

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

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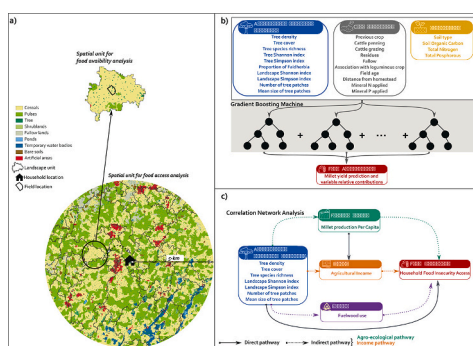
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### HIGHLIGHTS

- Sahelian agroforestry parklands are crucial to improving food security of farmers.
- We linked landscape diversity metrics with field monitoring and household surveys.
- Food availability was positively associated with tree density and species richness.
- Food access was linked to landscape diversity through an agroecological pathway.
- Food security policies should also paid regard to agroforestry parklands diversity.

### GRAPHICAL ABSTRACT



### ARTICLE INFO

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### ABSTRACT

**CONTEXT:** Fostering diversity within agricultural systems can substantially contribute to improved food security among smallholder farmers. Agroforestry parklands are diverse agricultural landscapes where trees can provide

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an array of ecosystem services. Previous studies analyzing the agricultural landscape diversity-food security nexus in agroforestry parklands have only considered tree cover.

**OBJECTIVE:** We propose an original empirical approach that combines the analysis of spatial data on agricultural landscape diversity with agricultural field monitoring and household surveys. These three sources of data were used to scrutinize the direct and indirect contributions of agricultural landscape diversity to food availability and food access.

**METHODS:** Millet yield was used as a proxy for food availability, and household food access was approximated using the Household Food Insecurity Access Scale (HFIAS) indicator. Two contrasted agroforestry parklands of Central Senegal were chosen as case studies. Firstly, we used a Gradient Boosting Machine (GBM) algorithm to disentangle the relative contribution of landscape diversity, biophysical and crop management variables in explaining millet yield variability. Secondly, we investigated the pathways linking agricultural landscape diversity to HFIAS using a Correlation Network Analysis (CNA).

**RESULTS AND CONCLUSIONS:** The GBM model explained 77% and 84% of millet yield variability for the two parklands, respectively, with landscape diversity variables accounting for 53% and 47% of relative influence. Among the landscape diversity variables, tree species richness and tree density were the most important ones. Millet yield was positively associated with tree density in the Niore site until a threshold of 5 trees/ha, and with tree species richness in the two sites. The CNA showed that greater tree cover and larger tree patches were moderately correlated with HFIAS. This suggests that tree species with large crown, as it the case for most fruit bearing tree species in the region, are the main species contributing directly to food access. Agricultural landscape diversity contributed mainly indirectly to household food access through an “agroecological pathway”, i.e. by the provision of ecosystem services regulating and supporting crop production.

**SIGNIFICANCE:** Using an integrated landscape approach relying on up-to-date remote sensing data and recent advances in data analysis methods, our study shows that tree species diversity matters as much as the amount of tree cover for the production of food, and it can contribute to improve food security. We bring a more nuanced picture of the contribution of agricultural landscape diversity to food security suggesting that land management policies supporting food security should consider both tree density and tree species diversity to optimize the co-benefits of trees for the different food security dimensions.

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

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

security through the provision of fuelwood (wood and charcoal) as it is the primary source of energy used by rural households for cooking (Adkins et al., 2012).

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

The underlying processes and effects of agricultural landscape diversity on food security are, however, complex. The spatial configuration of land use patches drives many processes occurring in agricultural systems, e.g., pest infestation (Kebede et al., 2019; Sow et al., 2020) and crop pollination through bee abundance (Otieno et al., 2015). For instance, it has been shown that a high proportion of semi-natural areas in the agricultural landscapes of the Senegalese Groundnut Basin can significantly contribute to the control of the 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, a density of 10 trees/ha is considered optimal to support crop productivity in *F.albida* parklands (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 from trees such as the African locust bean (*Parkia biglobosa*), decreases millet yield in parklands of Burkina Faso (Sanou et al., 2012). These trade-offs can 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.

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), whilst 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 Chavarría 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 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., total 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; Rasmussen et al., 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., 2019). 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 for 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 (Fig. 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 (Fig. 1a). Each site covers about 450-km<sup>2</sup>. The climate in Niakhar is sahelo-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 of trees (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 increased water and nutrient availability (Sileshi, 2016) and better 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, *A. digitata*, *Balanites aegyptiaca* and *Borassus aethiopicum* being the most important ones apart from *F. albida* (Fig. 1f). Nioro has less diverse parklands with about 50 species in total, largely dominated by *Cordia pinnata* (71% of the trees) followed by *Asadirachta indica*. *C. pinnata* is an important species for the local population, because it provides construction woods, fodder for livestock, medicinal plant parts and seedpulp of high nutritional value (Lykke, 2000; Sinare and Gordon, 2015). However, *C. pinnata* is overexploited (legal and illegal logging) and considered as a species in decline in the region (Lykke, 2000).

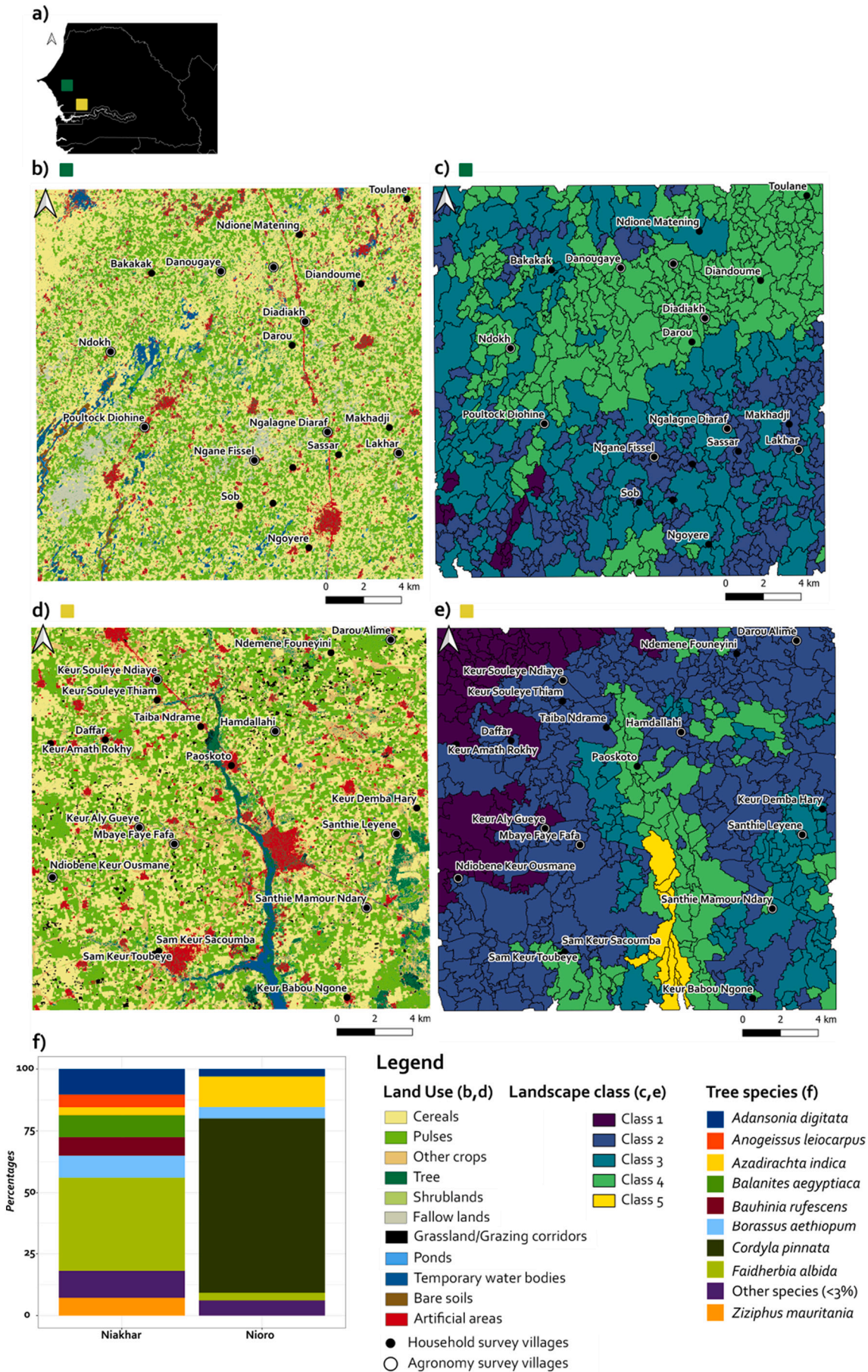
The population density of the Niakhar and Nioro sites was estimated at 122 hab/km<sup>2</sup> (standard deviation: 52 hab/km<sup>2</sup>) and 187 hab/km<sup>2</sup> (standard deviation: 82 hab/km<sup>2</sup>), respectively (<https://www.worldpop.org/>). In both sites, rural people practice small-scale 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 (Fig. 1b and Fig. 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 the rural households consume pearl millet twice a day, five days of the week. In particular, millet is the cornerstone of food security for rural population in both sites during the lean season 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 Fig. 1b and Fig. 1d).

### 2.2. General overview of the approach

Fig. 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; Fig. 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 sample of 40 agricultural fields. 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. assessed with the Household Food Insecurity Access Scale, HFIAS) using a conceptual model adapted from Gergel et al. (2020) based on Correlation Network Analysis (see Fig. 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.

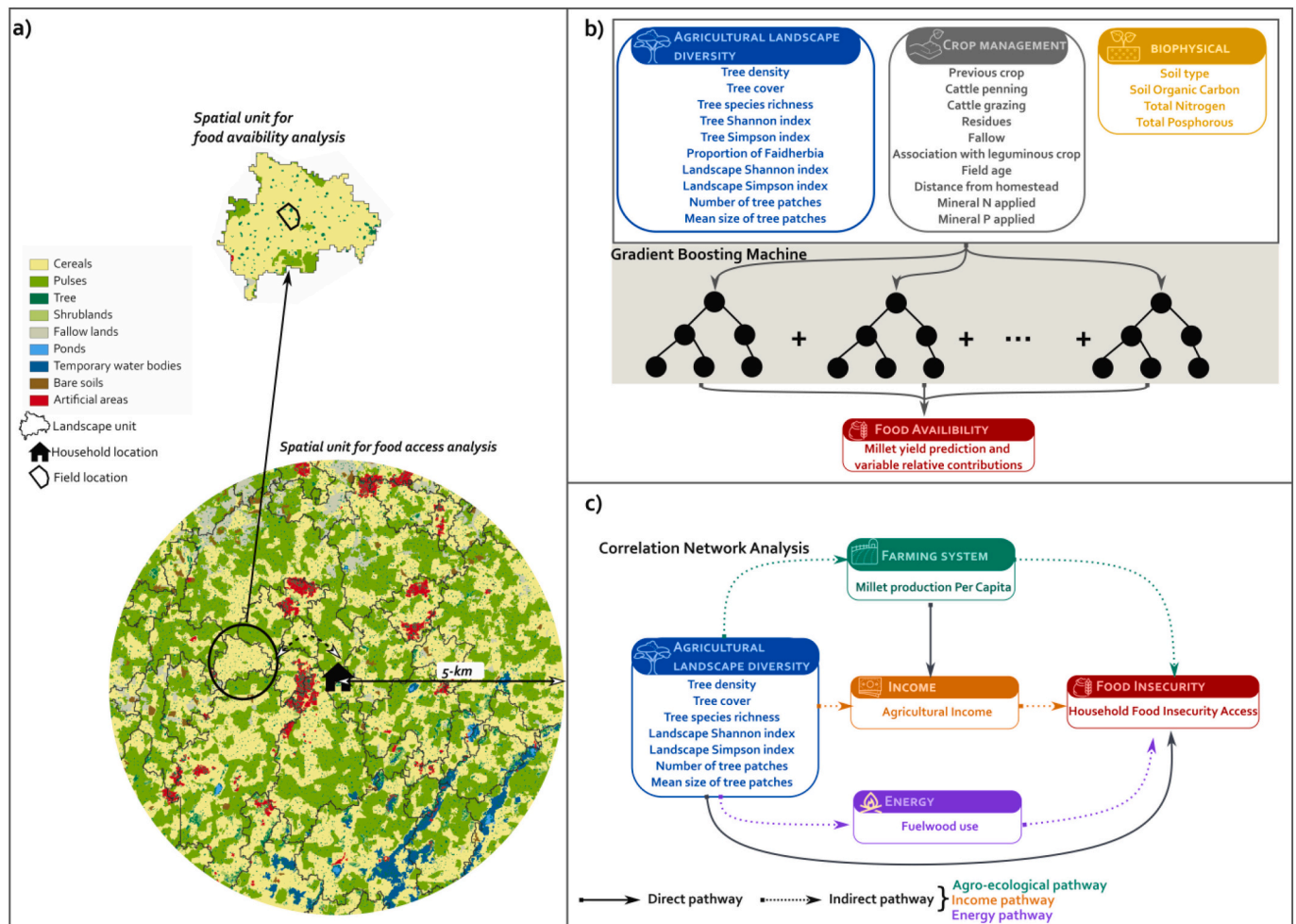
#### 2.2.1. Indicators of food security: millet yield and Household Food Insecurity Access Scale (HFIAS)

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



(caption on next page)

**Fig. 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). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



**Fig. 2.** a) Representation of the field scale (food availability) and household scale (food access), and their corresponding spatial units used for the estimation of the agricultural landscape diversity variables b) Conceptual model used to explore the different relationships between agricultural landscape diversity and food availability (millet yield) using Gradient Boosting Machine analysis and c) Conceptual model used to explore the different relationships between agricultural landscape diversity and household food insecurity access (HFIAS) using Correlation Network Analysis.

nutritional status of the individuals of a household. Food stability is a cross-cutting dimension referring to 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 household food security. However, to control the complexity of the studied systems, we selected a limited number of variables to determine the relationships 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., 2021a). 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 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 tend 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 limited number of classes (11 classes) and hence the landscape diversity information provided by the Shannon and Simpson indices can be considered as the “base level” of landscape diversity we can expect for our study sites. Tree cover, number of tree patches (i.e.

**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 <sup>b</sup> | 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                       | Trees/ha                            | 70                                       | Field monitoring                         |                  |
|                                   |                                      |                           | Tree species richness              | Count                               | 70                                       | Field monitoring                         |                  |
|                                   |                                      |                           | Tree Shannon index                 |                                     | 70                                       | Field monitoring                         |                  |
|                                   |                                      |                           | Tree Simpson index                 |                                     | 70                                       | Field monitoring                         |                  |
|                                   |                                      | Tree cover                | %                                  | 70                                  | Analysis of geospatial data <sup>c</sup> |  |                  |
|                                   |                                      | Number of tree patches    | Count                              | 70                                  | Analysis of geospatial data <sup>c</sup> |  |                  |
|                                   |                                      | Mean size of tree patches | ha                                 | 70                                  | Analysis of geospatial data <sup>c</sup> |  |                  |
|                                   |                                      | Biophysical variables     | Soil type                          |                                     | 70                                       | Field monitoring                         |                  |
|                                   |                                      |                           | Soil Organic Carbon <sup>e</sup>   | g/kg                                | 70                                       | Analysis of geospatial data <sup>c</sup> |                  |
|                                   |                                      |                           | Soil Total Nitrogen <sup>c</sup>   | ppm                                 | 70                                       | Analysis of geospatial data <sup>c</sup> |                  |
|                                   |                                      |                           | Soil Total Phosphorus <sup>c</sup> | ppm                                 | 70                                       | Analysis of geospatial data <sup>c</sup> |                  |
|                                   |                                      |                           | Crop management                    | Previous crop                       | Categorical                              | 70                                       | Field monitoring |
|                                   |                                      |                           |                                    | Cattle penning                      | Binary: yes = 1; no = 0                  | 70                                       | Field monitoring |
|                                   |                                      | Cattle grazing            |                                    | Binary: yes = 1; no = 0             | 70                                       | Field monitoring                         |                  |
|                                   | Residues kept on the plot            | Binary: yes = 1; no = 0   |                                    | 70                                  | Field monitoring                         |  |                  |
|                                   | Is the field regularly fallowed      | Binary: yes = 1; no = 0   |                                    | 70                                  | Field monitoring                         |  |                  |
|                                   | Association with leguminous crop     | Binary: yes = 1; no = 0   |                                    | 70                                  | Field monitoring                         |  |                  |
|                                   | Field age                            | Year                      |                                    | 70                                  | Field monitoring                         |  |                  |
|                                   | Distance from homestead              | Minutes                   | 70                                 | Field monitoring                    |  |  |                  |
|                                   | Amount of mineral nitrogen applied   | kgN/ha                    | 70                                 | Field monitoring                    |  |  |                  |
|                                   | Amount of mineral phosphorus applied | kgP/ha                    | 70                                 | Field monitoring                    |  |  |                  |
|                                   | Household                            | Landscape diversity       | Landscape Shannon index            |                                     | 391                                      | Analysis of geospatial data <sup>d</sup> |                  |
|                                   |                                      |                           | Landscape Simpson index            |                                     | 391                                      | Analysis of geospatial data <sup>d</sup> |                  |
|                                   |                                      |                           | Tree density                       | Trees/ha                            | 391                                      | Household survey                         |                  |
|                                   |                                      |                           | Tree species richness              | Count                               | 391                                      | Household survey                         |                  |
|                                   |                                      |                           | Number of tree patches             | Count                               | 391                                      | Analysis of geospatial data <sup>d</sup> |                  |
|                                   |                                      |                           | Mean size of tree patches          | ha                                  | 391                                      | Analysis of geospatial data <sup>d</sup> |                  |
|                                   |                                      |                           | Tree cover                         | %                                   | 391                                      | Analysis of geospatial data <sup>d</sup> |                  |
|                                   |                                      | Farming system            | Farm size Per Capita               | ha/capita                           | 391                                      | Household survey                         |                  |
|                                   |                                      |                           | Millet production Per Capita       | kg/capita                           | 391                                      | Household survey                         |                  |
| Income                            |                                      | Tree income               | Binary: yes = 1; no = 0            | 391                                 | Household survey                         |  |                  |
|                                   |                                      | Fuelwood use              | Binary: yes = 1; no = 0            | 391                                 | Household survey                         |  |                  |
| Energy Socio-demographic          |                                      | Size of household         | Capita                             | 391                                 | Household survey                         |  |                  |
|                                   |                                      | Proportion of men         | %                                  | 391                                 | Household survey                         |  |                  |
| HFIAS <sup>a</sup>                |                                      |                           |                                    |                                     |  |  |                  |

<sup>a</sup> HFIAS: 1 = severely food insecure, 2 = moderately food insecure, 3 = mildly food insecure, 4 = food secure.

<sup>b</sup> Final sample size after data curation.

<sup>c</sup> Extracted at landscape unit level.

<sup>d</sup> Extracted within a 5-km radius of household location.

<sup>e</sup> AfSoilGrids database (Hengl et al., 2017).

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; Rasmussen et al., 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 soil 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 were 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 co-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 does not contribute to household food access at the two study sites. Indeed, tree species commonly used as cash crops in the Sahel, such as *Parkia biglobosa* and *Vitellaria paradoxa*, accounted for less than 1% of the trees in our study sites (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 (Fig. 1). Each landscape unit was 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., 2021b). 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 (Fig. 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 with a Garmin GPS device (GSMAP®64). 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 on the farm 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 answers 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 using Google Earth images (<https://www.google.com/earth/index.html>). Aboveground biomass of millet was harvested at crop maturity in three quadrats of 6-m<sup>2</sup>. 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 (Toukara 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  $p$ -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 Fig. 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  $\leq 0.05$ ) 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 significant difference in millet yield on a per hectare basis between the two sites. However, millet production per capita was significantly smaller in Niakhar compared with Nioro ( $246 \pm 207$  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) than in Nioro (Fig. 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 *F. 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 with Nioro, while soil total phosphorus was lower in Niakhar compared with 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 (Fig. 4a) and Nioro (Fig. 4b) explained, respectively, 77% (relative Root Mean Square Error, rRMSE = 20%) and 84% (rRMSE = 21%) of millet yield variability ( $p$ -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.

Fig. 5 displays 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 (Fig. 5a). Millet yield exhibited a linear positive relationship with tree species richness above two tree species in Niakhar while the relationship started to stagnate above two tree species in Nioro (Fig. 5b).

### 3.3. Agricultural landscape diversity and food access (household food insecurity access scale)

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

#### 3.3.1. Niakhar

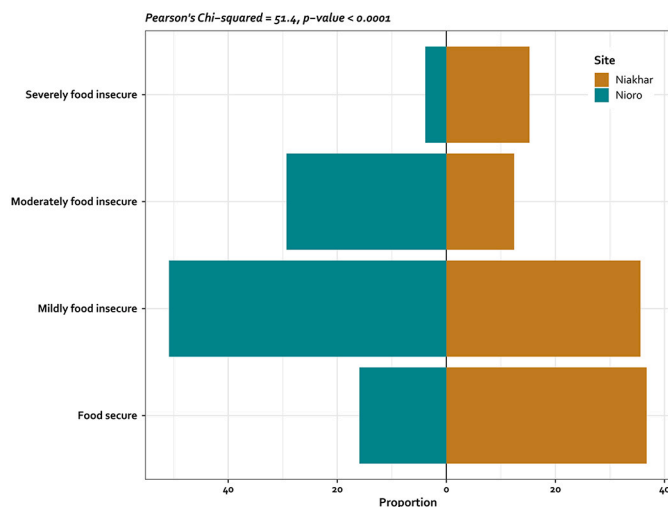
**3.3.1.1. Direct links between landscape diversity and food access.** HFIAS was significantly and positively correlated with the mean size of tree



**Table 2**  
Main characteristics (mean and standard deviation) in the two study sites.

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

Variables which significantly differ between sites (p-value <0.05) are displayed in bold.



**Fig. 3.** Comparison of food access (HFIAS) between sites (Niakhar and Nioro). Chi-squared and the associated p-values are shown.

patches ( $r = 0.25$ ), that was, in turn, positively correlated with tree cover ( $r = 0.34$ ) (Fig. 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 tree 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.

**3.3.1.2. 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” (Fig. 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” (Fig. 2c) based

on fuelwood supply.

### 3.3.2. Nioro

**3.3.2.1. Direct links between landscape diversity and food access.** In Nioro, HFIAS was significantly and positively correlated with the mean size of tree patches, although the correlation was weak ( $r = 0.17$ ) (Fig. 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.

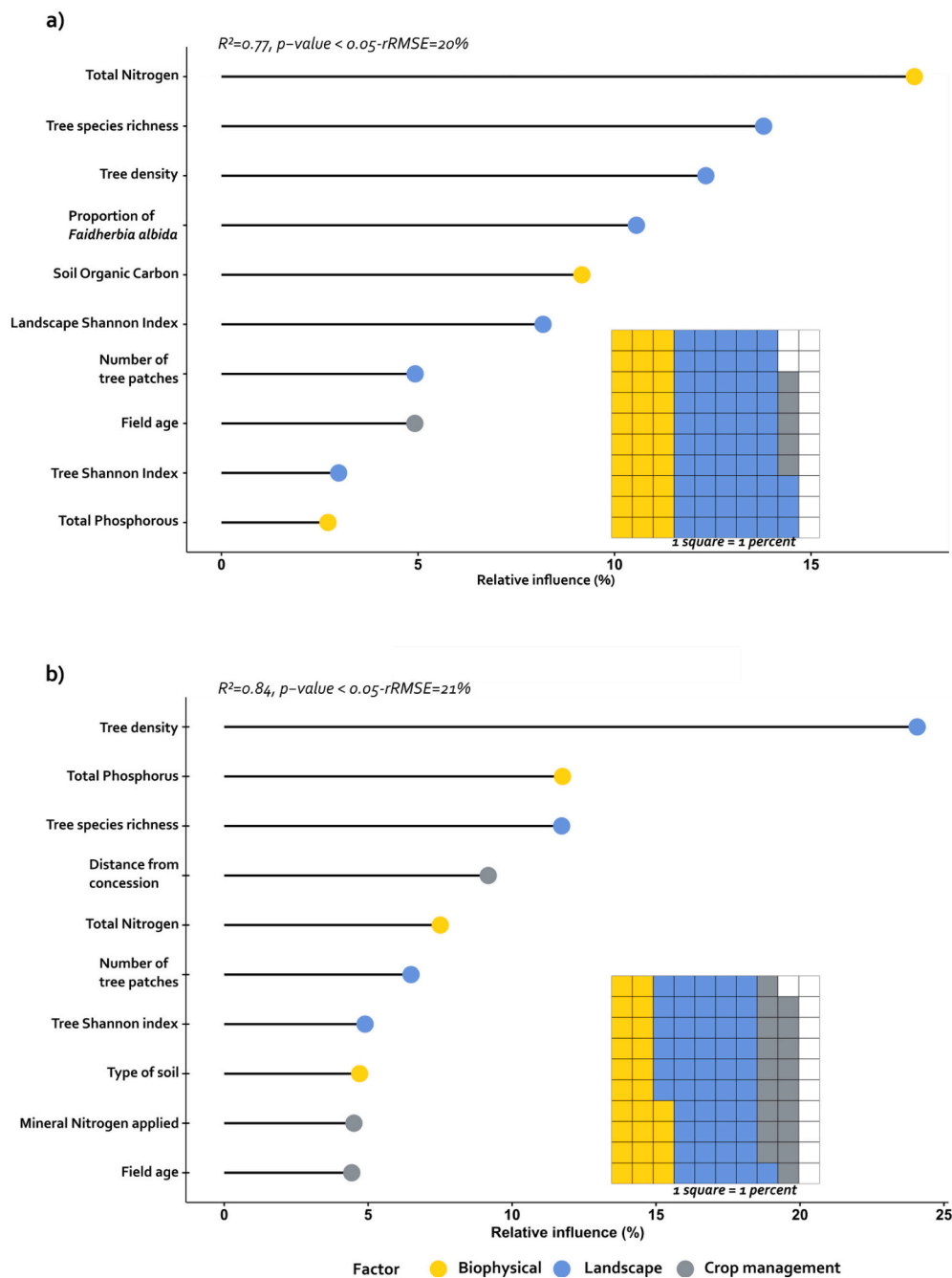
**3.3.2.2. Indirect links between landscape diversity and food access.** HFIAS was significantly and positively correlated with millet production per capita ( $r = 0.36$ ) indicating an increase in food access as millet production increases. Tree species richness was strongly correlated with millet production per capita ( $r = 0.49$ ), suggesting an indirect link (“agroecological pathway”, Fig. 2c) between landscape diversity and household food access, such as in 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” (Fig. 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 are important drivers of the yield of the millet crop that is associated with the trees (Fig. 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) as a result of improvements in soil water and nutrient availability and supply



**Fig. 4.** Relative contributions of cropping system, biophysical and agricultural landscape diversity factors to the 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%.

(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 (Fig. 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 optimizes 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 plant 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 (Fig. 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 complementarity among trees (Zheng et al., 2019), possibly leading to soil fertility improvements. Finally, higher tree species diversity can also facilitate soil 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

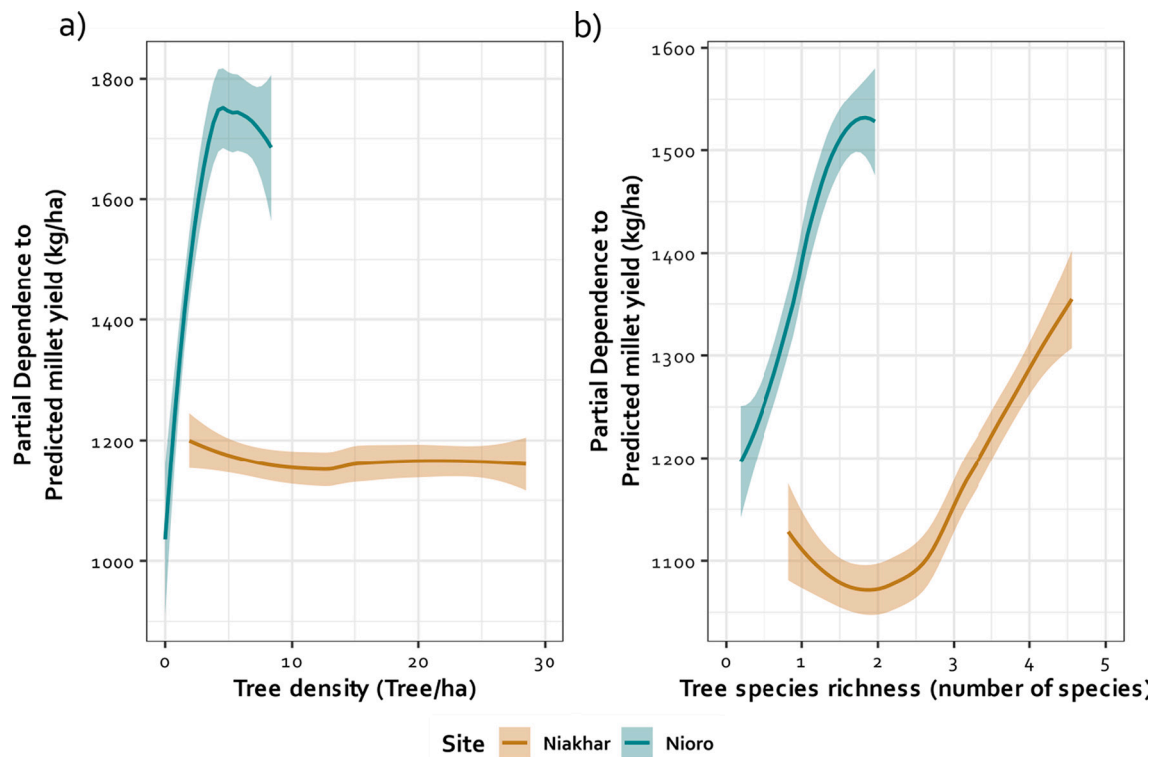


Fig. 5. Interaction between tree density a) and tree species richness b) using a partial dependence plot. The partial dependence plot depicts the marginal effect of tree density and tree species richness on predicted millet yield. A locally weighted smoothing was applied to the partial dependence smooth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

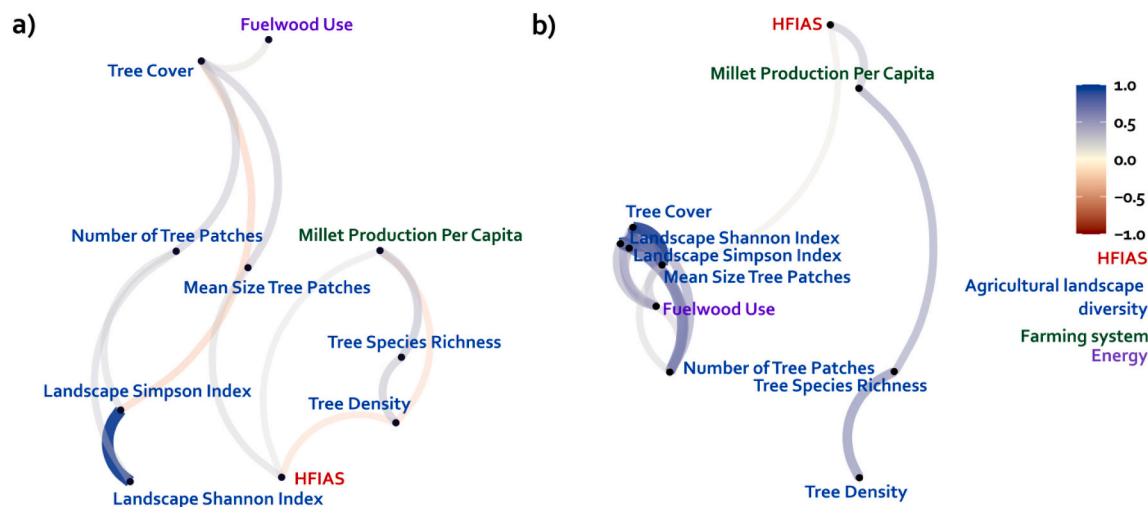


Fig. 6. Correlation-based network to analyze the different pathways linking agricultural landscape diversity to household food access (HFIAS indicator) (a) in Niakhar and (b) Nioro. HFIAS is displayed in red (HFIAS = Household Food Insecurity Access), agricultural landscape diversity variables in blue, 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 colour 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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 were 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.

It should, however, be noted that in this study we did not take into

account the effect of tree management on crop productivity, although it is known to have a strong direct effect on resource use competition (e.g. for light, water, nutrient) (Luedeling et al., 2016; van Noordwijk and Ong, 1999). For example, for *F. albida*, it has been shown that tree effects on crops are also driven by tree size, crown development and management of the trees. Mature trees have a stronger positive effect on crops than young trees (Sileshi, 2016), and tree pruning has a positive effect on crop yield since it affects the competition for light (Dilla et al., 2020).

Other nitrogen-fixing species (e.g. *Alnus acuminata*) were found to 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 importance of soil fertility (i.e. soil total nitrogen and phosphorus contents) for millet productivity in the parkland systems (Fig. 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 with crop yields in our study was probably due to the low variation in applied nitrogen ( $26 \pm 32$  kg N/ha). Possibly, with the small level of variation, our regression-based analysis could not reveal an association 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 and elsewhere. For instance, Sida et al. (2019) showed in Ethiopia and Rwanda that nitrogen and phosphorus 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), with 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 will 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 access. Our findings in 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 a 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 on a daily basis 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 Niore, 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 access 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 security, 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, and are 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 access, which can be explained by the provision of ecosystem services regulating and supporting crop production. This link held even true in the less diverse parklands of Niore (Fig. 6). It can be coined as the "agroecological pathway" (Fig. 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; Rasmussen et al., 2019), we found that tree species richness is of similar importance as tree density for improving food access. Households that are in more diverse agricultural landscapes, in terms of tree species composition, tend to be more food secure thanks to a higher 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", Fig. 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 surveys (see supplementary materials Fig. S1), i.e. when food stocks from the last rainy season start 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 household food security, 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 Chavarria et al., 2018). For instance, leguminous fodder trees (such as *F. 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). Finally, the provision of shade 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" (Fig. 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 single household survey. More detailed surveys, e.g. on a 5-day 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 feasible with the single survey carried out in our study. While the best approach 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 or housing characteristics, assuming that wealthier households might be able to purchase more diverse food (Rasmussen et al., 2019).

The rights to 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. Access rights may limit the direct contribution of certain tree species to food access. The rules of access to tree resources typically 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, at both study sites *A. digitata* is mainly planted in home fields 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 this tree, Senegal’s Forest Department has strictly limited its access and exploitation, particularly in the Niakhar site. The exploitation of useful tree species is also linked to ethnic groups and their relationships to trees. The main ethnic group in the Niakhar site are the 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 found evidence that agricultural landscape diversity, and particularly parkland diversity (i.e. tree species richness and tree density), are key drivers 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 an “agro-ecological pathway”.

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

Adopting an integrated landscape approach is required to better understand, assess, and optimize the contribution of agroforestry parklands to the 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 the co-benefits of trees for the different food security dimensions.

## 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.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.agsy.2021.103312>.

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