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Greening of the Earth and its drivers

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Greening of the Earth and its drivers

Global environmental change is rapidly altering the dynamics of terrestrial vegetation with consequences for the functioning of the Earth system and provision of ecosystem services[1,2]. Yet how global vegetation is responding to the changing environment is not well established. Here we use 3 long-term satellite leaf area index (LAI) records and 10 global ecosystem models to investigate four key drivers of LAI trends during 1982-2009. We show a persistent and widespread increase of growing season integrated LAI (greening) over 25 to 50% of the global vegetated area, whereas less than 4% of the globe shows decreasing LAI (browning). Factorial simulations with multiple global ecosystem models suggest that CO_2 fertilization effects explain 70% of the observed greening trend, followed by nitrogen deposition (9%), climate change (8%) and land cover change (LCC) (4%). CO_2 fertilization effects explain most of the greening trends in the tropics, while climate change resulted in greening of the high latitudes and the Tibetan Plateau. LCC contributed most to the regional greening observed in Southeast China and Eastern United States. The regional effects of unexplained factors suggest that the next generation of ecosystem models will need to explore the impacts of forest demography, differences in regional management intensities for cropland and pastures, and other emerging productivity constrains such as phosphorus availability.

Main

Changes in vegetation greenness have been reported at regional and continental scales based on forest inventory and satellite measurements[3-8]. Long-term changes in vegetation greenness are driven by multiple interacting biogeochemical drivers and land use effects[9]. Biogeochemical drivers include the fertilization effect of elevated atmospheric CO_2 concentration (eCO_2), regional climate change (temperature, precipitation, and radiation), and varying rates of nitrogen deposition. Land use related drivers involve changes in land cover and in land management intensity, including fertilization, irrigation, forestry and grazing[10]. None of these driving factors can be considered in isolation given their strong interactions with one another. Previously, a few studies had investigated the drivers of global greenness trends[6,7,11] with a limited number of models and satellite observations, which prevented an appropriate quantification of uncertainties[12].

Here, we investigate trends of Leaf Area Index (LAI) and their drivers for the period 1982 to 2009 utilizing 3 remotely sensed data sets (GIMMS3g, GLASS and GLOMAP) and outputs from 10 ecosystem models run at global extent (see Supplementary Information). We use the growing season integrated leaf area index (LAI hereafter – Methods) as the variable of our study. We first analyze global and regional LAI trends for the study period and differences between the 3 data sets. Using modeling results, we then quantify the contributions of CO_2 fertilization, climatic factors, nitrogen deposition and LCC to the observed trends.

Trends from the 3 long-term satellite LAI data sets consistently show positive values over a large proportion of the global vegetated area since 1982 (Fig. 1). The global greening trend estimated from the three data sets is 0.068 ± 0.045 $m^2m^{-2}yr^{-1}$. The GIMMS LAI3g data set that includes recent data up to 2014, shows a continuation of the trend from the 1982-2009 period (Fig.1 and Fig. S3). The regions with the largest greening trends, consistent across the 3 data sets, are in Southeast North America, Northern Amazon, Europe, Central Africa and Southeast Asia. The GLASS LAI data shows the most extensive statistically significant greening (Mann-Kendal test, $p<0.05$) over 50% of vegetated lands, followed by GLOBMAP LAI (43%) and GIMMS LAI3g (25%). All 3 LAI data sets also consistently show a decreasing LAI trend (browning) over less than 4% of global vegetated land – these are observed in Northwest North America and Central South America. Analyses of the changes in observed maximum LAI also show similar widespread greening trends (Section S8).

We compare satellite-based LAI anomalies with LAI anomalies simulated by 10 global ecosystem models driven by eCO_2 (+46 ppm over the study period), climate, nitrogen deposition and LCC (Section S7). Multi-Model Ensemble Mean (MMEM) LAI anomalies with all these drivers considered, generally agree with averaged satellite observations at the global scale ($r=0.85$, $p<0.01$; Fig. 2a). The trend in MMEM LAI anomalies (0.062 $m^2m^{-2}yr^{-1}$) is within the range of estimates from the 3 satellite data sets. The model simulations suggest that increasing gross primary productivity, although partly neutralized by increasing autotrophic respiration, and decreasing carbon loss due to fires are responsible for the increasing LAI during 1982 to 2009 (Section S9).The spatial pattern of LAI trends also matches well between satellite data and MMEM simulations (Fig. 3a, b). Consistent greening trends between models and observations are seen in Fig. 3 across the Southeast United States, the Amazon basin, Europe, central Africa, Southeast Asia and Australia. However, satellite LAI and MMEM results show different magnitude (or sign) of trends in the Southwestern United States, Southern South American countries, and Mongolia, indicating that models may be over-sensitive to trends in precipitation (Section S10).

We used an optimal fingerprint detection method[13] to assess the ability of the models to simulate observed patterns of LAI response to eCO_2, climate change, nitrogen deposition and LCC. We regressed the observed 2-year mean global average LAI time series against the MMEM simulated LAI reflecting the effects of single drivers, based on factorial runs where only one driver is varied at the time. A residual consistency test[13] suggests no inconsistency between the regression residuals and the model simulated internal variability in the absence of forcing (Methods), indicating that the fingerprint detection method is suitable for detection and attribution at the global scale (Fig. 2b). The 95% confidence intervals of the scaling factors of CO_2 fertilization (best estimates of scaling factor $\beta = 1.03$, 95% confidence interval $[0.84, 1.23]$) and climate change ($\beta = 1.06$, $[0.55, 1.64]$) are not only above zero but also span unity, which means that the modeled signals from these two drivers are successfully detected and suitable for attribution (Fig. 2b). The fingerprints of nitrogen deposition and LCC effects on the trend of LAI remain confounded with internal variability and cannot be clearly detected (not shown).

Globally, the model factorial simulations suggest that CO_2 fertilization explains the largest contribution to the satellite observed LAI trend (70.1±29.4%, 0.048±0.020 $m^2m^{-2}yr^{-1}$), followed by nitrogen deposition (8.8±11.8%, 0.006±0.008 $m^2m^{-2}yr^{-1}$), climate change (8.1±20.6%, 0.006±0.014 $m^2m^{-2}yr^{-1}$) and LCC (3.7±14.7%, 0.003±0.010 $m^2m^{-2}yr^{-1}$) (Fig. 2c). The contributions of CO_2 fertilization and climate change are reliable according to the optimal fingerprint analysis, while the effects of LCC and nitrogen deposition should be interpreted with caution. Our estimation of CO_2 fertilization effects on vegetation growth is more prominent than Los[6], which is likely due to the different attribution approaches. When using only those ecosystem models (5 out of 10) that incorporate N limitations and nitrogen deposition effects (Table S1), the fraction of the LAI trend that is unambiguously attributed to CO_2 fertilization is slightly smaller (66.2±13.2%, 0.045±0.009 $m^2m^{-2}yr^{-1}$) than when using models that ignore nitrogen processes (75.0 ± 42.6%, 0.051 ± 0.029 $m^2m^{-2}yr^{-1}$). This suggests that although incorporating nitrogen in ecosystem models does not significantly (t-test, $p<0.05$) change the contribution of the CO_2 fertilization effect to the global trend of LAI, it reduces the spread of model simulations (F-test, $p<0.05$).

Vegetation leaf area changes result from interacting factors, but factorial simulations help to attribute a dominant factor for the observed changes. Our analyses show that the CO_2 fertilization effect has a rather spatially uniform effect on the positive LAI trends. The modeled relative increases in global mean LAI due to CO_2 fertilization alone is about 4.7-9.5% (or 10.2-20.7% per 100ppm) during 1982 to 2009, which is comparable to measurements from the Free-Air CO_2 Enrichment (FACE) experiments (0.3-11.1%, or 0.6-24.1% per 100ppm)[14]. However, no FACE experiment covered tropical forests, where models suggest that eCO_2 is the dominant factor of the recent LAI trend (Fig. 3c, d). The spatial pattern is consistent with previous analyses[15] that posited large absolute LAI increases due to eCO_2 in the tropics, in the absence of temperature, water and nitrogen limitations[16], and large relative LAI increases due to eCO_2 in arid regions, where eCO_2 is expected to increase water use efficiency of plants (Fig. S12)[17]. A simple theoretical model[17,18] was used to diagnose the response of leaf level carbon assimilation to the observed 46 ppm increase of CO_2 over the study period, including the effect of vapor pressure deficit trends and stomatal closure. This model gave a similar relative response of carbon assimilation to eCO_2 as the ecosystem models did for LAI (Section S12).

Climate change explains about $8.1 \pm 20.1\%$ of the observed positive LAI trend, but unlike eCO_2 effects, climatic effects are negative in some regions. Although detected by the optimal fingerprint model, the effects of climate change are not consistent between models, and may even be opposite in individual model simulations. Overall, climate change has dominant contributions to the greening trend over 28.4% of the global vegetated area (Fig. 3c, d). Positive effects of climate change in the Northern high latitudes and the Tibetan Plateau are attributed to rising temperature, which enhances photosynthesis and lengthens the growing season[5], whereas the greening of the Sahel and South Africa are primarily driven by increasing precipitation (Fig. S13). South America is the only continent where negative climate effects were statistically significant (Fig. S10 and Fig. S11b). This is particularly important due to the role of the Amazon forests in the global carbon cycle[19,20]. Ecosystem models may tend to overestimate the responses of vegetation growth to precipitation[12] (Section S10) which is one of the reasons why the fate of the Amazon forests continues to be debated[10].

Considerable evidence points to nitrogen limitation of vegetation growth over many parts of the Earth[21], with local alleviation by nitrogen deposition in boreal and temperate regions[22,23]. Our analyses suggest that nitrogen deposition explains $8.8 \pm 11.8\%$ of the LAI trend at the global scale. However, this result is uncertain because only two models in the ensemble specifically performed factorial simulations with and without nitrogen deposition. A slightly negative trend in nitrogen deposition effect was observed in North America and Europe, where nitrogen deposition rates have stabilized or even declined during the last three decades[24,25].

LCC is a dominant driver of LAI greening only over 9.6% of the global vegetated area, mainly in Southeast China and Southeast United States. Models produce negative LCC effects on LAI trends in tropical and southern temperate regions where deforestation occurred (Fig. S11d)[26]. The individual effect of LCC seems however to be outweighed by other factors in these regions, and thus does not appear to be dominant. Trends of the LCC effect simulated by ecosystem models differ significantly in magnitude, and sometimes also in sign. This could be due to differences in model assumptions relating to whether the productivity of secondary vegetation is smaller or larger than that of the vegetation it replaces.

At the global scale, the observed LAI trend can be largely accounted for by CO_2, climate, nitrogen deposition and LCC. However, at regional scales, other factors (OF) not considered in models such as forest management, grazing, changes in cultivation practices and varieties, irrigation and disturbances such as storms and insect attacks, can be a cause of mismatch between observed and simulated LAI trends. The patterns of the effect of other factors were estimated as a residual, by subtracting the simulated trend caused by factors explicitly modeled from the observed local LAI trend. OF contributes the most to the observed LAI trend over 25.0% (increase) and 5.3% (decrease) of the vegetated area (Fig. 3d). OF can also encompass non-modeled processes such as plant diversity within a type of vegetation, hydrological and nutrient liberation during permafrost thawing, phosphorus and potassium limitations, access to ground water by deep roots, and rigid discretization of the simulated vegetation into few plant functional types. Further, uncertainties in existing model parameterization and structure (Section S7) and biases from the remote sensing data sets (Section S6) can cause a mismatch between simulated and observed LAI trends. Interestingly, positive effects tentatively attributed to OF are mainly found in areas of intensive ecosystem management such as northeast China, Europe, and India[27]. Negative OF

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effects are mainly found in northern high latitudes where most models lack a representation of regionally important ecosystems (peatlands, wetlands) as well as of specific disturbances[28,29].

Understanding the mechanisms behind LAI trends is a first, yet critical, step towards better understanding the influence of human actions on terrestrial vegetation, and towards improving future projections of vegetation dynamics. Utilizing three LAI data sets, an ensemble of 10 ecosystem models, and a fingerprinting technique, we assessed the consistency of observed greening and browning patterns with the effects of key environmental drivers. The use of a 10-model ensemble increases confidence in the attribution, although model simulations diverge in some aspect, particularly for the impacts of climate change and LCC, which suggests an area for future model improvements. Overall, the described LAI trends represent a significant alteration of the productive capacity of terrestrial vegetation through anthropogenic influences.

Methods

Methods and any associated references are available in the online version of the paper.

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Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to S. P.

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Author contributions

S. P., R. B. M. and Z. Z. designed the study. Z. Z. performed the analysis; Z. Z., S. P., J. G. C., P. C., and R. B. M. drafted the paper. Z. Z., M. H., Z. Z., C. C., Y. L., H. Y., X. W., X. L., Y. P., Y. L., R. L. and Z. X. collected data and prepared figures; S.S., P. F., A. A., B. D. S., B. P., C. K., E. K., J. M., J. P., L. C., N. V., N. Z., S. P., S. Z., T. P., and Y. W. ran the model simulations. All authors contributed to the interpretation of the results and to the text.

Competing financial interests

The authors declare no competing financial interests.

Figure Legends

Figure 1. The spatial pattern of trends in growing season integrated LAI derived from three remote sensing data (a) GIMMS LAI3g, (b) GLOBMAP LAI and (c) GLASS LAI. All data sets cover the period 1982 to 2009. Regions labeled by black dots indicate trends that are statistically significant (Mann-Kendal test, $p<0.05$). (d) Probability density function of LAI trends for GIMMS LAI3g, GLASS LAI, GLOBMAP LAI and the average of the three remote sensing data sets (AVG OBS).

Figure 2. (a) Interannual changes in anomalies of growing season integrated leaf area index (LAI) estimated by multi-model ensemble mean (MMEM) with all drivers considered (blue line) and average of the three remote sensing data (red line) for the period 1982 to 2009, and interannual changes in anomalies of LAI of GIMMS LAI3g (green line) for the period 1982 to 2014. The shaded area shows the intensity of EI Niño-Southern Oscillation (ENSO) as defined by the multivariate ENSO Index. The black dash lines label the sensor changing time of the AVHRR satellite series. Two volcanic eruptions (El Chichón eruption and Pinatubo eruption) were labeled in brown dash lines. (b) Best estimates of the scaling factors of CO_2 fertilization effects, climate change effects and simulated LAI under the four scenarios and their 5-95% uncertainty range from optimal fingerprint analyses of global LAI for 1982-2009. (c) Trend in global averaged LAI derived from satellite observation (OBS) and modeled trends driven by rising CO_2, climate change (CLI), nitrogen deposition (NDE) and land cover change (LCC) using the Mann-Kendal test. Error bars show the standard deviation of

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trends derived from satellite data and model simulations. Two asterisks indicate that the trend is statistically significant ($p<0.05$).

Figure 3. The spatial distribution pattern of the trend in growing season integrated LAI (a, b), its primary driving factors (c) and the latitudinal area fraction of the driving factors (d) for the period 1982 to 2009. LAI trends were derived (a) from average of GIMMS, GLOBMAP and GLASS LAI and (b) from multi-model ensemble mean with all drivers considered; Regions labeled by dots have trends that are statistically significant ($p<0.05$). The trend is calculated and evaluated using the Mann-Kendal test at 5% significance level. (c) The dominant driving factor is defined as the driving factor that contributes the most to the increase (or decrease) in LAI in each vegetated grid-cell. The driving factors include rising CO_2 (CO_2), climate change (CLI), nitrogen deposition (NDE), land cover change (LCC) and other factors (OF), the latter being defined by the non-modeled fraction of observed LAI trend (see text). Prefixed '+' of driving factors indicate their positive effect on LAI trends, while '-' indicate negative effect. (d) Fractional area of vegetated land in 15° latitude bands (90°N-60°S) attributed to different factors. The fraction of vegetated area (%) that dominantly driven by each factor was labeled on top of the bar.

Methods

The growing season integrated leaf area index was used as a proxy of vegetation growth in this study. We identified the growing season for each $0.5° \times 0.5°$ grid cell of global vegetated area utilizing GIMMS LAI3g data sets and freeze/thaw data sets. The growing season was first determined from the GIMMS LAI3g data set[30] using Savitzky-Golay filter and then refined by excluding the ground-freeze period identified by the Freeze/Thaw Earth System Data Record[31]. In particular, the growing season of evergreen broadleaf forests was set to 12 months and starts in January. All the satellite observed leaf area products and leaf area index outputs of ecosystem models were first aggregated to $0.5° \times 0.5°$ spatial resolution and then composited to annual growing season integrated leaf area index data.

Three satellite-observed leaf area index products (GIMMS LAI, GLOBMAP LAI and GLASS LAI) were used to analyze the changes in global vegetation for the period 1982 to 2009. We used a nonparametric trend test technique (Mann-Kendall test) to evaluate trends in growing season integrated leaf area index derived from the three satellite LAI products at the 95% significance level. We analyzed trends in LAI at pixel level, global level and continental level. When we tested trends in LAI at global and continental scales, we calculated the mean of LAI values of all the pixels in the specific region, weighting by the area of each pixel.

Ten ecosystem models were used to analyze the relative contributions of external

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driving factors to trends in global vegetation growth during 1982-2009. We performed 4 experimental simulations to evaluate the relative contribution of four main driving factors, i.e. CO_2 fertilization, climate change, nitrogen deposition and land cover change, to the global vegetation trends: (S1) varying CO_2 only, (S2) varying CO_2 and climate, (S3) varying CO_2, climate and nitrogen deposition and (S4) varying CO_2, climate and land cover change. S1, S2-S1, S3-S2 and S4-S2 were used to evaluate the effects of CO_2 fertilization, climate change, nitrogen deposition and land cover change to vegetation growth, respectively (see Section S7).

We used an optimal fingerprint method[13] to detect the signals of CO_2 fertilization, climate change, nitrogen deposition and land cover change effects simulated by ecosystem models at global scales. The optimal fingerprint expresses the observation (Y) as a linear combination of scaled (β_i) responses to external driving factors (x_i), and internal variability (ε): $\mathrm{Y} = \sum_{i=1}^{n} \beta_i x_i + \varepsilon$. The scaling factors ($\beta_i$) are estimated based on the total least square method to adjust the amplitude of the responses of LAI to each driving factors. We regressed the satellite observed LAI against responses of vegetation growth (expressed as LAI) to elevated atmospheric CO_2, climate change, nitrogen deposition and land cover change estimated by multi-model ensemble mean simulations of 10 ecosystem models. We also performed similar analysis for the simulated LAI under scenarios S1, S2, S3 and S4. These regressions provide best-estimate linear combinations of signals simulated by ecosystem models. The coefficients of the signals are the scaling factors (β_i). A residual consistency test was introduced to check the consistency between the residuals of satellite observed LAI and best-estimate combinations of signals and the assumed internal LAI variability[13]. The overall statistical model was considered suitable only if the residual consistency test passed at 95% significance level. If the 95% confidence interval of the estimated scaling factor lies above zero, the signal of the corresponding driving factor is detected. And the model simulations are suitable for attribution if the 95% confidence interval contains 1.

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Figure 1

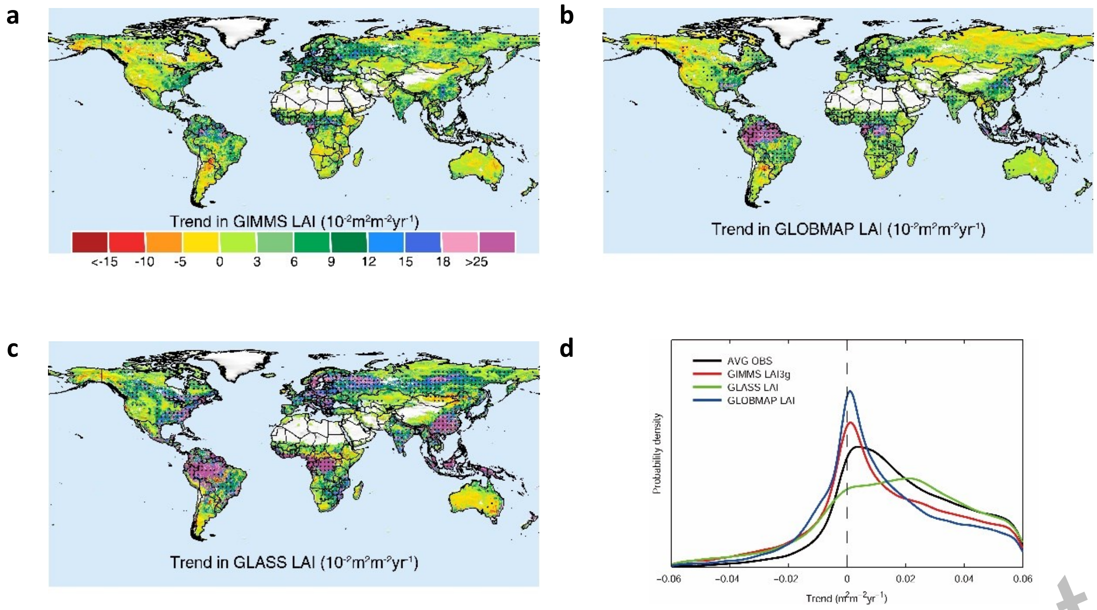

Figure 2

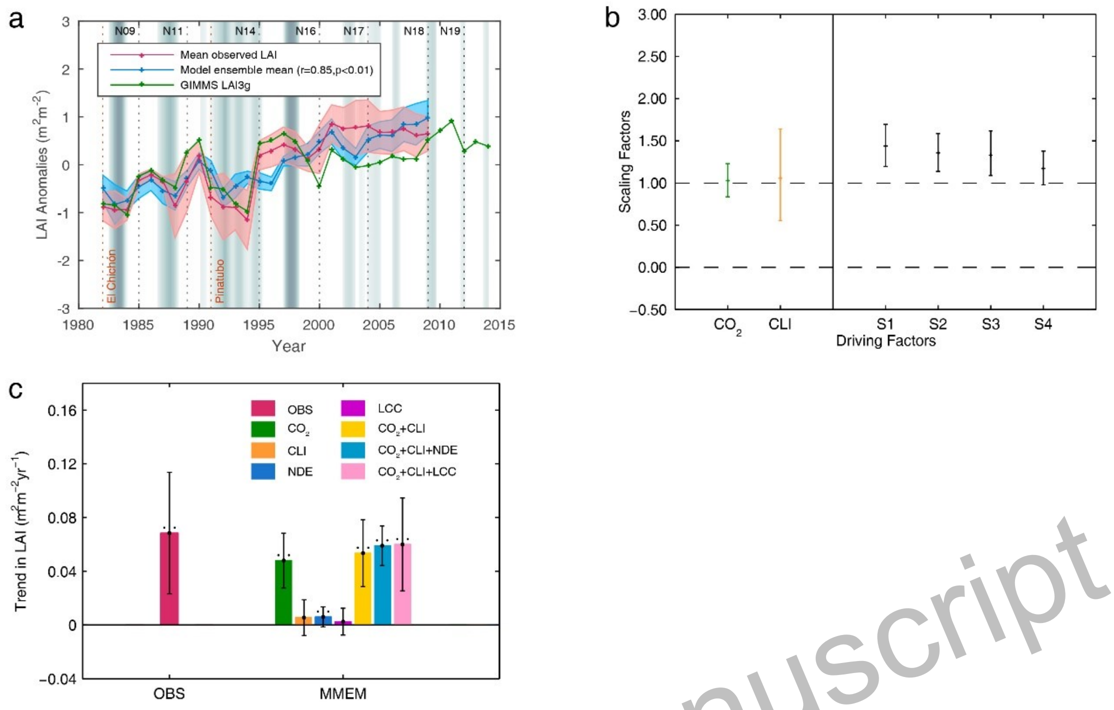
a
N09
N11
N14
N16
N17
N18
N19
Mean observed LAI
Model ensemble mean (r=0.85,p<0.01)
GIMMS LAI3g
LAI Anomalies ($m^2 m^{-2}$)
El Chichón
Pinatubo
Year
b
Scaling Factors
CO_2
CLI
S1
S2
S3
S4
Driving Factors
c
OBS
CO_2
CLI
NDE
LCC
CO_2+CLI
CO_2+CLI+NDE
CO_2+CLI+LCC
Trend in LAI ($m^2 m^{-2} yr^{-1}$)
OBS
MMEM

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Figure 3