



Exploring the agricultural landscape diversity-food security nexus: an analysis in two contrasted parklands of Central Senegal

L. Leroux, N.F. Faye, C. Jahel, G.N. Falconnier, A.A. Diouf, B. Ndao, I. Tiaw, Y. Senghor, G. Kanfany, A. Balde, et al.

► To cite this version:

L. Leroux, N.F. Faye, C. Jahel, G.N. Falconnier, A.A. Diouf, et al.. Exploring the agricultural landscape diversity-food security nexus: an analysis in two contrasted parklands of Central Senegal. *Agricultural Systems*, 2022, 196, 15 p. 10.1016/j.agsy.2021.103312 . hal-03553855

HAL Id: hal-03553855

<https://hal.inrae.fr/hal-03553855>

Submitted on 5 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

Exploring the agricultural landscape diversity-food security nexus: An analysis in two contrasted parklands of Central Senegal

Leroux L^{1,2,3,±}, Faye N.F⁴, Jahel C^{5,6}, Falconnier G.N^{2,7}, Diouf A.A³, Ndao B³, Tiaw I³, Senghor Y⁸, Kanfany G⁸, Balde A⁹, Dieye M⁶, N.Sirdey^{4,10,11}, Aloba Loison S¹⁶, Corbeels M^{2,12,13}, Baudron F¹⁴, Bouquet E^{11,15}.

1. CIRAD, UPR AIDA, Dakar, Senegal
2. AIDA, Univ Montpellier, CIRAD, Montpellier, France
3. Centre de Suivi Ecologique, Dakar, Senegal
4. Bureau d'Analyses Macro Economiques, ISRA, Dakar, Senegal
5. CIRAD, UMR TETIS, F-34398, Montpellier, France
6. TETIS, Univ Montpellier, AgroParisTech, CIRAD, CNRS, INRAE, Montpellier, France
7. CIRAD, UPR AIDA, Montpellier, France
8. Centre National de la Recherche Agronomique, ISRA, Bambey, Senegal
9. SODAGRI, Dakar, Senegal
10. CIRAD, UMR MoISA, Dakar, Sénégal.
11. MoISA, Univ Montpellier, CIHEAM-IAMM, CIRAD, INRAE, Institut Agro, IRD, Montpellier, France
12. CIRAD, UPR AIDA, Nairobi, Kenya
13. IITA, Nairobi, Kenya
14. CIMMYT, Southern Africa Regional Office, PO Box MP163, Mt Pleasant, Peg Mazowe, Harare, Zimbabwe
15. CIRAD, UMR MoISA, F-34398 Montpellier, France
16. Independent Consultant/Researcher, Agricultural Economist, Dakar, Senegal

± Corresponding author : louise.leroux@cirad.fr

Key words: Agroforestry, food availability, food access, integrated landscape approach, remote sensing, data science

1. Introduction

There is a growing awareness that (agro)biodiversity is crucial to agricultural production and food security, with an urgent call for agroecological farming approaches that enhance ecosystem services provided by biodiversity, such as biological pest control, pollination and nutrient cycling (FAO, 2019; IPBES, 2019). Important components of biodiversity in agricultural landscapes are compositional heterogeneity (i.e. number and proportions of different land use/cover types) and configurational heterogeneity (i.e. spatial arrangement of those land use/cover types) (Fahrig et al., 2011). Whilst agricultural intensification on large farms in developed countries has led to simplified landscape structures dominated by annual crops, smallholder farmers in developing countries typically manage

34 a diversity of crops, animals, trees and natural resources, creating complex and diverse agricultural
35 landscapes that often comprise natural and semi-natural lands (Ricciardi et al., 2021).

36 However, fostering biodiversity within agricultural landscapes can enhance farm productivity
37 through the provision of ecosystem services, but can also directly contribute to better food security
38 and income (Bommarco et al., 2013; Frison et al., 2011; Pilling et al., 2020), especially in the context
39 of smallholder farmers in the tropics who typically face multiple challenges with securing household
40 food security and nutrition (e.g. Muthayya et al., 2013). For example, it has been demonstrated that
41 integrated tree-crop-livestock systems on smallholder farms provide a greater diversity of nutritious
42 food products (Herrero et al., 2017). Whereas, conservation of wild vegetables in agricultural
43 landscapes is seen as important as they are usually rich in micronutrients and can complement
44 staple food crops (Bvenura and Afolayan, 2015; Mavengahama et al., 2013). Agricultural landscape
45 diversity can also support household food security through income diversification by e.g. the sale of
46 tree products (Alobo Loison, 2015; Sibhatu and Qaim, 2018; Waha et al., 2018). Fruits, fodder and
47 fuelwood from trees or shrubs can be sold on markets and can represent a significant proportion of
48 household income for smallholder farmers (Miller et al., 2017), particularly for poor households (Koffi
49 et al., 2020). This income can then be used to purchase food items on markets, which is an adaptive
50 strategy during food shortage periods (Koffi et al., 2017). Moreover, trees can improve food security
51 through the provision of fuelwood (wood and charcoal) as it is the primary source of energy used by
52 rural households for cooking (Adkins et al., 2012).

53 Agroforestry systems (Nair, 1993) are a tangible example of a diverse agricultural landscape. A
54 specific case of agroforestry systems are the “parklands” in the Sahel, where farmers have preserved
55 indigenous trees over the past centuries, and introduced exotic trees in their fields in relation to the
56 large spectrum of ecological, economic and cultural services they provide (Miller et al., 2017; Reed et
57 al., 2017; Sinare and Gordon, 2015). This has resulted in diverse agricultural landscapes (Lykke et al.,
58 2004; Sambou et al., 2017), where trees have an important and direct role in nutrition as they
59 produce fruits, nuts and leaves that can be consumed by humans. These food items, e.g. baobab
60 (*Adansonia digitata*) leaves, or jujube (*Ziziphus mauritania*) fruit pulp are additional sources of
61 carbohydrates and proteins in the diets of the local population (Chivandi et al., 2015).

62 The underlying processes and effects of agricultural landscape diversity on food security are,
63 however, complex. The spatial configuration of land use patches drives many processes occurring in
64 agricultural systems, e.g., pest infestation (Kebede et al., 2019; Sow et al., 2020) and crop
65 pollination through bee abundance (Otieno et al., 2015). For instance, it has been shown that a high
66 proportion of semi-natural areas in the agricultural landscape of the Senegalese Peanut Basin can

significantly contribute to the control of millet head miner moth (*Heliocheilus albipunctell*) by natural enemies (Soti et al., 2019). The spatial composition of landscape elements is determinant as well, but often implies trade-offs between ecosystem services. For example, at the tree scale, a density of 10 trees/ha would be optimal to support crop productivity in *F.albida* parkland (Roupsard et al., 2020). In agroforestry systems, trees can boost rural development (i.e., through increased incomes, Bado et al., 2021) while at the same time trade-offs occur between crop productivity and tree growth and products (Tschora and Cherubini, 2020). While trees can often increase crop yields, particularly in the case of nitrogen-fixing trees (e.g. Kho et al., 2001), they can also lead to yield penalties as a result of competition for light, water or nutrients. For instance, it has been observed that shading by fruit trees such as the African locust bean (*Parkia biglobosa*), decreases millet yield in parklands of Burkina Faso (Sanou et al., 2012). These trade-offs could be minimized by relying on a mix of tree species with contrasting functional diversity. In general, Sahelian parklands are made-up of a diversity of tree species, and their spatial arrangement can vary over short distances (Bayala et al., 2015). Hence, we can assume that in parklands, the direction and magnitude of the tree effects on food security is tightly linked to agricultural landscape composition and configuration resulting in trade-offs and or synergies among the existing ecosystem services.

Previous studies addressing the contribution of agroforestry to food security often relied on a simplified conceptualization of agricultural landscape diversity. Studies addressing the effects of trees on crop productivity mainly dealt with one tree species at a time (Bado et al., 2021; Ndoli et al., 2017; Roupsard et al., 2020; Sanou et al., 2012), and seldom considering tree diversity in the surrounding landscape of the field, and often only considering tree density or tree cover (Bado et al., 2021; Duriaux Chavarria et al., 2018; Hadgu et al., 2009; Leroux et al., 2020; Yang et al., 2020). However, it can be assumed that combinations of tree species will lead to different effects on crop productivity and hence on food availability. Similarly, when dealing with the contribution of agricultural landscape diversity to household food security, most studies focused on tree cover configuration (i.e., tree cover, tree density and number of tree patches) and did not account for tree species richness or agricultural landscape diversity *per se* (i.e. in terms of land use types) (Baudron et al., 2019; Ickowitz et al., 2014; Nyberg et al., 2020; Rasmussen et al., 2020, 2019). In these previous studies, tree cover configuration was derived from (i) publicly available global datasets of tree cover (e.g. Rasmussen et al., 2019) or (ii) simple forest/non forest maps derived from satellite images with a moderate spatial resolution (e.g. Baudron et al., 2019b). Such products are, however, not reliable to account for the fine-grained landscape diversity of complex parklands, such as in the Sahel. The use of publicly available, high-spatial resolution satellite images such as the Sentinel-2 constellation

has allowed improvement in land-use mapping in complex agricultural landscapes (Gbodjo et al., 2020).

The objective of this study is to assess the contribution of agricultural landscape diversity to food security of smallholder farmers in agroforestry parklands in Senegal. Specifically, we adopted an empirical approach to answer the following questions: (1) do diverse agricultural landscapes increase crop yields (in this case, millet), and (2) what are the direct and indirect links between agricultural landscape diversity and household food access? To answer these questions, we produced a fine-grained characterization of the agricultural landscape using up-to-date satellite images in combination with field monitoring and household surveys, and applied Gradient Boosting Machine and Correlation Network Analysis, respectively.

2. Material and Methods

2.1. Study area

The study was conducted in 2018 in the Groundnut Basin in Central Senegal (Figure 1) where groundnut has been the main cash crop since colonial times. The first study site, Niakhar (14°54'N, 16°44'W) is in the Northern part of the Groundnut Basin, while the second site, Nioro (13°75'N, 15°80'W) is in the Southern part at the border with Gambia (Figure 1a). Each site covers about 450 km². The climate in Niakhar is sahelio-sudanian with annual rainfall ranging from 400 to 650 mm, whilst Nioro has a sudanian climate with annual rainfall between 600 and 800 mm. The rainy season in both sites lasts from July to October, with August and September being the wettest months, whilst the dry season occurs from November to June. Tree cover in the region is greatly determined by annual rainfall (Brandt et al., 2015), and by farmers' selection and management (Sambou et al., 2017). The sites host the two dominant types of parklands of the region. Niakhar is dominated by *Faidherbia albida* (38% of the trees), a leguminous nitrogen-fixing species that improves crop yields through improvements in water and nutrient availability (Sileshi, 2016) and in microclimate conditions (Sida et al., 2018). Pods and leaves of *F. albida* are also used as livestock feed. Parklands in Niakhar are diverse with more than 60 species in total, *Adansonia digitata*, *Balanites aegyptiaca* and *Borassus aethiopum* being the most important ones (Figure 1f). Nioro has less diverse parklands with about 50 species in total, largely dominated by *Cordyla pinnata* (71% of the trees) followed by *Azadirachta indica*. *C. pinnata* is an important species for the local population, because it provides construction woods, fodder for livestock, medicinal plant parts and seedpod pulp of high nutritional value (Lykke, 2000; Sinare and Gordon, 2015). However, *C. pinnata* is overexploited (legal and illegal logging) and considered as a declining species in the region (Lykke, 2000).

The population density of the Niakhar and Nioro sites was estimated at 122 hab/km² (standard deviation: 52 ha/km²) and 187 hab/km² (standard deviation: 82 ha/km²) respectively (<https://www.worldpop.org/>). In both sites, rural people practice small-scale agriculture to secure their livelihoods, with low use of external inputs. Pearl millet (*Pennisetum glaucum* (L.) R. Br.) (cultivated on 50% and 33% of the total area in 2018 in Niakhar and Nioro, respectively) and groundnut (*Arachis hypogaea* L.) (on 30% and 40% of the total area in 2018 in Niakhar and Nioro, respectively) are the main cultivated food crops (Figure 1b and Figure 1d). Pearl millet and groundnut are mainly cultivated in a biennial rotation. Pearl millet contributes to food security and livelihood as it provides both food and income. In both sites, more than 65% of rural households eat pearl millet twice a day, five days of the week. Millet is the cornerstone of food security for rural population in both sites during the lean period as its consumption increases by more than 50% during this period (IPAR, 2017). Other crops are sorghum (*Sorghum bicolor* (L.) Moench), cowpea (*Vigna unguiculata* L.), roselle (*Hibiscus sabdariffa* L.) and maize (*Zea mays* L.). Due to demographic pressure and the resulting expansion of the cultivated area, natural woodlands have strongly decreased over the past decades (Brandt et al., 2016; Herrmann et al., 2013). Hence, natural vegetation is mainly present in the form of scattered trees in cropped fields (i.e. parklands), which account for 6% of the total area in both sites ("Tree" category in Figure 1b and Figure 1d).

2.2. General overview of the approach

Figure 2 gives an overview of the approach of our study. We empirically investigated the different pathways connecting agricultural landscape diversity to household food security. A first analysis was conducted to investigate the impact of agricultural landscape diversity on millet yield (as part of food availability; Figure 2b) and unravel the contribution of biophysical and crop management variables (see Table 1) using a Gradient Boosting Machine algorithm (Leroux et al., 2020; see Section 2.5.2) on a 40 fields sample. In a second analysis, using cross-sectional data on 412 households, we explored the direct and indirect relationships linking agricultural landscape diversity to household food access (i.e. HFIAS) using a conceptual model adapted from Gergel et al. (2020) based on correlation network analysis (see Figure 2c). Below we describe in more detail the methods used for data collection (geospatial data, field monitoring and household surveys) and for the statistical analyses and modelling.

2.2.1. Indicators of food security: millet yield and Household Food Insecurity Access Scale (HFIAS)

Food security at household level is complex and not easy to quantify since it encompasses food availability, food access, food utilization and food stability (FAO, 1983). Food availability means the

physical availability of food, focusing on the supply side and therefore includes all crop, livestock and tree foodstuff produced and/or collected on the farm. Food access refers to physical, social and economic access to available food and thus indicates the ability of a household to be in possession of sufficient resources to obtain appropriate foods for a nutritious diet. Food utilization, on the other hand, includes a wide range of factors, particularly the contribution of food consumption to the health and nutritional status of the individuals of a household. Food stability is a cross-cutting dimension meaning that the availability and access to food at all times. In this study, we focused on (i) food availability, using millet yield as a proxy, and (ii) food access, assessed with the Household Food Insecurity Access Scale (HFIAS) indicator. The food utilization dimension was not evaluated in this study.

It is acknowledged that the diversity of food crops produced and or bought contributes to food security. However, because our study integrates parkland diversity and a lot of variables related to this aspect, we had to rely on a limited number of variables to grasp the relationship between agricultural landscape diversity and food security. For crops, we decided to focus on millet. The choice of millet yield as a proxy for food availability was based on the fact that crop production accounts for a large part of food availability in the typical farming systems of the study sites (Ritzema et al., 2017), with millet being the main staple food crop (IPAR, 2017). A Household Food Insecurity Access Scale (HFIAS) categorical variable was used to measure household food access. HFIAS has been widely used as a monitoring indicator of food security at household level (Jones et al., 2013). It relies on nine questions to capture the occurrence of a specific condition associated with the experience of food insecurity in a household during the previous 30-days (Coastes et al., 2007).

2.2.2. Indicators of landscape and tree diversity

Landscape diversity was assessed using the landscape Shannon and Simpson diversity indices calculated from a land use and land cover (LULC) map (Table 1, Ndao et al., 2021). Both indices account for LULC richness (i.e. number of LULC classes) and LULC abundance (i.e. the number of pixels per LULC class), and hence are by definition sensitive to the level of detail of the land use classification system adopted. The Shannon index is sensitive to rare LULC classes while the Simpson index is sensitive to the dominant LULC classes (as it gives more weight to common LULC classes). However it has been shown that Simpson and Shannon indices tended to increase with the level of land use categorization (e.g. Liu et al., 2013; Peng et al., 2007). In this study we used a land cover-land use typology with a very limited number of classes (11 classes) and hence the landscape diversity information provided by the Shannon and Simpson indices can be considered as the “basis level” of landscape diversity we can expect for our study areas. Tree cover, number of tree patches

(i.e. contiguous pixels classified as tree in the LULC map) and mean size of tree patches (Table 1) were also derived from the LULC map and used as indicators of the potential amount of tree resources available to households (e.g. Rasmussen et al., 2020, 2019). Lastly, we also surveyed fields to quantify tree density, tree species richness, and the tree Shannon and Simpson indices (see Section 2.4 for details).

2.2.3. Co-variables

Further, a range of co-variables were included in the analysis to explain millet yield and HFIAS. For millet yield, these were biophysical field-level variables (e.g. soil organic carbon, total nitrogen and phosphorous) and crop management variables (e.g. amount of mineral nitrogen applied) (see Table 1 for the full list). Total soil nitrogen and total soil phosphorous are extracted from the AfSoilGrids database (Hengl et al., 2017). For HFIAS, the co-variables were farming system variables (e.g. millet production per capita), farm income (e.g. the presence or absence of revenue from tree resources) and energy-related variables (e.g. the presence or absence of fuelwood use) (see Table 1). However, after visual screening of the variability of each variable, the tree income variable was removed from the analysis since most of households did not sell tree products suggesting that cash income coming from agricultural landscape diversity do not contribute to household food access for the two parklands considered. Indeed, tree species generally used as cash crops over the Sahel such as *Parkia biglobosa* and *Vittelaria paradoxa* accounted for less than 1% of the trees of our study areas (Ndao et al., 2021a).

2.3. Household surveys and field monitoring

2.3.1. Village and household selection

A weighted stratified strategy was designed for the field monitoring and the household surveys, based on a remote sensing approach taking into account landscape diversity (Ndao et al., 2018, 2021b). The Niakhar and Nioro sites were first segmented into landscape units (Figure 1). Each landscape unit is assumed to be homogeneous in terms of agro-environmental conditions, landscape composition and farming practices (Bellón et al., 2018). Landscape units were subsequently classified into four and five landscape classes in Niakhar and Nioro respectively (see Table S1 for their description). The landscape classes were defined based on remote sensing and unsupervised hierarchical clustering using a set of biophysical variables (plant productivity and its inter-annual changes, evapotranspiration, woody cover and soil texture), assuming that changes in the plant productivity are due to changes in environmental conditions and farming practices (see Ndao et al. 2021). Based on this landscape classification, 19 and 18 villages were chosen in Niakhar and Nioro, respectively. The number of villages per landscape class was weighted by the proportion

of the total area of the study site occupied by that landscape class (Figure 1). For the study, 12 households per village were randomly selected within a households list provided by each village head, resulting in 228 and 216 households in Niakhar and Nioro for surveying, respectively. After cleaning of the database, 391 households were finally kept in the analysis.

2.3.2. Household surveys

The heads of the selected households were interviewed between July and August 2018, at the start of the cropping season when food stocks from the last rainy season started to run out. The standardized questionnaire addressed household composition and functioning, farm characteristics, parkland characteristics, tree use and included the nine generic occurrence questions used to construct the HFIAS indicator. The surveys were conducted with an Android Tablet and the Global Positioning System (GPS) coordinates of each household were recorded. The variables collected in the household surveys are presented in Table 1. Household heads were asked to make an inventory of all trees he/she had on his/her fields, and tree density and species richness were determined for the total cropped land area of the farm. Millet production per capita was computed based on reported total millet production and household size. Tree income (i.e. whether households have sold tree products over the last year) was reported as a binary variable.

Based on the answer to the nine occurrence questions related to the HFIAS indicator, households were categorized into four classes: severely, moderately, mildly food insecure and food secure (the rules of categorization are provided in Table S2).

2.3.3. Field monitoring

The field monitoring was conducted in 2018 on millet fields of five households (i.e. one field per household) among the 12 initially selected households per village in a random subset of eight villages per site, resulting in 40 millet fields per study site. Field boundaries and individual locations of tree species were recorded with a Garmin GPS device (GSMAP®64). Tree locations were adjusted by photointerpretation via Google Earth images (<https://www.google.com/earth/index.html>). Aboveground biomass of millet was harvested at crop maturity in three quadrats of 6-m². Threshed grains were dried at 70° for 48-h, and weighed. Grain yield (kg/ha) was averaged across the three replicates per field (Table 1). Tree density, the proportion of *Faidherbia albida*, tree species richness (i.e. the number of different species) and Shannon and Simpson diversity indices (i.e. summary indices that also account for the number of individuals per species) considering the trees inside the monitored fields and in their adjacent fields were derived. The R package “vegan” was used to compute the Simpson and Shannon indices (Oksanen et al., 2019). Field age, distance from the

homestead and cropping system information (e.g. previous crop, amount of nitrogen and phosphorus applied with chemical fertilizer, manure applied) were recorded (Table 1). To calculate the total nitrogen and phosphorus inputs from organic and inorganic sources, manure was assumed to contain 0.93% nitrogen and 0.28% phosphorus (Tounkara et al., 2020). A 1.5% mineralization rate over the growing season was considered to estimate mineralized nitrogen and phosphorus from manure. A range of yes/no binary variables that may drive soil fertility levels were also collected (e.g. presence of a cattle pen in the field, occurrence of cattle grazing during dry season, retention of crop residues on the plot, occurrence of regular fallowing, association with leguminous crop).

2.4. Analysis of geospatial data

A land use and land cover (LULC) map was derived from Sentinel-2 (10-m spatial resolution) and PlanetScope (3-m spatial resolution) images using object-based image analysis (Blaschke et al., 2014) combined with Random Forest (Breiman, 2001) and implemented with the MORINGA processing chain developed by the Theia Scientific Expertise Centre for land cover (<https://www.theia-land.fr/en/ceslist/land-cover-sec/>). Ground truth data was collected in each site at the end of the cropping season in 2018 (Ndao et al., 2021b). The land use and land cover dataset is available at <https://doi.org/10.18167/DVN1/P7OLAP>. Sahelian parklands are highly heterogeneous with small trees and shrubs. For this reason, a natural vegetation class (hereafter referred to as tree class) was added to the LULC map using a simple thresholding value of Normalized Difference Vegetation Index derived from a Pléiades image (0.5-m spatial resolution) taken at the end of the cropping season to discriminate natural vegetation (i.e. woody vegetation) from other land cover classes. Niakhar was classified into ten LULC classes and Nioro into eight classes. The classification produced LULC maps with 85% and 84% overall accuracy for Niakhar and Nioro, respectively (Ndao et al., 2021b).

Landscape variables were derived from the LULC data, i.e. landscape Shannon and Simpson diversity indices, number and mean size of tree patches and tree cover (Table 1). For millet fields, landscape diversity variables (i.e. landscape Shannon and Simpson indices, number of tree patches, mean size of tree patches) were extracted from the landscape unit in which the field is located (Fig. 1c, Fig. 1e and Fig. 2a). On the other hand, at household-level, the landscape diversity variables (i.e. tree cover, landscape Shannon and Simpson indices, number of tree patches and mean size of tree patches) were computed for all the fields (regardless of landscape classes) inside a 5-km radius circle around the location of each household homestead (Fig. 2a). Farmers travel by foot or with carts and we assumed that a radius of 5-km is a realistic distance for people to travel to the field for work or to collect tree resources (e.g. wood, leaves, fruits).

2.5. Statistical analysis

2.5.1. Descriptive statistics

Differences between the two parklands for the main field-level variables and household-level variables were assessed. A non-parametric unpaired two-sample Wilcoxon test was used to compare the medians of continuous variables. For categorical variables, counts were compared using a Chi-square test. Differences were considered significant for $p\text{-value} \leq 0.05$.

2.5.2. Gradient Boosting Machine method to investigate the link between agricultural landscape diversity and food availability (millet yield)

A Gradient Boosting Machine (GBM) algorithm (Friedman, 2001) was used to disentangle the contribution of the field-level crop management variables, biophysical variables and landscape variables (Table 1) in explaining millet yield variability (Leroux et al., 2020). GBM is a non-parametric machine learning approach that combines regression trees and boosting. It handles different types of independent variables and can fit complex non-linear relationships and interactions between independent variables (Elith et al., 2008). We assessed the relative contribution of each independent variable based on the GBM relative influence measure. Main parameters of the GBM model were set based on a grid search assessing the top-performing combination. Model performance was evaluated with a 5-fold cross validation. The partial dependence plot was used to analyze interaction between the predicted variable (millet yield in this study) and the independent variables. It allows visualizing the partial contribution of each independent variable, accounting for the average effect of the other variables (Friedman and Meulman, 2003). Partial dependence plots were built for the most contributive independent variables. To improve the visualization, a locally weighted smoothing was applied to the partial dependence with a smoothing parameter of 1.

2.5.3. Correlation network analysis to investigate the links between agricultural landscape diversity and food access (HFIAS)

Correlation-based network analysis (CNA) was used to investigate the links between HFIAS and agricultural landscape diversity, farming systems characteristics, income and energy variables. CNA is a data-mining tool for analyzing and visualizing functional relationships within large data sets. In these networks, associations are visualized by a graph of nodes and edges. The nodes represent variables and the edges between them the significant correlation coefficients (r). CNA is based on mathematically defined (dis)similarity measures that correlate different variables to each other, and the resulting correlation coefficients reflect the magnitude of the co-linear relationship of the variables. Here, the pairwise correlation coefficients between HFIAS and landscape diversity,

farming system characteristics and energy variables were computed (Table 1 and Figure 2b). Continuous variables were tested for normality using the Shapiro-Wilk test. Variables not normally distributed were transformed using the *bestNormalize* R package that selects the best normalizing transformations on the basis of Pearson P test statistics for normality (Peterson and Cavanaugh, 2019). The Pearson correlation was applied for all paired variables, except for correlation involving HFIAS and tree species richness (ordinal variables), for which Spearman's rank correlation was used. Only significant correlations (p-value ≤ 0.05) were kept in the correlation-based network. CNA was conducted for each site individually, resulting in two networks.

Except for the LULC classification, all geospatial processing, statistical analyses and graphical outputs were carried out using the R software version 3.6.3 (R Core Team, 2020). The full list of the R packages and the main functions used are given in Table S3.

3. Results

3.1. Characteristics of the two study sites

Average household size was significantly greater in Niakhar than in Nioro (13.9 and 12.5 persons, respectively). Average land per capita was smaller in Niakhar than in Nioro (0.22 and 0.36 ha/capita, respectively) (Table 2). There was no difference in millet yield on a per hectare basis between the two sites. However, millet production per capita was significantly smaller in Niakhar compared to Nioro (246 kg \pm 207 and 380 \pm 329 kg/capita respectively), despite great variations across households. The proportion of food secure households as assessed through the HFIAS was greater in Niakhar (the most diverse agricultural landscape, see below) compared to Nioro (Figure 3). However, Niakhar had the largest proportion of households that were experiencing severe food insecurity.

The two sites contrasted in terms of landscape diversity for all reported variables, except for the landscape Shannon diversity index, the latter indicating that the diversity of LULC classes was similar between the two sites (Table 2). The Niakhar parklands were, however, more dense and diverse than the Nioro parklands, as indicated by the greater tree density, larger relative number of *Faidherbia albida* trees (assessed through field survey monitoring), greater tree cover and tree species richness (assessed through geospatial analysis and household survey). On average, soil total nitrogen content of the millet fields was greater in Niakhar compared to Nioro, while soil total phosphorus was lower in Niakhar compared to Nioro. Overall, fields in Niakhar received lower amounts of mineral fertilizer than in Nioro.

3.2. Agricultural landscape diversity and food availability (millet yield)

Using a set of field-level crop management, landscape diversity and biophysical variables, the GBM model for Niakhar (Figure 4a) and Nioro (Figure 4b) explained, respectively, 77% (relative Root Mean Square Error, rRMSE = 20%) and 84% (rRMSE = 21%) of millet yield variability ($p\text{-value} \leq 0.05$). The main explanatory variables were landscape diversity variables, accounting for 53% and 47% of relative influence in Niakhar and Nioro, respectively. The explanatory landscape diversity variables were related to parkland configuration (i.e. tree species richness for Niakhar and tree density for Nioro). Besides, selected biophysical variables (i.e., total soil nitrogen for Niakhar and total soil phosphorus for Nioro) had a relatively high influence on millet yield (30% and 24% in Niakhar and Nioro, respectively). On the other hand, crop management variables only marginally explained millet yield variability, accounting for 5% and 17% of relative influence in Niakhar and Nioro, respectively.

Figure 5 displayed the partial dependence plot for tree density and tree species richness. Millet yield exhibited a linear positive relationship with tree density in Nioro when tree density was below 5 trees/ha, while no relationship was observed in Niakhar (Figure 5a). Millet yield exhibited a linear positive relationship with tree species richness above two in Niakhar while the relationship seemed to start to stagnate above two tree species in Nioro (Figure 5b).

3.3. Agricultural landscape diversity and food access (Household Food Insecurity Access Scale)

Results of the CNA are presented in Figure 6a for the Niakhar site and Figure 6b for the Nioro site. Only significant correlation coefficients with $p\text{-value}$ below 0.05 are displayed. The corresponding correlation matrixes are presented in Table S4.

3.3.1. Niakhar

Direct links between landscape diversity and food access

HFIAS was significantly and positively correlated with the mean size of tree patches ($r = 0.25$), that was, in turn, positively correlated with tree cover ($r = 0.34$) (Figure 6a). This suggests that large tree patches and tree cover were associated with greater levels of food access. HFIAS was significantly and negatively correlated with tree density ($r = -0.23$). Tree density, in turn, was significantly and positively correlated with tree species richness ($r = 0.36$). These correlations, although relatively weak, suggest that a high parkland density and diversity is associated with lower levels of food access. Thus, household food security in Niakhar appears to be sustained by the *Faidherbia albida* parklands through large tree species but negatively linked to tree density.

Indirect links between landscape diversity and food access

HFIAS was significantly and positively correlated with millet production per capita ($r=0.19$), which indicates a higher food access with increasing millet production per capita. In line with the findings of the analysis conducted at field-level (see section 3.2), tree species richness was, in turn, significantly positively correlated with millet production per capita ($r=0.38$), thus indicating an indirect link between landscape diversity and household food access. This can be referred to as an “agroecological pathway” (Figure 2c). Further, fuelwood use was significantly and positively correlated with tree cover ($r=0.21$), but not with food access, indicating the absence of an indirect link between landscape diversity and food access through an “energy pathway” (Figure 2c) based on fuelwood supply.

3.3.2. Nioro

Direct links between landscape diversity and food access

In Nioro, HFIAS was significantly and positively correlated to the mean size of tree patches, although the correlation was weak ($r=0.17$) (Figure 6b). The mean size of tree patches was significantly and positively correlated with tree cover ($r=0.90$), the number of tree patches ($r=0.65$), the landscape Shannon ($r=0.65$) and Simpson indices ($r=0.73$). This suggests that larger tree patches, greater tree cover and greater land use and land cover diversity were associated with higher levels of food access. Hence, as in Niakhar, household food security in Nioro seems to be supported by parklands.

Indirect links between food access and landscape diversity

HFIAS was significantly and positively correlated with millet production per capita ($r=0.36$) indicating an increase in food access as millet production increases. Tree species richness was strongly correlated with millet production per capita ($r=0.49$), suggesting an indirect link (“agroecological pathway”, Figure 2c) between landscape diversity and household food access, such as Niakhar. Further, fuelwood use was found to be significantly and positively correlated with variables of agricultural landscape diversity, i.e. tree cover ($r=0.41$), landscape Shannon index ($r=0.47$), landscape Simpson index ($r=0.45$), and with the mean size of tree patches ($r=0.37$). However, fuelwood use was not significantly correlated with food access (HFIAS), indicating the absence of an indirect “energy pathway” (Figure 2c) between landscape diversity and food access through fuelwood energy.

4. Discussion

4.1. Diverse parklands contribute to improved food availability

4.1.1. Greater millet yield is associated with greater tree density and tree species richness

We showed evidence that the configuration (i.e. tree density) and composition (i.e. tree species richness) of the parklands in the Groundnut Basin of Senegal is an important driver of the yield of the millet crop that is associated with the trees (Figure 4). Tree density up to a certain level is associated with a greater productivity of millet in the Nioro parkland while it has no relationships with millet yield in the Niakhar parkland. These results corroborate findings from earlier field based research, in which higher crop yields were observed in below-tree-crown compared to full-sun conditions (e.g. Bayala et al., 2015) through improvements in soil water and nutrient availability and supply (Sileshi, 2016) and in microclimate conditions (Sida et al., 2018). We found, however, that tree cover was no longer positively associated with millet yield above a tree density of 5 trees/ha (Figure 5a). Similarly, using a geostatistical approach, Roupsard et al. (2020) showed in a small area in the Groundnut Basin that a tree density of 10 trees/ha would optimize the benefit of trees on millet yield. The observed thresholds of tree density for crop productivity in parkland systems can be interpreted in the context of the balance between facilitation and competition between the trees and the associated crops for growth resources, i.e. light, water and nutrients (Bazié et al., 2012; Luedeling et al., 2016).

Further, our results demonstrated the positive effect of tree species richness of parklands on the yield of the associated millet for the two sites (Figure 5b). The processes governing these effects are, however, complex (Luedeling et al., 2016). It was found that natural pest control and regulation are enhanced by greater tree species diversity in parklands (Soti et al., 2019). For example, it was observed that in the northern part of the Groundnut Basin in Senegal the abundance of insectivorous birds, i.e. natural enemies of the millet head miller, increased with tree diversity. and effectively controlled pest damage on millet panicles, preventing grain losses (Sow et al., 2020). Tree species diversity can also boost litterfall productivity via increasing crown spatial complementary among trees (Zheng et al., 2019), possibly leading to soil fertility improvements. Finally, higher tree species diversity can also facilitate water availability for the associated crops in parkland systems through hydraulic redistribution (Bayala et al., 2008) or through partitioning of water use as a result of a different root stratification, whilst at the same time reducing soil water evaporation, drainage and run-off (Bayala and Wallace, 2015). In Niakhar, only tree species richness was associated with millet yield, while in the less dense and diversified parkland in Nioro, both tree density and tree species richness

was positively associated with millet yield. Increase in millet yield could probably be achieved by optimizing tree species in Niakhar, and tree species and tree density in Nioro.

However, in this study we did not take into account the effect of tree management, that also shapes the parklands diversity, on crop production, although it has a strong influence on resource use (e.g. light, water, nutrient) with trade-offs and or synergies occurring (Luedeling et al., 2016; van Noordwijk and Ong, 1999). For *F.albida*, tree influence on crops is also driven by tree size, crown development and management of trees. Mature trees having a stronger positive influence on crops than young trees (Sileshi, 2016), and tree pruning having a positive effect on crop yield since it affects the competition for light (Dilla et al., 2020). Whereas, other nitrogen-fixing species (e.g. *Alnus acuminata*) can decrease maize yields as the trees grow older (Ndoli et al., 2017).

4.1.2. ... but soil fertility remains a key driver

Our analysis also revealed the significance of soil fertility (i.e. soil total nitrogen and phosphorus contents) to millet productivity in the parkland systems (Figure 4). It is widely known that low inherent soil fertility is a major constraint to crop production on the sandy soils of the Senegalese Groundnut Basin (Affholder et al., 2013). The fact that fertilizer use was not associated to crop yields in our study was probably due to the low variations in applied nitrogen (26 ± 32 kgN/ha). Possibly, with this small level of variation, our regression-based analysis could not reveal a connection between N input use and crop yield. Integrated soil fertility management with appropriate use of mineral fertilizer (Vanlauwe et al., 2015) is critical to improve crop productivity in the parkland systems of the region. For instance, Sida et al. (2019) showed in Ethiopia and Rwanda that N and P use efficiencies varied according to the type of agroforestry systems. We anticipate that optimal configuration and composition of parklands can enhance fertilizer use efficiency, constituting a crucial aspect of integrated soil fertility management. However, additional experiments on tree-crop-fertilizer interactions would be needed to verify this assumption for the agroforestry systems of this study. In general, nutrient recycling by the trees is largely influenced by tree densities and species composition (Buresh et al., 1996). Several studies have shown that deep-rooted trees are able to capture subsoil nutrients that would have been lost to annual crops. These nutrients are "pumped up" by the trees and afterwards made available to the associated crops by leaf litter decomposition (Luedeling et al., 2016). The amount of leached nutrients (and the potential benefits of trees) strongly depends on soil type, rainfall patterns and root structures (Cadisch et al., 1997). For the sandy soils of the study region (Lericollais, 1999), and the intense rainfalls that are often observed during the growing season (Taylor et al., 2017), this leaching issue is likely to be non-negligible, especially if farmers intensify their cropping systems in the future.

4.2. Only large tree species have a direct positive association with household food access

Our study demonstrated a direct, but weak, link between parkland diversity and food accessibility. These findings in these two Senegalese parklands are in line with a recent review by Koffi et al. (2020) concluding that there is very little evidence of an increased use of tree products during periods of food shortage across Sub-Saharan Africa, except during extreme situations such as famine, which was not the case in our study. However, we found that households having higher mean size of tree patches and higher tree cover in their surrounding agricultural landscape (i.e. in a 5-km radius) tended to be more food secure (i.e. with greater food access). The observed large tree patches typically correspond to trees with large crowns, which often include fruit tree species such as *Adansonia digitata* (African baobab) or *Cordia alliodora*. The fruits of these trees are used for human consumption and can substantially contribute to the required micro and macro-nutrients in diets of rural populations (Chivandi et al., 2015; Félix et al., 2018; Ickowitz et al., 2014). *A. digitata* fruit pulp is widely consumed daily as juice called “bouye” in wolof. The fruits are particularly rich in minerals, vitamins (vitamin C) and carbohydrates (Chadare et al., 2008). The immature leaves of *A. digitata* are also often cooked and used as leafy vegetables (Asogwa et al., 2021). *C. alliodora*, a dominant tree in the parklands of Nioro, is also known as Cayor pear tree, and its fruit is cooked and consumed during the lean season.

It should be noted that our survey was conducted during the lean season and household food accessibility was assessed by considering the preceding 30 days, which is probably not sufficient to capture the overall direct contribution of the dry season fruit trees to food accessibility, such as *Ziziphus mauritiana* and *Balanites aegyptiaca* (Koffi et al., 2020; Lykke et al., 2004). Edible tree products (nuts, leaves, and fruits) of these trees are eaten fresh or dried all along the year as part of the normal diet, as essential components of the sauces or condiments.

4.3. Greater parkland diversity is indirectly associated with household food access

Our results showed an indirect positive link between parkland diversity and food accessibility, which can be explained by the provision of ecosystem services regulating and supporting crop production. This link held true even in the less diverse parklands of Nioro (Figure 6). This indirect link can be coined as the “agroecological pathway” (Figure 2c) that connects landscape diversity to food (access) (Gergel et al., 2020). Thus, the “agroecological pathway” includes a wide variety of ecosystem services that support agricultural production, and that were described earlier (tree density and tree diversity support millet production, see section 3.2 and section 4.1.1). In line with results of other studies conducted in Africa (Rasmussen et al., 2020, 2019), we found that tree species richness is of similar importance as tree density to improving food accessibility. Households

that are in more diverse agricultural landscapes, in terms of tree species composition, tend to be more food secure thanks to a greater agricultural production.

Finally, we did not find evidence of a contribution of parkland diversity to household food security through increased energy use from fuelwood (the “energy pathway”, Figure 2c, Gergel et al., 2020), despite fuelwood consumption being significantly linked to several variables related to wood supply (i.e. tree cover), as it is the case in other parklands of West Africa (Koffi et al., 2018). This means that farmers with more trees in their surroundings tend to use more fuelwood, but this did not seem to translate into a positive association with household food security. This can be explained by the fact that households relied also on gas for cooking food, with July and August being the most important months for buying gas as evidenced by the households survey (see supplementary materials Figure S1), when food stocks from the last rainy season started to run out and when the availability of natural resources is still limited.

4.4. Perspective for additional studies

Here, we assessed the production of the staple food crop, millet, and its contribution to food accessibility, but on the other hand disregarded livestock production, despite it being an integrated part of the farming systems in the study area. For instance, in Senegal, livestock income was found to be important for purchasing foods, engaging in non-farm activities, and hence acting as a real safety net in case of crop failure (Alobo Loison and Bignebat, 2017). Several studies have shown that agricultural landscape diversity can also contribute to improved livestock production (e.g. Baudron et al., 2017; Duriaux Chavarría et al., 2018). For instance, leguminous fodder trees (such as *Faidherbia albida*) provide a rich feed supplement for cattle, thereby increasing milk and meat production, and, hence, contribute indirectly to household food security (Rosenstock et al., 2019). Secondary, leguminous fodder trees can also augment the quantity and quality of manure, that is for most smallholder farmers in the study region the main source of nutrients for crop production (Baudron et al., 2017; Berre et al., 2021). The provision of shades by trees can also improve the livestock productivity.

In other sahelian parklands, the sale of tree products plays an important role in the total income of food insecure households (Koffi et al., 2017; Mortimore and Adams, 2001). In this study, we could not investigate this “income pathway” (Figure 2c) due to the lack of variability in our tree income variable. All households reported the sales of tree products, but this cash flow could not be quantified due to limited data reliability of the one-time survey. More detailed surveys, e.g. on a 5-days basis to coincide with the local market cycle (Koffi et al., 2017), would be needed to investigate the “income pathway” in more detail.

More broadly, we could have expected a positive relationship between tree diversity, food production and agricultural cash income with a domino effect on food access. Indeed, food production can be sold to generate cash income (Frelat et al., 2016), allowing households to buy food items not produced on-farm. Such strategy depends on market connection to sell and buy food products (Jones, 2017; Sibhatu and Qaim, 2018). Accurately capturing agricultural cash income is not easy with the type of on-time short survey carried-out in this study. While the optimal option to accurately assess this “income pathway” is to rely on more detailed and frequent surveys, other studies have relied on wealth-proxy derived from asset ownerships and or housing characteristics to overcome this limitation, assuming that wealthier households might be able to purchase more diverse food (Rasmussen et al., 2019).

The rights for access to land and use of tree resources can considerably shape the agricultural landscape diversity-food security relationships at field and household level and should be considered in future studies as well. Rights for access to land and use of tree resources may limit the direct contribution of certain tree species on food access. In the Groundnut Basin of Senegal, tree species diversity depends on land type (e.g. natural vs cultivated) (Sambou et al., 2017). The rules of access to tree resources also can depend on the nature of the land and tree species: the collection of wood, fruits, leaves or nuts is generally less restrictive in natural areas or fallow lands compared to cultivated fields. For example, *A. digitata* is mainly planted in home fields in both sites to guarantee tenure by farmers (Koffi et al., 2020). In contrast, *F. albida* is found mainly in bush fields, but due to high pressure on the resource, the Forest Department has strictly limited its access, particularly in the Niakhar site. Selection of useful species is also closely linked to ethnic groups and their relationships to trees. The main ethnic group in the Niakhar site is Serer who consider certain trees as totem, and hence deliberately preserve them from being cut down (Ba et al., 2018).

5. Conclusion

While a growing numbers of studies have shown the close link between tree resources and food security, these studies relied on a simplified description of the agricultural landscapes. Our study sheds more light on the agricultural landscape diversity- food security nexus in three ways: (1) we provided a detailed overview of landscape diversity that includes land use, parkland configuration and composition, (2) our analysis incorporated two levels of analysis, i.e. the field and the household, and (3) we investigated two dimensions of food security (food availability and access).

We find evidence that agricultural landscape diversity, and particularly parkland diversity (i.e. tree species richness and tree density), is a key driver of food availability, explaining more than half of

crop yield variability in both study sites. This positive impact of diverse and dense parkland on food availability contributes indirectly to a greater household food access through what can be called “agroecological pathway”.

Our results also suggested that the understanding of the trade-off occurring between tree density-tree species richness and food security deserves more attention: that positive association between field-level tree density and food availability is lost above a threshold of field-level tree density, and a greater tree density and tree species richness (assessed at household level) will not necessarily directly translate into a greater household food access.

Adopting an integrated landscape approach is required to better understand, assess, and optimize the contribution of agroforestry parklands to different dimensions of food security. Moreover, tree species diversity matters as much as tree density for food availability and food access. The general agreement that trees positively contribute to food security should be nuanced since there may be a density threshold above which the contribution of trees is limited. Optimal landscape management that accounts for tree density and tree functional diversity (fruit trees, leguminous trees, etc.) could help optimize co-benefits of trees for different food security dimensions.

Acknowledgements: This study was supported by the SERENA project funded by the Cirad-INRA metaprogramme GloFoodS and the LYSA project (DAR-TOSCA 4800001089) funded by the French Space Agency. Sentinel-2 data were obtained from the Theia processing center at CNES (<https://theia.cnes.fr/atdistrib/rocket>). We acknowledge Planet's Ambassador Program for the access to their Planet images. The Pléiades data were provided through the French Institutional Programme DINAMIS (<https://dinamis.data-terra.org>). B.Ndao was supported by the CGIAR Research Program on Grain Legumes and Dryland Cereals. We acknowledged also the CSE, ISRA and Cirad who provide technical and financial support for this study. Lastly, authors are very thankful to Master students (Marieme Diene, Soda Mbodj and Benjamin Gervanosi) for their support in the analysis of the agronomy and socio-economic databases.

References

- Adkins, E., Oppelstrup, K., Modi, V., 2012. Rural household energy consumption in the millennium villages in Sub-Saharan Africa. *Energy Sustain. Dev.* 16, 249–259. doi:<https://doi.org/10.1016/j.esd.2012.04.003>
- Affholder, F., Poeydebat, C., Corbeels, M., Scopel, E., Titttonell, P., 2013. The yield gap of major food crops in family agriculture in the tropics: Assessment and analysis through field surveys and modelling. *F. Crop. Res.* 143, 106–118. doi:[10.1016/j.fcr.2012.10.021](https://doi.org/10.1016/j.fcr.2012.10.021)
- Alobo Loison, S., 2015. Rural Livelihood Diversification in Sub-Saharan Africa: A Literature Review. *J. Dev. Stud.* 51, 1125–1138. doi:[10.1080/00220388.2015.1046445](https://doi.org/10.1080/00220388.2015.1046445)
- Alobo Loison, S., Bigneat, C., 2017. Patterns and Determinants of Household Income Diversification in Rural

617 Senegal and Kenya. *J. Poverty Alleviation Int. Dev.* 8, 93–126.

618 Asogwa, I.S., Ibrahim, A.N., Agbaka, J.I., 2021. African baobab: Its role in enhancing nutrition, health, and the
619 environment. *Trees, For. People* 3, 100043. doi:<https://doi.org/10.1016/j.tfp.2020.100043>

620 Ba, M., Bourgoin, J., Thiaw, I., Soti, V., 2018. Impact des modes de gestion des parcs arborés sur la dynamique
621 des paysages agricoles, un cas d'étude au Sénégal. *VertigO* 1–26. doi:10.4000/vertigo.20397

622 Bado, B.V., Whitbread, A., Sanoussi Manzo, M.L., 2021. Improving agricultural productivity using agroforestry
623 systems: Performance of millet, cowpea, and ziziphus-based cropping systems in West Africa Sahel.
624 *Agric. Ecosyst. Environ.* 305, 107175. doi:<https://doi.org/10.1016/j.agee.2020.107175>

625 Baudron, F., Duriaux Chavarría, J.Y., Remans, R., Yang, K., Sunderland, T., 2017. Indirect contributions of
626 forests to dietary diversity in Southern Ethiopia. *Ecol. Soc.* 22, art28. doi:10.5751/ES-09267-220228

627 Baudron, F., Tomscha, S.A., Powell, B., Groot, J.C.J., Gergel, S.E., Sunderland, T., 2019. Testing the Various
628 Pathways Linking Forest Cover to Dietary Diversity in Tropical Landscapes. *Front. Sustain. Food Syst.* 3.
629 doi:10.3389/fsufs.2019.00097

630 Bayala, J., Heng, L.K., van Noordwijk, M., Ouedraogo, S.J., 2008. Hydraulic redistribution study in two native
631 tree species of agroforestry parklands of West African dry savanna. *Acta Oecologica* 34, 370–378.
632 doi:<https://doi.org/10.1016/j.actao.2008.06.010>

633 Bayala, J., Sanou, J., Teklehaimanot, Z., Ouedraogo, S.J., Kalinganire, A., Coe, R., Noordwijk, M. va., 2015.
634 Advances in knowledge of processes in soil–tree–crop interactions in parkland systems in the West
635 African Sahel: A review. *Agric. Ecosyst. Environ.* 205, 25–35. doi:10.1016/J.AGEE.2015.02.018

636 Bayala, J., Wallace, J.W., 2015. The water balance of mixed tree-crop systems, in: Black, C., Wilson, J., Ong,
637 C.K. (Eds.), *Trees-Crop Interactions: Agroforestry in a Changing Climate*. pp. 140–190.

638 Bazié, H.R., Bayala, J., Zombré, G., Sanou, J., Ilstedt, U., 2012. Separating competition-related factors limiting
639 crop performance in an agroforestry parkland system in Burkina Faso. *Agrofor. Syst.* 84, 377–388.
640 doi:10.1007/s10457-012-9483-y

641 Bellón, B., Bégué, A., Lo Seen, D., Lebourgeois, V., Evangelista, B.A., Simões, M., Demonte Ferraz, R.P., 2018.
642 Improved regional-scale Brazilian cropping systems' mapping based on a semi-automatic object-based
643 clustering approach. *Int. J. Appl. Earth Obs. Geoinf.* 68, 127–138. doi:10.1016/J.JAG.2018.01.019

644 Berre, D., Diarisso, T., Andrieu, N., Le Page, C., Corbeels, M., 2021. Biomass flows in an agro-pastoral village in
645 West-Africa: who benefits from crop residue mulching? *Agric. Syst.* 187, 102981.

646 Blaschke, T., Hay, G.J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Queiroz Feitosa, R., van der Meer, F., van
647 der Werff, H., van Coillie, F., Tiede, D., 2014. Geographic Object-Based Image Analysis - Towards a new
648 paradigm. *ISPRS J. Photogramm. Remote Sens.* 87, 180–191. doi:10.1016/j.isprsjprs.2013.09.014

649 Bommarco, R., Kleijn, J., Potts, S.G., 2013. Ecological intensification: harnessing ecosystem services for food
650 security. *Trends Ecol. Evol.* 28, 230–238.

651 Brandt, M., Hiernaux, P., Rasmussen, K., Mbow, C., Kergoat, L., Tagesson, T., Ibrahim, Y.Z., Wélé, A., Tucker,
652 C.J., Fensholt, R., 2016. Assessing woody vegetation trends in Sahelian drylands using MODIS based
653 seasonal metrics. *Remote Sens. Environ.* 183, 215–225. doi:10.1016/j.rse.2016.05.027

654 Brandt, M., Mbow, C., Diouf, A.A., Verger, A., Samimi, C., Fensholt, R., 2015. Ground- and satellite-based
655 evidence of the biophysical mechanisms behind the greening Sahel. *Glob. Chang. Biol.* 21, 1610–1620.

656 Breiman, 2001. *Random Forest*. *Mach. Learn.* 45, 5–32.

657 Buresh, R.J., Jama, B., Ndufa, J.K., 1996. *Agroforestry Trees for Nutrient Cycling and Sustainable*
658 *Management*. *East African Agric. For. J.* 62, 115–127. doi:10.1080/00128325.1996.11663296

659 Bvenura, C., Afolayan, A.J., 2015. The role of wild vegetables in household food security in South Africa: A
660 review. *Food Res. Int.* 76, 1001–1011. doi:<https://doi.org/10.1016/j.foodres.2015.06.013>

661 Cadisch, G., Rowe, E., Van Noordwijk, M., 1997. Nutrient harvesting - the tree-root safety net. *Agrofor. Forum*
662 8, 31–33.

663 Chadare, F.J., Linnemann, A.R., Hounhouigan, J.D., Nout, M.J.R., Van Boekel, M.A.J.S., 2008. Baobab Food
664 Products: A Review on their Composition and Nutritional Value. *Crit. Rev. Food Sci. Nutr.* 49, 254–274.
665 doi:[10.1080/10408390701856330](https://doi.org/10.1080/10408390701856330)

666 Chivandi, E., Mukonowenzou, N., Nyakudya, T., Erlwanger, K.H., 2015. Potential of indigenous fruit-bearing
667 trees to curb malnutrition, improve household food security, income and community health in Sub-
668 Saharan Africa: A review. *Food Res. Int.* 76, 980–985. doi:[10.1016/j.foodres.2015.06.015](https://doi.org/10.1016/j.foodres.2015.06.015)

669 Coastes, J., Swindale, A., Bilinsky, P., 2007. Household Food Insecurity Access Scale (HFIAS) for Measurement
670 of Household Food Access: Indicator Guide (v. 3). Washington D.C.

671 Dilla, A.M., Smethurst, P.J., Huth, N.I., Barry, K.M., 2020. Plot-Scale Agroforestry Modeling Explores Tree
672 Pruning and Fertilizer Interactions for Maize Production in a *Faidherbia* Parkland. *Forests* 11, 1175.
673 doi:[10.3390/f11111175](https://doi.org/10.3390/f11111175)

674 Duriaux Chavarria, J.Y., Baudron, F., Sunderland, T., 2018. Retaining forests within agricultural landscapes as a
675 pathway to sustainable intensification: Evidence from Southern Ethiopia. *Agric. Ecosyst. Environ.* 263,
676 41–52. doi:[10.1016/J.AGEE.2018.04.020](https://doi.org/10.1016/J.AGEE.2018.04.020)

677 Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. *J. Anim. Ecol.* 77, 802–
678 813. doi:[10.1111/j.1365-2656.2008.01390.x](https://doi.org/10.1111/j.1365-2656.2008.01390.x)

679 Fahrig, L., Baudry, J., Brotons, L., Burel, F.G., Crist, T.O., Fuller, R.J., Sirami, C., Siriwardena, G.M., Martin, J.-
680 L., 2011. Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecol.*
681 *Lett.* 14, 101–112. doi:<https://doi.org/10.1111/j.1461-0248.2010.01559.x>

682 FAO, 2019. The State of the World's Biodiversity for Food and Agriculture. Rome, Italy.

683 FAO, 1983. World Food Security: a Reappraisal of the Concepts and Approaches. Rome, Italy.

684 Faye, M.D., Weber, J.C., Abasse, T.A., Boureima, M., Larwanou, M., Bationo, A.B., Diallo, B.O., Sigué, H.,
685 Dakouo, J.M., Samaké, O., Diaité, D., 2011. Farmers' preferences for tree functions and species in the
686 West African Sahel. *For. Trees Livelihoods* 20, 113–136. doi:[10.1080/14728028.2011.9756702](https://doi.org/10.1080/14728028.2011.9756702)

687 Félix, G.F., Diedhiou, I., Le Garff, M., Timmermann, C., Clermont-Dauphin, C., Cournac, L., Groot, J.C.J.,
688 Tittone, P., 2018. Use and management of biodiversity by smallholder farmers in semi-arid West Africa.
689 *Glob. Food Sec.* 18, 76–85. doi:[10.1016/J.GFS.2018.08.005](https://doi.org/10.1016/J.GFS.2018.08.005)

690 Frelat, R., Lopez-Ridaura, S., Giller, K.E., Herrero, M., Douxchamps, S., Djurfeldt, A.A., Erenstein, O.,
691 Henderson, B., Kassie, M., Paul, B.K., Rigolot, C., Ritzema, R.S., Rodriguez, D., Van Asten, P.J.A., Van
692 Wijk, M.T., 2016. Drivers of household food availability in sub-Saharan Africa based on big data from
693 small farms. *Proc. Natl. Acad. Sci. U. S. A.* 113, 458–463. doi:[10.1073/pnas.1518384112](https://doi.org/10.1073/pnas.1518384112)

694 Friedman, J.H., 2001. Greedy function approximation: A gradient boosting machine. *Ann. Stat.* 29, 1189–1232.

695 Friedman, J.H., Meulman, J.J., 2003. Multiple additive regression trees with application in epidemiology. *Stat.*
696 *Med.* 22, 1365–1381.

697 Frison, E.A., Cherfas, J., Hodgkin, T., 2011. Agricultural Biodiversity Is Essential for a Sustainable Improvement
698 in Food and Nutrition Security. *Sustainability* 3, 238–253. doi:[10.3390/su3010238](https://doi.org/10.3390/su3010238)

699 Gbodjo, J.E., Ienco, D., Leroux, L., Interdonato, R., Gaetano, R., Ndao, B., 2020. Object-based multi-temporal
700 and multi-source land cover mapping leveraging hierarchical class relationships. *Remote Sens.* 12, 2814.
701 doi:[10.3390/rs12172814](https://doi.org/10.3390/rs12172814)

702 Gergel, S.E., Powell, B., Baudron, F., Wood, S.L.R., Rhemtulla, J.M., Kennedy, G., Rasmussen, L.V., Ickowitz,
703 A., Fagan, M.E., Smithwick, E.A.H., Ranieri, J., Wood, S.A., Groot, J.C.J., Sunderland, T.C.H., 2020.
704 Conceptual Links between Landscape Diversity and Diet Diversity: A Roadmap for Transdisciplinary
705 Research. *Bioscience* 70, 563–575. doi:10.1093/biosci/biaa048

706 Hadgu, K.M., Kooistra, L., Rossing, W.A.H., van Bruggen, A.H.C., 2009. Assessing the effect of *Faidherbia*
707 *albida* based land use systems on barley yield at field and regional scale in the highlands of Tigray,
708 Northern Ethiopia. *Food Secur.* 1, 337–350. doi:10.1007/s12571-009-0030-2

709 Hengl, T., Leenaars, J.G.B., Shepherd, K.D., Walsh, M.G., Heuvelink, G.B.M., Mamo, T., Tilahun, H., Berkhout,
710 E., Cooper, M., Fegraus, E., Wheeler, I., Kwabena, N.A., 2017. Soil nutrient maps of Sub-Saharan Africa:
711 assessment of soil nutrient content at 250 m spatial resolution using machine learning. *Nutr. Cycl.*
712 *Agroecosystems* 109, 77–102. doi:10.1007/s10705-017-9870-x

713 Herrero, M., Thornton, P.K., Power, B., Bogard, J.R., Remans, R., Fritz, S., Gerber, J.S., Nelson, G., See, L.,
714 Waha, K., Watson, R.A., West, P.C., Samberg, L.H., van de Steeg, J., Stephenson, E., van Wijk, M.,
715 Havlík, P., 2017. Farming and the geography of nutrient production for human use: a transdisciplinary
716 analysis. *Lancet Planet. Heal.* 1, e33–e42. doi:10.1016/S2542-5196(17)30007-4

717 Herrmann, S., Wickhorst, A., Marsh, S., 2013. Estimation of Tree Cover in an Agricultural Parkland of Senegal
718 Using Rule-Based Regression Tree Modeling. *Remote Sens.* 5, 4900–4918. doi:10.3390/rs5104900

719 Ickowitz, A., Powell, B., Salim, M.A., Sunderland, T.C.H., 2014. Dietary quality and tree cover in Africa. *Glob.*
720 *Environ. Chang.* 24, 287–294. doi:10.1016/J.GLOENVCHA.2013.12.001

721 IPAR, 2017. Etude de la consommation des céréales de base au Sénégal. Dakar (Sénégal).

722 IPBES, 2019. Global assessment report on biodiversity and ecosystem services of the Intergovernmental
723 Science-Policy Platform on Biodiversity and Ecosystem Services. IPBES secretariat, Bonn, Germany.

724 Jones, A.D., 2017. Critical review of the emerging research evidence on agricultural biodiversity, diet diversity,
725 and nutritional status in low- and middle-income countries. *Nutr. Rev.* 75, 769–782.
726 doi:10.1093/nutrit/nux040

727 Jones, A.D., Ngure, F.M., Pelto, G., Young, S.L., 2013. What Are We Assessing When We Measure Food
728 Security? A Compendium and Review of Current Metrics. *Adv. Nutr.* 4, 481–505.
729 doi:10.3945/an.113.004119

730 Kebede, Y., Bianchi, F.J.J.A., Baudron, F., Tittone, P., 2019. Landscape composition overrides field level
731 management effects on maize stemborer control in Ethiopia. *Agric. Ecosyst. Environ.* 279, 65–73.
732 doi:https://doi.org/10.1016/j.agee.2019.04.006

733 Kho, R.M., Yacouba, B., Yayé, M., Katkoré, B., Moussa, A., Iktam, A., Mayaki, A., 2001. Separating the effects
734 of trees on crops: the case of *Faidherbia albida* and millet in Niger. *Agrofor. Syst.* 52, 219–238.
735 doi:10.1023/A:1011820412140

736 Koffi, C.K., Djoudi, H., Gautier, D., 2017. Landscape diversity and associated coping strategies during food
737 shortage periods: evidence from the Sudano-Sahelian region of Burkina Faso. *Reg. Environ. Chang.* 17,
738 1369–1380. doi:10.1007/s10113-016-0945-z

739 Koffi, C.K., Gazull, L., Gautier, D., 2018. Variability of household fuelwood consumption in a rural Sudano-
740 Sahelian context in Burkina Faso. *Energy Sustain. Dev.* 47, 75–83.
741 doi:https://doi.org/10.1016/j.esd.2018.09.001

742 Koffi, C.K., Lourme-Ruiz, A., Djoudi, H., Bouquet, E., Dury, S., Gautier, D., 2020. The contributions of wild tree
743 resources to food and nutrition security in sub-Saharan African drylands: a review of the pathways and
744 beneficiaries. *Int. For. Rev.* 22, 64–80.

745 Lericollais, A. (1940- . . .), 1999. Paysans sereer dynamiques agraires et mobilités au Sénégal. Institut de
746 recherche pour le développement (IRD).

747 Leroux, L., Falconnier, G.N., Diouf, A.A., Ndao, B., Gbodjo, J.E., Tall, L., Balde, A.A., Clermont-Dauphin, C.,
748 Affholder, F., Bégué, A., Rounsard, O., 2020. Using remote sensing to assess the effect of trees on millet
749 yield in complex parklands of Central Senegal. *Agric. Syst.* 184, 1–13.
750 doi:<https://doi.org/10.1016/j.agry.2020.102918>

751 Liu, D., Hao, S., Liu, X., Li, B., He, S., Warrington, D.N., 2013. Effects of land use classification on landscape
752 metrics based on remote sensing and GIS. *Environ. Earth Sci.* 68, 2229–2237. doi:[10.1007/s12665-012-](https://doi.org/10.1007/s12665-012-1905-7)
753 [1905-7](https://doi.org/10.1007/s12665-012-1905-7)

754 Luedeling, E., Smethurst, P.J., Baudron, F., Bayala, J., Huth, N.I., van Noordwijk, M., Ong, C.K., Mulia, R.,
755 Lusiana, B., Muthuri, C., Sinclair, F.L., 2016. Field-scale modeling of tree–crop interactions: Challenges
756 and development needs. *Agric. Syst.* 142, 51–69. doi:[10.1016/J.AGSY.2015.11.005](https://doi.org/10.1016/J.AGSY.2015.11.005)

757 Lykke, A.M., 2000. Local perceptions of vegetation change and priorities for conservation of woody-savanna
758 vegetation in Senegal. *J. Environ. Manage.* 59, 107–120. doi:[10.1006/jema.2000.0336](https://doi.org/10.1006/jema.2000.0336)

759 Lykke, A.M., Kristensen, M.K., Ganaba, S., 2004. Valuation of local use and dynamics of 56 woody species in
760 the Sahel. *Biodivers. Conserv.* 13, 1961–1990. doi:[10.1023/B:BIOC.0000035876.39587.1a](https://doi.org/10.1023/B:BIOC.0000035876.39587.1a)

761 Mavengahama, S., McLachlan, M., de Clercq, W., 2013. The role of wild vegetable species in household food
762 security in maize based subsistence cropping systems. *Food Secur.* 5, 227–233. doi:[10.1007/s12571-013-](https://doi.org/10.1007/s12571-013-0243-2)
763 [0243-2](https://doi.org/10.1007/s12571-013-0243-2)

764 Miller, D.C., Muñoz-Mora, J.C., Christiaensen, L., 2017. Prevalence, economic contribution, and determinants
765 of trees on farms across Sub-Saharan Africa. *For. Policy Econ.* 84, 47–61.
766 doi:[10.1016/J.FORPOL.2016.12.005](https://doi.org/10.1016/J.FORPOL.2016.12.005)

767 Mortimore, M.J., Adams, W.M., 2001. Farmer adaptation, change and ‘crisis’ in the Sahel. *Glob. Environ.*
768 *Chang.* 11, 49–57. doi:[https://doi.org/10.1016/S0959-3780\(00\)00044-3](https://doi.org/10.1016/S0959-3780(00)00044-3)

769 Muthayya, S., Rah, J.H., Sugimoto, J.D., Roos, F.F., Kraemer, K., Black, R.E., 2013. The Global Hidden Hunger
770 Indices and Maps: An Advocacy Tool for Action. *PLoS One* 8, e67860.

771 Nair, P., 1993. An introduction to agroforestry, Springer S. ed. Dordrecht, The Netherlands.

772 Ndao, B., Leroux, L., Diouf, A.A., 2021a. Tree species inventory in the *Faidherbia albida* parkland of Senegal.
773 doi:[doi:10.18167/DVN1/OAYDV3](https://doi.org/10.18167/DVN1/OAYDV3)

774 Ndao, B., Leroux, L., Diouf, A.A., Soti, V., Sambou, B., 2018. A remote sensing based approach for optimizing
775 sampling strategies in crop monitoring and crop yield estimation studies, in: Wade, S. (Ed.), *Earth*
776 *Observations and Geospatial Science in Service of Sustainable Development Goals : 12th International*
777 *Conference of the African Association of Remote Sensing and the Environment.* Springer, Muinzenburg,
778 South Africa, pp. 25–36. doi:https://doi.org/10.1007/978-3-030-16016-6_3

779 Ndao, B., Leroux, L., Gaetano, R., Diouf, A.A., Soti, V., Mbow, C., Bégué, A., Sambou, B., 2021b. Landscape
780 heterogeneity analysis using geospatial techniques and a priori knowledge in Sahelian agroforestry
781 systems of Senegal. *Ecol. Indic.* 125, 107481. doi:<https://doi.org/10.1016/j.ecolind.2021.107481>

782 Ndoli, A., Baudron, F., Schut, A.G.T., Mukuralinda, A., Giller, K.E., 2017. Disentangling the positive and
783 negative effects of trees on maize performance in smallholdings of Northern Rwanda. *F. Crop. Res.* 213,
784 1–11. doi:[10.1016/J.FCR.2017.07.020](https://doi.org/10.1016/J.FCR.2017.07.020)

785 Nyberg, Y., Wetterlind, J., Jonsson, M., Öborn, I., 2020. The role of trees and livestock in ecosystem service
786 provision and farm priorities on smallholder farms in the Rift Valley, Kenya. *Agric. Syst.* 181, 102815.
787 doi:<https://doi.org/10.1016/j.agry.2020.102815>

788 Oksanen, J., Blanchet, F.G., Friendly, M., Kindt, R., Legendre, P., McGlinn, D., Minchin, P.R., O’Hara, R.B.,
789 Simpson, G.L., Solymos, P., Stevens, M.H.H., Szoecs, E., Wagner, H., 2019. *vegan: Community Ecology*
790 *Package.*

791 Otieno, M., Sidhu, C.S., Woodcock, B.A., Wilby, A., Vogiatzakis, I.N., Mauchline, A.L., Gikungu, M.W., Potts,
792 S.G., 2015. Local and landscape effects on bee functional guilds in pigeon pea crops in Kenya. *J. Insect*
793 *Conserv.* 19, 647–658. doi:10.1007/s10841-015-9788-z

794 Peng, J., Wang, Y., Ye, M., Wu, J., Zhang, Y., 2007. Effects of land-use categorization on landscape metrics: A
795 case study in urban landscape of Shenzhen, China. *Int. J. Remote Sens.* 28, 4877–4895.
796 doi:10.1080/01431160601075590

797 Peterson, R.A., Cavanaugh, J.E., 2019. Ordered quantile normalization: a semiparametric transformation built
798 for the cross-validation era. *J. Appl. Stat.* 1–16. doi:10.1080/02664763.2019.1630372

799 Pilling, D., Bélanger, J., Hoffmann, I., 2020. Declining biodiversity for food and agriculture needs urgent global
800 action. *Nat. Food* 1–4. doi:10.1038/s43016-020-0040-y

801 R Core Team, 2020. R: A language and environment for statistical computing. R Foundation for Statistical
802 Computing, Vienna, Austria.

803 Rasmussen, L.V., Fagan, M.E., Ickowitz, A., Wood, S.L.R., Kennedy, G., Powell, B., Baudron, F., Gergel, S.,
804 Jung, S., Smithwick, E.A.H., Sunderland, T., Wood, S., Rhemtulla, J.M., 2019. Forest pattern, not just
805 amount, influences dietary quality in five African countries. *Glob. Food Sec.*
806 doi:10.1016/j.gfs.2019.100331

807 Rasmussen, L.V., Wood, S.L.R., Rhemtulla, J.M., 2020. Deconstructing Diets: The Role of Wealth, Farming
808 System, and Landscape Context in Shaping Rural Diets in Ethiopia. *Front. Sustain. Food Syst.* 4, 45.
809 doi:10.3389/fsufs.2020.00045

810 Reed, J., Vianen van, J., Foli, S., Clendenning, J., Yang, K., MacDonald, M., Petrokofsky, G., Padoch, C.,
811 Sunderland, T., 2017. Trees for life: The ecosystem service contribution of trees to food production and
812 livelihoods in the tropics. *For. Policy Econ.* 84, 62–71.

813 Ricciardi, V., Mehrabi, Z., Wittman, H., James, D., Ramankutty, N., 2021. Higher yields and more biodiversity
814 on smaller farms. *Nat. Sustain.* doi:10.1038/s41893-021-00699-2

815 Ritzema, R.S., Frelat, R., Douchamps, S., Silvestri, S., Rufino, M.C., Herrero, M., Giller, K.E., Lopez-Ridaura,
816 S., Teufel, N., Paul, B.K., Wijk, M.T. Van, Security, F., Ritzema, Randall S., 2017. Is production
817 intensification likely to make farm households food-adequate? A simple food availability analysis across
818 smallholder farming systems from East and West Africa. *Food Secur.* 1–17. doi:10.1007/s12571-016-0638-
819 y

820 Rosenstock, T.S., Dawson, I.K., Aynekulu, E., Chomba, S., Degrande, A., Fornace, K., Jamnadass, R., Kimaro,
821 A., Kindt, R., Lamanna, C., Malesu, M., Mausch, K., McMullin, S., Murage, P., Namoi, N., Njenga, M.,
822 Nyoka, I., Paez Valencia, A.M., Sola, P., Shepherd, K., Steward, P., 2019. A Planetary Health Perspective
823 on Agroforestry in Sub-Saharan Africa. *One Earth* 1, 330–344. doi:10.1016/j.oneear.2019.10.017

824 Roupsard, O., Audebert, A., Ndour, A., Clermont-Dauphin, C., Agbohessou, Y., Sanou, J., Koala, J., Faye, E.,
825 Sambakhe, D., Jourdan, C., le Maire, G., Tall, L., Sanogp, D., Seghieri, J., Cournac, L., Leroux, L., 2020.
826 How far does the tree affect the crop in agroforestry? New spatial analysis methods in a Faidherbia
827 parkland. *Agric. Ecosyst. Environ.* 296, 106928. doi:10.1016/j.agee.2020.106928

828 Sambou, A., Sambou, B., Ræbild, A., 2017. Farmers' contributions to the conservation of tree diversity in the
829 Groundnut Basin, Senegal. *J. For. Res.* 28, 1083–1096. doi:10.1007/s11676-017-0374-y

830 Sanou, J., Bayala, J., Teklehaimanot, Z., Bazié, P., 2012. Effect of shading by baobab (*Adansonia digitata*) and
831 néré (*Parkia biglobosa*) on yields of millet (*Pennisetum glaucum*) and taro (*Colocasia esculenta*) in
832 parkland systems in Burkina Faso, West Africa. *Agrofor. Syst.* 85, 431–441. doi:10.1007/s10457-011-9405-
833 4

834 Sibhatu, K.T., Qaim, M., 2018. Review: Meta-analysis of the association between production diversity, diets,
835 and nutrition in smallholder farm households. *Food Policy* 77, 1–18. doi:10.1016/J.FOODPOL.2018.04.013

- 836 Sida, T.S., Baudron, F., Kim, H., Giller, K.E., 2018. Climate-smart agroforestry: *Faidherbia albida* trees buffer
837 wheat against climatic extremes in the Central Rift Valley of Ethiopia. *Agric. For. Meteorol.* 248, 339–
838 347. doi:10.1016/J.AGRFORMET.2017.10.013
- 839 Sida, T.S., Baudron, F., Ndoli, A., Tirfessa, D., Giller, K.E., 2019. Should fertilizer recommendations be adapted
840 to parkland agroforestry systems? Case studies from Ethiopia and Rwanda. *Plant Soil* 1–16.
841 doi:10.1007/s11104-019-04271-y
- 842 Sileshi, G.W., 2016. The magnitude and spatial extent of influence of *Faidherbia albida* trees on soil properties
843 and primary productivity in drylands. *J. Arid Environ.* 132, 1–14. doi:10.1016/J.JARIDENV.2016.03.002
- 844 Sinare, H., Gordon, L.J., 2015. Ecosystem services from woody vegetation on agricultural lands in Sudano-
845 Sahelian West Africa. *Agric. Ecosyst. Environ.* 200, 186–199. doi:10.1016/j.agee.2014.11.009
- 846 Soti, V., Thiaw, I., Debaly, M.Z., Sow, A., Diaw, M., Fofana, S., Diakhate, M., Thiaw, C., Brévault, T., 2019.
847 Effect of landscape diversity and crop management on the control of the millet head miner, *Heliocheilus*
848 *albipunctella* (Lepidoptera: Noctuidae) by natural enemies. *Biol. Control* 129, 115–122.
849 doi:10.1016/j.biocontrol.2018.10.006
- 850 Sow, A., Seye, D., Faye, E., Benoit, L., Galan, M., Haran, J., Brévault, T., 2020. Birds and bats contribute to
851 natural regulation of the millet head miner in tree-crop agroforestry systems. *Crop Prot.* 132, 105127.
852 doi:10.1016/j.cropro.2020.105127
- 853 Taylor, C.M., Belušić, D., Guichard, F., Parker, D.J., Vischel, T., Bock, O., Harris, P.P., Janicot, S., Klein, C.,
854 Panthou, G., 2017. Frequency of extreme Sahelian storms tripled since 1982 in satellite observations.
855 *Nature* 544, 475–478. doi:10.1038/nature22069
- 856 Tounkara, A., Clermont-Dauphin, C., Affholder, F., Ndiaye, S., Masse, D., Cournac, L., 2020. Inorganic fertilizer
857 use efficiency of millet crop varies with organic fertilizer application in rainfed agriculture on
858 smallholdings in central Senegal. *Agric. Ecosyst. Environ.* 294, 106878.
- 859 Tschora, H., Cherubini, F., 2020. Co-benefits and trade-offs of agroforestry for climate change mitigation and
860 other sustainability goals in West Africa. *Glob. Ecol. Conserv.* 22, e00919.
861 doi:10.1016/j.gecco.2020.e00919
- 862 van Noordwijk, M., Ong, C.K., 1999. Can the ecosystem mimic hypotheses be applied to farms in African
863 savannahs? *Agrofor. Syst.* 45, 131–158. doi:10.1023/A:1006245605705
- 864 Vanlauwe, B., Descheemaeker, K., Giller, K.E., Huising, J., Merckx, R., Nziguheba, G., Wendt, J., Zingore, S.,
865 2015. Integrated soil fertility management in sub-Saharan Africa: Unravelling local adaptation. *SOIL* 1,
866 491–508. doi:10.5194/soil-1-491-2015
- 867 Waha, K., van Wijk, M.T., Fritz, S., See, L., Thornton, P.K., Wichern, J., Herrero, M., 2018. Agricultural
868 diversification as an important strategy for achieving food security in Africa. *Glob. Chang. Biol.* 24, 3390–
869 3400. doi:10.1111/gcb.14158
- 870 Yang, K., Gergel, S., Duriaux-Chavarria, J.-Y., Baudron, F., 2020. Forest Edges Near Farms Enhance Wheat
871 Productivity Measures: A Test Using High Spatial Resolution Remote Sensing of Smallholder Farms in
872 Southern Ethiopia. *Front. Sustain. Food Syst.* 4, 130. doi:10.3389/fsufs.2020.00130
- 873 Zheng, L.-T., Chen, H.Y.H., Yan, E.-R., 2019. Tree species diversity promotes litterfall productivity through
874 crown complementarity in subtropical forests. *J. Ecol.* 107, 1852–1861. doi:https://doi.org/10.1111/1365-
875 2745.13142

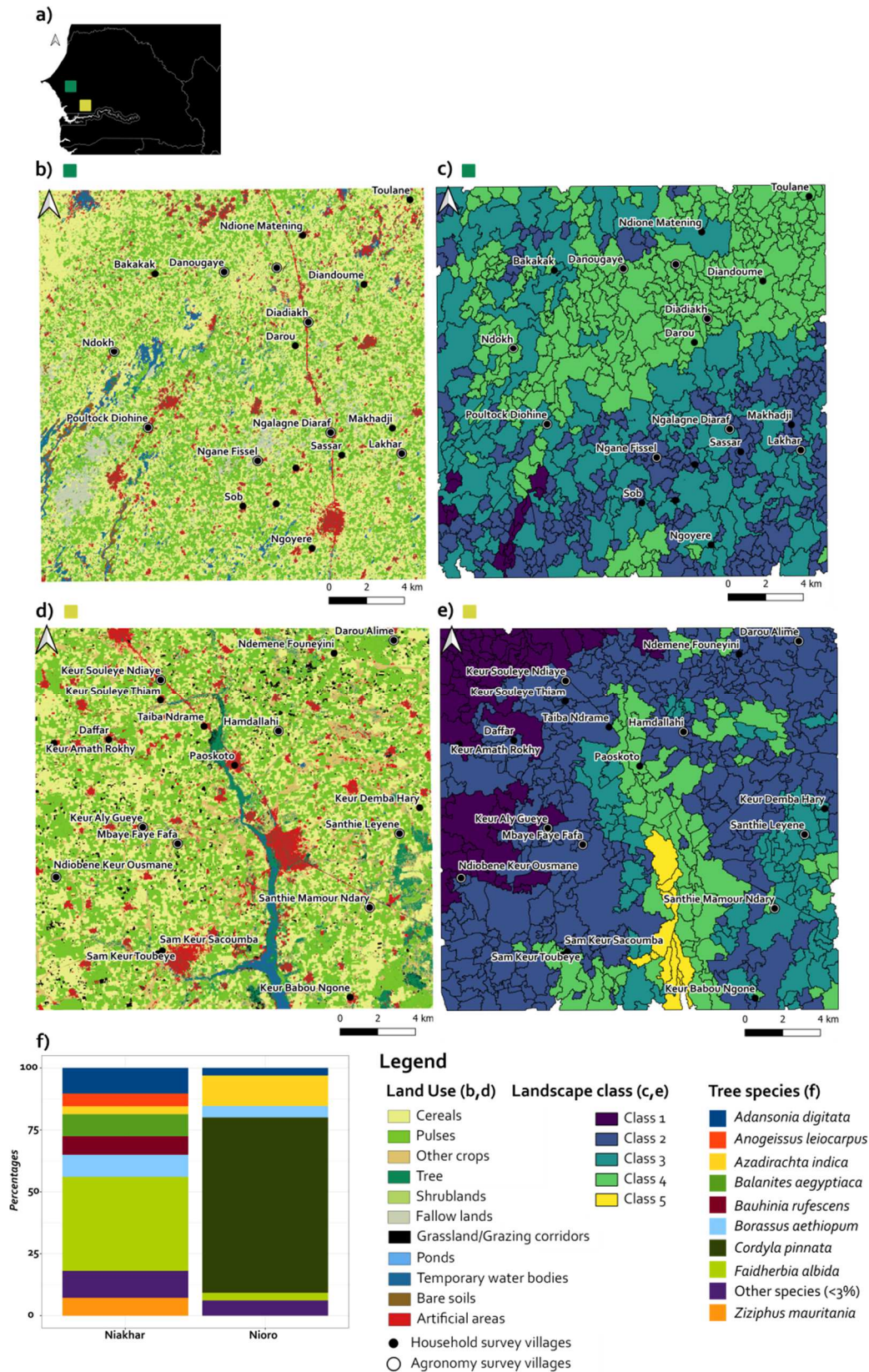
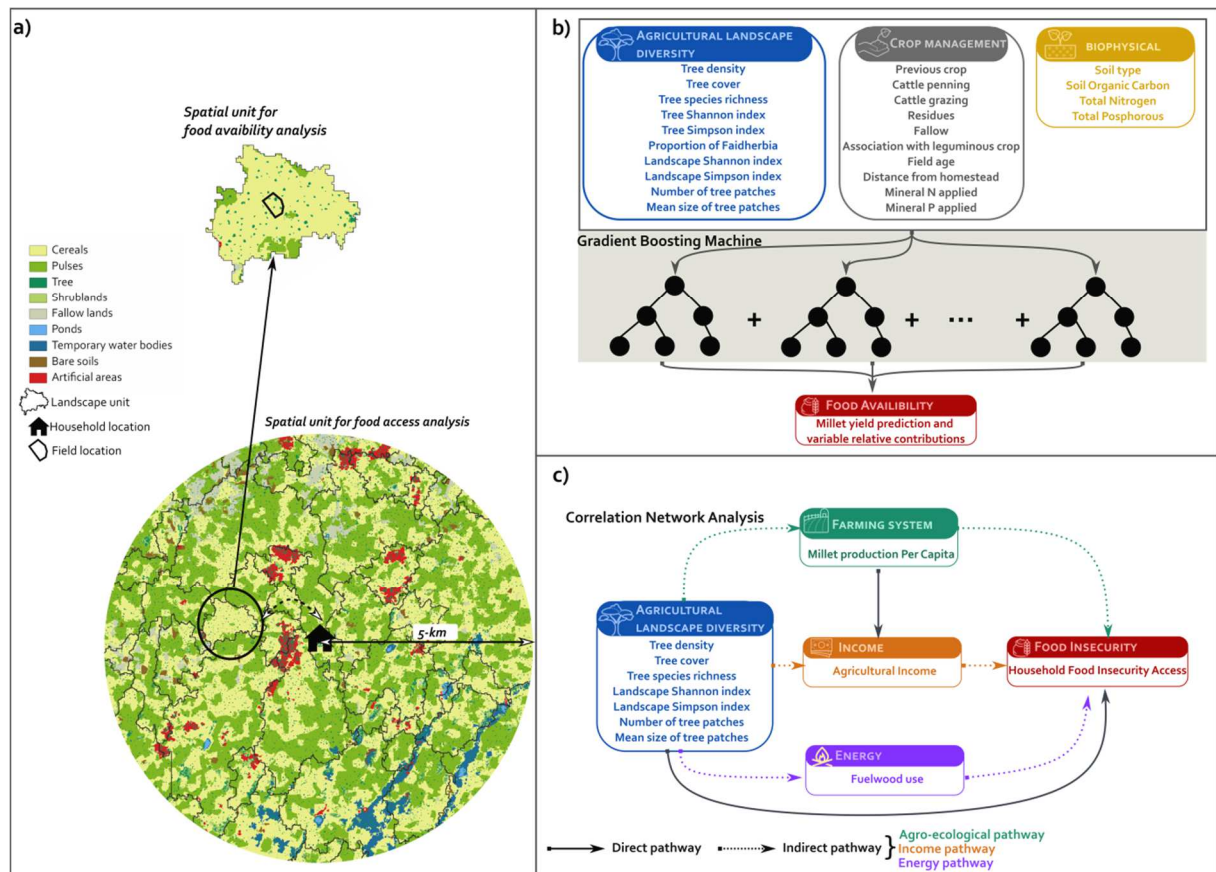


Figure 1. Main characteristics of the two study sites. a) location of the Niakhar site (green square) and Nioro site (yellow square), b) and d) main land use in 2018 for Niakhar and Nioro respectively, c) and e) landscape classes for Niakhar and Nioro respectively (from Ndao et al., 2021) and f) tree species composition for each study site. A description of the landscape classes are provided in supplementary materials (Table S2).



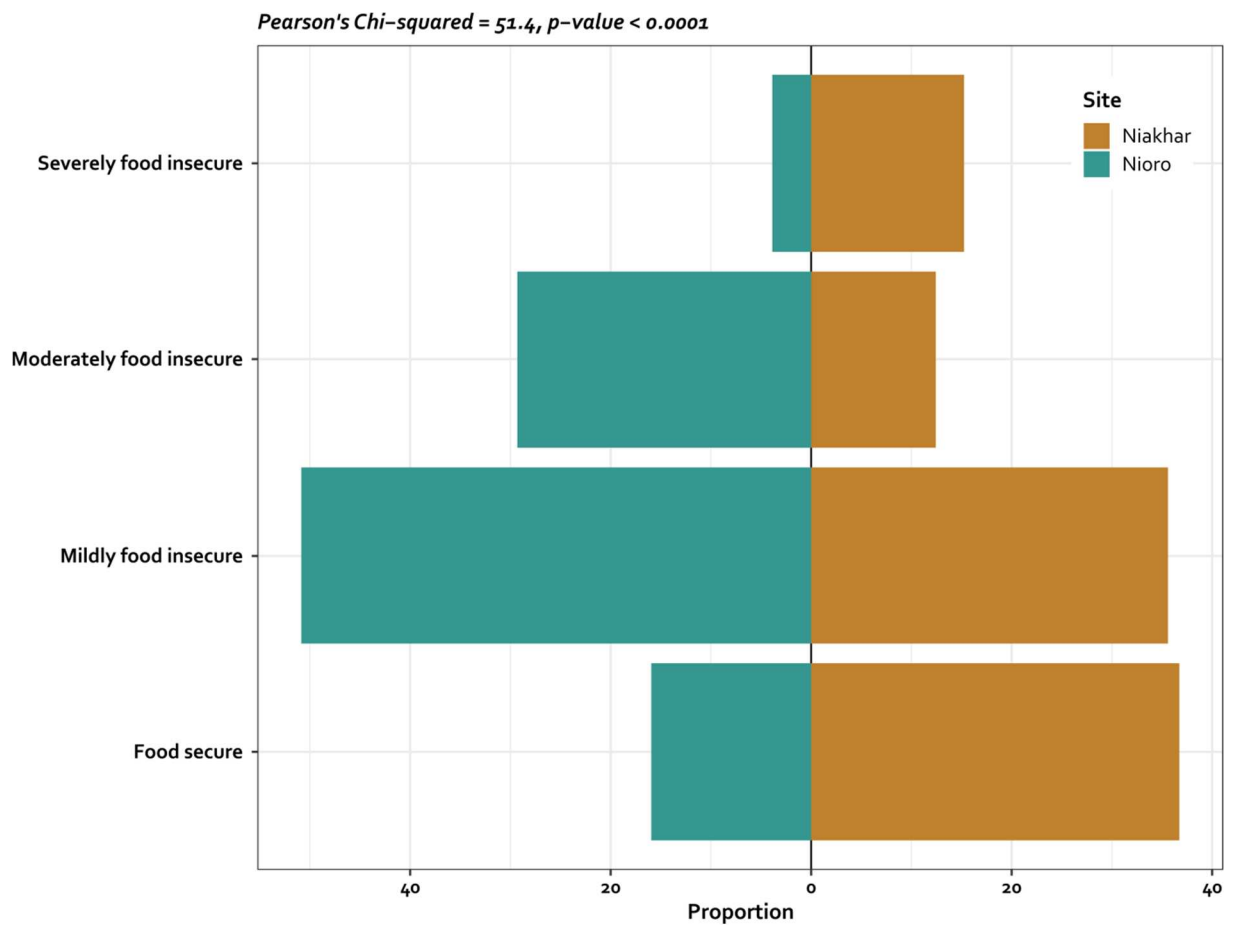


Figure 3. Comparison of food security (HFIAS) between sites (Niakhar and Nioro). Chi-squared and the associated p-values are provided.

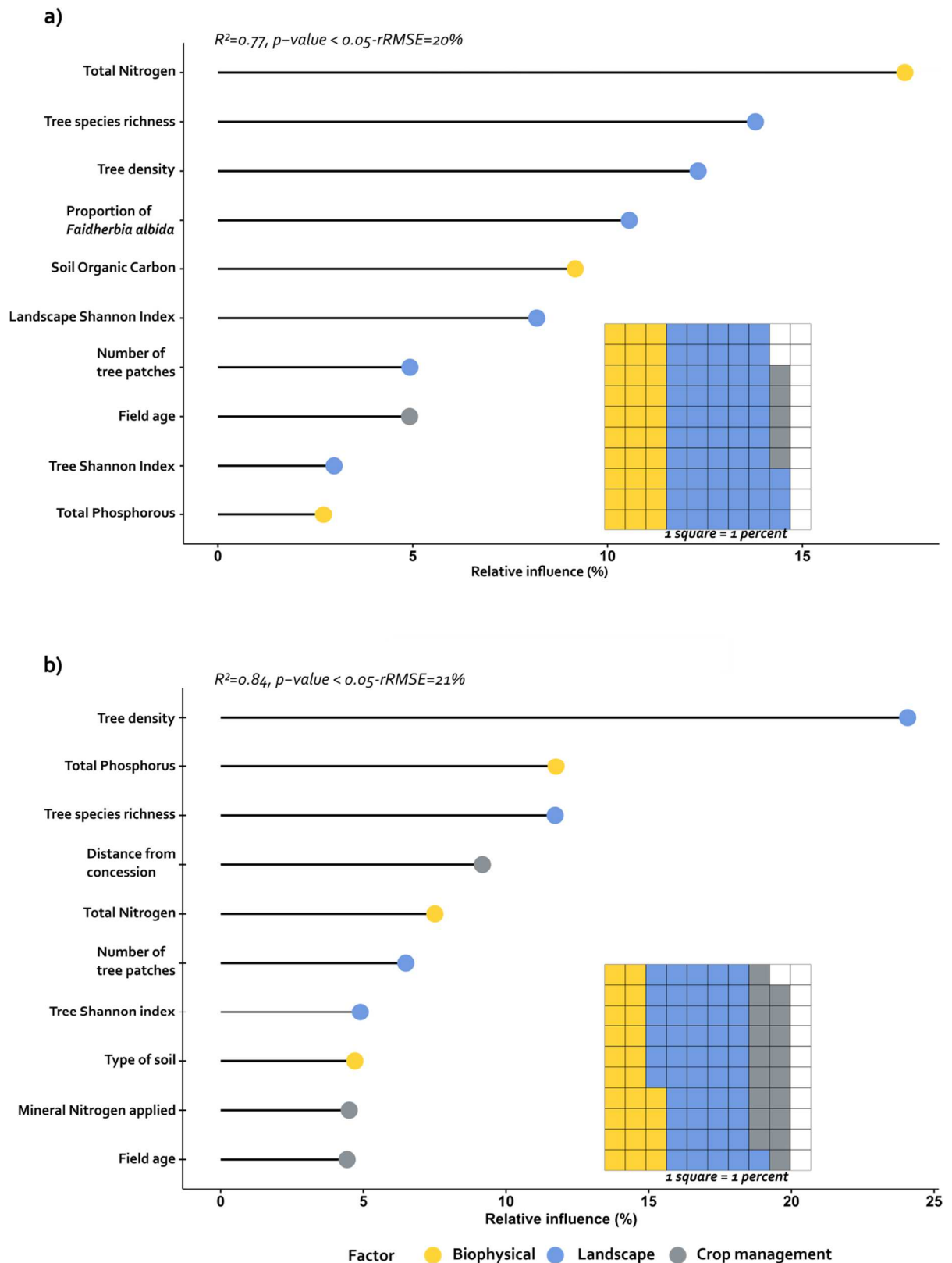


Figure 4. Relative contributions of cropping system, biophysical and agricultural landscape diversity factors on the pearl millet yields at farmer's field scale for (a) the Niakhar site and (b) the Nioro site. Only the top-10 most important factors are displayed. For each site, the waffle plot show the contribution of each type of factors to the relative influence, where one square represents 1%.

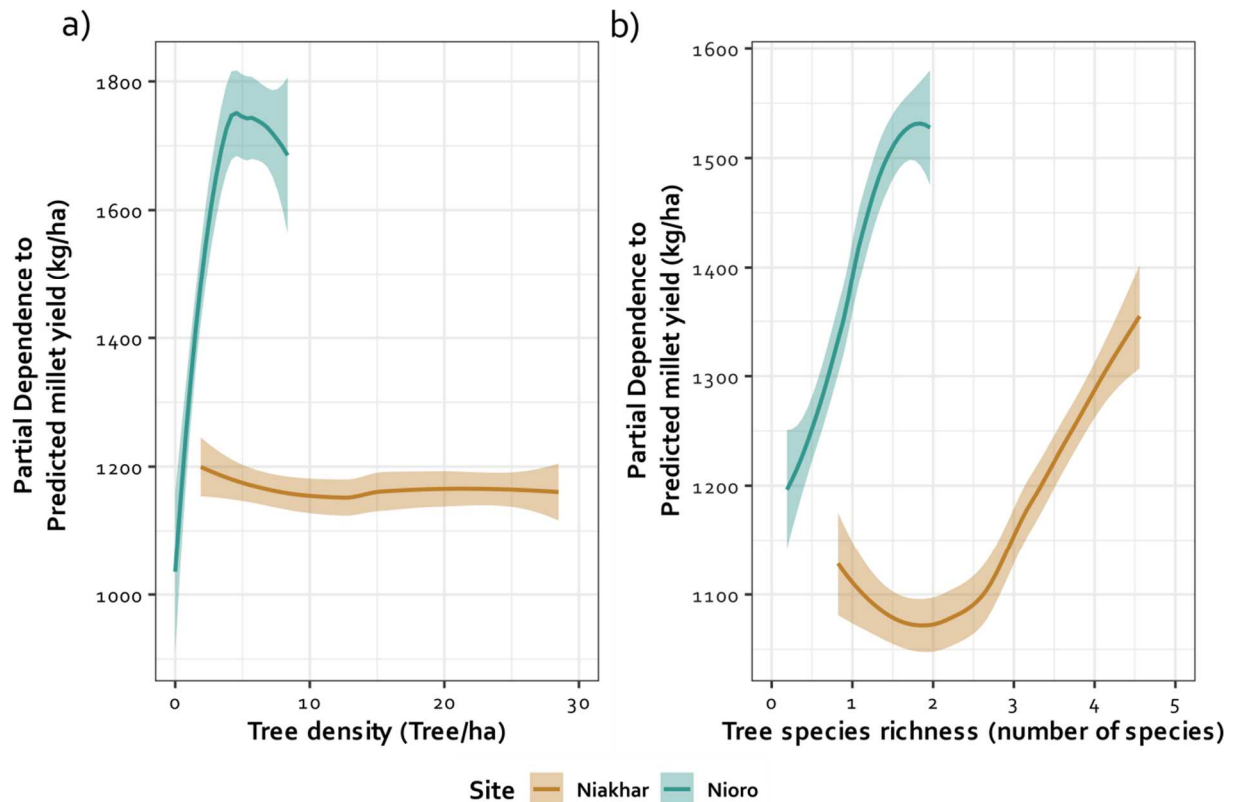


Figure 5. Interaction between tree density a) and tree species richness b) using a partial dependence plot. The partial dependence plot depicts the marginal effect of tree density and tree species richness on predicted millet yield. A locally weighted smoothing was applied to the partial dependence smooth regressions and standard deviation (ribbon) was added.

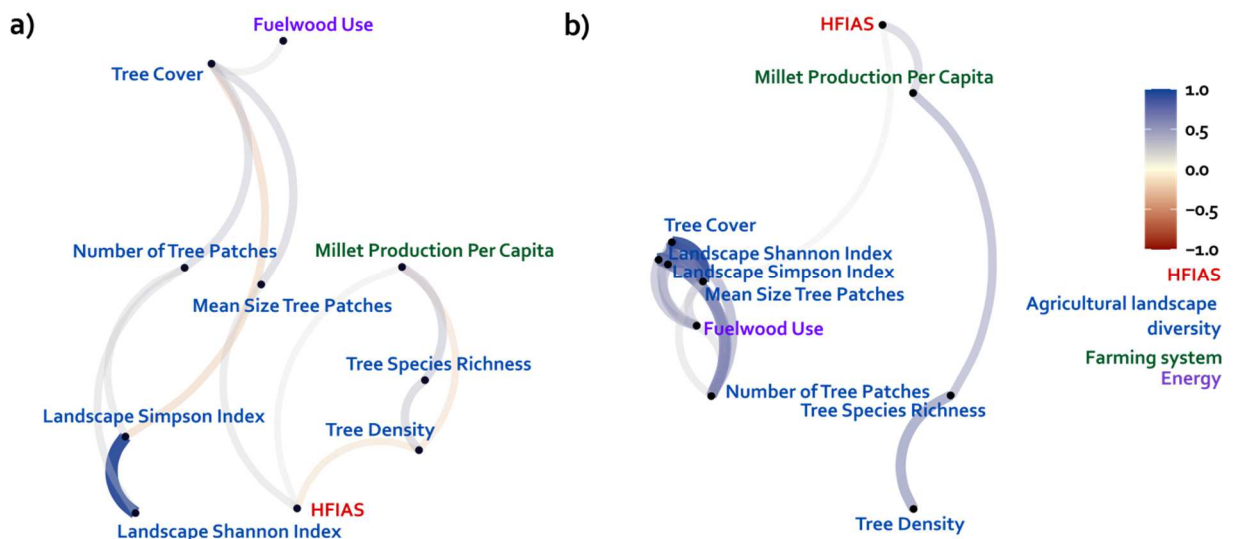


Figure 6. Correlation-based network to analyze the different pathways linking agricultural landscape diversity to household food access (HFIAS indicator) (a) in Niakhar and (b) Nioro. HFIAS is displayed in red (HFIAS = Household Food Insecurity Access), agricultural landscape diversity variables in blue, farming system variables in green and energy variable (fuelwood use) in yellow. HFIAS is classified as severely, moderately, mildly food insecure and food secure. For the links, the color scale depicts the value of the coefficient of correlation between the two connected variables. Only highly statistically significant correlation coefficients (p -value < 0.05) are displayed.

Table 1: List of variables collected to explain millet yield and household HFIAS

Food security variable to explain	Unit of observation	Explanatory variable	Unit	Number of observations**	method for data acquisition
Millet yield	Millet field	Landscape diversity	Landscape Shannon index	70	analysis of geospatial data
			Landscape Simpson index	70	analysis of geospatial data
			Share of <i>Faidherbia albida</i>	70	field monitoring
			Tree density	70	field monitoring
			Tree species richness	70	field monitoring
			Tree Shannon index	70	field monitoring
			Tree Simpson index	70	field monitoring
			Tree cover	70	analysis of geospatial data***
			Number of tree patches	70	analysis of geospatial data***
			Mean size of tree patches	70	analysis of geospatial data***
		Biophysical variables	Soil type	70	field monitoring
			Soil Organic Carbon*****	70	analysis of geospatial data***
			Soil Total Nitrogen*****	70	analysis of geospatial data***
			Soil Total Phosphorus*****	70	analysis of geospatial data***
		Crop management	Previous crop	70	field monitoring
			Cattle penning	70	field monitoring
			Cattle grazing	70	field monitoring
			Residues kept on the plot	70	field monitoring
			Is the field regularly fallowed	70	field monitoring
			Association with leguminous crop	70	field monitoring
			Field age	70	field monitoring
			Distance from homestead	70	field monitoring
			Amount of mineral nitrogen applied	70	field monitoring
			Amount of mineral phosphorus applied	70	field monitoring
HFIAS*	Household	Landscape diversity	Landscape Shannon index	391	analysis of geospatial data****
			Landscape Simpson index	391	analysis of geospatial data****
			Tree density	391	household survey
			Tree species richness	391	household survey
			Number of tree patches	391	analysis of geospatial data****
			Mean size of tree patches	391	analysis of geospatial data****
			Tree cover	391	analysis of geospatial data****
		Farming system	Farm size Per Capita	391	household survey
			Millet production Per Capita	391	household survey
		Income	Tree income	391	household survey
		Energy	Fuelwood use	391	household survey
		Socio-demographic	Size of household	391	household survey
			Proportion of men	391	household survey

*HFIAS : 1 =severely food insecure, 2=moderately food insecure, 3=mildly food insecure, 4=food secure

**Final sample size after data curation

*** extracted at landscape unit level.

****extracted within a 5-km radius of household location.

***** AfSoilGrids database (Hengl et al., 2017)

Table 2. Main characteristics (mean and standard deviation) in the two study sites. Variables which significantly differ between sites (p-value < 0.05) are displayed in bold.

Unit of observation	Type of variable	Variables	Niakhar		Nioro	
			Mean	Std.dev	Mean	Std.dev
Field	Food availability indicator	Millet yield (kg/ha)	1088	474	1253	607
	Landscape diversity	Landscape Shannon index	1.15	0.17	1.06	0.24
		Tree density (tree/ha)	12.2	13.57	1.27	1.37
		Proportion of <i>Faidherbia albida</i> (%)	51.3	37	2.84	11
	Biophysical variables	SOC (‰)	6.64	1	6.41	1.36
		Total Nitrogen (ppm)	603	228	496	33.9
		Total Phosphorus (ppm)	272	34	188	21
	Crop management	Amount of mineral Nitrogen applied (kg/ha)	20.2	26.7	34.0	37.7
		Amount of mineral Phosphorus applied (kg/ha)	10.4	11.8	19.5	11.6
Household	Landscape diversity	Tree cover (%)	7.3	0.8	5.6	0.4
		Tree species richness (count)	6.3	3.16	3	2.23
	Farming system	Farm size Per Capita (ha/capita)	0.22	0.23	0.36	0.23
		Millet production Per Capita (kg/capita)	246	207	380	329
	Socio-demographic	Size of household (capita)	13.9	6.4	12.57	5.99
		Proportion of men/boy (%)	51	25.3	48.4	27.6