

1 Associate Editor (Dr. Sönke Zaehle)

2  
3 *Dear authors,*

4  
5 *your revised manuscript has now been seen by two reviewers and myself. We all agree*  
6 *that you have made a good effort to respond to the reviewers comments. Nonetheless,*  
7 *both reviewers have added some minor concerns, which you are requested to address*  
8 *before this manuscript can be accepted for publication in Biogeosciences. I would like*  
9 *to add to these comments that in Section 2.1 you still (as already remarked in my initial*  
10 *editorial statement) only list eight models, while you claim that you have used all nine*  
11 *models from the TRENDY ensemble. Please do clarify in the manuscript whether you*  
12 *have indeed used all nine models (and add the missing name), or explain in a convincing*  
13 *manner why you have left out one out of the nine models for your analyses.*

14  
15 *Best wishes,*  
16 *Sönke*

17  
18 **Authors: Sincere apologies for having not corrected this earlier, but we did use all**  
19 **nine TRENDY models in our analysis. We added the ‘missing’ model (OCN) in the**  
20 **model list in the Section 2.1 in the revised ms.**

1 Referee (Chris Jones):

2  
3 *I'd like to thank the authors for a thorough revision in respect of the review comments.*  
4 *Addition of figures for all flux components from CASA and TRENDY makes the analysis*  
5 *a lot more complete.*

6  
7 *I have just one remaining query - I did not follow the added text about the "seasonal*  
8 *carry over" effect. It seems that CASA shows a bigger NPP jump in the 1980s than does*  
9 *the TRENDY ensemble and this was attributed to the fact that TRENDY models only*  
10 *respond in spring for that year, whereas CASA has the ability somehow to continue to*  
11 *respond to some forcing into the summer. This does seem to be the case from figures 2*  
12 *and 3. But I don't really follow the explanation.*

13  
14 *The implication is that CASA picks up from the driving data some ability of the system to*  
15 *continue to respond to a forcing event that happened in Spring. This seems plausible,*  
16 *although no details. But it implies that the TRENDY models are not able to do this. As*  
17 *process models, it's not clear which process is missing which prevents this happening -*  
18 *for example, vegetation drawdown of soil moisture or climate-driven drying of soil*  
19 *moisture would continue to have an impact for several months. Or under-development*  
20 *or later development of leaves would continue to have an effect. So can the authors be*  
21 *more specific about what process is operating in the real world which causes this carry-*  
22 *over, which can be seen in the CASA driving data but is not able to be represented in*  
23 *any of the TRENDY models?*

24  
25 **Authors: This point is well taken, and we made an attempt to shed a bit more light**  
26 **into this 'seasonal carry over' effect. To start, it should be noted that our**  
27 **knowledge of phenological responses to, for example, spring warming and**  
28 **corresponding seasonal impacts is still severely limited. But a good starting point**  
29 **may be the four conceptual 'early spring' scenarios that were postulated by**  
30 **Richardson et al. (2010; ref. provided in ms). In this regard, the scenario that would**  
31 **be consistent with our CASA simulations for Northern Eurasia would be the**  
32 **scenario in which an earlier spring onset increases productivity during spring and**  
33 **also during the peak of the growing season (model b in Figure 1 in Richardson et**  
34 **al. 2010), whereby it is thought that higher foliar N and/or higher leaf area index**  
35 **(LAI) may support the 'carry over' of the early spring onset signal. LAI is nearly**  
36 **linearly related to (satellite-based) fAPAR, which is a key driver in CASA. In**  
37 **addition, from Figure 2 in our present ms it can be seen that the increase in**  
38 **summer productivity is solely due to fAPAR, which would be consistent with**  
39 **Richardson's model b hypothesis.**

40 **In regards to what process(es) in the more 'process-based' TRENDY**  
41 **models is missing, a first check would be to see if the simulated LAI/fAPAR fields**  
42 **show a similar seasonal response to an early spring onset when compared to the**  
43 **responses seen in the satellite data. The TRENDY LAI and fAPAR fields are**  
44 **however not yet available (see also our responses to the previous reviews), and at**  
45 **this point we cannot further investigate this.**

46 **In the revised ms, we have added details in Section 3.2 and 3.3 in regards**  
47 **to how the early spring signal is carried over into the summer season (via fAPAR)**  
48 **in the CASA simulations. We have not further elaborated on this in regards to**

1 **process-based models, but hope that these results provide motivation to the**  
2 **modeling groups to further investigate the realism of the phenology responses in**  
3 **their models.**

4  
5  
6 Anonymous Referee #3:  
7

8 *Overall I think it is publishable - the topic is relevant and the approach is robust -, and*  
9 *the authors have made a good effort to address the reviewers' comments.*

10  
11 *I have a couple of outstanding issues*

12  
13 *1. Northern Africa is a poor geographical concept, because it is confused with North*  
14 *Africa, i.e. north of Sahara. The actual region the authors refer to is sub-Saharan, really*  
15 *the Sahel. The terminology should be changed. I suggest 'Sahel'.*

16  
17 **Authors: This point is well taken, and we have actually given quite some thought**  
18 **to this. But our northern African target region spans 20°W-50°E, 5°N-20°N and is**  
19 **thus a bit larger as the Sahel. Also when looking at Africa as a whole, the northern**  
20 **Africa designation may be justified. We therefore would rather stick with northern**  
21 **Africa despite the risk of confusing it with North Africa.**

22  
23 *2. The authors need to clearly state that their CASA runs did not include GFED fire.*  
24 *Currently this lack is not clear, but it is a significant caveat. There were significant*  
25 *increases in fire emissions during the 80s, e.g. in the US, that might confuse the*  
26 *analysis. It would help the discussion to note what data/models are needed to improve*  
27 *this historical analysis.*

28  
29 **Authors: In the revised version, we have added this important caveat in section**  
30 **2.1: 'Owing to the lack of consistent fire observations for our study period 1982-**  
31 **2011 (e.g. the GFED era starts in 1997; see van der Werf et al., 2006)**  
32 **corresponding effects on variability in NPP and NEP were not considered'. In our**  
33 **original submission, we did discuss potential fire-climate links in an entire**  
34 **paragraph (first paragraph in discussion) where we put our results in context and**  
35 **also highlight limitations due to lack of observations as well as in our present**  
36 **understanding of fire processes.**

1 **Climate-Driven Shifts in Continental Net Primary**  
2 **Production Implicated as a Driver of a Recent Abrupt**  
3 **Increase in the Land Carbon Sink**

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19

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22

1 **Abstract**

2 The World's ocean and land ecosystems act as sinks for anthropogenic CO<sub>2</sub>, and over the  
3 last half century their combined sink strength grew steadily with increasing CO<sub>2</sub>  
4 emissions. Recent analyses of the global carbon budget, however, uncovered an abrupt,  
5 substantial (~1 PgC yr<sup>-1</sup>) and sustained increase in the land sink in the late 1980s whose  
6 origin remains unclear. In the absence of this prominent shift in the land sink, increases in  
7 atmospheric CO<sub>2</sub> concentrations since the late 1980s would have been ~30% larger than  
8 observed (or ~12 ppm above current levels). Global data analyses are limited in regards  
9 to attributing causes to changes in the land sink because different regions are likely  
10 responding to different drivers. Here, we address this challenge by using terrestrial  
11 biosphere models constrained by observations to determine if there is independent  
12 evidence for the abrupt strengthening of the land sink. We find that net primary  
13 production has significantly increased in the late 1980s (more so than heterotrophic  
14 respiration) consistent with the inferred increase in the global land sink, and that large-  
15 scale climate anomalies are responsible for this shift. We identify two key regions in  
16 which climatic constraints on plant growth have eased: northern Eurasia experienced  
17 warming, and northern Africa received increased precipitation. Whether these changes in  
18 continental climates are connected is uncertain, but North Atlantic climate variability is  
19 important. Our findings suggest that improved understanding of climate variability in the  
20 North Atlantic may be essential for more credible projections of the land sink under  
21 climate change.

## 1 **1 Introduction**

2 The world's land ecosystems act as a major sink in the contemporary global carbon cycle  
3 and, hence, alleviates the rise of atmospheric CO<sub>2</sub> concentrations from global CO<sub>2</sub>  
4 emissions and as a consequence climate change (IPCC, 2013). Yet, while critical for  
5 society our present understanding of the evolution of the land carbon sink under global  
6 change is still severely limited (Le Quéré et al., 2009). This is in part because multiple  
7 complex factors can influence the carbon balance of terrestrial ecosystems, including  
8 climate change, land-use and land-cover change (forest regrowth, fire suppression etc.),  
9 nitrogen deposition, and CO<sub>2</sub> fertilization (Ciais et al., 2013). In this regard, it has been  
10 well documented that the land carbon sink (typically inferred as the 'residual' in the  
11 global carbon mass balance of fossil fuel and net land use change (LUC) emissions, the  
12 atmospheric CO<sub>2</sub> growth rate and oceanic uptake) is quite variable at decadal time scales  
13 (Denman et al., 2007). But, in recent global carbon budget (GCB) studies with longer (~  
14 last 5 decades) and annually resolved records a rather abrupt, substantial (~1 PgC yr<sup>-1</sup>)  
15 and sustained strengthening of the 'residual' land carbon sink in the late 1980s has been  
16 identified (Sarmiento et al., 2010; Beaulieu et al., 2012). Our overall confidence in this  
17 prominent shift, however, is somewhat limited since the 'residual' land sink is the most  
18 uncertain term in the GCB. This is because uncertainties embedded in the individual  
19 budget terms (e.g. LUC emissions and oceanic uptake) propagate into estimates of the  
20 'residual' land carbon sink (Le Quéré et al., 2013).

21 Here, we explore if there is further independent evidence for a late 1980s regime  
22 shift in the land carbon sink through analyzing carbon fluxes from biospheric models of  
23 various complexity and observational constraints (e.g. satellite-based vegetation activity).

1 Our emphasis is on global pattern of net primary production (NPP) since this key carbon  
2 flux is known to be a robust driver of carbon sink variability (Luysaert et al., 2007; Zhao  
3 and Running, 2010). A particular focus is in identifying which land regions may have  
4 contributed to the potential shift and what underlying mechanisms may have caused it.  
5 Specifically, we analyze data-driven NPP data based on an established satellite-  
6 constrained biogeochemical model as well as process-based NPP data from nine  
7 terrestrial biosphere models that participated in a recent model intercomparison project  
8 ‘trends and drivers of the regional-scale sources and sinks of carbon dioxide (TRENDY)’  
9 (Section 2).

10

## 11 **2 Methods**

### 12 **2.1 Data and models**

13 We analyze temporal patterns in various metrics of the terrestrial carbon cycle based on  
14 three independent data sources. First, we analyze data-driven NPP fields based on  
15 simulations with the satellite-constrained biogeochemical Carnegie-Ames-Stanford-  
16 Approach (CASA) model (van der Werf et al., 2006) for the period of available satellite  
17 vegetation data 1982-2011 (Zhu et al., 2013). This updated and extensively validated  
18 model runs at a 0.5° spatial resolution on a monthly time step. NPP is a measure of the  
19 amount of carbon fixed by plants during photosynthesis and accumulated as biomass. The  
20 CASA model is conceptually relative simple and a number of potentially important  
21 processes and mechanisms, such as related to nutrients (e.g., carbon and nitrogen) are not  
22 considered explicitly (van der Werf et al., 2006). However, factors that influence  
23 vegetation productivity may be indirectly captured through the satellite-based fraction of

1 available photosynthetically active radiation absorbed by plants (fAPAR), a key driver in  
2 the NPP CASA light use efficiency parameterization (van der Werf et al., 2006). This is  
3 demonstrated by two recent studies showing that trends in satellite-based vegetation  
4 cover are consistent with expectations of growth enhancement via the CO<sub>2</sub> fertilization  
5 effect (Donohue et al., 2013; Los, 2013). Yet there is also new evidence suggesting that  
6 in dense forested ecosystems (tropical rainforests) fAPAR may not be fully responsive to  
7 the CO<sub>2</sub> fertilization effect (Forkel et al. 2015). Temporally varying driver data used for  
8 the CASA simulations include in addition to satellite-based fAPAR (fAPAR3g) (Zhu et  
9 al., 2013) also land temperature (CRU TS3.21) (Harris et al., 2014) as well as  
10 precipitation and surface solar radiation. We pay particular attention to uncertainties in  
11 these observational-based datasets and corresponding effects on NPP estimates. While  
12 land surface temperature data are considered to be relatively robust, a substantial  
13 limitation is that presently only one consistent satellite fAPAR dataset exists that covers  
14 the last 3 decades (Zhu et al., 2013) which we consider a minimum record length for  
15 meaningful change point analysis. Nonetheless, to account at least partially for  
16 observational uncertainties we evaluated different data sources for precipitation and  
17 surface solar radiation which are known to have substantial uncertainties (Wild, 2009;  
18 Greve et al., 2014) (see Methods in the Supplement). Based on a final selection of driver  
19 datasets (1 fAPAR, 1 temperature, 3 precipitation and 3 solar radiation; see Table S4 in  
20 the Supplement) we performed multiple CASA simulations with all possible input  
21 combinations (a total of 9 simulations) and analyzed the NPP ensemble mean with our  
22 change point methodology. We used the spread in these simulations as a measure of  
23 ‘observational-based’ uncertainty. In a complementary analysis, we also analyzed the



1 heterotrophic respiration ( $R_h$ ) and net ecosystem production (NEP; estimated as  $NPP -$   
2  $R_h$ ) ensemble means from these sets of CASA simulations. Owing to the lack of  
3 consistent fire observations for our study period 1982-2011 (e.g. the GFED era starts in  
4 1997; see van der Werf et al., 2006) corresponding effects on variability in NPP and NEP  
5 were not considered. To ensure that the carbon pools are at steady state, the CASA model  
6 was spun up for 250 years using a driver climatology based on the study period 1982-  
7 2011.

8         Second, we analyze a GCB for the period 1959-2011 and consisting of  $CO_2$   
9 emissions from fossil fuel burning and cement production as well as net LUC emissions,  
10 atmospheric  $CO_2$  growth rates and oceanic uptake (Le Quéré et al., 2013). Uncertainties  
11 in these budget terms are also provided and utilized to estimate uncertainties in net land  
12 uptake and the residual land sink (through the sum of squared errors).

13         Third, we analyze process-based NPP,  $R_h$  and NEP data based on ensembles of  
14 nine single terrestrial biosphere models that participated in the recent TRENDY model  
15 intercomparison project (Sitch et al., 2015). Compared to CASA, the TRENDY models  
16 are substantially more complex and also run at significantly shorter time steps to resolve  
17 the diurnal cycle needed when coupled within Earth system climate models (Sitch et al.,  
18 2015). An important distinction is that in the TRENDY models vegetation characteristics  
19 (e.g. fAPAR) are simulated prognostically (unlike in CASA where such information is  
20 inferred from satellite observations). In the TRENDY experiments (Sitch et al., 2015) the  
21 models were driven with observed climate and atmospheric  $CO_2$  data (S2 experiments) as  
22 well as with observed atmospheric  $CO_2$  data only (S1) and in order to isolate the  
23 variability due to climate, the difference between these two experiments (S2 – S1) was

1 taken. We analyze the NPP,  $R_h$  and NEP ensemble means (based on anomalies) from the  
2 nine participating models (Community Land Model 4CN, Hyland, Lund-Potsdam-Jena  
3 (LPJ), LPJ-GUESS, ORCHIDEE, **ORCHIDEE-CN**, Sheffield-DGVM, TRIFFID and  
4 VEGAS; for model details see Sitch et al., 2015) and used the spread among them as a  
5 measure of ‘model-based’ uncertainty in our change point framework. Based on a recent  
6 comprehensive evaluation against observations, it was found that most of the TRENDY  
7 models are capable of simulating the short- and long-term first-order dynamics of the  
8 terrestrial carbon cycle (Piao et al., 2013).

9

## 10 **2.2 Statistical methodology**

11 We apply a consistent change point methodology on the various metrics of the terrestrial  
12 carbon cycle to identify pattern of regime shifts (characterized as abrupt, substantial and  
13 sustained changes) and to contrast them to pattern showing either no or more gradual  
14 changes. We thus determine in a first step the statistical model that best fits the time  
15 series under investigation based on three options: 1) a constant mean, 2) a shift in the  
16 mean and 3) a linear trend. While there are numerous alternative statistical models (e.g.  
17 shifting trends as seen in satellite vegetation data at local to regional scales  
18 (Piao et al., 2011)), our choice of these three models is based on our primary objective to  
19 identify large-scale pattern in global and continental carbon fluxes that would be  
20 consistent with the recently observed regime shift in the land carbon sink (Sarmiento et  
21 al., 2010; Beaulieu et al., 2012).

22 In the ‘shift in the mean’ model, the shift is located through a change point  
23 detection algorithm that includes discrimination against a trend and the background

1 autocorrelation (red noise) by considering all positions in a time series as a potential  
2 change point from 5 to  $n-5$ , with  $n$  being the record length (Beaulieu et al. 2012b). In a  
3 previous study, we found that by restricting the search for change points in this manner  
4 detection of spurious shifts at the beginning or end of a series can be avoided  
5 (Beaulieu et al. 2012a). In the change point method applied here, we also further  
6 developed the Beaulieu et al. (2012b) methodology to account for known explicit  
7 uncertainties in the time series under investigation. One important limitation here is that  
8 this statistical change point model cannot distinguish between a rather drastic shift (e.g.,  
9 change from one year to the next) and a more smooth shift over the span of several years.  
10 Adding additional parameters could in principle provide more information on the nature  
11 of the shift (e.g., smooth versus abrupt) but this would also make the model prone to  
12 overfitting given the rather short time series in this study.

13         The most likely model among the three statistical models fitted is determined  
14 based on the Schwarz Information Criterion (SIC), which compares their likelihoods with  
15 a penalty for the number of parameters fitted. If the ‘shift in the mean’ model seems the  
16 most likely, we calculate in a second step the direction and magnitude of the shifts  
17 (subtracting means prior and after the shift) and the corresponding  $P$ -value by integrating  
18 the full uncertainty of the data using Monte Carlo simulations. To perform the Monte  
19 Carlo simulation, we draw 1000 normally distributed synthetic series having the same  
20 statistical properties as the time series of interest. A new feature is that the series are  
21 simulated with uncertainty additivity: the squared variance of each data point is added to  
22 the overall time series squared variance and the square root of this sum provides the  
23 synthetic series variance. This therefore takes into account the explicit uncertainties in the

1 various time series under investigation. The change point method is applied to the  
2 synthetic time series and a SIC difference between the model with a shift in the mean and  
3 no shift is calculated for each time series. This provides a distribution for the SIC  
4 difference under the hypothesis of no shift in the mean. The  $P$ -value is the estimated  
5 probability to find a SIC difference at least as extreme as the one observed, under the  
6 hypothesis of no change. This methodology assumes that the errors of the model are  
7 independent and normally distributed with a constant variance. We test normality of the  
8 residuals using the Lilliefors test, the independence is verified using the Durbin-Watson  
9 test and the constant variance is verified using a Fisher test. All tests are available and  
10 performed using MATLAB. If independence is not respected, we generate synthetic  
11 series with the same first-order autocorrelation as observed in the respective time series  
12 residuals.

13

## 14 **3 Results**

### 15 **3.1 Shifts in data-driven NPP**

16 Applying our change point methodology (Section 2.2) on data-driven global NPP fields  
17 reveals a marked spatial clustering of abrupt and sustained increases in NPP across  
18 northern Eurasia and northern Africa in the late 1980s (Fig. 1). At more regional levels,  
19 the impact of severe disturbance events such as the mountain pine beetle outbreak in the  
20 late 1990s in the temperate and boreal forests of western North America  
21 (Kurz et al., 2008) is also disclosed (via rapid and sustained decreases in NPP). A similar  
22 analysis without constraining to only statistically significant results at the grid point level  
23 implies that the coherent pattern of abrupt and sustained NPP shifts across northern

1 Eurasia and northern Africa are spatially even more extensive (Fig. S1 in the  
2 Supplement).

3         This point is further illustrated when we apply our change point framework on  
4 data-driven NPP time series representative of large land regions and highlights the  
5 important role of the northern extratropics (magnitude of NPP shift:  $\sim 0.7 \text{ PgC yr}^{-1}$ ), and  
6 the northern Eurasian continent ( $\sim 0.5 \text{ PgC yr}^{-1}$ ) in particular, in the regime shift in carbon  
7 uptake by terrestrial plants in the late 1980s (Table 1 and Fig. S2 in the Supplement).  
8 While the northern African region also exhibits a robust albeit smaller increase in data-  
9 driven NPP ( $\sim 0.2 \text{ PgC yr}^{-1}$ ) in the late 1980s, no corresponding NPP shifts are  
10 discernable for tropical/southern and global land areas (Table 1). It is well known that  
11 factors like ENSO (van der Werf et al., 2004) and volcanic aerosols (Lucht et al., 2002)  
12 have a large influence on variability in the carbon balance of terrestrial ecosystems  
13 (particularly at interannual time scales) and these phenomena may have also played a role  
14 in the prominent late 1980s NPP regime shifts. An analysis that explicitly accounts for  
15 such effects however suggests that these two factors are not the causes of the shift, but  
16 indicates that a shift in data-driven NPP in the late 1980s emerges also for  
17 tropical/southern and global land regions albeit with limited statistical significance  
18 (Table 1). In a complementary analysis, we also re-assessed the robustness of the earlier  
19 reported abrupt shift in the ‘residual’ global land carbon sink in the late 1980s (Sarmiento  
20 et al., 2010; Beaulieu et al., 2012a) by analyzing a GCB for the period 1959-2011 (Le  
21 Quéré et al., 2013) with our change point methodology that also accounts for explicit  
22 uncertainties in the individual budget terms (Section 2.2). Results confirm the presence of  
23 a regime shift in the global ‘residual’ land sink ( $\sim 1\text{-}1.3 \text{ PgC yr}^{-1}$  depending on statistical

1 treatment) in the late 1980s (Table 1 and Fig. S3 in the Supplement). Taken together, the  
2 good agreement in the timing of regime shifts in the global ‘residual’ land carbon sink  
3 and continental data-driven NPP may imply that the latter is a significant driver of the  
4 increased terrestrial carbon uptake in the late 1980s.

5

### 6 **3.2 Drivers of the late-1980s shift in data-driven NPP**

7 In order to unravel the mechanisms leading to the continental shifts in data-driven NPP,  
8 we focus on the two target regions of northern Eurasia and northern Africa that  
9 predominantly contributed to this late 1980s shift (see Fig. 1a). A factorial analysis for  
10 specific seasons shows that the northern Eurasian continent experienced a marked  
11 increase in spring temperatures and spring satellite vegetation activity (fAPAR) in the  
12 late 1980s that together drove a substantial increase in spring NPP (Fig. 2a). This  
13 relatively sudden springtime warming was also associated with a marked earlier spring  
14 onset (~5 days; see Fig. S4 in the Supplement) and the enhanced productivity in the early  
15 part of the growing season appears to have also benefited plant productivity in  
16 subsequent summers (Fig. 2a and Fig. S4 in the Supplement). **A closer inspection shows**  
17 **that the increase in summer productivity stemmed solely from satellite fAPAR**  
18 **contributions (Fig. 2a), which is consistent with the notion of a more developed canopy**  
19 **during the peak of the growing season (as captured through fAPAR) that carries over the**  
20 **early spring onset signal (Richardson et al, 2010).** Increased plant productivity in the  
21 spring and summer seasons contributed predominantly to the pronounced and sustained  
22 increases in annual NPP in the late 1980s (Fig. 2a).

23 Over northern Africa including the dry Sahel, marked increases in data-driven

1 NPP during wet and dry seasons that are driven by both increases in rainfall as well as  
2 satellite fAPAR triggered a pronounced increase in annual NPP in the late 1980s (Fig.  
3 2b). A closer inspection shows that in the period after this shift rainfall increased  
4 specifically during the later portion of the rainy season, which effectively lengthened the  
5 more productive growing season (Fig. S4 in the Supplement).

6

### 7 **3.3 Shifts in process-based NPP**

8 The exploited biogeochemical model (CASA) for data-driven NPP simulations has a  
9 relatively simple structure and provides an integrated view (via satellite fAPAR) of the  
10 many interacting factors that influence NPP variability. Further, data-driven NPP  
11 estimates are also influenced by observational uncertainties in both satellite (e.g.,  
12 volcanic aerosols, cloud cover, signal saturation) and key climate driver data that are only  
13 partially accounted for in our data-driven NPP simulations (see Section 2.1). We thus  
14 explored if process-based terrestrial biosphere models driven by climate and atmospheric  
15 CO<sub>2</sub> observations also show evidence of a marked shift in NPP in the late 1980s. Results  
16 based on the TRENDY ensembles (Section 2) show that for the satellite period (~ last 3  
17 decades) a NPP shift in the late 1980s emerges as a prominent feature, but only in  
18 experiments that capture variability due to climate exclusively (Fig. 3, Fig. S5 and Table  
19 S1 in the Supplement). Regional attributions associated with the shift are similar as in the  
20 case for data-driven NPP, but differences in NPP sensitivities to climate (inferred from  
21 differences in the magnitude of the shifts) are evident (Table 1 and Table S1 in the  
22 Supplement). For example, the magnitude of the late 1980s NPP shift in northern Eurasia  
23 based on TRENDY is only about half the size of the corresponding shift in data-driven

1 NPP (Table 1 and Table S1 in the Supplement). One reason for this marked difference  
2 may be that seasonal carry-over effects in NPP are largely absent in the TRENDY  
3 models; e.g. the late 1980s Northern Eurasian annual NPP shift in TRENDY is solely due  
4 to spring contributions (coincident with the time of the climate forcing) whereas for data-  
5 driven NPP it is comprised of about equal contributions from spring and summer **with**  
6 **satellite fAPAR providing the link through which the early spring onset signal is**  
7 **propagated** (Figs 2a and 3a). It should be noted that such seasonal carry-over effects due  
8 to an earlier spring onset are observed at multiple eddy covariance flux sites across  
9 temperate and boreal ecosystems (Richardson et al., 2010) and that the phenology  
10 response (at seasonal and interannual time scales) in data-driven approaches is generally  
11 considered more robust (Raczka et al., 2013).

12 The TRENDY simulations are not restricted to the satellite period allowing us to  
13 assess whether the identified late 1980s NPP shifts also emerge as dominant pattern when  
14 the study period is extended to the last 5 decades (to be consistent with the time frame of  
15 the GCB). Results show that the late 1980s shift over northern Eurasia is a stable pattern.  
16 For northern Africa, however, an even more prominent shift is identified in the late 1960s  
17 (Fig. S5 and Table S1 in the Supplement). This may suggest that this region by itself is  
18 not important enough to influence the global land sink (since there is no evidence for a  
19 corresponding shift in the global residual land sink; see Table 1). Further, in TRENDY  
20 experiments in which atmospheric CO<sub>2</sub> and climate drivers are varied, the shift appears to  
21 be masked by an increasing trend in NPP associated largely with the CO<sub>2</sub> fertilization  
22 effect (Fig. 3, Fig. S6 and Table S1 in the Supplement). In fact, the high NPP sensitivity  
23 to changes in atmospheric CO<sub>2</sub> concentrations in many of the current generation of



1 terrestrial biosphere models (Arora et al., 2013) and the potential role of nutrient  
2 limitations (Zaehle, 2013) and/or climate feedbacks (Smith et al., 2015) in mitigating this  
3 sensitivity is presently a subject of intense research.

4

### 5 **3.4 Shifts in $R_h$ and NEP**

6 In how far the identified climate-driven regime shifts in NPP in the late 1980s translate  
7 into a sustained carbon sink (consistent with the shift seen in the residual land carbon  
8 sink from the GCB; Table 1) depends in part on associated responses in key carbon loss  
9 fluxes such as  $R_h$  which (apart from its dependence on substrate supply from NPP) often  
10 depends on climatic factors in a similar fashion as NPP (Lucht et al., 2002). A limitation,  
11 however, is that currently no data-driven analog for  $R_h$  estimation exists and one has to  
12 revert to alternative methods including more uncertain process-based simulations.

13 Nevertheless to estimate the degree at which shifts in NPP may be potentially offset by  
14 corresponding shifts in  $R_h$  we apply our change point framework also on the  $R_h$  as well as  
15 NEP fluxes from the CASA and TRENDY simulations (see Section 2). Results show that  
16 for the large land regions of interest regime shifts in NPP are repeatedly accompanied by  
17 substantial shifts in  $R_h$  (Table 1, Tables S1-S2 and Figs S2, S5-S6 in the Supplement)  
18 often with 1-2 year lags (seen most clearly when ENSO and volcanic influences are  
19 accounted for). A consequence is that corresponding shifts in NEP are often less robust or  
20 not detectable (Table 1 and Table S3 in the Supplement). For example, in the case of the  
21 two focal regions northern Eurasia and northern Africa, the late 1980s shifts in data-  
22 driven NPP are offset by corresponding shifts in  $R_h$  at levels of 64-66% and 80-90%  
23 (depending on statistical treatment), respectively (Table 1). As stated, the estimated shifts

1 in the  $R_h$  fluxes are more uncertain and may represent more upper bound estimates as a  
2 new study suggests that carbon models have a tendency to transfer carbon too quickly  
3 through the plant-soil systems because of severe biases in simulated soil carbon and/or  
4 too high  $R_h$  sensitivities to climate (Carvalhais et al., 2014).

5 At global scale, a shift in  $R_h$  can also be estimated as the residual between a NPP  
6 shift and a corresponding shift in the residual land sink based on the GCB (Anderegg et  
7 al., 2015). Using methods that include such residual calculations as well as our direct  
8 model estimates (see Methods in the Supplement), we estimate a shift in global NPP in  
9 the late 1980s of  $1.14 \pm 0.34 \text{ PgC yr}^{-1}$  and a corresponding shift in  $R_h$  of  $0.36 \pm 0.48 \text{ PgC}$   
10  $\text{yr}^{-1}$ . Our best estimate for an associated global shift in NEP is  $0.63 \pm 0.30 \text{ PgC yr}^{-1}$  that  
11 amounts to roughly 60% of the magnitude of the late 1980s shift in the residual land sink  
12 from the GCB ( $1.12 \pm 0.14 \text{ PgC yr}^{-1}$ ; based on the three estimates shown in Table 1).

13

#### 14 **4 Discussion**

15 Our findings provide independent evidence from a biospheric modeling perspective for  
16 the abrupt strengthening of the ‘residual’ land carbon sink in the late 1980s (Sarmiento et  
17 al. 2010) and suggest that the underlying driver is a shift in global NPP in response to  
18 coordinated large-scale climate shifts. However, the late 1980s climate perturbations may  
19 also substantially influence fire regimes, but the paucity of data on burned area and  
20 related carbon emissions extending back to the early 80s severely limits estimating  
21 corresponding impacts. For northern Eurasia (which is responsible for the largest  
22 contribution to the late 1980s regime shift in data-driven NPP), however, it is not  
23 anticipated that the observed profound spring warming and greening (inferred through

1 fAPAR) in the late 1980s may have lead to substantial changes in fire emissions since the  
2 fire activity peaks later in the season (van der Werf et al., 2006). For northern Africa,  
3 changes in fire regimes associated with the late 1980s shift towards wetter conditions  
4 may have a substantial influence on net carbon balance albeit with uncertain direction  
5 since a shift towards wetter conditions may increase (more fuel load) or reduce  
6 (shortening the dry season) fire emissions (Andela and van der Werf, 2014). Models that  
7 can potentially quantify this influence are still in their early phase of development. While  
8 much uncertainty (specifically pertaining to magnitude) remains in estimating the  
9 contribution of climate-driven changes in the major land carbon fluxes to the late 1980s  
10 regime shift in the land carbon sink, our regional NPP attributions are consistent with a  
11 reported decrease in the interhemispheric gradient in atmospheric CO<sub>2</sub> in the 1990s  
12 relative to the 1980s that is attributed to an increase in the northern carbon sink (Wang et  
13 al., 2013).

14 Other factors not related to climate may have also played a role in the late 1980s  
15 regime shift of the land carbon sink. A potential large contribution in this regard may be  
16 from land-use and land cover changes across northern Eurasia through agricultural  
17 abandonment and rapid changes in forest management in the aftermath of the late 1980s  
18 post-Soviet collapse. While such processes are accounted for in net LUC emission  
19 estimates compiled in the GCB (and therefore included in our analysis; see Table 1)  
20 corresponding effects may not be fully captured due to a lack of robust data especially in  
21 the period prior the Soviet collapse (Achard et al., 2006). However, at least in the case of  
22 agricultural abandonment newly available estimates (Schierhorn et al., 2013) of  
23 associated carbon sinks for the post-Soviet period 1990-2009 suggest a minor

1 contribution ( $\sim 0.03 \text{ PgC yr}^{-1}$ ).

2 A remarkable finding is that two key climatic constraints on plant growth  
3 (temperature and precipitation) have shifted in the late 1980s in a way as to facilitate an  
4 abrupt and sustained increase in continental-scale terrestrial NPP. This bears the question  
5 if there is an underlying link that would explain why these large-scale climate pattern  
6 varied nearly synchronously. The Arctic Oscillation (AO) is the most important climate  
7 mode in the northern extratropics (Thompson and Wallace, 1998) and also a prominent  
8 mode in coupled global (Los et al., 2001) and hemispheric (Buermann et al., 2003)  
9 climate and satellite vegetation greenness data. Consistent with these results, we find that  
10 over the satellite period 1982-2011 the winter AO is tightly correlated with northern  
11 Eurasian spring temperatures ( $r=0.60$ ,  $P<0.001$ ) and spring fAPAR ( $r=0.40$ ,  $P=0.03$ ),  
12 respectively (Fig. 4). In the late 1980s, the AO together with its regional manifestation  
13 the North Atlantic Oscillation (NAO) (Hurrell, 1995) underwent an extreme shift into  
14 their respective positive phases, thereby moving North Atlantic winter storm tracks  
15 northward and enabling advection of mild maritime air deep into the northern Eurasian  
16 land mass (Thompson and Wallace, 1998). Our results show that the northern Eurasian  
17 biomes responded rapidly to the associated substantial spring warming as evidenced  
18 through synchronous increases in satellite-based vegetation activity (Fig. 4a). Change  
19 point analysis on these drivers of NPP also confirms the existence of this prominent late-  
20 1980s shift (showing significant shifts in winter (JFM) AO (1989,  $p=0.07$ ), Northern  
21 Eurasian spring temperature (1989,  $p<0.001$ ) and Northern Eurasian spring fAPAR  
22 (1990,  $p<0.001$ ), respectively). In the aftermath of this shift, however, spring  
23 temperatures and vegetation activity stayed at elevated levels (causing a sustained impact

1 on plant carbon uptake; see Fig. 2a) while the AO/NAO exhibited a negative trend, a fact  
2 that may be explained by a more gradual warming response to greenhouse gas forcing  
3 that is superimposed on the more oscillatory influence of the AO/NAO.

4 Northern African wet season rainfall pattern are strongly influenced by Atlantic  
5 sea surface temperature (SST) variability (Hoerling et al., 2006). In this regard, the  
6 warming of the North Atlantic relative to the South Atlantic that resumed in the late  
7 1980s to mid 1990s caused a northward displacement of the Atlantic intertropical  
8 convergence zone (ITCZ) and increased rainfall rates across northern Africa, which led to  
9 a recovery from earlier severe drought conditions (Hoerling et al., 2006). This increased  
10 moisture supply also led to rapid increases in satellite fAPAR (Fig. 4b). An open question  
11 is to what extent AO/NAO and Atlantic SST forcings may have interacted (Xie and  
12 Carton, 2004) in the wake of the apparent coordinated regional climate shifts over  
13 northern Eurasia and northern Africa in the late 1980s. It is well established that ENSO  
14 (van der Werf et al., 2004) and volcanic eruptions (Lucht et al., 2002) have a dominant  
15 influence on the terrestrial carbon cycle at interannual time scales and much of recent  
16 research has focused on associated links (Cox et al., 2013; Wang et al., 2014). Our  
17 findings here may suggest that North Atlantic climate variability and corresponding  
18 impacts on adjacent vast land masses may be more important in regards to abrupt,  
19 substantial and more sustained shifts in the terrestrial carbon cycle.

20

## 21 **5 Conclusions**

22 Our results point to a mechanism whereby North Atlantic climate variability modulates  
23 the global terrestrial carbon cycle. New research suggests that a large portion of the

1 variability in the North Atlantic may be externally forced by anthropogenic aerosols  
2 (Booth et al., 2012) and the pronounced warming trend in the Arctic regions, known as  
3 Arctic amplification (Cohen et al., 2014). Arctic amplification specifically is thought to  
4 intensify under climate change (Deser et al., 2010) and this may drive the AO/NAO more  
5 into their respective negative phases (Cohen et al., 2014) which, based on our results,  
6 would substantially reduce carbon uptake by terrestrial plants and weaken the land carbon  
7 sink. This illustrates the pressing need for improved knowledge of North Atlantic  
8 climate variability and associated forcing mechanisms in order to more credibly  
9 project the evolution of the land carbon sink and carbon cycle climate feedbacks  
10 under climate change.

11

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13

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21

#### 22 **Author Contributions**

23 W.B., C.B., B.P. and G.J.C. designed the analyses. W.B., C.B. and B.P. conducted the

1 analyses. All authors contributed to the writing of the manuscript.

2

3 **Competing financial interests**

4 The authors declare no competing financial interests.

1 **Table 1. Timing and magnitude of abrupt changes in the terrestrial carbon cycle at**  
2 **global and continental scales.** Timing of abrupt change (first data entry) as well as  
3 corresponding direction and magnitude (second data entry in units of PgC yr<sup>-1</sup>) and *P*-  
4 values (in brackets; estimated through Monte Carlo simulations) are provided if a ‘shift in  
5 the mean’ model fits the respective time series best (see Section 2). The timing of a shift  
6 indicates the first year of a new regime. Shifts that are statistically significant ( $P < 0.05$ )  
7 are highlighted in bold. Additional tests were carried out for assessing the nature and  
8 robustness of the shifts including accounting for influences related to ENSO and volcanic  
9 eruptions (Covariates), and specifically removing the two years of largest impact of the  
10 strong Mt. Pinatubo volcanic eruption in the original time series (No Pinatubo). Plots of  
11 all time series analyzed are also provided (Figs S2-S3 in the Supplement).  
12

1

Region	Original data	Covariates <sup>f</sup>	No Pinatubo <sup>g</sup>
<i>Global Carbon Budget 1959-2011</i>			
Residual land sink <sup>e</sup>	<b>1989, +1.03 (0.003)</b>	<b>1989, +1.28 (&lt;0.001)</b>	<b>1989, +1.06 (0.003)</b>
Net land uptake <sup>e</sup>	<b>1989, +1.19 (0.004)</b>	<b>1989, +1.43 (&lt;0.001)</b>	<b>1989, +1.23 (0.001)</b>
<i>Data-driven (CASA) NPP 1982-2011</i>			
Global	1995, +1.18 (0.239) <sup>c</sup>	1989, +1.12 (0.124) <sup>c</sup>	1989, +1.49 (0.084) <sup>c</sup>
Northern land (>30°N)	<b>1988, +0.72 (0.010)<sup>c</sup></b>	<b>1989, +0.62 (0.008)<sup>c</sup></b>	<b>1988, +0.76 (0.003)<sup>c</sup></b>
Tropic./south. land (<30°N)	1995, +0.73 (0.266) <sup>c</sup>	1989, +0.50 (0.526)	1995, +0.70 (0.388) <sup>c</sup>
Northern Eurasia	<b>1988, +0.53 (&lt;0.001)<sup>b</sup></b>	<b>1989, +0.45 (0.001)</b>	<b>1988, +0.54 (&lt;0.001)<sup>b</sup></b>
Northern Africa	<b>1989, +0.20 (0.005)</b>	<b>1989, +0.17 (0.003)</b>	<b>1989, +0.21 (0.001)</b>
<i>Process-based (CASA) R<sub>h</sub> 1982-2011</i>			
Global	<b>1996, +0.96 (0.001)</b>	<b>1990, +0.80 (0.028)<sup>c</sup></b>	<b>1996, +0.94 (0.001)</b>
Northern land (>30°N)	<b>1990, +0.44 (0.003)<sup>c</sup></b>	<b>1990, +0.42 (&lt;0.001)<sup>a,c</sup></b>	<b>1990, +0.46 (&lt;0.001)<sup>c</sup></b>
Tropic./south. land (<30°N)	<b>1996, +0.63 (0.003)</b>	1996, +0.49 (0.054)	<b>1996, +0.61 (0.002)</b>
Northern Eurasia	<b>1988, +0.35 (0.004)<sup>a,c</sup></b>	<b>1990, +0.29 (0.004)<sup>b,c</sup></b>	<b>1988, +0.37 (&lt;0.001)<sup>a,c</sup></b>
Northern Africa	<b>1988, +0.18 (&lt;0.001)</b>	<b>1991, +0.14 (0.003)<sup>b</sup></b>	<b>1988, +0.19 (&lt;0.001)</b>
<i>Process-based (CASA) NEP 1982-2011</i>			
Global	1987 <sup>d</sup>	1999, -0.68 (0.122)	1987 <sup>d</sup>
Northern land (>30°N)	1987, +0.30 (0.318)	1989 <sup>d</sup>	1987, +0.31 (0.304)
Tropic./south. land (<30°N)	1999 <sup>d</sup>	1999, -0.56 (0.087)	1999 <sup>d</sup>
Northern Eurasia	1988, +0.18 (0.061)	1989, +0.15 (0.154) <sup>b,c</sup>	1988, +0.18 (0.074)
Northern Africa	1992 <sup>d</sup>	2003 <sup>d</sup>	1992 <sup>d</sup>

2 a. Not normally distributed (Lilliefors test, 5% critical level)

3 b. Variance not constant (F-test, 5% critical level)

4 c. Residuals not independent (Kruskal-Wallis, 5% critical level)

5 d. 'Linear trend' or 'constant mean' model fits data better than a 'shift in the mean' model

6 d. In the global carbon budget (Le Quéré et al., 2013), the net land uptake is estimated as the difference

7 between global fossil fuel emissions and the sum of atmospheric CO<sub>2</sub> growth rate and oceanic uptake,

8 while the residual land sink is the difference between net land uptake and LUC emissions

9 e. Variability related to ENSO and volcanoes were removed in the original time series through regressions

10 against the multivariate ENSO index and stratospheric optical thickness after Beaulieu et al. (2012a)

11 f. The two Pinatubo years (1992, 1993) were removed in the original time series prior change point analysis

12

1 **Figure captions**

2 **Figure 1. Spatial pattern of abrupt shifts in data-driven NPP.** Maps show (a) timing  
3 and corresponding (b) direction and magnitude of abrupt shifts in data-driven (CASA)  
4 annual NPP for the satellite period 1982-2011. All robust NPP shifts shown here have  
5 passed the two key statistical criteria: (i) a ‘shift in the mean’ model fits the time series at  
6 each grid point best (evaluated through the Schwarz Information Criterion) and (ii) the  
7 shift is also statistically significant ( $P < 0.05$ ) based on Monte Carlo simulations that take  
8 into account explicit uncertainties (Section 2). Maps of shifts that passed only the first  
9 criteria are also provided (Fig. S1 in the Supplement). In (a), the focus regions northern  
10 Eurasia (10°W-180°E, 40°N-70°N) and northern Africa (20°W-50°E, 5°N-20°N) are  
11 outlined. The shifts are only assessed for the period 1987-2006, since for robust change  
12 point detection a minimum span of 5 years of data prior and after a shift is required  
13 (Section 2).

14

15 **Figure 2. Temporal changes in continental data-driven NPP.** Panels show annual and  
16 seasonal (CASA-based) NPP anomalies corresponding to the (a) northern Eurasian and  
17 (b) northern African focus regions (see Fig. 1a). All anomalies are relative to 1982-2011.  
18 Shaded contours represent  $1\sigma$  uncertainties that account for biases in model driver data  
19 (Section 2). To understand which factors are mainly responsible for the identified shifts  
20 (see Table 1), we performed factorial NPP simulations in which only one model driver is  
21 varied whereas all others are kept constant (e.g., ‘fAPAR only’ corresponds to NPP  
22 simulations in which only fAPAR was varied, whereas temperature, precipitation and  
23 solar radiation data were kept at their climatological mean values). It should be noted that

1 satellite fAPAR, a proxy for vegetation cover, is often correlated with climate variables  
2 and this places limits on attributing a single model driver to changes in NPP. The first  
3 year of a new regime in annual NPP is outlined (thick dark red vertical lines; see Table 1)  
4 and the means in NPP anomalies prior and after the shift are also shown (dashed lines).

5

6 **Figure 3. Temporal changes in continental process-based NPP based on nine**

7 **terrestrial biosphere models.** Panels show annual and seasonal NPP anomalies for the  
8 (a) northern Eurasian and (b) North African focus regions, based on ensembles of nine  
9 biosphere models that participated in the recent TRENDY model intercomparison study  
10 (Sitch et al. 2015). In the annual case, results for two sets of model simulations are  
11 shown: one in which climate and CO<sub>2</sub> as model drivers were varied (S2) and another one  
12 that only takes into account the effect of climate variations (S2 – S1; see Section 2). All  
13 anomalies are relative to the 1982-2010 overlapping satellite era to facilitate comparisons  
14 with the data-driven NPP simulations (see Fig. 2). Mean ensembles were formed based  
15 on anomalies in the single TRENDY models to emphasize temporal changes in NPP and  
16 to suppress uncertainties arising from model differences in magnitudes. Shaded contours  
17 represent 1 $\sigma$  uncertainties corresponding to the spread in the single TRENDY models.  
18 The first year of a new regime in annual NPP is outlined (thick dark red vertical lines;  
19 Table S1 in the Supplement) and the means in NPP anomalies prior and after the shift are  
20 also shown (dashed lines). In panel (b), the last data point for the year 2010 is omitted  
21 since tropical rainfall input data for the TRENDY runs were erroneous for that year (S.  
22 Sitch, personal communication).

23



1 **Figure 4. Synchronous continental shifts in climate and satellite vegetation data and**  
2 **links to North Atlantic climate variability.** In panel (a), temporal variations in spring  
3 (MAM) temperature and satellite-based vegetation activity (fAPAR) representative of the  
4 northern Eurasian target region are plotted alongside the winter (JFM) Arctic Oscillation  
5 (AO) and North Atlantic Oscillation (NAO) time series. In panel (b), temporal variations  
6 in wet season (May-Oct) precipitation and fAPAR for the northern African target region  
7 are plotted alongside the annual Atlantic Multidecadal Oscillation (AMO) time series.  
8 Plotted are both annual values (thin dotted lines) and a smoothed time series based on a  
9 seven-point binomial filter (thick lines). All time series are standardized anomalies  
10 relative to the satellite period 1982-2011. All climate indices time series are obtained  
11 from *www.esrl.noaa.gov*. Definitions of the AO and NAO are given in Thompson and  
12 Wallace (1998) and Hurrell (1995), respectively. The AMO is a detrended area-weighted  
13 average of North Atlantic SSTs (0°-70°N) (Enfield et al., 2001).