recurring droughts cause long-term browning trends (Xu et al., 2011), in line with our  
587 results of intensified browning of Amazonian forests (Figure S6).

### 588 3.11 *Drying trend in central African humid forests*

589 African tropical forests have been experiencing a long-term drying trend since the 1970s  
590 (Malhi and Wright, 2004; Asefi-Najafabady and Saatchi, 2013; Zhou et al., 2014). In contrast to  
591 South America, the steady decline in rainfall is seen during both dry and wet seasons (Figure  
592 S5). The origin of this decreasing trend in year-round rainfall is still under debate. Precipitation  
593 in equatorial Africa is expected to increase under climate change (Weber et al., 2018), so  
594 it is hypothesized that this trend is associated with the Atlantic Multidecadal Oscillation  
595 and/or changes in the West African Monsoon system (Asefi-Najafabady and Saatchi, 2013).  
596 Long-term drying in rainforests could also be connected to the physiological effect of rising  
597 CO<sub>2</sub>. Recently, it has been demonstrated that the reduction in stomatal conductance and  
598 transpiration induces a drier, warmer, and deeper boundary layer, resulting in a decline in local  
599 rainfall (Langenbrunner et al., 2019). Regardless of what the causes may be, this long-term

600 water deficiency most likely has led to the most pronounced cluster of vegetation browning in  
601 Earth's tropical forests ( $\sim 174 \times 10^3 \text{ km}^2$  net loss of leaf area in the time period of 2000–2017).  
602 No robust attribution is possible with the set of models analyzed in this study, since they  
603 fail to capture this substantial decrease in leaf area in the all forcing runs (Figure S7). In the  
604 case of the TRENDYv7 models, this finding is particularly noteworthy as they are driven with  
605 observed precipitation estimates: The spatial patterns of negative trends in LAI and dry season  
606 precipitation in the Central African tropical forests coincide to a large extent (Figure S5).

607 Interestingly, the MODIS record does not exhibit this browning cluster (Chen et al., 2019),  
608 though it has been reported in other independent observational datasets (Zhou et al., 2014).  
609 Also, atmospheric  $\text{CO}_2$  inversion studies have identified negative trends in carbon uptake for  
610 this region (Fernández-Martínez et al., 2019), which corroborates our results based on the  
611 LAI3g dataset.

### 612 3.12 *Tropical forests in Oceania are afflicted by deforestation*

613 Although we exclude anthropogenic land cover changes (Figure S1, Table S1) as well as  
614 abrupt changes (Mann-Kendall test for monotonic trends, Section 2.6), the LAI trend maps  
615 nevertheless show characteristic deforestation patterns, e.g. the so-called "arc of deforestation"  
616 in the Amazon region (Figure S6; Aldrich et al., 2012). Hence, deforestation practices may  
617 explain some part of the observed gradual browning of the Amazon (Song et al., 2015) and  
618 African tropical forests (Mayaux et al., 2013; Tyukavina et al., 2018).

619 In Oceania, however, deforestation appears to be a crucial driver of the observed browning in  
620 the pristine tropical forests. Significant negative trends align strongly with patterns of drastic  
621 deforestation during recent decades, described in detail by Stibig et al. (2014, in comparison to  
622 Figure 1). As opposed to Central Africa and the Amazon region, climate changes are unlikely  
623 to be the key driver of browning regions in Oceania. There, precipitation, although highly  
624 variable in the dry season, appears to increase (Figure S5) and the increase in VPD is rather  
625 minor (Yuan et al., 2019) in tropical forests.

626 3.13 *Climate change drives an asymmetrical development of North American and Eurasian ecosystems*

627 The boreal forests show strong positive trends in Eurasia (Observations:  $\sim 2.69$  % decade<sup>-1</sup>,  
628 MPI-ESM:  $\sim 3.48$  % decade<sup>-1</sup>, and TRENDYv7:  $\sim 2.08$  % decade<sup>-1</sup>), which can mostly be  
629 attributed to amplified warming of the temperature-limited northern high latitudes (PNS =  
630 71% for TRENDYv7, PNS = 44% for MPI-ESM; Figure S8). North American boreal forests  
631 exhibit a negative response to rising CO<sub>2</sub>, which has amplified over the last two decades  
632 ( $\sim -0.95$  % decade<sup>-1</sup>, 2000–2017). Models do not reproduce the dominant browning pattern  
633 (Figure S9), which is most likely connected to inadequate representation of disturbances (Sitch  
634 et al., 2015). Several studies have proposed that browning has occurred as consequence of  
635 droughts, wildfire, and insect outbreaks in the North American boreal forests (Goetz et al., 2005;  
636 Sitch et al., 2015; Beck and Goetz, 2011; Kurz et al., 2008). Macias Fauria and Johnson (2008)  
637 showed that the frequency of wildfires is strongly related to the dynamics of large-scale climatic  
638 patterns (Pacific Decadal Oscillation, El Niño Southern Oscillation, and Arctic Oscillation) and  
639 thus, cannot be tied conclusively to anthropogenic climate change. However, there is also  
640 evidence that the residing tree species suffer from drought stress induced by higher evaporative  
641 demand as the temperature rises (Verbyla, 2011). Moreover, models lack a representation of  
642 the asymmetry in tree species distribution between North America and Eurasia, which could  
643 explain their divergent reactions to changes in key environmental variables (Abis and Brovkin,  
644 2017). Further observational evidence for the browning of North American boreal forests and  
645 the associated decline in net ecosystem productivity can also be inferred from CO<sub>2</sub> inversion  
646 products (Fernández-Martínez et al., 2019; Bastos et al., 2019).

647 Tundra ecosystems also reveal a dipole-type development between North America and  
648 Eurasia, however with a reversed sign. Hence, North American tundra is strongly greening  
649 (Observations:  $\sim 4.23$  % decade<sup>-1</sup>, MPI-ESM:  $\sim 4$  % decade<sup>-1</sup>, and TRENDYv7:  $\sim 4.51$  %  
650 decade<sup>-1</sup>), which is *virtually certain* (PNS = 99% for TRENDYv7) and *about likely as not* (PNS  
651 = 51% for MPI-ESM) caused by warming (Figure S10). The trend decreases for the period  
652 2000–2017, which could be linked to the warming hiatus in the years 1998–2012 (Bhatt et al.,  
653 2013; Ballantyne et al., 2017; Hedemann et al., 2017). This is in line with the observed slow  
654 down in tundra greening due to short-term cooling after volcanic eruptions (Lucht et al., 2002).

655 Eurasian tundra show a positive trend for the years 1982–2017, but a reversal in trend sign for  
 656 the years 2000–2017 (Figure S11). Models exhibit some evidence of a strengthening browning  
 657 signal, but fail to capture the full extent of the emerging browning clusters seen in observations.  
 658 If we only consider the grid cells that show significant browning in observations and models,  
 659 we are able to conduct a robust driver attribution. According to the TRENDYv7 ensemble,  
 660 the browning cluster in Eurasian tundra can *very likely* be attributed to CO<sub>2</sub> induced climate  
 661 change (PNS = 93%, PNS = 47% for MPI-ESM). These results are in line with studies showing  
 662 that tundra ecosystems are susceptible to warm spells during growing season (Phoenix and  
 663 Bjerke, 2016) and to frequent droughts (Beck and Goetz, 2011). The asymmetry between Eurasia  
 664 and North America can be explained by changes in large-scale circulation. Eurasia is cooling  
 665 through increased summer cloud cover, whereas North America is warming through more  
 666 cloudless skies (Bhatt et al., 2013; Bhatt et al., 2014). Also linkages between regional Arctic sea  
 667 ice retreat, subsequent increasing ice-free waters, and regional Arctic vegetation dynamics have  
 668 been postulated (Bhatt et al., 2014).

### 669 3.14 *Vegetation in arid climates is greening, except in South America*

670 Non-forested greening clusters beyond the high northern latitudes coincide with semi-arid  
 671 to arid climates (Park et al., 2018). The Northern Sub-Saharan African savannas and grasslands  
 672 greened extensively in recent decades ( $\sim 4.63$  % decade<sup>-1</sup>; Figure S12), which is reproduced by  
 673 the observation-driven TRENDYv7 models ( $\sim 4.55$  % decade<sup>-1</sup>), and is *likely* caused by climatic  
 674 changes (PNS = 68%). No robust attribution is feasible based on the MPI-ESM simulations.  
 675 However, it is noteworthy, that the fully-coupled Earth system model points to climate change  
 676 as having a negative effect in these regions, thus, not reproducing the observed increase in  
 677 rainfall (Figure S12). This provides evidence for the hypothesis that African precipitation  
 678 anomalies are not induced by rising CO<sub>2</sub>, but rather follow a multidecadal internal climatic  
 679 mode (Asefi-Najafabady and Saatchi, 2013).

680 Internal variability in LAI changes is strong in the Southern African grasslands and savannas,  
 681 and thus, no robust long-term change can be identified (Figure S13). It has been shown  
 682 that shrublands in the more southern regions are greening in response to increased rainfall  
 683 (Fensholt and Rasmussen, 2011). In general, the literature suggests that greening and browning

684 patterns in arid climates are mainly driven by precipitation anomalies (Fensholt and Rasmussen,  
685 2011; Fensholt et al., 2012; Gu et al., 2016; Adler et al., 2017). Close resemblance arises when  
686 comparing the spatial patterns of precipitation trends throughout the satellite era (Adler et al.,  
687 2017) with significant changes in vegetation in arid environments, especially so in the African  
688 continent. Decreased rainfall in arid South America coincides with strong browning clusters  
689 (Fensholt et al., 2012). This is in disagreement with the expected strong manifestation of CO<sub>2</sub>  
690 fertilization in water-limited environments (Ukkola et al., 2016).

691 Australian Shrublands show a persistent positive LAI trend ( $\sim 3.84$  % decade<sup>-1</sup>), intermit-  
692 tently perturbed by climatic extreme events (e.g. strong anomalous rainfall with subsequent  
693 extensive vegetation greening in 2011, Figure S14; Poulter et al., 2014). Models reproduce  
694 the steady greening of Australia, but no robust driver attribution is feasible due to strong  
695 internal variability. However, both model setups point to the physiological effect of CO<sub>2</sub> as the  
696 dominant driver (Figure S14). These results are congruent with recent studies (Donohue et al.,  
697 2009; Ukkola et al., 2016) that show CO<sub>2</sub> fertilization enhanced vegetation growth by lowering  
698 the water limitation threshold.

699 Grasslands in the cool arid climates exhibit persistent positive trends ( $\sim 2.03$  % decade<sup>-1</sup>,  
700 Figure S15). Simulated estimates are in the range of the observations (MPI-ESM:  $\sim 2.33$   
701 % decade<sup>-1</sup> and TRENDYv7:  $\sim 1.81$  % decade<sup>-1</sup>). Our analysis suggests that the positive  
702 response of cool arid grasslands to rising CO<sub>2</sub> can be explained by the physiological effect of  
703 CO<sub>2</sub> (PNS = 85% for TRENDYv7, PNS = 88% for MPI-ESM). These ecosystems are dominated  
704 by C<sub>3</sub>-type plants (Still et al., 2003), which are susceptible to CO<sub>2</sub> fertilization (Sage et al.,  
705 2012), thus, consistent with our results. In the warm arid areas, C<sub>4</sub>-type grasses dominate  
706 (Still et al., 2003), which are less sensitive to the physiological effects of CO<sub>2</sub> (Sage et al., 2012).  
707 As discussed above, vegetation changes there are mostly driven by precipitation anomalies,  
708 although CO<sub>2</sub> fertilization might also contribute to a limited extent (Sage et al., 2012).

## 709 4 CONCLUSIONS

710 In this paper we examine nearly four decades of global LAI changes under rising atmospheric  
711 CO<sub>2</sub> concentration. We find that the Earth's greening trend is weakening and clusters of  
712 browning are beginning to emerge, and importantly, expanding during the last two decades.  
713 Leaf area is primarily decreasing in the pan-tropical green belt of dense vegetation. Leaf area  
714 gain is occurring mostly in sparsely vegetated regions in cold and/or arid climatic zones, and  
715 in temperate forests. Thus, vegetation greening is occurring mainly in regions of low LAI,  
716 whereas browning is seen primarily in regions of high LAI. Consequently, these opposing  
717 trends are decreasing the texture of leaf area distribution in natural vegetation.

718 We identify clusters of greening and browning spread across all continents and conduct  
719 a regional, *i.e.* biome-specific, driver attribution based on factorial model simulations. The  
720 results suggest that the physiological effect of CO<sub>2</sub> (*i.e.* CO<sub>2</sub> fertilization) is the dominant  
721 driver of increasing leaf area only in temperate forests, cool arid grasslands and likely the  
722 Australian shrublands. A cause-and-effect relationship between CO<sub>2</sub> fertilization and greening  
723 of other biomes could not be established. This finding questions the study by Zhu et al. (2016)  
724 that identified CO<sub>2</sub> fertilization as the most dominant driver of the Earth's greening trend.  
725 We find that many clusters of greening and browning bear the signature of climatic changes.  
726 The greening of Sub-Saharan grasslands and savannas can be explained by increased rainfall.  
727 Climatic changes, primarily warming and drying, determine the patterns of vegetation changes  
728 in the northern ecosystems, *i.e.* greening of Eurasian boreal forests and North American tundra,  
729 but also emerging browning trend in the Eurasian tundra. Models fail to capture the browning  
730 of North American boreal forests. Models suggest rising CO<sub>2</sub> has compensatory effects on  
731 LAI in the tropical forests. Climatic changes induce browning, which is opposed by greening  
732 due to a strong physiological effect in the models. Hence, if the physiological effect of CO<sub>2</sub>  
733 is "turned-off", models simulate the emerging browning trend in the tropics comparable to  
734 observations. Our analysis of changes in rainfall during the satellite age underpins climate  
735 changes as the main cause of tropical forest browning: recurrent droughts and decline in dry  
736 season precipitation in the Amazon as well as long-term drying trends in Africa.

737 Models represent a simplified view of the real world reduced to its essential processes.  
738 Some of these processes are under-represented or lacking in the current generation of land  
739 surface models. Whether they are driven with observed climatic conditions or operate in a  
740 fully-coupled Earth System model, they fail to capture the full extent of adverse effects of  
741 rising CO<sub>2</sub> in natural ecosystems. In particular, the deficiency of reproducing the observed  
742 leaf area loss in North American boreal and in pan-tropical forests - biomes which account  
743 for a large part of the photosynthetic carbon fixation - has considerable implications for  
744 future climate projections. Thus, it is important to focus model development not only on a  
745 better representation of disturbances such as droughts and wildfires, but also on revising the  
746 implementation of processes associated with the physiological effect of CO<sub>2</sub>, which currently  
747 offsets browning induced by climatic changes.

748 Another vital issue for future research is the impact of large-scale climatic anomalies on  
749 vegetation. All three major clusters of browning are hypothesized to be associated with  
750 temperature or precipitation anomalies modulated by climatic modes. Many droughts in  
751 the Amazon were attributed to El Niño events (Bonal et al., 2016). The long-term drying  
752 trend in tropical Africa is possibly connected to the Atlantic Multidecadal Oscillation (Asefi-  
753 Najafabady and Saatchi, 2013). Likewise, disturbances in North American boreal forests  
754 are likely controlled by an interplay between large-scale climatic patterns (Pacific Decadal  
755 Oscillation, El Niño Southern Oscillation, and Arctic Oscillation; Macias Fauria and Johnson,  
756 2008). Little is known about how these large-scale patterns might change in a warming  
757 climate. Current Earth system models struggle to simulate these climatic modes and related  
758 precipitation patterns, which is likely rooted in their coarse spatial resolution. New tools, such  
759 as high-resolution simulations or large ensembles, offer possibilities to study these phenomena.

760 Finally, it is important to note that the impacts of leaf area changes are not comparable  
761 between biomes. Regarding biodiversity, the consequences of leaf area loss in tropical forests  
762 that harbor the most diverse flora and fauna of the planet are not compensated for by leaf area  
763 gain in temperate and arctic ecosystems. A similar caveat is in order with respect to the carbon  
764 cycle, e.g. an additional leaf in the tundra does not offset the reduction in primary productivity  
765 of a leaf lost in the tropical rainforest. Thus, our results indicating loss of tropical leaf area  
766 should be of concern. A recent study suggested that the tropical forests have already switched

767 to being a net source of carbon, also considering land-use emissions (Baccini et al., 2017). The  
768 uncertainty in future projections is large, ranging from a stable CO<sub>2</sub> fertilization-driven carbon  
769 sink to a collapse of the system at a certain CO<sub>2</sub> concentration (Cox et al., 2000). Concerning leaf  
770 area, the models project a steady greening of the tropical forests in the high-end CO<sub>2</sub> emissions  
771 scenario (business-as-usual) and a slight browning in the low-end scenario (mitigation) by  
772 the end of the century (Piao et al., 2019). Altogether, the tropical forests have the potential to  
773 crucially influence the evolution of climate throughout the 21<sup>st</sup> century and should be a vital  
774 issue for future research.

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#### 1044 4.1 *Data availability*

1045 All data used in this study are available from public databases or literature, which can be  
1046 found with the references provided in respective Methods section. Processed data and analysis  
1047 scripts are available from the corresponding author upon request and will also be published in  
1048 public repositories together with this article.

#### 1049 4.2 *Author Contributions*

1050 A.J.W. performed the research and drafted the manuscript with inputs from R.B.M., V.B.,  
1051 S.S., V.H., D.L, V.K.A., J.P., J.E.M.S.N., D.S.G., E.K., H.T., A.A., and P.F.; A.J.W. carried out the  
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1064 The Authors declare no conflict of interests. Correspondence and requests for materials  
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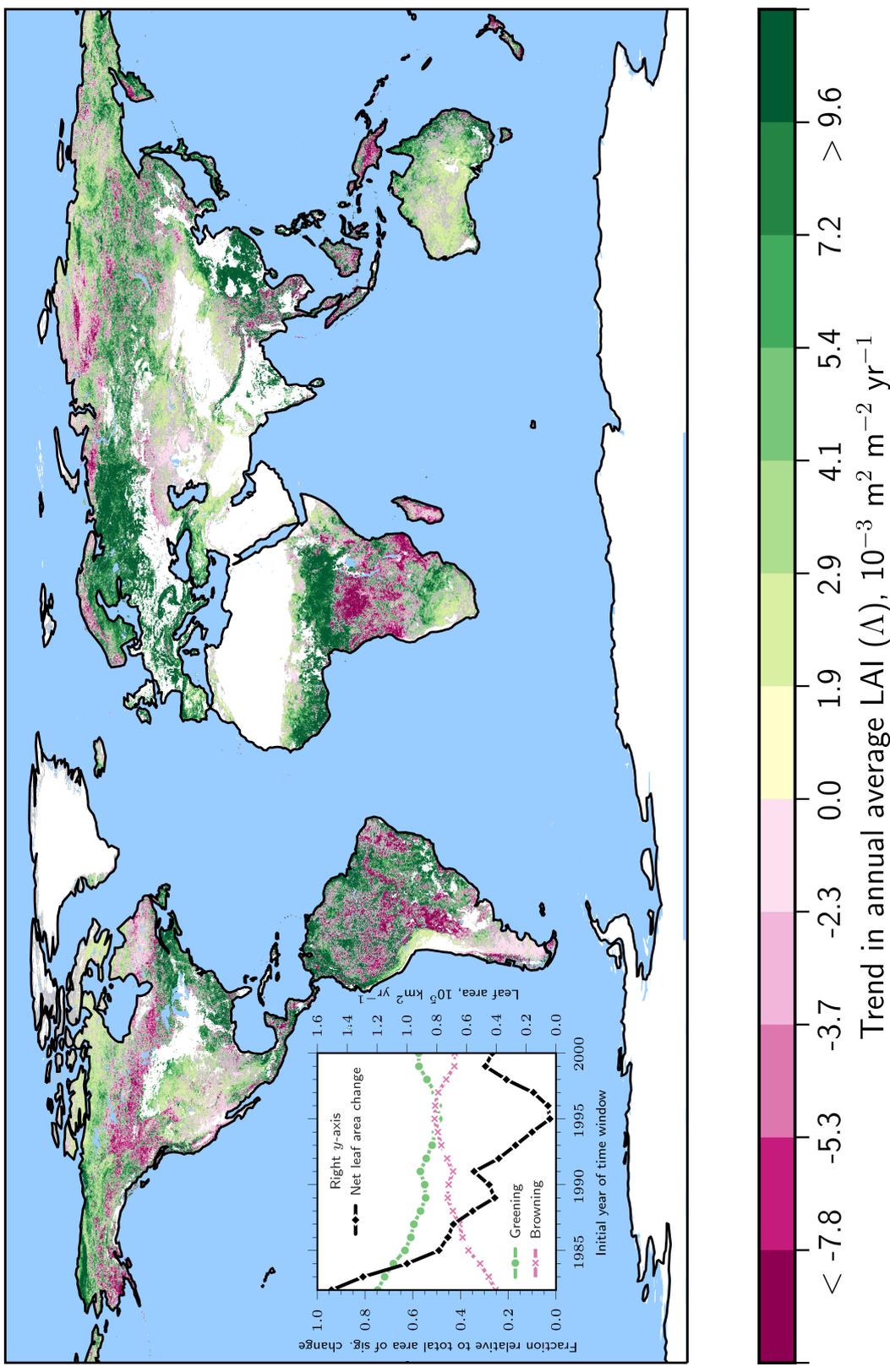
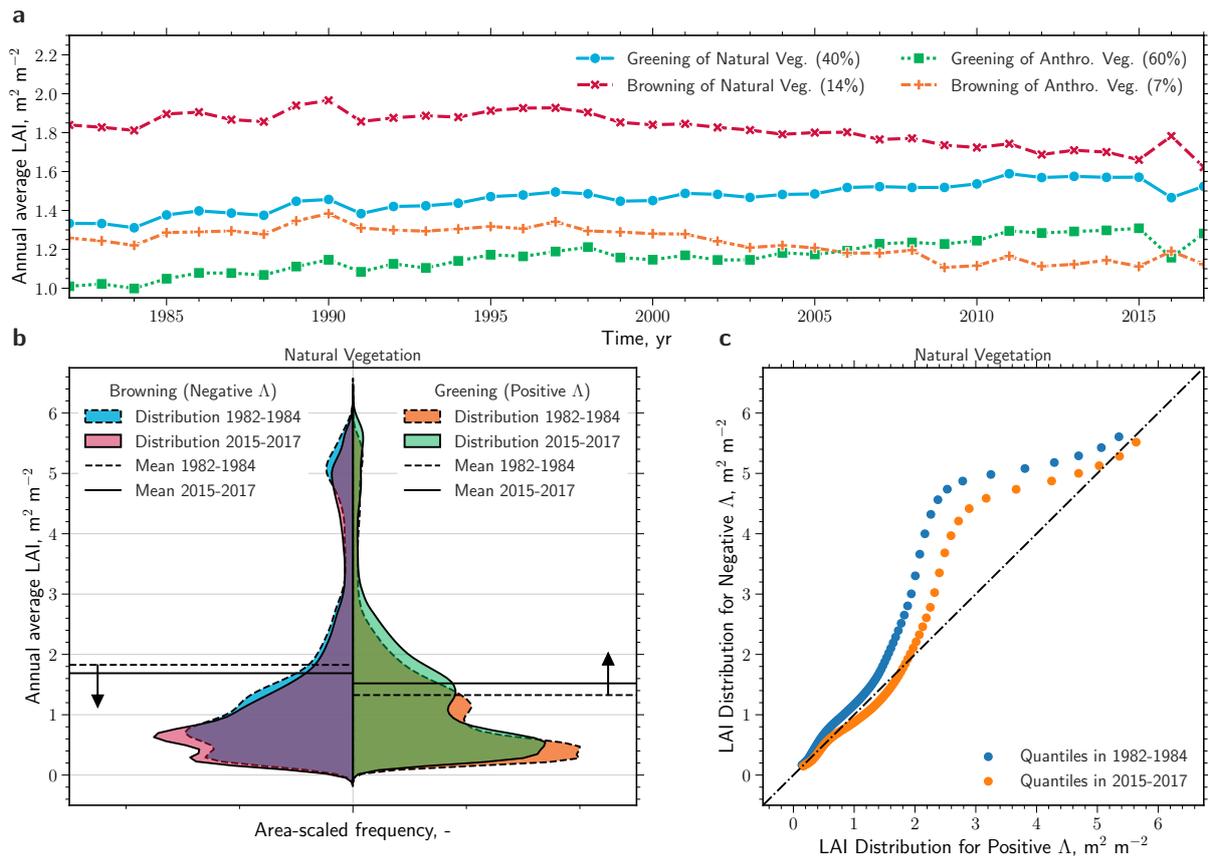
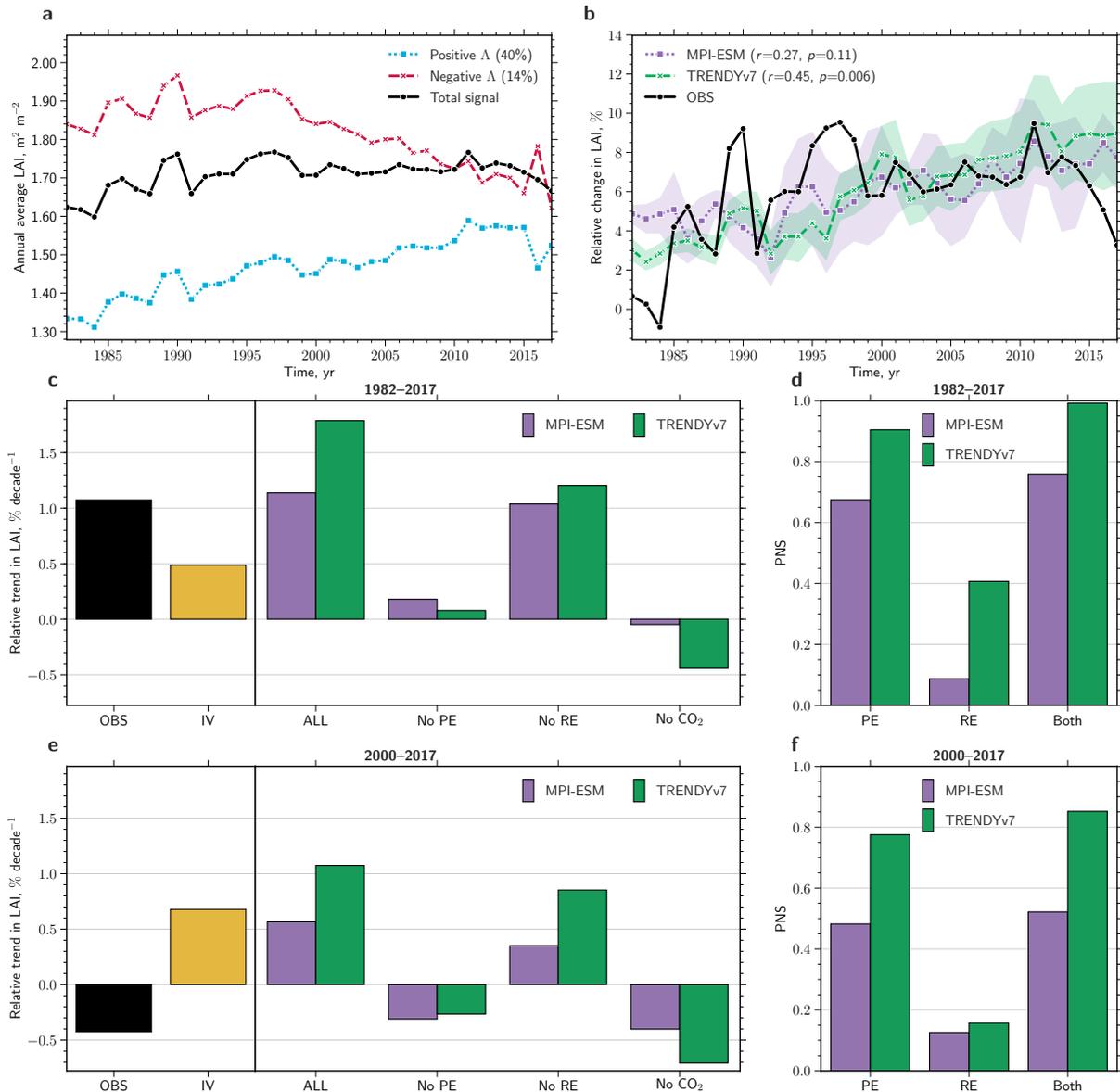


Figure 1 | **Natural vegetation exhibits patterns of opposing long-term LAI trends with rising CO<sub>2</sub>.** Global map of statistically significant (Mann-Kendall test,  $p < 0.1$ ) annual average LAI trends (denoted  $\Delta$ ) for the entire period 1982–2017 (AVHRR, color-coded). Areas of non-significant change are shown in gray. Anthropogenic vegetation (defined as croplands, Materials and Methods) is masked in white. Other white areas depict ice sheets or barren land. The inset line plot illustrates the change in fraction of positive (green dots) and negative  $\Delta$  (red crosses) relative to the total area of significant change, and net leaf area change (black squares; right  $y$ -axis) for time windows of moving initial year (final year fixed at 2017). The  $x$ -axis shows the advancing initial year of the time window.



**Figure 2 | Observed homogenization of the global natural vegetation.** **a** Time series of the area-weighted annual average LAI (AVHRR, 1982-2017) of natural and anthropogenic vegetation for regions of positive (greening) and negative trends (browning). Only regions exhibiting significant trends are considered (Mann-Kendall significance test,  $p < 0.1$ ) and are referred to as  $\Delta$ . The percentages in brackets in the legend represent the respective proportions with respect to the total area. **b** Violin plot comparison of probability density functions (PDF, Gaussian kernel density estimation; all PDFs scaled to contain the same area) of LAI distributions of natural vegetation for negative (left) and positive  $\Delta$  (right), and in time, 1982-1984 (dashed) versus 2015-2017 (solid). The horizontal lines represent the mean values for the respective period. **c** Q-Q (quantile-quantile) plot comparing the distributions of LAI for negative ( $x$ -axis) and positive  $\Delta$  ( $y$ -axis) and their change over time, 1982-1984 (blue dots) versus 2015-2017 (orange dots).



**Figure 3 | Global driver attribution of changing natural vegetation for the entire period versus the second half of the observational record.** **a** Time series of the area-weighted annual average LAI (AVHRR, 1982–2017) for regions of positive (blue dotted line) and negative sensitivity (red dashed line) to rising atmospheric CO<sub>2</sub> concentration ( $\Delta$ ) of natural vegetation. Black solid line represents the overall signal of all pixels. The percentages in brackets in the legend represent the greening and browning proportions with respect to the total area. **b** Time series of changes in LAI relative to the average state from 1982–1984, comparing observations (black solid line) with historical simulations, where the green dashed line denotes the ensemble mean of 13 offline-driven land surface models (TRENDYv7, Data and Methods), and the purple dotted line denotes the average of an ensemble of multi-realizations with a fully-coupled Earth system model (MPI-ESM, Data and Methods). The colored shading represents the 95% confidence interval estimated by bootstrapping. The correlation coefficients (including significance level) of the observed and simulated time series are displayed in brackets in the legend. **c** Bar chart showing relative trends in LAI (in % yr<sup>-1</sup>) of the total observed signal (black) and for factual (all historical forcings; ALL) as well as for counterfactual simulations, i.e. no historical CO<sub>2</sub> forcing (No CO<sub>2</sub>), all historical forcings except the physiological effect (No PE) or the radiative effect (No RE) of atmospheric CO<sub>2</sub>, as estimated by TRENDYv7 (green) and MPI-ESM (purple). The yellow bar represents internal variability (IV) derived from all simulations (control, factual and counterfactual). **d** Probabilities of necessary and sufficient causation (PNS) of the change in LAI, comparing the physiological (PE) and radiative effect (RE) of CO<sub>2</sub> as well as their combined effect (Both). **e** as in **c** but for the period 2000–2017. **f** as in **d** but for the period 2000–2017.

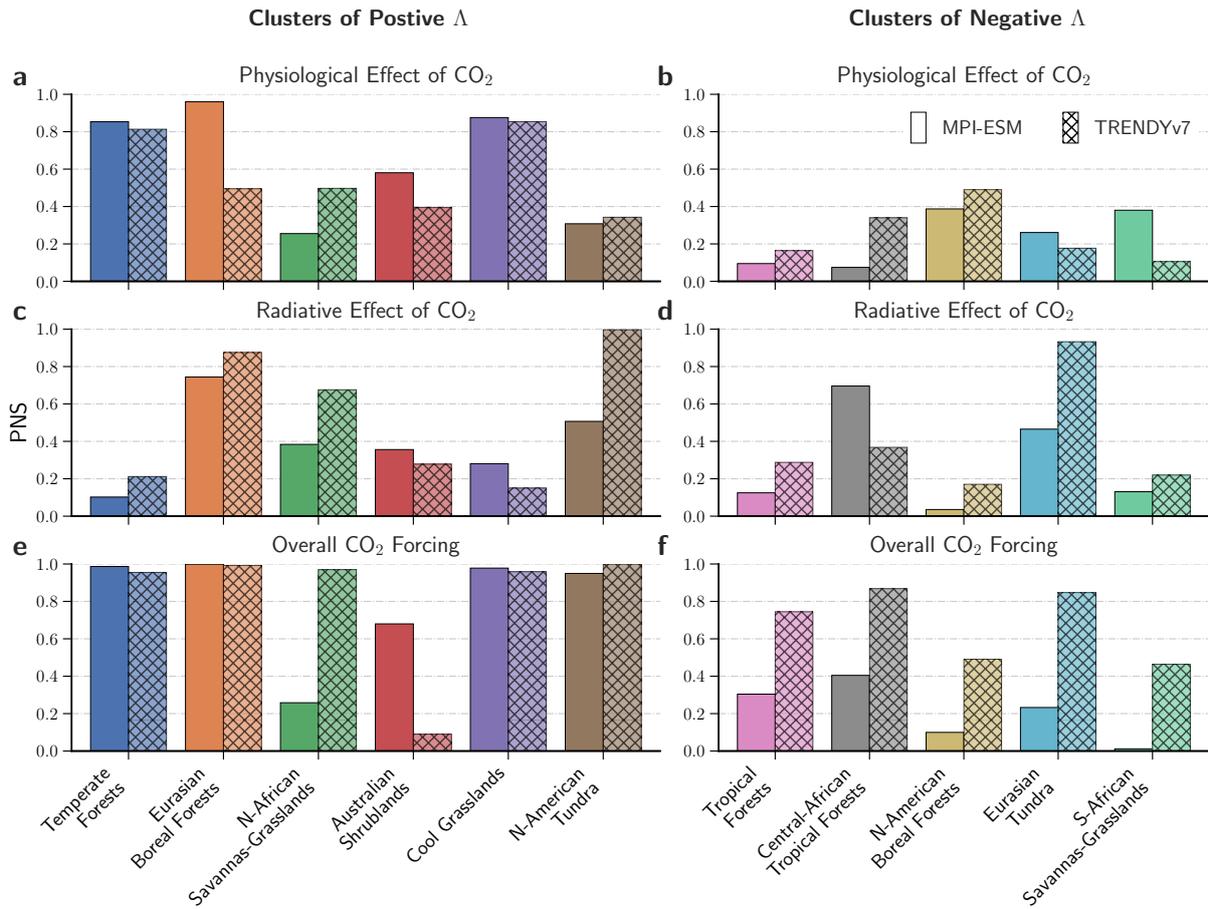


Figure 4 | **Probabilities of sufficient and necessary causation (PNS) of LAI changes in response to CO<sub>2</sub> for eleven clusters.** Bar charts represent PNS of LAI changes in response to the physiological effect (a, b), radiative effect of CO<sub>2</sub> (c, d) and all anthropogenic forcings (e, f). Different colors represent the identified clusters of substantial change in LAI. Panels on the left comprise clusters that show consistent greening, panels on the right represent emerging browning clusters (observed net leaf area loss in the period 2000–2017; attribution is conducted only for significant decreasing trends, Data and Methods). The two types of bar illustrate the two different ensembles of model simulations (left: MPI-ESM, right: TRENDYv7).

Table 1 | Greening (positive  $\Delta$ ), browning (negative  $\Delta$ ) and non-changing fractions of vegetated area for different biomes and prominent clusters of change for the time period 1982–2017. Significant changes are determined by the means of the Mann-Kendall significance test ( $p < 0.1$ ). The abbreviations used to describe the different clusters are explained in Materials and Methods.

Area	Vegetated Area	Positive $\Delta$ Fraction	Negative $\Delta$ Fraction	No-Change Fraction
<i>Unit</i>	$10^6 \text{ km}^2$	-	-	-
All Vegetation	109.42	0.43	0.13	0.45
Anthro. Vegetation	15.37	0.6	0.07	0.32
Natural Vegetation	94.05	0.4	0.14	0.47
<b>Biomes</b>				
Grasslands	26.77	0.4	0.12	0.48
Tropical Forests	20.32	0.28	0.16	0.55
Boreal Forests	13.69	0.4	0.19	0.41
Temperate Forests	11.2	0.56	0.08	0.36
Shrublands	10.37	0.41	0.1	0.49
Tundra	7.03	0.41	0.14	0.45
Savannas	4.22	0.48	0.13	0.38
<b>Clusters</b>				
Cool Gl	12.32	0.4	0.12	0.48
EA Brl F	8.0	0.53	0.1	0.37
NAm Brl F	5.69	0.23	0.31	0.46
NAf Sv Gl	5.6	0.59	0.06	0.35
CAf Trp F	5.35	0.3	0.25	0.45
SAf Sv Gl	4.6	0.24	0.24	0.52
Aus Sl	4.43	0.49	0.03	0.49
EA Tundra	3.57	0.35	0.2	0.44
NAm Tundra	3.46	0.46	0.07	0.47

Table 2 | Leaf area gain, loss, and net change for different biomes and prominent clusters of change for the time period 1982–2017. Significant changes are determined by the means of the Mann-Kendall significance test ( $p < 0.1$ ). The abbreviations used to describe the different clusters are explained in Materials and Methods.

<b>Leaf Area</b>	<b>Leaf Area Gain</b>	<b>Leaf Area Loss</b>	<b>Net Leaf Area Change</b>
<i>Unit</i>	$10^3 \text{ km}^2 \text{ yr}^{-1}$	$10^3 \text{ km}^2 \text{ yr}^{-1}$	$10^3 \text{ km}^2 \text{ yr}^{-1}$
All Vegetation	296.87	-85.71	211.16
Anthro. Vegetation	67.12	-6.47	60.65
Natural Vegetation	229.75	-79.24	150.51
<b>Biomes</b>			
Grasslands	48.01	-12.51	35.50
Tropical Forests	58.42	-34.31	24.11
Boreal Forests	32.11	-14.45	17.66
Temperate Forests	53.32	-7.45	45.87
Shrublands	10.9	-2.4	8.50
Tundra	8.74	-3.69	5.05
Savannas	17.99	-4.21	13.78
<b>Clusters</b>			
Cool Gl	15.06	-3.75	11.31
EA Brl F	25.93	-4.26	21.67
NAm Brl F	6.18	-10.18	-4.00
NAf Sv Gl	23.42	-0.98	22.44
CAf Trp F	16.76	-13.76	3.00
SAf Sv Gl	5.51	-6.76	-1.25
Aus Sl	4.48	-0.16	4.32
EA Tundra	3.96	-3.04	0.92
NAm Tundra	4.78	-0.64	4.14