



Exploring the landscape scale influences of tree cover on crop yield in an agroforestry parkland using satellite data and spatial statistics

Martin Karlson^{a,*}, David Bolin^b, Hugues Roméo Bazié^c, Abraham Sotongo Ouedraogo^c, Boukary Soro^c, Josias Sanou^d, Jules Bayala^e, Madelene Ostwald^a

^a Department of Thematic Studies/Environmental Change, Linköping University, 58183, Linköping, Sweden

^b Statistics Program, Computer, Electrical and Mathematical Sciences and Engineering Division, King Abdullah University of Science and Technology (KAUST), Thuwal, 23955-6900, Saudi Arabia

^c Laboratoire Biosciences, Unité de Formation et Recherche en Sciences de la Vie et de la Terre, Université Joseph Ki-Zerbo, Ouagadougou, Burkina Faso

^d Département Environnement et Forêts, Institut de l'Environnement et de Recherches Agricoles, Ouagadougou, Burkina Faso

^e Center for International Forestry Research-World Agroforestry (CIFOR-ICRAF), Sahel Office, Ouagadougou, 06 BP 9478, Burkina Faso

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ABSTRACT

Trees in agroforestry parklands influence crops both through competitive and facilitative mechanism, but the effects are challenging to disentangle due to the complexity of the system with high variability in tree cover structure and species diversity and crop combinations. Focusing on a landscape in central Burkina Faso dominated by *Vitellaria paradoxa* and *Parkia biglobosa*, this paper examines how tree cover influences crop yield at landscape scale using satellite data and spatial statistics. Our analysis is based on data from 2017 to 2018 with differences in rainfall to assess the stability in identified relationships. Our findings showed that tree canopy cover and tree density inside the fields tended to decrease crop yield because of competition, but also that these variables when considering the surrounding landscape exerted an opposite effect because of their buffering effects. The explanatory variables representing soil properties did have limited effects on crop yield in this study. These patterns were consistent during the two years of monitoring. Overall, our results suggest that farmers in this area might manage the tree cover in a way that optimizes sustainable yields as canopy cover and tree density in most parklands is below the limits identified here where competition outweigh the facilitative effects.

1. Introduction

Smallholder farming in agroforestry parklands is the dominating agricultural strategy in the Sudano-Sahelian zone of West Africa and provide the subsistence base for a large proportion of the population (Bayala et al., 2014). Parklands are basically agricultural landscapes characterized by the coexistence of scattered trees and crops. Specifically, trees of selected species are retained in the fields mainly for their perceived positive influence on soil quality and erosion, and for providing food and fodder, as well as other non-timber forest products (Sinare and Gordon, 2015). These parkland systems reflect strategies developed by the farmers for generations to reduce their vulnerability to risks primarily related to climate variability. However, food security is a chronic problem in these Sahelian countries due to a heavy reliance on rainfed crops and the highly unpredictable rainfall patterns that has frequently led to agricultural drought in the past decades, and will

continue to do so in the future (Laudien et al., 2022). In addition, increasing demand for agricultural land from a growing population means that sustainable intensification is a critical pathway to ensure sufficient food production in the near future. Tree cover management in parklands could be one important action in this context.

Much research efforts have been directed to explore the crop yield potential of different agroforestry systems as sustainable options to improve food production in sub-Saharan Africa. For example, according to a meta-analysis (Kuyah et al., 2019), average yields of staple crops were almost twice as high in agroforestry compared to yields in treeless systems. Using 64 observations from 15 studies conducted in Burkina Faso, Mali, Niger and Senegal, Bayala et al. (2012) found that parkland trees increase crop yield between 0.14 and 0.24 Mg ha⁻¹ depending on species composition and structure of the tree cover, which suggests that management practices can have important implication for crop yield in these landscapes. Furthermore, Roupsard et al. (2020) recently

* Corresponding author.

E-mail address: martin.karlson@liu.se (M. Karlson).

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demonstrated the production benefits of agroforestry parklands by assessing the land equivalent ratio (LER) focusing on an area in the Peanut Basin in Senegal. LER defines the amount of land needed by monoculture agricultural to give the same yield as an agroforestry system. Rouspard et al. (2020) estimated LER to 1.16 in this system dominated by *Faidherbia albida*. Hence, the parkland systems are highly relevant from a food security perspective, especially in situations when land is a scarce resource and climate resilience is a high priority. Tree-based agricultural systems have also proven to be superior monoculture systems in terms of biodiversity for both fauna and flora and has been suggested as a rational option of human dominated landscapes when strict conservation efforts are out of reach (Baudron et al., 2019).

While having several livelihood benefits, trees in agroforestry systems, such as parklands, also influence the availability of the key resources controlling crop growth and yield, including water, nutrients, and sunlight (Ilstedt et al., 2016; Luedeling et al., 2016). Consequently, trees can compete with crops over sparse resources both above and below ground depending on spatial arrangement, structural characteristics and species composition of the tree cover. On the other hand, trees can also facilitate crop growth and yield through mechanisms such as nitrogen fixation and nutrient cycling, hydraulic lift to improve water availability, replenishment of soil organic matter, control of erosion, as well as moderation of temperature and wind, all of which are mechanisms that depend on tree cover properties (Bayala et al., 2014). The balance between competition and facilitation exerted by trees on crops is thus a key consideration in agroforestry management aiming to improve crop yield. In addition, significant declines in parkland tree densities is taking place in many parts of the Sudano-Sahel because of changing climate condition, increasing livestock pressure on seedlings, altered land management practices and high population growth (Brandt et al., 2017; Gonzalez et al., 2012). The effects of such changes on crop yield is highly uncertain but critical to understand for effective land management decisions aiming to slow down or reverse the trend.

Consequently, the direction and magnitude of trees' influence on crop yield, and thus indirectly on food security, in agroforestry parklands is highly complex, dependent on the agroecological conditions and is thus still a debated topic despite extensive research (Bayala et al., 2014, 2015). A key challenge to this type of agro-ecological research has been a scale issue, much related to the heavy workload associated with field data collection usually resulting in a limited sample size. Field trials are generally conducted at the scale of individual trees focusing on the effects on crops beneath the crown or in intercanopy areas where the dominant approach is to compare crop performance within the tree zone of influence with areas outside of it (Bayala et al., 2015; Sanou, 2010). However, the influence zone of trees is very difficult to constrain and can differ between tree species depending on resource extraction rate, root system characteristics and shading capacity, which can make it difficult to identify areas not affected by trees, potentially introducing bias in the analysis. A key question in the context of such studies is if the effects of individual trees scale up to the landscape (Riginos et al., 2009). Another limitation is that individual tree scale studies often focus on the effects of specific tree species on specific crop types, while the more complex real situation with multiple crop combinations and a tree cover with high diversity in species composition and structural characteristics is more difficult to assess due to potentially overlapping and combined influences. The complexity that is introduced when the spatial scale is increased is large and has led to that these analytical approaches have contributed insufficient understanding about the influence of trees on the landscape scale, which is crucial for effective decision-making regarding land management related to the tree cover. The landscape scale effect on crop performance includes not only trees within the agricultural field, but also those in the surrounding areas (Luedeling et al., 2016).

Recent studies have employed Earth Observation data to enhance the knowledge about the landscape scale effect of trees in dryland agriculture, including in parklands. Such datasets enable efficient collection of

key agroecological variables over large areas at low cost and workload, including vegetation productivity and tree cover structure. For example, Leroux et al. (2020) applied high-resolution satellite imagery to map spatial variability in tree cover structure and crop yield at landscape scale in Senegal focusing on the effect of *Faidherbia albida* on millet yield. These two spatial datasets were then analyzed using the Gradient Boosting algorithm to explore the influence of trees on crop yield. In addition to tree cover, other explanatory variables known to influence crop growth in this study included soil properties and water stress. Through this method they could explain 81% of the yield variability based on the woody cover in the surrounding landscape of the fields, while the largest influence was by soil nutrients. On a more geostatistical note, Rouspard et al. (2020) used drone imagery to map millet yield and tree cover, and concluded through semi-variogram analysis that trees influenced crop growth up to 17 m from a *Faidherbia albida* tree. They also found that the yield was three times higher below the tree crown than at a 5 m distance from the crown edge. Further landscape scale evidence of the positive influence of *Faidherbia albida* on crop yield, but also on other important ecosystem services provided by trees, including microclimate regulation, carbon sequestration and pest control, is presented in the recent study in Senegal by Leroux et al. (2022a).

A key aspect of our study is that we focus on a more complex parkland type characterized by high tree species diversity, varying tree densities and sizes, as well as multiple crop combinations of cereals (sorghum and pearl millet) and legumes (cowpea). The overall aim of the study is to determine the influence of parkland trees on crop yield at landscape scale across a range of different tree cover characteristics. This is achieved by using a novel analytical approach that combines high resolution remote sensing and field data from two years (2017 and 2018) within a spatial framework for data processing and statistical analysis. We assessed the influence of several explanatory variables characterizing the tree cover structure both in agricultural fields and in the surroundings. We also include variables characterizing soil properties linked to the tree cover in the analysis to study their influence on crop yield. Soil properties in focus included soil carbon which promotes formation of soil aggregates and constitutes food for soil fauna, the activity of which can improve physical soil properties important for crop growth (Bayala et al., 2015). Key physical properties in this context include soil density, soil porosity and water infiltrability. Another soil property of high importance for crop growth in the Sudano-Sahel included in the analysis is nitrogen availability (Buah and Mwinkaara, 2009; Robertson and Rosswall, 1986). The following two questions have guided the work:

- How does tree cover structure and soil properties influence crop yield at the landscape scale and what are the implications for parkland management?
- Focusing on two years with differences in rainfall (2017 and 2018), is there consistency in the influence of tree cover structure and soil properties on crop yield?

2. Material and methods

2.1. Study area

The study area is an agroforestry parkland in the commune of Saponé (12°04'48"N, 1°34'00"W), located 30 km south from Ouagadougou in central Burkina Faso (Fig. 1). The area around Saponé is a typical Sudano-Sahelian parkland landscape where subsistence farming is practiced and the fields are primarily rainfed and sown in the end of the dry season in (May to July), usually without ploughing. Weeding takes place two to three times during the growing season and the dominant crops include pearl millet (*Pennisetum glaucum* (L.) R. Br.), sorghum (*Sorghum bicolor* (L.) Moench) and legumes, such as cowpea (*Vigna unguiculata*). Some irrigated areas can be found close to a constructed dam in the southern parts of the study area. Grain yield (sorghum, millet

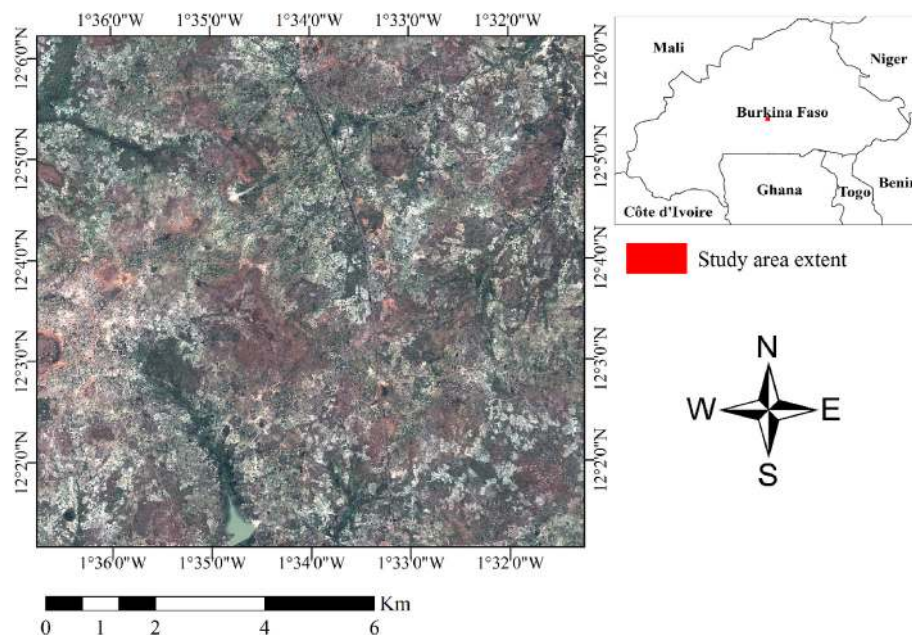


Fig. 1. Location and extent of the study area in Saponé, Burkina Faso (Pléiades© CNES, 2018; Distribution AIRBUS DS). The image is a true-color composite based on band 2 (red), band 1 (green) and band 0 (blue).

and cowpea) range from 100 to 1500 kg ha⁻¹ with most fields producing yields between 100 and 600 kg ha⁻¹ (Bazié et al., 2012). Farmers fertilize the fields with various forms and amounts of organic amendment, including manure, crop residues, woody litter, and compost, but rarely mineral fertilizers.

The local terrain is gently undulating with small variations in elevation (293–363 m above sea level). The soils are shallow (on average 60 cm), sandy loamy regosols (FAO classification) with very low nutrient content in terms of nitrogen, phosphorus and organic material (Bazié et al., 2012). The soil composition of the top 10 cm is 7% clay, 19% silt, 74% sand and 0.5% organic matter (Pallo, 2001). In addition, the soils are weakly acidic with low cation exchange capacity (Bayala et al., 2002). The average tree density in the fields is between 21 and 27 trees per hectare (see section 2.6; Bazié, 2013), and the tree layer is the result of farmer's selection and retention of certain individuals when clearing natural woodlands for cultivation. Mean tree canopy cover in the fields is 13.7% (see section 2.6) and mainly consists of traditional agroforestry species, in particular *Vitellaria paradoxa*, *Parkia biglobosa*, *Lannea microcarpa*, and *Mangifera indica* (Karlson et al., 2016). The herbaceous cover is composed perennial herbaceous species such as *Andropogon gayanus*, *Andropogon pseudapricus*, *Loudetia togoensis* and *Pennisetum pedicellatum*.

The climate in Saponé is Sudano-Sahelian, with a single rainy season marked by intermittent rains in April and May, followed by more persistent rainfall from June to October (Bazié et al., 2012). Average annual potential evapotranspiration (PET_{Penman}) is 1900 ± 210 mm, with a maximum monthly mean temperature of 34.9 °C and a minimum of 21.5 °C (Bazié et al., 2018). Average annual rainfall is around 800 mm (between the isohyets 600 mm and 900 mm) with high inter-annual variability, which strongly influences the timing for sowing, conditions for crop development, levels of yield and time of harvest. The rainy season generally starts in May and ends in October and the main proportion of rain usually falls between July and September. Sowing of crops begins between June and July, depending on crop type and the onset of the rainy season, whereas harvesting generally takes place between late October and early November. However, unreliable rainfall at the start and end of the rainy season can lead to large windows for both sowing (May 15–July 15) and harvesting (October 15–December 15). This is even more unreliable nowadays due to high climate variability, as

evidenced by farmers sometimes continuing to sow in August, as well as rains continuing to the beginning of November. Total rainfall in Saponé was 850.7 mm in 2017 and 789.1 in 2018, with relatively large inter-annual differences in the monthly distribution (Fig. 2). For the 2018 rain season, the wettest month was July with a monthly total accumulation of 323.5 mm with 10 days of rain.

2.2. Field data

To produce the input variables to our statistical analysis, several data sets were used (see section 2.6). The response variable, i.e., crop yield, was estimated using a combination of field data and satellite remote sensing. We quantified above-ground biomass (AGB) of crops and grain yield in a total of 22 plots (20 × 20 m) during the harvest period in 2017 and 2018 (Karlson et al., 2020). Plot locations included agricultural fields with different crop combinations and tree canopy cover, where agreements with the farmers were obtained. Each plot was geo-referenced using a Garmin Oregon GPS device with a locational error <3 m. Three different crops were cultivated in the sampled fields: sorghum, pearl millet and cowpea, including both single crop of cereals (sorghum and pearl millet) and mixed crop cereal-cowpea fields (Table 1). At the end of growing season, for each plot and crop, we cut, dried, and weighed the different plant components. The millet and

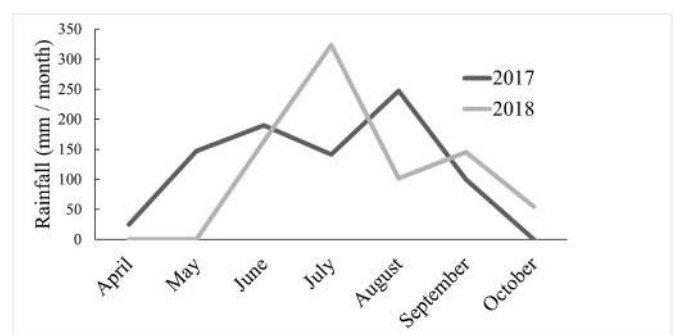


Fig. 2. Monthly rainfall distribution in 2017 and 2018 reported by Saponé Agricultural Service.

Table 1

Description of field plots used for collection of yield data in 2017 and 2018, including distribution of crop type combinations and descriptive statistics.

Year	Crop combination	Grain yield ton ha ⁻¹		
		Min	Max	Mean
2017	Sorghum (n = 4)	0.17	0.57	0.33
	Millet (n = 6)	0.01	0.38	0.15
	Sorghum – cowpea (n = 7)	0.05	0.89	0.36
	Millet – cowpea (n = 1)	0.15	0.15	0.15
	Millet– sorghum – cowpea (n = 4)	0.16	0.87	0.41
	Total	0.01	0.89	0.30
2018	Sorghum (n = 8)	0.04	1.12	0.37
	Millet (n = 5)	0.08	0.82	0.35
	Sorghum – cowpea (n = 3)	0.05	0.73	0.31
	Millet – cowpea (n = 5)	0.14	0.26	0.22
	Millet– sorghum – cowpea (n = 1)	0.36	0.36	0.36
	Total	0.04	1.12	0.32

sorghum plant components included ears, grain, and straw, and for cowpea the components included pods, grain, and residues. The crop type proportions in the mixed fields were 86% cereals and 14% cowpea in 2017 and 74% cereals and 26% cowpea in 2018. Grain yield data were used for calibrating yield estimation models for landscape scale mapping based on Sentinel-2 imagery (section 2.5.2).

In addition to the yield data, we also georeferenced, measured, and determined species of trees inside or on the borders of the sampled fields. Measured dendrometric variables included tree height, stem diameter at breast height and crown diameter. The tree data was used to visually assess the quality of the tree cover map derived from Pléiades data (section 2.5.3).

2.3. Satellite data and pre-processing

Crop yield estimation requires satellite data with high temporal resolution, both to capture key stages in the plant development and to increase the probability of acquiring relatively cloud-free observations during the growing period in this type of geographical region (Lobell, 2013). In addition, relatively high spatial resolution satellite data is needed to enable a sufficiently accurate delineation of smallholder fields and to resolve crop yield within them (Leroux et al., 2020). We used data from the Sentinel-2 system for field delineation and yield estimation because it provides relatively high spatial resolution (10 m) and short revisit periods due to the dual satellite configuration.

Tree cover mapping in agroforestry parklands also benefits from high spatial resolution data, as well as imagery with a high contrast between trees and the ground cover. We used a combination of end of growing season Pléiades images that fulfills both these requirements, as well as an early growing season image to compensate for differences in leaf development, to resolve individual trees or groups of trees.

2.3.1. Sentinel-2

To map crop yield over our area, we acquired Sentinel-2A and 2B growing season time-series for 2017 and 2018 processed to surface reflectance (Level 2A) using a processing chain called “Sentinel-2 for Agriculture” (Bontemps et al., 2015; Defourny et al., 2019). Individual steps in the processing chain include atmospheric correction, cloud and cloud shadow detection, and aerosol optical thickness retrieval by application of the MACCS algorithm (Hagolle et al., 2015). Setting a cloud cover threshold of <30% produced growing season time series consisting of six granules (30PXU) for 2017 (9/6, 29/6, 29/7, 7/9, 7/10, 22/10) and seven for 2018 (14/6, 14/7, 24/7, 17/9, 27/9, 7/10, 22/10). The 20 m red-edge bands of Sentinel-2 were resampled to 10 m using bilinear interpolation to enable integration with the visible and near-infrared bands.

2.3.2. Pléiades

For mapping tree cover structure, we acquired two Pléiades images from November 19, 2017 and May 20, 2018 that represent the early dry season and early growing season, respectively. Using observations from both these periods compensate for phenological variations of both trees and undergrowth, such as crops and grasses (Karlson et al., 2016). The Pléiades data was delivered as pansharpened products with four 0.5 m spectral bands, including blue, green, red and near infrared wavelengths. Both the November and May images were spatially aligned to a WorldView-2 image from October that had previously been georeferenced using ground control points (Karlson et al., 2014).

2.4. Soil data

Data on soil properties important for crop growth were acquired from the SoilGridstm data base (Poggio et al., 2021) released in May 2020. This database consists of several layers of soil properties representing a range of different depth intervals delivered in 250 × 250 m grids produced from spatial modelling of soil profile data and a large set of environmental covariates. For this study, we acquired the layers nitrogen (N; cg/kg), soil organic carbon (SOC; g/kg) and organic carbon density (OCD; g/dm³) at three different depth intervals (0–5 cm, 5–15 cm, 15–30 cm).

2.5. Satellite data processing and variables for statistical modelling

2.5.1. Cropland extent

We produced annual cropland maps for both 2017 and 2018 because of the dynamic nature of agricultural practices in the area where fields are fallowed on a regular basis, although the frequency and duration has decline recently due to high pressure on the land. We used field reference data and Sentinel-2 growing season time-series at 10 m spatial resolution to train random forest models producing land cover maps with five thematic classes, including cropland, tree cover, water, bare land, and fallow. All classes except cropland were then collapsed generating binary cropland maps with users' accuracy >90% for both years. A detailed description of the cropland map production can be found in Masimula (2020), including the land cover reference polygons (n = 488). Both cropland maps were then vectorized to polygons.

2.5.2. Yield estimation

To estimate crop yield over our study area in 2017 and 2018, we applied the linear regression models calibrated in Karlson et al. (2020) within areas delineated by our cropland map (see section 2.5.1). Specifically, the calibration was done using the total yield, including the yield from both cereals (pearl millet and sorghum) and legumes (cowpea). This type of modelling is usually done for specific crop types, creating separate models for each crop (e.g., sorghum, maize and cotton; Lambert et al., 2018; Leroux et al., 2020). While differences in phenology between the two crop types may influence the accuracy of the models negatively, mixing of crops in the fields is the common situation in this area and the general models for yield estimation used here therefore better reflects the actual conditions on the ground.

Vegetation index time-series based on visible and red-edge Sentinel-2 band combinations and the field data described in section 2.2 were used as input variables in ordinary least squares regression models. Several different vegetation indices, as well as temporal imagery compositing periods and individual acquisition dates, were initially evaluated to identify models producing the most accurate yield estimates for both years. This assessment revealed that a vegetation index produced from red-edge and near infrared wavelengths (Karlson et al., 2020) produced the most accurate yield estimates in both years. In terms of the effectiveness of image acquisition date and compositing period, results differed between years. For 2017, a model using a single image from 7 September produced the most accurate yield estimates, with a coefficient of determination (R^2) of 0.80 and a relative root mean square

error (relRMSE) of 32.2%. For 2018, a median composite generated the most accurate yield estimates ($R^2 = 0.68$, relRMSE = 47.5%). Karlson et al. (2020) provide descriptions detailing the development and assessment of the yield estimation models.

2.5.3. Tree cover

A binary tree cover mask covering the study area was derived using the following processing sequence. Firstly, NDVI was computed from both Pléiades images (November 2017 and May 2018). We then visually identified NDVI thresholds for both dates delimiting tree crowns through comparisons with false colour composites of the Pléiades images and trees measured in the fields. The NDVI thresholds for creating binary tree cover masks were set to >0.35 for November 2017 and >0.23 for May 2018. These two masks were then aggregated to one raster. The combination of two dates facilitated the detection of tree species with differences in the timing of leaf development and senescence. We then performed morphological filtering on the combined tree cover mask using the Binary Morphological Operation application implemented in Orfeo Toolbox 6.6.0 (Grizonnet et al., 2017) to prepare for vectorization. Specifically, we used the morphological opening filter with the circular structuring element (i.e., ball) set to a radius of 2 pixels. This filtering effectively removes small spurious objects ($<1\text{m}$ in diameter) and smooths boundaries of large objects. The filtering also splits tree objects with interlocking crowns to some extent. The filtered tree cover mask was then vectorized and visually validated through comparison with the two Pléiades images and field data collected within or on the borders of the sampled agricultural fields (section 2.2). By combining the tree cover mask with the cropland maps (section 2.5.1), we quantified tree crown cover (CC; %) and tree density (TD; trees/ha) both within and outside of agricultural fields.

2.5.4. Soil properties

Data on the three soil properties were delivered in three different depth intervals (0–5 cm, 5–15 cm and 15–30 cm). These depth intervals were averaged to produce individual layers of N, SOC and OCD. Each soil layer (250 m) was then resampled to a 10 m grid using bilinear interpolation to facilitate integration with the cropland layer. Specifically, we aimed to extract precise soil property values within cropland areas.

2.6. Spatial analytical framework and value extraction

The core of the spatial analytical framework used in this study is a regularly spaced grid consisting of $150 \times 150\text{ m}$ cells. The grid cells are the primary unit used in the statistical analysis described below (section 2.7). The cell size aims to approximate the mean field size found in the study area through visual assessment of the Pléiades imagery. We choose this grid-based framework over using individual crop patches as the spatial unit of analysis because of difficulties in accurately delineating individual crop patches in both the Sentinel-2 and Pléiades imagery. The

size of the grid cells ($150 \times 150\text{ m}$) is small enough to capture field specific homogeneity in biophysical conditions that control crop yield. The full grid covering the $10 \times 10\text{ km}$ study area consists of 4356 cells. However, cells without cropland as well as cells in which the yield estimation was affected by spurious cloud cover not detected by the MACCS processing chain were excluded from the analysis, resulting in 3030 cells in 2017 and 2730 in 2018.

As a first step, the grid was overlaid on the cropland mask and the boundaries of the cells thereby created new, artificial cropland objects (Fig. 3). In other words, all cropland pixels within each cell are considered individual multipart objects. These cropland objects represent the primary spatial unit used for extracting values of the explanatory variables and crop yield, as described in the following sections.

2.6.1. Crop yield

Firstly, pixels in the crop yield layers (2017 and 2018) covering trees inside agricultural fields were removed using the tree cover mask described in section 2.5.3. The mean of crop yield values was then extracted within each cropland object for both years (Table 2).

2.6.2. Tree cover variables

Canopy cover (CC; %) represents the percentage of a reference area covered by tree crowns delineated in the Pléiades imagery. Tree density (TD), on the other hand, is defined here as the number of tree crown objects delineated in the Pléiades imagery located within a specified area (e.g., hectare). This implementation of TD has some limitations mainly because individual tree crown could not be resolved in the Pléiades imagery when they formed interlocking groups of trees, hence the result may under estimate the number of individual trees.

Within each grid cell, average CC and TD was computed inside the agricultural fields and in the area outside of them, but within each cell (Table 2). We also quantified average CC and TD in buffer zones extending from the cropland object boundaries with buffer distances set to 100, 250 and 500 m (Fig. 4). The buffer distances were selected to disentangle potential influence of trees on crops taking place at different spatial scales. Calculations in the buffer zones exclude the interior of the cropland object.

2.6.3. Soil variables

The mean soil data values on N, OCD and SOC from the three depth interval layers (0–5 cm, 5–15 cm, 15–30 cm) produced soil property layers that were overlaid on the cropland layer followed by the calculation of mean values for each cropland object (Table 2).

2.7. Statistical analysis

To better understand the effects that the explanatory variables (tree cover structure and soil properties) have on crop yield, we first assigned the response variable on the cell level which is the mean crop yield per cropland area. This variable, which is shown in Fig. 5 and Table 3, is our

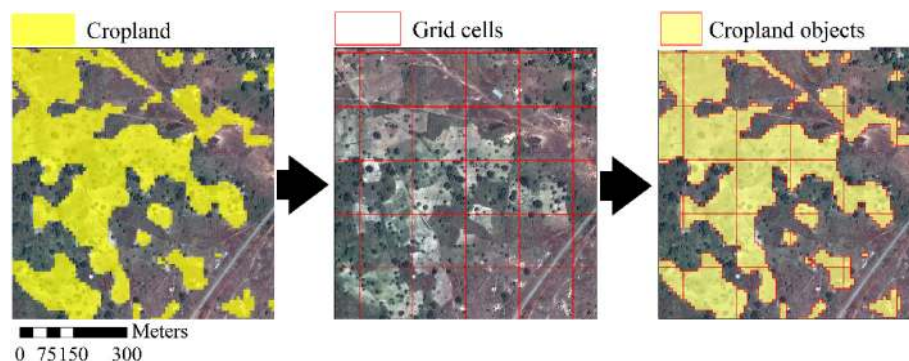


Fig. 3. Creation of multipart cropland objects over a smaller example area.

Table 2
Variables used as inputs in the statistical analysis.

Variable	Unit	Abbreviation	Type	Source	Min	Max	Mean	Stdv
Yield per land	Tons ha ⁻¹	Yld	Response	Sentinel-2 & field data	0.0	3.7	0.7	0.4
Cropland	% cell area	Crop	Response	Sentinel-2	0.4	100	63.6	29.6
Canopy cover in field	% field area	CC ^{field}	Explanatory	Pléiades	0	57.2	13.7	7.8
Canopy cover outside field	%	CC ^{out}	Explanatory	Pléiades	0	100	25.6	19.8
Canopy cover 100 m buffer	%	CC ¹⁰⁰	Explanatory	Pléiades	0.5	29.7	12.8	4.6
Canopy cover 250 m buffer	%	CC ²⁵⁰	Explanatory	Pléiades	1.7	40.0	15.9	5.5
Canopy cover 500 m buffer	%	CC ⁵⁰⁰	Explanatory	Pléiades	3.2	38.1	17.4	5.3
Tree density in field	Trees ha ⁻¹	TD ^{field}	Explanatory	Pléiades	0	133.3	20.8	12.9
Tree density outside field	Trees ha ⁻¹	TD ^{out}	Explanatory	Pléiades	0	134	22.4	21.1
Tree density 100 m buffer	Trees ha ⁻¹	TD ¹⁰⁰	Explanatory	Pléiades	2	58	16.8	6.9
Tree density 250 m buffer	Trees ha ⁻¹	TD ²⁵⁰	Explanatory	Pléiades	3	39	18.0	6.0
Tree density 500 m buffer	Trees ha ⁻¹	TD ⁵⁰⁰	Explanatory	Pléiades	5	32	18.0	5.2
Nitrogen	g/kg	N	Explanatory	SoilGrids tm	0	57	43.9	4.0
Organic carbon density	g/dm ³	OCD	Explanatory	SoilGrids tm	0	141.2	117.6	6.7
Soil organic carbon	g/kg	SOC	Explanatory	SoilGrids tm	0	197.6	56.5	10.8

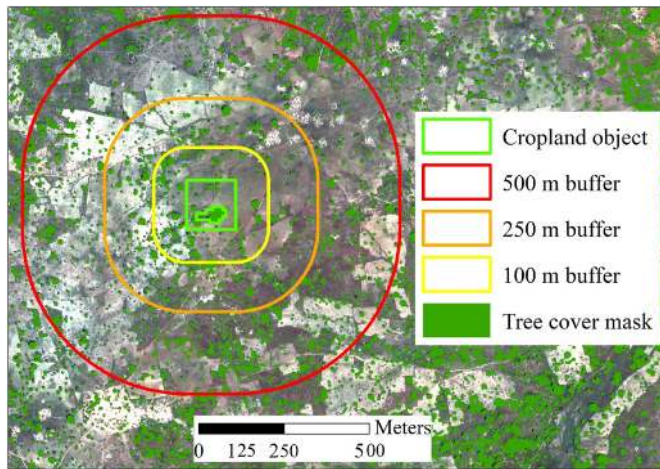


Fig. 4. Buffer zones for quantifying tree cover structure outside agricultural fields.

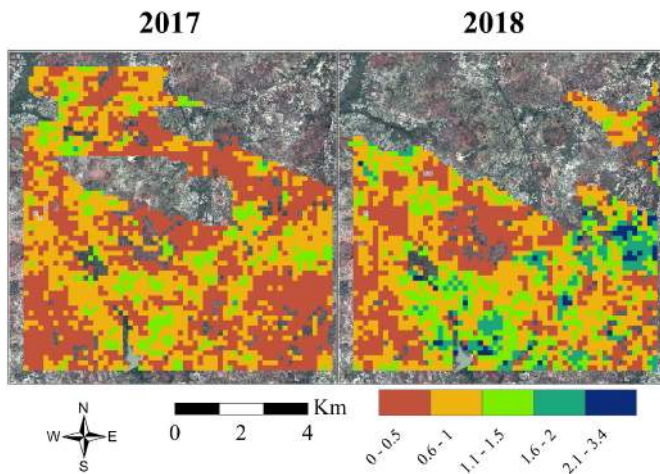


Fig. 5. The response variable representing yield per cropland area. The areas with no data in 2017 and 2018 are the result of cloud cover obstructing yield estimation based on Sentinel-2 imagery.

response variable throughout the analysis.

The construction of the statistical model is done in several steps. In an initial exploratory analysis, we first performed simple linear regression in the form

Table 3
Mean yield in 2017 and 2018.

Crop yield (tons/ha)	2017 (nr cells)	%	2018 (nr cells)	%
0–0.5	1447	48	751	28
0.6–1	1289	43	1102	40
1.1–1.5	285	9	527	19
1.6–2	9	0	283	10
2.1–3.4	0	0	67	2
Total	3030		2730	

$$Y_i = \sum_{k=1}^K \beta_k X_k(s_i) + \varepsilon_i,$$

to detect which explanatory variables that seem to influence the amount of crop yield significantly. Here Y_i is the response variable evaluated at the i :th grid cell, $X_k(s_i)$ is the k :th explanatory variable (or an interaction effect between two different explanatory variables) evaluated at the i :th grid cell, and ε_i are independent and mean-zero Gaussian random variables representing measurement noise. Besides the explanatory variables described in Table 2, we also included separate intercepts in the regression for each year, so that we can detect differences in the baseline level (in the sense that this would be the expected level for a location where all other explanatory variables were zero) between the two years.

At this initial stage, we first included all explanatory variables in the regression model and then removed those that did not have a significant effect. We also removed some explanatory variables that were highly correlated with other explanatory variables, in the sense that they had high variance inflation factors and therefore poorly estimated due to multicollinearity with the other explanatory variables. We used the standard choice of 10 for the threshold in the VIF analysis. All covariates had VIF number below 6, whereas CC^{250} and TD^{250} had values above 7000. Thus, we removed those two covariates because of the results of the VIF analysis.

After this initial variable selection, we tested for the presence of interaction effects (i.e., non-additive effects of the explanatory variables) by including interaction variables of the form $X_k(s_i) X_l(s_i)$, $k \neq l$, for the different canopy cover and tree density variables that were found to have significant effects on crop yield in the previous step.

For the initial regression, which included significant explanatory variables and interaction effects, we investigated the residuals visually and found a significant spatial correlation in those. To obtain quantitative measures of the spatial dependence in the data, we computed Moran's I statistic using inverse distance as weight. The observed values of the statistics for 2017 and 2018 were 0.043 and 0.130, respectively. Since these values are positive, it indicates a positive autocorrelation in the residuals. To confirm this, we performed hypothesis tests with null-

hypothesis “no autocorrelation (Moran’s $I = 0$)” and a two-sided alternative (Moran’s I different from zero). For both years, the null-hypothesis could be rejected with a very high confidence (the p-values were below 0.0001). In order to account for this spatial dependence in the data, we constructed a new model that included a spatially correlated random field in the regression model, resulting in a model of the form

$$Y_i = \sum_{k=1}^K \beta_k X_k(s_i) + U(s_i) + \varepsilon_i,$$

where $U(s_i)$ is the random field evaluated at the i :th grid cell. We denote this as the spatial model. The random field is chosen as a mean-zero Gaussian random field with a Matérn covariance function to model the spatial dependence. That is, we assume that the covariance between the random field at two locations, $C(U(s_i), U(s_{ij}))$, is of the form $C(U(s), U(t)) = r(|s-t|)$, where $|s-t|$ is the distance between the locations and

$$r(h) = \sigma^2 \frac{2^{v-1}}{\Gamma(v)} (\kappa h)^v K_v(\kappa h),$$

where σ^2, κ, v are positive parameters determining the variance, practical correlation range, and smoothness of the field, respectively. This covariance function is the most popular choice in geostatistics due to its flexibility, having these three parameters that capture the most important aspects of the random field (Matérn, 1960; Rasmussen and Williams, 2005).

We fit the spatial model in a fully Bayesian framework using the R-INLA software (Lindgren and Rue, 2015; Rue et al., 2009). To do so, the random field is approximated using the stochastic partial differential equation (SPDE) approach (Lindgren et al., 2011), resulting in a computationally efficient Gaussian Markov random field representation that reduces computational cost. The main idea behind this approach is to use a finite element approximation of the following SPDE representation of the random field,

$$(\kappa^2 - \Delta)^\beta (\tau u(s)) = W(s),$$

where W denotes Gaussian white noise on the domain, $\kappa > 0$ is a correlation range parameter, $\tau > 0$ is a parameter that determines the variance of the random field, and $\beta = (\nu+1)/2$ where ν determines the smoothness of the field. In the original SPDE approach, the parameter β has to be fixed to an integer value, which means that we cannot estimate it from data. Since we want to be able to infer all three parameters of the covariance function, we use the recently developed rational SPDE approach (Bolin and Kirchner, 2020) that extends the original SPDE approach implemented in R-INLA. Practical details of this method can be found in Bolin et al. (2022) and Bolin and Simas (2023). It should be noted that these SPDE-based methods are solely used to reduce computational cost of estimating the model, and the computational details are not of importance for understanding the results.

Since it is not clear that the explanatory variables have linear effects, we also estimated a non-linear model of the form

$$Y_i = \sum_{k=1}^K f_k(X_k(s_i)) + \varepsilon_i,$$

where the functions f_k were modelled as second order random walks (Lindgren and Rue, 2008). Since the residuals of this model also were found to be spatially correlated (see the next section), and because the effects of some of the explanatory variables are linear, we arrive at a final model which is a combination of the non-linear effects and the spatial model

$$Y_i = \sum_{k=1}^{K_1} \beta_k X_k(s_i) + \sum_{k=K_1+1}^K f_k(X_k(s_i)) + U(s_i) + \varepsilon_i,$$

3. Results

In this section, we show the results of the three different models that were explored in order to derive the final model used for determining the effects of tree cover structure on crop yield, as well as how they give answers to our initial questions. We start with the simple regression model, then the spatial model and non-linear models, and finally the combination of the two which leads to the final model for the data.

3.1. Screening for significant effects (the simple regression model)

The results of the initial simple regression that combined data for both years (2017 and 2018) showed that the following explanatory variables significantly influenced crop yield at the 95% level or higher: yearly intercepts, CC^{field} , TD^{field} , CC^{out} , CC^{100} , TD^{100} , CC^{500} , N , OCD , SOC , and the two interaction effects $CC^{\text{field}} \times TD^{\text{field}}$ and $CC^{\text{field}} \times CC^{\text{out}}$. The estimates and standard errors for the fixed effects and the interaction effects are shown in Table 4. The results show that trees inside fields (both CC and TD) generally have a negative effect on crop yield. On the other hand, CC outside fields (CC^{out}) and in the 100 m (CC^{100}) and 500 m (CC^{500}) buffers have a positive effect on crop yield, whereas TD inside the 100 m buffer (TD^{100}) has a negative effect. There are also significant interaction effects between CC and TD inside fields ($CC^{\text{field}} \times TD^{\text{field}}$) that have a positive effect on crop yield and CC inside and outside of fields ($CC^{\text{field}} \times CC^{\text{out}}$) that has a negative effect. Both soil carbon variables (OCD and SOC) positively influence crop yield, whereas nitrogen (N) has a negative effect.

To get an understanding of the overall explanatory power of the fixed effects (tree cover structure and soil properties) and the interaction effects we can compute the R^2 value based on the posterior means of the coefficients in Table 4, which gives a value of 0.38.

3.2. Detecting and accounting for spatial autocorrelation (the spatial model)

A visual inspection of the spatial distribution of the residuals resulting from the initial regression model (the Simple Regression Model) indicated the presence of significant spatial autocorrelation for both 2017 and 2018 (Fig. 6). To account for this, a spatially correlated random field was included in the Spatial model, as explain in section 2.7. This model included all significant explanatory variables identified in section 3.1. The estimates of the random fields used to account for the spatial autocorrelation for the two years are shown in Fig. 7.

The following explanatory variables were significant when the random field was included in the regression model (Spatial Model): CC^{field} , TD^{field} , CC^{100} , TD^{100} , N , and the intercepts of 2017 and 2018 (Table 5). However, several explanatory variables were not significant when the random field was added to the model, including CC^{out} , TD^{500} , OCD , SOC , and the two interaction effects ($CC^{\text{field}} \times TD^{\text{field}}$ and $CC^{\text{field}} \times CC^{\text{out}}$).

Table 4

Significant variables and estimates of the effects of the Simple Regression Model.

Variable	Estimate	Standard error	Effect
CC^{field}	-1.9e-02	1.5e-03	Negative
TD^{field}	-1.1e-02	8.5e-04	Negative
CC^{out}	3.1e-03	5.3e-04	Positive
CC^{100}	1.2e-02	1.6e-03	Positive
TD^{100}	-1.7e-02	1.3e-03	Negative
TD^{500}	8.5e-03	1.4e-03	Positive
OCD	9.0e-03	8.5e-04	Positive
SOC	2.7e-03	4.6e-04	Positive
N	-1.9e-02	1.4e-03	Negative
$CC^{\text{field}} \times TD^{\text{field}}$	2.1e-04	4.1e-05	Positive
$CC^{\text{field}} \times CC^{\text{out}}$	-7.0e-05	2.9e-05	Negative
Intercept 2017	5.1e-01	8.4e-02	Positive
Intercept 2018	3.0e-01	9.8e-03	Positive

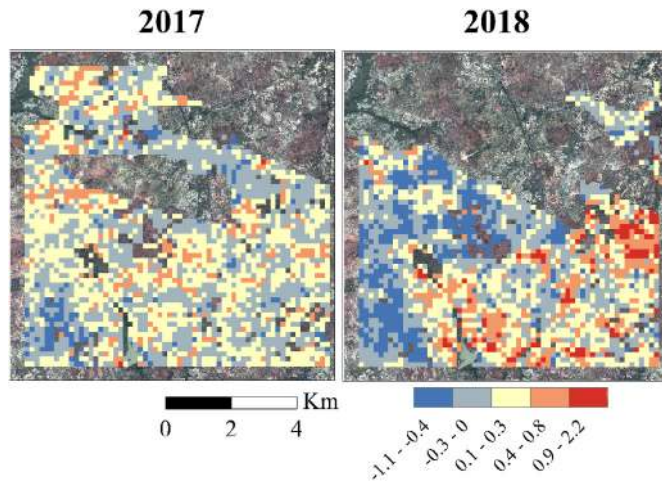


Fig. 6. Residuals from the Simple Regression Model.

CC^{out}). The R^2 of the regression part of the spatial model was 0.35, which is slightly lower compared to the regression model without the spatial field. This is expected since the random field (which was not included when computing the R^2) will explain part of the variation that is captured by the fixed effects if the field is not included.

3.3. Testing for non-linear effects (the Non-linear Model)

In the following step we investigated whether the explanatory variables had non-linear effects on crop yield using first a model without the random field (the Non-linear Model). These initial results showed that the explanatory variables representing trees just outside of fields (CC^{out}), as well as trees in buffer zones (CC^{100} , TD^{100} , TD^{500}), have clearly non-linear effects on crop yield (Fig. 8). On the other hand, trees inside fields (CC^{field} and TD^{field}) and soil carbon (OCD and SOC) had linear effects on crop yield, whereas the interaction effects and nitrogen were not significant.

When analysing the spatial distribution of the residuals resulting from the Non-linear Model it became clear that the spatial dependency was still present (Fig. 9), thus prompting the inclusion of the random field in the model. We therefore constructed a new model (the Spatial Non-linear Model) that included the explanatory variables identified as significant in the previous step (the Non-linear Model) as well as the random field. This resulted in a model with the following significant linear effects, CC^{field} and TD^{field} , and the non-linear effects CC^{out} , CC^{100} and TD^{100} , whereas TD^{500} and the soil carbon variables (OCD and SOC) were not significant when including the random field, as was also the case for the first model that included the random field (Spatial Model).

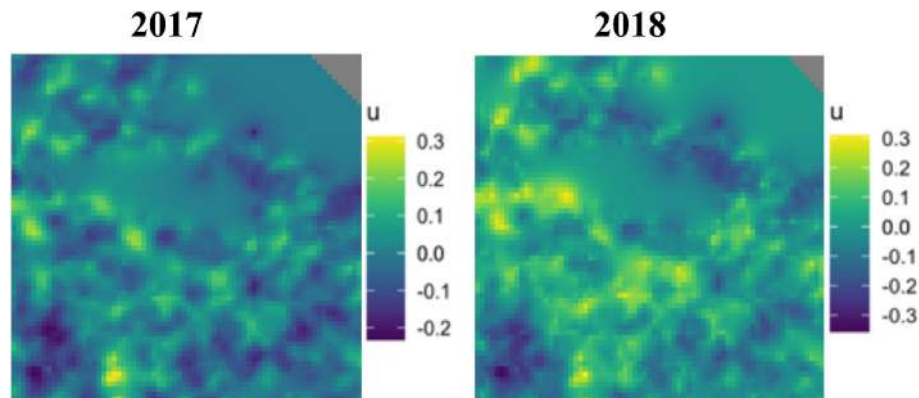


Fig. 7. Estimates (the expected value conditionally on the observations) of the random field at the two years given the data.

3.4. Constructing the final model

Based on these results, we constructed the Final Model that, in addition to the random field, included the two linear and negative effects CC^{field} and TD^{field} , and the non-linear effects CC^{out} , CC^{100} and TD^{100} (Fig. 10; Table 6). For CC^{out} , the highest positive effect can be observed around 50%, after which it starts to decline (Fig. 10). CC^{100} shows a similar non-linear effect, but with a lower maximum value of around 20%. For TD^{100} , there is a consistent negative effect until a threshold of around 40 trees^{ha} was reached. After this threshold, the effect starts to become slightly positive, but these results are uncertain due to a limited sample in this data range. The Final Model resulted in an R^2 of 0.36 (when excluding the random field as an explanatory factor), which is higher compared to the previous model (the Non-linear Model) and can be attributed to the inclusion of non-linear effects.

3.5. Assessing consistency of models between years

To investigate the stability of the results between the two years, we also fitted the Final Model to the data of each year separately. The resulting estimates of the intercepts and the linear effects are shown in Table 7, whereas Figs. 11 and 12 show the behaviours of the non-linear effect. Overall, these results are quite stable between the two years.

4. Discussion

Individual parkland trees are known to influence crop growth below the canopy and in inter-canopy areas, with both positive and negative effects on crop yield (Bayala et al., 2012, 2015). However, less is known about how variations in tree cover structure at larger spatial scales affect crop yield and whether the better understood effects of individual trees

Table 5

Significant variables and estimate of effects and credible intervals of the Spatial Model.

Variable	Mean	95% credible interval	Effect
CC^{field}	-1.5e-02	-1.7e-02 to -1.3e-02	Negative
TD^{field}	-6.3e-03	-7.4e-03 to -5.2e-03	Negative
CC^{out}	6.6e-04	-5.1e-05 - 1.4e-03	Not significant
CC^{100}	4.8e-03	2.1e-03 - 7.5e-03	Positive
TD^{100}	-1.1e-02	-1.3e-02 to -8.6e-03	Negative
TD^{500}	-1.1e-03	-7.3e-03 - 5.0e-03	Not significant
OCD	2.2e-03	-1.4e-04 - 4.5e-03	Not significant
SOC	5.9e-04	-6.0e-04 - 1.8e-03	Not significant
N	-5.4e-03	-9.8e-03 to -1.0e-03	Negative
$CC^{field} \times TD^{field}$	4.3e-05	-1.2e-05 - 9.7e-05	Not significant
$CC^{field} \times CC^{out}$	-1.7e-05	-5.7e-05 - 2.2e-05	Not significant
Intercept 2017	9.5e-01	7.1e-01 - 1.2e+00	Positive
Intercept 2018	1.3e+00	1.0e+00 - 1.5e+00	Positive

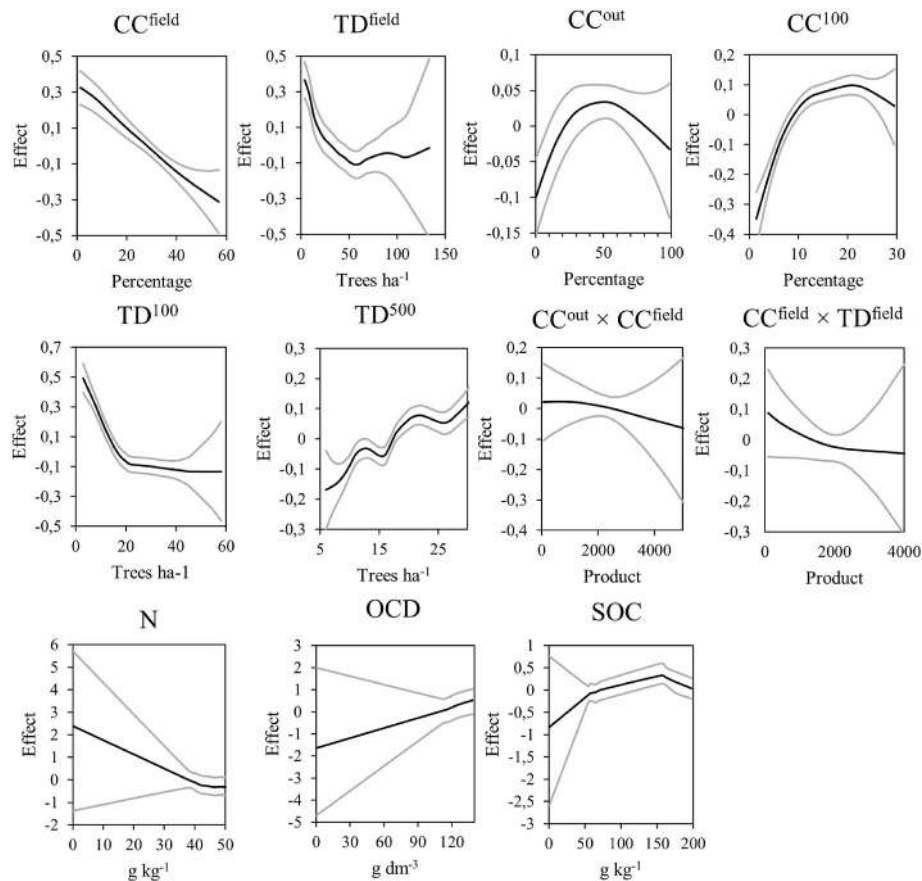


Fig. 8. Non-linear relationships between explanatory variables and crop yield. The black curve in each panel is the posterior mean, and the grey curves are 95% credible bands.

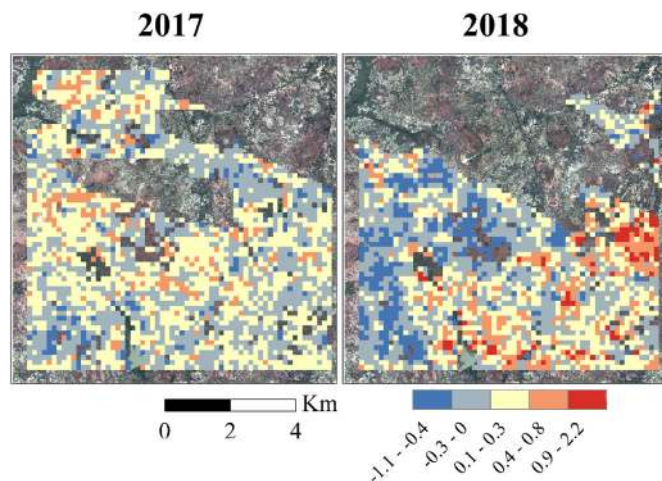


Fig. 9. Spatial distribution of residuals resulting from the Non-linear Model without spatial field.

scale up to the landscape (Bayala et al., 2015). Using high-resolution satellite imagery, we mapped patterns of trees and crop yield across a typical parkland landscape characterized by varying tree cover structure and species composition, as well as crop types and combinations. We used a general model combining both cereals and cowpea to estimate total yield from Sentinel-2 imagery. However, the contribution of cowpea to the total yield was relatively low overall. In addition, cowpea being a C3 plant is less sensitive to two of the main influences of trees on crops, including shade and water use. Hence, our results mainly relates

to the influence of trees on the two cereals grown in our study area, pearl millet and sorghum. Our finding suggests that mechanisms operating at landscape scale to some extent can enhance and override local effects of individual trees on crop yield. Such landscape-scale effects are important considerations for policy efforts aiming for sustainable intensification of agroforestry parklands through tree cover management.

4.1. Tree cover structure in the landscape can sustain or improve crop yield in parklands

Many studies have shown that trees inside agricultural fields often have a positive influence on crop yield in agroforestry systems (Kuyah et al., 2019), including parklands in West Africa (Bayala et al., 2012; Rouspard et al., 2020). The reasons for this effect can differ, but a key feature of agroforestry systems with high increases in yield is that the trees contribute to improving soil fertility by replenishing nutrient levels through organic matter and nitrogen fixation, or by reducing the loss of organic matter and nutrients through erosion control and promotion of nutrient recycling (Sileshi, 2016). Another reason for the association between trees and improved soil fertility is that birds and livestock tend toglomerate in and around trees for nesting and shade with considerable deposition of urine and faeces as a result (Bayala and Ouedraogo, 2008). Furthermore, soil fertility improvements can occur when trees act as traps for organic dust, which is then distributed in the fields (Mills et al., 2012). In this study, soil carbon (OCD and SOC) and nitrogen did not come out as explanatory variables in the model that significantly influenced crop yield, possible because of quality limitations in the SoilGrids product used as input data, which can differ between geographical regions (Poggio et al., 2021). However, our results show that tree cover structure alone explained around 35% of the crop

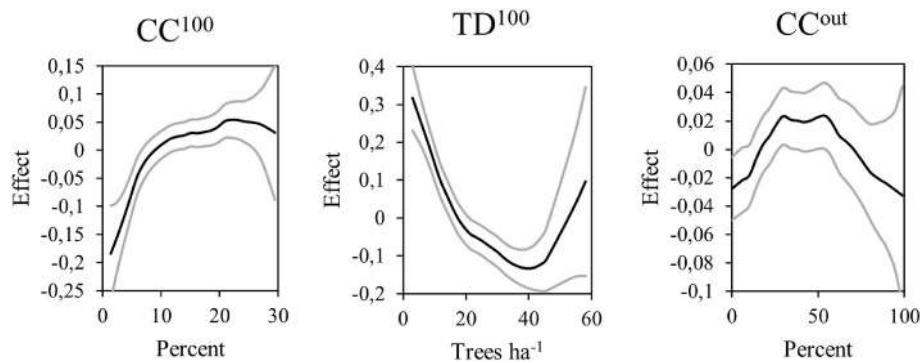


Fig. 10. Non-linear effects of the final model with non-linear effects and the random field.

Table 6

Significant variables and estimate of linear effects and credible intervals of the Final Model.

Variable	Mean	95% credible interval	Effect
CC ^{field}	-0.015	-0.016–0.0139	Negative
TD ^{field}	-0.006	-0.007–0.005	Negative
Intercept 2017	0.822	0.751 0.893	Positive
Intercept 2018	1.141	1.072 1.210	Positive

Table 7

Significant variables and estimates of linear effect and credible intervals of the Final Model in 2017 and 2018.

Variable	Mean 2017	95% credible interval 2017	Mean 2018	95% credible interval 2018
Intercept	0.247	0.231–0.262	0.294	0.251–0.337
CC ^{field}	-0.011	-0.012–0.009	-0.015	-0.017–0.014
TD ^{field}	-0.004	-0.005–0.003	-0.004	-0.006–0.003

yield variability, which suggests that important explanatory variables are missing in the final model, including those related to management efforts by the farmer, such as application of manure, crop rotation and tree crown pruning. Mineral fertilizer inputs are generally low in the study area, as well as in most of sub-Saharan Africa, and small levels of available phosphorus is a likely limiting factor not included in our model (Beza et al., 2017). Previously studies in Saponé using the WaNuLCAS (Water, Nutrient, and Light Capture in Agroforestry Systems) model (Van Noordwijk and Lusiana, 1998) indicate that phosphorus and water are the most strongly limiting factors after light in parklands dominated by *P. biglobosa* and *V. paradoxa*, respectively (Bayala et al., 2008b). While the effect of trees in fields on crop yield was generally negative in our model, a positive effect was present when canopy cover is below 20% and tree density is below 10 trees ha⁻¹ (Fig. 8). This implies that a

few larger trees in a field is preferable over many small trees in order to promote crop yield in this type of parkland system dominated by *Vitellaria paradoxa* and *Parkia biglobosa*. In addition, the results from this study was highly consistent between the two years with relatively large differences in rainfall distribution. Specifically, the same explanatory variables with the direction and magnitude in the relationships to crop yield were found significant for both years. This suggests that competition for water between trees in fields and crops is not an important factor in this specific case. While the mechanisms by which trees facilitate crop growth can not be empirically proven using this data, our results suggests that they are temporally stable and possibly independent of agroecological conditions, in particular rainfall amount and temporal distribution. However, an extended data time series of multiple years would be needed to confirm this. Previous research has identified availability of light as the dominating tree related factor limit crop growth in this type of parkland (Bazié et al., 2012). The range of tree canopy cover and tree density in which the effect on crops is positive identified in this study support this conclusion.

While trees in agricultural fields tended to have a negative influence on crop yield, the opposite situation was observed for trees in the surrounding landscape, including for the explanatory variables CC^{out} and CC¹⁰⁰. Similar results were reported by Leroux et al. (2020) who identified a strong positive influence of landscape woody cover (within 500 m from fields) on millet yield in a *Faidherbia albida* dominated parkland in Senegal. The positive influence of trees next to fields (CC^{out}) on crops can be explained by their function as windbreaks protecting from mechanical crop damage during high wind events (Mayus et al., 1998). Trees further away from fields within a 100 m buffer also had a significant positive influence on crop yield. Potential mechanisms for this landscape scale effect of the tree cover structure could be by providing adjacent habitats for animal species acting as biological pest control (Soti et al., 2019) and pollinators (Tibesigwa et al., 2019). Beyond 100 m from the fields no significant influence of trees on crop yield was detected. This contrast the findings of Leroux et al. (2020) who

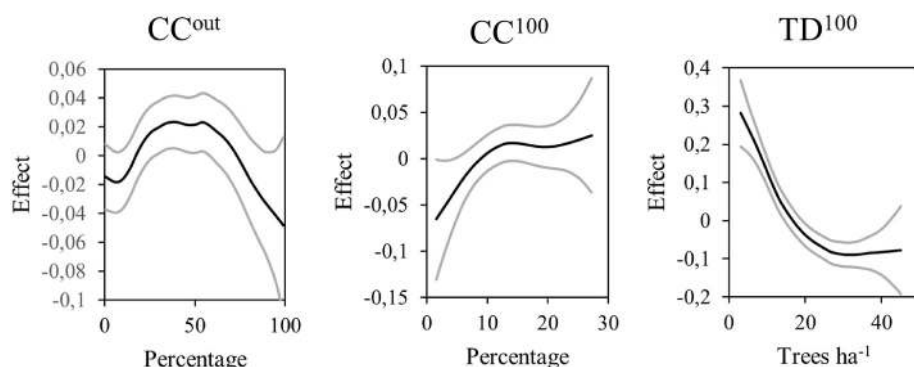


Fig. 11. Graphs showing non-linear effect for 2017.

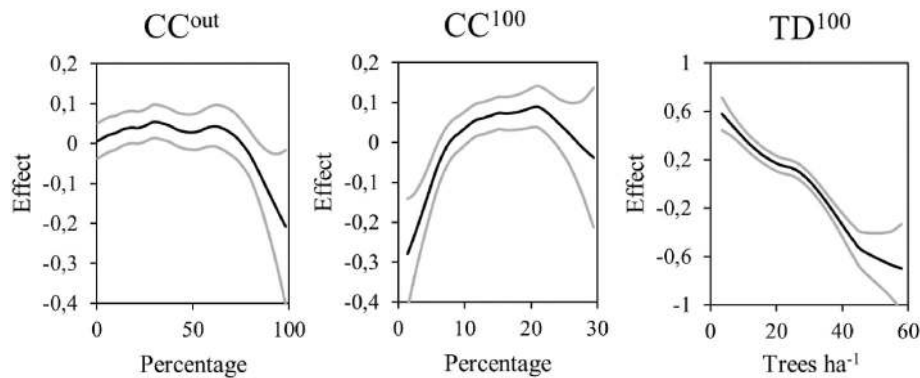


Fig. 12. Graphs showing non-linear effects for 2018.

attributed a strong positive influence of tree cover structure within 500 m from field boundaries on millet yield in an agroforestry landscape in Senegal dominated by *Faidherbia albida*.

4.2. Implications for parkland policy and management

Our results clearly show how important parkland trees are to sustain crop productivity in these vital agricultural systems. While our study provides limited insights to the specific mechanisms of competition and complementarity between trees and crops, it does show the aggregated effects of tree cover structure at landscape scale, which alone explains 35% of crop yield variability. Given the importance of trees in the close surroundings of fields (within 100 m), a key takeaway to inform policy is the necessity of maintaining a substantial tree cover in the landscape. According to our model, the optimal canopy cover is between 15 and 20% on the landscape scale, which is close to the present overall mean value in our study area. This suggests that local tree cover management practices are effective in terms of promoting crop yield. In the same study area, [Ilstedt et al. \(2016\)](#) also showed that canopy cover between 10 and 20% maximize groundwater recharge. Our results also show that fewer but relatively large trees contributing to a higher canopy cover at the landscape scale is preferable over many small trees, similar to results reported for *Faidherbia albida* parklands ([Sileshi, 2016](#)), with an optimal number of below 20 trees per hectare. This number is lower compared to the recommendation by [Boffa et al. \(2000\)](#) of 30–42 medium sized *Vitellaria paradoxa* trees per hectare to optimize crop yield in southern Burkina Faso. On a more local level focus should be directed to promoting increased tree cover close to field boundaries at strategic locations to improve protection of crops, particularly tall crop types such as millet and sorghum, from strong winds which can cause substantial damage. Other benefits with a substantial tree cover around fields is the protection from soil erosion and provision of habitats for pollinators that can benefit crop yield ([Bayala et al., 2014](#); [Stein et al., 2021](#)). Both these strategies for tree cover management (landscape and local) could be achieved largely through assisted natural regeneration or planting of parkland tree species with low cost and limited workload. Such efforts could also be used to rehabilitate degraded parkland landscapes. In the case of planting of trees, attention should be given to the draught tolerance of selected tree species or provenances since past research points to a ongoing shift in climate that could make some of the preferred species vulnerable in the future ([Maranz, 2009](#)).

For management of tree cover inside fields, the aim should be to control competition and increase complementarity to optimize crop yield ([Bazié et al., 2012](#)). Of high importance in this particular parkland type dominated by *Vitellaria paradoxa* and *Parkia biglobosa* with crop combinations of millet, sorghum and cowpea is to ensure sufficient availability of light ([Bazié et al., 2012](#)) while still maintaining a canopy cover around 15%. This can be achieved by crown pruning that in addition to limiting shading of crops also reduce fine root density of trees and hence

reduce competition for soil moisture ([Bayala et al., 2004](#)). Crown pruning can also rejuvenate trees and improve fruit production while at the same time generating wood and mulch material that can be used as an additional source of nutrients to improve crop yield ([Bayala et al., 2008a](#)). Other options include growing shade-tolerant crops under the trees ([Bazié et al., 2012](#)). Results presented here demonstrate the importance of managing the tree cover to ensure the long-term sustainability of the parkland system and possibly to improve livelihoods in the less-productive agro-ecological conditions in the Sudano-Sahelian zone in general.

4.3. Method limitations and further development

The potential to map crop yield in smallholder system like agroforestry parklands at landscape scale has increased substantially in recent years with the availability of satellite systems such as Sentinel-2 that provides data at sufficiently high spatio-temporal resolutions. This opens up new possibilities to study mechanisms that influence crop yield variability, given that ancillary data of such mechanisms are available at landscape scale. However, availability of yield data collected in the field, which is usually low in Africa ([Bayala et al., 2015](#)), is important to calibrate empirical models based on satellite data and ensure accurate yield estimation at landscape scale. Our yield modelling was based on a relatively low number of field plots that affected the yield estimation accuracy negatively. This data limitation may have affected the magnitude of the identified relationships between yield and tree cover structure. The combination of crop model simulations with satellite imagery and statistical modelling can represent an interesting alternative approach to yield estimation that limits the need for field data ([Deines et al., 2021](#); [Lobell et al., 2015](#)).

While our study focused on the influence of tree cover structure, recent studies have also studied how the species richness of the tree cover affects crop yield. For example, [Leroux et al. \(2022b\)](#) combined satellite data with field surveys and showed a relatively strong positive influence of tree species diversity on millet yield in two parkland sites in Senegal. Similar studies could clarify the importance of tree species richness for crop yield in other types of parklands systems with variations in tree species composition and crop combinations. Such studies could also provide insight to potential interaction effects between tree cover structure (e.g., tree density) and species richness. Recent advances in automated tree crown delineation and tree species mapping using very-high resolution imagery show promise for extending the spatial scope to the landscape scale of such assessments ([Brandt et al., 2020](#); [Lelong et al., 2020](#); [Lu et al., 2022](#); [Tucker et al., 2023](#)).

In this study we used data from two consecutive years that differed in terms of total amount and temporal distribution of rainfall. Adding more years to the analysis would strengthen the interpretation of the results and could provide additional insights to how tree cover affect crop yield under different growing conditions. There is evidence that parkland

trees primarily improve crop yield on relatively poor fertile soils with enough rainfall but tend to compete with crops when moisture is limiting and soils are inherently infertile, thus requiring appropriate management to minimize trade-offs (Bayala et al., 2015). Given projected changes in Sudano-Sahelian climate, including strong temperature increase and changing rainfall patterns, knowledge about how parkland trees affect crop yield under varying growing conditions is of increasing importance to promote sustainable management strategies.

5. Conclusions

Tremendous efforts have been deployed to better understand the functioning of the agroforestry parkland systems in West Africa, including modelling approaches even though still in their infancy. One of the difficulties remains the way to scale observed individual tree effect to the landscape which often includes a diversity of tree species and mix of crop types. By combining high resolution remote sensing and field data collection we have been able to study the influence of tree cover structure on crop yield at landscape scale using a spatial statistical approach. Overall, our final model explained around 36% of the crop yield variability, which suggests that tree cover structure does have a significant influence on crops, but also that important explanatory variables are missing in the model. Specifically, our findings showed that tree canopy cover and density inside the agricultural fields tended to decrease yield because of the competition, but also that these variables when considering the surrounding landscape exerted an opposite influence, probably because of their buffering effects. The maximum positive effect of tree canopy cover just outside of agricultural fields was observed around 50% whereas the lower maximum value was around 20% for areas further away from the field boundaries. This suggests that tree cover management in this type of agroforestry parkland should consider proximity to agricultural fields when shaping the tree cover structure. Of particular importance seems to be to manage the tree cover close to the field boundaries. In addition, our results point to that a lower number of larger trees both inside field and in the surrounding is preferable to promote crop yield. Explanatory variables representing soil properties, including soil carbon and nitrogen, did not significantly influence crop yield in this study possibly do to limitations in input data quality. These observed patterns were consistent during the two years of monitoring characterized by differences in rainfall amount and distribution. Of course, longer term monitoring will provide more robust data. Based on the consistent yield decline when the threshold of 20 trees ha⁻¹ in the landscape surrounding agricultural fields is reached indicates farmers might be doing the right thing to optimize sustainable yields as density in most parklands is below that limit. However, density effect cannot be dissociated from the sizes of the trees composing the parklands. Therefore, this variable must be handled with care taking into consideration the species, tree age, tree size as well as the management applied. Lastly, this study focuses on the effects of trees on crops and did not consider the overall production that benefits local farmers, including fruit, fodder and other valuable tree products, which needs to be included when planning tree cover management in parklands (Koffi et al., 2020; Sinare and Gordon, 2015).

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CRediT authorship contribution statement

Martin Karlson: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **David Bolin:** Methodology,

Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Hugues Roméo Bazié:** Investigation, Data curation, Writing – original draft, Writing – review & editing. **Abraham Sotongo Ouedraogo:** Investigation, Data curation, Writing – review & editing. **Boukary Soro:** Investigation, Data curation, Writing – review & editing. **Josias Sanou:** Investigation, Data curation, Writing – review & editing. **Jules Bayala:** Investigation, Writing – original draft, Writing – review & editing. **Madelene Ostwald:** Investigation, Data curation, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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