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Effect of land use change on carbon stocks in an agricultural region of southern Benin

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Abstract

Land use change is one of the most important determinants of carbon storage and dynamics in ecosystems. Areas in the proximity of metropoles undergo land use changes but are poorly studied for their soil and biomass carbon budget, especially in Africa. Close to Benin's economic capital, the Lama Territory located on the Allada Plateau and is subject to high demographic and urbanization pressures. Carbon (C) stocks in the region are likely to be rapidly changing. This research assessed the land use changes and quantified the spatial distribution and variation of C stocks between 2000 and 2018 on the Ferralsols of the study area. Random forest models using spectral bands of LANDSAT images and some spectral indices as predictors were calibrated to classify the land use. C stocks of four C pools (aboveground, belowground biomass, litter, and soil) were mapped with InVEST (integrated valuation of ecosystem services and tradeoffs) model. Land use change occurred in 61% of the Ferralsol area between 2000 and 2018. The surface of forests and crop-plantation associations decreased in benefit of tree plantations, adult palm groves, and built-up areas. With the loss of forest surface and the increasing urbanization, C stocks of the region decreased by −218 Gg C with 4% uncertainty (−175 Gg C in soil pools, and − 125 Gg C in aboveground biomass with both 6% uncertainty) between 2000 and 2018. Results highlight: (i) the need for soil C stock accounting to avoid underestimation of C stocks evolution in a rural region; and (ii) the relevance of tree plantations and deforestation control to maintain the C stocks in tropical areas.

KEYWORDS
carbon pools, land use, Random forest, tropical systems, uncertainty

1 | INTRODUCTION

Land use change is the second largest source of global warming, after fossil fuel combustion. (FAO, 2019; IPCC, 2019a). Land use change increases or decreases atmospheric carbon (C) emissions and contributes significantly to climate regulation. (Scharlemann et al., 2014; Tieszen et al., 2011). For example, urbanization and expansion of agricultural land often lead to deforestation and biomass and soil carbon stock depletion (Olorunfemi et al., 2018; Zhang et al., 2017). On the contrary, reforestation through tree plantations or forest natural regeneration enhance

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terrestrial C stocks (Dibaba et al., 2019; Yirdaw, 2018). In addition to C stocks evolution, the evolution of ecosystem services due to land use change has attracted international attention, as these services affect the economies, environment, and thus the well-being of human societies (Adhikari & Hartemink, 2016). For example, a large majority of the nationally determined contributions (NDCs) presented by countries under the Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC) suggest actions in the agriculture and forestry sector to both mitigate and adapt to climate change. Nevertheless, a mere 10% of the Green Climate Fund's budget is used to implement agriculture and forestry projects, often due to a lack of data on greenhouse gas (GHG) emissions or on the evolution of carbon stocks in ecosystems. (Buto et al., 2021). In Benin, the ambition is to reduce GHG emissions by 16% by 2030. The government of Benin strives to protect the vegetation cover, restore degraded land and forest landscapes in the country along with the implementation of an ambitious energy transition policy to reduce pressure on forests and agroforestry parks. The intention is to reduce the deforestation rate by 42% by 2030 (DGEC/MCVDD, 2017). It is, therefore, necessary to characterize and monitor the dynamics of land use changes and to measure their effect on the functioning of various terrestrial ecosystems, particularly regarding the C stocks (Leh et al., 2013; Newbold et al., 2015).

Carbon stock in terrestrial ecosystems includes several pools: soil, dead wood and litter, living above- and belowground biomass (UNFCCC, 2015). The global soil organic carbon (SOC) pool was estimated at more than 2300 Gt C in 0–300 cm soil layers, compared to 650 Gt C stored in vegetation and 840 Gt C in the atmosphere. (FAO, 2019; Lorenz & Lal, 2018). The amount of the SOC stock and its dynamics has an important role in regulating CO_2 emissions to the atmosphere (Minasny et al., 2017). Plants fix CO_2 from the atmosphere through photosynthesis and a part of this carbon is further incorporated into the soil as litter residues or root exudates. The carbon remains in the soil within the soil organic matter and SOC during contrasted periods of time. As SOC represents a major but dynamic reservoir of terrestrial C, C sequestration in soils contributes to climate regulation. The SOC stock is affected by soil type, soil-climatic conditions, and land use and management (Fujisaki et al., 2018). Similarly, the evolution of C stock in living or dead biomass is mainly conditioned by climate and land use (Menezes et al., 2021). Thus, the C stock of the different terrestrial C pools may either decrease or increase as a result of a change in land use such as deforestation (e.g., Grinand et al., 2017; Guo & Gifford, 2002) or afforestation, or any change in agricultural practices (Corbeels et al., 2019; Fujisaki et al., 2018). In subSaharan Africa, land use change and land use intensification, including agricultural expansion and overexploitation of forest resources, led to degradation of forest landscape (FAO, 2016) and depletion of C stocks in different pools (Ciais et al., 2011).

Despite global attention on climate change and the rise of initiatives such as Reducing Emissions from Deforestation and Forest Degradation (REDD+), knowledge of the evolution of C stocks associated with land use change in all regions is growing but still fragmentary (Grinand et al., 2017; Tao et al., 2015) especially in developing countries. In Southern countries, studies on the dynamics of C stocks at a regional scale are recent and mainly focused on deforestation areas (Babbar et al., 2021; Grinand et al., 2017; Zhang et al., 2017), very few concern agricultural areas (Zhao et al., 2018). However, besides deforestation, land use changes can be highly dynamic in agricultural areas, notably around cities with a high demographic pressure on land. To our knowledge, there is no study on land use and C stock changes in agricultural areas affected by the proximity of an African city such as is the case in the Lama Territory close to Cotonou in Benin.

The Lama Territory located in the Allada Plateau region (214,000 ha) shows a heterogeneous and transforming agricultural landscape (natural forest relics, tree plantations, food crops) mainly developed on Ferralsols. Close to Cotonou with a high demographic pressure, the area experienced urbanization and changes in agricultural activities. The evolution of agricultural and economic activities since several decades led to the development of private tree plantations, oil palm plantations (*Elaeis guineensis*), pineapple cultivation (Aoudji et al., 2014; Brun et al., 2018; Tchibozo, 2020). We hypothesized that these changes in land use have affected large areas and have modified C stocks of the Allada Plateau. We focused the study on the Ferralsols, which are soils with quite homogeneous texture and are the dominant soil type of the Allada Plateau (Houssoukpèvi et al., 2022), in order to be able to attribute the eventual C stock variations to the land use change and not to the soil type. Our study was built on existing estimates of terrestrial C pools, that is, living biomasses (aboveground and belowground), litter + woody necromass and soil (Ferralsols), measured in representative natural and agricultural systems of the area (Houssoukpèvi et al., 2022). This previous study took into account the diversity of local vegetation cover, age, and farming practices of the respective land uses to calculate carbon stocks and their variability. This study focused on the characterization of the spatial evolution of land use. The main objective of this study is to characterize the spatial evolution of land use over almost two decades on the agricultural Allada Plateau and to estimate the consequences of these evolutions on global C stocks in all compartments, soil, biomass, and necromass. The specific goals of the study were (i) to describe the evolution of land use on the Allada Plateau between 2000 and 2018 and (ii) to analyse the consequences of changes in land use on the terrestrial C stocks pools. A special attention has been made on the calculation of the uncertainties associated with the estimates of C stocks.

2 | MATERIALS AND METHODS

2.1 | Study area

The study area covers the three municipalities of the Lama Territory (Allada, Zè, and Toffo) on the Allada Plateau (6°20′–6°50′ N and 2°00′ E, 3–175 m altitude) in the Atlantic Department of southern Benin (Figure 1). It is located near Cotonou, the capital of Benin, and its agglomeration. This area is classified as a tropical savannah with a dry winter (Aw) according to the Köppen-Geiger climate classification scheme (Rubel & Kottek, 2010). Ferrallitic and ferruginous soils, Vertisols, and Hydromorphic soils are the principal soil types in the area. (CPCS, 1967; Volkoff, 1976). Ferrallitic soils, or Ferralsols in the World Soil Resources Database (IUSS-WRB, 2015) are dominant on the

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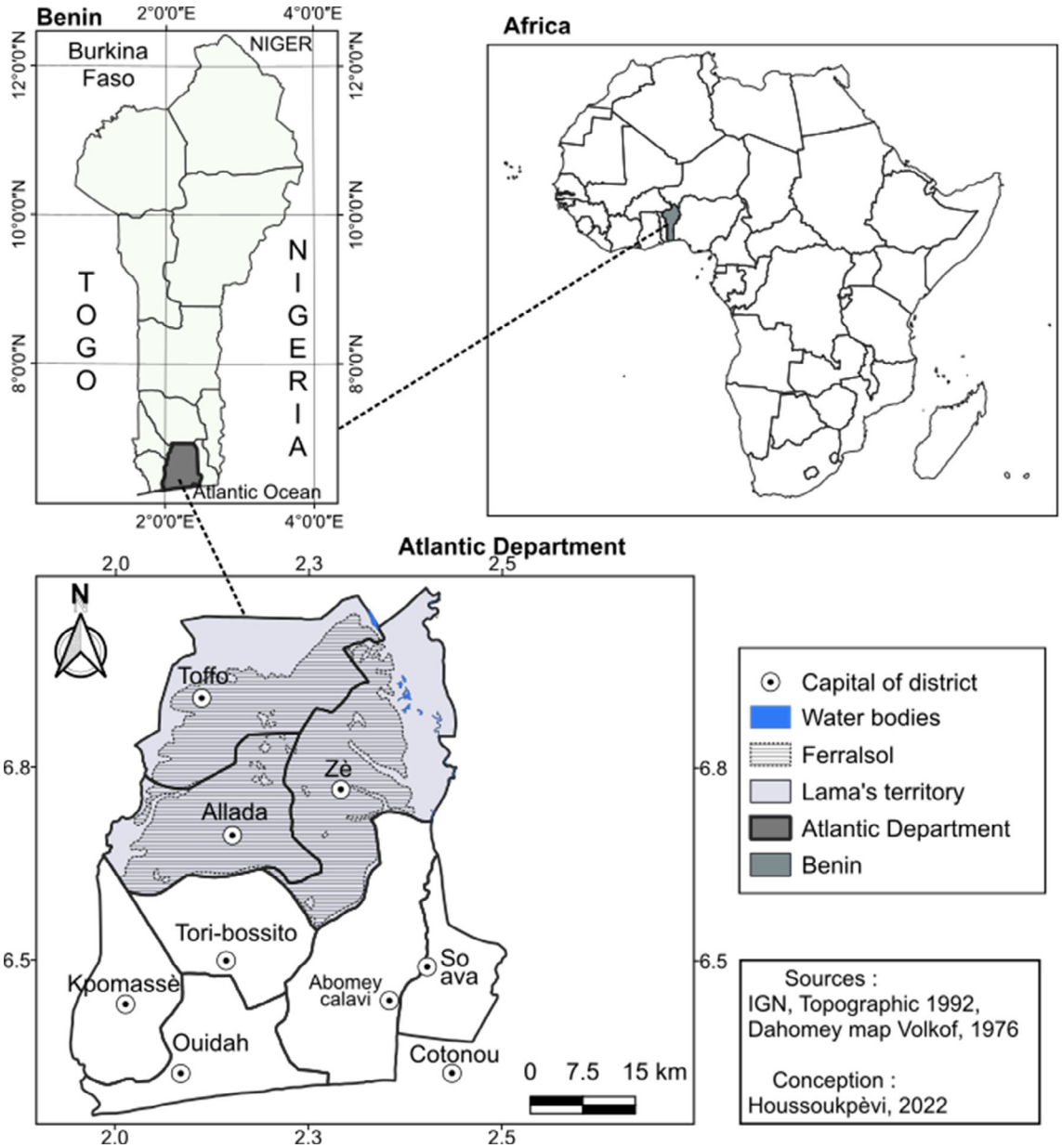

FIGURE 1 Location of Benin, the Atlantic Department and the study area [Colour figure can be viewed at wileyonlinelibrary.com]

Allada Plateau and cover an area of 106,221 ha, that is, 70% of the area of the three municipalities (Volkoff, 1976). The present study was conducted exclusively on this type of soil (106,221 ha; Figure 1). These soils are generally sandy in texture with about 75% sand in in the 0–30 cm depth (Houssoukpèvi et al., 2022).

2.2 | Determination and evolution of the land use on Ferralsols

2.2.1 | Satellite image acquisition and processing

Two subscenes of LANDSAT imagery from the years 2000 (Enhanced Thematic Mapper Plus sensor: ETM+) and 2018 (Operational Land Imager sensor: OLI) were used to map and analyse land cover changes in the study area (Figure 2). Low cloud cover LANDSAT images (Path 190, Rows 055 with a spatial resolution of 30 m) were obtained for the study area from the United States Geological Survey (USGS) archive (Table 1). The images are orthorectified and corrected for atmospheric effects on reflectance (to obtain 'surface reflectance'). Both 2000 and 2018 images were collected in dry season to minimize variations in vegetation phenology (Clerici et al., 2007). The spectral bands used in this study were blue (441–514 nm for ETM+ and 452–512 for OLI), green (519–601 nm for ETM+ and 533–590 nm for OLI), red (631–692 nm for ETM+ and 636–673 nm for OLI), near infrared (NIR; 772–898 nm for ETM+ and 851–879 nm for OLI), shortwave infrared 1 (SWIR1; 1547–1749 nm for ETM+ and 1566–1651 nm for OLI), and shortwave infrared 2 (SWIR2; 2064–2345 nm

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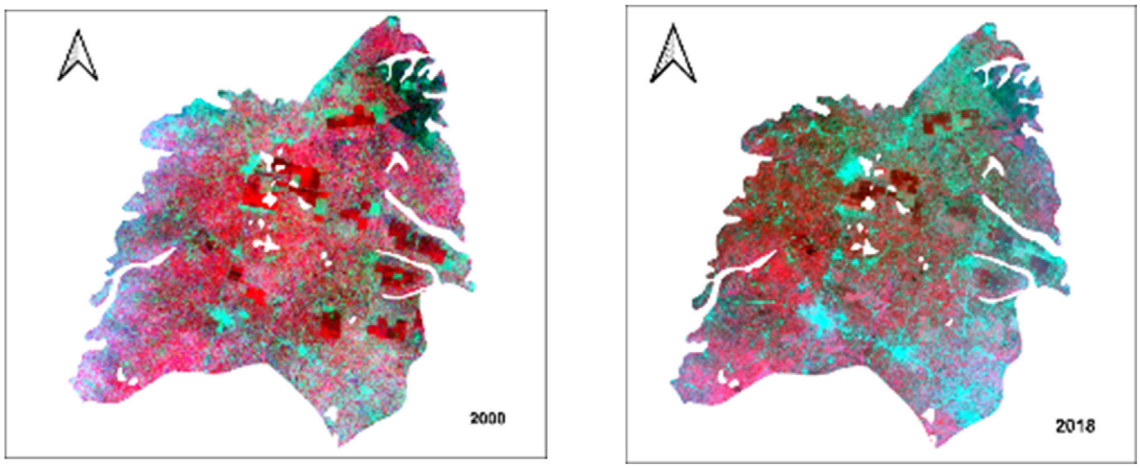

FIGURE 2 LANDSAT-7 ETM + (432 false colour composite) and LANDSAT 8-OLI (543 false colour composite) sub-images [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Characteristics of the LANDSAT images used

Images	Date of acquisition	Cloud cover (%)	Strips used	Spectral indices used
LANDSAT-7 ETM+.	Dec 13, 2000	5.00	Blue	$NDVI = (NIR - Red)/(NIR + Red)$
			Green	
			Red	$NIRI = (NIR - SWIR1)/(NIR + SWIR1)$
LANDSAT-8 OLI/TIRS	Jan 5, 2018	0.86	NIR	
			SWIR	$NIRI.2 = (NIR - SWIR2)/(NIR + SWIR2)$
			SWIR.2	

for ETM+ and 2107–2294 nm for OLI). We calculated the normalized difference vegetation index (NDVI; Rouse et al., 1974) and the normalized infrared indices (NIRI and NIRI.2; Hardisky et al., 1984) (Table 1). These indices in addition to the spectral bands of the LANDSAT images were used to improve the quality of the image classification (Grinand et al., 2013; Kamusoko, 2019).

2.2.2 | Classification of LANDSAT images

The images were classified according to six land use categories: built-up areas (BA), forests (FO), tree plantations (PL), adult palm groves (PA), crop-plantation associations (CP), and croplands (CL) (Table 2). Waterbodies were not considered as the study focused on Ferralsols.

Satellite image classifications are most often performed by combining the remote sensing data with reference data from the ground or from aerial photographs at or near the time of the satellite pass (Benz et al., 2004; Zhou et al., 2009). However, in Benin, such data are not widely available for retrospective analysis of remote sensing data (Kamusoko et al., 2009). For our area, the absence of aerial photographs led us to use very high-resolution images acquired from different satellites gathered on Google Earth as reference data. To classify the 2000 LANDSAT image, 938 points of interest were defined using the Google Earth images of 2005. We used the 2005 google image because the 2000 image was of poor quality. We checked that the selected Google Earth image give the same land cover class spectral signature as the LANDSAT image through visual interpretation of the images. For the classification of the 2018 LANDSAT image, in addition to the 1621 points of interest identified on a 2017 Google Earth image, 100 points of interest were collected in the

TABLE 2 Description of mapped land use patterns

Land use patterns	General description
Built-up areas (BA)	Commercial and residential buildings, industrial sites, institutional areas, roads, and other man-made structures.
Forests (FO)	Relics of natural forests, sacred forests: consisting of evergreen and deciduous trees.
Tree plantations (PL)	Forestry plantations: monospecific plantations of Teak, Gmelina.
Adult palm groves (PA)	Mature oil palm plantations (>10 years)
Crop-plantation associations (CP)	Annual crop association with trees or in young palm groves (<4 years).
Croplands (CL)	Annual or bi-annual crops (in the area mainly maize, cassava, pineapple), fallow land, sparsely vegetated land; this category also includes bare soil at the time of image acquisition

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field for each land use in December 2019 (Appendix A). The six land use types are clearly distinguishable visually on the Google Earth images. In addition, each measured point is representative of an area of approximately 50 m radius around the point on the Google Earth image. In the end, a minimum of 100 points of interest for the year 2000 and 200 for the year 2018 were considered per land use mode.

The *Random forest* algorithm, that is, a Machine Learning method (Breiman, 2001), has been used for image classification (Grinand et al., 2013; Hounkpatin et al., 2018; Kamusoko, 2019). The *Random forest* algorithm was used because: (i) it is robust in analysing complex and numerous numerical or categorical data; (ii) it is free from normal distribution assumptions; and (iii) it is robust to outliers and noise (Mather & Koch, 2011; Rodriguez-Galiano et al., 2012). In addition, it provides an internal measure of classification accuracy (*out-bag error*).

We calibrated *Random Forest* models using spectral bands (Table 1) and some spectral indices (i.e., NDVI and NIRI) as input variables (predictors). For each of the two classifications (i.e., for 2000 and 2018), 70% of the data were randomly selected for each land use (stratified random sampling) as training data, and the remaining 30% were used as model validation data. The hyperparameters (*mtry*, number of tree) of the *random Forest* model were obtained by a systematic search maximizing the accuracy on the 70% of training points, and by performing five cross-validations repeatedly for five times (Kamusoko, 2019).

2.2.3 | Land use change parameters calculation

The images classified at both dates were used to calculate the area of the different land uses. The overall rate of change (Equation 1) and the annual rate of change (Equation 2) are the parameters used to assess the evolution of land use patterns (Puyravaud, 2003).

$$\mathrm{OC} = \frac{S2 - S1}{S1} \times 100, \tag{1}$$

Where: OC is the overall rate of change and $S1$ and $S2$ are the initial and final areas of land use at the dates studied (2000 and 2018) respectively. Positive values of OC indicate increases in a specific land use while negative values reflect losses in land use (Toyi et al., 2013).

$$r = \frac{1}{t2 - t1} \times \ln\left(\frac{S2}{S1}\right), \tag{2}$$

Where: r is the annual rate of change, t_1 and t_2 are the initial (2000) and final (2018) dates of the images used to determine the occupancy patterns.

2.3 | Mapping the carbon stocks

Mapping the carbon stocks used the classification of Landsat images (see Section 2.2) and the C stocks measured in each land uses (Figure 3). The C stocks in the four pools of each land use, except built-up, that is, urbanized areas, were measured on representative fields in a previous study in 2019 (details in Houssoukpèvi et al., 2022). Briefly, to ensure that the C stocks were representative, the C stocks were measured in classified and sacred forests, in state tree plantations and smallholder tree plantations of different ages and different tree species, in palm tree plantations with different previous history, and in annual or bi annual croplands (Pineapple, tomato, maize, and cassava). In total, 19 plots on Ferralsols were sampled. Soil and litter replicates and tree replicates were performed when estimating biomass and soil C stocks. The C stocks were mapped with a spatial resolution of 30 m using the module named carbon of the InVEST 3.9.0 software (integrated valuation of environmental services and tradeoffs) developed by the Natural Capital Project team (Bagstad et al., 2013; Daily et al., 2009). InVEST is a geospatial tool used to assess the impacts of land use change on ecosystem services (Goldstein et al., 2012; Qiu & Turner, 2013). Using the carbon module of InVEST implies a strong assumption: the estimation of C stocks per land use and per pool does not vary across time if the land use does not change (Sharp et al., 2020). The input parameters of the carbon model in InVEST were the land use maps of the years 2000 and 2018 and, for each land use, the C stock data (Mg ha^{-1}) of the four pools: living aboveground biomass, belowground biomass, litter and deadwood, and SOC (depth 0–30 cm) (Table 3). The details of the quantification of the C stocks for each pool are in Houssoukpèvi et al., (Houssoukpèvi et al., 2022). Briefly, these stocks were estimated according to UNFCCC (2013) guidelines. Aboveground biomass, belowground biomass, and litter (dead wood, grasses, and plant debris) were estimated in 0.25 ha square plots distributed in four forests, four tree plantations, and three adult and four young palm groves. The number of 0.25 ha square plot replicate per forest and plantations (from 10 to 35) depended of the size of the forest or the plantation. The carbon stocks in aboveground and belowground biomass were quantified after estimating the biomass stock based on allometric models developed for the species in the study area. These models consider the height of tree and diameter of the trees measured at 1.30 m from the floor (Goussanou et al., 2016; Guendehou et al., 2012; Kora et al., 2018). Litter and soil samples were collected in 1 m^2 quadrat along the diagonal of each 0.25 ha square plot in forests and tree plantations. In four different croplands, the C stocks were estimated in litter and soil (0–30 cm) in five plots. The C stocks of aboveground and belowground biomass were considered null because the biomass in croplands is either burnt or used for livestock feed. The SOC stocks were calculated based on IPCC procedures (Gelaw et al., 2014; IPCC, 2019b). This calculation took into account SOC content (g C kg^{-1} soil); soil bulk density (g cm^{-3}) and soil layer thickness (cm). We considered that the C stock of built-up areas are null. The Carbon model of InVest produced a map of C stocks for each of the four pools, in each pixel of the whole study area. The regional C stock in the different pools by land use is obtained by multiplying the C stock of land use by its surface area.

2.4 | Statistical analysis

2.4.1 | Evaluation of LANDSAT images classification accuracy

A confusion matrix of the validation data (30% of the selected independent points) was used to summarize the classification results for

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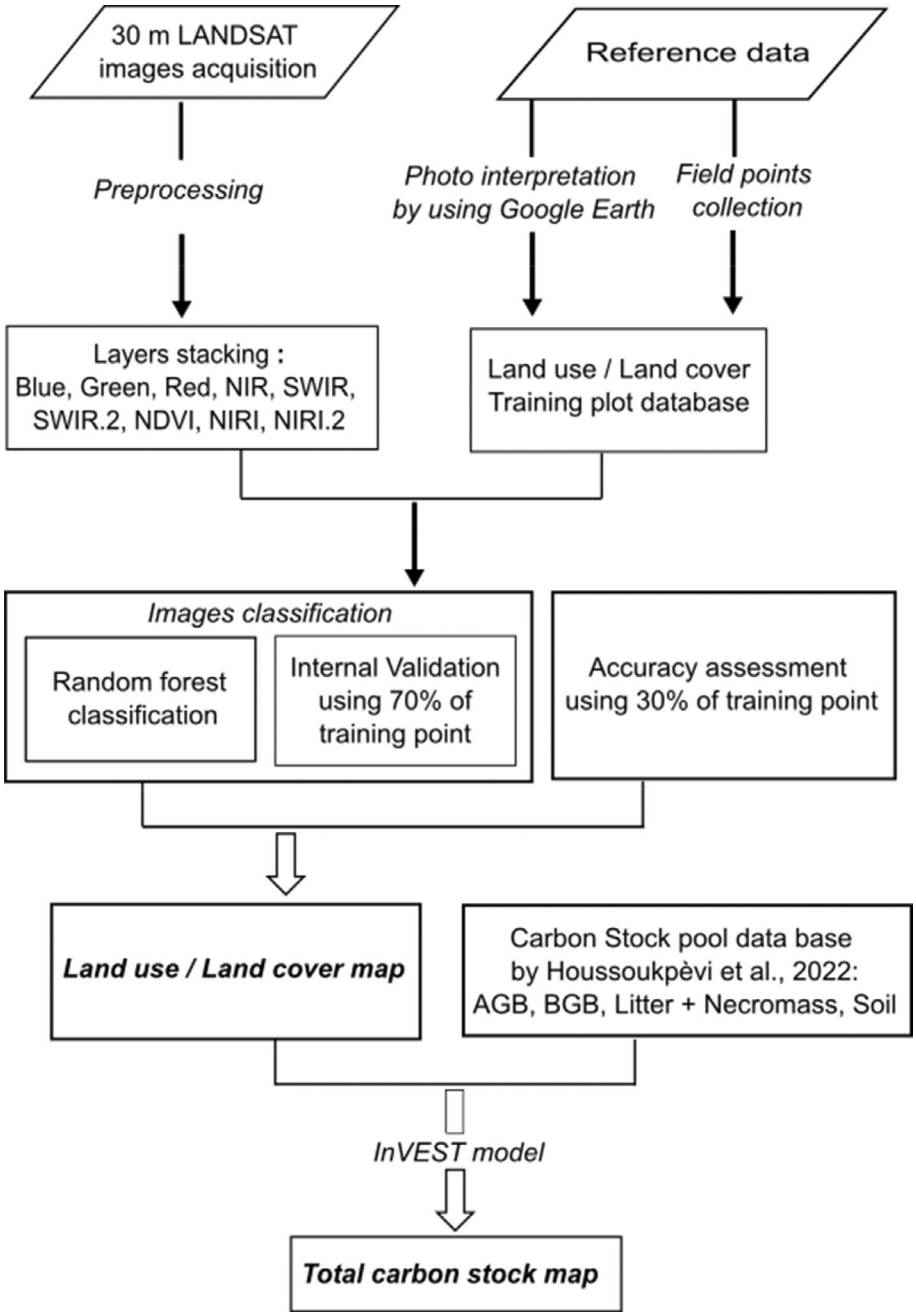

FIGURE 3 Flowchart of the steps followed to obtain the maps

TABLE 3 Carbon stock (Mg C ha^{-1}, mean ± standard deviation) of the four pools in the land use (excluding BA) (from Houssoukpèvi et al., 2022)

Land cover	Aboveground biomass	Belowground biomass	Litter+ Necromass	Soil (0–30 cm)	Total
Forests (FO)	225 ± 43.53	54 ± 11	28 ± 5.1	43 ± 1.9	350 ± 45
Tree plantations (PL)	113 ± 26.71	27 ± 6.41	16 ± 3.3	31 ± 1.2	187 ± 28
Adult palm groves (PA)	63 ± 4.43	15 ± 1.06	11 ± 0.8	23 ± 1.1	112 ± 5
Crop-plantation associations (CP)	39 ± 0.87	9 ± 0.21	2 ± 0.2	23 ± 1.3	73 ± 2
Croplands (CL)	0	0	1 ± 0.2	31 ± 2.8	32 ± 3

each of the two classifications. From this confusion matrix, the user accuracy, producer accuracy, and overall accuracy of the classification were calculated. In addition, a non-parametric kappa test was also performed to measure the accuracy of the classification. Kappa value usually ranges between 0% and 100%. The classification is considered satisfactory from 70% to 100% (Lillesand et al., 2015). The confusion

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matrix was also used to calculate the errors related to the estimated areas (Equation 3) of the different land use based on a 95% confidence interval (Olofsson et al., 2014).

$$S = 1.96 \times A_i \times \sqrt{\sum W_i^2 \times \frac{\frac{n_{ik}}{n_{i.}}\left(1 - \frac{n_{ik}}{n_{i.}}\right)}{n_{i.} - 1}}, \quad (3)$$

Where: S is the error associated to the estimation of the area with 95% of confidence, A_i is the area of the land class i, W_i the proportion area of classification for the land class i, n_{ik} the number of samples at cell (i, k) of the confusion matrix, and $n_{i.}$ the sum of the samples classified as land class i in the confusion matrix.

The classification and processing of the images were done using the open-source software R (version 3.6.3; package *caret* and *RandomForest*) and Quantum GIS (QGIS 3.18.2). The transition matrix was obtained using the MOLUSCE (modules for land use change evaluation) plugin of QGIS (Asia Air Survey & Next GIS, 2012). This matrix was used to analyse the changes in land use between 2000 and 2018.

2.4.2 | Evaluation of the C stocks uncertainty

For each land use, the uncertainty in the C stocks was obtained by combining the standard deviations around the mean of the measured C stocks (Houssoukpèvi et al., 2022) and the errors related to the estimation of the land use area (Olofsson et al., 2014). These combinations were realized using the error propagation (IPCC Tier 1) as advised in international guidelines (GOFC-GOLD, 2016; IPCC, 2006). This method is based on two equations: one for addition and subtraction used to add the different C pools and compare C stocks between two dates (Equation 4), and one for multiplication used to estimate the C stock of a specific land use (Equation 5).

$$U_{\text{total}} = \frac{\sqrt{(U_1 * x_1)^2 + (U_2 * x_2)^2 + \ldots + (U_n * x_n)2}}{|x_1 + x_2 + \ldots + x_n|}, \quad (4)$$

Where: x_i referred to the value of the variables (e.g., the C stocks of one specific C pool), U_i referred to percentage uncertainty associated with each of the variables x_i (i.e., standard deviation/mean) and U_{total} referred to the percentage uncertainty associated with the sum of the variables x_i.

$$U_{\text{total}} = \sqrt{U_1{}^2 + U_2{}^2 + \ldots + U_n{}^2}, \quad (5)$$

Where: U_{total} is the percentage uncertainty associated with the product of the variables and U_i is the percentage uncertainty associated with each of the variable (i.e., C stocks per area of a specific land use multiplied by its corresponding surface area).

Then the accuracy of the C stock maps and the calculated C stock values per land use or per C pools for the whole studied area (Table 5) depend on the accuracy of the land cover maps (assessed in Section 2.2.3, Table 4), and the accuracy of the measured C stock data (Table 3). No external validation or cross-validation to validate the C stock maps were performed, because we assumed that the accuracy of the C stock map mostly depend on the accuracy of the land cover maps, which is already evaluated by cross-validation.

3 | RESULTS

3.1 | Ferralsols land use/land cover classification in 2000 and 2018

The land cover maps generated from the supervised classification of satellite images for the study years 2000 and 2018 are presented in Figure 4. The error matrix shows an overall accuracy and *Kappa* statistics of 82% and 78% (Appendix B) for 2000 and 87% and 84% for 2018 (Appendix C) respectively. All values were above the minimum requirement (70%) for a satisfactory classification. However, in the classification of the 2000 image, the land use crop-plantation associations has low producer and user accuracies (Appendix B). Some confusions in pixel allocation were possible between crop-plantation associations and other land uses. In the classification of the 2018 image, these confusions are mainly identified between forests and adult palm groves land uses (Appendix C). The lowest producer accuracy was obtained for tree plantations and the lowest user accuracy for the forests land uses.

The mapping of land use in 2000 showed that croplands, crop-plantation associations, and adult palm groves were the dominant land uses of the Ferralsols on the Allada Plateau (Table 4). These land uses cover 48,774 ± 1394 ha (46% of the 106,221 ha apprehended), 36,234 ± 1078 ha (34%) and 8149 ± 254 ha (8%) respectively. In 2018, the dominant land use was still croplands, with a development of the areas occupied by adult palm groves, tree plantations, and built-up areas covering 50,703 ± 1018 ha (48%), 19,106 ± 389 ha (18%), 12,511 ± 220 ha (12%), and 12,395 ± 131 ha (12%) respectively (Table 4). It should be noted that the uncertainty in the estimated areas of land use varied from 1% to 3% for the year 2000 image and from 1% to 2% for the year 2018 image (Table 4).

3.2 | Land use dynamics (2000–2018)

Examination of land use changes over the period 2000–2018 revealed a significant increase in built-up areas, adult palm groves, and tree plantations, with a consequent decrease in forests and crop-plantation associations (Table 4). In general, all land uses except croplands have experienced a significant overall rate of change. Some land uses have experienced a significant increase in area. This is especially the case for tree plantations with an increase of +115% (+6692 ha), adult palm groves by +134% (+10,957 ha) and built-up areas by +207% (+8356 ha). On the contrary, crop-plantation associations and forests decreased in area, respectively, −70% (−25,340 ha) and − 81% (−2595 ha). However, the annual rate of change was low (Table 4).

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TABLE 4 Areas represented by land use (in ha, estimated area ± standard error, and as % of area occupied by Ferralsols) in 2000 and 2018

Land cover	2000		2018		Global rate of change (%)	Annual rate of change (%)
	Area (ha)	Area (%)	Area (ha)	Area (%)		
Built-up areas (BA)	4039 ± 58	4	12,395 ± 131	11	207	6
Forests (FO)	3206 ± 96	3	612 ± 11	1	−81	−9
Tree plantations (PL)	5819 ± 83	5	12,511 ± 220	12	115	4
Adult palm groves (PA)	8149 ± 254	8	19,106 ± 389	18	134	5
Crop-plantation associations (CP)	36,234 ± 1078	34	10,894 ± 123	10	−70	−7
Croplands (CL)	48,774 ± 1394	46	50,703 ± 1018	48	4	1
Total	106,221	100	106,221	100		

TABLE 5 Distribution of the stock of C (gg C) in the various pools and all pools combined (total stock) according to the land use of Ferralsols for the years 2000 and 2018 for the whole study area

Land use	Aboveground biomass		Belowground biomass		Litter + woody necromass		Soil (0–30 cm)		Total stock	
	2000	2018	2000	2018	2000	2018	2000	2018	2000	2018
Forests (FO)	721 (20)[a]	138 (19)	173 (21)	33 (20)	90 (18)	17 (18)	138 (5)	26 (5)	1122 (13)	214 (13)
Tree plantations (PL)	658 (24)	1414 (24)	157 (24)	338 (24)	93 (21)	200 (21)	180 (4)	388 (4)	1088 (15)	2340 (15)
Adult palm groves (PA)	513 (8)	1204 (7)	122 (8)	287 (7)	90 (8)	210 (8)	187 (6)	439 (5)	913 (5)	2140 (5)
Crop-plantation associations (CP)	1413 (4)	425 (3)	326 (4)	98 (3)	72 (10)	22 (10)	833 (6)	251 (6)	2645 (4)	795 (2)
Croplands (CL)	0 (3)	0 (2)	0 (3)	0 (2)	49 (20)	51 (20)	1512 (9)	1572 (9)	1561 (9)	1622 (9)
Total stocks	3305 (7)	3180 (11)	779 (7)	755 (11)	394 (7)	500 (7)	2851 (5)	2676 (6)	7329 (4)	7111 (6)
Δ Stocks	−125 (6)		−24 (6)		106 (6)		−175 (6)		−218 (4)	

[a]Values in brackets are the percentage uncertainty (%) of C stock values.

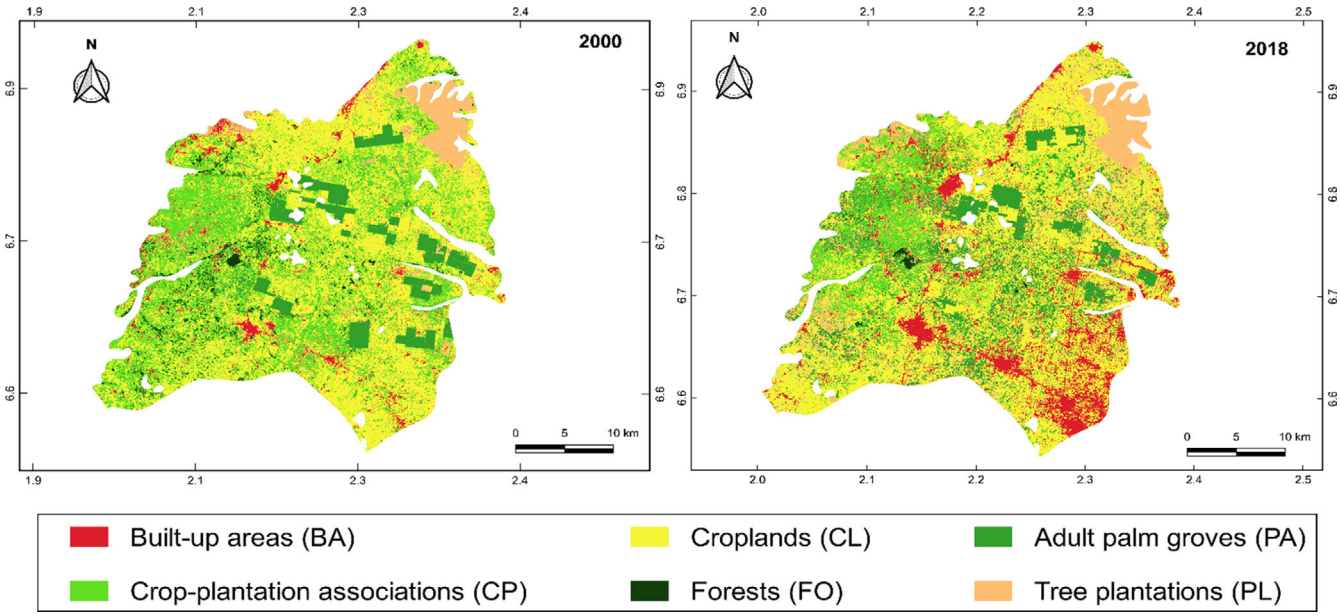

FIGURE 4 The classified maps of Ferralsol occupation in the study area in 2000 (left) and 2018 (right) [Colour figure can be viewed at wileyonlinelibrary.com]

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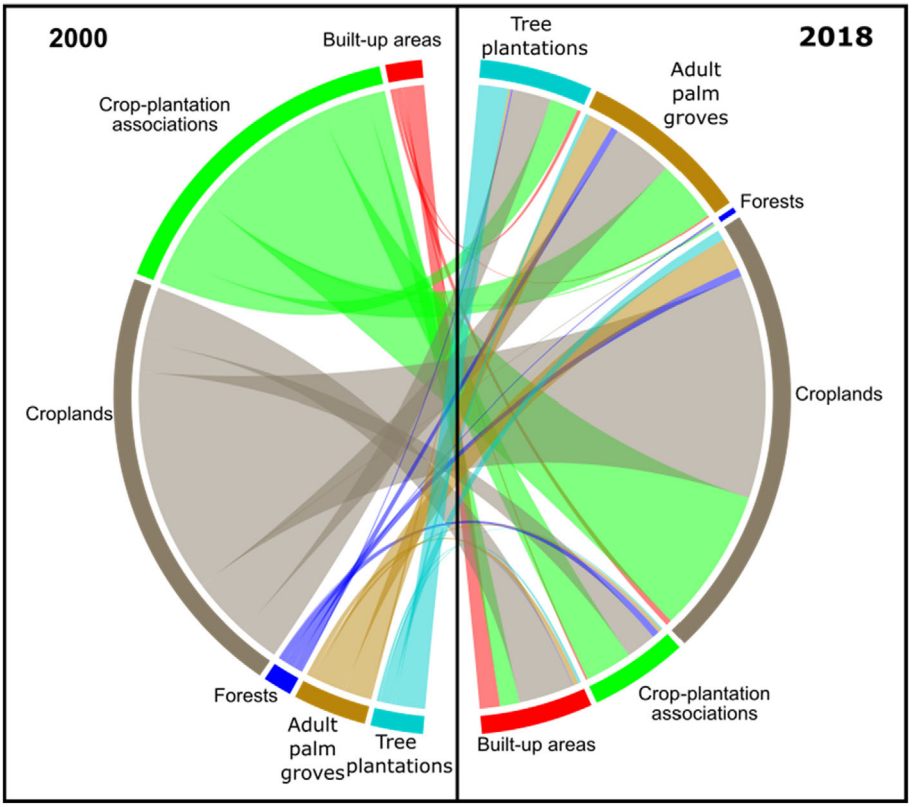

FIGURE 5 Chord diagram showing the conversion of land area in terms of land use over the period 2000–2018. [Colour figure can be viewed at wileyonlinelibrary.com]

Built-up areas, adult palm groves, and tree plantations increased annually by 6%, 5%, and 4% respectively. In contrast, forests and crop-plantation associations lost 9% and 7% of their area annually.

The transition matrix analysis (Appendix D) indicates that 61% of the total area has been affected by the land use change between 2000 and 2018 in the study area. The changes in land use are mainly observable on a myriad of small areas represented by few pixels (Figure 4). Land uses on large plots (e.g., state tree plantations and palm groves under the management of rural development cooperatives) were less modified (Figure 4).

A chord diagram shows the transfers of area from one land use to another between 2000 and 2018 (Figure 5). Croplands were the land use which were most transformed into built-up areas. As a result, croplands gained on forests and on crop-plantation associations' areas. At the same time, some area of crop-plantation associations has been significantly transformed into adult palm groves and croplands. Forests area has been reduced in favour of adult palm groves, croplands, and crop-plantation associations. The increase in the area of tree plantations was mainly due to the conversion of croplands and crop-plantation associations between 2000 and 2018. The conversion of a small area of built-up area into tree plantations, adult palm groves and croplands could more likely be explained by classification errors (Appendices B and C).

3.3 | Evolution of the C stocks distribution among the land uses

The total C stock map was presented in Figure 6. The total C stock of the Allada Plateau slightly decreased, about 3%, between 2000 and 2018 (7329 cf 7111 Gg C) (Table 5). The distribution of total C stocks of the Plateau showed that the smallest C reservoir of the area are respectively adult palm groves and forests in 2000 and 2018 (Table 5). In 2000, the total C stock of the area is mainly distributed in the crop-plantation associations and in croplands accounting for, respectively, 36% and 21% of the total C stock considering the Ferralsols occupation of the Allada Plateau. In 2018, due to changes in land use since 2000, the total C stock of the area is mainly distributed in the tree plantations and adult palm groves (33% and 30% of the total C stock respectively).

As a result of the decrease in the area of forests and crop-plantation associations, the total C stocks of these land uses, respectively, decreased of −908 and −1850 Gg C (Tables 4 and 5). In contrast, due to the increase in the area of tree plantations, adult palm groves, and croplands, 1252, 1227, and 61 Gg of extra C were respectively stored in these land uses in 2018 in the study area. However, the uncertainties associated with the calculated C stocks for each land use ranged between 2% and 15%. The uncertainties associated with the total C stocks in 2000 (7329 Gg C) and 2018 (7111 Gg C) were 4% and 6% respectively (Table 5).

3.4 | Evolution of the C stocks distribution among the different C pools

The distribution of C stocks in the different pools shows that the most important C pools are the aboveground biomass and the soil (0–30 cm). These two pools represent, respectively, 45% and 39% of the total C stock in the considered area in 2000 and 45% and 37% in 2018 (Table 5).

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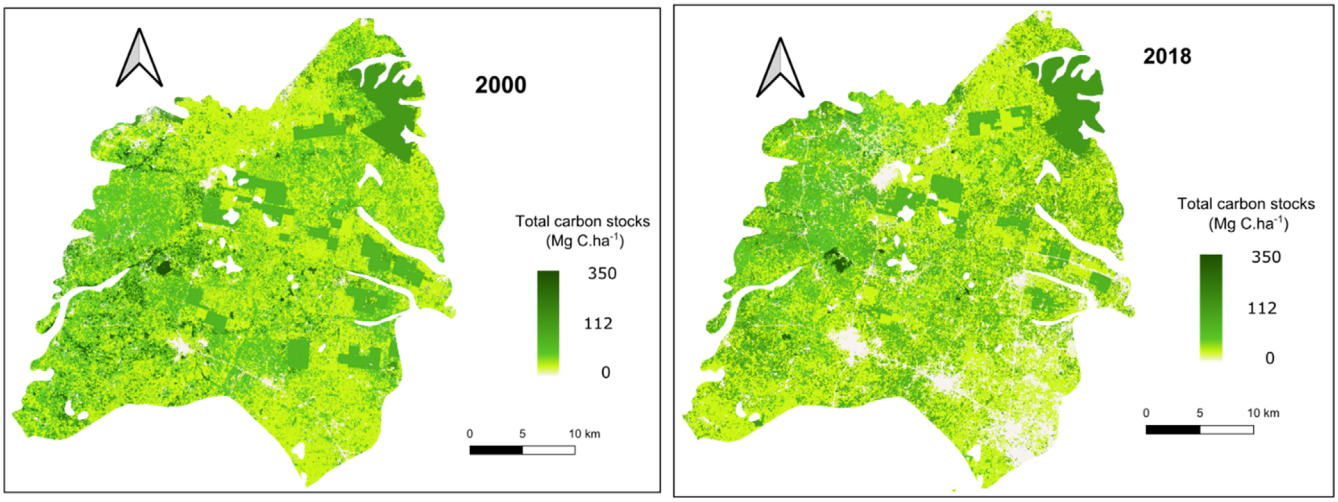

FIGURE 6 Map of total carbon stocks in the study area in 2000 and 2018 (spatial resolution: 30 m). [Colour figure can be viewed at wileyonlinelibrary.com]

From 2000 to 2018, only the C stocks contained in litter and deadwood have increased (Table 5). This increase is estimated at +106 Gg C with an uncertainty of 6% (Table 5). The other pools of C have decreased overall over the 18-year period (Table 5). The greatest losses were observed in the soil (−175 Gg C) and aboveground biomass (−125 Gg C) with 6% uncertainty around these calculated values. The C stock balance of areas on Ferralsols from 2000 to 2018 is slightly negative (Table 5). It is estimated at - 218 Gg C, that is, about 2 Mg C ha^{-1} globally over the whole region, with an uncertainty of 4%. However, if the surface of built-up areas is excluded from the calculation, since the C stocks of built-up areas were considered to be null, the average C stocks per hectare of the total C stocks are 71 and 76 Mg C ha^{-1}, respectively, for the year 2000 and 2018. There would therefore be a positive trend in C stock of +5 Mg C ha^{-1} in the non-built-up areas of areas on Ferralsols of the Allada plateau.

4 | DISCUSSION

4.1 | Land use classification and changes analysis

The Ferralsols occupy 106,221 ha on the Allada Plateau. Land use change of this area was dynamic between 2000 and 2018, with 61% of the surfaces modified (Appendix D). This change particularly affected small private plots rather than large state or cooperatives plantations (Figure 3). This dynamic was also characterized by a significant extension of built-up areas (207%), adult palm groves (134%), and tree plantations (115%) to the detriment of forests (−81%) and crop-plantation associations (−70%). These results are in line with other observations made throughout the country (Brun et al., 2018; Guidigan et al., 2018; MCVDD, 2017; Tchibozo, 2020). From 2000 to 2018, the annual loss of forest area is estimated at 90,000 ha at the national scale, resulting in an overall change of 27% (FAO, 2020). Most research on land use dynamics pointed to agriculture as the main driver of land degradation and deforestation (Guidigan et al., 2018; Olorunfemi et al., 2018). However, in our study, only a slight increase in the area of the land use type 'croplands' was recorded (+1929 ha). This can be explained by the reforestation actions of the Beninese Government to compensate as soon as possible for the loss of forest formations. Forest plantations were carried out, both by the national authorities and by farmers. In 2018, they cover a total area of 20,000 ha nationwide (FAO, 2020) with teak (*Tectona grandis* L.f.) and gmelina (*Gmelina arborea Roxb*) as the main species (Akouehou et al., 2013; Aoudji et al., 2014; Atindogbé et al., 2013). The state-owned teak plantations have difficulty ensuring the high demand for service wood (furniture making, carpentry, etc.) (Atindogbé et al., 2013). Therefore, many farmers invest in tree plantation, for example, teak plantation, to diversify and improve their incomes and/or secure their land (Aoudji et al., 2014). Increase in the surface area of smallholder teak and gmelina plantations can be observed on the Allada Plateau (+6692 ha) on small-sized plots (Figure 4). In the study area, the agriculture or tree plantation plots of smallholders are comprised between 0.25 and 1.5 ha, and the private palm groves areas are less than 5 ha (Aholoukpè et al., 2013; Aoudji et al., 2012). This increase in tree plantation surface areas is also associated with a strong increase in surface under oil palm plantations, that is, the land use of 'adult palm groves'(+10,957 ha, Figure 5).

The decrease in 2018 of crops-plantation association is explained by the fact that a large part of this land use is left under croplands (Figure 5). The decrease is probably also linked to the increase of oil palm plantations (Figure 5). The land use named 'crop-plantation associations' is dominated by a temporary oil palm agroforestry system. In the south of Benin, and particularly on the Allada Plateau, the landscape is dotted with oil palm trees, often family-owned. These oil palm trees have a particular life cycle (Akouehou et al., 2013). Oil palm plantation cycles last from 15 to 25 years (Aholoukpè, 2013). On smallholder farms, the first three years are often grown in association with annual or bi-annual crops (e.g., cassava, tomatoes, pineapple,

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maize) (Aholoukpè et al., 2013; Koussihouèdé et al., 2019; Nchanji et al., 2016). This temporary agroforestry system is motivated by the lack of arable land for family agriculture less than 5 ha and by the cost of maintaining the palm trees, which yield nothing in their first few years (Koussihouèdé et al., 2019). The large area of crop-plantation associations land use in 2000 is composed by these temporary oil palm agroforestry system. The large area is partly the result of the successful distribution of selected planting material in rural areas in the 1990s as part of a government programme supporting palm oil production after the decline of state plantations (Adje & Adjadi, 2001). It is also explained by the social, cultural, and cultic importance of this plant for the local population. In this region, a farmer's wealth is measured by his holdings of palm trees (Akouehou et al., 2013). The decrease in the area of crop-plantation associations and the strong increase of adult palm groves land uses in 2018 compared to 2000 can be explained by the age of the young palm groves installed 20 years ago and in association with crops only during the first years, that is, in their immature stage.

The sharp increase in built-up areas is due to the increase in population density requiring the development of housing, administrative, and road infrastructures (Brun et al., 2018; Tchibozo, 2020). Benin's population increased from 6.7 million in 2002 to 10.6 million in 2015 (INSAE, 2015). Based on the last population census, the population density of the Atlantic epartment, where the Allada Plateau is located, close to the Cotonou and its agglomeration, increased from 225 inhabitants km^{-2} in 2000 to 316 inhabitants km^{-2} in 2015 (INSAE, 2015).

4.2 | The carbon stocks and carbon stock changes between 2000 and 2018

The land use on the Ferralsols of the Allada Plateau affected the C stocks of the four pools considered. At the plot scale, C was mainly located in the aboveground biomass of forests, tree plantations, adult palm groves, and crop-plantation associations. In the same way, the variation in C stock per hectare between land uses was mainly explained by large variations in the aboveground biomass (Houssoukpèvi et al., 2022, Table 3). The sandy soils of the study area store small amounts of C, unlike the biomass of forest and tree plantation ecosystems (Logah et al., 2020; Olorunfemi et al., 2020). By consequence at the landscape scale C stock was mainly located in biomass (45%). Nevertheless, the upper (0–30 cm) layer of soils accounted for 37%–39% of the total C stock because croplands surface represented about 50% of the surface of the area and did not account for biomass C.

The land use change between 2000 and 2018 modified the distribution of the C stocks from the forest to the plantations, as forest areas decreased and tree plantations and palm groves plantations increased (Figure 5). The land use change modified slightly the distribution of the C in the different carbon pools. All the C pools were affected by land uses except the litter + woody necromass, thanks to the installation of adult palm groves areas and tree plantations on croplands, or due to the growth of the palm groves from the crop-plantation association. Litter in these land uses contained per hectare less C than in forest (Table 3), but these land uses represented much higher surface in the area. Because 50% of the surface is used for croplands and do not present C biomass, the variation of C stocks of the region between 2000 and 2018 was quite similar in both the soil and the aboveground biomass pools. The C stock variations were, respectively, −175 and −125 Gg C for the soil and aboveground biomass pools (Table 5). The decrease of biomass C stocks is attributed to a significant decrease in the area of forests. However, accounting only for C losses in the biomass would strongly underestimate the overall C stock losses in the region. Our results illustrate the need to measure or at least to estimate all C pools to have accurate estimation of C balance.

Our study estimated that between 2000 and 2018, the change in total C stocks in the study area tend to be slightly negative (− 218 Gg C) and was estimated to be 3%. This result is surprising as the land use changes concern 61% of the surface of the study area. The strong decrease in forest area (−2594 ha), that is, the land use with the highest C stocks in all pools compared to other land uses (Table 3), was the main cause of this C stock decrease. This result confirms that the loss of C stocks was due to land use conversion and in particular to the decrease in woody cover as observed in other studies (MCVDD, 2017; Woomer et al., 2004; Zhang et al., 2017). However, the decrease of C stocks is slight and if built-up areas are excluded of the calculation, the mean C stock showed a positive trend with a mean gain of 5 Mg C ha^{-1}. This can be explained by the large increase in the area of plantations (+6692 ha) and adult palm groves (+10,957 ha). The high aboveground biomass of these land uses with the large increase of the area dedicated to them, have been able to compensate for the loss of woody forest cover. State efforts in promoting the expansion of tree plantations and palm groves (Adje & Adjadi, 2001; Ganglo et al., 1999) have minimized C losses through the C stock of biomass, litter, and soil at a regional scale. Nevertheless, to secure the C stocks, the lifetime of wood harvested for supply services (carpentry, furniture, poles, etc.) should be considered in the long term.

4.3 | Accuracy of the estimated C stocks

The estimated C stocks at each date present uncertainties between 4% and 15% depending on the C pools, the land use or the date considered. These uncertainties are linked to (i) the heterogeneity of agricultural or forestry practices for a given land use and (ii) the errors in attributing areas to different land uses (GOFC-GOLD, 2016; IPCC, 2006; Olofsson et al., 2014). To ensure the representativeness of C stocks, a diversity of vegetation cover, and management practices were measured in each land use type (Houssoukpèvi et al., 2022). For example, state plantations of different ages (last cut 5 years ago and 21 years ago) and private teak and gmelina plantations (last cut 10 years ago and 5 years ago, respectively) were measured to represent C stocks in tree plantations and presented biomass C stocks from 55 to 295 Mg C ha^{-1}. It seems difficult to distinguish

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such heterogeneities on satellite images, but field surveys and monitoring with a higher sampling pressure could help to characterize the distribution of C stocks according to different vegetation cover or management practices inside a given land use, that is, by age, type of plantation, or cultivation. Also, the methodology used for land use mapping leads to area errors which could be counted twice, once per date, and explains part of the uncertainty. The classical diachronic analysis of land use change 'wall to wall' involved a pair-wise comparison of images (Houessou et al., 2013; Padonou et al., 2017). Individual errors on both the 2000 and the 2018 maps were accounted twice when estimating the land use change. The weak distinction between two land uses detailed in the confusion matrices, for example, in the 2000 map between crop-plantation associations and croplands or in the 2018 map between forests and adult palm groves, could be an individual error that can be considered as a change of cover from 1 year to the next (Fuller et al., 2003).

These errors in the land use change are recognized to be the main source of error in the carbon emission estimates (Harris et al., 2012; Pelletier et al., 2011). Improvements could be to use a supervised classification of several stacked satellite images acquired at different dates in a single analysis in order to directly identify changes (Grinand et al., 2013). Training data for the classification algorithm were not land uses but land use changes. This approach of the land use changes could be associated to long term monitoring of diachronic studies of C stocks. This method would reduce uncertainty but was not usable in our studied area due to the lack of data and knowledge on accurate localized land use changes on the Allada Plateau. Obtaining such information is challenging because precise historical land use changes are not well known or referenced in Benin yet. An improvement in the classification of land use patterns could also be envisaged by using high-resolution satellite images such as PLEIADES images (resolution 0.5 m per pixel).

Improvements in estimation of the C stocks evolution could also be suggested. The method we used imposes a strong assumption: the non-variation of C stocks of the pools (living, dead, litter, and soil biomass) if the land use pattern is unchanged. Thus, the study assumes that there has been no major change in forest vegetation structure, no forest degradation, no increase in plantation biomass, no change in the age structure of plantations, and no alteration of soils under cultivation. However, between 2000 and 2018, it is possible that changes in climate or in forest and crop management practices have altered soil or vegetation C stocks (including through C fluxes between pools). Future research should take these possible C stock variations into account, thanks to diachronic monitoring of C stocks over the long term. Finally, the study made the strong assumption that the C stock in built-up areas was negligible. The recent inclusion of urban parks and trees in cities, notably through green cities programmes, could significantly improve regional C balances. Given the high level of urbanization observed (+207% in 18 years in this study, Table 4), inventories of urban C stocks are necessary even in rural regions and in Africa, as is currently being done in large Northern cities (Cambou et al., 2018).

5 | CONCLUSIONS

The agricultural area of the Allada Plateau at the proximity of the economic capital of Benin experienced multiple changes in land use on small private plots as a result of human activities: 61% of the total area has undergone a land use change between 2000 and 2018. The expansion of built-up areas, tree, and palm plantations were particularly notable with a decrease in forest surface area. This strong dynamic of land use, and particularly the increase of tree plantations and adult palm groves, led to a small loss of C stock (≈3%) mainly in soil and aboveground biomass pools. Our results confirm the need to account for soil C, even in sandy areas, as responsible for non-negligible C stock variations. Our results should contribute to help planning and monitoring carbon stocks at the landscape level in climate mitigation effort plans. For instance, urgently secure the small remaining forested areas, because forest represent only 1% of the total surface of the studied area but still stored 3% of the total C; encourage plantations, as these could limit the loss of C stocks while improving the socio-economic conditions of the smallholders, and save land from urbanization. However, it is important to carry out interdisciplinary research on different services provided by the different land use on the Allada Plateau (food, energy, habitat, and biodiversity) and not only focused on C stocks. In addition, the uncertainties in the C stocks, between 4% and 15%, and the assumptions in this study encourage future research to be developed. To improve studies on the evolution of C stocks from local to national scales, long term field studies in rural areas as well as in the cities, characterization studies on the forestry and agricultural practices affecting soil C pools and stocks, studies on the history of the area, and the development of calibration and validation of satellite images methods should be performed.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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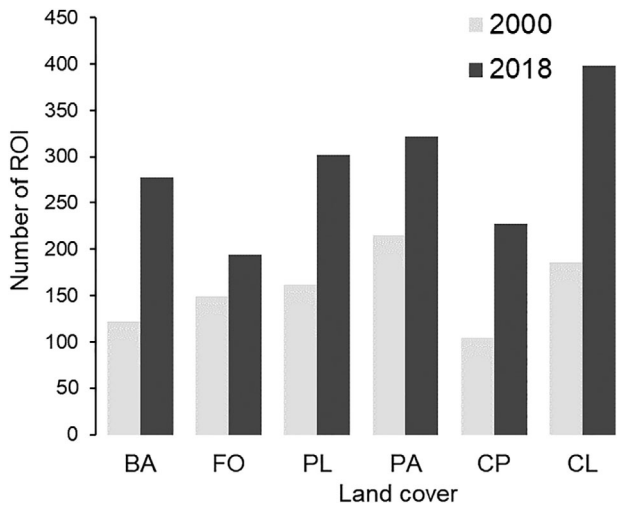
APPENDIX A: Total number of points of interest used on the Google Earth 2005 and 2017 images for the classification of the respective LANDSAT images of 2000 and 2018



BA, built-up area; CL, croplands; CP, crop-plantation associations; FO, forests; PA, adult palm groves; PL, tree plantations

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APPENDIX B: Confusion matrix from the 2000 image classification

	Ground truth							Producer accuracy	User accuracy
Classification	BA	CP	CL	FO	PA	PL	Total	%	
BA	33	0	1	0	0	1	35	92	94
CP	1	19	7	2	1	0	30	61	63
CL	1	7	45	0	0	1	54	82	83
FO	0	3	1	35	12	0	51	80	69
PA	0	2	0	7	51	1	61	80	84
PL	1	0	1	0	0	45	47	94	96
Total	36	31	55	44	64	48	278		

Note: Out-of-bag error (OOB) = 17.7%; Overall accuracy = 82%; *Kappa* Index = 0.78.
Abbreviations: BA, built-up area; CP, crop-plantation associations; CL, croplands; FO, forests; PA, adult palm groves; PL, tree plantations.

APPENDIX C: Confusion matrix from the 2018 image classification

	Ground truth							Producer accuracy	User accuracy
Classification	BA	CP	CL	FO	PA	PL	Total	%	
BA	79	0	3	0	0	1	83	95	95
CP	0	68	2	1	2	0	73	97	93
CL	2	1	105	0	1	12	121	88	87
FO	0	1	0	49	13	3	66	84	74
PA	0	0	5	7	78	3	93	81	84
PL	2	0	4	1	2	71	80	79	89
Total	83	70	119	58	96	90	516		

Note: Out-of-bag error (OOB) = 13.8%; Overall accuracy = 87%; *Kappa* Index = 0.84.
Abbreviations: BA, built-up area; CP, crop-plantation associations; CL, croplands; FO, forests; PA, adult palm groves; PL, tree plantations.

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APPENDIX D: Transitions between the main lain use between 2000 and 2018 in the study area

Land cover 2000–2018	BA	CP	CL	FO	PA	PL	Total (ha)	Area with change of occupation	
								Area (ha)	Area (%)
BA	2423[a]	224	711	11	219	451	4039	1616	2
CP	2320	5600[a]	17,259	236	7425	3394	36,234	30,634	29
CL	6586	3588	26,681[a]	132	7185	4602	48,774	22,093	21
FO	76	855	1047	184[a]	852	192	3206	3022	3
PA	667	435	3764	30	2957[a]	296	8149	5192	5
PL	323	192	1241	19	468	3576[a]	5819	2243	2
Total (ha)	12,395	10,894	50,703	612	19,106	12,511	106,221	64,800	61

Abbreviations: BA, built-up area; CP, crop-plantation associations; CL, croplands; FO, forests; PA, adult palm groves; PL, tree plantations.

[a] Represent the permanence of the land use type.

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