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Landscape heterogeneity analysis using geospatial techniques and a priori knowledge in Sahelian agroforestry systems of Senegal

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ABSTRACT

Agroforestry plays a pivotal role for Sahelian communities by allowing simultaneous improvement of food security and conservation of natural ecosystems and their biodiversity. However, agroforestry systems (AFSs) are particularly heterogeneous in sub-Saharan Africa due to small to very small fields, a large variety of agricultural practices and a diversity of parkland compositions and configurations. This makes spatial sampling processes very important but problematic in terms of representativeness of the landscape heterogeneity to allow an effective study of Sahelian AFSs. In this paper, we proposed, tested and assessed a methodological approach for landscape sampling, mapping and characterization while considering the different types of spatial heterogeneity in complex landscapes, such as Sahelian AFSs. Several complementary methods were combined on the basis of *a priori* knowledge of agroforestry landscape functioning using multisource data, remote sensing methods, and statistical and spatial analyses applied to landscape ecology. First, the landscape heterogeneity was stratified and used to design two weighted, stratified sampling plans for field surveys of tree species and land use/land cover types. Then, with multisource satellite images together with collected field data, the agroforestry systems were mapped, with a satisfactory accuracy of 85.12% and a Kappa index of 0.81. Finally, we used landscape metrics and diversity indices derived from AFS mapping and the tree species inventory to analyze the diversity of the studied AFS located in the Senegalese Peanut Basin. The results of the analysis evidenced the compositional, configurational and functional heterogeneity found in the study area. This allowed us to demonstrate the ability of the sampling strategy proposed in this paper to capture the various types of heterogeneity in agricultural landscapes. We also showed by implementing the method that it can be used for (i) tree biodiversity analysis, (ii) mapping and (iii) characterization of a complex AFS in sub-Saharan Africa.

1. Introduction

Feeding the world's continuously growing population and meeting the accelerated land expansion needs are leading to both the loss of agricultural land through urbanization (e.g., D'Amour et al., 2017) and biodiversity loss through agricultural expansion into natural habitats (e.g., Kehoe et al., 2017). In this context, many scientists and experts on agriculture and food security suggest that diversification and sustainable intensification of agricultural production are necessary to achieve the global goal of feeding a growing population (e.g. Mbow et al., 2014; Ickowitz et al., 2019) while conserving natural ecosystems and their biodiversity (e.g., Phalan et al., 2011; Andres and Bhullar, 2016) as pledged by the Sustainable Development Goals (SDG#2 and SDG#15).

To meet this challenge, agroforestry systems (AFSs) are highly recommended, particularly in sub-Saharan Africa, where smallholder farmers are the dominant form of agriculture (e.g., Agroforestry

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Network, 2018; Mbow et al., 2014). In Africa, AFSs come in a wide variety of shapes and forms (Mbow et al. 2014).

Sahelian agricultural landscapes are particularly heterogeneous due to the small to very small fields (Fritz et al., 2015), large variety of agricultural practices (Chikowo et al., 2014) and diversity of parkland compositions and configurations. Therefore, to effectively study Sahelian AFSs, implementing a representative sampling strategy that takes into account the spatial heterogeneity at the landscape scale is crucial (Ndao et al., 2017; Soti et al., 2018). However, due to the multidisciplinary nature of landscape research, many sampling approaches for studying and characterizing landscapes have been proposed in the scientific literature (Simensen et al., 2018).

Generally, the spatial distribution of sampling sites is based on criteria related to the landscape composition: along roads (Waldner et al., 2016), along streams or following typical habitats (Bueno et al., 2019). Other methods set more relevant distribution criteria based on the composition and structure or even the functioning of the landscape. In these methods, the definition of the criteria is guided by the objective of the study, e.g., the bioecological variables of crop pests (Soti et al., 2018). The distribution of observation sites is done within spatial units according to a stratification of landscape heterogeneity (Soti et al., 2018; Ndao et al., 2017) or following a landscape gradient (Erikstad et al., 2015). Spatial units can be regular geometric forms resulting from landscape gridding (Soti et al. 2018) or landscape units derived from remote sensing and geospatial analysis methods (Bellón et al., 2018; Ndao et al., 2017; Bisquert et al., 2015). In satellite imagery, the temporal profile of a landscape depends on the spatiotemporal dynamics of its elements. Therefore, using geospatial analysis methods to delineate landscape units could allow us to better take into account both landscape organization and functioning in the distribution of sampling sites.

Once observed data have been collected according to a representative sampling strategy, quantitative analyses of AFS landscapes and their spatial heterogeneity, including tree diversity, can be performed using landscape metrics and diversity indices. The structure of a landscape is primarily a series of patches surrounded by a matrix (Forman and Godron, 1981). Therefore, metrics are often used in landscape ecology to describe the composition and structure of the landscape (Walz, 2011; Uuemaa et al., 2009), to analyze the relationship between landscape structure and plant diversity (Uuemaa et al., 2009; Hernández-Stefanoni and Dupuy, 2008; Moser et al., 2002) and to assess or model the habitats of individual species or species groups (Betbeder et al., 2015; Fernández et al., 2007; Fauth et al., 2000). There are many indices in the literature for analyzing landscape and tree species diversity. For the latter, it is often necessary to combine several indices that frequently appear in the literature to assess its three main characteristics: species richness, abundance and evenness (You et al., 2009; Kindt and Coe, 2005). Various compound indices have been developed to combine these different diversity aspects. Shannon's (H') and Simpson's (D1) diversity indices are most commonly used as compound indices (Morris et al., 2014; Marcon, 2017). However, none of the diversity indices provide sufficient information on richness, abundance and evenness at the same time to allow for a comparison of the diversity of landscape classes and ordering them from lowest to highest diversity (Kindt and Coe, 2005). Thus, it is recommended to use diversity ordering techniques, such as Renyi diversity profiles (Rényi, 1961), which provide enough information for comparison (Oldeland et al., 2010; Tothmeresz, 1995).

In addition, geospatial data and remote sensing methods are very useful in landscape studies and characterization (Singh et al., 2010; Newton et al., 2009) due to their synoptic and repetitive coverage of landscape components and features, which allow landscape variations to be captured in an objective and complete fashion (Groom et al., 2006). There is in the literature a wide range of proxies derived from geospatial data to discriminate vegetation and crop types, allowing evidence of different components of agricultural landscapes. Good results were achieved for agricultural landscape mapping from Sentinel-2 time series data using object-based image analysis (Csillik and Belgiu, 2017) and a multisource approach (Lebourgeois et al., 2017). Because of both their high spatial (10 m) and temporal (5 days) resolutions, Sentinel-2 images are well adapted for monitoring agroforestry landscapes (Mercier et al., 2019). Studies have combined Sentinel-2 images with very high spatial resolution (VHSR) images to refine the segmentation and detection of crop types and other small objects in agricultural landscapes (Lebourgeois et al., 2017).

In this paper, we propose combining the different methods previously reviewed to optimize the sampling processes in complex landscapes, such as Sahelian AFSs. We hypothesized that by combining several complementary methods, we would be able to design a robust sampling strategy that considers the different types of spatial heterogeneity within agroforestry landscapes related to their composition, organization (structure) and functioning. We aimed to propose, test and assess a methodological approach for agroforestry landscape sampling, mapping and characterization. First, an optimized sampling strategy was carried out on the basis of landscape stratification. We then used this sampling strategy to map and characterize the agroforestry landscape and finally analyzed the heterogeneity of the AFS - including tree diversity - to assess the ability of the proposed sampling strategy to capture the different forms of landscape heterogeneity. The approach was based on *a priori* knowledge of agroforestry landscape functioning and used multisource data, including landscape ecology indices and remote sensing data. It was applied to an agroforestry parkland in the Senegalese Peanut Basin.

2. Materials and methods

2.1. Overall approach

The proposed methodology is illustrated by the flowchart presented in Fig. 1. It was organized around a sequence of four consecutive steps: (i) landscape stratification, (ii) sampling implementation, (iii) AFS mapping, and (iv) AFS heterogeneity analysis.

(i) First, the area was segmented into agricultural landscape units using an object-based image analysis method. These units were then classified with a hierarchical clustering method (HCPC) according to relevant landscape functioning variables to stratify the landscape spatial heterogeneity. These variables were derived from geospatial data on the basis of *a priori* knowledge of agricultural landscape functioning (see section 2.3.1).

(ii) Then, two weighted stratified sampling plans based on landscape stratification were implemented to collect field data on tree species and on the land use/land cover (LULC) types (see section 2.3.2).

(iii) From multisource satellite images together with the collected field data, remote sensing methods were used to carry out agroforestry system mapping (see section 2.3.3).

(iv) Finally, the landscape metrics and diversity indices derived from AFS mapping and the tree species inventory were used to analyze the diversity of the studied AFS. This allowed evidence of the ability of the sampling strategy to capture the various types of heterogeneity in agricultural landscapes (see section 2.3.4).

2.2. Materials

2.2.1. Study area

The study area was located in the Senegalese Peanut Basin, covering an area of approximately 20 km × 20 km centered on the commune of Ngayokheme (district of Fatick; Fig. 2). The region is characterized by a tree-based agricultural system dominated by *Faidherbia albida,* which is a nitrogen-fixing species with an inverted phenology that is reported to increase soil fertility and crop yields (Félix et al., 2018). Pearl millet, which is used for on-farm consumption, and groundnut, which is used as a cash crops, are the main staple crops of the study area. The climate is semiarid with an annual rainfall that ranges between 400 mm and 600 mm. Soils can generally be classified into two main types: dior soils,

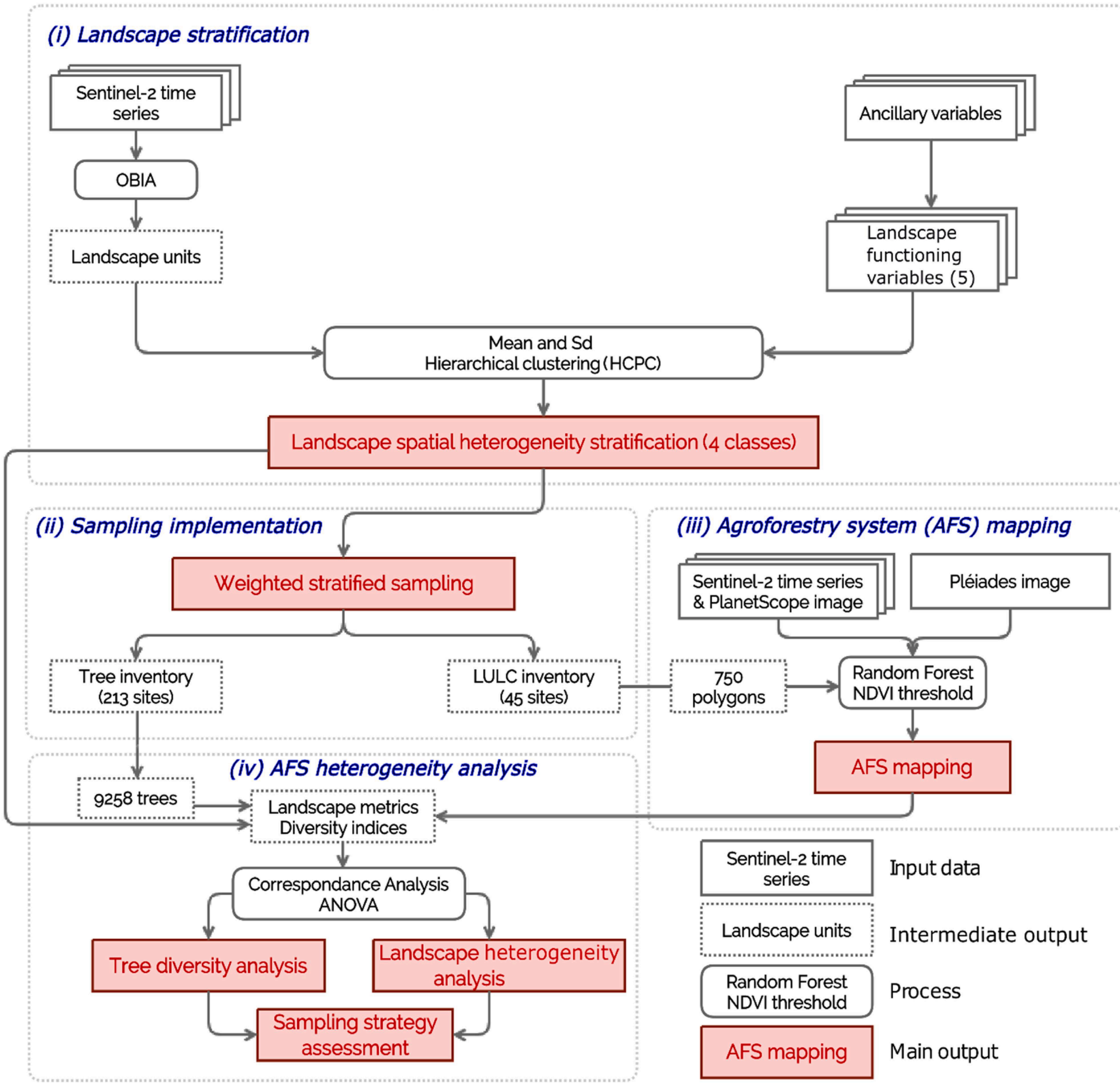

Fig. 1. Data used and flowchart of the proposed methodology with (i) landscape stratification, (ii) sampling implementation, (iii) AFS mapping, and (iv) AFS diversity analysis. **OBIA**: Object-based image analysis.

which are ochre-colored, and deck soils, which are gray to black; some intermediate categories are also present (deck-dior and dior-deck). Dior soils are sandy, occupying flat areas and dune patterns, while deck soils are more clayey and are located in interdune and lowland areas (Lericollais, 1999). Dior and deck-dior soils generally correspond to tropical ferruginous soils, while deck soils with a high water retention capacity are instead hydromorphic (Lericollais, 1999; BPS, 1993). The relief is not very uneven. Between the plain slightly raised by the dunes and the lowlands the difference in altitude is a few meters. The hydrographic network, more pronounced in the southwestern part, consists of small rivers and temporary ponds in small depressions and interdunes (Lericollais, 1999, 1969).

With more than 60% of the country's rural population and cultivated lands, the Senegalese Peanut Basin is facing strong demographic pressure, a reduction in the fallow period and crop management using many kinds of external inputs. This leads to vegetation degradation, erosion of biodiversity and a decline in soil fertility (Bignebat and Sakho-Jimbira, 2013).

2.2.2. High and very high spatial resolution (HSR & VHSR) images

To carry out the segmentation of the study area into agricultural landscape units, a time series of Sentinel-2 images (10 m spatial resolution) from January (start of the dry season) to October (end of the cropping season) in 2017 was used. Sentinel-2 data were subjected to Level-2A processing by the French *Centre National d'Etudes Spatiales* (CNES) and were retrieved from the Theia center (https://theia.cnes.fr/atdistrib/rocket/#/home). For each image in the Sentinel-2 time series, the normalized difference vegetation index (NDVI) was computed as proposed by Rouse et al. (1974).

A second Sentinel-2 image time series acquired in 2018 together with a PlanetScope image from October 4th, 2018 were used for AFS mapping in 2018. This second time series was used because the field surveys were conducted in 2018. The PlanetScope image was a Level-3B Analytic Ortho Scene product, which was acquired with an approximately 3 m pixel size. It was converted into top-of-atmosphere (TOA) reflectance using at-sensor radiance and the coefficients supplied with each scene (Planet Team, 2018).

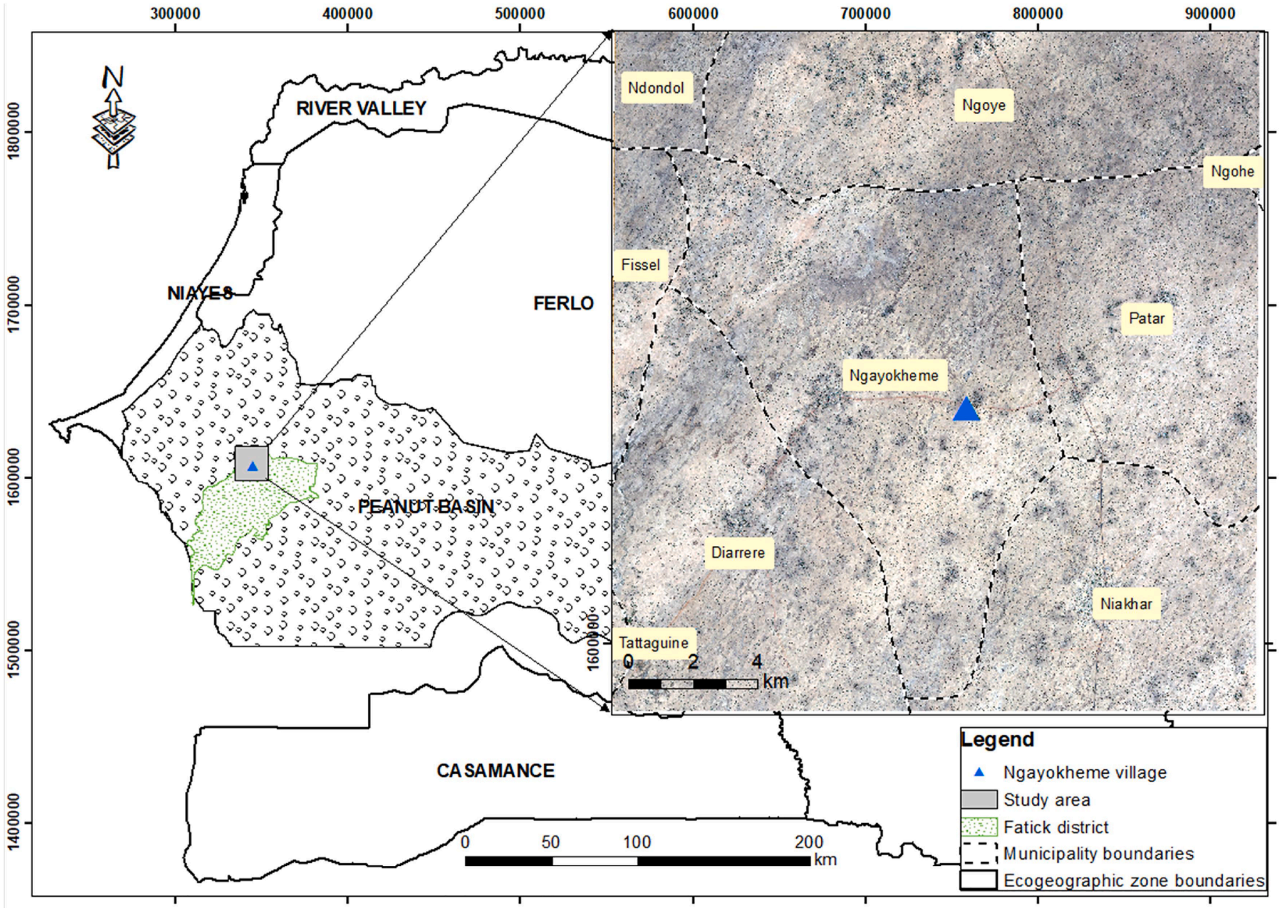

Fig. 2. Location of the study area. Zoom on a *Pléiades* image (Dry season, April 29th, 2018) of the study area. Names on the study area represent the municipality names.

To extract the woody vegetation, in particular the parkland with scattered trees, a *Pléiades* image acquired during the dry season on April 29th, 2018, was used. *Pléiades* satellites provide very high-resolution panchromatic (0.5 m) and multispectral (2.5 m) optical imagery with high-quality product standards (https://earth.esa.int/web/eoportal/satellite-missions/p/pleiades). This enables the detection of small trees and shrubs in Sahelian areas.

2.2.3. Ancillary variables

With the knowledge that agroforestry landscape structures are driven by environmental and anthropic factors, five proxies of landscape functioning and vegetation productivity were inferred from geospatial data, including satellite imagery and its derived products, and then used for landscape stratification.

Two ecophysiological variables, namely, vegetation productivity and its dynamics during the 2000–2015 period, were derived from 16-day MODIS NDVI time series (MOD13Q1; spatial resolution: 250 m) (Didan, 2015). The average annual integral of NDVI was computed and used as an indicator of the overall vegetation productivity. The vegetation productivity dynamics were obtained from annual MODIS NDVI linear trends over the 2000–2015 period (see Leroux et al., 2017).

An agrometeorological variable, namely the actual evapotranspiration (AET), which allows the soil-air interface and plant functioning (WMO, 2012) to be considered, was extracted from the FAO WaPOR database (https://wapor.apps.fao.org/home/1). These data comprise a time series of the averaged AET available from 2010 to 2016 at a spatial resolution of 250 m.

A woody cover map derived from MODIS FAPAR (Fraction of Absorbed Photosynthetically Active Radiation from MODIS; Brandt et al., 2016) was also used to derive information related to tree density as an ecological and anthropic (related to the cropping practices) variable.

For information on soil properties, a soil type map from the *Institut National de Pédologie* (*INP* –Senegalese National Institute of Soil Sciences – http://inp-senegal.com/) was used. It is an extract of a 1:500,000 soil type map at the national scale (INP, 2013). Soils were classified according to the CPCS's classification (CPCS, 1967). In the study area, three main types of soils were distinguished: tropical ferruginous soils which usually correspond to dior and deck-dior soils, hydromorphic soils, and saline hydromorphic soils which are rather deck soils.

2.3. Methods

2.3.1. Landscape spatial heterogeneity stratification

The methods used to stratify the landscape spatial heterogeneity were based on geographic object-based image analysis (OBIA; Blaschke, 2010) in which NDVI time series from Sentinel-2 images in 2017 were merged into objects corresponding to agroforestry landscape units. Then, the landscape units were classified according to landscape functioning variables to obtain the major landscape classes. These two steps are described in the two following subsections.

2.3.1.1. Delineation of agroforestry landscape units. Agroforestry landscapes with the same environmental dynamics, e.g., with similar parkland, crop cover composition and ecoclimatic factors, are expected to have, on average, similar vegetation productivity and phenological development and thus to have similar NDVI temporal profiles. On this basis, an OBIA was performed on the Sentinel-2 NDVI time series to obtain homogeneous landscape units in terms of environmental conditions, vegetation development, and farming practices. NDVI is known as an indicator of vegetation productivity (Tucker, 1979) and therefore of vegetation development. It is well adapted to capture the difference among agricultural land use systems within a landscape (Bellón et al., 2018). To this end, the feature extraction module from the ENVI © software was used to carry out segmentation on the NDVI time series. It proceeded in two stages: (1) the images were segmented by setting the "scale level", then (2) the segments were merged by setting the "merge level". The "scale level" (ranging from 0.0 to 100.0) controls the relative segment size. A high "scale level" causes fewer segments to be defined, and a low "scale level" causes more segments to be defined. The "merge level" (ranging from 0.0 to 100.0) represents the threshold lambda value to aggregate small segments within the larger (ITT Vis, 2008). Several "scale level" and "merge level" values were iteratively tested by performing a qualitative analysis consisting of a visual inspection based on a Pleiades image in the background (Srivastavak, 2006). The best delineation of landscape units was obtained with values of 90 for the "scale level" and 30 for the "merge level".

2.3.1.2. Classification of the landscape units. The objective of this classification was to stratify the study area into landscape subtypes in terms of composition and dynamics. Therefore, the landscape units, which were previously obtained through the OBIA, were classified according to the five identified landscape functioning variables (i.e., the vegetation productivity, the vegetation productivity dynamics, the AET, the woody cover and the soil type; see section 2.2.3).

To do so, the means and standard deviations of the five variables were first computed for each landscape unit. The mean value represents the general trend, while the standard deviation value includes the spatial variability within a landscape unit. Then, the landscape units were classified using a hierarchical clustering on principal components (HCPC) approach. HCPC is an unsupervised hierarchical clustering method that finds subgroups or clusters of similar observations in a dataset (Kassambara 2017b). It enables the combination of the three standard methods used in multivariate data analyses, which are principal component methods, hierarchical clustering, and k-means clustering (Husson et al., 2010). Due to the presence of both quantitative and qualitative data in the variable dataset, we used a factor analysis of mixed data (FAMD) to carry out factor analysis, which defines the principal components (Kassambara 2017a). To appreciate the coherence of clustering, i.e., of landscape spatial heterogeneity stratification, we used descriptive statistics, including analysis of variance (ANOVA), for first assessment.

2.3.2. Sampling implementation

AFS mapping and tree biodiversity monitoring require both land use/land cover (LULC) and tree species field surveys. Based on the landscape stratification (see section 2.3.1.), an optimized sampling strategy was developed for the field campaigns. The observation sites were regularly distributed across the landscape heterogeneity classes and according to the weight of each class. We applied weighted stratified sampling, whereby the number of observation sites in each class of landscape stratification was proportional to the number of landscape units within the class. The spatial distribution of the observation sites in each class was determined using an HCPC of the landscape units within the class. These HCPCs for observation site distributions were still based on the identified landscape functioning variables (see section 2.2.3).

From this process, two sampling plans were designed for two field campaigns. The first one was an *in situ* inventory of trees conducted at the end of the dry season in July 2018 at 213 observation sites. At each site, an exhaustive tree inventory was conducted in a one-hectare plot. To optimize the diversity of the species collected (including all/almost all tree species in the area), this plot inventory was supplemented by a nonexhaustive survey within a 400 m radius of the observation plot targeting species that were not yet registered. The name of each tree species and its location were recorded using a GPS (GSMAP 64S). The second campaign for LULC data collection was conducted in September 2018 during the cropping season at 45 observation sites. At each site, the geographic coordinates of the different LULC types were recorded using a GPS. Then, on the basis of the collected coordinates, a total of 750 polygons of land use/land cover types were digitized and labeled using a VHSR image in the background.

2.3.3. Agroforestry system mapping

The *MORINGA* processing chain (https://gitlab.irstea.fr/raffaele.gaetano/moringa) developed by CIRAD researchers was used to perform the agroforestry system mapping. Based on the research of Lebourgeois et al., (2017), *MORINGA* is an automatic image processing chain that uses multisensor fusion for crop mapping and generally LULC mapping and is particularly adapted to tropical agricultural systems. It produces a land use map based on a VHSR image, a time series of Sentinel-2, and a training database (labeled polygons). The processing chain uses functions from the Orfeo Toolbox (OTB), which are coordinated by Python scripts (Gaetano et al., 2019).

The PlanetScope image with TOA reflectance and 3 m spatial resolution (see section 2.2.1) was used as the VHSR image. In the processing chain, the VHSR image was used for object segmentation (i.e., the land units to which a unique LULC type will be assigned). Then, the zonal statistics of the segmented objects were computed using time series images of Sentinel-2 spectral bands (TOA reflectance), and five radiometric indices are presented in Table 1.

Finally, the LULC classification was carried out using a random forest (RF) classifier (Breiman, 2001; Cutler et al., 2007; Sharma et al., 2017) applied to the zonal statistics dataset with the field survey polygons as the training data. The accuracy of the classification was assessed using 5-fold cross validation (Sharma et al., 2017).

The *MORINGA* LULC map was subsequently postprocessed to include a "woody vegetation" class, which was identified using a VHSR *Pléiades* image (0.5 m resolution) because of the small size of trees and shrubs in the Sahel (Hashim et al., 2019; Thierion et al., 2014). In particular, an image acquired during the dry season was used, when woody vegetation was less likely to be confused with surrounding deciduous vegetation, enabling identification through a simple thresholding of the NDVI values (Hashim et al., 2019; El-Gammal et al., 2014)

The LULC map obtained was subsequently used to calculate landscape metrics and indices for the analysis and characterization of agroforestry landscape diversity.

2.3.4. Agroforestry system heterogeneity analysis

The objective was to demonstrate the different forms of landscape heterogeneity that the stratification (sampling strategy) proposed in this paper allowed us to highlight. Landscape heterogeneity is expressed in terms of compositional heterogeneity (the number and proportions of different cover types) and configurational heterogeneity (the spatial arrangement of cover types) (Fahrig et al., 2011). The concept "functional heterogeneity" was included in this study to account for the functioning of LULC types. Analyses were performed by using statistical methods with landscape metrics and diversity indices according to the landscape stratification classes.

2.3.4.1. Landscape metrics and diversity indices. For tree diversity analysis, we first derived a set of four indices commonly used in the literature (Kindt and Coe, 2005; You et al., 2009), namely, the richness index (i.e., the measure of the number of patch types present in the area, Mcgarigal, 2015), Shannon's diversity index (SHDI; Shannon, 1948) and Simpson's diversity index (SIDI; Simpson, 1949), to appreciate the abundance and species diversity (Morris et al., 2014; Marcon, 2017), and Pielou's evenness index (Pielou, 1966) to take into account the spatial evenness. The SHDI and SIDI indices were both retained because descriptive

Table 1
Radiometric indices used for LULC classification with NIR: near-infrared band, R: red band, G: green band, SWIR: shortwave infrared band.

Indices	Formulas	Uses	References
NDVI	(NIR-R)/(NIR + R)	Vegetation density and health	Rouse et al., 1974
NDWI	(G-NIR)/(G + NIR)	Discrimination of water vs. vegetation	McFeeters, 1996
MNDWI	(G-SWIR)/(G + SWIR)	Improves water detection vs. certain built-up areas	Xu, 2006
MNDVI	(NIR-SWIR)/(NIR + SWIR)	Sensitive to water within vegetation	Gao, 1996
NDRE	(NIR-Red Edge)/(NIR + Red Edge)	Less sensitive to the upper part of the canopy (more reliable in the later crop stages)	Barnes et al., 2000

analyses of species abundance showed significant presence of both rare and dominant species. In fact, SHDI is sensitive to rare species, while SIDI is sensitive to dominant species (Marcon, 2017). In addition, the Renyi diversity profile (Rényi, 1961) was used for comparison by ordering tree diversity from lowest to highest across the classes of landscape heterogeneity stratification. For this, the order of superposition of the profile curves defines the order of the class diversity ranking (Oldeland et al., 2010; Kindt and Coe, 2005).

For landscape heterogeneity analysis, it has been reported that there are "many quantitative measures of landscape composition, including the proportion of the landscape in each patch type, patch richness, patch evenness and patch diversity" (Mcgarigal, 2015). Landscape diversity metrics were thus used to analyze the landscape heterogeneity in terms of the LULC type diversity (patch diversity) according to the landscape stratification classes. We used landscape metrics that included patch richness and Shannon and Simpson's diversity indices.

Furthermore, to better appreciate landscape heterogeneity regarding the topic of agroforestry, we focused on three classes of interest, namely, (i) cereal crops (millet and sorghum), (ii) leguminous crops (peanut and cowpea), and (iii) woody vegetation (trees). Two class metrics were used for analysis: the land proportion (LP), which provides information on dominance, and the number of patches (NP), which informs about the abundance.

2.3.4.2. Statistical analyses. Statistical methods, including descriptive analysis of species abundance, correspondence analysis (CA) and analysis of variance (ANOVA), were applied to the datasets (tree inventory data, calculated metrics and indices). The abundance analysis provided a description of the distributions of the different tree species and therefore allowed us to identify rare species and those dominating the studied environment. Correspondence analysis was carried out on the dominant species to understand the frequencies of species according to the landscape stratification classes and to deduce their relative relationships and attachment to landscape classes (Coly et al., 2005). Finally, using ANOVA with the calculated landscape metrics and diversity indices, we compared the landscape stratification classes to identify different forms of agroforestry landscape heterogeneity. ANOVA is suitable for comparing more than two independent samples of quantitative data with more than 30 observations and homogeneous variances (AnaStat, 2020). Statistical analysis was performed using R software (R Core Team., 2018).

3. Results and discussion

The results were structured as follows:

- "Designing field sampling plans based on landscape stratification" (section 3.1.) reveals the landscape spatial heterogeneity stratification and the two field sampling plans derived from this stratification;
- "Agroforestry system mapping" (section 3.2.) presents the map resulting from remote sensing processing using multisource satellite images with training data from the previous field sampling plan.
- "Tree diversity and landscape heterogeneity analysis" (section 3.3.) reports the results of the tree species diversity analysis (section 3.3.1.) and the results of the landscape heterogeneity analysis (section 3.3.2.).

3.1. Designing field sampling plans based on landscape stratification

Using OBIA on the Sentinel-2 NDVI time series in 2017, 668 agroforestry landscape units were delineated (Fig. 3). The unit areas varied from 10.61 ha to 489.68 ha. The hierarchical clustering of these landscape units according to the landscape functioning variables resulted in a landscape spatial heterogeneity stratification map that was composed of four classes (or landscape subtypes; Fig. 3). This landscape stratification map, which refers to the within class variance which is less than the between class variance (Wang et al., 2016), represents the spatial variability of the landscape functioning and structure among classes.

Descriptive statistics allowed us to characterize the four classes according to the landscape functioning variables and thus to appreciate the coherence of the landscape spatial heterogeneity stratification. The p-values from ANOVA showed a significant difference between landscape stratification classes for the variables vegetation productivity, AET, vegetation productivity dynamics and woody cover (Fig. 4a). Regarding the soil type distribution, class 1 consisted of saline hydromorphic soils, class 2 was largely dominated by tropical ferruginous soils, and class 4 as largely dominated by hydromorphic soils. The tropical ferruginous soils and the hydromorphic soils were mixed in class 3 (Fig. 4b).

Based on this landscape heterogeneity stratification map, two optimized and spatially representative field sampling plans were designed (Ndao et al. 2017). The first sampling plan utilized 213 observation sites for tree species inventories, and the second involved 45 observation sites for georeferenced data collection of landscape elements (LULC). The observation sites were regularly distributed among the 4 classes of landscape spatial heterogeneity stratification and according to the weight of each class (Fig. 3). This weighted stratified sampling design respected the proportions of the different entities within the studied population, i.e., within the landscape.

3.2. The agroforestry system mapping

The LULC map of the AFS was obtained using the LULC field training data with satellite images (Sentinel-2 time series and PlanetScope). It included 9 classes: (i) cereal crops (millet and sorghum), (ii) leguminous crops (peanut and cowpea), (iii) woody vegetation, (iv) artificialized land (villages and roadways), (v) ponds, (vi) fallow land, (vii) shrubbery, (viii) marshlands and valley, and (ix) shores and bare ground. All LULC classes were relatively well classified, with accuracies between 69.87% and 97.85%. The overall accuracy was satisfactory, at 85.12% with a Kappa index of 0.81 (Fig. 5). These results showed that the combined use of VHSR images, such as PlanetScope, with a Sentinel-2 image time series was appropriate to obtain a relevant LULC map in complex agroforestry systems. The high spatial resolution of the PlanetScope image was indicated for accurate segmentation of landscape features, while the spectral and temporal resolutions of Sentinel-2 were important for the discrimination of crop classes and other landscape objects. The relevance of combining different sources of geospatial data to improve the accuracy of LULC classification and mapping has already been demonstrated (Chen et al., 2017; Shi et al., 2019), in particular the use of multisource data (simulated Sentinel-2 time series, VHRS images and DEMs) for crop mapping in smallholder agricultural landscapes (Lebourgeois et al., 2017).

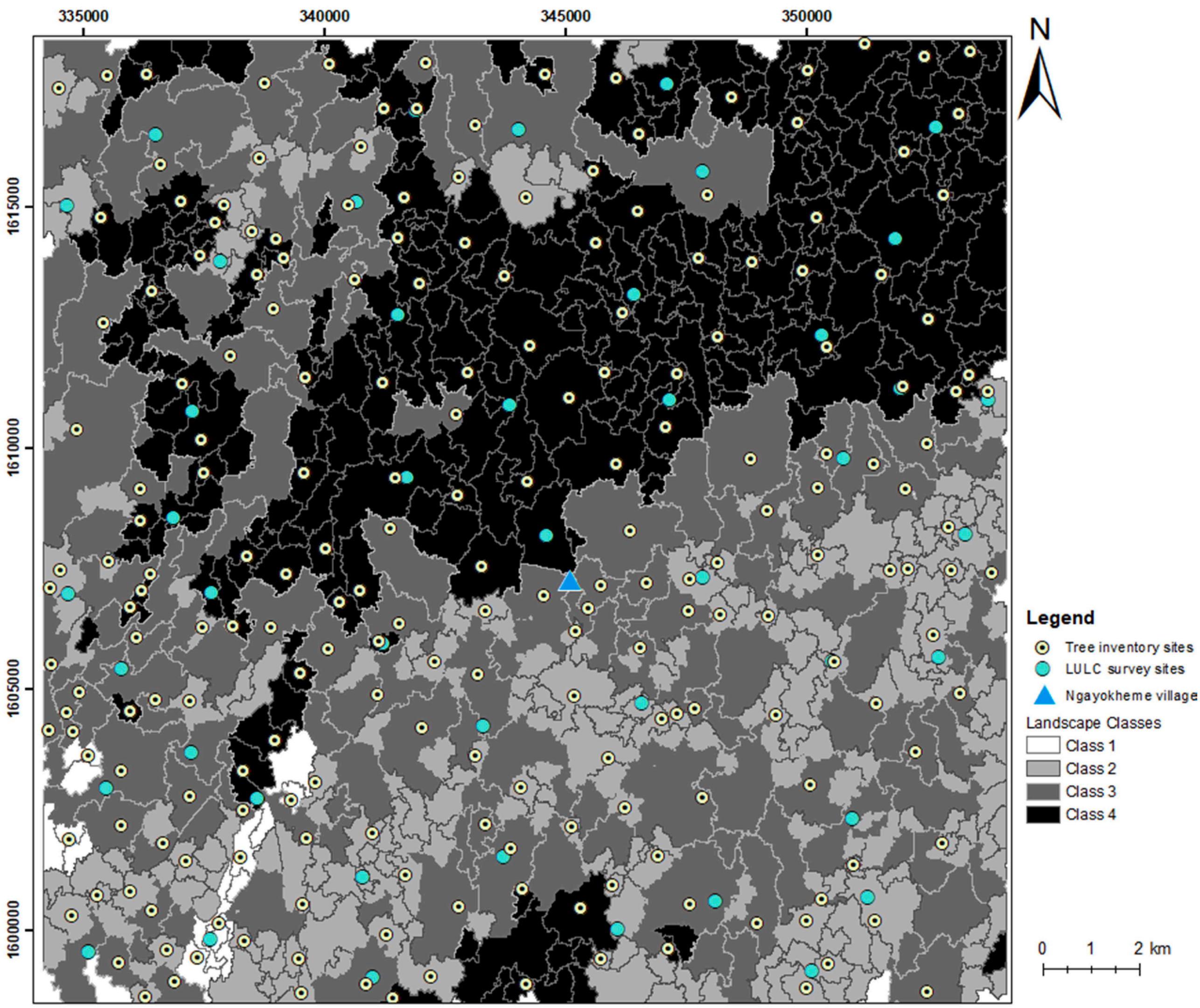

Fig. 3. Landscape spatial heterogeneity stratification map and landscape units of the study site, which were obtained from an OBIA and a hierarchical clustering approach based on landscape functioning variables. The symbols represent the location of the sample sites used for tree inventory (black circles) and LULC (blue circles) surveys. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.3. Tree diversity and landscape heterogeneity analysis

3.3.1. Tree diversity analysis

During the tree inventory campaign, 9258 trees distributed among 63 species were identified and georeferenced in the study area. This tree dataset allowed the analysis of tree diversity according to classes of landscape spatial heterogeneity stratification. Fig. 6 shows the distribution of species abundance throughout the study area and according to the landscape classes. *F. albida* was by far the most abundant, making up 42% of the recorded trees. Four other dominant species were *Balanites aegyptiaca*, *Anogeissus leiocarpus*, *Adansonia digitata* and *Acacia nilotica*, which were the predominant species, representing 71.6% of all individuals. On the other hand, 52 species that represented more than 80% of the species richness of the area can be considered uncommon or even rare in the study area, each with less than 1% of the inventoried individuals. In addition, comparison of the distribution of the five main species through their proportions in the landscape classes shows some discrepancy between them. Indeed, the distribution is relatively more balanced in class 1 than in the other classes. Classes 2 and 3 seem quite similar while class 4 compared to classes 2 and 3 has a higher proportion of *B. aegyptiaca* with less *F. albida* (Fig. 6). In a complex AFS (Jagoret, 2011; Michon and De Foresta, 1999, 1997), tree diversity is generally characterized by a dominant community (dominant species) coexisting with many other plant components (trees, treelets, lianas, and herbs). In agroforestry parklands, dominant species are deliberately favored by farmers due to their useful properties, either in terms of high agroforestry potential or because they are food species or sources of revenue (Sambou et al., 2017; Bayala et al., 2014; Michon and De Foresta, 1999). For example, the species *F. albida*, which was very dominant in the studied AFS, is a nitrogen-fixing species that acts as a ‘fertility hot spot’ (see Sileshi, 2016 for a review). Farmers know that under these trees, plants grow more vigorously (Manfo et al., 2015), and the improvement of millet yields in the vicinity of *F. albida* trees in the region has long been studied (Bayala et al., 2012; Kho et al., 2001; Louppe et al., 1996).

Through a correspondence analysis, species frequencies were analyzed according to their respective frequencies in the four landscape classes (Fig. 7). In terms of the tree species composition, the landscape class 1 was very different from the other classes. Additionally, classes 2 and 3 were not very different, but they could be differentiated from class 4. The frequency of species such as *Mytragina inermis, Diospiros mespiliformis* and *Acacia seyal* in class 1 indicated heavy soils of varying clay content in temporarily flooded lowlands and wetlands, such as pools and rivers (Arbonnier, 2019). On the other hand, the species *Sclerocary birrea,* which is frequent in classes 2 and 3, revealed a preference for

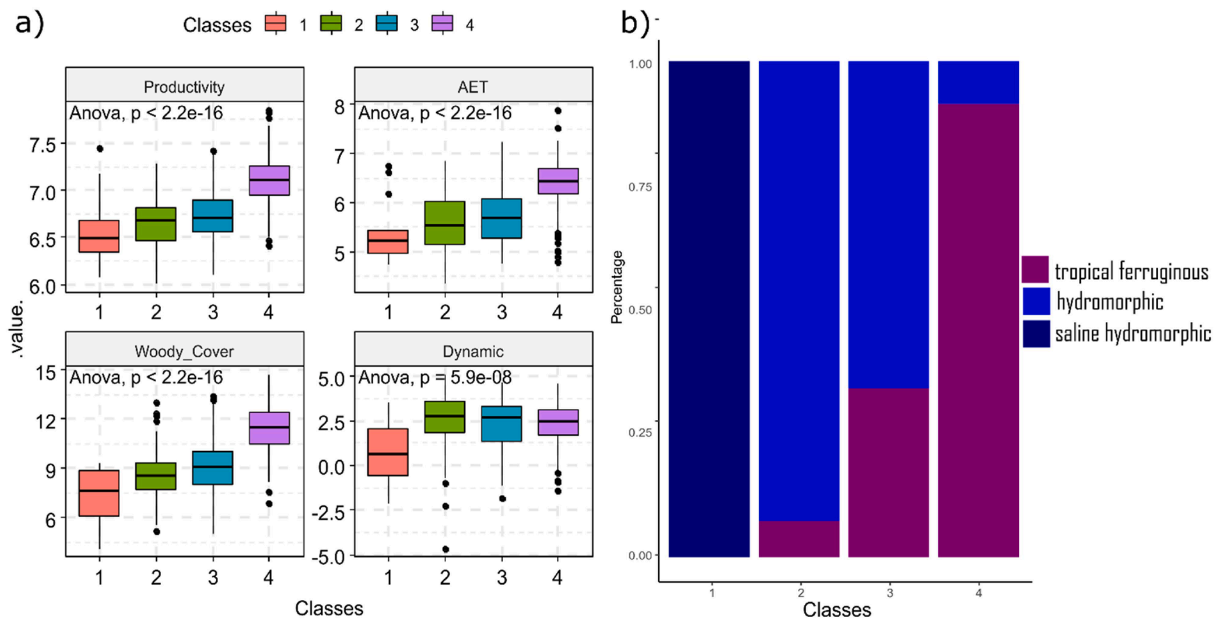

Fig. 4. Descriptive statistics of the mean landscape functioning variables according to the four classes resulting from the HCPC: **a)** Populations were compared using an ANOVA; Boxplot of vegetation productivity, actual evapotranspiration (AET), woody cover and vegetation productivity dynamics; **b)** Partitioning of soil types among the four landscape classes.

generally dry and sandy soils (Arbonnier, 2019). The heterogeneous distribution of the soil types was already shown by the assessment of the coherence of the landscape stratification (see section 3.1.; Fig. 4). The variations in soil cover defined ecological gradients that explained a significant part of the variability in plant stands in terms of the dendrometric structures and floristic composition (Freycon et al., 2003). Finally, it should be noted that the dominant species, *F. albida*, was more abundant in classes 2 and 3.

To better appreciate the spatial organization of tree diversity, comparative analyses of the indices were carried out among the classes from the landscape heterogeneity stratification.

First, the average tree density per sampling site was calculated instead of the abundance per class because the classes did not have the same sample sizes (number of sampling sites). According to this indicator, classes 2 and 3 had the highest tree densities, while class 1 had the lowest (Fig. 8a). In terms of the species richness, classes 2, 3 and 4 were not very far away, unlike class 1, which had a small number of species, with approximately one-third of the species encountered (Fig. 8b). However, it should be noted that class 1 had a rather homogeneous spatial distribution of species. Even so, the spatial distribution of species in the three remaining classes (2, 3 and 4), as in the landscape in general, was very heterogeneous (Fig. 8c). As previously shown in section 3.1, class 1 was dominated by saline soils, which were already known to have a negative influence on tree density and diversity and canopy cover in the study area (Sambou et al., 2017). In contrast to trends in species richness measures (Fig. 8b), SHDI and SIDI showed that class 1 had the highest diversity and class 3 the lowest (Fig. 8d & Fig. 8e). Actually, diversity refers to both richness and evenness (Kindt and Coe, 2005). Between classes 2 and 4, the two indices SHDI and SIDI made contradictory assessments, giving a mixed ranking (Fig. 8d & Fig. 8e). In some situations such as this, where there are both many rare species and very dominant species, the SHDI and SIDI indices used separately are not always sufficient to compare tree diversities, and only the combination of several diversity indices allows for a better appreciation.

Thus, to better rank the class diversities, the Renyi diversity profiles were calculated (Oldeland et al., 2010; Kindt and Coe, 2005; Tothmeresz, 1995). However, the resulting profile curves intersected, meaning that it was impossible to order them from the lowest to the highest diversity (Fig. 8f).

Indeed, the descriptive analyses showed the significant occurrence of both very dominant and rare species. Shannon's index is sensitive to rare species, whereas Simpson's index is sensitive to abundant species. Additionally, as recognized by Hill (1973) and Pielou (1966), the indices that are most commonly used by ecologists, namely, species richness, SHDI and SIDI, are specific cases of Rényi's entropy formula (Oldeland et al., 2010).

The combination of these different indices provided a more balanced assessment that considered the influence of both rare and dominant species. This was even more important since SHDI and SIDI can deliver contradictory results, such as that in this study for tree diversity in classes 2 and 4 of the landscape stratification.

3.3.2. *Landscape diversity analysis*

ANOVAs of the main landscape diversity indices, namely, the patch richness (PR) and Shannon and Simpson's indices, yielded significant to very significant differences (p-values) among the landscape classes (Fig. 9). This revealed compositional heterogeneity and configurational heterogeneity between the four classes of landscape stratification.

Indeed, the patch richness showed that there was a significant difference in the composition of LULC types according to the landscape classes. Additionally, Shannon's index and Simpson's index, which take into account both richness and the evenness (Dejong, 1975; Strong, 2016), showed that in addition to the difference in the composition of LULC types, there was also a significant difference in their organization, i.e., in the spatial distribution of the landscape elements (structure of the landscape) (Fig. 9). In particular, class 3 and class 1 had the greatest diversity of landscape elements, i.e., compositional heterogeneity. In terms of the configuration, the diversity was less marked, but class 1 remained the most diverse. On the other hand, classes 2 and 4, in terms of both composition and configuration, remained the least diverse.

Studies have reported that species diversity is dependent on the structure of the landscape (Walz and Syrbe, 2018) and that agroforestry landscapes and their heterogeneity contribute to biodiversity conservation (Udawatta et al., 2019; Jose, 2012; 2009). It was noted in model experiments that if the degree of landscape heterogeneity decreases, then both the local and regional species diversity decrease (Steiner and Köhler in Walz, 2011). However, this relationship was not verified by our results. In fact, the tree diversity analysis showed that class 3 had the

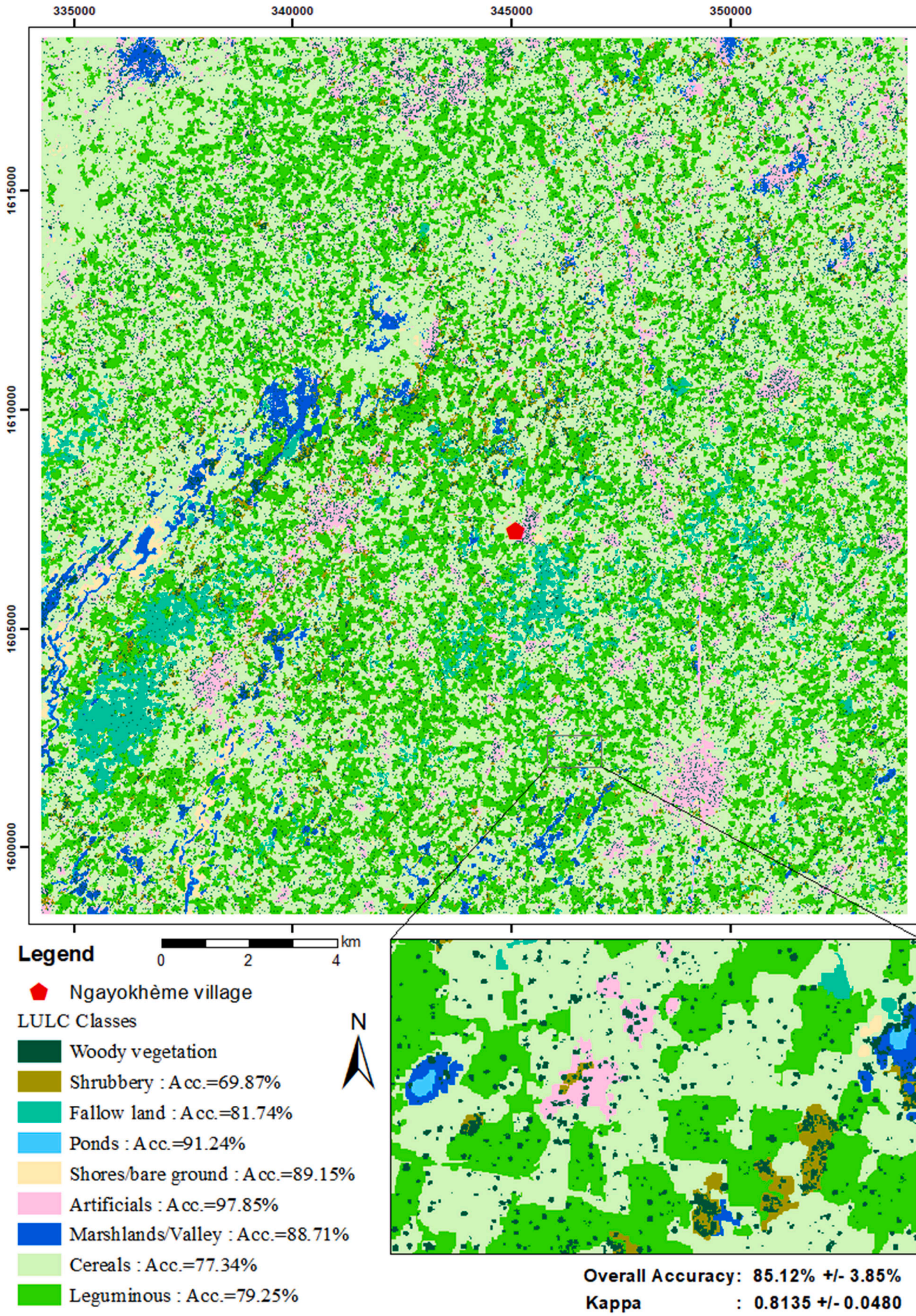

Fig. 5. Final LULC map of the AFS obtained from the MORINGA processing chain. Acc. = Accuracy. Zoom on a representative part of the identified classes (8 out of the 9 classes present). Leguminous and cereals fields are visible as the scattered trees inside fields forming the parkland.

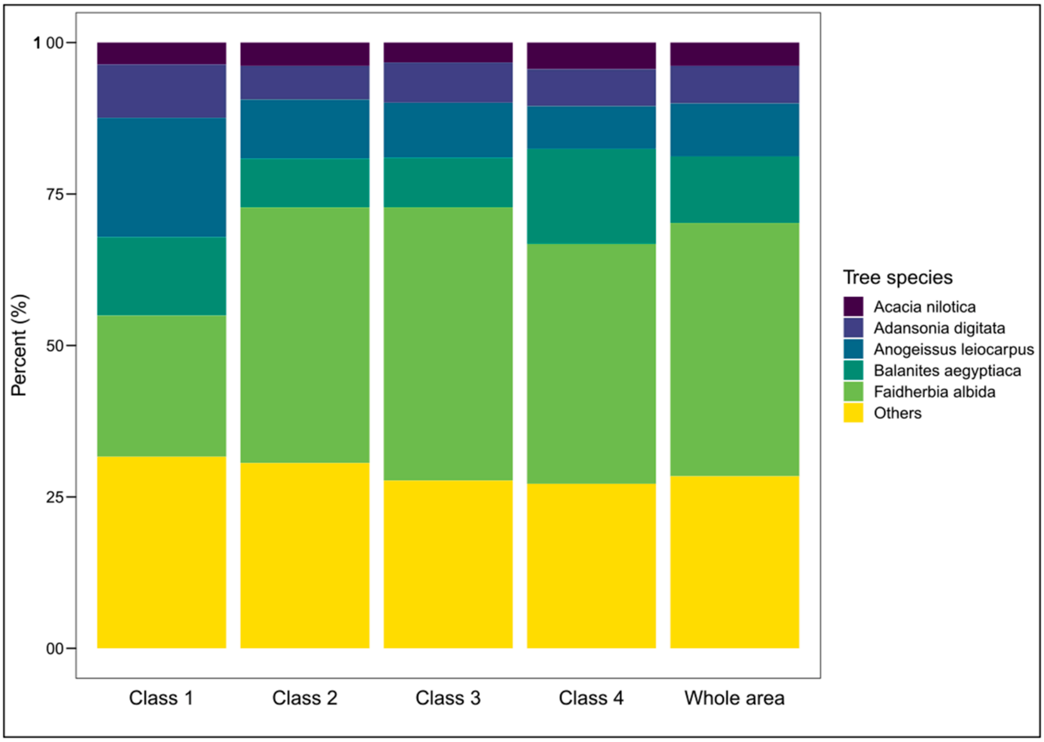

Fig. 6. Descriptive analysis of the abundance of tree species: species distribution and percentage per landscape class and over the whole area.

lowest tree diversity (Fig. 8d & Fig. 8e), whereas the landscape diversity metrics conferred the greatest heterogeneity to class 3. Our result in class 3 could be explained by the fact that the region was highly anthropized (Bignebat and Sakho-Jimbira, 2013). It is well known that in sub-Saharan Africa, the diversity of parklands in AFSs is largely dependent on their socioecological properties, including human activities and the role of farmers in the conservation of tree species (Bayala et al., 2014; Faye et al., 2010). Recently, Sambou et al. (2017) evidenced the farmer's contributions to tree diversity in three villages of the Peanut Basin, which were particularly different in terms of species composition according to the land use types.

These results from the landscape metrics have been deepened using analyses at the level of land use classes. The ANOVA p-values showed very significant differences between the landscape classes according to the abundance and dominance of the LULC classes of interest (i.e., woody vegetation, cereal crops and leguminous crops) (Fig. 10).

Landscape class 1 was relatively heterogeneous given the low land proportion (LP) of the three LULC classes of interest, which suggested the presence of several LULC classes (Fig. 10a, Fig. 10b & Fig. 10c). In particular, both cereal and leguminous crops were relatively less extensive in landscape class 1. This could be due to the presence of saline hydromorphic soils, which characterized landscape class 1, as already shown in section 3.1. (Fig. 4). Landscape class 2 appeared to be the most cultivated class, with a higher proportion of cereals and leguminous crops (Fig. 10b & Fig. 10c). It was also relatively homogeneous in terms of landscape composition given its low number of patches (NP) (Fig. 10d, Fig. 10e & Fig. 10f) together with its high proportion of crops. Landscape class 3 was characterized by a high level of fragmentation, suggesting high heterogeneity in terms of landscape configuration, as revealed by its high NP in the three LULC classes of interest (Fig. 10d, Fig. 10e & Fig. 10f). Landscape class 4 was characterized by higher proportions of cereal crops (Fig. 10b). These results still testify, as previously, to configurational and compositional heterogeneity that follows landscape heterogeneity stratification.

Concerning the woody vegetation in particular, the LP and NP values presented contradictions among the landscape classes that revealed a difference in the landscape functioning. Indeed, in Fig. 10d, the NP showed that there were more trees in terms of abundance in landscape class 3 than in landscape class 4, as already shown in Fig. 8a, whereas in Fig. 10a, the LP showed that trees covered more area (dominance) in landscape class 4 than in landscape class 3. Trees therefore appeared to be more developed in terms of growth (larger size) in landscape class 4 than in landscape class 3. This difference in tree growth reflected a functional heterogeneity of the studied landscape that could be inferred from different biophysical conditions, leading to a diversity of tree species. These are additional arguments towards the importance of trees for the diversity of agroforestry landscapes and their functioning. As reported by Sinare and Gordon (2015) and Kuyah et al. (2016) in their literature review, trees provide numerous ecosystem services in AFSs in sub-Saharan Africa. In fact, natural communities of trees that characterize complex agroforestry systems (Michon and De Foresta, 1999) are an ecological asset in terms of biodiversity, soil protection and nutrient recycling (Sinare and Gordon, 2015).

3.4. General discussion

Landscape studies and characterization approaches are very diverse. Recently, Simensen et al. (2018) highlighted in their literature review several approaches to landscape characterization and mapping. Generally, the different approaches, especially in landscape ecology, require field sampling, which allows inferences to be made about the functioning of ecological processes (Samalens, 2009). For landscape sampling, Godard (2007) argued that there are, in absolute terms, no good or bad methods to collect field samples. Several landscape sampling approaches are reported in the literature (Thorpe et al., 2016; Froger et al., 2016; Godard, 2007). However, it must be recognized that the accuracy of inference depends on the representativeness of the field sample. A representative field sample is one that allows to capture the variability of the surveyed landscapes and is similar to these in terms of composition and structure (Godard, 2007). In complex AFSs, especially in sub-Saharan Africa, the question of representativeness remains crucial because of their high heterogeneity in terms of composition

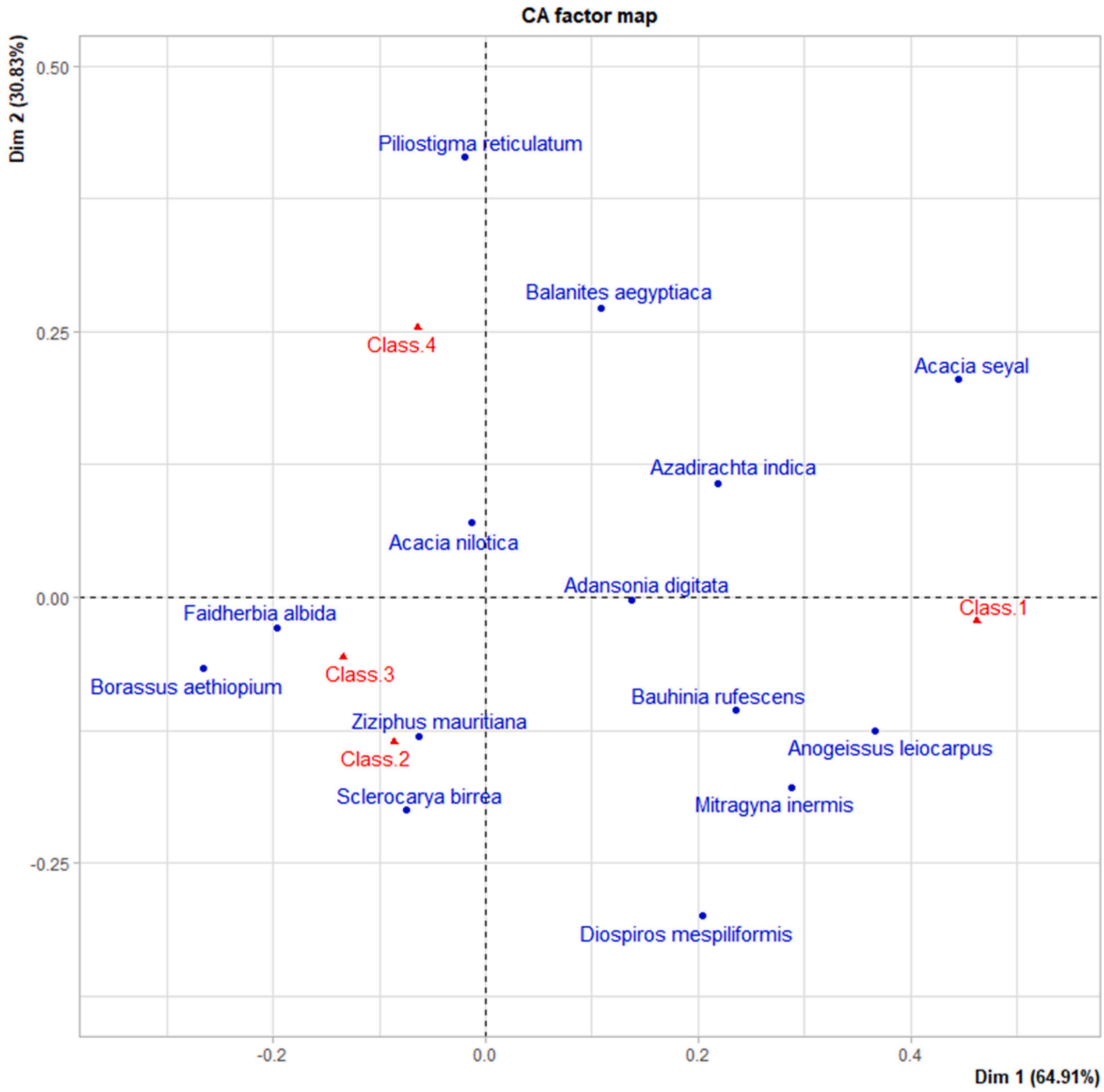

Fig. 7. Correspondence analysis of the common species.

(number of different cover types), structure (spatial arrangement of cover types) and functioning (Fahrig et al. 2011).

The approach proposed in this study was robust insofar as it allowed us to simultaneously capture the different forms of heterogeneity in a complex agroforestry landscape. The results highlighted (i) compositional, (ii) configurational, and (iv) functional heterogeneities of the landscape classes obtained through an original method of stratification and landscape sampling. We showed that this stratification approach effectively represented the variability of the landscape subtypes present in the area.

An appropriate field sampling strategy takes into account the three main aspects of field sampling processes (Wang et al., 2013): the variable of interest, the sampling approach, and the distribution of sampling locations (Sedda et al. 2019). In our approach, the choice of stratification variables (variable of interest) is guided by the theme of interest, i. e., biodiversity and AFS functioning. The variables of interest were identified on the basis of *a priori* knowledge of agroforestry landscape functioning and on the assumption that the landscape is mainly structured by the variety of natural conditions (Jedicke, 2001). Regarding the sampling approach and sampling location distribution, hierarchical clustering techniques are commonly used in combination with unsupervised classification (Simensen et al., 2018). In this study, we used hierarchical clustering techniques, namely, HCPC methods, to stratify the landscape into classes and for the spatial distribution of observation sites. The number of observation sites was defined by weighting according to the landscape classes. Thus, taking into account landscape functioning variables when designing landscape stratification and using a weighted distribution of sampling sites provides better representativeness than the approaches based on criteria related to landscape composition or structure only (Bueno et al., 2019; Waldner et al., 2016).

Furthermore, if the landscape quantification and characterization approach is based on the analysis of landscape metrics, the choice of appropriate spatial observational units is another critical issue because landscape metrics are sensitive to the extent over which they are calculated (Hunsaker et al. 1994). According to Mcgarigal (2015), landscape metrics can be defined at four levels corresponding to a logical hierarchical organization of spatial heterogeneity in patch mosaics: *cell-level metrics, patch-level metrics, class-level metrics,* and *landscape-level metrics*. However, Yang and Liu (2005) reported that the landscape ecology literature does not provide much guidance on how to choose spatial observational units and suggested further efforts to design spatial observational units. Thus, to optimize the analyses in this study, assuming that landscapes with the same environmental dynamics will have similar temporal profiles for remote sensing, the landscape metrics

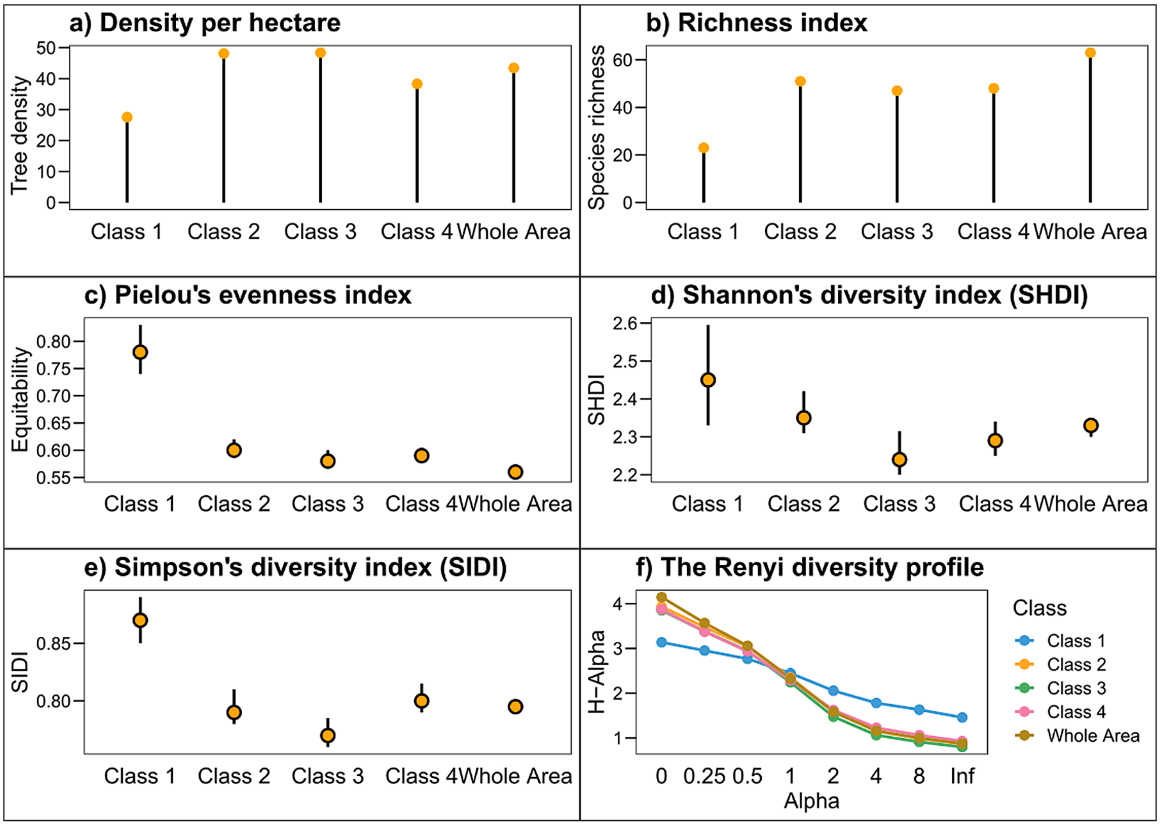

Fig. 8. Tree diversity analysis based on the tree inventory with the (a) density, (b) richness index, (c) Pielou's evenness index, (d) Shannon's diversity index (SHDI), (e) Simpson's diversity index (SIDI), and (f) Renyi diversity profile, per landscape class and for the whole area.

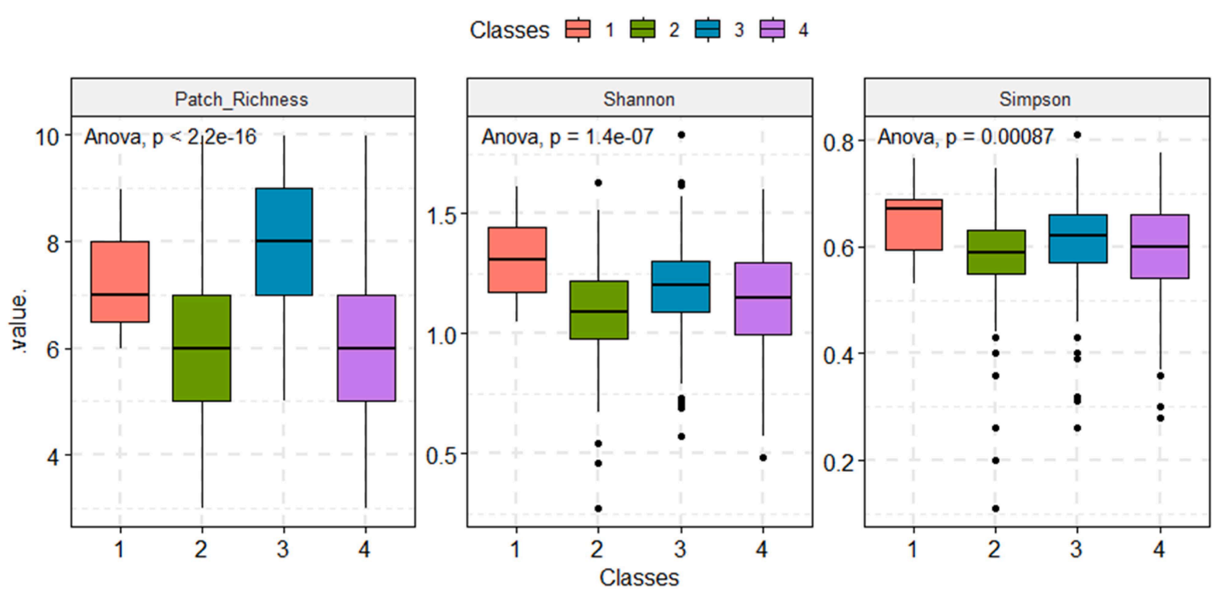

Fig. 9. Boxplot comparing landscape metrics (patch richness, Shannon's diversity index and Simpson's diversity index) according to the four classes of landscape heterogeneity stratification. P-values resulting from the ANOVA are provided as well.

were analyzed at the level of landscape units derived from satellite image time series segmentation. The choice of the segmentation scale being crucial to delineate relevant landscape units, it was assessed by an approach of trial-and-error. Different scales were tested while assessing accuracy by visual inspection overlaying the resulting landscape units on a VHSR image. The best chosen scale allowed to identify relevant landscape units relatively detailed. Studies have shown the relevance of using only Earth observation data and remote sensing methods to delineate homogeneous landscape units in terms of the phenological development of vegetation, agro-environmental conditions and farming practices (Bellón et al., 2018; Bisquert et al., 2015). Choosing spatial observational units derived from satellite image time series processing allows landscape metrics to be performed at a hierarchical level related to both landscape organization and functioning. This is another strong

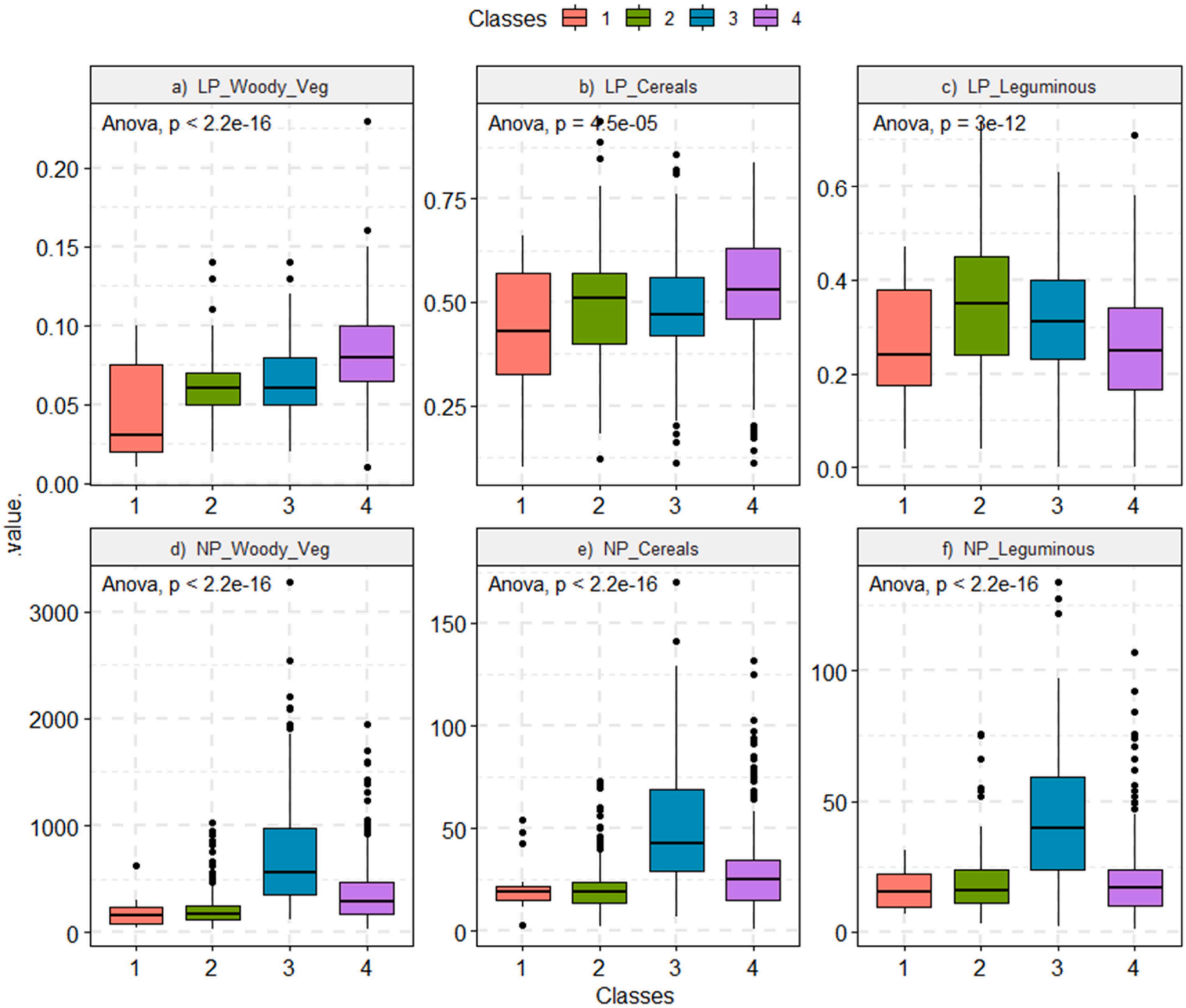

Fig. 10. Boxplot comparing the class metrics according to the four classes of landscape heterogeneity stratification. LP stands for land proportion and NP for number of patches. P-values resulting for the ANOVA are provided as well.

contribution of the approach proposed in this paper.

The analysis of the implementation of the sampling strategy showed that it can be used for (i) tree biodiversity analysis, (ii) mapping, and (iii) characterization of a complex AFS in sub-Saharan Africa. Analyses of tree datasets from field surveys using this sampling strategy approach revealed the occurrence of three dimensions of landscape heterogeneity (compositional, configurational and functional) in the collected tree sample. Additionally, AFS mapping was carried out with good accuracy with remote sensing methods using training data from this sampling strategy. The analysis of agroforestry classes of interest (trees and crops) resulting from that mapping strategy also showed the three dimensions of landscape heterogeneity (compositional, configurational and functional). Finally, the approach to designing spatial observational units using remote sensing methods was simultaneously validated.

In a general context of improving food security and biodiversity conservation in Sahelian AFS, it remains essential to understand their functioning taking into account their specific characteristics in terms of landscape heterogeneity. Indeed, the three levels of landscape heterogeneity captured by our study, i.e. compositional, configurational, and functional, are closely linked and should be analyzed together to optimize designing and implementing successful interventions in Sahelian AFS. For example, Harlio et al. (2019) reported for semi-natural grasslands that "incorporating landscape heterogeneity into multi-objective spatial planning improves biodiversity conservation". Particularly it is well known that, because of their diversity and according to their composition and structure, Sahelian AFS provide a variety of socio-ecosystem services to smallholder farmers (Sinare and Gordon, 2015; Miller et al., 2017). Benefits range from producing food that can be directly used for consumption (Chivandi et al., 2015) or improving the production of crops and livestock (Foli et al., 2014; Leroux et al., 2020) to the improvement of pest regulation (Soti et al., 2019; Sow et al., 2020) or the increase of household income (Koffi et al., 2020). For instance, over our study area, Leroux et al. (2020) have reported that increasing the tree density in *F. albida* parklands would have a positive effect on staple crops only up to a woody cover of 35%. Subsequently, it appears that having an efficient approach to analyze the heterogeneity of the landscape as proposed by this study is needed in order to incorporate it in the management of the AFS in particular.

4. Conclusion

The originality of this reproducible approach for optimizing field sampling plans in complex landscapes lies in its multidisciplinary character, which combines landscape agro-climatological and ecological properties, Earth observation techniques, and statistical and spatial analyses that are applied to landscape ecology. The implementation of the proposed sampling strategy showed that this approach was effective in representing the spatial heterogeneity of an agroforestry landscape and thus enabled improved AFS mapping and characterization.

From the geospatial data sources using OBIA combined with a hierarchical clustering method, landscape spatial heterogeneity stratification was performed by relying only on *a priori* knowledge of landscape functioning. The landscape heterogeneity stratification made it possible to develop an optimized sampling strategy that allowed us to collect samples that were spatially representative of the varieties of heterogeneity in agroforestry landscapes.

The representativeness of the collected data was important to properly mapping AFS with an overall accuracy of 85% and then to analyze tree biodiversity and agroforestry landscape heterogeneity. Diversity indices and other landscape and class metrics that were extracted from the LULC map at the level of spatial observational units derived from remote sensing methods were efficient for correctly analyzing agroforestry landscape heterogeneity in all its dimensions.

Implementing this sampling strategy demonstrated after analysis that the three dimensions of landscape spatial heterogeneity (compositional, configurational and functional heterogeneities) were captured in the collected field samples. In feedback, these results confirmed the validity of the landscape heterogeneity stratification approach based only on *a priori* knowledge of landscape functioning combined with geospatial data and remote sensing methods. In landscape studies, this approach will enable the stratification of landscape spatial heterogeneity before sampling in the field, allowing us to take into account the different landscape subtypes in the sampling process and in the study in general. This reproducible approach was applied to illustrate that it can be used for tree biodiversity analysis, characterization and mapping of a complex AFS in sub-Saharan Africa.

To conclude, it should be noted that tree components represent an important dimension in the definition and conservation of biodiversity and in the improvement and sustainability of AFS productivity. Thus, to contribute to effective monitoring of the state of biodiversity conservation in AFSs (SDG15), as well as food security (SDG2), which is closely linked to AFS productivity and tree species diversity, these results should be further developed towards more exhaustive mapping of tree species. This tree dataset (9258 individuals) could then be used as training data to perform multisource remote sensing techniques using VHSR images. The density and representativeness of the tree dataset could also enable experimentation with species distribution modeling techniques.

CRediT authorship contribution statement

Babacar Ndao: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Louise Leroux:** Methodology, Formal analysis, Software, Funding acquisition, Writing - review & editing. **Raffaele Gaetano:** Resources, Formal analysis. **Abdoul Aziz Diouf:** Methodology, Data curation, Software, Conceptualization. **Valérie Soti:** Conceptualization, Methodology. **Agnès Bégué:** Writing - review & editing, Supervision, Validation. **Cheikh Mbow:** Supervision, Writing - review & editing. **Bienvenu Sambou:** Supervision, Project administration.

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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