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2 **West African farmers decrease woody cover in savanna-woodlands but promote it in semi-arid**
3 **savannas**

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25 **ABSTRACT**

26 Woody vegetation in farmland acts as a carbon sink and provides ecosystem services for local people,
27 but no macro-scale assessments of the impact of management and climate on woody cover exists for
28 drylands. Here we make use of very high spatial resolution satellite imagery to derive wall-to-wall
29 woody cover patterns in tropical West African drylands. Our study reveals a consistently high woody
30 cover in farmlands along all semi-arid and sub-humid rainfall zones (16%), on average only 6% lower
31 than in savannas. In semi-arid Sahel, farmland management increases woody cover to a greater level
32 (12%) than found in neighbouring savannas (6%), whereas farmlands in sub-humid zones have a
33 reduced woody cover (20%) as compared to savannas (30%). In the region as a whole, rainfall, terrain
34 and soil are the most important (80%) determinants of woody cover, while management factors play
35 a smaller (20%) role. We conclude that agricultural expansion cannot generally be claimed to cause
36 woody cover losses, and that observations in Sahel contradict simplistic ideas of a high negative
37 correlation between population density and woody cover.

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41 **INTRODUCTION**

42 Concerns about declining woody cover in West Africa have been raised since the early 20th century^{1,2}.
43 In the 1970s and 80s, negative trends in woody vegetation, presumably associated with the ‘Sahel
44 drought’ and agricultural expansion, were observed and became part of the desertification/land deg-
45 radation discourse, later termed the ‘Sahel syndrome’³. Rapidly growing settlements and urban mar-
46 kets demanded large amounts of firewood and charcoal, and concerns about an upcoming ‘fuelwood
47 crisis’ were widespread⁴. Certain parts of the Sahel experienced an increase in export-oriented agri-
48 culture (e.g. groundnut production in Senegal and cotton production in Mali), which was understood
49 to have contributed to a downward trend in woody cover as well⁵. All these concerns had substantial
50 impact on natural resource policies of the Sahelian countries and the donors supporting them: New
51 forests were planted (e.g. “shelterbelts” in northern Nigeria, village wood-lots in Mali and Burkina

52 Faso) and new attempts were made to regulate firewood harvesting and charcoal production⁶. Grand
53 schemes of ‘green belts’ across the Sahel, already suggested before the 2nd World War by Stebbing¹,
54 were taken up again. However, from the 1980s and onwards, research by botanists⁷, foresters⁸, geog-
55 raphers⁹⁻¹² and anthropologists¹³ painted a more complex picture on the relationship between humans
56 and woody vegetation: Studies at village and landscape scales showed that increase and decrease in
57 woody cover occurred simultaneously in different parts of the Sahel^{7,11,14}. The ‘case study’ character
58 of this research, however, made it difficult to generalize findings, since the representativeness for the
59 larger region was difficult to establish¹⁵.

60 The idea of a progressing land degradation in arid and semi-arid West Africa was also challenged
61 from another side: Regional-scale analyses of time series of vegetation indices derived from different
62 satellite systems showed that fluctuations of the Sahara desert boundary are common¹⁶ and that the
63 Sahel was experiencing a ‘re-greening’ after the drought years of the 1970s and 1980s¹⁷. These studies
64 did not, however, allow separation of the contributions from the herbaceous and woody vegetation
65 components. Only recently has this been achieved^{18,19} revealing that the greening may be partly at-
66 tributed to an increase in woody cover. The coarse spatial and limited temporal resolution of the
67 satellite images used and the complexities of the methods applied imply that such assessments of
68 vegetation change in the Sahel do not necessarily form a robust basis for estimating trends in woody
69 cover locally, and leave considerable room for speculations regarding the nature of the woody vege-
70 tation changes. Attempts to produce global maps^{20,21} of tree cover focus mainly on forests in humid
71 areas and yield unrealistically low canopy cover estimates in drylands, which are thus commonly
72 ignored in woody vegetation assessments²². These obstacles have made it difficult to study linkages
73 between woody vegetation, rainfall and humans for West African farmlands and savannas -
74 knowledge that is essential in the face of demographic and climatic change.

75 The recent access to large volumes of DigitalGlobe, Inc. commercial satellite images with a spatial
76 resolution as low as 0.3 m in the panchromatic band marks a technical tipping point in dryland re-
77 search²³ and allows us to produce a reliable, fine-scaled assessment of woody cover²⁴. While the short

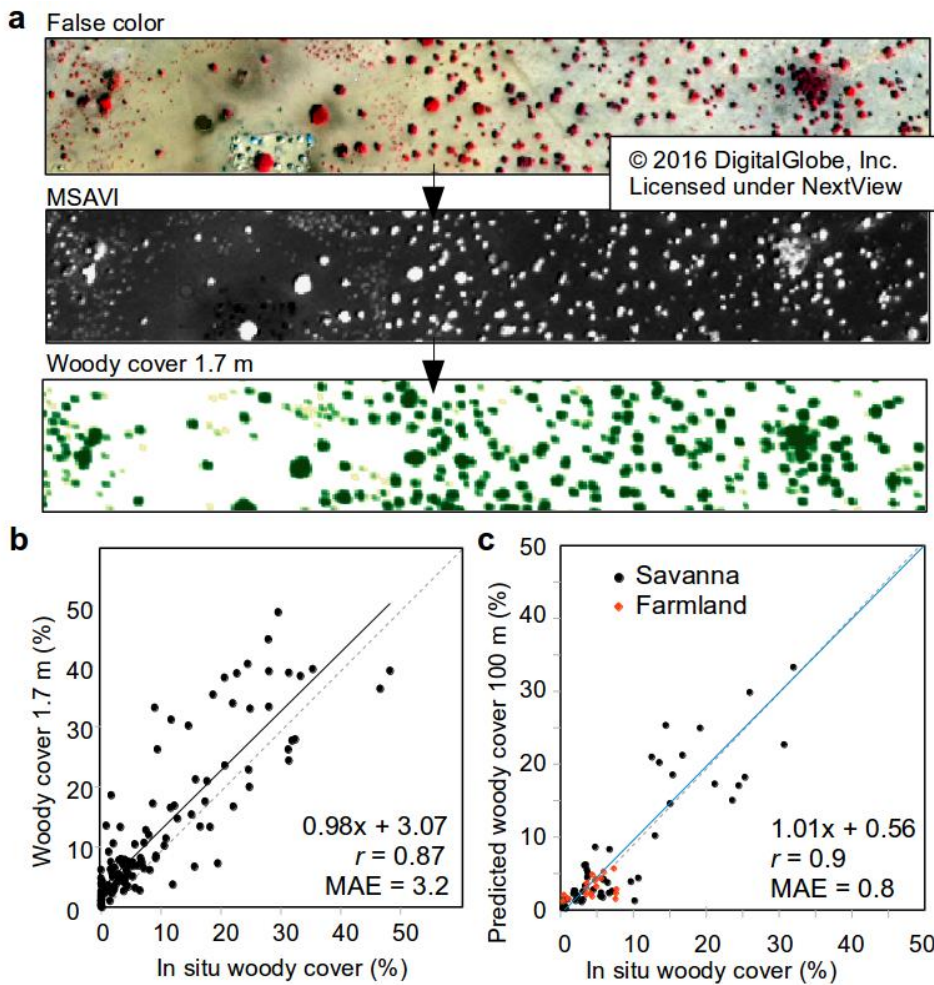
78 period for which these data have been available does not allow to estimate long term trends, the high
79 level of detail of such maps makes it possible to analyze how woody cover is spatially correlated with
80 the above-mentioned causal factors, from which explanations for changes in woody cover over time
81 can be inferred: if woody cover is threatened by the expansion of cultivation, we would expect woody
82 cover to be substantially lower in farmlands than in the adjacent uncultivated savannas. If local har-
83 vesting of firewood is a cause of loss of woody cover, we would expect woody cover to be lowest
84 close to settlements. Here we test these hypotheses in order to obtain a complete understanding of the
85 distribution of woody cover in relation to human presence and thus provide a valuable reference for
86 individual case studies that generate in-depth contextual knowledge but have a limited scope for gen-
87 eralization.

88

89 **RESULTS**

90 **High resolution woody cover mapping.** The assessment of woody vegetation at hectare level re-
91 quires high spatial resolution satellite data in order to highlight nuanced spatial differences (Supple-
92 mentary Fig. 1). Here we derived canopy cover from multispectral DigitalGlobe QuickBird-2, Geo-
93 Eye-1 and WorldView-2 satellite images at 1.7 m resolution without using the panchromatic band
94 (Fig. 1, Supplementary Figs 2, 3) to train Synthetic Aperture Radar (SAR) and Normalized Difference
95 Vegetation Index (NDVI) imagery and predict continuous woody cover from 0 to 100% at 100 m
96 resolution for the arid (150-300 mm rainfall), semi-arid (300-600 mm) and sub-humid (600-1000 mm)
97 zones of West Africa. The validation pixels are fairly in line with the prediction (Mean Absolute Error
98 (MAE) of 3.7, $r=0.69$, slope=0.84, $n=661,708$; Supplementary Figs 4,5) which also agrees well with
99 independent *in situ* data (Fig. 1b,c). The woody cover maps shown in Fig. 2 reveal a broad scale
100 pattern following the biogeographical regions but also a high level of detail showing differences at
101 hectare scale. Woody cover is on average 3% in the arid zone, increases to 9% in the semi-arid, and
102 exceeds 20% in the sub-humid zone (Fig. 2).

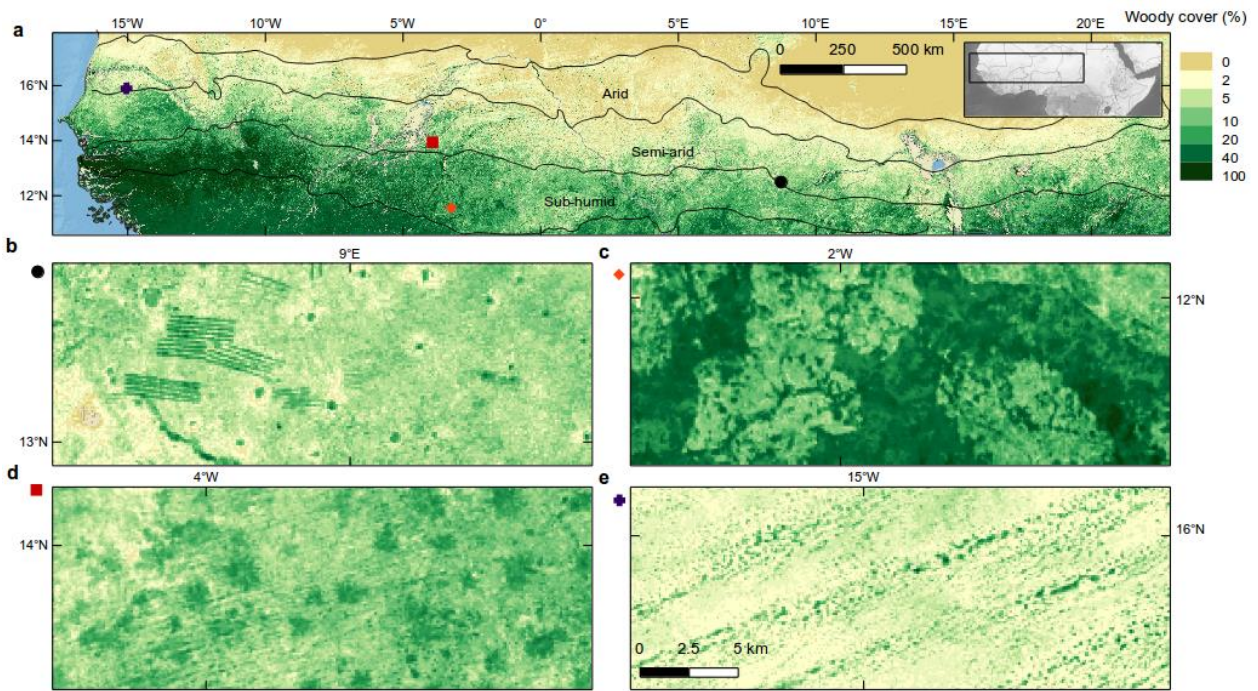
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105 **Figure 1 | High resolution woody cover mapping and validation with field data.** *a*, Woody cover
 106 derived from MSAVI at 1.7 m resolution (Supplementary Figs 2-5). *b*, The woody cover map at 1.7
 107 m resolution was validated with in situ data from northern Senegal (MAE of 3.2, $r=0.87$, slope=0.98,
 108 $n=144$). Woody cover >10% ($r=0.76$); woody cover <10% ($r=0.77$). *c*, The predicted woody cover
 109 map (100 m) was validated with independent in situ data from Senegal ($n=24$), Mali ($n=23$) and
 110 Niger ($n=25$) (MAE=0.8, $r=0.9$, slope=1.01) both for woody cover >10% ($r=0.75$) and woody cover
 111 <10% ($r=0.86$).

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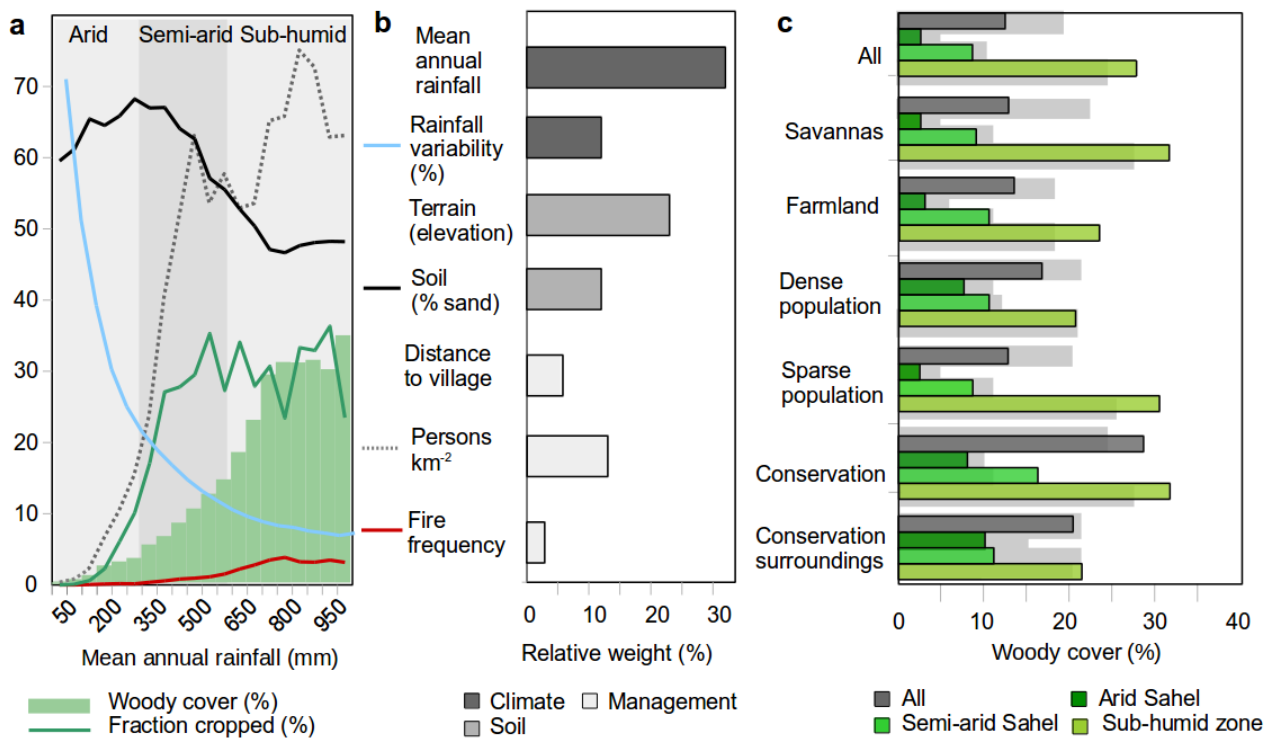
114 **Figure 2 | Predicting woody cover.** *a*, Predicted woody cover at 100 m resolution with locations of
 115 the close-up views (*b-e*) indicated. *b*, Woody cover in farmlands at the semi-arid Nigeria/Niger border.
 116 The presence of trees within villages makes them stand out as green clusters. Woody corridors (shel-
 117 terbelts) can be identified. *c*, Farmlands in sub-humid Burkina Faso are expanding into remnants of
 118 forest reserves. *d*, The villages in the Malian Seno Plain are surrounded by a well managed woody
 119 vegetation *e*, The sandy pastoral zone of arid Senegal has locally high concentrations of woody plants
 120 on fine textured soils of inter-dunes..

121

122 **Determinants of woody vegetation cover.** The coexistence of herbaceous and woody plants in sa-
 123 vanna is governed by rainfall regime (mediated by run-off and water table), soil, human management
 124 (including cutting, clearing for cropping, crop-fallow management, fire and grazing)²⁵. These factors
 125 are interlinked and vary both spatially and temporally with available rainfall (Fig. 3a). Here we tested
 126 environmental variables in a decision tree ensemble model, which explained in total 67% of the pre-
 127 dicted woody cover at 100 m resolution (Fig. 3b). Out of these, mean annual rainfall²⁶ is the major
 128 factor limiting woody cover (32%). It is followed by terrain (elevation, 23%) and human population

129 density²⁷ is ranked third (13%), shortly before soil²⁸ (sand fraction, 12%) and inter-annual rainfall
 130 variability (12%). Distance to villages (6%) and fire frequency (2%) have a rather low relative weight.
 131 Taken together, climatic (44%) and edaphic (35%) factors are more important than management fac-
 132 tors (21%) (Fig. 3b). Elevation here is used to represent the terrain morphology including dune struc-
 133 tures, depressions, plateaus, valleys, etc. Already a moderate topography can have significant impact
 134 on rainfall run off/on and soil texture, explaining the high percentage explained by terrain. A land use
 135 and rainfall zone grouping is conducted to further explore the relationships between humans and
 136 woody cover and to rule out a bias by the rainfall gradient (Fig. 3c).

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139 **Figure 3 | Determinants and patterns of woody cover.** *a*, Factors potentially impacting woody cover
 140 are averaged along the rainfall gradient (50 mm steps). *b*, The relative weight of variables in a
 141 decision tree model explaining predicted woody cover (150-1000 mm) with an overall explaining
 142 power of 67%. *c*, Mean woody cover grouped into savannas ($n=148,286,890$) and farmland
 143 ($n=43,374,091$), areas of dense (>50 persons km^{-2} ; $n=23,127,786$) and sparse (<50 persons km^{-2} ;

144 $n=167,752,160$) population densities, as well as conservation areas ($n=8,902,702$) and their sur-
145 roundings (5 km) ($n=6,040,825$). Standard deviations are shown as grey background bars. Total pix-
146 els: 191,660,981.

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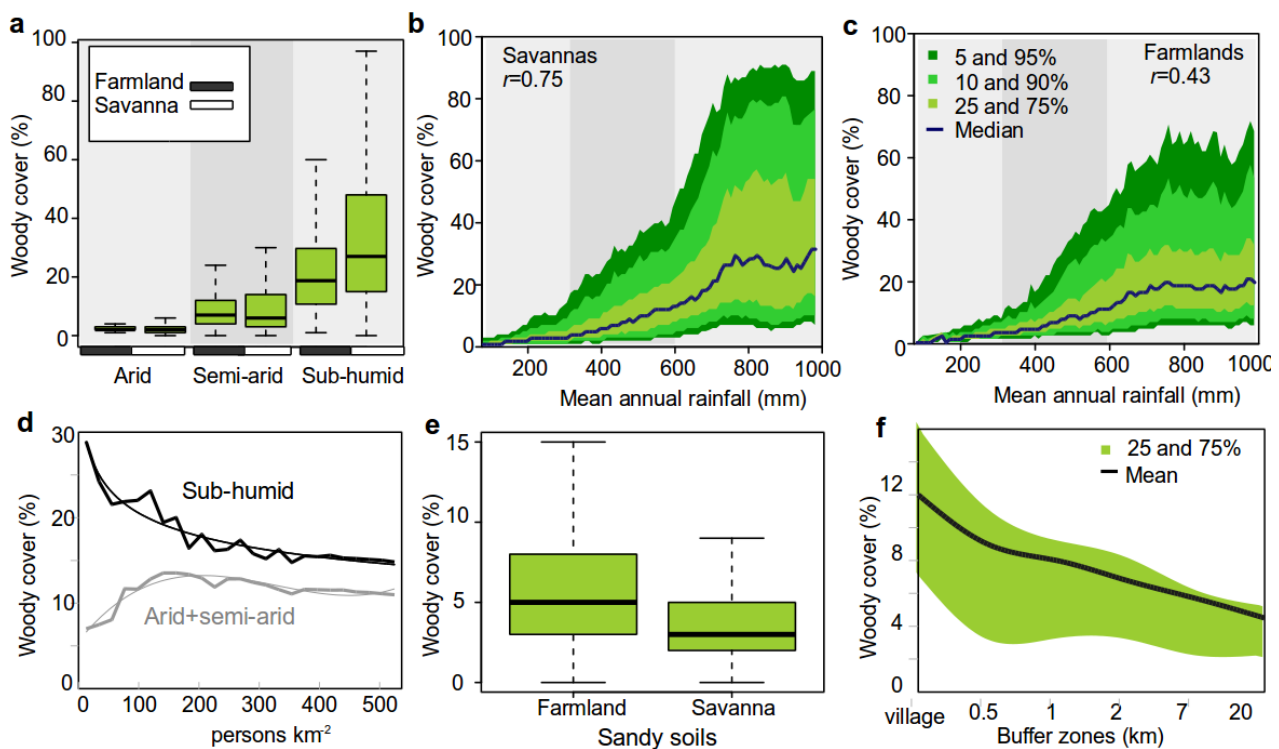
148 **Rural management impacts on woody cover.** We applied a new farmland mask at 100 m resolu-
149 tion²⁹ to separate the study area in uncultivated savannas and farmland (Fig. 4a-c). For savannas, there
150 is a high positive correlation between woody cover and rainfall ($r=0.75$, $P<0.05$) with saturation
151 around 30% canopy cover in the sub-humid zone, and with considerable spatial variations (Fig 4b).
152 The pattern is strikingly different for farmlands (Fig. 4c): Although woody cover increases with in-
153 creasing rainfall ($r=0.45$, $P<0.05$), the majority of the cultivated areas have a canopy cover of around
154 12%, independent of rainfall, and variability is much lower than in savannas (Fig. 4a-c). Average
155 woody cover in arid and semi-arid Sahel is higher and less variable in farmlands (arid: 3%, semi-arid:
156 11%) than in savannas (arid: 2%, semi-arid: 9%). Sub-humid savannas on average have a higher
157 woody cover (33%) and wider range than woody cover in farmlands (23%) (Figs 3c, 4a). More pre-
158 cisely, the median of farmland woody cover is higher as compared to savannas below 680 mm annual
159 rainfall but lower from 680 to 1000 mm (Fig. 4a-c).

160 In the sub-humid zone, woody cover reaches high values primarily in rural areas with low population
161 density, and decreases in urban areas with >100 persons km^{-2} (Fig. 4d). Interestingly, a different pat-
162 tern is observed in the arid and semi-arid Sahel, where both woody cover and population density are
163 increasing along the rainfall gradient up to 160 persons km^{-2} . Woody cover decreases at higher pop-
164 ulation densities in and around larger cities. On average, areas with a higher population density also
165 have a higher woody cover than sparsely populated areas in the arid (7/2%) and semi-arid (12/10%)
166 Sahel, but the opposite is observed in the sub-humid zone (31/21%) (Figs. 3c, 4a-c).

167 Woody cover in conservation areas is generally higher (29%) in comparison to surrounding areas (5
168 km) (21%) (Fig 3c). This difference is most pronounced in the semi-arid Sahel (conservation 16%;

169 conservation surroundings 11%) and sub-humid zone (conservation 35%; conservation surroundings
 170 23%). Differences between farmland (typically occupying sandy soils) and savannas (including vast
 171 areas of non-arable soils) become more comparable and exclude a bias by environmental pre-conditions
 172 when studying woody vegetation on sandy soils only²⁸. Sandy soils used for cultivation have
 173 remarkably higher woody cover than comparable sandy soils which are uncultivated (Fig. 4e). Buffer
 174 zones were drawn around 37,294 villages on sandy soils (Supplementary Fig. 6). Shade trees are
 175 responsible for a high canopy cover in the village centers (~12%), and areas surrounding villages
 176 within a distance up to 1.5 km have a moderately high woody cover (7-9%) which decreases gradually
 177 further away (<5%).

178



179

180 **Figure 4 | Land management impacts on woody cover.** *a*, Woody cover grouped into farmland and
 181 savanna for each bioclimate zone. *b*, Woody cover (a random sample of 1%; $n=2,812,563$) is shown
 182 along the rainfall gradient (10 mm steps) for savannas and *c*, for farmlands. *d*, Woody cover is aver-
 183 aged within intervals of population density showing opposing patterns for arid/semi-arid (150-600
 184 mm) and sub-humid (600-1000 mm) zones. *e*, Comparison between woody cover on farmland and on

185 savannas, both on sandy soils only (entire region; $n= 73,848,805$). *f*, Woody cover as a function of
186 distance to the village center (entire region; average for 37,294 villages on sandy soils).

187

188 **DISCUSSION**

189 The traditional assumption that human presence has an exclusively adverse impact on West Africa's
190 woody vegetation has been challenged by local studies showing that human presence can also have
191 positive impacts on tree cover¹³, as in the case of agroforestry systems encouraging and maintaining
192 high tree densities³⁰. Farmers' awareness of reforestation as a climate change adaptation measure has
193 been shown³¹, and farmer managed natural regeneration or tree planting programs are common
194 throughout West Africa. However, there regional assessments of their success are rare, and our study
195 shows that farmlands indeed support significant woody vegetation densities, supporting the results of
196 ³². However, this is not the case in all landscapes and under all agricultural management regimes. The
197 expansion of farmland leads to an initial reduction of woody vegetation, especially in higher rainfall
198 zones with dense human population where savanna and woodland woody cover is dense¹⁰. If the rural
199 population is dense, this expansion is ongoing, and forest reserves and savannas are being progres-
200 sively reduced and converted into farmland, with no woodland vegetation left except in protected
201 areas. It has also been proposed that the recent increase in woody vegetation, which is a global phe-
202 nomenon in semi-arid lands supposedly driven by climate and altered atmospheric CO₂^{33,34}, often
203 takes place in sparsely populated regions whereas high population growth decreases woody cover³⁵.
204 However, our current study shows that this is not always the case, and once savannas and woodlands
205 are transformed into farmland, management often aims at promoting and protecting valuable species
206 (e.g. *Faidherbia albida*, *Vitellaria paradoxa*) by clearing/coppicing other species which also favours
207 the growth of a few tall trees. Additionally, shade trees in village areas (e.g. *Azadirachta indica*)
208 provide numerous ecosystem services which are more valuable for the local people³⁶ than those of
209 typical savanna species (e.g. *Combretum glutinosum*, *Guiera senegalensis*) and also contribute to
210 carbon storage at landscape scales.

211

212 The results presented allow a robust generalization concerning woody cover and the relationships
213 between woody cover and various explanatory factors. First of all, we describe rainfall as the main
214 determinant of woody cover. We confirm increases in woody cover in arid and semi-arid Sahel with
215 rainfall up to ~ 650 mm³⁷. The median woody cover stabilizes in the sub-humid zone (650 - 1000 mm)
216 around 30% woody cover.

217 Secondly, and most importantly, we show that the role of climate is modified by humans. The way
218 management affects woody cover relates to the amount of annual rainfall and livelihood strategy: The
219 median woody cover in arid and semi-arid zones is equal and partially higher in farmlands than in
220 savannas up to an average annual rainfall of around 650 mm year⁻¹. In sub-humid zones, this differ-
221 ence is reversed, with median woody cover being lower in farmlands than in savannas. Unlike the
222 rainfall driven gradient of woody cover found in savannas, the woody cover in farmlands is spatially
223 homogeneous (constant median, narrow range) across all rainfall zones. Local studies are likely to
224 show considerable differences between countries and eco-regions, but on average the claim that cul-
225 tivated areas in the arid and semi-arid Sahel have a relatively high woody cover compared to savannas
226 is robust. Two possible explanations may be suggested: (1) Farmers protect or plant trees due to a
227 strong interest in the ecological services they provide³⁶. Harvesting of wood for fuel and building
228 material mostly takes place further away from the village areas in uncultivated land (and in fallows,
229 which are here classified as farmland). (2) Farmland is generally located on the most suitable and
230 fertile soils, whereas savannas also includes soil conditions less favorable for vegetation growth. Our
231 results show, however, that the difference is still clear and even more evident when comparing only
232 areas of sandy soils in both the cultivated and non-cultivated areas, so the latter explanation does not
233 affect our conclusions.

234 Thirdly, analysis of the effect of proximity to villages on woody cover discloses that woody cover is,
235 on average, densest within village areas and decreases with distance. This is based on a great number
236 of villages that are very different in size and structure and this distance-function may differ depending

237 on village size, rainfall level, agricultural practices and ethnicity of the population. Yet, at the regional
238 scale it is clearly demonstrated that the idea that high local population pressure causes woody cover
239 to decrease around villages does not hold true. Rather, the alternative notion that farmers protect or
240 plant trees in and around villages¹³ is supported. The cause of a dense woody cover around villages
241 is related to the above mentioned finding that farmlands have a relatively high woody cover. Fields
242 are often located close to villages, while more distant savannas are mainly exploited for fuelwood.
243 Our results showing a positive relationship between population density and woody cover seems to
244 support the ‘more people, less erosion’ argument³⁸ of environmental recovery and sustainability as-
245 sociated with agricultural intensification. However, this only holds true in semi-arid areas and only
246 up to a certain threshold of population agglomeration, i.e. at rural village level but not for larger urban
247 settlements.

248 With an average canopy cover of $13 \pm 17\%$, we found substantially higher values (including larger
249 variations) than other studies and data sets (e.g. $1.9 \pm 3\%$ in MODIS continuous fields²⁰). It has to be
250 taken into consideration that our definition of canopy cover is more inclusive, since we include scat-
251 tered woody vegetation, whereas the MODIS product is limited to forests with large sized trees. Stud-
252 ies based on these data sets²² are thus unable to provide detailed assessments of patterns and determi-
253 nants of dryland woody cover.

254 The data and methods we used do not allow us to move beyond ‘woody cover’, which is the simple
255 projected coverage of canopies. For many research applications additional variables would be of in-
256 terest. From a botanical and ecological perspective, information on species would be desirable; from
257 a climate change point of view, carbon stocks and transpiration may be in focus; foresters may require
258 woody volume and quality; and from a pastoralist’s perspective, the annual production of green foli-
259 age of fodder species is most important. Finally, from a socio-economic perspective, we would profit
260 from estimating the amount of trees available for each person. Additional work, more fully exploiting
261 very high resolution imagery (e.g. mapping height and canopy size of individual trees), is likely to
262 bring us further in these directions. This study was, however, able to demonstrate the potential of

263 West African farmland and savannas to provide a range of ecosystem services. Moreover, the wall-
264 to-wall coverage and the high number of pixels in our analysis provide a solid basis for understanding
265 woody cover in different landscapes at the regional West Africa drylands scale and this can be applied
266 to other dryland regions globally. Case studies will still remain extremely valuable as a means of
267 obtaining insights into the complex processes linking environmental factors and land management
268 decisions to woody cover across the variety of local circumstances. By combining wall-to-wall anal-
269 ysis with process studies at local scale, a more robust basis for developing environmental policies
270 may be established.

271

272 **METHODS**

273 We define woody cover as the percentage of ground surface covered by the vertical projection of
274 woody plant crowns. The technical framework of this study adapts local-scale approaches of model-
275 ing dryland woody cover^{39,40} into reproducible regional/global scale assessments, as the unprece-
276 dented amount of very high spatial resolution (VHR) satellite images now available via the NextView
277 license across the region allows for a new level of detail and larger geographic coverage. Most of the
278 2006 available images are from November/December (2008-2015) when most of the evergreen and
279 deciduous woody species have green leaves, whereas the herbaceous vegetation is senescent. If no
280 images from these months were available, the period was extended to February. The modified soil-
281 adjusted vegetation index (MSAVI) was calculated with a spatial resolution of 1.7 m, and woody
282 cover was extracted by using a texture based feature extraction method. Field measurements (2000-
283 2015) of woody cover at selected sites served as an independent validation of the remote sensing
284 mapping approach. To achieve a woody cover map of the entire area, the spatially detailed woody
285 cover data derived from VHR images were used to train a gradient boost decision tree regressor to
286 predict woody cover from PROBA-V NDVI and PALSAR-2 images at high resolution (100 m). We
287 tested several filtering approaches and seasonal metrics derived with various methods^{41,42} and decided
288 to apply a moving median window for filtering the time series and filtered 10 day composites as input

289 variables for the regressor to keep the process reproducible. A farmland map²⁹, satellite based rainfall
290 estimates²⁶ (CHIRPS), fire (MCD45A1) and population data²⁷ (Worldpop) were used for analysis of
291 woody cover patterns in relation to climate and land management determinants (Supplementary Fig.
292 7).

293 **Rainfall zones of the study area.** We used rainfall isohyets derived from CHIRPS²⁶ mean annual
294 rainfall (1981-2016) to divide the study area in arid Sahel (150-300 mm), semi-arid Sahel (300-600
295 mm), and sub-humid lands (600-1000 mm) (Supplementary Fig. 8a). The zones correspond well with
296 expected bioclimatic zones with different woody species⁴³. Whereas *Acacia ssp* and *Capparidaceae*
297 are dominant in the arid and semi-arid, it is *Combretaceae* and *Fabaceae* in more sub-humid parts.
298 In general, woody cover changes from sparsely scattered in the arid areas to closed canopies in the
299 open woodland and riverine forest of the sub-humid zones.

300 **Field data.** Field data is available from extensive field work in the Ferlo in Senegal (144 sites sur-
301 veyed in 2015), from the CSE (Centre de Suivi Ecologique) campaigns in Senegal (24 sites surveyed
302 between 2000 and 2015 every other year)¹⁸, from the Gourma region in Mali (23 sites)⁴⁴ and the
303 Fakara in Niger (25 sites)⁴⁵. All surveys measure the projected canopy cover⁴⁴ over plots of various
304 areas (50 m to 1 km), and the data were recalculated in m² per ha and percentage canopy cover.

305 **Extraction of canopy cover from very high spatial resolution data.** The mapping technique was
306 designed to be robust to the use of different sensor types, acquisition dates (i.e. different leaf density),
307 atmospheric conditions, as well as being applicable to various situations ranging from sparse shrub
308 population in arid zones to closed canopy cover woodland in the sub-humid zone. The robustness was
309 assessed by independent field data (Fig. 1b) and is demonstrated in Supplementary Fig. 5. Digital-
310 Globe QuickBird-2, GeoEye-1 and WorldView-2 were orthorectified and the scenes were screened
311 for clouds and other disturbances. All selected multispectral images were resampled (nearest neighbor)
312 to 1.7 m resolution matching GeoEye-1. MSAVI was calculated and rescaled from 0 to 100⁴⁵ to pro-
313 duce a quantitative base for estimation of canopy cover. Only if a pixel is fully covered with a green

314 leaved canopy, the MSAVI will reach higher values, partly covered pixels (e.g. parts of the crown
315 area or small size shrubs and bushes) have relatively lower values. Visual screening of numerous
316 images showed that most woody plants have MSAVI values above 50, which was robust across all
317 rainfall zones and image acquisition dates. A texture based Haralick feature extraction (8 bins) was
318 then run considering all pixels with values between 50 and 100⁴⁷. The advanced texture filter can be
319 parameterized to extract objects (in our case crown canopies) from their surroundings and from larger
320 objects. The feature termed “mean” was used - the objects have grayscale values depending on their
321 distinctiveness - which was rescaled between 0 and 100, resulting in a quantitative estimate of the
322 areas covered by canopies. Each image was visually screened and images dominated by obvious mis-
323 estimations (strong under- or overestimation) were discarded. The final values represent the subpixel
324 woody coverage, with 100 being fully covered and 0 free of any green leaved woody vegetation. The
325 advantage of this weighted method over a binary tree/no tree classification is that a sub-pixel coverage
326 (i.e. small crowns and edge pixels) receives a lower weight, thus preventing overestimation (Supple-
327 mentary Figs 3,5). Moreover, using such weighting emphasizes larger canopies, which makes the
328 product more robust against a rapidly changing (fire, field clearing, etc.) bush layer, which receives
329 a lower weight. Burned areas were manually clipped to keep only high quality training images. In
330 total, 219 images were used for the model (about 1% of the study area). The accuracy of the method
331 was calibrated and tested with field data (144 plots) from Senegal. The square field plots are small
332 (50 x 50 m) and include canopies of all size classes thereby being well suited to validate the VHR
333 product. For the accuracy assessment, canopy cover surveyed for each field plot was compared with
334 VHR imagery derived canopy cover averaged for polygons marking exactly the surveyed area.

335 **Prediction of canopy cover at 100 m resolution.** Advanced Land Observing Satellite (ALOS)
336 Phased Arrayed L-band Synthetic Aperture Radar (PALSAR)⁴⁸ and PROBA-V NDVI⁴⁹ were used for
337 a large scale assessment of woody vegetation (wall-to-wall coverage of West African drylands). For
338 PALSAR-2, we used 100 m cross-polarized HV mosaics converted to gamma-naught values and av-
339 eraged from 2009 and 2010 over the study area⁴⁸. For PROBA-V, daily atmospherically corrected

340 images at 100 m resolution were combined into 10 day maximum value composites to achieve full
341 coverage in the lower latitudes, which are more frequently affected by cloud cover. Images are avail-
342 able from 2014 to 2016 and the maximum value for each 10 day composite over the 3 years was
343 selected to avoid low values which can be caused by clouds and burned areas. To further filter out
344 noise, a 30 day running median window was applied, choosing the median value of 3 images. This
345 procedure does not only filter out low value spikes caused by clouds, but also high value spikes which
346 can be caused by herbaceous vegetation (also dry season rainfall events can lead to a flush of herba-
347 ceous plants). Both possibilities potentially introduce noise in our analysis dedicated to woody vege-
348 tation and this filter is a simple way of reducing noise but keeping the original seasonality.

349 The woody cover derived from the VHR imagery was used to train the PALSAR and 36 (10-day
350 frequency) PROBA-V NDVI images to obtain a regional-scale woody cover map at 100 m resolution.
351 First, the canopy cover images at 1.7 m resolution were aggregated to 100 m by summing all values
352 (representing sub-pixel canopy coverage), multiplying each pixel with the original pixel size ($1.7 \times$
353 1.7 m) and dividing it by 100 so the derived map shows the projected area within the pixel covered
354 by woody plants with the unit percent woody cover. The data was then split into training and valida-
355 tion sets by randomly dividing all pixels in two groups, each including 50% of the original pixels. A
356 large number of pixels ($n=1,323,416$) were available for training and for validation. The training set
357 was then used to fit a non-parametric gradient boost regressor (GBR), which produces a prediction
358 model by means of an ensemble of boosted decision trees⁵⁰. The input data were the PALSAR and 36
359 filtered 10 day NDVI composites covering an entire year. The quality of the model was assessed by
360 comparing the independent validation set with the predicted woody cover. Predicted values above
361 100 were masked out and below 0 set to 0. Due to the large amount of training and validation pixels
362 and their spread and representation of different landscapes, over-fitting is not a concern and the model
363 output is expected to be robust. It should be noted that the woody cover is predicted continuously
364 from 0 to 100 (but rounded to 1% steps), leading to a lower statistical fit than similar approaches
365 binning canopy cover into classes of e.g. 10% intervals.

366 Even though all woody plants have a distinctively different phenological behavior than herbaceous
367 annuals, six different forms of evergreen and deciduous leaf phenologies exist, ranging from short
368 deciduous plants shedding their leaves early in the dry season to evergreen species keeping their
369 leaves throughout the year⁵¹. To avoid an underestimation of the crown cover of stands dominated by
370 deciduous species, the median NDVI ratio between November (a period where all trees have leaves)
371 and February-March (most deciduous species are without or only little leaves at this time) was calcu-
372 lated. Field data from Senegal on species composition (ratio deciduous/evergreen per site) was com-
373 pared with the NDVI-ratio for corresponding sites (Supplementary Fig. 4b). The output of the GBR
374 prediction was then multiplied with this ratio, enhancing the predicted cover of stands with deciduous
375 species but keeping evergreen stands unchanged. The impact of fire is mitigated by the multi-year
376 maximum and median value over several images. Finally, wetlands and irrigated areas were masked
377 out by combining Globland30⁵² and ESA LC CCI (2010) land cover maps. An independent accuracy
378 assessment was conducted with field data from Senegal, Mali and Niger. These data are based on
379 circular plots along 1 km transect lines (representing larger areas of homogeneous landscapes), spaced
380 at 200 m intervals. The canopy cover of all woody plants was surveyed for these plots and averaged
381 for each transect⁵¹. Polygons (3x3 km) covering the field sites were drawn and model-estimated
382 woody cover extracted and averaged for each site giving valuable information on the overall fit of the
383 predicted canopy cover.

384 **Environmental data.** Several data sets were used to analyze the relationship between woody cover,
385 rainfall and management. CHIRPS rainfall was summed from 1981 to 2016 for each year and an
386 average annual climatology was calculated (Supplementary Fig. 8a). The original CHIRPS resolution
387 of 5 km was resampled (bilinear interpolation) to match the 100 m resolution of PROBA-V. A recently
388 developed farmland map was used²⁹, which reflects the area under agriculture around 2014 (Supple-
389 mentary Fig. 8b). The original resolution of the farmland map was 100 m and villages areas are
390 masked out. Conservation areas were derived from the World Database on Protected Areas⁵³. It in-
391 cludes National Parks and protected forests of which most have been established during colonial time

392 by the administration in charge of forest and wild life. The conservation areas are found predomi-
393 nantly in low populated regions characterized by poor soil fertility, but population growth and expan-
394 sion of farmlands has often encroached into these areas. They are however edaphically different and
395 the woody cover is therefore not entirely comparable to neighboring farmlands. Woody cover in the
396 conservation areas was compared with woody cover in adjacent areas (within 5 km buffer around
397 conservation area boundaries). We used Worldpop for the year 2010³⁰ as human population data set.
398 The resolution of 1 km was resampled (bilinear interpolation) to 100 m for this study.

399 To improve the comparability between farmlands and savannas, we used the newly developed African
400 soil map at 250 m resolution²⁸ to extract sandy soils (from rock outcrops, shallow soils with dense
401 shrubland, clayey valleys, etc) (Supplementary Fig. 8c). We used the soil texture fraction to calculate
402 a mask leaving only areas with >70% sand in the depth 0-1 m.

403 To test the impact of rural population on woody vegetation, all settlements with a size smaller than 5
404 km² were extracted from the Globeland30⁵² data set, resulting in 37,294 villages. The original reso-
405 lution of 30 m was resampled to 100 m. We established buffer zones with 0.5, 1, 2, 5 and 20 km
406 distance to the village areas (Supplementary Fig. 6).

407 A gradient boost classifier⁵⁰ was applied to test the determinants of predicted woody cover. Explana-
408 tory variables of this model based on an ensemble of decision trees were (1) mean annual rainfall, (2)
409 fire frequency deriving the number of fires between 2000 and 2015 from MODIS burned area product
410 MCD45A1 (Supplementary Fig. 8d), (3) rainfall variability (the coefficient of variation of annual
411 sums between 1981 and 2016), (4) the sand fraction from the soil map, (5) the elevation derived from
412 SRTM digital elevation model (90 m), (6) human population³⁰, and (7) distance from the villages
413 (buffer zones). Predicted woody cover was grouped in classes (0-3%, 3-10%, 10-20% and >20%) to
414 meet the requirements of the classifier and a random sample of 1% of the pixels was chosen ($n=$
415 2,812,563) which was used as response variable. The model was run with 10 different random sets of
416 pixels to ensure that no bias emerges by the selection. Due to the decision tree structure of the model,

417 correlations between the explanatory variables can be neglected. The accuracy of the model is calcu-
418 lated by setting aside 60% of the pixels, which are then used to test the predicted results.

419 **Data availability.** Commercial very high resolution satellite images were acquired within the
420 NextView license program. The copyright remains at DigitalGlobe and a redistribution is not possible.
421 PROBA-V NDVI data is freely available at VITO (<http://proba-v.vgt.vito.be/>). Worldpop population
422 data is freely available at the University of Southampton (<http://www.worldpop.org.uk/>). MODIS
423 MCD45A1 burned area product is can be freely obtained at [http://modis-](http://modis-fire.umd.edu/pages/news.php)
424 [fire.umd.edu/pages/news.php](http://modis-fire.umd.edu/pages/news.php). The soil map is freely available at ISRIC ([http://www.isric.org/con-](http://www.isric.org/content/african-soilgrids-250m-geotiffs)
425 [tent/african-soilgrids-250m-geotiffs](http://www.isric.org/content/african-soilgrids-250m-geotiffs)). CHIRPS rainfall data is freely available at the Climate Hazard
426 Group (<http://chg.geog.ucsb.edu/data/chirps/>). PALSAR mosaics are freely available from JAXA
427 (http://www.eorc.jaxa.jp/ALOS/en/palsar_fnf/fnf_index.htm). The farmland mask is available from
428 Marie-Julie Lambert upon request. The woody cover map at 100 m resolution is available from the
429 corresponding author upon request.

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546

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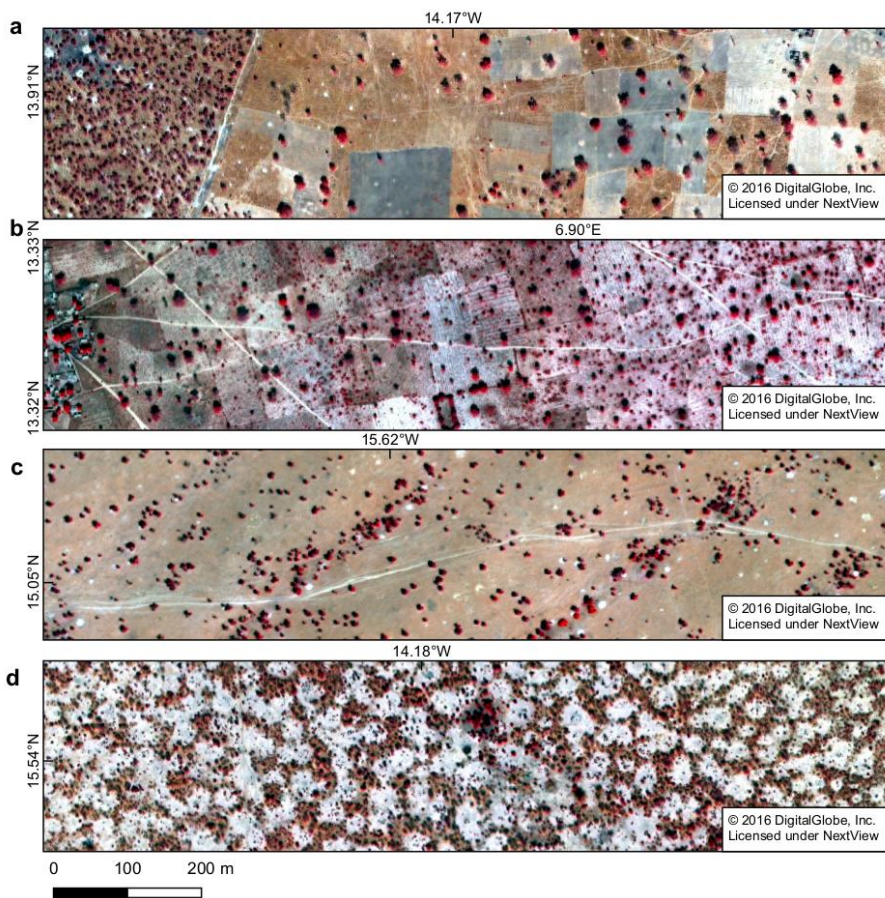
554 **Author Contributions.** M.B., R.F., S.H., P.H. and K.R. designed the study. M.B., X.T. and F.T. con-
555 ducted the analyses with support by LK, OM, KR, RF, SH, MD, PH. The data was provided by CT,
556 JD, KM, MD, LK, CV and PH. KR and MB drafted the manuscript with contributions by all authors.

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

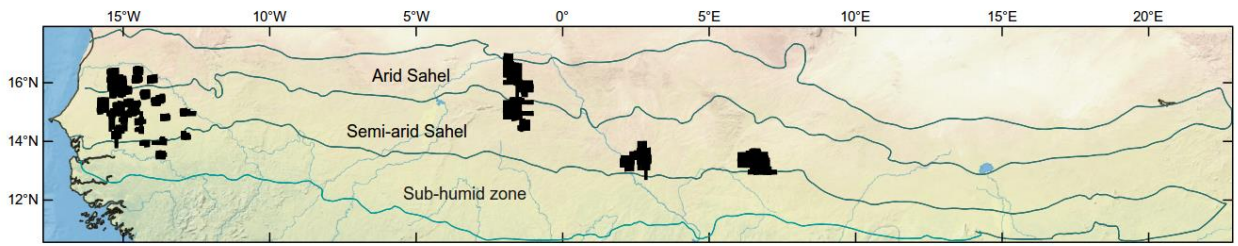
559 **Materials & Correspondence.** Correspondence and material requests should be addressed to M.B.
560 (mabr@ign.ku.dk).

561 **Supplementary Information**



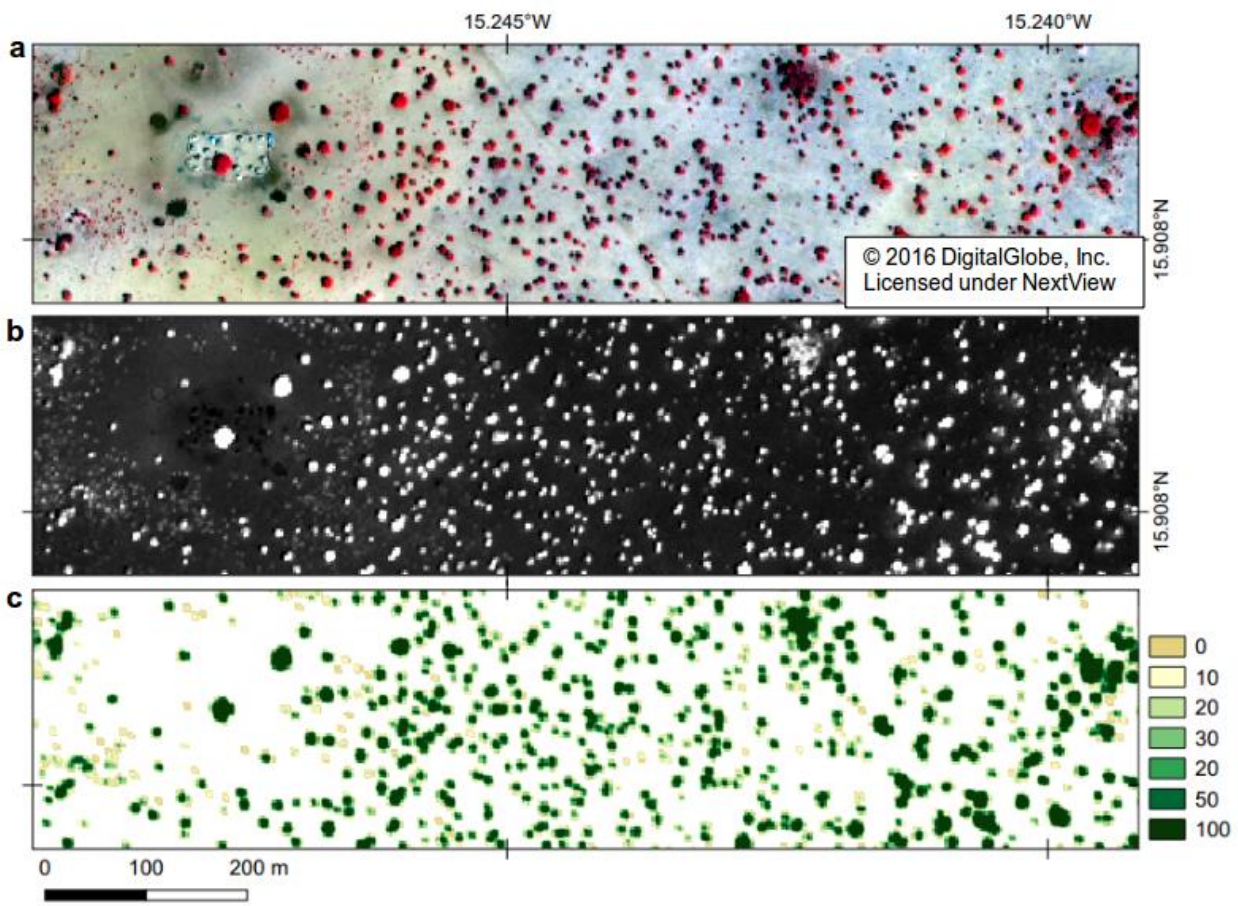
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563 **Figure S01 | Examples of woody vegetation patterns.** The images are pansharpened false color
564 composites showing woody plants in reddish colors. **a**, Farmland in central Senegal including tall
565 trees (to the right) with a sharp border to uncultivated land with dense cover of small trees and shrubs
566 (to the left). **b**, Farmland in northern Nigeria surrounding a village with both trees and coppiced
567 bushes. **c**, Rangeland in the sandy Ferlo, Senegal. Trees and shrubs are denser in the linear inter-dune
568 depressions than on the dune. **d**, Woody vegetation in the pastoral lands of eastern Senegal forms a
569 reticulate thicket of shrubs. These soils are not arable and woody cover can be high.



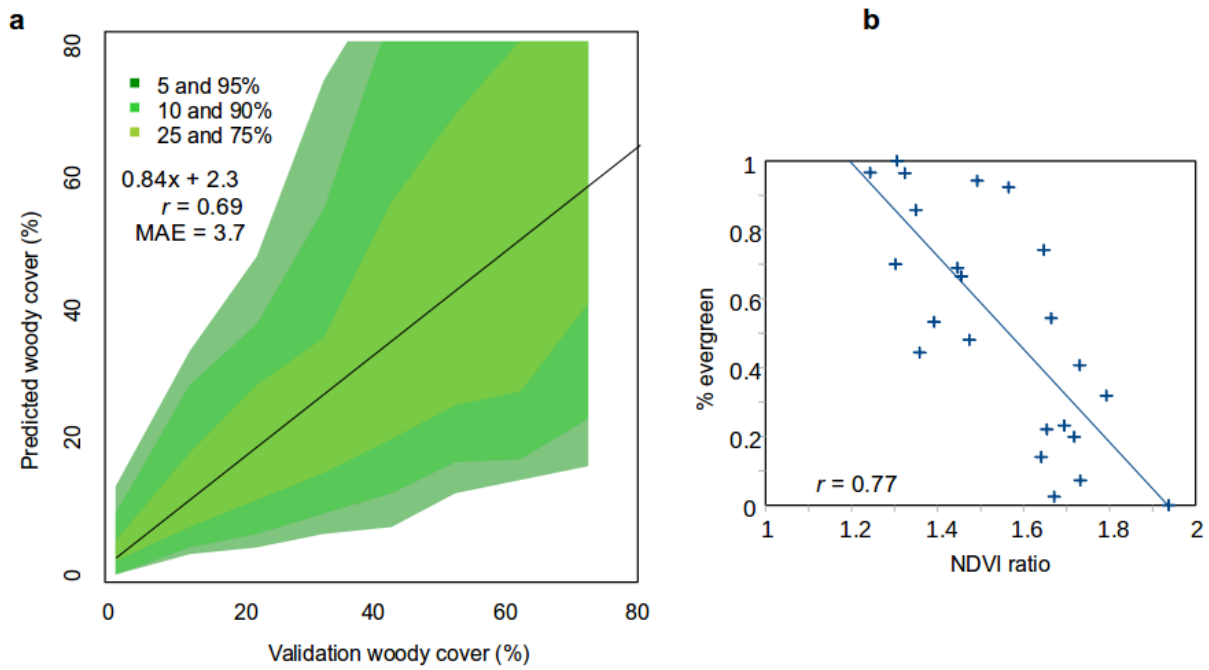
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571 **Figure S02 | Study area and location of the available VHR images.** The location of the images
572 correspond to field sites which are described in details in literature^{20,49,50}.



573

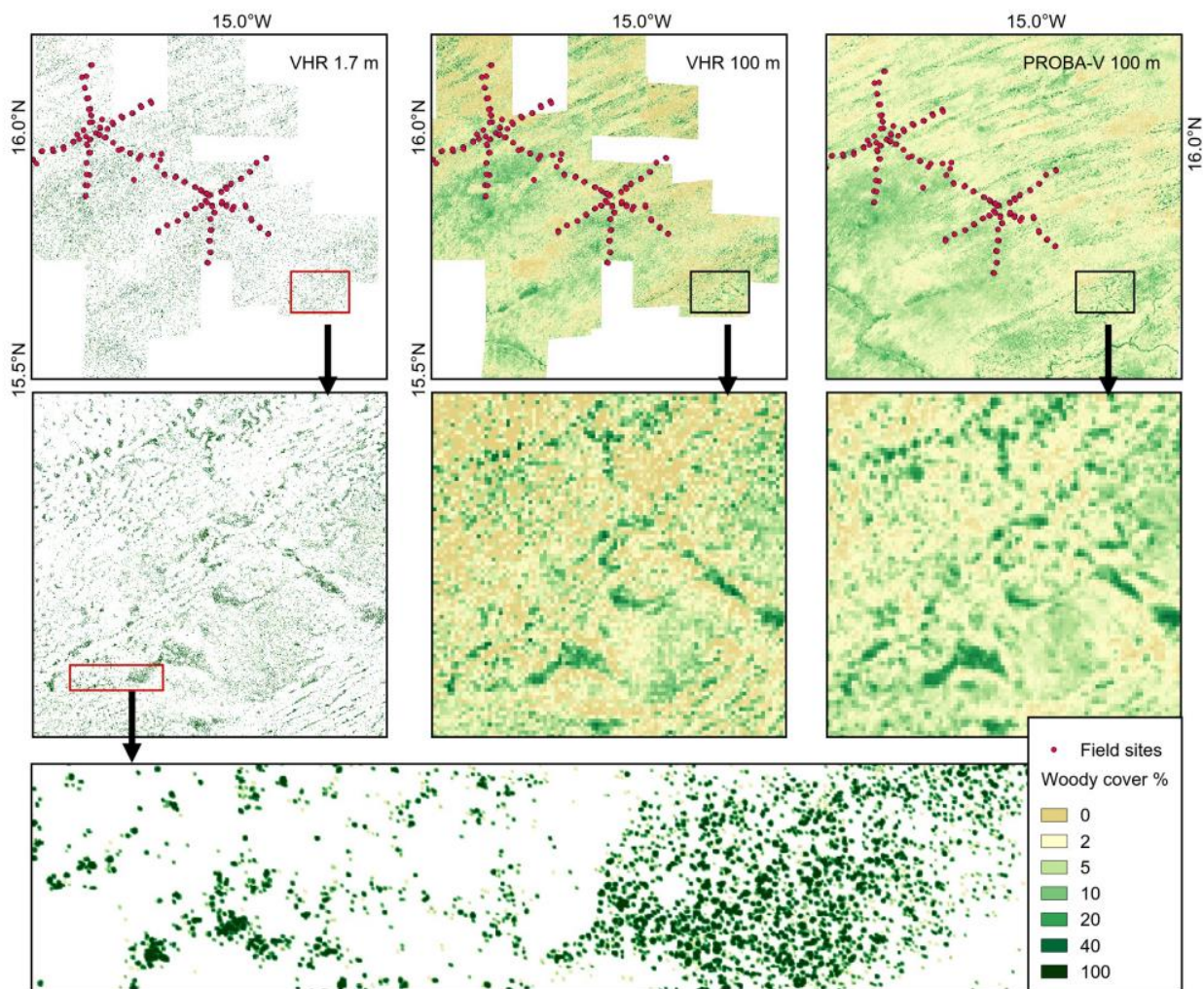
574 **Figure S03 | Development of the very high spatial resolution woody cover map.** **a**, A pansharp-
 575 ened WorldView-2 false color composite (band 753) from January 2012 shows different size classes
 576 of woody plants. **b**, MSAVI was calculated from WorldView-2, GeoEye-1 and QuickBird-2 and high-
 577 lights all woody vegetation from their surroundings. MSAVI was rescaled from 0 to 100. **c**, MSAVI
 578 values between 50 and 100 (thus not considering tree shadows, very small shrubs and non-woody
 579 vegetation across different land cover) were used for a Haralick feature extraction using Orfeo toolbox
 580 (advanced textures, x radius=1, y radius=1, histogram number of bins=8). The output channel mean
 581 was calculated as follows: $\sum_{i,j} ig(i, j)$, where $g(i, j)$ is the frequency of elements in the Grey Level Co-
 582 occurrence Indexed List (GLCIL) whose index is (i, j) . The result of the Haralick feature extraction
 583 was rescaled (0-100) to provide an estimation of the woody cover at very high spatial resolution. Note
 584 that the small bushes around the settlement receive a lower canopy cover value than grown up trees.
 585 Also note that (b) and (c) are not pansharpended.



586

587 **Figure S04 | Prediction of woody cover at 100 m.** **a**, Woody cover predicted with the gradient boost
 588 regressor at 100 m is compared against the validation pixels, which were separated from the training
 589 pixels (50% of the values) before the model was established. **b**, The NDVI ratio used to balance an
 590 underestimation of deciduous stands is compared with field data (24 sites, 1 km transects) from Sen-
 591 egal. The field data shows the percentage of evergreen species for each stand. See Brandt et al., 2016
 592 for further details on the methodology and the field sites (location and data collection).

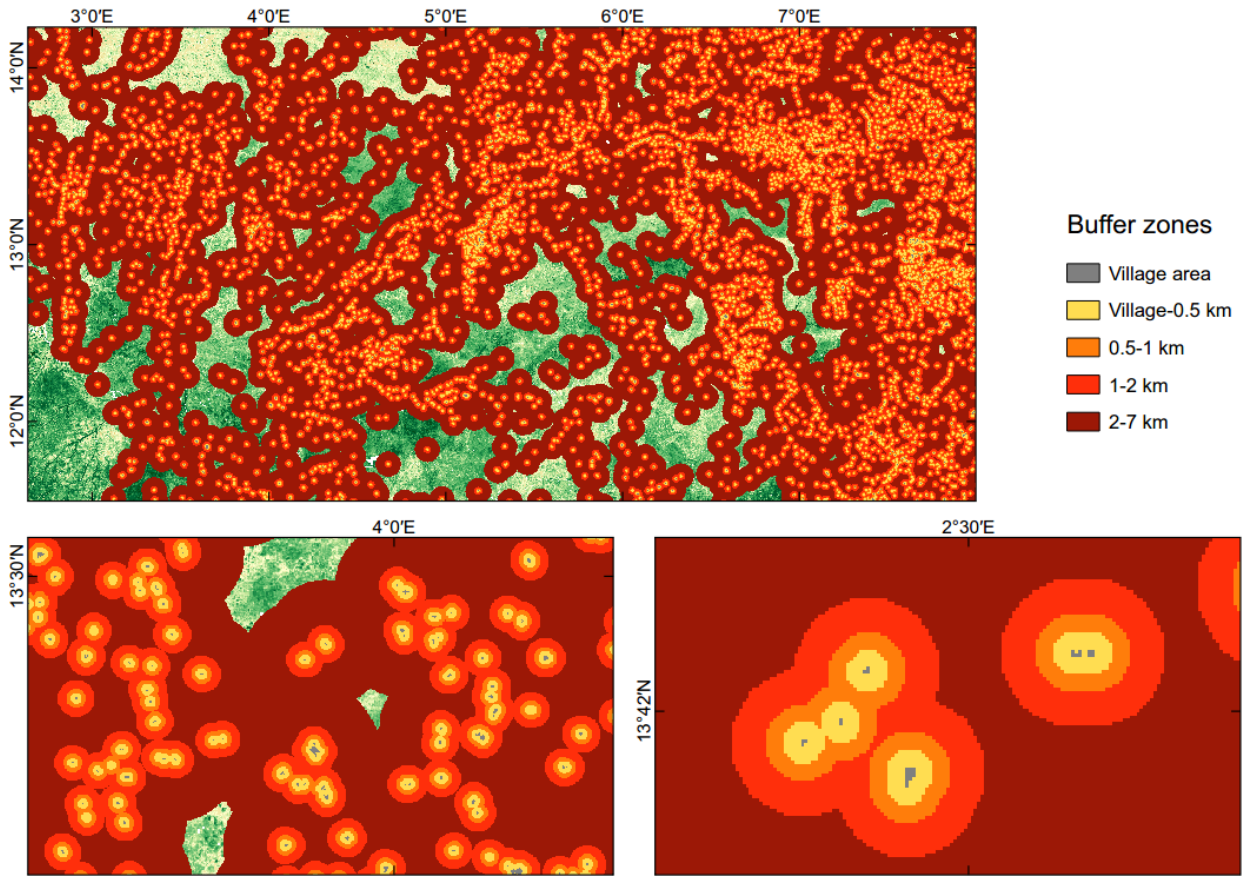
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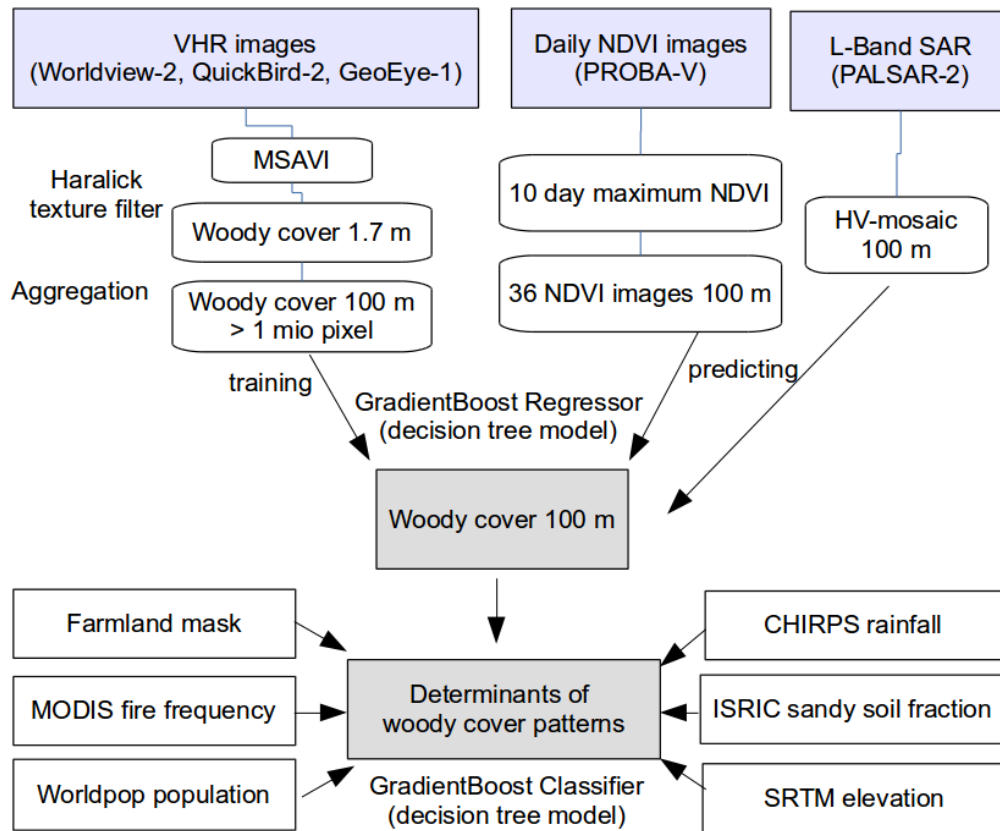
595 **Figure S05 | Testing the work-flow in northern Senegal.** Canopy cover was derived from very high
 596 spatial resolution satellite images (1.7 m; left side and bottom), aggregated to 100 m (middle), and
 597 used to train PROBA-V and PALSAR to retrieve a woody cover map at 100 m resolution (right side).
 598 The example is from the Ferlo region in Senegal (boarder region of arid and semi-arid Sahel) and
 599 demonstrates that the method is able to derive woody cover from about 30 different VHR images
 600 from different sensors and different dates with a seamless transition between the images. The range-
 601 land of northern Senegal (Ferlo) was selected as the core testing area. The landscape consists of fixed
 602 dune systems with alternating sand dunes and linear inter-dune depressions with finer textured soils
 603 (from silty sands to loamy clay). Woody cover follows nutrient and water availability, with higher
 604 density on fine textured soils, low and scattered density on sandy soils and a denser shrub-cover on
 605 shallow silty sand soils on ferricrete. A higher density of larger trees can be observed along the Ferlo
 606 river. This pattern is further interfered by human management (plantations, grazing, cutting, fires).

607 Modeling of woody cover is challenging due to the low dynamic range of values with only depres-
608 sions having a higher woody cover at 100 m scale. At coarser scale (e.g. 1 km), even depressions are
609 merged with the remaining areas and the overall canopy cover remains below 10%, which is com-
610 monly merged into a single class. A separation of depressions and a successful estimation of subtle
611 differences in canopy cover below 10% is thus an important step in dryland woody cover modeling
612 by means of satellite data. The canopy cover map at 1.7 m resolution agrees well with field data with
613 an MAE of 3.2 (% woody cover), $r=0.87$ and slope=0.98.



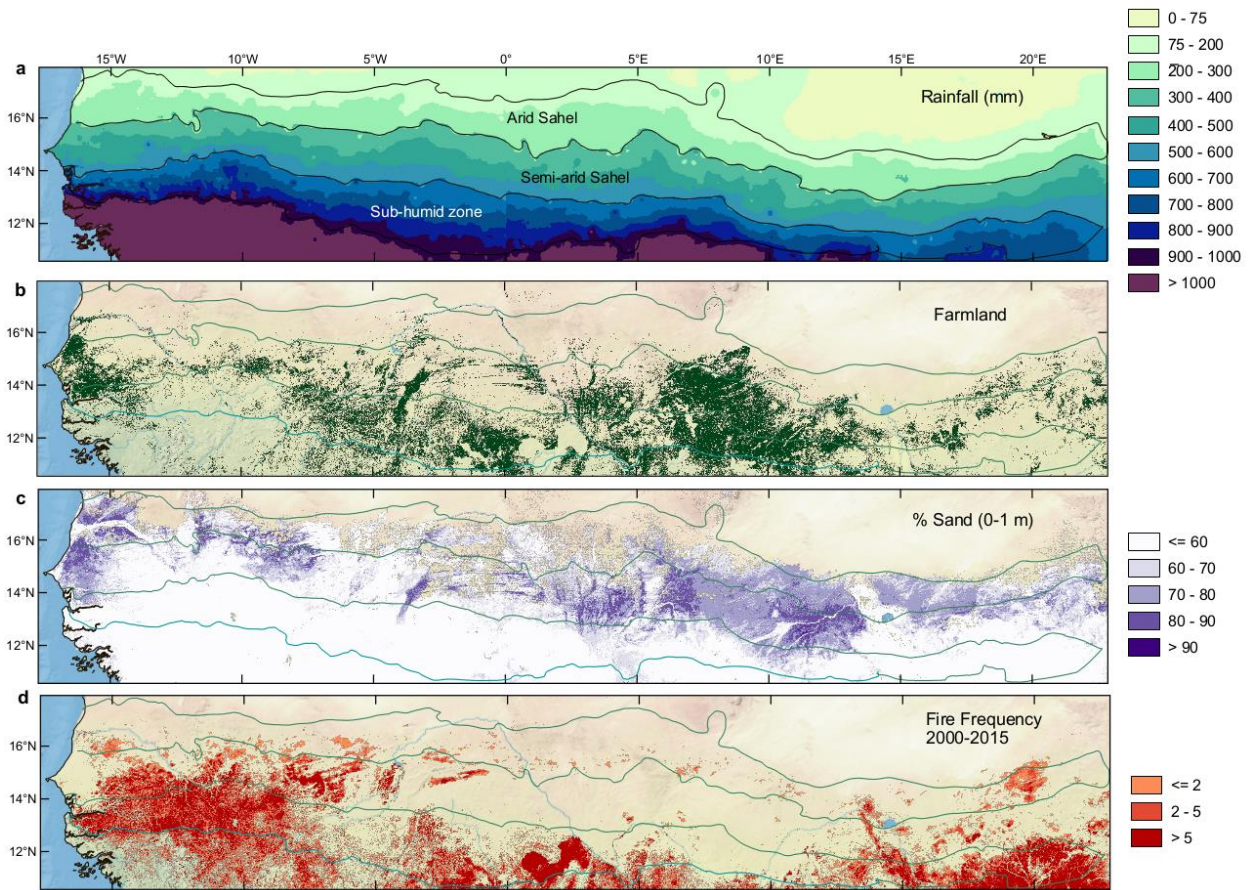
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615 **Figure S06 | The principle of the buffer zone analysis is shown.** The villages are derived from
 616 Globeland30 and buffer zones of different distances were applied. The zones represent areas within a
 617 certain distance to settlements. The area class being more remote from villages (7-20 km) is not shown
 618 here.



619

620 **Figure S07 | Flowchart showing data and methods.**



621

622 **Figure S08 | Environmental data sets. a**, Rainfall zones derived from CHIRPS 2.0 (1981-2016).
 623 Only areas with rainfall between 150 and 1000 mm are used for this study. **b**, The farmland mask
 624 applied. **c**, Sand fraction of soils. **d**, Fire frequency from MCD45A1 (number of fires per year).