Human population growth offsets climate-driven increase in woody vegetation in sub-Saharan Africa

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2 **Human population growth offsets climate-driven increase in woody vegetation in sub-Saharan Africa**

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23 **Abstract**

24 The rapidly growing human population in sub-Saharan Africa generates an increasing demand for agricultural

25 land and forest products which presumably leads to deforestation. Conversely, a greening of African drylands

26 has been reported but this has been difficult to associate with changes in woody vegetation. There is thus an in-

27 complete understanding of how woody vegetation responds to socio-economic and environmental change. Here

28 we used a passive microwave Earth Observation data set to document two different trends in woody cover for

29 1992-2011: an increase of 36% on the land area (6,870,000 km²), largely in drylands, and a decrease of 11%

30 (2,150,000 km²), mostly in humid zones. Increases in woody cover were associated with areas of low population

31 growth and driven by increases in CO_2 in the humid zones and by increases in precipitation in drylands, whereas

32 decreases in woody cover were associated with areas of high population growth. The spatially distinct pattern of

33 these opposing trends reflects (1) the natural response of vegetation to precipitation and atmospheric CO_2 and (2)

34 deforestation in humid areas, minor in size but important for ecosystem services, such as biodiversity and carbon

35 stocks. This nuanced picture of changes in woody cover challenges widely held views of a general and ongoing

36 reduction of the woody vegetation in Africa.

Introduction

Africa's human population has increased from about 230 million in 1950 to over 1000 million in 2010 and is expected to grow to as high as 5700 million by the end of the 21st century[1]. This growth has led to the expansion of agricultural land and the reduction of natural forests and other woody vegetation[2,3,6], affecting biodiversity and carbon storage[3]. Severe droughts in recent decades have also had an adverse impact on humid and sub-humid forested areas[7]. In contrast, studies of drylands have shown an increase in vegetation productivity over the last 30 years[4,8], also highlighting the importance of drylands for global carbon variability and as land CO_2 sink[9]. Whether this increase in vegetation productivity is driven by the growth of woody vegetation and/or by an increase in productivity of herbaceous vegetation is not clear. This is because the scattered nature of woody plants in drylands is very different from forests with closed canopies and challenging to detect with optical satellite imagery at regional to continental scales[10,11]. Previous studies have used vegetation indices as proxies for net primary productivity, but these indices measure the photosynthetically active part of the vegetation and most studies do not distinguish between woody and herbaceous vegetation[12,13]. Furthermore, studies of deforestation in humid areas traditionally report the presence or absence of forests[3] and do not assess gradual changes in forest biomass within existing forests (e.g., forest degradation). They are also based on temporal snapshots of satellite imagery at a higher spatial resolution and only capture forests based on given definitions, e.g. tree height and canopy cover percentage[3,14], which substantially underestimate shrubs and scattered trees in drylands[10]. Consequently, little quantitative information is available about the state, rate, and drivers of change in the cover of woody vegetation at the scale of the African continent. This information is crucial for ensuring that the design of natural resource management in relation to deforestation and desertification is based on observations rather than those based on narratives.

Results

Africa's woody cover is under change

We used a new passive microwave Earth Observation (EO) data set (Vegetation Optical Depth, VOD) that cap-

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62   tures continuous changes in the coverage of canopies of all woody phanerophytes, regardless of size, in both dry-

63   lands and humid areas[15-17]. We applied VOD as a proxy for annual woody cover and documented changes in

64   Africa's woody vegetation between 1992 and 2011, with a special focus on the changes in drylands and humid

65   areas (defined by the ratio between annual precipitation and potential evapotranspiration, Supplementary Fig.

66   1a). Woody vegetation changed significantly (slope of linear regression, $p<0.05$) during 1992–2011 in approxi-

67   mately half of sub-Saharan Africa (47% of land areas). A majority (77%) of the significant trends were positive,

68   covering 36% of sub-Saharan Africa and representing an overall increase of 2.1 woody cover (%) (Fig. 1a).

69   Most (70%) of the significant positive changes were in drylands covering approximately 4 900 000 km² (overall

70   change +2.9 woody cover (%)), mainly in the Sahel and southern Africa[18-20] (Fig. 2a). Positive trends are also

71   observed in the humid zones to a much smaller extent (2 100 000 km²), with an overall change of +0.8 woody

72   cover (%). Negative changes affected 11% of sub-Saharan Africa, of which 75% were in humid areas (approxi-

73   mately 1 600 000 km² in humid zones and 530 000 km² in drylands). The decline in woody cover primarily af-

74   fected areas that are also characterized by high carbon stocks (Supplementary Figs 2a, 2b), suggesting that areas

75   with the largest carbon sinks have been disturbed at the fastest rate. The classification of woody cover change in-

76   to bioclimate zones[21] confirms the overall tendency with larger increases in drier zones (except extremely hot xe-

77   ric) and lower increases and decreases in moister zones (Fig. 2d).

78

79   **Drivers of woody cover changes**

80   The positive changes in woody cover in Africa's drylands are significantly related to precipitation (Fig. 1a). In

81   contrast to herbaceous vegetation, woody plants can benefit from a higher variability and intensity of precipita-

82   tion[22], as in southern Africa and the Sahel (Supplementary Fig. 1c). The dependence on precipitation was corro-

83   borated with simulations of the vegetation using the dynamic vegetation model LPJ-GUESS[23], which simulated

84   an increase in woody biomass for 1992-2011, consistent with the satellite estimates of woody cover (Fig. 3). The

85   relative increase of both woody cover and biomass was largest in drylands, and factorial simulations of the indi-

86   vidual driving variables indicated that precipitation accounted for most of the simulated increase in woody bio-

87   mass in drylands such as the Sahel and southern Africa (Fig. 3, Supplementary Fig. 3). Increasing concentrations

88   of atmospheric CO_2 was a minor contributor to these dryland trends yet was the main variable driving the growth

89   of woody vegetation in humid areas, enhancing primary production[24] (Fig. 3, Supplementary Figs. 2, 3). The ab-

90   solute increase in woody biomass was largest in humid areas (mean increase of 0.04 kg C m^{-2} y^{-1} near the equa-

91   tor, Supplementary Fig. 2), coinciding with overall large stocks of woody biomass. Solar radiation, nitrogen dep-

92   osition and temperature had minor impacts on the changes in woody biomass (Supplementary Fig. 2).

93   This increase in woody vegetation driven by climate and CO_2, however, was offset by anthropogenic impacts,

94   especially in humid areas. The increase in woody cover in the VOD analysis was thus most pronounced in areas

95   of low human population density and change (Fig. 4). Areas and countries with a higher population density and

96   growth (Fig. 1b, Supplementary Fig. 1d) had decreases in VOD-based woody cover (Figs. 1a, 4, Supplementary

97   Fig. 4), offsetting the climate-driven increases in other parts of the humid zones (Figs. 2c, 3). This separation in

98   areas of high and low human pressure applied to both drylands and humid tropics. The average trend, however,

99   remained positive in drylands, even in areas with strong population growth, but was negative in humid areas

100 with strong population growth, regardless of the trends in precipitation and CO_2 (Fig. 2b, c). Populations in-

101 creased by an average of 40 persons km^{-2} over 20 years in areas where woody cover decreased supposedly due

102 to agricultural expansion, logging, and other uses of woody products. In contrast, populations increased by an

103 average of only 6 persons km^{-2} in areas where woody cover increased. Human population increase was highest

104 in moist and mesic bioclimate zones and woody cover changes were accordingly negative or low, whereas popu-

105 lation growth was lower in xeric areas and woody cover increases were higher (Fig. 2d). At the continental scale,

106 a simultaneous autoregressive model (SAR) explained nearly half of the spatial pattern of changes in woody cov-

107 er in terms of changes in population and precipitation ($r^2=0.46$), with population being more important than pre-

108 cipitation (standardized slopes of -0.27 and 0.08, respectively) (Supplementary Table 1).

109

110 **Discussion**

111 The opposing trends in dry and humid zones have implications for our understanding of environmental change in

112 sub-Saharan Africa. While areas of high population growth, mostly in humid zones, on average experience a de-

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crease in woody vegetation, areas with low population growth on average experience an increase in woody vegetation, mainly driven by changes in precipitation and CO_2 concentrations. This latter increase is not captured in official forest statistics, since much of it takes place outside of humid forests.

This implies that the 'problem' of woody cover loss - and thus carbon stocks decreases - in the humid forest zones is at least partly balanced by an increase in drylands. 'Bush encroachment' in savannas of southern Africa, however, has traditionally been considered an undesired effect[14,25]. Since the VOD data used to estimate woody cover does not allow direct estimation of carbon stocks, the exact balance between gains and losses in carbon cannot be directly assessed in this study. Further work combining field measurements, ecosystem modelling and new satellite-based passive microwave sensors is required to further understand these linkages. In humid areas, woody biomass may actually increase without any change in woody cover.

The close relationship between population growth and decreased woody cover suggests that agricultural expansion, urbanization and wood fuel harvest were the main causes of the decrease in woody cover, as also found in studies of tropical deforestation[3,26]. The reduction in woody cover tends to primarily affect areas with high carbon stocks and other studies suggest that these are also areas characterized by the highest biological diversity[27]. There is, however, no simple relation between losses and gains in woody cover and biodiversity. While diversity and productivity of natural vegetation are generally positively correlated[28], this does not exclude the possibility that great losses may be experienced in areas of deforestation, while only smaller gains are seen in drylands with increasing woody cover.

Due to the impact on land surface albedo, woody cover changes in dryland areas may trigger climate feed-backs. Since the hypothesized existence of a 'biogeophysical feed-back'[29], many studies have attempted to model such effects[30,31], with some research claiming that man-made afforestation efforts would give rise to increased precipitation[32]. The extent of the observed increase in woody cover in African drylands may impact climate if the increase continues in the coming decades, and this altered feed-back should preferably be implemented and tested in regional climate models.

Methods

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139 **VOD data and calibration to woody cover.** We define woody cover as the percentage of a given area covered

140 by woody vegetation, including both leaf and woody components (stem/branches) of woody plant canopies. The

141 unit is woody cover (%). The VOD data was retrieved from satellite passive microwave observations quantified

142 as brightness temperature based on the NASA-VU Land Parameter Retrieval Model (LPRM)[33]. Three passive

143 microwave sensors, i.e. the Special Sensor Microwave Imager, the Advanced Microwave Scanning Radiometer

144 – Earth Observing System, and the radiometer of WindSat are used to form the long-term data set by applying a

145 trend-preserving cumulative distribution function matching without changing the inter-annual variations and

146 long-term trends of the original retrievals[34,35]. The merged long-term VOD data set was gridded at a 0.25° spatial

147 resolution and monthly interval from 1992 to 2011 and is consistent between different sensors[11]. VOD is sensi-

148 tive to the total aboveground water content in both the photosynthetic (foliar) and non-photosynthetic (woody)

149 components of the vegetation stratum[15,36]. Soil moisture conditions are retrieved simultaneously with the VOD

150 information in LPRM and large variations in soil moisture can influence the accuracy of VOD, especially for

151 dense rainforest regions. Thus VOD values exceeding 1.2 are suggested to be excluded in vegetation studies[16].

152 The VOD signal has been separated from soil moisture and is used as a proxy for vegetation biomass globally[34].

153 The VOD seasonal variation is a combined effect of the seasonal dynamics of both herbaceous (including crops)

154 and woody vegetation[15]. We used the annual minimum VOD values as a proxy for woody vegetation cover to

155 minimize the influence of annual herbaceous vegetation[10] and avoided values exceeding 1.2 (Supplementary Fig.

156 5). Areas with perennial herbaceous vegetation may lead to an over-estimation of woody cover; however, the

157 woody cover % is usually higher in these areas concealing the influence from the herbaceous plant understory.

158 Also, VOD data have been used to estimate forest change in South America by limiting the range of VOD values

159 to 0.6-1.2[16]. We did not restrict the VOD range to also include young trees and shrubs, which form an important

160 part of the community of woody vegetation. Minimum VOD agrees well with field data based on a map of

161 woody cover for Sahel (r^2=0.80)[10] (Supplementary Fig. 5). A global map calibrated with optical high spatial res-

162 olution images and also assessing smaller trees produced similar results[37] and was thus used to transform the an-

163 nual minimum VOD to the unit woody cover (%) for further analyses (r^2=0.85, slope=0.86) (Supplementary Fig.

164 5). A third-degree polynomial regression was used for the transformation. Woody cover <10% was predicted

165 with an exponential regression to avoid underestimation of very low values. The VOD is insensitive to the ef-

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166   fects of atmospheric and cloud contamination, ensuring reliable retrievals in cloudy regions e.g. central Africa.

167   **Correlation between the trends in woody cover and changes in human population and precipitation.** Pre-

168   cipitation data were derived from the Climate Research Unit (CRU) (data set version 3.23), which is globally

169   available for a 0.5° grid at monthly scale and is based on the upscaling of data from rain gauges[38]. CRU precipi-

170   tation data intrinsically includes some uncertainty, as the number of stations used for each grid cell varies con-

171   siderably between cells and years. Even though consistency with other data sets has been shown (DINKU) and it

172   is the most widely used precipitation data set in dynamic vegetation modelling[39], results have to be considered

173   with caution[7]. We have tested the blended GPCP data set, without significant changes of the results, still it has to

174   be noted that a linear trend analysis on annually summed data includes uncertainties and simplifications. We

175   summed the monthly observations to obtain annual sums from 1992 to 2011 and resampled the data to 0.25° us-

176   ing a bicubic interpolation. Population data were acquired from Gridded Population of the World (GPW) v3[40],

177   which includes estimates for 1990, 1995, 2000, 2005, and 2010, gridded with an output resolution of 2.5 arc-mi-

178   nutes, resampled for this study to 0.25° (nearest neighbor). GPW population data were acquired from national

179   statistical offices and gridded based on the proportional method, which allocates population counts to grid cells

180   based on the proportion of each administrative areal unit that overlaps the cell. The gridded counts for existing

181   census years are then projected to the set of output years based on a simple model of population growth. The

182   modeling was thus not based on any additional layers of data, such as land cover, avoiding potential problems of

183   endogeneity between VOD and simulated population grids. A linear trend analysis was conducted for annual

184   woody cover and precipitation data, and the slope multiplied with the number of years to retrieve the absolute

185   change over time in the corresponding unit, facilitating the direct comparison with the human population data.

186   We quantified the relationships between the changes in woody cover (estimated by VOD), population increase

187   (GPW), and precipitation (CRU) by applying a simultaneous autoregressive model (SAR) (spatial error type[41])

188   to the three gridded data sets. The SAR model accounts for spatial autocorrelation and uses change in woody

189   cover as response and log(change in population) and change in precipitation as explanatory variables. The loga-

190   rithm of the human population data was applied since the relation between woody cover changes and human

191   population is non-linear at pixel scale, i.e. if a high number of population is reached (mostly in cities), the woody

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192 cover stops to decrease further. Standardized variables were used to enable model coefficients inter-comparison

193 (standardized variable = (variable - mean) / standard deviation).

194 Fires frequently occur in most African ecosystems. However, at the spatial and temporal scale of our analysis,

195 we do not expect changes in fire regimes as a major cause of changes in woody cover in itself but rather as a

196 consequence of human induced deforestation and land use change[42].

197 **Dynamic ecosystem model.** The dynamic ecosystem model LPJ-GUESS[23] was applied to simulate changes in

198 woody-biomass carbon in natural vegetation for 1992-2011. LPJ-GUESS simulates the distribution of plant func-

199 tional types, and each type is represented by four pools of biomass carbon: leaves, roots, sapwood, and heart-

200 wood. The latter two were added to represent the amounts of stem (wood) carbon. This variable is closely related

201 to the woody cover estimated by VOD, but especially in tropical forests, differences are expected, as VOD is not

202 able to fully penetrate the tree crowns[43]. Simulations were run for 1992-2011, applying monthly climate data

203 (temperature, precipitation, sunshine duration) from meteorological stations, gridded to 0.5°×0.5° resolution

204 (CRU TS 3.21[37]), monthly model-derived estimates for nitrogen deposition[44], and annual mean atmospheric CO_2

205 concentrations[45,46] based on ice-core data and atmospheric observations as forcing. Land use and land use

206 change were not accounted for in the simulations, which were only applied to quantify the changes in natural

207 vegetation. The simulations were preceded by a two-stage spinup: For the first stage, vegetation growth starts

208 from bare-ground conditions, using climatic data for 1901-1930, and CO_2 levels were kept constant at the con-

209 centration for 1901. For the second stage, representing 1901-1991, the actual climate data, atmospheric CO_2 con-

210 centration and N deposition were used.

211 In addition to a full simulation with the forcing as described above, five factorial simulations were performed to

212 separate the impact of individual driving variables. Only one of the four parameters (temperature, precipitation,

213 radiation, or CO_2) was applied using the transient data as described above, whereas the other three parameters

214 used a climatology for 1992-2011, applying monthly means over this 20-year period for the climatic parameters

215 and an annual mean for CO_2. In the fifth factorial simulation, similar to the transient CO_2 simulation above, the

216 changing CO_2 concentration was combined with a climatology for N deposition, to separate the impacts of at-

217 mospheric CO_2 and N deposition on the CO_2 fertilization. These simulations were applied to determine the im-

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218   pact of the individual driving variables on the simulated trend.

219   **Data availability** CRU precipitation data are available from the University of East Anglia

220   (http://www.cru.uea.ac.uk/). The global tree cover map is available from the Geospatial Information Authority of

221   Japan, Chiba University (http://www.iscgm.org/gm/ptc.html#use). VOD raster data are provided and available

222   by Yi Liu, University of New South Wales. Gridded population maps are provided by CIESIN (http://sedac.cie-

223   sin.columbia.edu/). Humidity zones are available from http://www.grid.unep.ch/index.php.

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241 **Figure 1 | Changes in woody vegetation and human population over two decades. a**, Significant trends of

242 woody cover (VOD) for 1992-2011, separated by the presence or absence of a significant (p<0.05) pearson cor-

243 relation with cumulative 2-year precipitation during this period. **b**, Changes in human populations for 1990-

244 2010. The maps in a and b share a clear pattern, especially areas with a decrease in woody cover, and no relation

245 to precipitation coincide with a high population pressure. **c**, SAR model of the changes between woody cover,

246 precipitation (both 1992-2011), and population (1990-2010). The units are expressed as change in the corre-

247 sponding unit over the period of analysis.

248

249 **Figure 2 | Changes in woody cover (VOD) in different humidity zones. a**, Areas with changes in woody cov-

250 er (linear regression of change in woody cover for 1992-2011). Annual profiles of woody cover for areas of stat-

251 istically significant changes in woody cover in **b**, drylands and **c**, the humid areas of sub-Saharan Africa (Supple-

252 mentary Fig. 1a). Black lines characterize areas of high human population increase (>30 persons km) and grey

253 lines areas of low human population increase (<10 persons km). **d**, Woody cover and human population changes

254 are grouped according to bioclimatic zones21.

255

256 **Figure 3 | Climatic drivers of changes in woody cover and biomass in sub-Saharan Africa.** Relative trends

257 (% of mean year-1) for 1992-2011 in woody cover (estimated with VOD) and woody biomass (simulated with

258 LPJ-GUESS) had similar patterns of change from north to south. The trends of woody biomass were mainly

259 driven by CO_2 (humid areas) and precipitation (drylands) (Supplementary Figs. 2, 3).

260

261 **Figure 4 | Links between changes in woody cover and human population**. Intervals of mean population den-

262 sity (1990-2010, Supplementary Fig. 1d) were used to group the changes in woody cover (VOD) associated with

263 population increases and the number of pixels showing significant woody cover change. A Chi-squared test be-

16

264 tween woody cover and population change indicated the statistically significant dependency between the two

265 variables.

266 **Supplementary Figure 1 | Humidity zones, changes in woody cover, trends in precipitation variability, and**

267 **mean population density. a,** Humidity zones showing Africa's drylands (arid, semi-arid, and dry-subhumid re-

268 gions) and humid areas. These zones are based on the ratio between annual precipitation and potential evapo-

269 transpiration for 1951-1980 and were obtained from http://www.grid.unep.ch/index.php. **b,** Absolute changes in

270 woody cover (%) (estimated from annual VOD minimum) for 1992-2011. **c,** Significant ($p<0.05$) slope of linear

271 regression of the annual coefficient of variation (CV) of CRU precipitation for 1992-2011 showing an increasing

272 CV in southern Africa and parts of the Sahel. **d,** Mean population density for 1990-2010.

273

274 **Supplementary Figure 2 | Trends of woody biomass and their drivers. a,** Mean woody cover (VOD) and **b,**

275 Mean woody-biomass carbon (LPJ-GUESS) averaged per latitude. Differences are due to the different variables

276 (woody cover vs total woody aboveground biomass, which differs mostly in humid forests because most woody

277 material is stored in the stems hidden below the canopy), the saturation of VOD in the humid forests, and the

278 poor capability of LPJ-GUESS to assess dryland shrubs, which omits large parts of southern Africa's woody veg-

279 etation. **b,** The deviation from the inter-annual mean woody biomass shows a steady temporal increase in woody

280 biomass. **c,** The total trends of woody biomass from north to south confirm the positive trend. The relative ef-

281 fects of CO_2, precipitation, radiation, and temperature on the trends identify CO_2 and precipitation as the main

282 drivers.

283

284 **Supplementary Figure 3 | Drivers of simulated trends of woody biomass (LPJ-GUESS). a, b,** Deviation

285 from the mean for 1992-2011. **c, d,** Contribution of CO_2 and precipitation to the total trend. A negative value in-

286 dicates an opposing trend and a positive value implies a high contribution to the total trend. CO_2 is identified as

287 the dominant driver of the trends of woody biomass in humid areas, and precipitation is the dominant driver in

288 drylands. Gray indicates non-significant trends.

289

17

Supplementary Figure 4 | Changes in woody cover and human population by country. Note that not only forests but all woody vegetation is captured, so these statistics are not comparable with forest losses and gains. Moreover, a change does not imply a replacement of a forest by a non-forested area.

Supplementary Figure 5 | VOD and woody cover calibration and validation. a, Raw annual VOD minimum is plotted against the woody cover map (http://www.iscgm.org/gm/ptc.html#use) which was used for transforming VOD minimum to the unit woody cover for sub-Saharan Africa. A third-degree polynomial regression was used for the transformation. Woody cover <10% was predicted with an exponential regression to avoid underestimating very low values. **b**, The predicted woody cover map (using VOD) agrees well with the global map[37] (r^2=0.85, slope=0.86) and the unit woody cover (%) was thus used throughout the manuscript. **c**, For validation purpose, VOD minimum is plotted against a field data trained woody cover map of Sahel[10]. **d**, The mean woody cover estimated with VOD minimum is shown.

Supplementary Table 1 | SAR model of the changes in woody cover. Response variable: VOD (woody-cover change, 1992-2011). Explanatory variables: log(change in population) (persons km^{-2}, 1990-2010), log(population density) (persons km^{-2}, 1990-2010), change in precipitation (mm year^{-1}, 1992-2011), and mean annual precipitation (mm year^{-1}, 1992-2011).

Supplementary Figure 6 | Flowchart of the applied data sets and methods.

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