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2 **Satellite passive microwaves reveal climate-induced carbon losses in African drylands, 2010-**  
3 **2016**

4

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## 23 **Introductory paragraph**

24 The African continent is facing one of the driest periods in the past three decades and continuing  
25 deforestation. These disturbances threaten vegetation carbon (C) stocks and highlight the need for  
26 improved capabilities of monitoring large-scale aboveground carbon stock dynamics. Here we used  
27 a new satellite data set based on vegetation optical depth derived from low frequency passive micro-  
28 waves (L-VOD) to quantify annual aboveground woody carbon changes in sub-Saharan Africa be-  
29 tween 2010 and 2016. Gross gains in carbon stocks (+1.74 Pg C y<sup>-1</sup>) were slightly overbalanced by  
30 gross losses (-1.84 Pg C y<sup>-1</sup>) of which ~40% (-0.7 Pg C y<sup>-1</sup>) occurred in drylands (53% of the land  
31 area). The overall net change in drylands was -0.07 Pg C y<sup>-1</sup> associated with drying trends, and a net  
32 change of -0.03 Pg C y<sup>-1</sup> was observed in humid areas. These trends reflect a high inter-annual varia-  
33 bility with very wet years (2011 and 2013; net changes +0.33 and +1.13 Pg C) and a very dry year  
34 (2015; net change -1.1 Pg C) associated with carbon gains and losses respectively. This study demon-  
35 strates, first, the applicability of L-VOD to monitor the dynamics of carbon loss and gain due to  
36 climate variations, and second, the importance of the highly dynamic and vulnerable carbon pool of  
37 dryland savannahs for the global carbon balance, despite the relatively low carbon stock per unit area.

## 38 **Introduction**

39 The forests and savannahs of Africa have attracted particular attention because both climate change  
40 and land-use pressure have large impacts on the carbon stocks of woody vegetation, with immediate  
41 consequences for the global carbon balance<sup>1-4</sup>. Whereas deforestation is a well-known threat to rain-  
42 forests<sup>2,5-8</sup>, savannahs occur in areas of climatic extremes and the mostly sparse vegetation is very  
43 sensitive to dry years<sup>9</sup>. However, the net balance of carbon stocks in the savannah vegetation, changes  
44 in plant growth rates (negatively impacted by humans and dry periods but positively affected by ele-  
45 vated CO<sub>2</sub><sup>1</sup>) and altered mortality of the woody vegetation are currently unknown<sup>10,11</sup>. We also do not  
46 know if semi-arid Africa, which was identified as an important carbon sink with a peak in the ex-  
47 tremely wet year of 2011<sup>12</sup>, has become a carbon source following the recent extreme El Nino in

48 2015-2016<sup>13</sup>. Recent work showed that the number of trees in global drylands has been greatly un-  
49 derestimated<sup>14</sup>: a carbon stock neglected in global assessments<sup>15</sup>. Knowledge of the amount, distribu-  
50 tion, and turnover of carbon in African vegetation is crucial for understanding the effects of human  
51 pressure and climate change<sup>16</sup>, but the shortcomings of optical and radar satellite products and the  
52 lack of systematic field inventories have led to considerable uncertainty in documenting patterns of  
53 carbon stocks, and their long-term change over the African continent<sup>3,4</sup>. Static carbon maps have been  
54 developed based on field plots and satellite data using LIDAR, visible/infrared reflectivities and radar  
55 backscattering. These maps constitute the best benchmarks to date for carbon stored in the live woody  
56 vegetation<sup>17-21</sup>. The application of different techniques, however, complicates the direct comparison  
57 of these maps, and results differ in magnitude and spatial patterns<sup>20</sup>. Importantly, also the temporal  
58 dynamics of carbon stocks cannot be derived from the above benchmark maps, impeding timely,  
59 repeated, and reliable carbon assessments<sup>22</sup>.

60

61 In contrast, the vegetation optical depth (VOD) derived from high frequency (>5 GHz) passive mi-  
62 crowave-based satellite systems has been used to monitor changes in vegetation carbon<sup>23,24</sup>. Although  
63 the coarse spatial resolution of passive microwaves (43 km gridded at 25 km) has limited their appli-  
64 cation for detecting the spatial extent of deforestation, this technology is an attractive alternative to  
65 other remote sensing systems because microwaves at frequencies lower than 15 GHz are almost  
66 insensitive to atmospheric and cloud effects. However, high frequency VOD saturates over forested  
67 areas and is generally not considered as an accurate tool for carbon monitoring<sup>5,7</sup>. The Soil Moisture  
68 and Ocean Salinity (SMOS) mission launched in 2009 was the first passive microwave-based satellite  
69 system operating at L-band (1.4 GHz) frequency<sup>25</sup>. These low frequencies allow the satellite to sense  
70 deeper within the canopy layer with less influence by the green non-woody plant components. The  
71 VOD derived from SMOS, henceforth L-VOD, is thus less sensitive to saturation effects<sup>26</sup>, marking  
72 an important step forward in the monitoring of carbon as a natural resource. In this study, we apply  
73 for the first time L-VOD to quantify the inter-annual dynamics of aboveground carbon stocks for the

74 period 2010-2016. This study does not attempt at improving current aboveground carbon stock maps  
75 nor at a comparison with state-of-the-art data and maps on carbon stocks<sup>24,19,21</sup>. Based on calibrated  
76 relationships between L-VOD and an existing benchmark map we present and analyse temporal pat-  
77 terns of gains and losses in different humidity zones of sub-Saharan Africa in response to recent dry  
78 years.

79

## 80 **RESULTS**

81

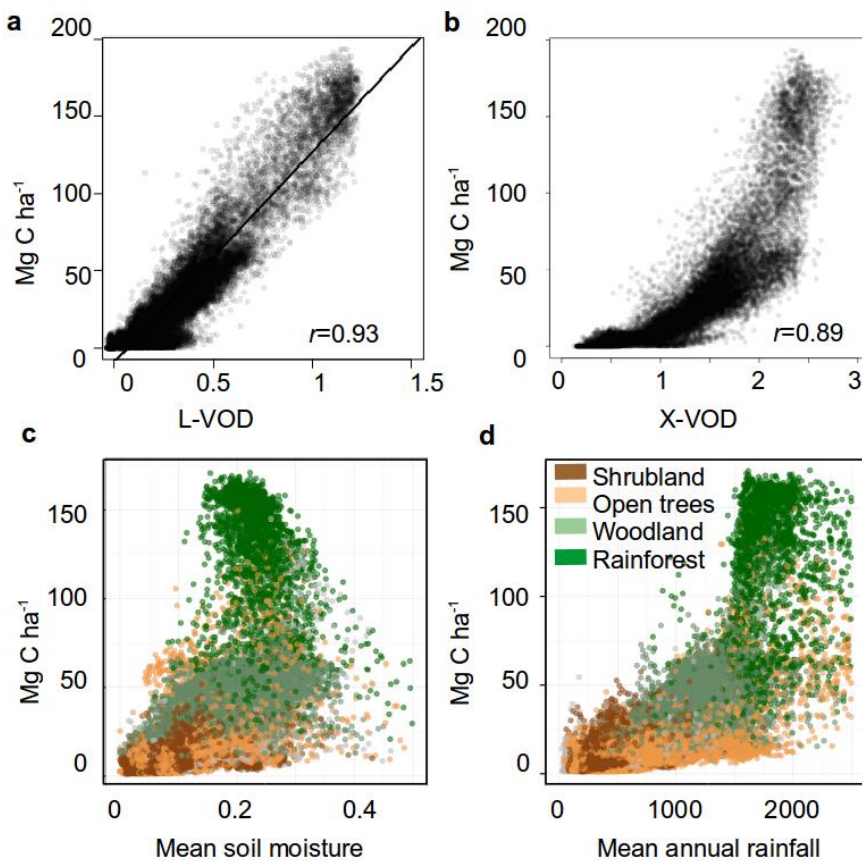
### 82 **Estimating Africa's carbon stocks with passive microwaves**

83 L-VOD averaged for 2010-2016 was linearly correlated with a benchmark map on aboveground live  
84 biomass carbon (hereafter the term carbon stocks is used) over Africa<sup>20</sup> (Fig. 1a). Although the bench-  
85 mark map contains bias and uncertainties (Supplementary Fig. 1, Supplementary Table 1), the com-  
86 parison clearly demonstrates the strong relationship between L-VOD and carbon stocks. The refer-  
87 ence map<sup>20</sup> was thus used as a training set to convert L-VOD to carbon per unit area ( $\text{Mg C ha}^{-1}$ ). The  
88 L-VOD carbon density map was strongly and linearly correlated with the reference map (cross vali-  
89 dated  $r^2=0.92$  and  $RMSE=12 \text{ Mg C ha}^{-1}$ ,  $p<0.01$ ,  $n=26199$ ) (Supplementary Figs 1,2). Baccini et al.<sup>20</sup>  
90 reported the total C stocks of Africa to be  $64.5 \text{ Pg C}$  ( $\pm 13$  at the 95% confidence level (CL)), which  
91 was reproduced (Fig. 1b) using L-VOD predicting a C stock of  $64.0 \text{ Pg C}$  ( $\pm 10$  at the 95% CL, esti-  
92 mated by 10-fold cross validated  $RMSE$ ). In contrast to L-VOD, high-frequency X-band VOD<sup>24</sup> from  
93 AMSR-2 saturated for values  $>100 \text{ Mg C ha}^{-1}$  (Fig. 1b) and optical satellite data for values  $>50 \text{ Mg}$   
94  $\text{C ha}^{-1}$  (Supplementary Fig. 2).

95 We stratified the L-VOD time series analysis of African vegetation into (1) drylands versus humid  
96 areas, as defined by the ratio between annual precipitation and potential evapotranspiration<sup>14</sup>, and (2)  
97 four merged land cover classes<sup>27</sup> (Supplementary Table 1). The ability of L-VOD to predict C stocks  
98 was similarly strong for both drylands at  $10.5 \pm 2.9 \text{ Pg C}$  ( $r^2=0.74$ ,  $p<0.01$ ,  $RMSE=2.4 \text{ Mg C ha}^{-1}$ ,  
99  $n=13418$ ) and for humid areas at  $53.1 \pm 7.9 \text{ Pg C}$  ( $r^2=0.92$ ,  $p<0.01$ ,  $RMSE=7.5 \text{ Mg C ha}$ ,  $n=12781$ ).

100 The spatial distribution of carbon stocks at continental scales was relatively even among the land  
 101 cover classes, with open trees/shrubs (including agricultural lands) comprising almost half the carbon  
 102 stocks of rainforests (Supplementary Table 1). Mean carbon density was correlated with mean soil  
 103 moisture and mean annual rainfall with changing classes of land cover along the rainfall gradients  
 104 (Fig. 1c,d). The correlation between carbon density and rainfall disappears at around 1600 mm rainfall,  
 105 and carbon density was markedly higher for rainforests than for the remaining classes (Fig. 1d).

106



107

108 **Figure 1: Relationships between carbon density in biomass and VOD in sub-Saharan Africa. a,**  
 109 *Regression between biomass carbon density from Baccini et al.<sup>20</sup> (obtained from GLAS space-borne*  
 110 *data and forest inventories 2007/2008) and average low frequency L-VOD (2010-2016) from this*  
 111 *study, showing no saturation in the relationship. b, Same regression with high frequency X-band VOD*  
 112 *from AMSR-2 (average 2012-2015); This relationship saturates at biomass values > 100 Mg C ha<sup>-1</sup>.*  
 113 **c,** *Relationship between L-VOD estimated carbon density (mean 2010-2016) and SMOS-IC surface*  
 114 *soil moisture (mean 2010-2016) and with d, mean annual rainfall (CHIRPS) for 2010-2016 (colours*

115 *attribute a land-cover class to each pixel of 25 x 25 km).*

116

### 117 **Africa's carbon stocks are highly dynamic**

118 To compute annual changes in C stocks, the coefficients derived from the relationship between Bac-  
119 cini's aboveground biomass carbon map<sup>20</sup> and mean L-VOD (Fig. 1a) were applied for each yearly  
120 median L-VOD map separately. This space-for-time substitution was applied because no inventory  
121 data at such a fine temporal resolution were available. Significant trends in carbon were found using  
122 per-pixel linear trends in annual carbon density for 2010-2016 ( $p < 0.05$ , 7 years) (Fig. 2a). Carbon net  
123 changes (increases and decreases) were computed by comparing the difference in C stocks between  
124 the years 2010 and 2016 (Supplementary Table 1). Gross losses and gains were calculated by cumu-  
125 lating positive (respectively, negative) changes between all the consecutive years from 2010 to 2016  
126 (Fig. 2b-f). Gross changes are larger than net changes as losses and recovery occur in the same  
127 pixel/region over the study period. The balance between gross gain and gross loss equals the net  
128 changes and is shown in Fig. 2b.

129 Over the study period, net changes in carbon were relatively balanced in most latitudinal bands (Fig.  
130 2c). Across sub-Saharan Africa, gross gains (+1.74 Pg C  $y^{-1}$ ) were offset by gross losses (-1.84 Pg C  
131  $y^{-1}$ ) with an overall negative net carbon budget for Africa (-0.1 Pg C  $y^{-1}$ ). The majority of the net  
132 losses occurred in drylands (-0.07 Pg C  $y^{-1}$ ) and humid areas experienced a smaller carbon loss (-0.03  
133 Pg C  $y^{-1}$ ). Notably, a gross carbon loss of -0.7 Pg C  $y^{-1}$  occurred in drylands and is partly compensated  
134 by a gross gain of +0.63 Pg C  $y^{-1}$ . This gross loss per year represents ~5% of the dryland total carbon  
135 stocks in Africa ( $10.3 \pm 3.2$  Pg C in 2010) (Fig 2f). By contrast, yearly gross losses from humid areas  
136 represent ~2% (-1.13 Pg C  $y^{-1}$ ) of the total stock ( $54.9 \pm 8.1$  Pg C in 2010), with noticeable areas in the  
137 Democratic Republic of Congo, Ethiopia, Uganda, Ivory Coast, Ghana and Nigeria (Fig. 2b,d). Gross  
138 gains in humid areas were +1.10 Pg C  $y^{-1}$  mainly located around the central African forest of the  
139 Congo basin (Fig. 2b,c,e,f). The magnitude of gross fluxes being much larger than net fluxes illus-  
140 trates the highly dynamic variations of carbon stocks during the study period.



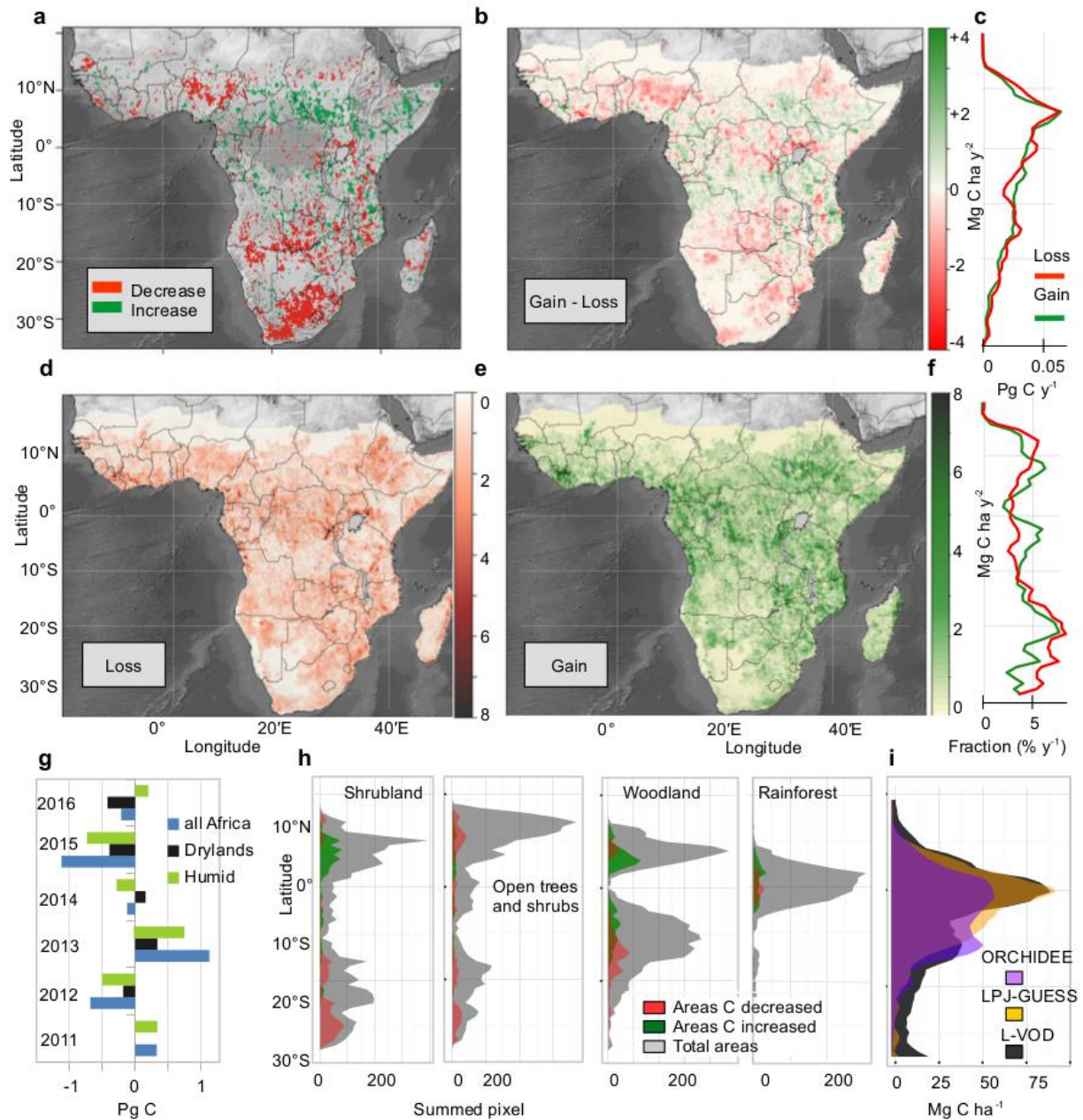
141 Areal and net changes in carbon stocks were close to zero when averaged per land cover class at  
142 continental scale (Fig. 2h) except in the open trees/shrubs class with gross gains being  $0.09 \text{ Pg C y}^{-1}$   
143 below gross losses (Supplementary Fig. 5, Table 1). Using Senegal as a case study site, the observed  
144 L-VOD decrease was related with a mass dying of shrubs (2013-2015) caused by a prolonged dry  
145 period which was documented by very high spatial resolution satellite and field data from 2015, see  
146 ref<sup>28</sup> for further documentation of this event (Fig. 3, Supplementary Fig. 6). Stocks of woodlands  
147 considerably increased north  $\sim 10^\circ\text{S}$  but decreased further south. Gross losses in rainforests were  $-0.3$   
148  $\text{Pg C y}^{-1}$ , presumably caused by deforestation (Fig. 2b-d). Gross gains ( $-0.29 \text{ Pg C y}^{-1}$ ) almost com-  
149 pensated C losses in rainforests. Using a simple bookkeeping model, Houghton et al.<sup>29</sup> reported an  
150 annual carbon loss from deforestation of  $-0.4 \text{ Pg C y}^{-1}$  in Africa, which is comparable to our observed  
151 values for rainforests ( $-0.3 \text{ Pg C y}^{-1}$ ), although below-ground biomass carbon changes and delayed  
152 soil carbon emissions after deforestation, which are part of the bookkeeping model<sup>29</sup>, are not included  
153 in the L-VOD based carbon estimates.

154 For individual years, the largest net losses ( $-1.1 \text{ Pg C}$  for all Africa,  $-0.39$  for drylands and  $-0.73 \text{ Pg}$   
155  $\text{C}$  for humid areas) were for found in 2015 (Fig. 2g), which is a comparable numbers as the net carbon  
156 fluxes measured by the Orbiting Carbon Observatory-2 for tropical Africa ( $-0.8 \text{ Pg C}$ ) during the  
157 severe El Niño<sup>30</sup>. Overall positive net changes were observed in 2011 ( $+0.33 \text{ Pg C}$ ) and 2013 ( $+1.12$   
158  $\text{Pg C}$ ). Interestingly, net changes in 2014 were positive in drylands ( $+0.16 \text{ Pg C}$ ) but negative in humid  
159 areas ( $-0.28 \text{ Pg C}$ ). Contrastingly, the year 2016 was a considerable C source in drylands ( $-0.42 \text{ Pg C}$ )  
160 but a sink for humid areas ( $+0.2 \text{ Pg C}$ ).

161 We applied two ecosystem models to test the performance of state-of-the-art methods commonly used  
162 to assess large-scale temporal C dynamics. The spatial patterns of carbon stored in woody vegetation  
163 simulated by LPJ-GUESS ( $r=0.85$ ,  $p<0.01$ ) and ORCHIDEE-MICT ( $r=0.87$ ,  $p<0.01$ ) agreed reason-  
164 ably well with L-VOD carbon estimations (Fig. 2i; Supplementary Fig. 2). Drylands, however,  
165 showed a share of the total pool of African carbon stocks of 17% in L-VOD but only 6% in LPJ-  
166 GUESS and 8% in ORCHIDEE-MICT, possibly because models describe vegetation as either grass

167 or tree plant functional types but do not incorporate mixed types occurring in savannahs.

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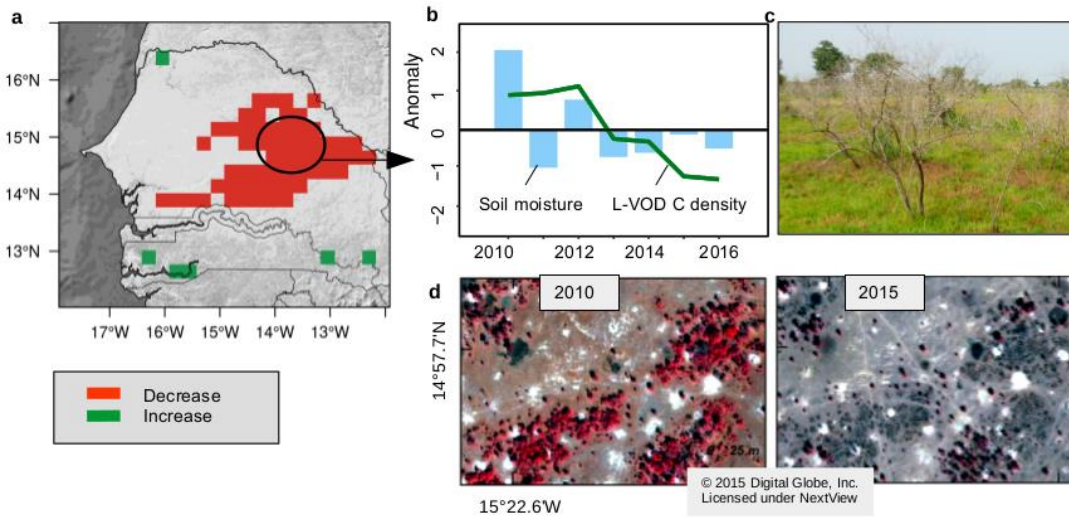


169

170 **Figure 2: Changes in carbon stocks for 2010-2016.** *a*, Pixels of significant ( $p < 0.05$ ) positive (green)  
171 and negative (red) changes (linear trend;  $p < 0.05$ ) in aboveground carbon density based on L-VOD  
172 for the 2010-2016 period. *b*, Net changes in C density between 2010 and 2016. *c*, latitudinal sums of  
173 gross losses and gains. *d*, Cumulative gross losses (time integral of losses) and *e*, cumulative gross  
174 gains in C density. *f*, Fractional gross losses and gains per year in the L-VOD data. *g*, Net carbon  
175 changes for individual years. *h*, Areas affected by significant ( $p < 0.05$ ) positive (green) and negative

176 (red) changes in carbon density for L-VOD 2010-2016 summed per latitude band. **i**, Latitudinal av-  
 177 erages of L-VOD carbon density (dark grey) compared to LPJ-GUESS (orange) and ORCHIDEE-  
 178 MICT (purple) simulated values of above ground biomass carbon.

179



180

181 **Figure 3: Shrub die off in Senegal.** *a*, Pixels of significant changes (linear trend;  $p < 0.05$ ) in L-VOD  
 182 carbon density (2010-2016). *b*, L-VOD carbon density (average of pixels in the circle) decreased  
 183 rapidly after 2013, reflecting widespread mortality of *Guiera senegalensis* shrubs between 2013 and  
 184 2015 due to a prolonged dry period. This event was documented by *c*, field photos (2015) and *d*, very  
 185 high spatial resolution satellite imagery (from the WorldView-2 and QuickBird-2 satellites; Supple-  
 186 mentary Fig. 6)<sup>28</sup>.

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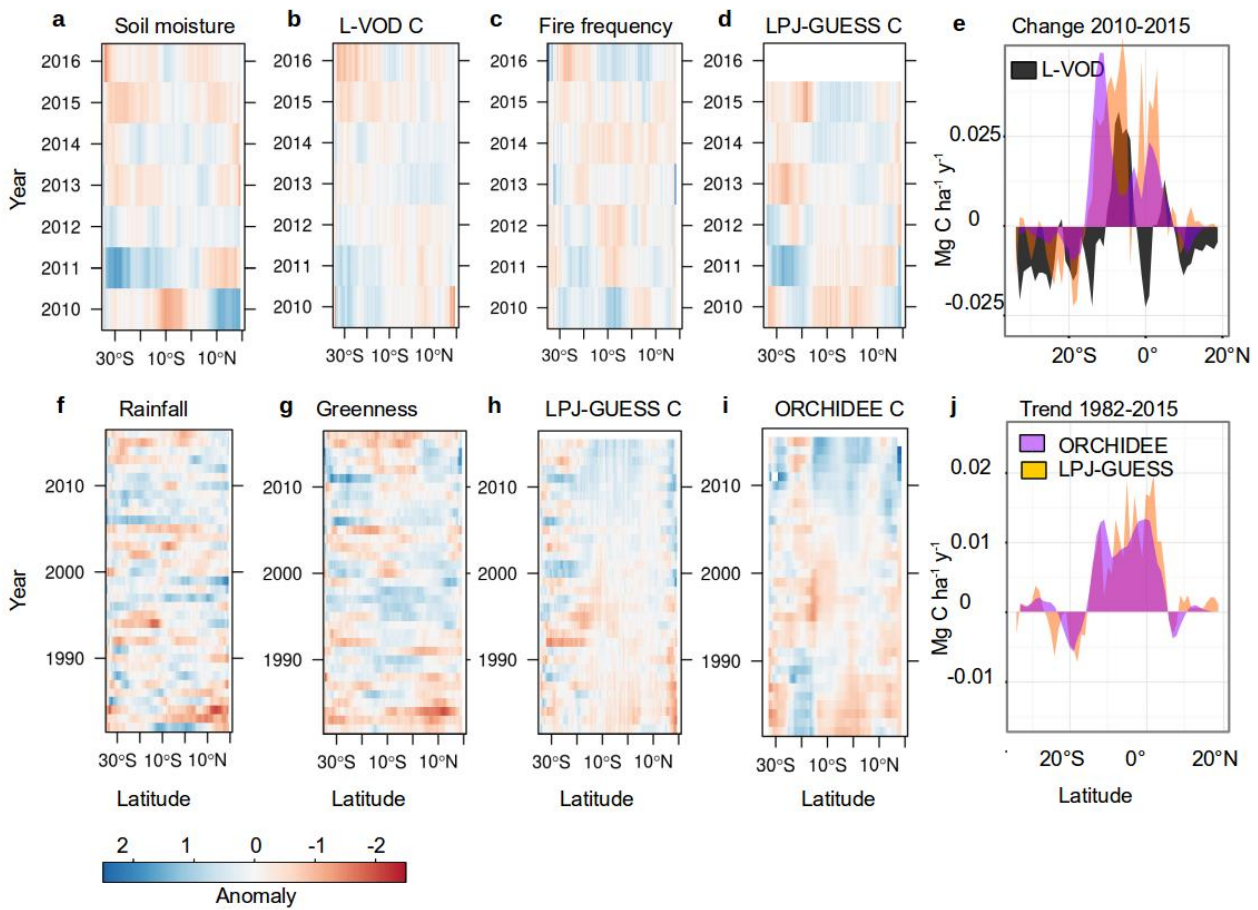
188 **Recent dry periods have reduced carbon stocks in dryland areas**

189 Soil moisture<sup>31</sup> showed similar latitudinal patterns as L-VOD carbon density and explained a large  
 190 fraction of the observed dynamics in carbon stocks between 2010 and 2016 (Fig. 4a,b). Although the  
 191 fire frequency increased in 2016, fewer fires occurred in areas of major L-VOD decreases (Fig. 4c).  
 192 These recent decreases in L-VOD estimated carbon stocks were most dramatic in southern Africa,  
 193 which was approximately reproduced by the ecosystem models (Fig. 4d,e). Moreover, rainfall data<sup>32</sup>  
 194 and vegetation greenness indicated abnormally dry conditions in most parts of Africa in recent years,  
 195 particularly during the severe El Niño episode of 2015/2016 (Fig. 4f,g), indicating that dry years have

196 caused the changes in L-VOD, rather than impacts from human disturbance and fires. Prior to 2010,  
197 conditions were stable and extraordinarily positive anomalies in carbon density and soil moisture  
198 were recorded for 2011 (Fig. 4a,b), confirming previous studies based on ecosystem models and  
199 greenness satellite data<sup>12</sup>. After 2011, carbon stocks estimated by L-VOD and simulated by ecosystem  
200 models decreased considerably (Fig. 4b,d,e) and southern Africa turned from being a carbon sink into  
201 a source, with considerable carbon losses in 2015/2016. Simulations by ecosystem models suggested  
202 that the negative trend in dryland carbon stocks persisted over the 1982-2015 period, beyond the  
203 SMOS observation era (Fig. 4h-j). Simulated increases in humid areas around 5°N-10°S were less  
204 strong in L-VOD (Fig. 4e), but observed decreases around 0° were not shown in the climate driven  
205 ecosystem models, suggesting deforestation.

206 Overall, most of the detected decreases in carbon stocks were related with abnormally low soil mois-  
207 ture (Fig. 5a). Note however that neither rainfall nor soil moisture can explain the large-scale in-  
208 creases of carbon for ~5°N that may either reflect non-symmetrical net primary productivity responses  
209 to wet years (positive convexity), improved forest management or a decrease in wood fuel gathering  
210 in regions affected by conflicts and migration to urban areas (such as South Sudan, Central African  
211 Republic). At country scale, carbon stocks were found to increase in Sudan, the Central African Re-  
212 public, Cameroon, Gabon, Congo, Somalia, and Tanzania (Fig. 5b), in spite of mostly dry conditions  
213 and significant FAO reported deforestation in these countries<sup>33</sup>. Carbon stocks decreased considerably  
214 in Ghana, Ivory Coast, Nigeria, Uganda and Zambia, which may partly be caused by deforestation.  
215 Despite their lower woody covers compared to forested areas, large losses of carbon were found in  
216 South Africa, and are related with dry years.

217 The sensitivity of inter-annual variability in carbon density to dry years was assessed by a Spearman  
218 rank correlation between carbon density and soil moisture (Fig. 5c; Supplementary Fig. 7). This  
219 showed that country level carbon stocks were less sensitive to dry years in countries of humid regions  
220 whereas stocks were most sensitive in countries of drylands.



222

223

224 **Figure 4: Hovmöller diagrams showing anomalies (z-score) for Africa for each year and latitude.**

225 **a**, Anomalies for 2010-2016 of SMOS soil moisture, **b**, L-VOD carbon density, **c**, MOD14CMH fire

226 frequency **d**, LPJ-GUESS simulated aboveground woody carbon density. Model results for the year

227 2016 could not be displayed because harmonized gridded climate forcing data were not available to

228 drive these models at the time of this analysis. **e**, Change of aboveground carbon density simulated

229 by the ecosystem models and observed in the L-VOD product between 2010 and 2015. **f**, Anomalies

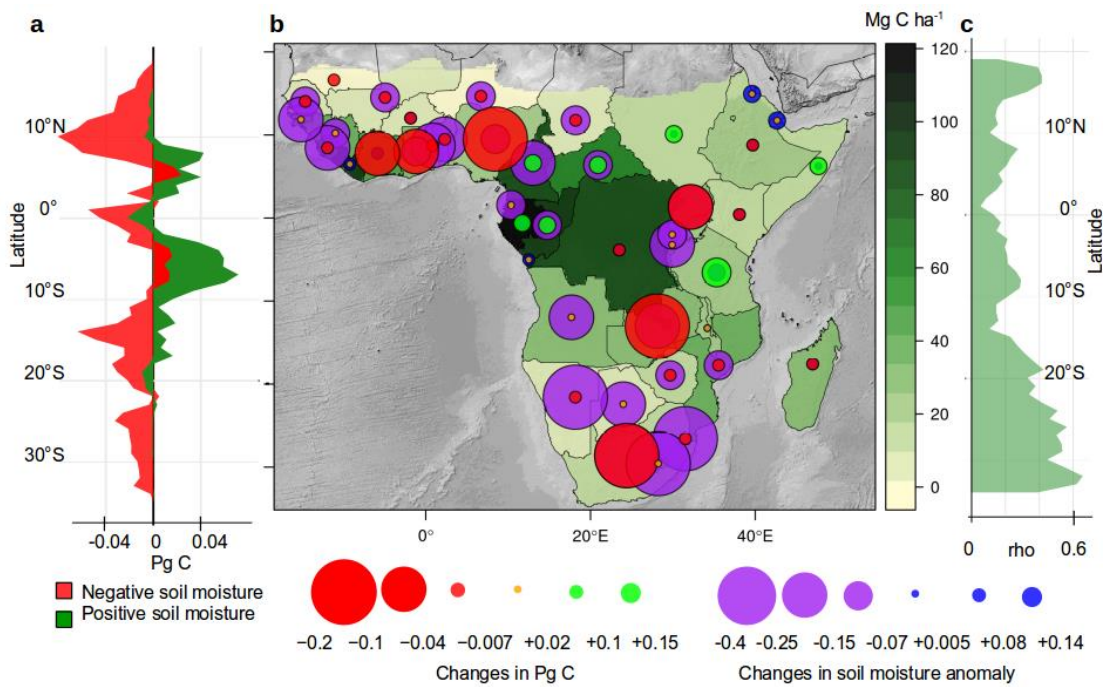
230 for 1982-2016 of the number of rainy days (>1 mm), **g**, vegetation greenness (annually summed nor-

231 malised difference vegetation index (NDVI)), carbon density simulated with the ecosystem models **h**,

232 LPJ-GUESS and **i**, ORCHIDEE-MICT. **j**, Linear trends of above-ground carbon density in the eco-

233 system models for 1982-2015.

234



235

236

237 **Figure 5: Soil moisture as driver of carbon stock dynamics.** *a*, Direction and magnitude of carbon  
 238 change (2016 compared with 2010; summed per latitude) are shown for areas with positive (green)  
 239 and negative (red) linear trends in soil moisture (2010-2016). *b*, Average carbon density (in Mg C ha<sup>-1</sup>)  
 240 and changes in carbon stocks at the country level (2016 compared with 2010) summed for each  
 241 country (in Pg C). Trends in annual soil moisture (slope of linear regression for 2010-2016) averaged  
 242 for each country are shown as purple (negative trend) and blue (positive trends) circles. *c*, Correla-  
 243 tions between annual carbon stocks and annual soil moisture (Spearman's rho, n=26711) averaged  
 244 along the latitudes.

245

246 **Discussion**

247 Assessing aboveground carbon stocks and their changes using repeated inventories with a gridded  
 248 sampling scheme is laborious and impossible to implement in all African countries, so assessments  
 249 with short intervals for understanding changes in stocks from year to year are unrealistic at continental  
 250 scale<sup>18</sup>. SMOS-IC L-VOD data provide a valuable alternative and the first tool for rapid monitoring  
 251 of carbon stocks and their changes. Our comparison with an existing benchmark map<sup>20</sup> provided  
 252 highly satisfactory correlations, supporting the utility of the data. The coarse spatial resolution (25

253 km) sets clear limits for the operational application of the L-VOD data set in relation to local scale  
254 forest monitoring, yet it is a major leap forward in assessments of C dynamics at the regional to global  
255 scale. Also, the applied benchmark map inevitably includes propagated uncertainty (Supplementary  
256 Table 1), and also the conversion adds some uncertainty to the final prediction. However, a deviation  
257 of L-VOD does not imply that the benchmark map is closer to reality, and an independent calibration  
258 of L-VOD with field survey, LIDAR and very high spatial resolution imagery for a stand-alone bio-  
259 mass product is a logical next step. For this study, however, the strong correlation between L-VOD  
260 and the benchmark map enabled us to provide a first application of low frequency passive microwaves  
261 to estimate temporal changes in C units at the sub-continental scale. The method applied in this study  
262 is preferable to optical remote sensing, because the L-VOD data are only controlled by the biomass  
263 of the vegetation and do not seem to saturate in forests. Moreover, although high frequency X-band  
264 VOD has been successfully applied for global biomass mapping<sup>24</sup>, the X-VOD sensor is more sensi-  
265 tive to green vegetation and restricted to the upper green canopy layer when the vegetation is dense<sup>23</sup>.  
266 This is visible from a higher inter-annual variability in mean annual values of X-VOD ( $0.2\pm 0.16$  SD)  
267 than we observed in L-VOD ( $0.04\pm 0.02$  SD), and also intra-annual variations of monthly L-VOD  
268 data are low (mean amplitude of  $0.2\pm 0.13$  SD). The advantage of L-VOD over previous methods is  
269 thus that it allows the continuous monitoring of carbon stocks, annually or even more frequently, for  
270 both forests and savannahs. Our results demonstrated the potential utility of L-VOD as a complemen-  
271 tary data source for quantifying and monitoring carbon stocks for national reports and large-scale  
272 efforts, such as the United Nations Framework Convention on Climate Change (UNFCCC) and the  
273 Intergovernmental Panel on Climate Change (IPCC), especially for semi-arid regions with little in-  
274 ventory data.

275 Continuing deforestation and forest degradation supposedly contributed to the high cumulative C  
276 losses in humid areas. Forest degradation does not strongly reduce carbon stocks and is followed by  
277 permanent recovery, hence it needs to be explored whether this process may be concealed by satura-  
278 tion or whether it could be detected from L-VOD.

279 In spite of C losses presumably caused by deforestation, we found that carbon stocks in rainforests  
280 remained relatively stable over the period 2010-2016 and were not evidently correlated with varia-  
281 tions in rainfall and soil moisture. On the other hand, carbon stocks outside densely forested areas  
282 were much more variable and were highly sensitive to climatic fluctuations, with two extreme events  
283 consisting of a very wet year in 2011 and a very dry one in late 2015-early 2016. Earlier studies<sup>1,34,12</sup>  
284 have often reported global increases in dryland carbon stocks, which has led to the general under-  
285 standing that drylands may serve as carbon sinks. Our study found that dry years have reversed this  
286 trend for 2010-2016 in areas where such increases in woody vegetation (and thus carbon stocks) have  
287 occurred in the past (e.g. southern Africa and Senegal<sup>1,34,35,36</sup>), demonstrating that climate controls  
288 short-term variations in carbon stocks at large scales.

289 Previous studies of carbon dynamics in Africa were based on ecosystem models and optical satellite  
290 observations both only measuring changes in the green fraction rather than in biomass. Our observa-  
291 tional data on dryland vegetation C stocks showed substantially higher values than simulated in the  
292 two ecosystem models, suggesting that models underestimate the crucial role of woody vegetation in  
293 savannahs as carbon sinks and sources<sup>14,20</sup>. The large losses of carbon from African drylands during  
294 2010-2016 support the view that the large area of drylands and their highly variable carbon stocks  
295 make these ecosystems important in the global accounting of the carbon balance, even though mean  
296 carbon stocks are generally quite low per unit area. With such inter-annual variability, it is difficult to  
297 conclude from the 7 years of observation presented here if the observed trends reflect quasi-decadal  
298 variations or if it is a sign of longer-term dynamics. However, considerable losses were observed in  
299 2010-2016, so we need to reassess whether, in the long term, woody vegetation in African savannas  
300 will indeed continue to be a carbon sink<sup>37</sup>. If dry years become more frequent<sup>38</sup>, large-scale carbon  
301 losses may exacerbate climate change, particularly in dry areas. Our study thereby highlights the  
302 importance of timely monitoring of both tropical deforestation and the highly dynamic woody carbon  
303 stocks of savannah ecosystems for assessments of global carbon stocks.



## 304 **Data and Methods**

305

306 **Passive microwaves for soil moisture, VOD and carbon estimation.** The estimates of biomass were  
307 computed from the SMOS L-VOD product in the IC version<sup>39</sup>. It is a global product gridded at 25 km  
308 spatial resolution and 1-day temporal frequency. The SMOS products (soil moisture and L-VOD) are  
309 computed from a two-parameter inversion of the L-MEB model (L-band Microwave Emission of the  
310 Biosphere) from the multi-angular and dual-polarized SMOS observations<sup>26,40</sup>. Soil moisture and L-  
311 VOD products are independent and weakly correlated (Fig. 1c). In the newly developed IC version,  
312 these products are independent of the use of auxiliary data from other space-borne observations or  
313 simulations from atmospheric models (only surface temperature estimates from ECMWF (European  
314 Centre for Medium-Range Weather Forecasts) products are used in the L-MEB inversion). We applied  
315 several steps of filtering to retrieve relatively robust and stable annual estimates: First, water bodies  
316 and pixels with on average less than 30 valid observations per year were masked out from the analysis.  
317 Then, daily L-VOD values were aggregated to yearly (median) values for 2010-2016. If less than 50  
318 observations were valid for a particular year, the pixel values of these years were replaced by the  
319 long-term mean. This left 82% (2010), 93% (2011), 95% (2012), 92% (2013), 93% (2014), 94%  
320 (2015) and 93% (2016) of the pixels with more than 50 observations per year which were used for  
321 the analysis. SMOS L-VOD was then converted to carbon density using the biomass map from Bac-  
322 cini et al.<sup>20</sup> (which was obtained with GLAS space-borne data and forest inventories from 2007/2008)  
323 as a reference (aggregated to 25 km by averaging) by a linear regression with mean L-VOD (2010-  
324 2016). Biomass was converted to carbon by using a factor of 0.5<sup>20</sup>. The coefficients from the regres-  
325 sion were used to convert L-VOD into carbon density ( $\text{Mg C ha}^{-1}$ ), which was then applied separately  
326 to each year from 2010 to 2016 to quantify the dynamics in  $\text{Mg C ha}^{-1}$ . Conversion to carbon stocks  
327 was achieved by multiplying carbon density with the amount of hectare covered by a pixel. C stock  
328 statistics per land-cover/humidity class were derived by summing the values of the pixels.

329 **Uncertainty.** Due to the coarse spatial resolution of the SMOS data, a pixel may contain a mix of

330 deforestation, regeneration, livestock pressure, conservation, fires, shrub encroachment and other  
331 events, resulting in a mix of carbon gains and losses that cannot be singled out. Moreover, different  
332 land cover types (e.g. forests, cropland and savannas) are often mixed within a single pixel. The coarse  
333 spatial resolution therefore renders the clear attribution of carbon changes to specific events impos-  
334 sible, unless they are large scale events (like climate perturbations). Our analysis thus presents the  
335 results of large scale averages (e.g. latitudinal) and concentrates on temporal rather than spatial vari-  
336 ations. Furthermore, although annual median values have shown to be stable, remaining noise cannot  
337 be entirely excluded, and may locally impact on inter-annual variations. It is, however, unlikely that  
338 averages per latitude, land cover class or per humidity zone are biased by noise, which is supported  
339 by the very low inter- and intra-annual variations of L-VOD (on average 0.04 and 0.2 respectively).  
340 This study does neither aim at improving existing biomass maps nor did we assume the values of the  
341 benchmark map as free of errors and representing reality. The benchmark map includes propagated  
342 uncertainties from allometric equations, the LIDAR model and the random forest extrapolation<sup>20</sup>.  
343 These uncertainties are shown in Supplementary Table 1 and the numbers have to be taken into ac-  
344 count when interpreting the results; we refer to Baccini et al.<sup>20</sup> for further details. Furthermore, the  
345 conversion of L-VOD to carbon density propagates uncertainty which was assessed by a 10-fold cross  
346 validation. Here the data were randomly split in 10 folds of equal size, which were used to predict the  
347 omitted values. The root of the mean squares of all folds gives the cross validated RMSE. We reported  
348 the median RMSE at the 95% confidence level for different classes as  $\pm xy$ ; for a full list, see Supple-  
349 mentary Table 1.

350 Yearly anomalies were calculated by the z-score:  $(\text{value} - \text{mean})/\text{standard deviation}$ . Net C changes  
351 were estimated by the difference of the carbon maps of 2010 and 2016. Gross losses (gains) were  
352 calculated by cumulating negative (positive) differences between the consecutive years. This allows  
353 to quantify the effect of deforestation (or dry years) without considering regeneration. That calcula-  
354 tion assigns a per-pixel deforestation fraction per pixel and per year, with a corresponding amount of  
355 C regrowth being deduced from the deforestation rate during the next year.

356

357 As for L-VOD, soil moisture from the SMOS mission<sup>29,40</sup> was applied in the IC version<sup>39</sup>. A 30-day  
358 median was averaged for each year as a robust proxy for available soil moisture in the root zone.  
359 Although soil moisture was derived from the same sensor as L-VOD, the variables are independent  
360 thanks to the multi-angular capabilities of the SMOS sensor<sup>40</sup> and Fig. 1c shows that the correlation  
361 between SM and L-VOD is weak.

362

363 **Rainfall data.** We used CHIRPS (v2) daily rainfall data<sup>32</sup>, aggregated to SMOS resolution (average).  
364 The number of rainy days per year were counted as days with rainfall >1 mm. Yearly anomalies in  
365 rainfall and soil moisture were calculated using the z-score: (value - mean)/standard deviation.

366

367 **Landcover and humidity classes.** ESA's CCI L4 land cover<sup>27</sup> for 2015 was aggregated to 25 km  
368 (majority). We reduced the number of classes to four (open trees/shrubs, shrubland, woodland, and  
369 rainforest), sorted by potentially increasing woody cover and carbon density. We merged all classes  
370 having scattered trees and shrubs in the class open trees/shrubs, which includes croplands along all  
371 rainfall zones, open trees, sparse vegetation and grassland. Note that areas converted from forest to  
372 cropland (e.g. in West Africa, Madagascar) are thus included in this class, which thus also includes  
373 remnants of forests, i.e. cropland/forest mosaics (Supplementary Fig. 3). Moreover, due to the large  
374 pixel size, a pixel free of trees or shrubs does not exist. Shrublands potentially have a dense woody  
375 cover, but the general capacity to store C is low due to the small size of the shrubs. Woodlands include  
376 open and closed tree cover, mostly located in the sub-humid and humid zones. This included the  
377 Miombo woodlands. Rainforest are closed forest areas around the equator and at the West African  
378 coast, located in areas above 1500 mm rainfall per year.

379

380 **Additional data.** Commercial satellite data were available via the NextView licence from Digital-  
381 Globe Inc. and were used for illustration (Fig. 3 and Supplementary Fig. 6). The images were from

382 the WorldView-2 and QuickBird-2 satellites and included multispectral imagery, which were  
383 pansharpened to a spatial resolution of 50 cm<sup>28</sup>. GIMMS-3g NDVI was used as a proxy for vegetation  
384 greenness. We summed the bi-monthly NDVIs for each year for 1982-2016 which is widely used to  
385 estimate the annual activity of green vegetation<sup>42</sup>. Annual fire frequency was derived from  
386 MOD14CMH by averaging monthly values.

387

388 **Ecosystem models.** ORCHIDEE (ORganizing Carbon and Hydrology in Dynamic EcosystEms) is a  
389 process-based dynamic global vegetation model (DGVM) developed for simulating carbon fluxes,  
390 and water and energy fluxes in ecosystems, from site level to global scale<sup>43</sup>. In this study, an updated  
391 version known as ORCHIDEE-MICT (aMeliorated Interactions between Carbon and Temperature)  
392 revision 4080 was run on an African grid using the 6-hourly CRU+NCEP reconstructed climate data  
393 at 2° × 2° spatial resolution<sup>44</sup>. The ESA CCI Land Cover product<sup>27</sup> for the year 2010 was used to  
394 produce a Plant Functional Type (PFT) map used in ORCHIDEE-MICT model, following the meth-  
395 odology presented by Poulter et al.<sup>45,46</sup>. An updated release of the historical land-use forcing dataset  
396 LUHv2h (<http://luh.umd.edu/data.shtml>; updated from LUHv1<sup>47</sup> were applied to this reference PFT  
397 map to constrain the land-cover changes of forest, natural grassland, pasture, and cropland during the  
398 period 1860-2015 using the backward method (BM3) following Peng et al.<sup>48</sup>. The simulation run for  
399 this study used forced vegetation distribution maps and outputs on woody carbon density (sap- &  
400 heartwood) were resampled to L-VOD resolution (bilinear).

401

402 LPJ-GUESS<sup>49</sup> is a dynamic vegetation model that simulates the global distribution of vegetation as  
403 well as the carbon and nitrogen cycling within vegetation and soils. It applies a set of 12 plant func-  
404 tional types (PFTs) with different morphological, phenological and physiological characteristics, of  
405 which 10 represent tree types and 2 represent herbaceous vegetation. For the simulation of woody  
406 aboveground biomass, LPJ-GUESS was forced with monthly gridded meteorological station data at  
407 a spatial resolution of 0.5°×0.5° from the Climatic Research Unit of the University of East Anglia

408 (CRU ts 3.24.01<sup>50</sup>), monthly model-derived estimates of nitrogen deposition<sup>51</sup> and annual atmos-  
409 pheric CO<sub>2</sub> concentration based on ice core data and atmospheric observations<sup>52,53</sup> in a simulation for  
410 the period 1901-2015. The simulation was preceded by a 500-year spinup applying the first 30 years  
411 from the climate forcing in a repeated manner. Land use was represented with a simple implementa-  
412 tion following Ahlström et al.<sup>34</sup>, applying historical reconstructions of land use from Hurtt et al.<sup>47</sup>.  
413 Annual maps of woody carbon density (sap- & heartwood) were resampled to L-VOD resolution  
414 (bilinear).

415 **Data availability.** CHIRPS rainfall data is freely available at the Climate Hazard Group  
416 (<http://chg.geog.ucsb.edu/data/chirps/>). SMOS-IC soil moisture and L-VOD data will be made pub-  
417 licly available via CATDS (Centre Aval de Traitement des Données SMOS) upon acceptance of the  
418 manuscript. Also available for public are soil moisture and L-VOD in the versions L3 and L4 at  
419 CATDS (<https://www.catds.fr/>). Baccini's biomass map including an uncertainty map is freely avail-  
420 able from Global Forest Watch. Model results and the L-VOD carbon maps are available from the  
421 authors upon request.

422

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548

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560

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562 JPW, MB, JC, FT and RF designed the study. JPW, AAY, NR, YK and AM prepared the SMOS-IC  
563 data. PC and JC prepared the ORCHIDEE data, GS prepared the LPJ-GUESS data, CT prepared the  
564 high spatial resolution satellite data. MB, FT and WZ analysed the data. The results were interpreted  
565 by JC, JPW, TT, JP, PC, LVR, KR, CM, AV and RF. MB, KR, JC, RF, JPW and PC drafted the man-  
566 uscript with contributions by all authors.

567

568 **Competing financial interest.** The authors declare no competing financial interests.

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571 **Supplementary**

572

573 **Table 1 | Changes in carbon per land cover and humidity zone.** Carbon density, above-ground bio-  
 574 mass carbon stocks, net and gross (cumulative gain or loss of the consecutive years) changes and  
 575 area per land cover class and humidity zone (drylands=arid+semi-arid+dry-subhumid). The cross  
 576 validated RMSE is shown as  $\pm$ , the propagated uncertainty from the benchmark map is shown in  
 577 brackets (both uncertainty values at the 95% CL). Note that open trees/shrubs include croplands and  
 578 appear along all rainfall zones (Fig 1c). Woodlands are located in sub-humid and humid zones (>600  
 579 mm rainfall) and rainforests around the equator with rainfall being above 1500 mm. See also Sup-  
 580 plementary Figs 3,4.

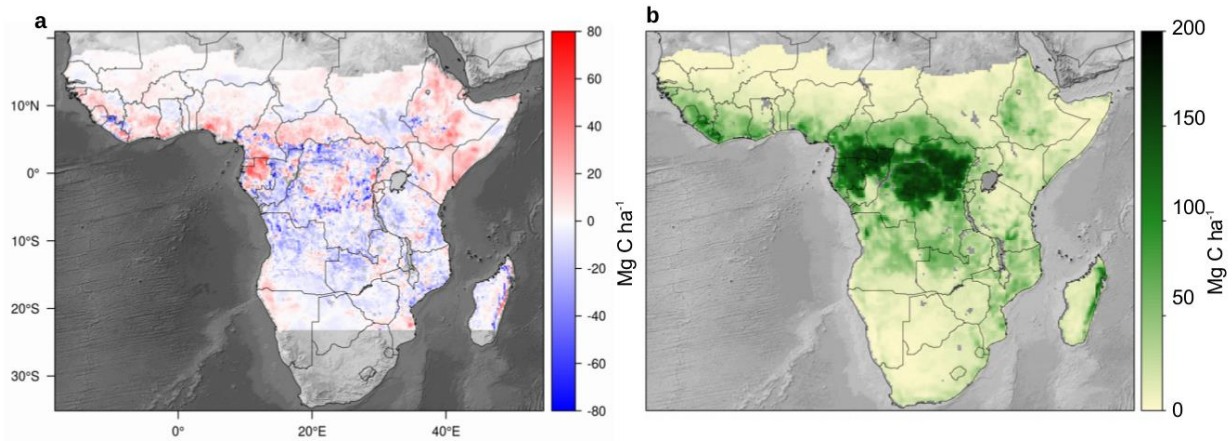
		<i>C density (Mg C ha<sup>-1</sup>)</i>	<i>C stock 2010 (Pg C)</i>	<i>C stock 2016 (Pg C)</i>	<i>Net C change * (Pg C y<sup>-1</sup>)</i>	<i>Gross C gain # (Pg C y<sup>-1</sup>)</i>	<i>Gross C loss ## (Pg C y<sup>-1</sup>)</i>	<i>Area (km<sup>2</sup> *1000)</i>
<i>Land cover clas- ses</i>	<i>Shrubland</i>	13.1 $\pm$ 3.6 (2.8)	5.3 $\pm$ 1.4 (1)	5.3 $\pm$ 1.4 (1)	0.002	+0.35	-0.35	4 123
	<i>Open trees/shrubs</i>	15.8 $\pm$ 2.6 (3.3)	11.2 $\pm$ 2.3 (2.1)	10.4 $\pm$ 2.1 (2.1)	-0.08	+0.45	-0.54	7 030
	<i>Woodland</i>	41.6 $\pm$ 6 (12)	22.9 $\pm$ 3.4(7)	22.9 $\pm$ 3.4(7)	-0.004	+0.58	-0.57	5 550
	<i>Rainforest</i>	112 $\pm$ 12 .7(22)	24.2 $\pm$ 3 (5)	24.1 $\pm$ 3 (5)	-0.008	+0.29	-0.30	2 214
<i>Humidity classes</i>	<i>Drylands</i>	10.2 $\pm$ 2.4 (2)	10.3 $\pm$ 3.2 (1.8)	9.8 $\pm$ 3.1 (1.8)	-0.07	+0.63	-0.70	11 322
	<i>Humid areas</i>	56.6 $\pm$ 7.5 (14)	54.9 $\pm$ 8.1 (11)	54.6 $\pm$ 8.0 (11)	-0.03	+1.10	-1.13	9 923
<i>Africa</i>		32.5 $\pm$ 4.5 (7.5)	65.5 $\pm$ 11 (13)	64.8 $\pm$ 11(13)	-0.1	+1.74	-1.84	21 245

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582 \* defined as the difference between 2016 and 2010

583 # defined as the time integral of all carbon gains counted positively since 2010

584 ## defined as the time integral of all carbon losses counted negatively since 2010

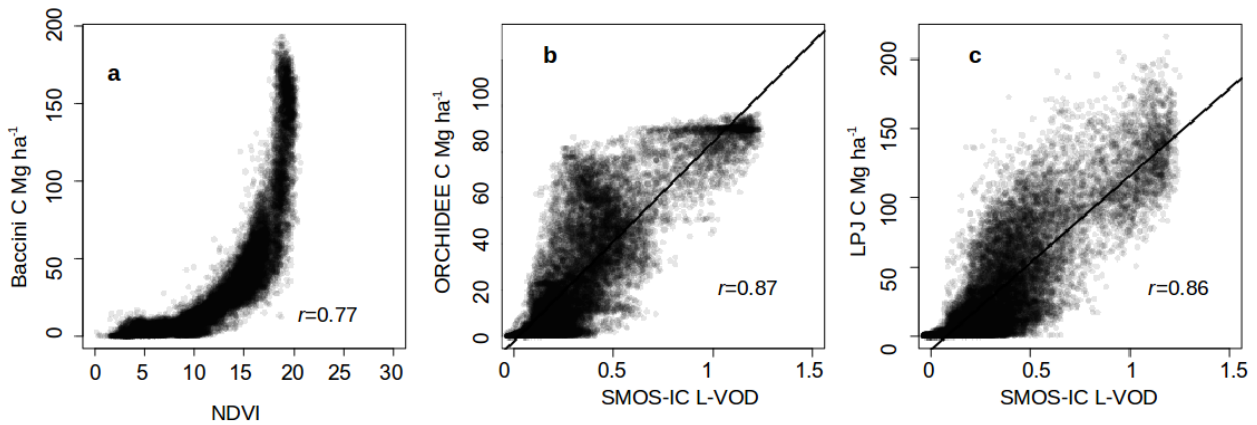


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587

588 **Figure 1** | **a**, Difference in carbon density estimated with SMOS-IC L-VOD and Baccini's benchmark  
 589 map<sup>1</sup>. Positive (red) values mean higher values in L-VOD carbon density and negative (blue) values  
 590 mean higher values in Baccini's carbon density. **b**, Carbon density estimated with SMOS-IC L-VOD  
 591 (mean 2010-2016).

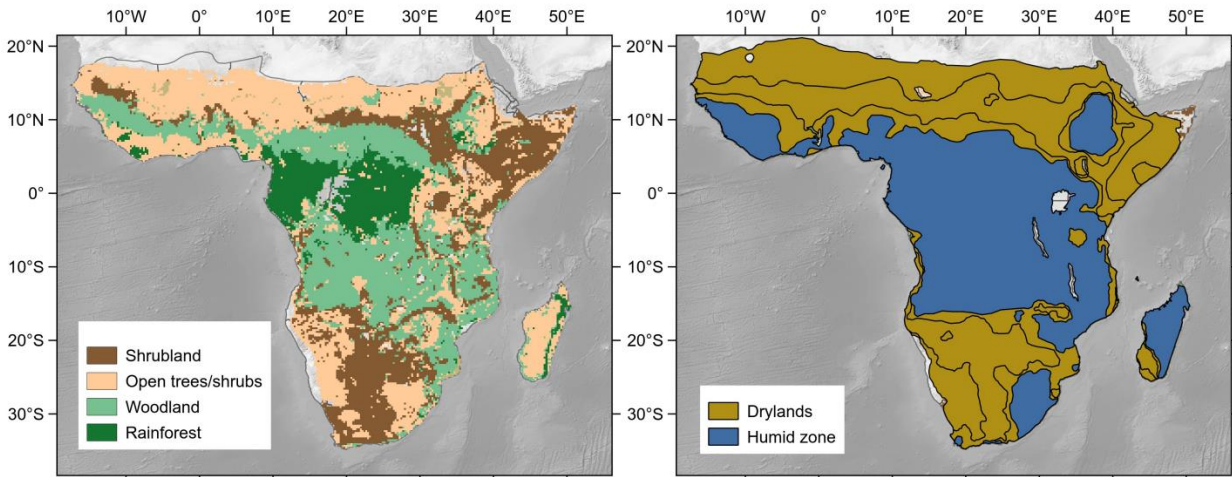
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594 **Figure 2** | Comparing **a**, optical (annually summed GIMMS-3g NDVI, mean 1982-2016). **b**, OR-  
 595 CHCIDEE-MICT and **c**, LPJ-GUESS simulated carbon density are compared with SMOS-IC L-VOD.

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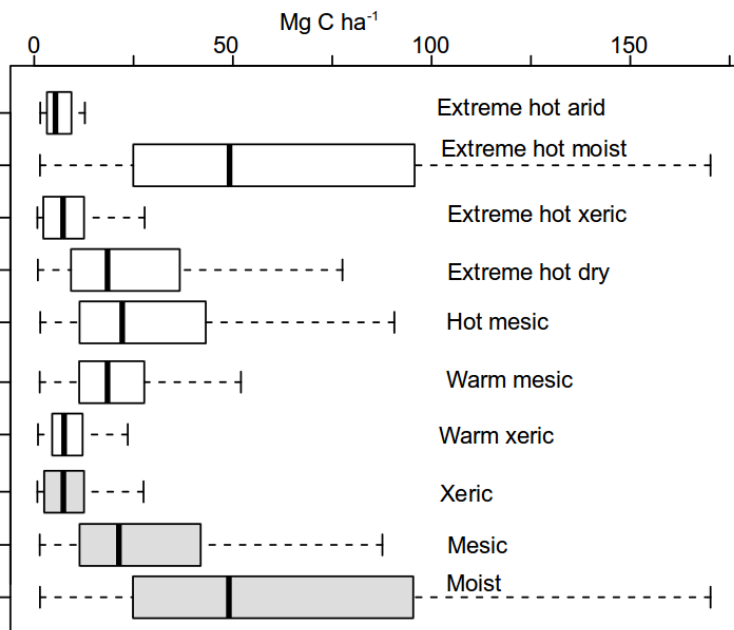


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599 **Figure 3** | ESA CCI 2015 simplified land-cover classes<sup>3</sup> and humidity zones. Please note that the  
 600 class open tree/shrub includes croplands.

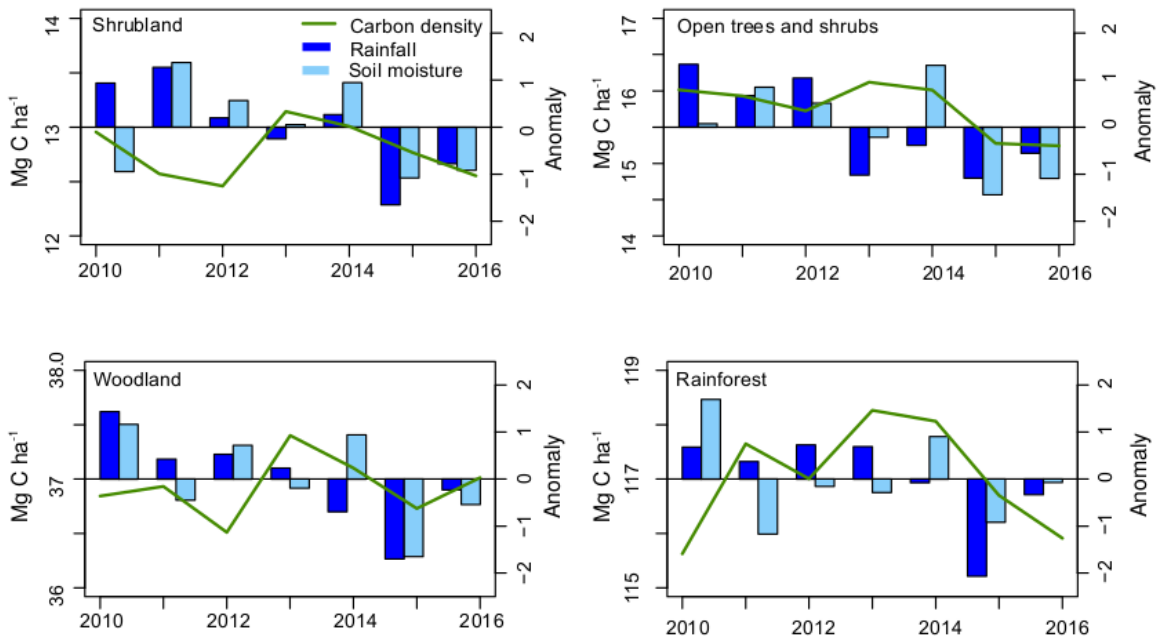
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603 **Figure 4** | Carbon density of the bioclimatic zones<sup>4</sup>. Note that the xeric, mesic, and moist zones (grey  
 604 bars) include the remaining sub-zones.

605

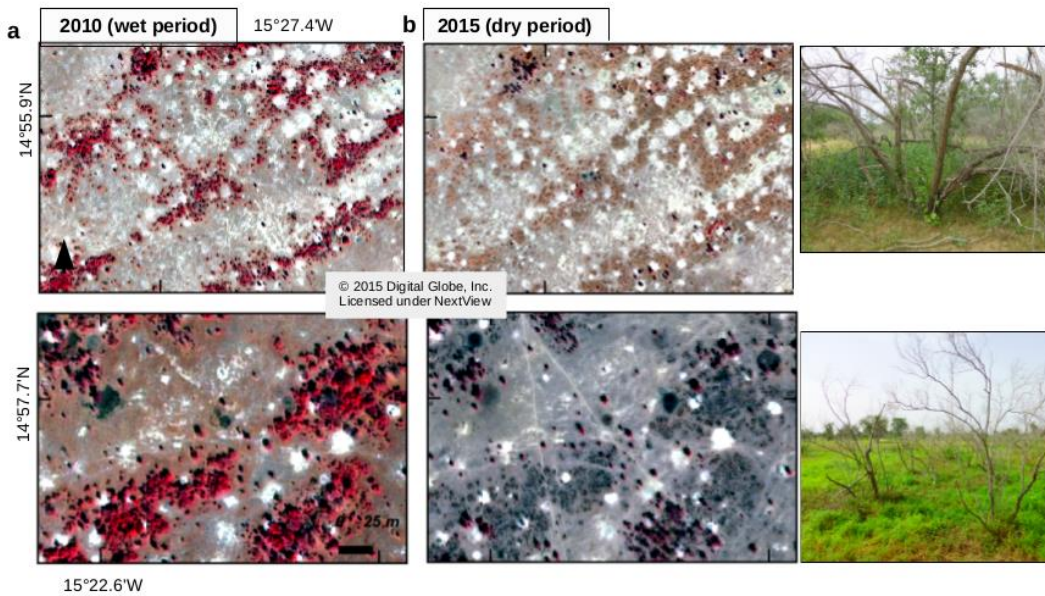


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608 **Figure 5** | Annual dynamics in L-VOD-estimated C density (in Mg C ha<sup>-1</sup>), as well as rainfall and  
 609 soil moisture anomalies per land cover class.

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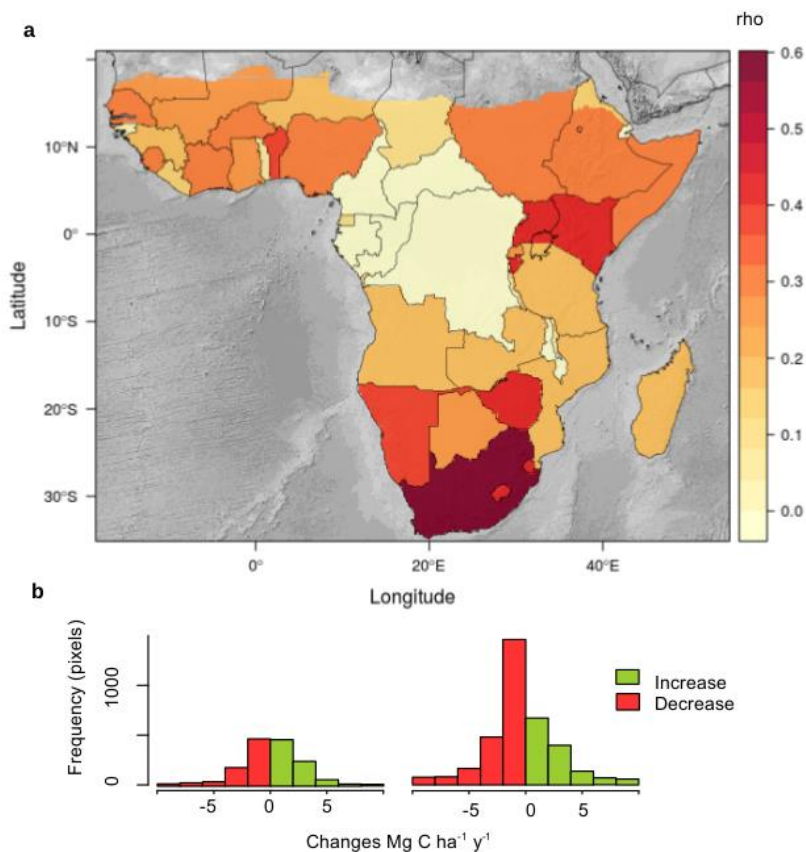


611

612 **Figure 6** | The mass death of *Guiera senegalensis* shrubs induced by dry years in large parts of Sen-  
 613 egal detected by L-VOD was also documented by very high spatial resolution satellite photos and  
 614 field photos. The satellite images show live woody plants as red objects. **a**, The red was captured by  
 615 the near-infra-red channel sensing photosynthetically active leaves, which were very dense after a

616 wet period in 2010. Images are from late December (2010) and early February (2015), both dates  
 617 where *G. senegalensis* typically has green leaves. **b**, Very limited shrub cover survived the dry period,  
 618 and only large trees had photosynthesizing leaves in 2015. Photos by M. Brandt October 2015<sup>5</sup>. See  
 619 Brandt et al.<sup>5</sup> for further details on the die-off.

620



621

622 **Figure 7 | a**, Spearman correlation between annual C density and soil moisture, averaged per country.

623 **b**, Left: changes in carbon density with no relationship to soil moisture (Spearman's rho < 0.2). Right:

624 changes in carbon density with a relationship to soil moisture (rho > 0.2).

625

626

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