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1 How far does the tree affect the crop in agroforestry? New spatial
2 analysis methods in a *Faidherbia* parkland

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28 **Abstract**

29 The trees in agroforestry plots create spatial heterogeneity of high interest for adaptation,
30 mitigation, and the provision of ecosystem services. But to what distance, exactly, from the
31 tree? We tested a novel approach, based upon geostatistics and Unmanned Aerial Vehicle
32 (UAV) sensing, to infer the distance at which a single agroforestry tree affects the
33 surrounding under-crop, and to map yield, litter (i.e. stover) and crop-partial Land Equivalent
34 Ratio (LER_{cp}) at the whole-plot level.

35 In an agro-silvo-pastoral parkland of semi-arid western Africa dominated by the multi-
36 purpose tree *Faidherbia albida*, we harvested the pearl-millet under-crop at the whole-plot
37 scale (ca. 1 ha) and also in subplot transects, at three distances from the trunks. We observed
38 that the yield was three times higher below the tree crown (135.6 g m^{-2}) than at a distance of
39 five tree-crown radii from the trunk (47.7 g m^{-2}). Through geostatistical analysis of multi-
40 spectral, centimetric-resolution images obtained from an UAV overflight of the entire plot, we
41 determined that the 'Range' parameter of the semi-variogram (assumed to be the distance of
42 influence of the trees on the Normalized difference vegetation index (NDVI)) was 17 m. We
43 correlated the yield ($r^2 = 0.41$; RRMSE = 48%) and litter production ($r^2 = 0.46$; RRMSE =
44 35%) in subplots with NDVI, and generated yield and litter maps at the whole-plot scale. The
45 measured whole-plot yield (0.73 t ha^{-1}) differed from the one estimated via the UAV mapping
46 by only 20%, thereby validating the overall approach. The litter was estimated similarly at
47 $1.05 \text{ tC ha}^{-1} \text{ yr}^{-1}$ and mapped. Using a geostatistical proxy for the sole crop, LER_{cp} was
48 estimated 1.16, despite the low tree density.

49 This new method to handle heterogeneity in agroforestry systems is a first application. We
50 also propose strategies for extension to the landscape level.

- 51 **Keywords:** Geostatistics / Unmanned Aerial Vehicle (UAV) / Land Equivalent Ratio (LER) /
- 52 Spectral indices / distance of influence

53 **1 Introduction**

54 Agroforestry provides attractive alternatives to monoculture, especially when the benefits of
55 association can be quantified and explained convincingly based upon phenomena such as
56 extended resource acquisition, complementarity, and facilitation. Even before modern science
57 provided such explanations, the benefits of agroforestry systems had been clear to traditional
58 societies, which made those systems a prominent and enduring feature of their agriculture,
59 especially in the tropics. Agroforestry was largely abandoned during the green revolution Jain
60 (2010), but is enjoying a strong revival and increased interest, particularly in Africa (Mbow *et*
61 *al.*, 2014), in the context of climate change, food-security concerns, limits to growth
62 (Meadows and Meadows, 2007), and sustainable-development goals (Griggs *et al.*, 2013).
63 Agroforestry systems are part of the bedrock of sustainable intensification because they are
64 compatible with options such as conservation agriculture, agro-silvo-pastoralism, and
65 precision agriculture (Aune *et al.*, 2017).

66 To what distance does a tree affect specific crop traits, e.g. biomass, productivity, yield, C
67 sequestration, root distribution, resource acquisition, or hydraulic redistribution? Assessing
68 the distance (radial extent) of influence of trees on the under-crops and adjusting tree density
69 are key to managing agroforestry systems, with direct impacts on the system's productivity,
70 provision of ecosystem services and capacity to mitigate and adapt to climate changes.
71 However, the difficulty and expense of manipulating tree densities (whether in orchards or in
72 long-term scientific trials) discourages efforts. A partial remedy is the modeling of
73 agroforestry *in silico*, which extends our ability to test optional densities under various
74 scenarios (van Noordwijk and Lusiana, 1998; Luedeling *et al.*, 2016; Vezy *et al.*, 2018;
75 Dupraz *et al.*, 2019; Vezy *et al.*, 2020), although within the limits of validation.

76 A common assumption is that trees must influence the crop anyhow, even at large distances,
77 above or belowground (Luedeling *et al.*, 2016) and that the distance of influence depends on
78 the crop trait of interest. Can we assess that distance for a single crop trait at least, like yield
79 for instance? What is the pattern of influence? Is the effect multinomial, such as for
80 windbreaks for example (McNaughton, 1988) or rather monotonic? Solving the question, trait
81 by trait and statistically would simplify the process of adjusting tree density, according to the
82 local priority. The usual way to address this issue experimentally is by designing subplot
83 arrays in the form of rings or logarithmic spirals (Tomlinson *et al.*, 1998) around the
84 agroforestry trees, or in the form of transects between them (Louppe *et al.*, 1996). Given the
85 large heterogeneity induced by the trees, this requires a huge amount of replicates and field
86 work and it is unlikely that it could be extrapolated at the whole-plot or landscape scale.
87 However, the issue can also be framed as a problem in spatial- or geo-statistics, and
88 investigated using interpolation solutions that treat the phenomena of interest (such as crop
89 traits, or in-soil C stocks) as random variables within the tree interspace. In a recent review,
90 Bayala *et al.* (2015) proposed combining yield mapping with geostatistics to address parkland
91 effects on crops, accounting for directional variability. Surprisingly, there were few
92 geostatistical applications under agroforestry so far: most of them characterize spatial
93 dependence of soil properties (e.g. Simon *et al.* (2013)), fewer on crop traits (e.g. Mora and
94 Beer (2013)) and hardly any or none on crop yield. We argue that given the high spatial
95 heterogeneity of edapho-climatic conditions induced by the trees in agroforestry systems
96 (Charbonnier *et al.*, 2013; Charbonnier *et al.*, 2014), and the large number of microclimate
97 and productivity random variables that could truly be mapped therein, a great deal of valuable
98 information may yet be brought to light through studies that complement classical
99 experimental designs with geostatistical methods.

100 That same geostatistical information may help agroforestry systems fulfil their potential to
101 provide reasonable options for mitigation, adaptation, and resilience in the face of climate
102 changes (Albrecht and Kandji, 2003; Kumar and Nair, 2011; Lorenz and Lal, 2014; Zomer *et*
103 *al.*, 2016). In that respect, too, the densities of an agroforestry system's trees and under-crop
104 are important. Regarding mitigation, the build-up of tree perennial biomass stores C rapidly,
105 but in the short term, whereas soil stores C for the long term, but via slow processes of uptake
106 from the litter (crop residues, or stover), and only a small part of this achieves long residence
107 times in stable organic matter pools. Crop productivity, litter, and SOC build-up are key
108 factors in the long term (e.g. throughout rotations). We argue that neither the crop biomass
109 and productivity (and its partitioning between residuals and exports), nor the soil component,
110 nor the spatial variability of C sequestration inside the agroforestry plot should be neglected
111 when estimating mitigation, especially for the long term. Here, again, is where geostatistics
112 may prove valuable. The under-crops and the soil were long neglected or assumed to be
113 neutral for C sequestration in agroforestry systems. They were not even accounted for in the
114 IPCC guidelines (Smith *et al.*, 2014). Only recently did Cardinael *et al.* (2018b) review
115 coefficients for estimating C storage rates in biomass and soil, according to the type of land-
116 use change (LUC) and the world region—an effort to be further incorporated into Tier 1 IPCC
117 guidelines. We argue that any method that could map metrics for crop biomass, C stock, NPP,
118 and litter inside heterogeneous agroforestry systems has the potential to further improve Tier
119 1 coefficients.

120 Similar comments—including those regarding the crucial importance of tree density and of
121 the distance to which the trees influence the under-crop— apply to agroforestry systems'
122 capacities for adaptation. It is often assumed that agroforestry trees create 'islands of fertility'
123 around them (Félix *et al.*, 2018). That is, trees may improve the microclimate locally, along
124 with the soil's infiltrability and its physical, chemical, and biological conditions.

125 Overall, the tree density and distance of influence of the trees on crops appear as a crucial
126 aspect facing climate changes, both for mitigation and adaptation. Climate change could
127 imply afforestation, reforestation and increase in tree density in conditions where the
128 ecosystems were degraded, or where ecological intensification is needed, with consequences
129 for mitigation and adaptation of climate change policies. The trade-offs between ecosystem
130 services carry to scrutiny in the context of a modification of tree density and the question of
131 adoptability is crucial. Any means to demonstrate the benefits on crop productivity and C
132 stock or storage inside heterogeneous agroforestry systems, such as mapping and quantifying
133 finely those variables under a range of tree densities, should be reflected in the impact.

134 Remote sensing and proxy-detection are attractive tools for the necessary mapping of target
135 crop traits. As one example, the estimation of yields of cereal crops in a complex agricultural
136 landscape was made possible by the democratization of satellite imagery of high spatial-
137 temporal resolution (VHR: e.g. Sentinel-2, Landsat 8 or PlanetScope). Leroux *et al.* (2019)
138 exploited the VHR pathway in their recent study of an agroforestry parkland with an under-
139 crop of millet. They showed how the assessment of agronomic performances at the whole-plot
140 level can be improved by integrating structural information from the parkland with a
141 statistical model for estimating millet yields via remote sensing. However, this type of
142 approach based upon yield subplots chosen randomly in the landscape could not integrate the
143 intra-plot variability: therefore, it could not investigate the effects of environmental micro-
144 variability, or the farmers' precision practices, or the local impact of trees.

145 In contrast, unmanned aerial vehicles (UAVs) can assess intra-plot variability even in
146 heterogeneous agricultural landscape of smallholder farming system, thereby complementing
147 satellite VHR data (Schut *et al.*, 2018). The potential of UAVs for that purpose remains to be
148 exploited fully. In Padua *et al.* (2017), a review of practical applications of UAVs in
149 agroforestry, and in Adao *et al.* (2017), a forecast of developments in hyperspectral imaging,

150 we found few examples where UAVs were used to study systems with perennials and an
151 under-layer. Rare examples were studied of orchards, considering only the fruit trees therein
152 (Sarron *et al.*, 2018). None considered the under-crop in an agroforestry system. Indeed, we
153 are not aware of any studies that used UAV to obtain fine-scale data that was then analysed by
154 geostatistical methods to address the central question of the distance at which the trees
155 influence the under-crop. Therefore, we propose this novel approach here: we first assess
156 yield and litter (a proxy for C input to the soil) of the under-crop classically, from subplot
157 arrays. Second we scale those variables to the whole-plot level via a method that involves
158 UAV-based mapping of spectral vegetation indices and correlation between spectral indices
159 and groundtruth. Third we compute the distance of influence of the trees according to the
160 geostatistical parameter ‘Range’.

161 Based upon our results, we also propose a new variant of the land-equivalent ratio (LER).
162 LER is a standard index for comparing the performances of crops in association vs. sole crops
163 (i.e., those in separate monoculture fields) (Mead and Willey, 1980). The LER is defined as
164 the ratio of the amounts of land that each of those agricultural systems requires in order to
165 give the same production.

166 For a crop under trees, Mead and Willey (1980) computed the LER as

$$167 \quad LER = LER_C + LER_T = \frac{Y_{iC}}{Y_{sC}} + \frac{Y_{iT}}{Y_{sT}}, \quad (\text{eq. 1})$$

168 where the subscripts C and T denote the crop and the tree, respectively; Y_i is the yield in
169 intercropping; and Y_s is the yield in sole-cropping.

170 A LER greater than 1 indicates that the agroforestry system uses land more productively than
171 sole-cropping. Although equation 1 gives a single LER value for the system, each term on the
172 right-hand side is, in effect, the LER for its respective species. These partial LER are useful
173 when data for only one crop partner is available or of direct interest: for instance it can be

174 calculated for the crop only, if there is no pure tree plot available. However, even when
175 targeting the crop-partial LER (LER_{cp}) only, one is limited when landscape of interest has few
176 treeless areas. Because the few treeless patches that do exist therein may not be representative
177 of (for example) prevailing soil conditions, basing an LER upon crop yields from those
178 patches is risky. The work that we report here may offer a way out of that conundrum. We
179 propose a method, based upon geostatistical inference, for determining the distance beyond
180 which a tree in the agroforestry system of interest does not affect the under-crop, allowing to
181 compute the crop-partial LER (LER_{cp}) directly within complex agroforestry systems.

182 In summary, the aims of the present study are to: (i) quantify the distance of influence of the
183 tree on the under-crop; (ii) upscale productivity and litter results from small sampling plots to
184 the whole stand through UAV-based mapping of spectral indices; and (iii) propose a simple
185 method to assess LER_{cp} within agroforestry systems where no true sole-crop control is
186 available.

187 Our study site is a *Faidherbia albida* parkland located in the groundnut basin of Senegal,
188 western Africa, with pearl millet as the under-crop. *Faidherbia albida* is a multipurpose tree.
189 It is emblematic of agroforestry in dry Africa because of its widespread adoption by rural
190 peoples, with generally positive effects upon associated crops (CTFT, 1988). In contrast,
191 pearl-millet (*Pennisetum glaucum*, L.) is the sixth cereal in terms of world production, with
192 crucial role for food security in arid areas of sub-Saharan Africa and India. It is considered a
193 “cereal of last resort” for farmers in especially challenging, arid conditions (Debieu *et al.*,
194 2017), where other crops would fail. Thus, pearl millet is a bastion of food security in the face
195 of climate changes.

196 2 Materials and methods

197 2.1 Study site, soil and climate:

198 The study was conducted in the agroforestry parkland of Niakhar/Sob, in the groundnut basin
199 of Senegal, western Africa (region of Fatick, 135 km East of Dakar). Within the site is a 50-
200 year-old observatory, the Health and Demographic Surveillance System (HDSS-Niakhar,
201 <https://lped.info/wikiObsSN/?HomePage>) (Delaunay *et al.*, 2018). The soil is sandy and very
202 poor (0-20 cm layer: >85% sands; <1% clay; CEC < 2%; pH_{H2O} ca. 5.7) and several meters
203 deep. It overlies an Eocene limestone bedrock. A brackish water table is present at around 6
204 m.

205 The climate is soudano-sahelian, with a wet season from June to October, followed by an
206 eight-month dry season. According to Lalou *et al.* (2019), rainfall decreased from 900 to 400
207 mm between 1950 and 1995 (the driest period), then recovered partially to ca. 500 mm by
208 2015. The seasonal distribution shifted during that recovery period: less rain now falls during
209 the early part of the wet season, and more at the end. The year 2018 was typical of the new
210 distribution: only one heavy rain (*haboob*) fell by the end of June, allowing pearl millet to
211 germinate. The ensuing dry spell, which lasted until August, reduced crop growth and
212 threatened the crop's very survival. The year's total rainfall, as was measured on site with an
213 automatic tipping bucket (Texas Electronics, model TE525mm), was 454 mm.

214 Early that year, during the dry season, we launched the highly instrumented "Faidherbia-
215 Flux" site (<http://agraf.msem.univ-montp2.fr/Senegal.html>). It was set up within farmers'
216 active agro-silvo-pastoral bush fields, which are dominated by the multipurpose tree
217 *Faidherbia albida* (Del.) A. Chev. In an area of 15 ha surrounding the experiment, the
218 *faidherbia* density was 6.8 tree ha⁻¹ and the canopy cover was 5.14 %. The under-crop here is
219 a mosaic of crops, including pearl-millet ('Souna', a traditional, 90 days cycle duration, low

220 photoperiodic and heterogenous millet variety), groundnut, watermelon, cowpea, and fallow
221 (Fig. 1). Faidherbia-Flux is located N: 14°29'44.916"; W: 16°27'12.851". It is registered with
222 FLUXNET (<http://daac.ornl.gov/FLUXNET/fluxnet.shtml>) as 'Sn-Nkr'. To accommodate the
223 research needs of multidisciplinary teams, it has instruments and facilities for monitoring
224 micro-meteorology; eddy-covariance fluxes of sensible heat, latent heat, and CO₂; soil water;
225 temperatures of land surface and soil; NDVI; soil respiration; sapflow; LAI; tree growth;
226 growth of fine roots; crop productivity; and yields. Faidherbia-flux hosts several and multi-
227 disciplinary research teams and is widely open to collaboration

228 *2.2 Production, sampling, and laboratory analyses of the millet under-crop*

229 All of the agricultural practices (e.g. land preparation, sowing, thinning and weeding) were
230 performed by the farmer, according to his usual preferences, habits, and calendar, in order to
231 avoid disrupting long-term dynamic equilibria and ensure that results would be representative.
232 Most management practices were identical whatever the tree presence, with exception to
233 weeding probably, that occurred to be more necessary at large distances from the tree (see
234 Results section). However, this should not affect the relationships between crop traits and
235 vegetation indices which are fundamental for our purpose. The geostatistical model is
236 assumed to take the whole intra-plot variability into account.

237 Only the subplot harvest was performed by the scientific team. For crop yield, growth and
238 litter (i.e. crop residues, or stover) variables, we tested the factor "Distance to tree" with three
239 levels: below the tree crown, and at distances of 0.5 R, 2.5 R, and 5 R, where R is the radius
240 of the tree crown (Fig. 2). We used N = 4 replicates per distance to tree, for a total of 12
241 subplots.

242 We pre-selected the four trees and transects using a recent dry-season Google Earth[®] image,
243 in order to avoid the subjectivity of subplot selection directly in the field. We distributed the

244 subplots accordingly. The radius of each chosen tree was measured on the image, and later
245 confirmed in the field. The average value of the distance from the tree trunk to the 5R
246 subplots always exceeded 20 m.

247 We fixed the number of sowing pockets (for whatever live or dead plant) per subplot at about
248 15 (16.4 ± 1.6). Therefore, the area of each subplot varied somewhat ($18.8 \pm 6.9 \text{ m}^2$),
249 according to the sowing density used by the farmer. The area per pocket was $1.16 \pm 0.5 \text{ m}^2$.

250 During the second week of October 2018, a team of six scientists was dispatched into the field
251 to collect the subplots. We first collected all the ears (millet spikes) from each subplot, then
252 split the vegetative biomass into leaves, stems, and roots (all roots collected in a 20 cm radius
253 hemisphere below the plant) and measured the fresh weights in the field with scales accurate
254 to within one gram. Only five pockets per plot were sent back to the lab for air drying, oven
255 drying (65°C , 72h), and weighing. From the differences between fresh and dry weights, we
256 calculated water contents for each pocket, from which we then inferred the dry biomasses of
257 the whole subplots. We also measured the specific leaf area (SLA: $\text{m}^2 \text{ kg}^{-1}$) on samples of
258 fresh leaves, and computed the leaf area and the leaf area index (LAI) per subplot. The aerial
259 part of weeds was likewise collected and weighed. LAI of weeds was estimated from above-
260 ground weed biomass, using (as a default) the SLA measured for millet.

261 To secure an independent validation for the exercise of scaling-up yield from subplots to
262 whole-plot, we assessed the whole-plot yield as well. For the whole-plot harvest, we relied on
263 the farmer and his family. All ears were harvested the day after we collected our subplots, and
264 then packed into bundles before transport to the village. We counted and weighed every
265 bundle, then applied the ratio of fresh weight of ears to dry weight of grain obtained in the lab
266 on the subplot samples.

267 The litter (amount of crop and weeds residues left-over in the field after harvest, or stover)
268 was computed as the whole biomass minus the crop ears. It was converted into gC m^{-2} ,

269 assuming a conversion rate of 0.47 (Smith *et al.*, 2014) for illustration applications in the field
270 of climate-change mitigation.

271 All subsequent measurements are reported per unit ground area.

272 2.3 UAV sensing and derived proxies for vegetation productivity

273 UAVs were flown on 8 October 2018—the day before the pearl-millet harvest. Due to their
274 reverse phenology, the *faidherbia* trees were defoliated at that date. To characterize the land
275 cover of the agroforestry system (Fig. 1), we analysed UAV photogrammetry images
276 according to the method described in Sarron *et al.* (2018). For spectral images, the UAV
277 system was a FeHexaCopterV2 hexaCopter (Flying Eye Ltd., www.flyingeye.fr), with two
278 onboard cameras fixed on a two-axis gimbal to point vertically downward. The first camera
279 was an RGB ILCE-6000 digital camera (Sony Corporation, New York, NY, USA) with a
280 6000 x 4000 pixel sensor equipped with a 60 mm focal length lens. To minimize the blurring
281 effect and noise in the images, the camera was set on speed priority (1/1250 sec) and auto ISO
282 mode. The second camera was an AIRPHEN multispectral camera (www.hiphen-plant.com,
283 Avignon, France) equipped with an 8 mm focal length lens and acquiring 1280 x 960 pixel
284 images. The AIRPHEN comprises six individual cameras equipped with filters centered on
285 450, 530, 560, 675, 730 and 850 nm, with a spectral resolution of 10 nm. The flight plan was
286 designed with Kopter tools (<http://wiki.mikrokoetter.de/fr/MikroKopterTool>) to cover the
287 entire area and ensure an 80% frontal and lateral overlap along the track. The UAV was flown
288 at 4.5 m s⁻¹ and at 50 m.a.g.l. with both cameras capturing images simultaneously at one-
289 second intervals. With this set up, we obtained a ground sample distance (spatial resolution of
290 the images) of 0.6 and 2.7 cm for the RGB and Airphen Multispectral cameras, respectively.
291 The area below the tree crowns was not covered because the UAVs could not navigate those
292 spaces safely.

293 As a radiometric-calibration target, we followed the recommendations of Jay *et al.* (2019) in
294 using a 2.5 m² carpet panel placed horizontally on the ground at a distance of 1.5 times the
295 height of the closest plants in order to limit adjacency effects. In addition, as geometric
296 ground control points (GCPs) (Kääb *et al.*, 2014), we placed six red discs of 50 cm diameter
297 at corners of the field. The exact positions of these GCPs were defined with a GNSS-GPS
298 providing an accuracy of 2 cm. Each UAV flight was performed around solar noon and lasted
299 about 15 min., during which solar radiation was assumed to be stable.

300 An automatic image-processing pipeline was designed to generate radiometrically calibrated
301 and geometrically corrected multiband orthoimages using Agisoft PhotoScan digital
302 photogrammetric software (PhotoScan Professional 1.4, Agisoft LLC, Russia). Radiometric
303 calibration included automatic correction of vignetting effects. Real reflectances were
304 computed using a reference target positioned to the ground during UAV flights. This target
305 was previously spectrally characterized in controlled conditions. Geometric correction
306 involved, firstly, multiband co-registration to modify and adjust the images' coordinate
307 system to decrease geometric distortions and make pixels in different pictures coincide with
308 the corresponding map-grid points. The co-registration process was based upon the internal
309 GPS from raw image metadata. Orthorectification was then performed using GCPs to increase
310 the accuracy of the generated orthoimages.

311 We used RGB orthoimages to segment the pearl millet under-crop and remove the soil and the
312 trees. For that purpose, we converted orthoimages from RGB to HSV color space, then carried
313 out thresholding operations over green crops to create a millet mask. Calibrated reflectances
314 in NIR, Red, and Green bands were extracted based on that mask, then used to derive the
315 Normalized difference vegetation index ((NDVI) Rouse *et al.* (1974), according to the
316 following equation:

$$317 \quad NDVI = \frac{NIR-Red}{NIR+Red} \quad (eq.2)$$

318 We used mostly the NDVI because it is the most widely used index for monitoring and
 319 estimating crop physiology and green biomass. We had six other well-known spectral indices
 320 for crop vegetation monitoring at hand, namely CTVI (Corrected Transformed Ratio
 321 Vegetation Index), GCVI (Green Chlorophyll Vegetation Index), GNDVI (Green Normalized
 322 Difference Vegetation Index), NDRE (Normalized Difference Red Edge Index), TTVI
 323 (Thiam's Transformed Vegetation Index) and MSAVI2 (Seconded Modified Soil-Adjusted
 324 Vegetation Index). Since they were highly correlated, we decided not to combine them into
 325 multiple regressions. However, since MSAVI2 presented slightly better correlation results
 326 with e.g. yield and litter than NDVI, we presented its results as well. MSAVI2 is a vegetation
 327 index modified for the soil effects (Richardson and Wiegand, 1977; Qi *et al.*, 1994) and it is
 328 thus well-designed for crop monitoring in sparsely vegetated areas.

$$329 \quad MSAVI2 = \frac{(2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - RED)})}{2} \quad (eq.3)$$

330 Where MSAVI2 is the index value, NIR and RED are respectively the Near Infrared and Red
 331 band reflectance from the UAV sensor.

332 2.4 Geomatics: chain of processes

333 For this task, we used QGIS (QGIS_Development_Team, 2019) and R (R_Core_Team,
 334 2017). To allow an intersection of the different geospatial layers used in our methodological
 335 framework, all layers were projected under the UTM 28 N /WGS84 coordinated references
 336 system. The TIF multi-band UAV ortho-image was converted into a mono-layer NDVI or
 337 MSAVI2 TIF raster using the rgdal (Bivand *et al.*, 2014) and raster (Hijmans, 2015) libraries
 338 in R.

339 We created shape files in QGIS for the following: the whole-plot; non-cultivated areas
 340 (shelters and tower); the cultivated area; crowns of faidherbia trees; and the periphery of those

341 crowns (a proxy for under-crown conditions). We also created shapefiles for eight of the
342 twelve harvested subplots (i.e., only for those at 2.5R and 5R). No shape files were created for
343 the four subplots at 0.5R (below the crown). Indeed, we observed that the UAV could not
344 sense below *faidherbia*'s crowns, despite the trees' defoliated state. We thus used proxies for
345 the 0.5R subplots, i.e., shape files just in the periphery of the four target-tree crowns,
346 assuming that the yield conditions were representative of the 0.5R subplots (verified in
347 Results section). Next, we computed the position of *faidherbia* centroids. Given the very high
348 resolution (a few cm²) of the UAV ortho-image, we aggregated each whole image into a grid
349 of *ca.* 5 m² cells for the whole-plot and *ca.* 1 m² cells for the subplots. Average NDVI or
350 MSAVI2 ± SD was computed for each cell of the grids, and its coordinates recorded.
351 A distance matrix was computed between each grid cell and the *faidherbia* centroids. We used
352 the proximal tree only (k = 1), and also took into account the trees outside the limits of the
353 whole-plot.
354 We used the resulting file, which combined NDVI or MSAVI2 and distance to the proximal
355 tree, to perform geostatistics at the whole-plot scale. The average NDVI or MSAVI2 and per
356 harvest subplot and tree-periphery file was used to correlate with crop productivity and litter.

357 2.5 *Geostatistics*

358 The distance to tree effect, corresponding to the 'Range' parameter, was analyzed with
359 geostatistics in R, from the table of attributes supplied at the end of the geomatics chain, using
360 the libraries *gstat* (Pebesma, 2004) and *sp* (Bivand *et al.*, 2008). We plotted semi-variograms
361 of the grid cells' NDVIs according to the distance to the proximal tree crown centroid (a
362 proxy for the position of the tree trunk), up to a maximum distance of 60 m, and following
363 four azimuths (N, S, E, W). The tree crown radius in the plot covered by UAV was quite
364 homogeneous, 4.67 m +/- 0.88 m (SD) so we used absolute distances to the trunk rather than

365 e.g. distances relative to the crown radius. We used the automap library and the
366 autofitVariogram function to select the best geostatistical model, here 'Ste', which is the
367 Matern model parameterized according to (Stein, 2012).

368 2.6 Land Equivalent Ratio (LER_{cp})

369 The Land equivalent Ratio (LER) is usually computed following equation 1. In the present
370 case, the LER of interest is the crop-partial LER (LER_{cp}) since we have no information on
371 tree-partial LER (absence of pure tree control in the parkland).

372 We discarded the option of computing LER_{cp} using the measured (i.e. from plant harvest in
373 5R subplots) values of sole crop yield (Y_s), due to the low spatial representability of the 5R
374 subplots and to our aim of developing a LER_{cp} method independently from harvest. Instead,
375 we used the estimated yields per zone (from UAV-NDVI flights, combined with
376 geostatistics). The estimated yield was mapped using the correlation from Fig. 7d. We split
377 the map into three distinct zones within the whole-plot: (i) below the tree crown (not sensed
378 by UAV, but we used polygons just around the tree crown instead), (ii) between the edge of
379 the tree crown and the limit of the Range, and (iii) beyond the limit of the Range. To compute
380 Y_s , we used the area beyond the Range. The estimated whole-plot yield, Y_i was thus the sum
381 of the average estimated yield in each zone, weighted per area in each zone. We computed the
382 yield estimated for the pixels below the value of the Range only, as another metrics for Y_i .
383 Finally we compared two LER_{cp} values, depending on both options for Y_i .

384 2.7 Statistical analysis

385 This task was performed using the R software (R_Core_Team, 2017). One-way ANOVAs
386 were performed when the variables met criteria of (i) variance homogeneity according to the
387 Bartlett test, and (ii) normality of distribution of the residues, according to the Shapiro-Wilk

388 test and Q-Q plot. Otherwise, we performed a Kruskal-Wallis non-parametric test. A Tukey
389 honestly significant difference test was then performed between levels inside each factor.

390 **3 Results**

391 *3.1 Millet performance in subplots according to the distance to Faidherbia*

392 In the subplots experiment, millet yield was significantly higher ($p = 0.028$; and by a factor of
393 about three) below the tree crown (0.5R: 136 ± 35 SD $\text{g}_{\text{grain}} \text{m}^{-2}$) than at the largest distance
394 (5R: 48 ± 33 SD $\text{g}_{\text{grain}} \text{m}^{-2}$) (Fig. 3a; Tab. 1). The yield at the intermediary distance (2.5 R)
395 was not significantly different than and 0.5R and 5R extremes ($p = 0.13$ and $p = 0.56$,
396 respectively) and will not be discussed further.

397 The stem biomass and total biomass (above + belowground) of millet was also significantly
398 higher at 0.5 R than at 5R ($p = 0.03$ and $p = 0.04$, respectively), again by a factor of about
399 three (Tab. 1). The biomass of weeds was significantly higher ($p = 0.021$) far from the trees,
400 indicating that they may have introduced significant noise in the NDVI or MSAVI2 signals in
401 this study (Fig. 3b).

402 The litter (i.e. crop residues, or stover) of millet crop + weeds (expressed in gC m^{-2}) was
403 significantly higher at 0.5R (Tab. 1).

404 The following variables were not significantly different (at the 0.05 level) between 0.5R and
405 5R (Tab. 1): the NDVI ($p = 0.09$), the MSAVI2 ($p = 0.07$), the leaf dry mass ($p = 0.1$), the
406 specific leaf area (SLA: $p = 0.83$), the leaf area index (LAI: $p = 0.2$), the root dry mass ($p =$
407 0.14) and the ratio of root mass to total dry mass ($p = 0.33$).

408 *3.2 Distance of influence of faidherbia on the millet crop*

409 We zoomed on the NDVI ortho-image (Fig. 4a) to show one transect example (Fig. 4b) of
410 NDVI in the pearl-millet (left), according to the distance to a faidherbia tree (right). Greener
411 pixels (high NDVI) predominated close to the faidherbia tree and beneath, whereas white bare
412 soil was abundant at a distance. When the UAVs were flown (October), faidherbia was still

413 defoliated, and high NDVI values can be perceived below the tree crowns. However, the high
414 density of branches prevented us from sampling cell grids directly below tree crowns. This
415 finding suggests that optical sensors mounted on UAVs do not give satisfactory results
416 through tree crowns, even for a defoliated tree. Fig 4c shows one pearl millet pocket. The
417 centimetric resolution allows leaves to be distinguished.

418 Semi-variograms were performed to contrast NDVI of grid cells in the whole-plot cultivated
419 with pearl-millet, and the distance to the centroid of the proximal faidherbia-tree crown (Fig.
420 5, 6), up to a maximum distance of 60 m. The best model fit (Fig. 6) was 'Ste', displaying a
421 monotonic and asymptotic shape. The 'Range', which is assumed here to indicate the
422 statistical distance of influence of the faidherbia tree on the crop NDVI, was 17 m. We found
423 little or no effect of the azimuth on the shape of the semi-variograms (Fig. 5). Therefore, on
424 the further assumption that the system was isotropic, we pooled all grid cells before applying
425 the model fit (Fig. 6). The Range was identical for MSAVI2 (data not shown). This distance
426 of influence (the Range) was substantially less than the distance from the 5R plots to the tree
427 (always > 20 m), suggesting that 5R plots were located in an area little affected by the tree,
428 regarding the NDVI or MSAVI2 at least.

429 *3.3 Upscaling yield and productivity from small subplots to the whole plot*

430 At the whole-plot scale, we harvested 52 bundles, whose fresh mass averaged 23.36 ± 2.96 kg
431 each. In the subplots, we obtained a conversion rate (from fresh mass of ears to dry mass of
432 grain) of 0.52 (Tab. 3). The total harvest was thus $632 \text{ kg}_{\text{grain}}$, to which we added the 17.63 kg
433 obtained in the subplots. The effective whole-plot area for crops was 8929 m^2 . Thus, the
434 measured (from harvest) whole-plot yield was $0.73 \text{ t}_{\text{grain}} \text{ ha}^{-1}$.

435 We sought correlations between crop traits, or between one single vegetation productivity
436 index, NDVI or MSAVI2, and some crop traits of interest within the 12 harvested subplots

437 (Fig. 7; Tab. 2). We found a reasonable positive correlation between millet grain yield and
438 millet LAI (Fig. 7a; $r^2 = 0.63$; RRMSE =33%). The correlation was even better between LAI
439 and the whole-plant biomass (Fig. 7b; $r^2 = 0.80$; RRMSE =23%), suggesting that LAI is a
440 good indicator of the millet productivity. However, we found a weaker correlation between
441 LAI and NDVI, for millet + weeds altogether (Fig. 7c; $r^2 = 0.47$; RRMSE =22%): indeed, the
442 NDVI sensed by the UAV was influenced by both crop and weeds; therefore, we had to group
443 them before correlating. Please recall that because the UAV could not sense the 0.5R plots,
444 we used a proxy NDVI from the surroundings of the tree where the 0.5R plot had been
445 harvested. We compared the yield measured in the 0.5R subplots (1.36 t ha^{-1}) with the one
446 estimated from NDVI around the same trees (1.21 t ha^{-1}) and they were actually similar
447 (Table 3), suggesting that using the surrounding of the trees was a reasonable proxy.
448 For the most crucial correlation here—that between millet grain yield and spectral index of
449 millet+weeds—MSAVI2 (Fig. 7e) performed only marginally better than NDVI (Fig. 7d),
450 thus we decided to stick to NDVI in order to remain more generic. However, both correlations
451 remained pretty loose (NDVI: Fig. 7d and Table 2, $r^2 = 0.41$, RRMSE = 48%; MSAVI2: Fig.
452 7e and Table 2, $r^2 = 0.47$, RRMSE = 46%).
453 We found a better correlation between NDVI and litter (expressed in gC m^{-2}) of the millet +
454 weeds (Fig. 7f and Table 2; $r^2 = 0.46$; RRMSE = 35%).
455 We used coefficients from Fig. 7d to further convert NDVI values into millet grain yield at
456 the whole-plot scale. In the whole-plot millet yield map that we computed using this
457 relationship (Fig. 8a), it can be seen that yield appeared higher near the trees. A slight
458 distance-decay effect is visible as well. We finally validated the yield map (Fig. 8a) using the
459 whole-plot measured yield. The yield estimated from NDVI was $811 \text{ kg}_{\text{DM}} \text{ grain}$ for the plot
460 (Tab. 3). Therefore, the error was 20%, which is considered reasonable, in spite of the rather
461 weak relationship obtained in Fig. 7d.

462 In Fig. 8b, we propose a crop + weed litter map (expressed in gC m^{-2}) as an example for
463 mitigation applications. The UAV-estimated litter production was 1.05 tC ha^{-1} (Tab. 3).

464 *3.4 Measuring and estimating crop-partial LER without a true sole crop reference*

465 In Tab. 3, we computed the crop-partial LER (LER_{cp}) from Eq. 1. The measured LER_{cp} using
466 the estimated whole-plot yield was 1.1. Using the plot yield in the area below the Range only,
467 LER_{cp} was 1.16, both suggesting that the agroforestry system, even at that low tree density
468 (6.8 tree ha^{-1}) spared more than 10% of land.

469 **4 Discussion**

470 What agroforestry research lacks desperately, in order to move beyond the classical
471 dichotomy between shaded and non-shaded plots (Charbonnier *et al.*, 2014), are maps of
472 random variables inside heterogeneous agroforestry systems, for whatever tree spacing. For
473 instance, the MAESPA 3D model (Duursma and Medlyn, 2012) has been applied in
474 agroforestry and 2D horizontal maps have been proposed recently for the light distribution
475 within the crop (Charbonnier *et al.*, 2013), for the crop's surface temperature (Vezy *et al.*,
476 2018), for crop photosynthesis, transpiration, and water-use efficiency (Charbonnier, 2013),
477 and for light-use-efficiency (LUE) (Charbonnier *et al.*, 2017). 2D and 3D maps of root
478 distribution have been proposed as well, with the uptake of water and nutrients (van
479 Noordwijk and Lusiana, 1998; Dupraz *et al.*, 2019).

480 Indeed, the ability to produce intra-plot yield maps and inter-plot LER_{cp} is crucial to fostering
481 agroforestry research. This could aid as well in the management of cropping systems, in
482 particular for precision agriculture (for instance varying the crop density according to the
483 distance to the tree), or in mixed-cropping (distributing the crops responsive and non-
484 responsive to the tree effects in the adequate plot locations). In this article, we combined state-
485 of-the-art proxy-sensing technology with a geostatistical method in an original way, to
486 propose a novel statistical approach for assessing the distance at which trees influence crops.

487 *4.1 Upscaling yield from the subplots to the whole-plot through UAV-NDVI*

488 The weak but statistically significant correlation that we found between NDVI and pearl-
489 millet yield (Fig. 7d; $r^2 = 0.41$; RRMSE = 48%) is below the range of correlation found in
490 studies that used remote sensing to estimate pearl-millet yields in West Africa and the
491 MSAVI2 relationship is only marginally better. For example, Rasmussen (1992) in an early
492 study and Leroux *et al.* (2015) both used low-resolution satellite images and were able to

493 explain more than 90% and 65% of the millet-yield variability in northern Burkina Faso and
494 south-western Niger, respectively. The difference between the strength of their correlations
495 and the strength of our own requires some explanations. The first reason is that our study is
496 based on one single plot, so we focused on the intra-plot variability, which is assumed to be
497 much lower than the inter-plot variability normally observed at the landscape scale, thus
498 affecting the correlation; (ii) we used pure spectral indices only, not mixed with covariates
499 such as microclimate or soil or practices that do co-vary at the landscape scale (indeed, we
500 tried to combine 7 spectral indices that we had at hand but they were so correlated that we
501 abandoned such a pathway); (iii) the millet was a traditional variety, by nature very
502 heterogeneous, and it suffered from a severe drought in July 2018 (representative of the new
503 rainfall period after the big drought 1970-2000, though), with impact on survival, which
504 increased the fraction of visible soil and noise; (iv) we could not fly the UAV below the tree
505 crown and relied on a proxy (the difference between measured yield in 0.5R subplots and
506 estimated yield in the periphery of the crown remained small though, Table 3) ; last, the
507 significantly greater amount of weeds (Tab. 1) in the sole crop (5R) may have compensated
508 for the decline of its crop NDVI.

509 The weakness of our correlation between NDVI and pearl-millet yield likely affected the
510 scaling-up of yield from subplots to the whole-plot, and therefore the value of LER_{cp} that we
511 obtained. Nevertheless, the match between the measured yield and the yield estimated through
512 UAV-NDVI remained satisfactory, with an error below 20% (Tab. 1). It is probable that
513 compensation effects occur at that scale. We suggest that the method proposed here, although
514 affected by a locally-weak calibration at the subplot-scale, may find interesting developments,
515 provided that the calibration phase is improved.

516 We stress also that one weakness of the work reported here is that the UAV-NDVI yield
517 predictions are based upon a single UAV image acquisition (at harvest), rather than upon

518 images obtained throughout the cropping season. The latter approach generally gives more-
519 accurate estimates of yield because the processes of plant development and growth are
520 nonlinear (Rasmussen, 1992; Maselli *et al.*, 2000; Leroux *et al.*, 2015).

521 4.2 A new method to assess the distance of influence of the tree on specific crop 522 traits

523 The distance to which the tree influences the crop is a key topic when designing agroforestry
524 systems. It is a specific trait of a given agroforestry system that underpins the system's overall
525 performances (e.g. net primary productivity, yield, response to climate changes and LER_{cp}). It
526 has received much attention in the past from researchers, who assessed it through complex
527 field experiments that used subplot arrays around the agroforestry trees: e.g. rings (Louppe *et*
528 *al.*, 1996), logarithmic spirals (Tomlinson *et al.*, 1998), and transects between trees. However,
529 such experiments are so time-consuming and costly that in practice, the tree density is
530 normally fixed by the farmer according to empirical observations or preferences. Scientific
531 experiments come later, by which time the arrangement of trees is generally fixed. As a result,
532 the classical experiment compares agroforestry plots with sole-crop plots, if by chance any are
533 available nearby (Cannavo *et al.*, 2011; Hergoualc'h *et al.*, 2012; Schnabel *et al.*, 2018).

534 Bayala *et al.* (2015) proposed to combine yield mapping and a geostatistical approach as a
535 more systematic way of assessing the tree effects on crop productivity. We developed that
536 approach in the present study. The positive effect of the *Faidherbia albida* tree on the crop
537 yield was demonstrated here in three ways: by photography (Fig. 2), by subplot transects at
538 three distances to the tree (Fig. 3; Tab. 1), and by spectral indices (e.g. NDVI, MSAVI2)
539 measured on the subplot transects (Tab. 1: significant but only at 10%, though). The distance
540 effect itself was quantified through geostatistics of NDVI at the whole-plot scale (Figs 5, 6):
541 we obtained a Range of 17 m, indicating that crop NDVI (same result for MSAVI2), itself

542 correlated to crop yield, was influenced by the tree up to that distance. Even if 17 m is just the
543 beginning of the plateau observed on Fig. 6, it remains a statistical metrics with strong
544 advantages when compared to the classical approach: it statistically defines an unequivocal
545 metrics. Therefore, it can be argued that beyond that limit, the crop's NDVI is statistically
546 unaffected by the trees, according to the model. We stress that this metrics is valid first for the
547 crop spectral index of interest, second for crop traits well correlated to this spectral index, but
548 not for all crop traits in general. Obviously, the tree could affect some other crop traits at
549 larger distances. However, the better the spectral index is correlated to a crop trait of interest
550 (e.g. yield or litter), the better the Range parameter is representative of a statistically
551 significant limit for the trait, between affected and non-affected areas. That latter condition,
552 applied to yield, by definition constitutes sole-cropping. This assertion is in agreement with a
553 recent review by Sileshi (2016), which evidenced through classical methods that *faidherbia*
554 does not affect pearl millet at distances greater than 16 m from the tree trunk. More
555 specifically, Sileshi (2016) reported that the response ratio, used as a measure of the effect
556 size, was lower than 1, meaning no influence of trees on the crop at a distance of more than 16
557 m from the trunk.

558 Actually, the distance of influence on yield and litter measured here by the geostatistical
559 metric Range could vary, according for instance to: other crop traits of interest but not related
560 to a spectral index (e.g. grain quality); the crop species; the microclimate and soil conditions;
561 the density of the crop; the diameter of the tree-crowns and the agricultural practices (e.g. tree
562 pruning, thinning, root cutting, fertilization)... Basically here, we just proposed a method to
563 measure that Range locally, a gateway to test its variability more widely.

564 *4.3 Added value of a metrics for the distance of influence of the tree on crops*

565 Specifically here, we found that the distance of influence for faidherbia upon millet crop
566 NDVI in a range of spacings between trees was, on average, 17 m. We computed that 9.99
567 (~10) discs of radius = 17 m fit into one ha, according to a staggered arrangement (a 60°
568 diamond pattern being the pattern with the minimum possible empty space left). We can
569 compute that at 10 trees ha⁻¹, 9.3% of the plot is not benefiting from the tree influence. At the
570 tree density in the surroundings of our experimental plot (6.8 tree ha⁻¹, measured on 15 ha),
571 the non-influenced area represents 38% of the plot.

572 Above 10 trees ha⁻¹, the area of influence of several trees merges. Do we know already how a
573 crop placed under the influence of several trees will behave? No, actually it might depend on
574 (i) the fit of the geostatistical model (Fig. 6), which was monotonic and asymptotic here with
575 a shape very consistent to what was observed through classical methods (Sileshi, 2016), but
576 merging areas could have complex effects with multinomial shapes, such as those
577 encountered for temperature and evapotranspiration in the leeward portions of windbreaks for
578 instance (McNaughton, 1988); (ii) interactions between trees and livestock: a higher tree
579 density might dilute the beneficial effect of the tree, which in the case of faidherbia in a agro-
580 silvo-pastoral parkland is at least partly a result of manure deposition by the livestock (the
581 more trees, the less manure is likely to be deposited under each).

582 What the Range informs is that 10 trees per ha would minimize the spaces where the millet
583 crop yield is not supported by the trees. There is still a long way, from proposing a metrics for
584 the distance of influence of trees on specific traits of crops, to adjusting the tree density for a
585 variety of ecosystem services or responses to climate changes. However, the above-described
586 method allows to at least minimizing the spaces of no influence, without taking much risk in
587 merging areas of influence, which is an added value when the effect of the tree on the target
588 crop is positive. Therefore, we argue that we can reasonably estimate the yield of crops up to

589 tree densities corresponding to the maximum compaction of discs with radius = Range.
590 Beyond that density, interactions between areas of influence remain unknown.
591 In addition, the same Range metrics allows to compute LER_{cp} , which is discussed below to
592 extend the added-value.

593 *4.4 Trade-offs when adjusting tree density*

594 Regarding the various ecosystem services that might be worth targeting during the design of
595 tree spacing, a multi-criteria approach is recommended. Trade-offs between ecosystem
596 services should be considered as well: the *faidherbia* has a positive effect on millet yield and
597 its density could probably be increased from this simple point of view However, a higher
598 density of *faidherbia*, which is essentially a phreatophytic species (Roupsard *et al.*, 1999),
599 may lower the level of the water table, thereby affecting partitioning between blue and green
600 waters. This specific trade-off is analogous to that for irrigation, and needs to be quantified:
601 consumption of groundwater may be beneficial to food security in the short term, but harmful
602 to sustainability.

603 A further consideration is that although *faidherbia* is the parkland's dominant tree species, it is
604 not the only one, and the spatial distributions of the others may affect resources-use patterns
605 among the different components of parkland (Luedeling *et al.*, 2016). Hence, according to the
606 land-use system, effects of *faidherbia* on crop yields can be mitigated, as already shown in
607 studies conducted at landscape scale (eg. Hadgu *et al.* (2009)).

608 A final—and delicate—point to consider is the farmer's receptiveness to changing the current
609 tree density, which is the result of tradition combined with his own preference and labour,
610 modulated by constraints (Sambou *et al.*, 2017). Of interest is to investigate how the distance
611 of influence of trees on crops converges with the design that he actually adopted. The Serer
612 tradition recommends 7 *faidherbia* trees per plot (of ca. 1 ha each) to fill one family's granary

613 (of ca. 5 m³ each) (R. Diatte, pers. comm.) which is very consistent to what was measured
614 here (6.8 tree ha⁻¹), or also in Lericollais (1972).

615 4.5 *Computing the crop-partial Land Equivalent Ratio (LER_{cp})*

616 The method proposed here offers the possibility to estimate the crop-partial LER in conditions
617 where no true sole crop is available, basing on a metrics for defining the distance of influence
618 of the trees, which is provided by the geostatistical ‘Range’ parameter.

619 Using that information, researchers can (potentially) identify multiple areas of unaffected
620 under-crop throughout the landscape, for the variable of interest. This method could
621 dramatically extend the range of locations for which LER_{cp} can be estimated. Application of
622 this method at the landscape scale could provide LER_{cp} data for future model validation as
623 well.

624 The yield of the crop in the agroforestry system, Y_i (eq. 1) is certainly dependent upon the tree
625 density, d , as is the value computed for LER_{cp}: therefore, it would be worth writing them both
626 $Y_{i,d}$ and LER_{cp,d}. As we provide the possibility to compute LER_{cp,d} in a wide range of tree
627 densities, such as usually occurring at the landscape scale, it becomes possible to study the
628 relationship between tree density and LER_{cp}. This approach also gives the yield in absence of
629 tree influence (Y_s). Y_s can be seen as a local reference, to study the effect of other variables
630 that affect yield, other than the presence of trees, and that vary in the landscape (e.g. soil
631 fertility, management, etc.). It is a way of standardizing for the effect of trees in the landscape
632 Model simulations could address $Y_{i,d}$, Y_s and LER_{cp,d} as well.

633 4.6 *Applications for Mitigation*

634 The net carbon balance of an ecosystem, often referred to as net ecosystem productivity
635 (NEP) is actually the difference between net primary productivity (NPP) and heterotrophic
636 respiration (R_h) (Roy *et al.*, 2001). Other GHG gases contributing to CO₂eq were considered

637 out of scope here. Therefore, the task of finding ways to calculate the NPP and R_h more
638 conveniently and accurately is central to mitigation accounting. In heterogeneous systems
639 such as agroforestry, maps of fluxes (e.g. yield, NPP per organ, and litter, i.e. crop residues or
640 stover) should improve the C accounting at the whole-plot scale. Tree NPP is key for short-
641 term mitigation (e.g. one rotation), and assessing tree NPP is rather easy from tree-volume
642 functions. Litter input is a fraction of NPP, which in turn is a relatively small fraction of NPP
643 in woody perennials. In contrast, it is a large fraction of NPP in palms, for example (Navarro
644 *et al.*, 2008; Fan *et al.*, 2015), and up to 100% of NPP in annual crops. Assessment of tree
645 litter remains challenging, especially belowground, but can be approached by determining
646 fine-root lifespan in rhizotrons or by sequential coring (Navarro *et al.*, 2008; Defrenet *et al.*,
647 2016). For crops, which mostly produce litter or exports, we stress that the UAV method
648 proposed above not only allows mapping of crop yield, but potentially, too, of the partitioning
649 of crop NPP into organs that will be exported (e.g. ears) or left to decompose in the plot
650 (litters of stems, leaves, and below-ground biomass). Here, we used UAV to upscale crop
651 litter from subplot to whole plot, and estimated that $1.05 \text{ tC ha}^{-1} \text{ yr}^{-1}$ was left in the field by
652 millet and weeds. R_h does depend upon litter, but its relative contribution to NEP is affected
653 strongly by the local soil's physical, chemical, and biological properties. R_h is difficult to
654 measure, but can be computed from the difference between soil respiration and soil
655 autotrophic respiration, both easier to measure.

656 Litter is probably the most important variable in SOC build-up (Cardinael *et al.*, 2018a;
657 Fujisaki *et al.*, 2018), together with soil properties, following eq. 4:

$$658 \Delta C_{soil} = L_A + L_B - R_{soil} + C_{inputs} - C_{exports} \quad (\text{eq. 4})$$

659 Where: ΔC_{soil} is the net soil C balance; L is litter (subscripts a is for above-ground and B is for
660 below-ground); R is respiration; C is carbon (inputs are for instance manure; exports is litter
661 removed post-harvest). All expressed in $\text{tC ha}^{-1} \text{ yr}^{-1}$.

662 If ΔC_{soil} can be assessed from soil sampling in e.g. synchronic or diachronic experiments, it
663 can also be inferred from the net balance of its C fluxes, as from eq. 4, where above and
664 below-ground litter play key roles.

665 In this respect, our work is relevant to the Clean Development Mechanisms (CDM) projects.
666 CDM projects could take crops and soil into account, rather than the trees alone. Our
667 methodology also offers the possibility of developing diachronic approaches, which are
668 considered to be more accurate (Costa Junior et al., 2013). In a recent review, Cardinael *et al.*
669 (2018b) stressed that in agroforestry systems worldwide, the ageing and heterogeneity of a
670 plot affects, strongly, the rates at which SOC and biomass accumulate after LUC. Because
671 those rates depend upon the tree density, the method proposed here to improve the crop
672 contribution throughout the landscape should help improve the estimates needed by the CDM
673 projects.

674 4.7 *Applications for Adaptation*

675 Any method that can map crop productivity on a fine scale within heterogeneous agroforest
676 plots will be capable, inherently, of providing the data needed for studying the links between
677 crop performance, distance to tree (or tree planting pattern), microclimate, and fertility. At the
678 landscape scale, that same capability should be useful in screening for favourable or adverse
679 conditions, and for further investigating their determinants (e.g. soil, fertility, or
680 management). Precision agriculture, taking into account the maps of tree influence to adjust
681 crop density or distribute mixed crop species at the field scale could enhance crop
682 productivity and adaptation. We argue here that fine-scale mapping of complex landscapes
683 can identify conditions conducive to adaptation to climate changes. For instance, analysis of
684 the landscape could provide data for drawing response curves relating productivity or LER_{cp}
685 to tree density. This suggestion assumes that trees create ‘islands of fertility’ and buffer the

686 adverse environment, thereby improving adaptation and resilience. Moreover, from the
687 interpretation of maps of productivity at the landscape scale, it should be possible to survey
688 the ‘good practices’ of farmers regarding adaptation, after which those practices would be
689 further disseminated.

690 4.8 *Improving the process*

691 Although we argue that the overall process proposed here is valid, we also propose an
692 improved protocol that would refine it: (i) harvest the georeferenced subplots arrays according
693 to randomly chosen distances from the tree (a freedom offered by the geostatistical approach),
694 not necessarily in transects under a factorial plan; (ii) assess the spectral index of the areas
695 below tree crowns manually, using the same camera as on the UAV; (iii) correlate yield (Y_i
696 and Y_s) and crop-partial LER of locations throughout the landscape using co-variables such as
697 microclimate, soil, and agricultural practices; (iv) combine several spectral indices with co-
698 variables to improve yield prediction. This improved methodology can be used also in
699 combination with classical remote sensing (Schut *et al.*, 2018) to bridge intra-plot and inter-
700 plot scales and provide local calibrations for remote-sensing purposes.

701 **5 Conclusions**

702 The distance of influence of the trees upon the under-crops of agroforestry systems, according
703 to specific target services, is crucial to adjusting the tree density for improving productivity
704 and resilience, and to avoiding or minimizing trade-offs. The methodology we propose here is
705 original and infers that distance from UAV mapping of a spectral index, a geostatistical
706 approach, a field calibration, and a validation of the whole-plot yield map.

707 Although the method still needs development, especially to (i) sense the yield below the tree
708 crown and (ii) combine several spectral indices with co-variables to improve yield prediction,
709 it already opens new avenues for filling some gaps in agroforestry research. Among those
710 gaps are the distance of influence of the tree (a gateway to adjusting tree density); the
711 estimation of litter (i.e. crop residues, or stover) per ha (a gateway for soil C-sequestration
712 models); the computation of crop-partial LER (LER_{cp}) using a reasonable proxy (found
713 directly within the agroforestry plot) for the sole crop; the downscaling of remote-sensing
714 approaches inside agroforestry plots; and the mapping of crop yields at landscape scale while
715 accounting for tree effects.

716 We invite a large community to test and further develop this new tool, by mapping and
717 comparing yield, NPP, litter, yield under agroforestry, sole-crop yield and crop-partial LER at
718 the levels of the agroforestry plot and landscape.

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[NB: Figures can be printed in colour on the web and in gray scale on paper]

Figure Captions:

Figure 1 Study site, land cover, and experimental display. a/UAV-based map (September 2018, wet season) of “Faidherbia-Flux”, located in farmers’ agro-silvo-pastoral bush fields, dominated by the multipurpose tree *Faidherbia albida*, here defoliated (white crowns); b/ land-cover map, a mosaic of under-crops (e.g. pearl millet, groundnut, cowpea, watermelon, and grass fallow); c/Overview of the landscape from the eddy-covariance tower (30 m high) during the wet season. The *Faidherbia albida* trees are defoliated, underneath.

Figure 2: Millet-crop sampling at three distances from the *Faidherbia albida* trees. We compared three distances to tree: below the tree crown (0.5 R), at 2.5 radii (2.5 R), and at 5 radii (5R), where R is the radius of the tree crown. N = 4 replicates (4 transects) per distance to tree. Total number of subplots = 12. Note that the development of the millet crop appears to be better below the tree crowns. Image taken from the eddy-covariance tower (September 2018).

Figure 3: Effect of the distance from the faidherbia tree upon two crop traits, as assessed in 12 harvest subplots: a/ pearl-millet yield; b/aerial biomass of weeds. Distances are: below the tree crown (0.5 R), at 2.5 radii (2.5 R) and at 5 radii (5R), where R is the radius of the tree crown. N = 4 replicates (4 transects) per distance to tree.

Figure 4: NDVI sensed by UAV above the agroforestry plot, just before pearl-millet harvest, in October 2018. The greener the color, the higher the NDVI. Faidherbia trees were defoliated, and appear as white discs in the landscape. Bare soil appears white, as well: a/: general overview of the central whole-plot, cultivated in pearl-millet and surrounded by other crops; b/ example of NDVI transect between pearl-millet (left) and a faidherbia tree (right); c/ detail of one pearl-millet plant showing the centimetric resolution of the UAV image.

Figure 5: Directional (N,S,E,W) semi-variograms between NDVI of grid cells in the area of the whole-plot that is cultivated with pearl-millet, and the distance to the centroid of the proximal *faidherbia* tree crown. The semi-variograms are very similar when using MSAVI2.

Figure 6: Distance of influence of the *faidherbia* tree upon NDVI of pearl millet. Semi-variogram between NDVI of all grid cells in the area of the whole-plot that is cultivated with pearl-millet, and the distance to the centroid of the proximal *faidherbia* tree crown. The 'Range', or distance of influence is 17 m, corresponding to the red dotted line. The semi-variogram is very similar when using MSAVI2.

Figure 7: Correlations between a single reflectance index (NDVI or MSAVI2) and some crop traits within the harvested subplots (N=12). Because the UAV could not sense the 0.5R plots, we used pixels from the surroundings of the tree where the 0.5R plot had been harvested, as proxy to compute NDVI or MSAVI2,.

Figure 8: Whole-plot maps. a/ yield mapping (orange area) using the relationship from Fig. 7e (scale is in $\text{g}_{\text{grain}} \text{m}^{-2}$; RMSE = 41.45; RRMSE = 48%); b/map of litter from crop+weeds (scale in gC m^{-2} ; RMSE = 48.65; RRMSE = 35%) using the relationship from Fig. 7f. The grey shapes correspond to the *faidherbia* trees. The grey rectangles are shelters. It can be seen that yield and litter are higher in the surroundings of the trees.

Figure 9

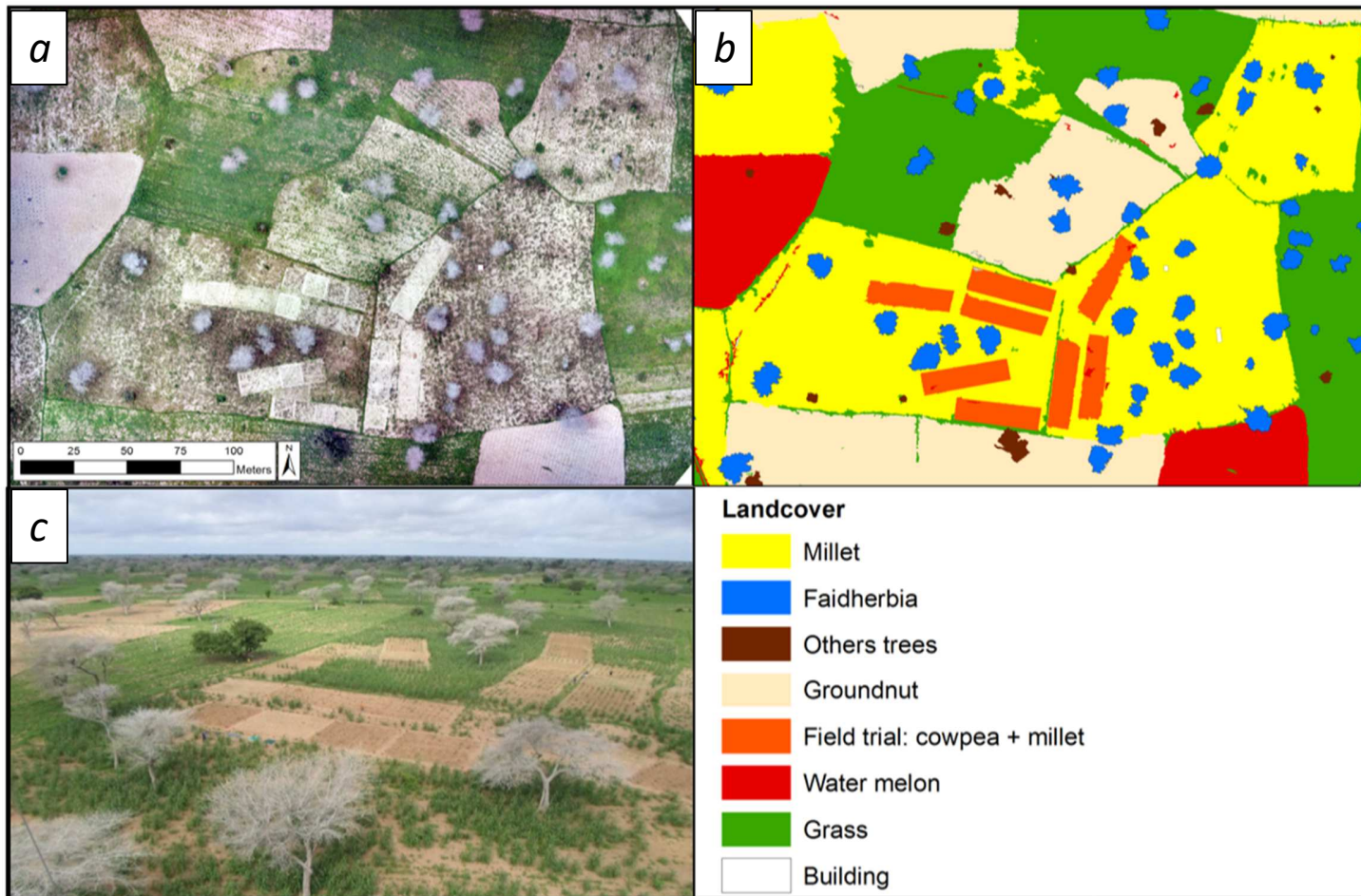


Figure 10:

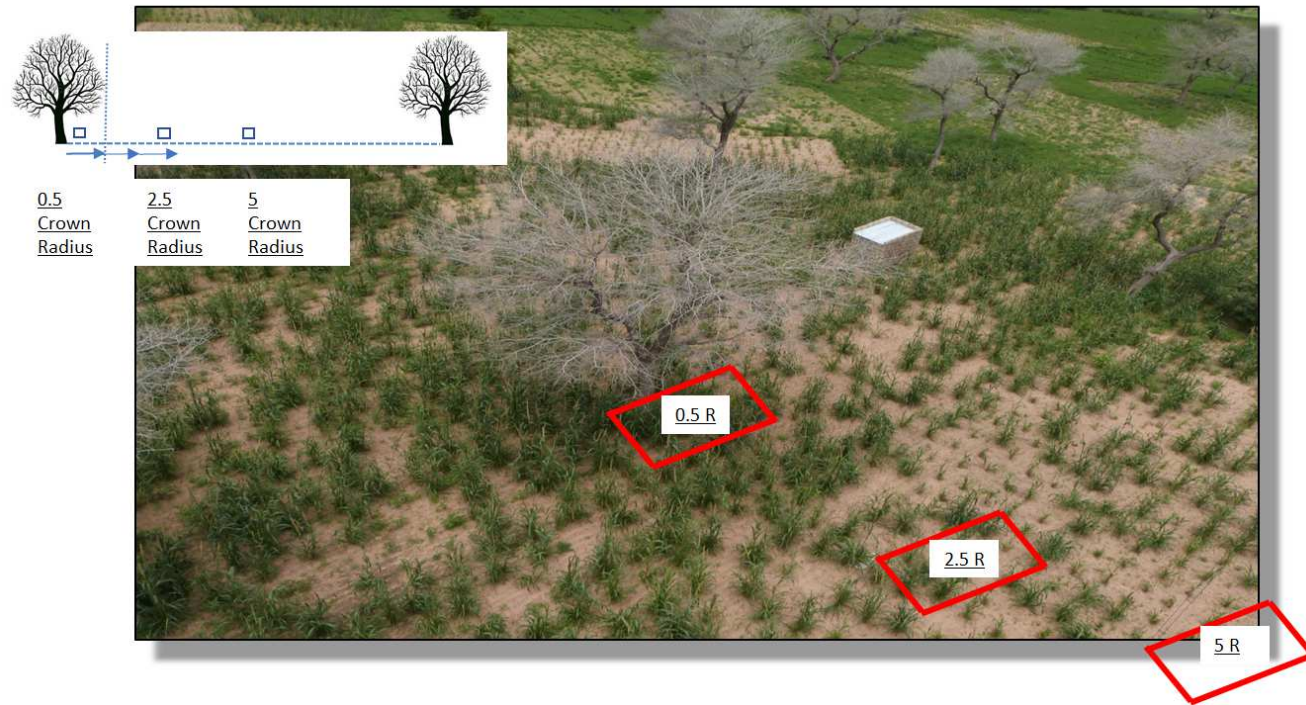


Figure 11:

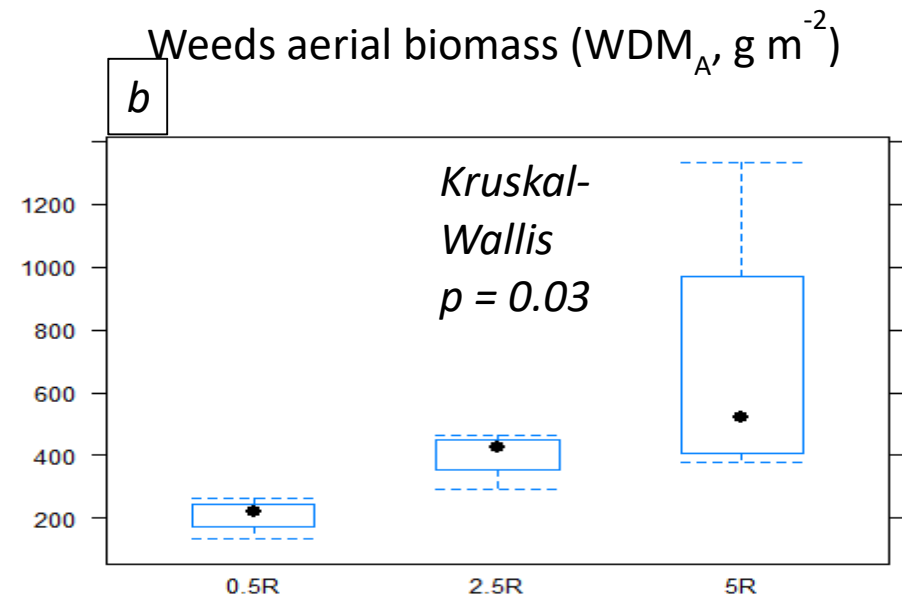
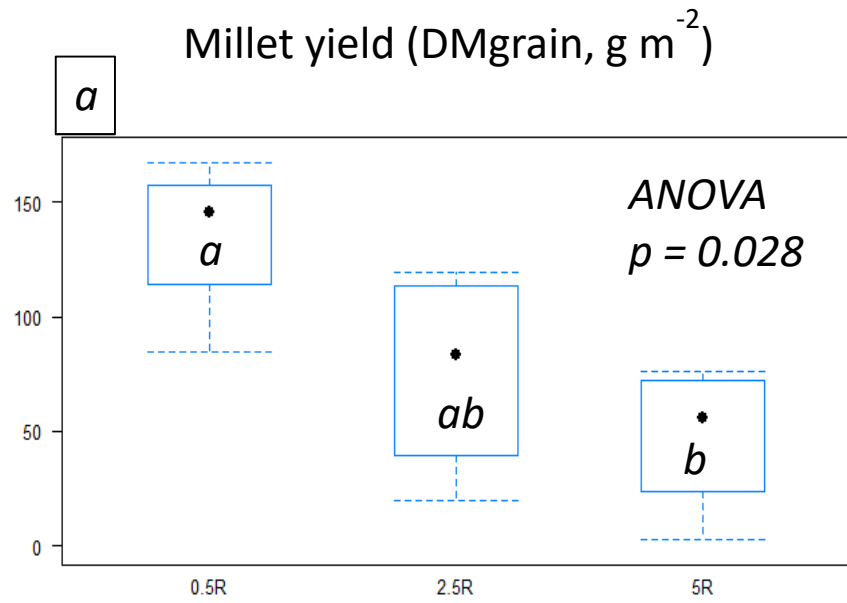


Figure 12:

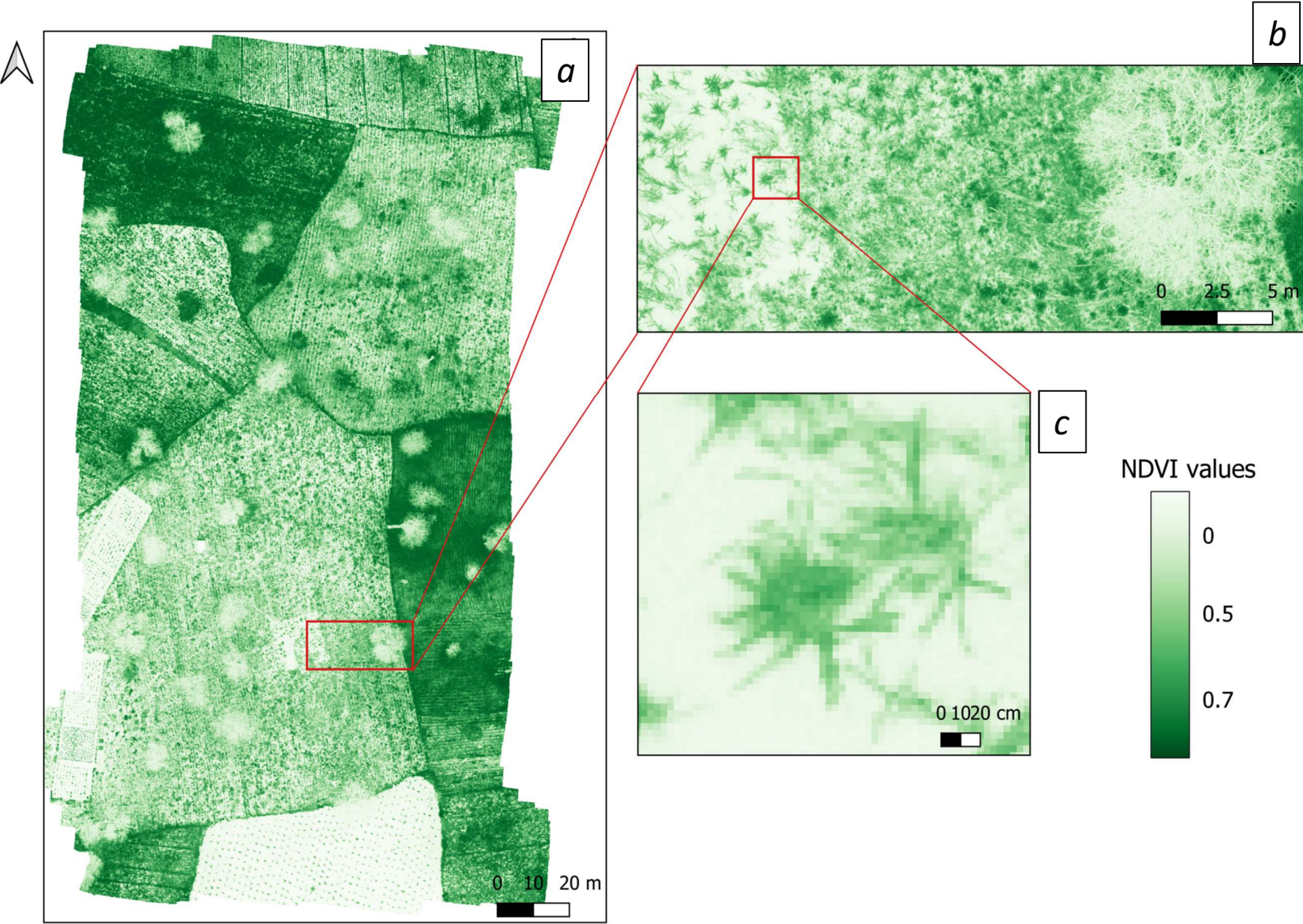


Figure 13:

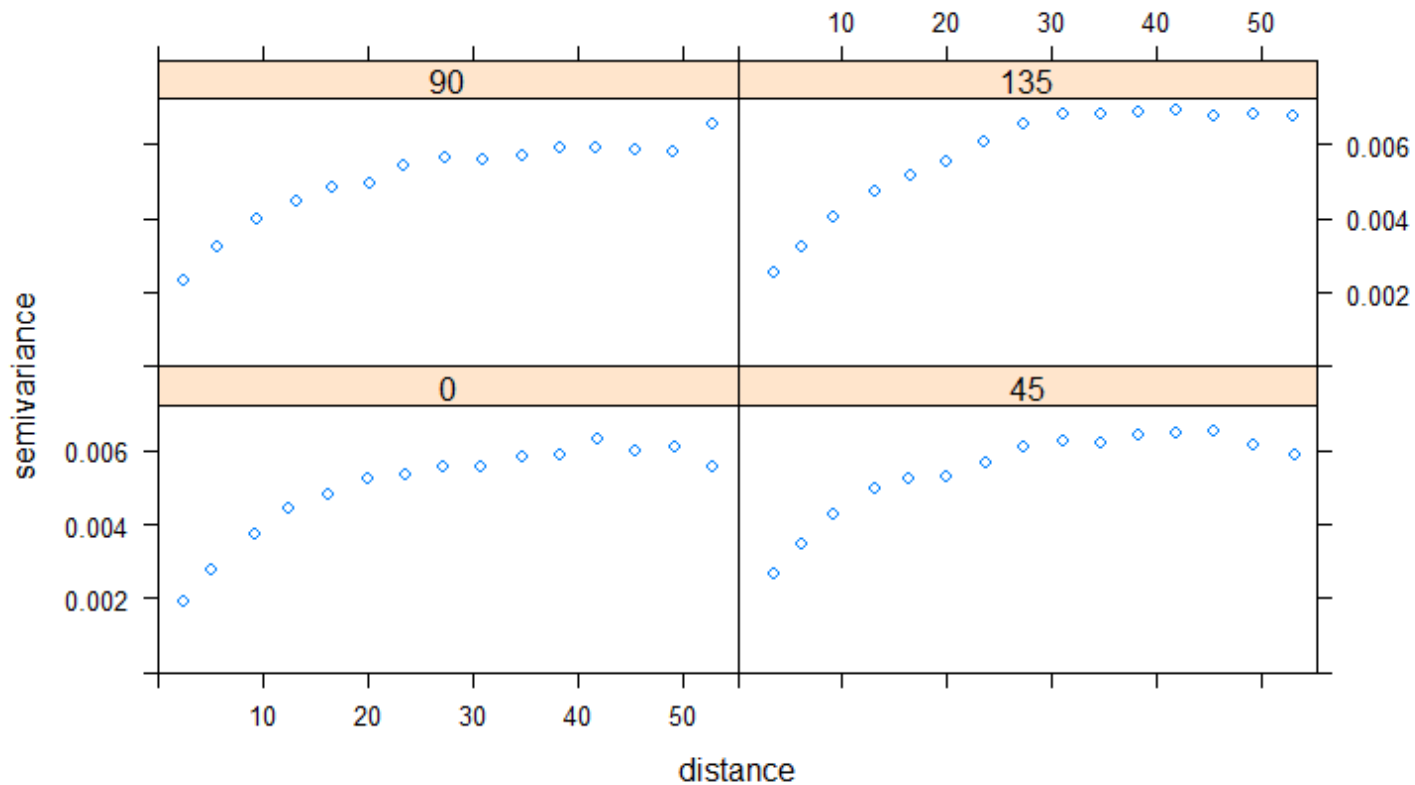


Figure 14:

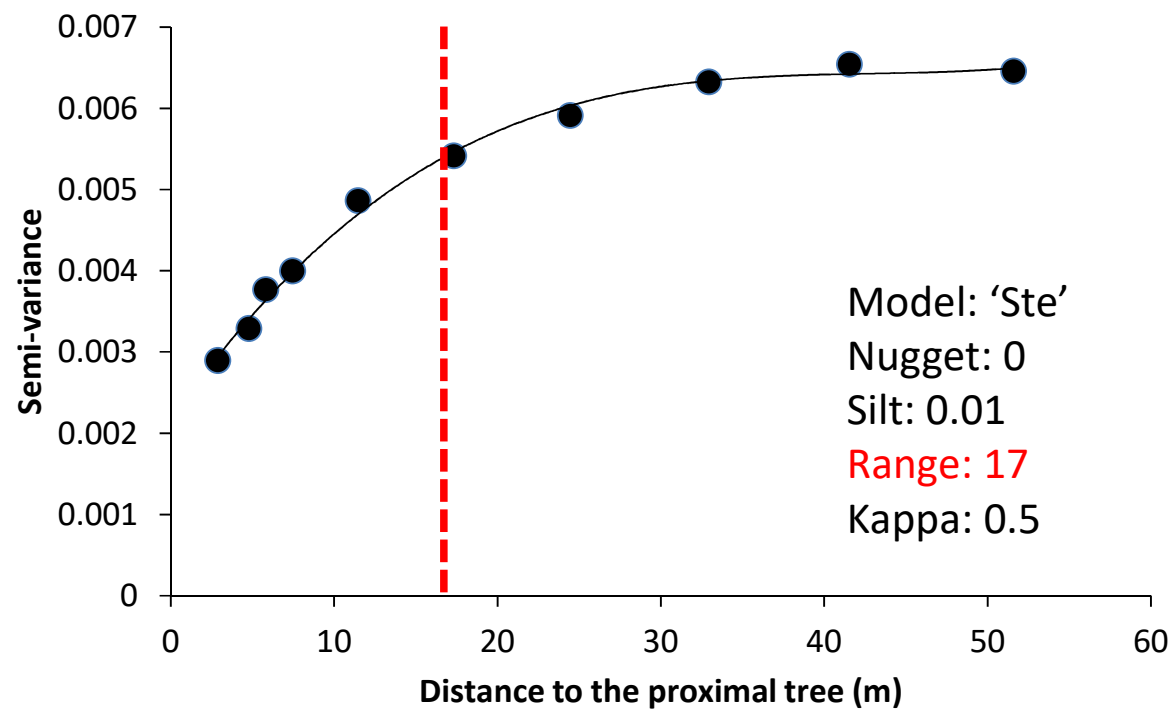


Figure 15:

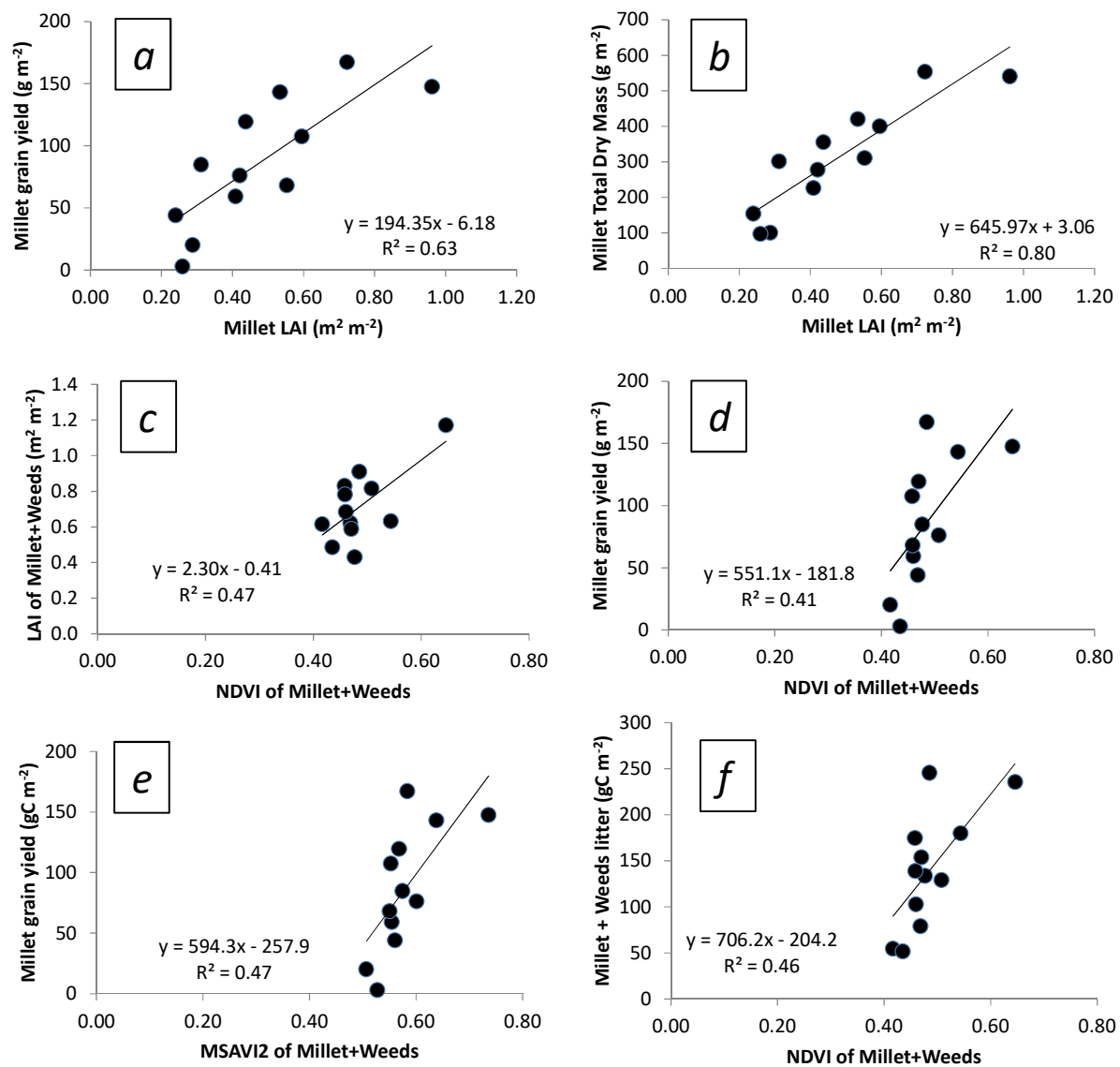


Figure 16:

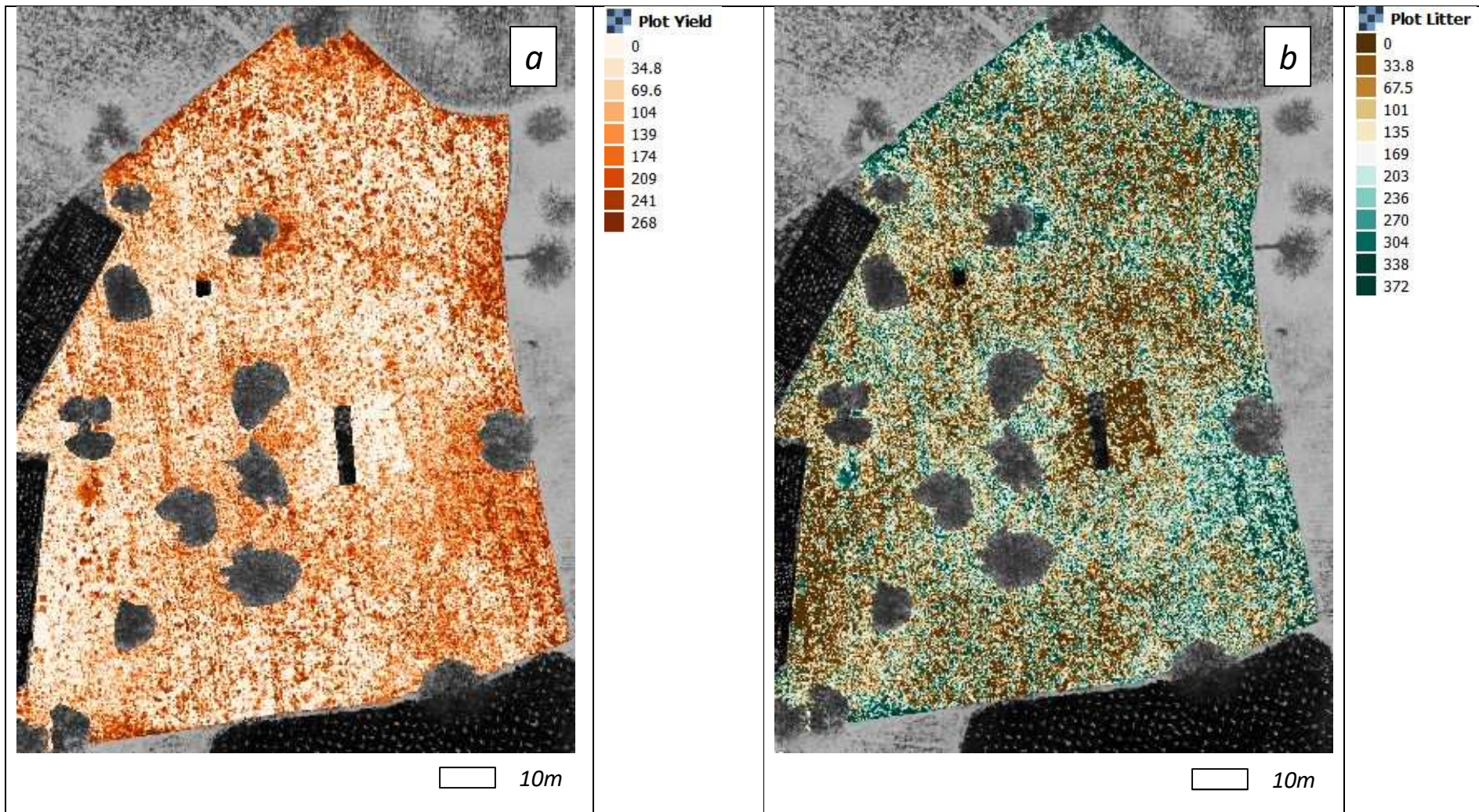


Table 1: One-way ANOVA statistics for effect of the *Faidherbia albida* tree upon average \pm SD crop traits, as assessed in 12 harvest subplots according to three distances from the tree: below the tree crown (0.5 R), at 2.5 radii (2.5 R), and at 5 radii (5R), where R is the radius of the tree crown. N = 4 replicates (4 transects) per distance to tree.

Variable	0.5R	2.5R	5R	Variances homogeneity (Bartlett)	Normality of the residues (Shapiro)	Test	F-value	p-value
Grain Dry Mass ($g_{\text{grain}} m^{-2}$)	a 135.60 \pm 35.47	ab 76.49 \pm 45.74	b 47.77 \pm 32.89	0.85	0.14	ANOVA	5.43	0.028
Stem Dry Mass ($g m^{-2}$)	a 156.06 \pm 37.69	ab 86.61 \pm 45.42	b 70.56 \pm 31.86	0.85	0.42	ANOVA	5.51	0.027
Whole-plant Dry Mass ($g m^{-2}$)	a 453.89 \pm 118.12	ab 270.68 \pm 135.27	b 209.94 \pm 101.08	0.90	0.10	ANOVA	4.56	0.043
Weeds aerial Dry Mass ($g m^{-2}$)	a 210.12 \pm 53.48	ab 403.47 \pm 76.28	b 689.20 \pm 439.40	0.003	0.01	Kruskal-Wallis	-	0.021
Millet + Weeds Litter ($gC m^{-2}$)	a 198.50 \pm 52.10	ab 121.35 \pm 53.80	a 99.47 \pm 41.45	0.91	0.08	ANOVA	4.43	0.046
NDVI	a 0.54 \pm 0.08	a 0.45 \pm 0.03	a 0.47 \pm 0.03	0.16	0.32	ANOVA	3.13	0.093
MSAVI2	a 0.63 \pm 0.07	a 0.55 \pm 0.03	a 0.56 \pm 0.03	0.18	0.37	ANOVA	3.69	0.068
Leaf Dry Mass ($g m^{-2}$)	a 59.76 \pm 19.45	a 40.84 \pm 14.95	a 33.45 \pm 12.50	0.77	0.37	ANOVA	2.91	0.106
SLA ($m_{\text{leaf}}^{-2} kg_{DM}^{-1}$)	a 10.37 \pm 2.10	a 10.92 \pm 1.60	a 10.97 \pm 0.61	0.20	0.78	ANOVA	0.18	0.835
LAI ($m_{\text{leaf}}^{-2} m_{\text{soil}}^{-2}$)	a 0.63 \pm 0.28	a 0.44 \pm 0.13	a 0.37 \pm 0.15	0.39	0.99	ANOVA	1.96	0.197
Root Dry Mass ($g m^{-2}$)	a 56.21 \pm 21.05	a 32.07 \pm 14.21	a 31.59 \pm 17.45	0.82	0.15	ANOVA	2.51	0.136
Root-to-tot. ratio ($g_{\text{root}} g_{\text{plant}}^{-1}$)	a 0.17 \pm 0.03	a 0.19 \pm 0.05	a 0.24 \pm 0.09	0.25	1.00	ANOVA	1.26	0.330
Head minor effect (% or ear)	a 6.74 \pm 4.60	a 7.59 \pm 6.70	a 6.54 \pm 3.36	0.54	0.48	ANOVA	0.05	0.953

Table 2: Correlation statistics between crop traits, or between NDVI or MSAVI2 and some crop traits, within the 12 harvested subplots.

Figure	Y Variable	X Variable	Equation	Normality of the residues (Shapiro)	r ²	RMSE	RRMSE (%)	p-value
7a	Millet grain yield (g m ⁻²)	Millet LAI (m _{leaf} ² m _{soil} ⁻²)	Y = 194.347*X - 6.178	0.22	0.63	32.87	37.9	0.002
7b	Millet total dry mass (g m ⁻²)	Millet LAI (m _{leaf} ² m _{soil} ⁻²)	Y = 645.968*X + 3.055	0.23	0.80	71.84	23.1	<0.001
7c	LAI of millet + weeds (m _{leaf} ² m _{soil} ⁻²)	NDVI of millet + weeds	Y = 2.2956*X - 0.4054	0.79	0.47	0.15	21.6	0.014
7d	Millet grain yield (g m ⁻²)	NDVI of millet + weeds	Y = 551.1*X - 181.8	0.52	0.41	41.45	47.9	0.024
7e	Millet grain yield (g m ⁻²)	MSAVI2 of millet + weeds	Y = 594.3*X - 257.8	0.58	0.47	39.37	45.5	0.014
7f	Millet+weeds litter (gC m ⁻²)	NDVI of millet + weeds	Y = 706.2*X - 204.2	0.15	0.46	48.65	34.8	0.016

Table 3: Computation of pearl-millet yield and crop-partial Land Equivalent Ratio (LER_{cp}) from subplots to the whole-plot scale; comparison (error) between measurements (in subplots and at the whole-plot scale) and estimations via UAV-NDVI product. Y_i is the yield in agroforestry used to compute LER_{cp} .

	Method	Variable of interest	Value	Unit
Whole-plot characteristics	QGIS	Whole plot area	8994	m ²
	QGIS	Shelter area	62	m ²
	QGIS	Trunk basal area	2.4	m ²
	QGIS	Whole plot effective area	8929	m ²
	Manual	Subplots area	226	m ²
	QGIS	<i>F. albida</i> canopy projected area	862	m ²
	QGIS	<i>F albida</i> canopy cover	9.6	%
Harvest	Measured	Subplots harvest	17.6	kgDM grain
	Measured	Whole-plot bundle harvest (without subplots)	52.0	# bundles
	Measured	Whole-plot bundle harvest (without subplots)	1214.6	kgDM bundles
	Measured	Rate of conversion bundle-to-grain	0.52	/
	Measured	Whole-plot grain harvest (without subplots)	632.0	kgDM grain
	Measured	Whole-plot harvest	650	kgDM grain
	UAV-NDVI (Estimated)	Estimated Whole-plot harvest	811	kgDM grain
Yield	Measured	Millet yield as sole crop (5R)	0.48	tDM grain ha-1
	Measured	Millet yield half-distance (2.5R)	0.76	tDM grain ha ⁻¹
	Measured	Millet yield under tree crown (0.5R)	1.36	tDM grain ha ⁻¹
	Measured	Whole-plot Yield	0.73	tDM grain ha ⁻¹
	UAV-NDVI (Estimated)	Estimated Millet yield sole crop (dist>Range)	0.82	tDM grain ha-1
	UAV-NDVI (Estimated)	Estimated Millet yield agroforestry (Crown<dist<Range)	0.92	tDM grain ha-1
	UAV-NDVI (Estimated)	Estimated Millet yield agroforestry (dist<Crown)	1.21	tDM grain ha-1
	UAV-NDVI (Estimated)	Estimated Whole-plot Yield	0.91	tDM grain ha-1
Error	Yield Error	19.9	%	
LER_{cp}	UAV-NDVI (Estimated)	LER_{cp} with Y_i = actual whole plot yield	1.10	/
	UAV-NDVI (Estimated)	LER_{cp} with Y_i = whole plot yield for dist <Range	1.16	/
Millet+Weeds litter	UAV-NDVI (Estimated)	Estimated Litter (Crop + weeds)	1.05	tC ha-1