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Research Article

CO2 EMISSIONS FROM LAND USE/COVER CHANGE IN OUAGADOUGOU MUNICIPALITY, BURKINA FASO

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ABSTRACT. This study was conducted to quantify carbon dioxide (CO_2) emission from land use/cover (LULC) change in the municipality of Ouagadougou in Burkina Faso. Historical LULC maps were obtained from Random Forest classification of cloud free Landsat TM image of 1990 and OLI image of 2022 in Google Earth Engine platform. Field measurements were carried out to estimate the aboveground carbon stock of different LULC types using an allometric equation. The LULC change and the carbon stock data were integrated to quantify CO_2 emission using the IPCC method. The results showed that, between 1990 and 2022, the municipality of Ouagadougou was characterized by built-up and cropland expansions at the detriment of the savanna vegetation. Built-up area increased from 5.75% to 52% of the study area and cropland from 14.47% to 24.74%. At the same time, tree savanna and shrub savanna reduced from 58.64% to 11.66% and from 20.44% to 10.96% respectively. The highest mean carbon stock was recorded in tree savanna (36 ± 4.5 tC/ha), followed by shrub savanna (21.9 ± 6.1 tC/ha) and cropland (18 ±3.3). The change in LULC caused more emission of CO_2 (2630490.96 ±0.74% tCO2e) than absorption (207867.93 ± 0.67% tCO2e). The expansion of built-up appeared as the main source of CO_2 emission (83.65% of total emission) from LULC change. CO_2 absorption is mainly driven by the conversions to tree savanna (85.13% of total absorption), particularly the conversion of shrub savanna to tree savanna (63.07%) that released 131111.20 ± 0.28 tCO2e into the atmosphere. The findings of this study can be used to address sustainable land use planning in Ouagadougou, since they highlight the issue of land use planning and call for mainstreaming climate change adaptation into the city's master plan or land use policies.

Keywords: *Aboveground carbon stock, CO2 emission, LULC change, Ouagadougou, Burkina Faso*

INTRODUCTION

Climate change is a global phenomenon with worldwide impacts. It is defined as "a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer [1]. Climate change can be due to natural internal processes or external forcings (e.g., modulations of the solar cycles, volcanic eruptions) and persistent anthropogenic changes in the composition of the atmosphere or in land use [1].

As many other places, cities and urban areas are not spared from climate change. Cities and urban areas are home for about 4.2 billion people [2]. By 2050 about 0.6 to 1.3 million km^2 of land will be under urban areas and the world's total urban population will reach 6.7 billion [3]. The Second Assessment Report on Climate Change and Cities (ARC3.2) showed key facts of climate change in cities. According to the ARC3.2, temperatures are rising in cities around the world due to both climate change and the urban heat island effect [4]. For example, an increase of mean annual temperatures was observed in 39 ARC3.2 cities at a rate of 0.12 to 0.45°C per decade over the 1961-2010 period. Moreover, mean annual temperatures are projected to increase by 1.3 to 3.0°C by the 2050s, and 1.7 to 4.9°C by the 2080s in the 100 ARC3.2 cities around the world [4]. Furthermore, in the 100 ARC3.2 cities, mean annual precipitation is expected to change by -9 to +15% and -11 to +21% by the 2050s and the 2080s respectively [4]. As consequences of changes in climate parameters trends, cities are facing the impacts of sea levels rising, extreme weather events like floods, droughts, storms and heatwaves. These climate change related hazards have increased in all cities and urban areas worldwide [5]. For instance, according to [6], about 200 million people from 250 cities have experienced extreme heat conditions, and 1.6 billion people living in 950 cities will be probably exposed to extreme summer temperatures by 2050. All these climate change related hazards have costly impacts on infrastructure, housing, basic services, human livelihoods and health across cities.

Geographically, the impacts of climate change are mainly felt in regions where economies are highly dependent on natural resources, such as West Africa [7] which has been found as a hotspot of exposure and vulnerability to climate risks [8]. Thus, cities, in this part of the world, are particularly more vulnerable to climate change and suffer more severely than cities in developed countries, partly because of inadequate basic services and infrastructure [5]. The impacts of climate change are going to increase, since it is predicted greater exposure to climate change–related hazards by 2030–40 for cities in low-income countries, such as those in West Africa [5]. At the same time, cities contribute to climate change, as urban activities are important sources of greenhouse gas emissions into the atmosphere. According to the World Bank's Climate Change Action (2021-2025), cities generate over 70% of global carbon dioxide (CO_2) emission [9]. In West African cities, land use dynamics is one of the key driving factors contributing to CO2 emission. In those cities, land use dynamics is mainly characterized by the horizontal development of built-up areas, among others, driven by the demographic explosion, the lack of city extension policies or the inadequate implementation of master plans [10]. The observed land use/cover (LULC) change in the landscape of West African cities occur at the detriment of forest cover, leading to the loss of aboveground carbon stock and the release of CO_2 into the atmosphere. Indeed, forests, through their biomass, store an important amount of carbon. So, when forest cover is converted into land use type, it emits its carbon into the atmosphere as CO_2. In general, the loss of cities' vegetation cover affects the local climate by altering the fluxes of energy, water, and greenhouse gases between the land and the atmosphere [5].

Urban LULC change analysis has drawn the attention of several researchers worldwide [11, 12, 13, 14]. However, the existing studies on CO_2 emission from urban LULC change focused mainly on developing countries 'cities [15, 16]. In West Africa, despite the rich literature on urban areas [10, 11, 17], the emission of CO_2 from urban LULC change remains poorly documented. Researchers have rather paid attention to the spatiotemporal dynamics of urban land use and agreed on a built-up expansion at the detriment of vegetation cover [10, 11]. There is therefore a need to fill this gap by adopting a comprehensive method to estimate CO_2 emission from urban LULC dynamics.

Different methods were applied in literature to quantify CO_2 emission from LULC change. Modeling approaches have been applied to explore CO_2 emission from urban land use, such as machine learning models [18,19, 20], PLUS model [21] and STIRPAT model combined with spatial adaptive semi-parametric model [22]. Others combined remote sensing derived LULC change maps with carbon density data obtained from forest inventories [15, 23, 24].

Similar to the other West African cities, the municipality of Ouagadougou, in Burkina Faso, is facing rapid urbanization due to the increasing demand for land and the unplanned development [11]. Consequently, there is a rapid LULC change in the city expressed by sprawling of built-up area replacing the natural vegetation cover and aggravating the inhabitants vulnerable to climate risks and environmental threats, such as flooding and the urban heat island effect [11]. There is therefore a need to quantify the emission of CO_2 driven by the LULC change in the municipality of Ouagadougou. Such information is critical to build a more resilient city and to set up a new development trajectory, as advocated by the Paris Agreement on Climate Change, Sustainable Development Goals 11 (sustainable cities and communities) and 13 (climate action), and the New Urban Agenda. Moreover, scientific estimation of CO_2 emissions induced by LULC change are needed to improve the accuracy of terrestrial ecosystem carbon budget estimates [25].

The present investigation aimed at quantifying CO_2 emission from LULC change in the municipality of Ouagadougou in Burkina Faso. For that, it combined earth observation data with field data to quantify and analyze the emission CO_2.

MATERIALS AND METHODS

Study area

The study was carried out in the municipality (commune) of Ouagadougou, the largest city of Burkina Faso. The municipality of Ouagadougou is located between longitudes 1°4'00'' W and 1°21'05'' W and between latitudes 12°16'42'' N and 12°30'14'' N (figure 1) Ouagadougou belong the Region of Centre of Burkina Faso and cover covers an area of 970 km2 [11]. Geomorphologically, the area of Ouagadougou is a peneplain, with altitudes ranging between 272 and 368 meters above sea level. The climate is Sudano-Sahelian, modulated by the movement of the Inter-Tropical Convergence Zone (ITCZ), and characterized by a dry season, from November to April, and a rainy season from May to October [26]. The average monthly temperature and the total annual rainfall range from 25.2◦C to 33.3 ◦C and from 571 to 1003 mm/year [11]. The land use/cover is dominated by built-up area and cropland as well as savanna vegetation cover belonging to the North Sudanian sector with dominance species such as *Parkia biglobosa, Vitellaria paradoxa Adansonia digitata, Faidherbia albida, Lannea macrocarpa, Tamarindus indica* [27]. The population of Ouagadougou is dynamic and has increased from 172,661 inhabitants in 1975 up to 2,415,266 inhabitants in 2019 [11].

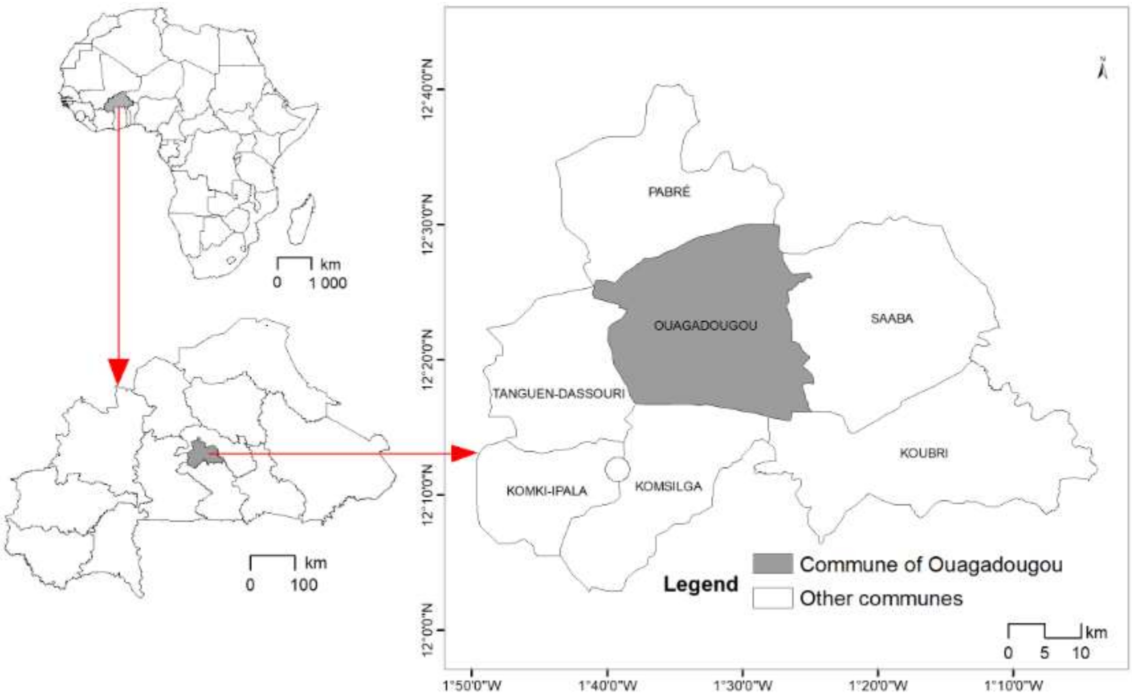

***Fig. 1**. Location of the commune of Ouagadougou*

Data collection

Landsat images and LULC reference data collection

Google Earth Engine (GEE) platform was used to collect satellite images. GEE is a cloud-based platform for scientific data analysis, and it provides access to several earth observation data. Cloud free Landsat 5 Thematic Mapper (TM) image of 1990 and Landsat 8 Operational Land Imager (OLI) image of 2022, with 30 m spatial resolution and covering the study area, were collected to assess land use/cover change. All the images are from October, since this period enables a better separation of the spectral signature of several land cover types (e.g., cropland vs natural vegetation) in the study area [28]. The images are geometrically adjusted and contain atmospherically corrected surface reflectance values. Five spectral bands (blue, green, red, near infrared and middle infrared) as well as two spectral indices (normalized difference vegetation index, NDVI; Modified Normalized Difference Water Index, MNDWI) were considered in this analysis.

Reference data collection for LULC and LULC change

LULC reference data were gathered to train and validate the classifications. For that, a Global Positioning Systems (GPS) field campaign was conducted during field work to gather ground truth samples (reference data) of LULC. The GPS was set to the projection system UTM WGS84 zone 30 north as the Landsat images. The LULC reference data were collected within plots of 30 m×30 m to match the pixel size of the Landsat images. For each plot, the name of the LULC as well as the geographical coordinates of the center were recorded with the GPS and a notebook. LULC reference data were also collected using high-resolution images of Google Earth platform. Moreover, local knowledge-based and historical aerial photographs helped to gather reference samples as well, mainly for the image of 1990. Five (05) broad LULC classes were identified across the municipality of Ouagadougou, and these are built-up area, tree savanna, shrub savanna, water body and cropland. In total, 500 LULC reference data were collected for each year and prepared for the images' classification into LULC classes.

LULC change reference data were also collected using a stratified random sampling [28, 29] to assess the accuracy of the change map. Google earth historical images, Landsat images and local knowledge-based enable the collection of reference data for change areas, essentially forest loss and forest gain areas.

Forest inventory data

With a view of estimating the aboveground carbon stock, vegetation data were obtained through field measurements (diameter at breast height at 1.3 m from the ground, height) in the study area and its surrounding. Following a stratified random sampling, the measures were done within 65 inventory plots established in the vegetation types encountered in the municipality of Ouagadougou. These are tree savanna, shrub savanna and cropland. Fixed plot sizes of 30 m x 30 m were used as recommended by [30] for the savanna zone. The inventory plots were shared proportionally to the area of tree savanna, shrub savanna and cropland with 16, 15 and 34 plots respectively. The dendrometric measures targeted woody species having diameter at breast height (DBH) $\geq$ 5 cm.

Data processing and analysis

LULC classification and change detection

The satellite images were processed and classified in GEE. All the spectral bands and the indices were stacked to create multispectral images for 1990 and 2022. The LULC reference data of each year were imported to GEE, then divided into classification training and validation data. Supervised classifications of the multispectral images into LULC classes were performed with the non-parametric Random Forest (RF) classifier in GEE. RF is an ensemble machine learning algorithm that can be used for classification and regression. It is a non-parametric method and robust against nonlinearity and overfitting [28]. The algorithm of RF is based on bagging technique which is used for training data creation by randomly resampling the original dataset with replacement [28, 31]. RF was selected because it was found outperforming other classifiers, such as maximum likelihood classification, support vector machine and neural networks [31, 32] and achieving good accuracies in the Sudanian domain [31], and in West African cities [11]. The overall accuracy was set as an indicator to assess the performance of the classifications. A post-classification change detection between the two classified images provided a LULC change map. Accuracy assessment was performed using the LULC change reference data and an adjusted error matrix to validate the change map.

Estimation of aboveground carbon (AGB) stock

Owing to the lack of allometric equations for all the woody species encountered in the study, the allometric equations for mixed species (Equation 1 and 2), developed by [33] in the Sudanian savanna, were used to calculate the biomass of each woody species (in kg). The equation is based on two dendrometric parameters: diameter at breast height (DBH) and height. The biomass of trees, in kg, was multiplied by the expansion factor (FE = 10000 m^2 / surface area of the plot in m^2) to obtain the biomass per hectare (kg. ha^{-1}), then by 0.001 to convert kilograms to tone. The carbon stock (in $tCha^{-1}$) was computed by multiplying the biomass by the conversion factor (FC= 0.5) of the carbon fraction of the dry matter in the living aboveground biomass. Carbon stock was calculated for each tree and added up to obtain the aboveground carbon stock of the plot. The mean aboveground carbon stock of a given LULC was estimated by averaging all plots in that LULC. The allometric equation used for tree savanna and shrub savanna is given by equation 1, while equation 2 was used for cropland. Finally, aboveground biomass is provided by equation 3.

$$\mathrm{Ln}\ (\mathrm{AGB}) = -0.051323 + 0.160755(\mathrm{DBH}) + 0.456829(\mathrm{H}) - 0.011051(\mathrm{DBH} * \mathrm{H})$$

Eqn. 1

$$\mathrm{Ln}\ (\mathrm{AGB}) = 0.0871685 + 0.1549490(\mathrm{DBH}) + 0.4660558(\mathrm{H}) - 0.0113066(\mathrm{DBH} * \mathrm{H})$$

Eqn. 2

$$AGB = exp\ [Ln\ (AGB)]$$

Eqn. 3

Where, *AGB* aboveground biomass (kg/m^2); DBH: Diameter at Breast Height (cm); and H: height (m).

The aboveground carbon stock is computed by equation 4.

$$\mathrm{Cstock}\ (tCha^{-1}) = AGB(kg/m^2) \times FE \times 0.001 \times 0.5$$

Eqn. 4

Where, Cstock: carbon stock; FE: expansion factor from m^2 to ha; 0.001: convert kg to tone; 0.5: conversion factor of biomass to carbon stock.

Estimation of CO_2 emission

In this investigation, two sets of data were exploited to quantify CO_2 emission from LULC change in the commune of Ouagadougou. Aboveground carbon stock of tree savanna, shrub savanna and cropland were derived from the field measurement described above, while water and built-up stand with none aboveground carbon stock in the case of this study. Activity data (AD) were also gathered from the LULC change data between 1990 and 2022, resulting from the classified Landsat images of 1990 and 2022. For that, a transition matrix, expressing LULC change area in ha, was built with the LULC maps of 1990 and 2022. The quantification of CO_2 emissions by LULC change is done by multiplying the activity data (AD) by the change in carbon stock between 1990 and 2022, then by the molecular weight of CO_2 (44/12), as suggested by the IPCC guidelines on good practice in greenhouse gas inventory, and this is provided by equation 5 below.

$$CO_2\ emission(tCO2e) = AD\ \times\ EF$$
Eqn. 5

Where, EF: emission factor of CO_2 ($tCha^{-1}$), and $EF\ =\ Carbon\ stock\ change\ \times \frac{44}{12}$
AD is the change area between 1990 and 2020 in ha; $44/12$ is the molecular weight of CO_2.

A summary of the global process for estimating CO_2 emission from LULC change is illustrated in figure 2 below.

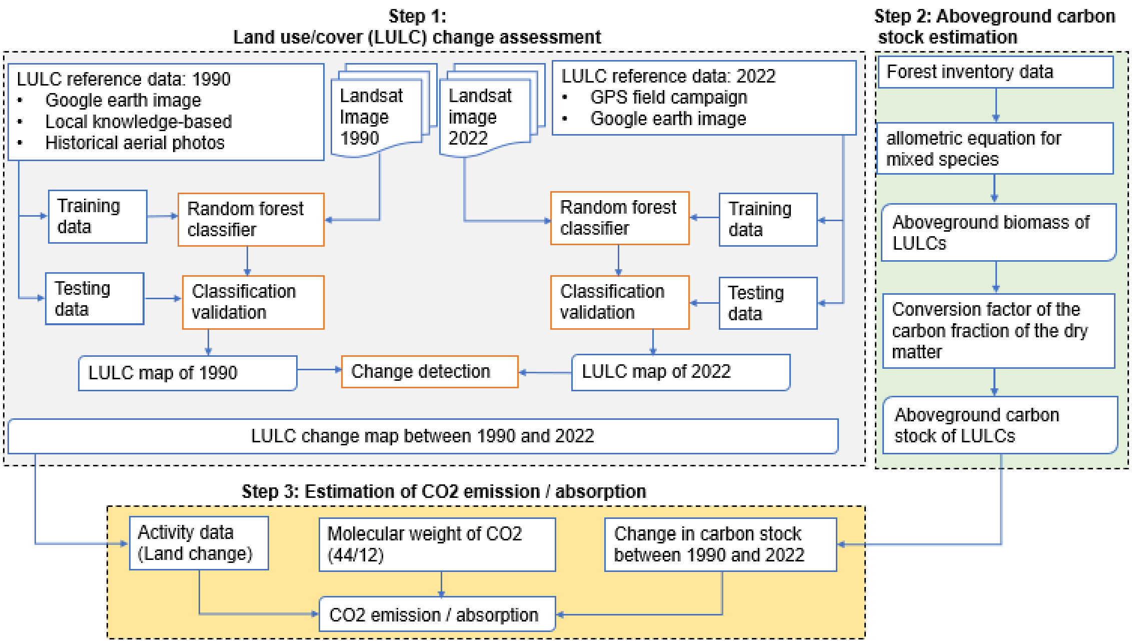

Fig.2. *Process for estimating CO_2 emission from LULC change in the municipality of Ouagadougou*

Assessment of change area and uncertainties

The area and area uncertainty of the LULC change map were computed based on the method of adjusted error matrices [29]. Here, the error matrix of the LULC change map was used to adjust the area estimates and to derive uncertainty expressed by the confidence interval. This method can be applied when assessing the accuracy of LULC change map based on stratified random sampling strategies [28]. The LULC change reference data were used to produce the error matrix with focus on the areas that knew changes between 1990 and 2022, that is, all the LULC conversions highlighting forest loss and forest gain. However, the areas of LULC change classes derived from the map are often biased because of classification errors. Thus, an area estimator can be based on the reference classification of each sample unit [29]. This area estimator is an error-adjusted estimator of area that includes the area of map omission error of category j and removes the area of map commission error [28].

Practically, an error matrix is built in which map classes are the rows, while the reference classes are the columns. The value of each cell of the error matrix based on area proportions ($\hat{P}_{ij}$) is given by equation 6. This adjusted error matrix was then used to calculate an area estimator based on the proportion of the area of category j (Equation 7) as recommended by Olofsson et al.

$$\hat{P}_{ij} = W_i \frac{n_{ij}}{n_{i+}}$$

Eqn. 6

Where, W_i: proportion of area of category i in the map; n_{ij}: number of samples mapped as i and belonging to category j in the reference data; n_{i+}: number of samples mapped as category i in the map. $\hat{P}_{ij}$ indicates the probability that a randomly selected area is classified under category i in the image and under category j in the reference data.

The area of category j ($\hat{A}_j$) is computed as:

$$\hat{A}_j = A_{tot} \times \hat{P}_{+j}$$

Eqn. 7

Where, A_{tot} is the total area, and

$$\hat{P}_{+j} = \sum_{i=1}^{q} W_i \frac{n_{ij}}{n_{i+}}$$

Eqn. 8

The standard error $S(\hat{A}_j)$ of the area estimator is given by equation 9 below.

$$S(\hat{A}_j) = A_{tot} \times S(\hat{P}_{+j})$$

Eqn. 9

Where the standard error for the stratified estimator of proportion of area $S(\hat{P}_{+j})$ is calculated as:

$$S(\hat{P}_{+j}) = \sqrt{\sum_{i=1}^{q} \frac{W_i \hat{P}_{ik} - \hat{P}_{ik}^2}{n_{i+} - 1}}$$

Eqn. 10

$\hat{P}_{+j}$ (estimated from the reference samples) allows the computation of uncertainty of the area estimates in the form of sampling variability that can be expressed as confidence interval. For $\hat{A}_j$ the approximate 95% confidence interval (*CI*) is given by the equation 11 below.

$$CI = \hat{A}_j \pm z \times S(\hat{A}_j)$$

Eqn. 11

Where, z: the percentile from the curve of the standard normal distribution. z = 1.96 for 95% confidence.

Uncertainties assessment in carbon stock and emission estimation

Uncertainty in carbon stock estimation is expressed by the confidence interval (95%) of which absolute value is given by equation 12.

$$CI = \mp t \times \frac{s}{\sqrt{n}}$$

Eqn. 12

Where, CI: confidence interval; s: standard deviation; n: sample size; and t: t-value for "n-1" degrees of freedom.

The equations for estimating uncertainty propagation for a sum suggested by [34] was used to compute uncertainties in carbon stock change. The aggregated uncertainty is calculated by equation 13 using the absolute uncertainties, and it is defined as the square root of the sum of the squares.

$$U(abs)_{x+y+\cdots n} = \sqrt{U_x^2 + U_y^2 + \cdots U_n^2}$$

Eqn. 13

Where, U(abs): absolute uncertainty

For the estimation of uncertainties in CO_2 emission (emission factor x activity data), the equation for estimating uncertainty propagation for a product is used (equation 14). However, here the relative uncertainties are rather considered.

$$U(rel)_{x+y+\cdots n} = \sqrt{\left(\frac{U_x}{x}\right)^2 + \left(\frac{U_y}{y}\right)^2 + \cdots \left(\frac{U_n}{n}\right)^2}$$

Eqn.14

Where, U(rel): relative uncertainty

RESULTS AND DISCUSSION

LULC distribution in Ouagadougou between 1990 and 2022

The classification of the LULC maps yielded an overall accuracy of 92% for the Landsat image of 1990 and 91% for the image of 2022. Figure 3 shows the spatiotemporal distribution of the LULC types in the study area. In 1990, the municipality of Ouagadougou was largely dominated by shrub savanna (58.64%) and tree savanna (20.44%) (Table 2). Cropland occupied 14.47% of the land, while built-up and water body covered 5.75% and 0.70% respectively. In 2022, built-up (52%) and cropland (24.74%) increased at the detriment of tree savanna (11.66%) and shrub savanna (10.96%).

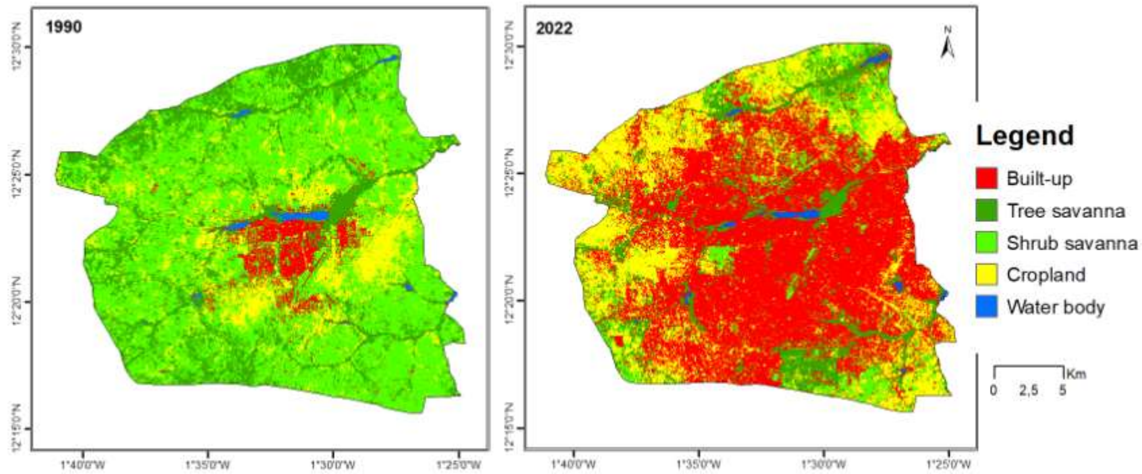

***Fig.* 3.** *Spatiotemporal distribution of land use/cover in the commune of Ouagadougou in 1990 and 2022*

Table 1. *Statistics of land use/cover in 1990 and 2022*

		2022					
	LULC	Built-up	Tree savanna	Shrub savanna	Cropland	Water	Total
1990	Built-up	5.18	0.26	0.14	0.13	0.04	5.75
	Tree savanna	7.13	5.83	1.78	5.61	0.08	20.44
	Shrub savanna	29.79	4.78	8.31	15.72	0.03	58.64
	Cropland	9.76	0.71	0.72	3.27	0.00	14.47
	Water	0.10	0.07	0.00	0.00	0.53	0.70
	Total	51.97	11.66	10.96	24.74	0.67	100.00

Forest loss and gain in Ouagadougou between 1990 and 2022

Between 1990 and 2022 forest losses affected 38173.81 ±19.67ha in the municipality of Ouagadougou (Table 2). They are featured in the ground mainly by the conversions of shrub savanna to built-up (16119.79 ±14.79 ha) and to cropland (7853.48 ± 7.72 ha) as well as cropland to built-up (5242.71 ±3.21 ha) and tree savanna to built-up (4242.51±8.37). Patterns of land use-induced deforestation are illustrated in figure 4. Built-up appeared as the land use type that occasioned more deforestation. Indeed, between 1990 and 2022, built-up induced deforestation affected 46.68% of the total land of Ouagadougou. Croplands replaced natural vegetation over 21.34% of the study area, particularly in the surrounding of the built-up areas. The degradation of natural vegetation, expressed by the degradation of tree savanna to shrub savanna, affected 1241.22 ±4.08 ha. However, forest gain occurred over 3759.13 ±3.7 ha (Table 3). The greening areas are mainly highlighted by the conversions of shrub savanna to tree savanna (2536 ±3ha), cropland to tree savanna (397.29 ±0.16 ha) and cropland to shrub savanna (367.93 ±0.14 ha).

Change in aboveground carbon stock

Table 4 shows a variability of aboveground carbon stock between the LULC types of the study area. The highest mean carbon stock was recorded for tree savanna (36 ± 4.5 tC/ha), followed by shrub savanna (21.9 ± 6.1 tC/ha) and cropland (18 ±3.3). Shrub savanna had the highest total carbon stock (56.3%) in 1990, while cropland exhibited the smallest carbon stock (11.4%). This distribution of carbon stock reversed in 2022, with cropland having the highest value of carbon stock (40.3%), followed by tree savanna (38%) and shrub savanna (21.7%). Between 1990 and 2022, the change in the LULC areas favored an increase of carbon stock for cropland (71%) and a reduction for shrub savanna (-81.3%) and tree savanna (-42.9%) in the municipality of Ouagadougou.

Table 2. *Areas affected by forest loss between 1990 and 2022 in the municipality of Ouagadougou*

Forest loss classes	Area (ha)	CI (ha)
Shrub savanna to built-up	16119.79	±14.79
Shrub savanna to cropland	7853.48	±7.72
Cropland to built-up	5242.71	±3.21
Tree savanna to built-up	4242.51	±8.37
Tree savanna to cropland	2909.92	±0.49
Tree savanna to shrub savanna	1241.22	±4.08
Tree savanna to water	313.49	±2.9
Shrub savanna to water	250.69	±1.7
Total	38173.81	±19.67

Table 3. *Areas of forest gain between 1990 and 2022 in the municipality of Ouagadougou*

Forest gain classes	Area (ha)	CI (ha)
Shrub savanna to tree savanna	2536	±3
Cropland to tree savanna	397.29	±0.16
Cropland to shrub savanna	367.93	±0.14
Built-up to tree savanna	148.66	±0.06
Built-up to shrub savanna	138.75	±1.53
Built-up to cropland	121.16	±1.51
Water to tree savanna	49.34	±0.04
Total	3759.13	±3.7

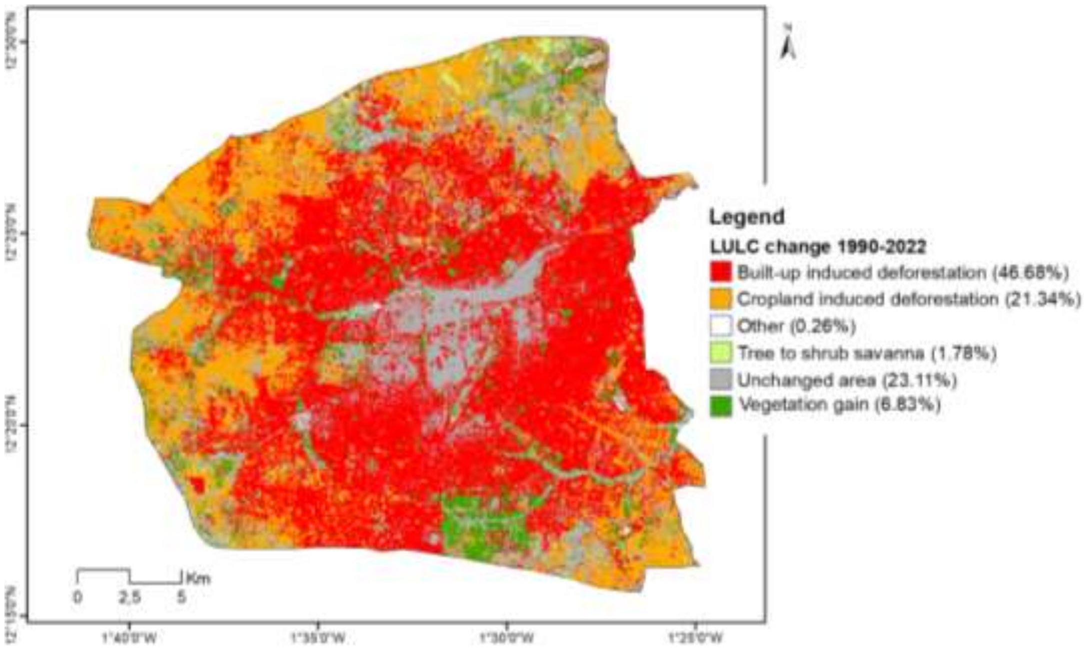

Fig. 4. *Land use/cover change between 1990 and 2022*

Table 4. *Aboveground carbon stock of LULC types in Ouagadougou*

LULC	Mean carbon stock (tC/ha)	Total carbon stock in 1990 (%)	Total carbon stock in 2022 (%)	Carbon stock growth 1990-2022
Tree savanna	36 ± 4.5	32.3	38	-42.9
Shrub savanna	21.9 ± 6.1	56.3	21.7	-81.3
Cropland	18 ±3.3	11.4	40.3	71.0
Water	0	0	0	0
Built-up	0	0	0	0

CO_2 emission/ absorption from LULC change between 1990 and 2022 in Ouagadougou

CO_2 emission and absorption from LULC change between 1990 and 2022 in the commune of Ouagadougou is shown in table 5 and 6 respectively. LULC change has occasioned more CO_2 emission (2630490.96 ±0.74% tCO_2e) than absorption (207867.93 ± 0.67% tCO_2e). The expansion of built-up appeared as the main source of CO_2 emission (83.65% of total emission), particularly built-up expansion at the detriment of shrub savanna (1294419.14 ± 0.28% tCO_2e), tree savanna (560011.32± 0.13% tCO_2e) and cropland (346018.86 ± 0.18% tCO2e). The conversions of savanna vegetation to cropland were the second source of emission (11.57% of the total CO_2 emission).

CO_2 absorption is largely driven by the conversions to tree savanna (85.13% of total absorption), mainly the conversion of shrub savanna to tree savanna (63.07%) that released 131111.20 ± 0.28 tCO_2e into the atmosphere.

Table 5. *CO_2 emission from LULC change between 1990 and 2022 in Ouagadougou*

Forest loss classes	**CO_2 emission**	**CI (%)**	**%**
Shrub savanna to built-up	1294419.14	± 0.28	49.21
Tree savanna to built-up	560011.32	± 0.13	21.29
Cropland to built-up	346018.86	± 0.18	13.15
Tree savanna to cropland	192054.72	± 0.31	7.3
Shrub savanna to cropland	112304.76	± 1.78	4.27
Tree savanna to shrub savanna	64171.07	± 0.54	2.44
Tree savanna to water	41380.68	± 0.13	1.57
Shrub savanna to water	20130.41	± 0.29	0.76
Total	2630490.96	± 0.74	100

Table 6. *CO_2 absorption from LULC change between 1990 and 2022 in Ouagadougou*

Forest gain classes	**CO_2 absorption**	**CI (%)**	**%**
Shrub savanna to tree savanna	131111.2	± 0.54	63.07
Cropland to tree savanna	26221.14	± 0.31	12.61
Built-up to tree savanna	19623.12	± 0.13	9.45
Built-up to shrub savanna	11141.63	± 0.28	5.36
Built-up to cropland	7996.56	± 0.18	3.85
Water to tree savanna	6512.88	± 0.13	3.13
Cropland to shrub savanna	5261.4	±1.78	2.53
Total	207867.93	± 0.67	100

DISCUSSION

The Landsat satellite images were classified with Random Forest (RF) that provided satisfactory and acceptable maps. Such results highlight the performance of the machine learning algorithm for the classification of urban environments using medium resolution satellite images. Our findings are in line with those of [11] that reached classification overall accuracy between 80% and 94% with the RF classifier in Ouagadougou. The strength of the RF algorithm in LULC classification has been also noticed by previous studies for the West African rural landscapes [31, 35, 36]. Moreover, built-up area and cropland were found as the current dominant land use/cover types in the study area. Moreover, between 1990 and 2022, built-up and cropland increased in the study, while regressive dynamics were noted for the savanna vegetation, these findings concur with those of previous investigations in the study area [11].

The increasing trend of built-up areas in Ouagadougou is a continuity of the urban sprawl observed in other developing countries' cities [10, 12, 37]. Built-up extension occurred at the detriment of natural vegetation cover and cropland as well, and towards the peri-urban. This conclusion is in accord with the work by [10] conducted in the Greater Lomé (Togo). The authors found an increase of 33% of built-up area to the detriment of natural vegetation and cultivation areas in Lomé between 2007 and 2020. Based on supervised classification of Landsat images, [37] also noticed a significant increase in habitat from 22,119 ha in 1986 to 31,579 ha in 2017 in the city of Abidjan in Côte d'Ivoire. In Niamey municipality (Niger), [38] found similar conclusions. They show that land cover changes in Niamey are caused by land use dynamics, particularly through built-up areas and agriculture expansion in the city of Niamey. One of the driving forces of urban sprawl is the demographic growth due to natural growth and rural-urban migration [39]. In Burkina Faso, the migration of people from rural areas to urban areas has been amplified by the insecurity in the country that occasioned an important number of internally displaced populations toward the main cities, such as Ouagadougou. For instance, according to [40], Ouagadougou sheltered 45.1% of the total urban population of Burkina Faso in 2019. Its population increased from 441,514 inhabitants in 1985 to 1,475,839 inhabitants in 2006 to reach 2,415,266 inhabitants in 2019 [41]. Many of the migrants and the internally displaced populations usually settled in the peri-urban area, and as a result, there is high pressure on land resources [39], contributing then to land cover change.

The results of built-up and cropland expansion are the significant reduction of the initial savanna vegetation cover of Ouagadougou, as noticed in this study between 1990 to 2022. The essential of the remaining forest and vegetation species of the city can be found in the protected forest "Bangr-weogo" which became the key green area of Ouagadougou. Large portions of the green belt of the city, set up during the revolution period of the 80s, were occupied by built-up [41], among others, because of the lack of law enforcement. The anthropogenic land use induced reduction of natural vegetation cover noticed in the landscape of Ouagadougou is a common feature of several spots in the Sudanian savanna of West Africa [42,43,44]. The changes in LULC affects the carbon sequestration potential of the vegetation cover.

From our findings, tree savanna had the highest stock of carbon among the LULC types, followed by shrub savanna and cropland. However, contrasted conclusions were made by other studies; for example, [36] found cropland with higher aboveground carbon stock than tree savanna and shrub savanna in the Dano watershed located in the southwestern Burkina Faso. The discrepancy of results might reside in the phytogeographical sectors in which both studies were carried out (North Sudanian vs South Sudanian), and the methodology used for (e.g., types and shapes of plots, allometric equations). The change in LULC in Ouagadougou between 1990 and 2022, favored the loss of aboveground carbon stocks with important emission of CO_2 into the atmosphere. Our results are in line with those of [45] that estimated the level of CO_2 emission generated by LULC induced-deforestation in the middle Sota catchment in Benin. The authors revealed that historical emissions due to deforestation amount to about 295.87 Mt $CO2e.ha^{-1}$. Due to its paramount contribution into savanna conversion, built-up appeared as the main driving factors of CO_2 emission from LULC change in the study area. Actually, this happened because of the high pressure on land associated with the increase of unplanned settlements in the outskirt areas favored by the insufficient number of developed parcels, lack of financial resources for their acquisition as well as land speculation [26]. LULC change induced absorption of CO_2 was also notified in the municipality of Ouagadougou. The reason behind this result is the reforestation activities undertaken in the city. However, in terms of comparison, LULC change has led to more emission of CO_2 than absorption in the period of 1990-2022 in Ouagadougou.

The expansion of built-up and land degradation in the municipality of Ouagadougou favored the increase of the land surface temperature, which is likely to impact the living conditions of the population [17]. It also poses the problem of the non-respect of the existing city's master plan and climate change mainstreaming into land use and planning policies. Burkina Faso has recently revised his National Adaptation Plan (NAP) to climate change which emphasized on the different development sectors (agriculture, water resources and forestry, etc.), and does not provide deep details on urban areas. However, the NAP calls for climate change integration into policies. Therefore, there is an urgent need to consider climate change in cities' master plan or land use policy in Burkina Faso. A clear climate change mitigation strategy and adaptation plan must be set up for the municipality of Ouagadougou regarding land use/cover dynamics.

The findings achieved have policy implications regarding land use in the city of Ouagadougou. The existing master plan of the city foresees forest safeguarding via the green belt of Ouagadougou and the protected urban forest of "Bangre-weogo". However, the fact is that this is not fully respected as our results show a lack of city extension policies or an inadequate implementation of the city's master plan. [39] also came to this end regarding land use in Ouagadougou. There is therefore an urgent need for the urban development actors to reinforce or reshape land use policies in the municipality of Ouagadougou to preserve the remaining forest cover and to rehabilitate the green belt. This is of paramount importance to set up a new development trajectory by building a resilient city in the context of climate Change and high population growth.

The present study has limitations that deserve to be highlighted. Indeed, the use of allometric equations for mixed species due to the lack of equations for specific woody species is likely to influence the carbon stock and emission factors estimations. Moreover, the use of allometric equations developed within and according to the realities of the study area could be an asset to reduce uncertainties. The use of more sample size is also needed to further improve carbon stock measurements. Lastly, despite the higher accuracy obtained during the classification of Landsat images, mapping errors, due to confusions between LULC classes, may have led to overestimation or underestimation of change area and the quantification of CO_2 emission. Owing to that, the results of this study were provided accounting for uncertainties in land change area, carbon stock estimation and CO_2 emission. Future investigations should consider addressing those limitations to improve CO_2 emission analysis. Despites the limitations, the results achieved in our study agree with the general dynamics about LULC change in the West African cities [10, 11, 37], which reinforces the reliability of our findings.

CONCLUSION

Analysis of carbon emissions from land use/cover change is of paramount importance in the combat for climate change mitigation and adaptation. The present study investigated carbon dioxide (CO_2) emission from land use/cover (LULC) change in the municipality of Ouagadougou in Burkina Faso. The study entailed the estimation of aboveground carbon stock via field measurement, and the processing of earth observation satellites images to assess the historical LULC change which served to activity data for the estimation of CO_2 emission. The municipality of Ouagadougou is characterized by the expansion of built-up area and cropland, which take place at the detriment of the savanna vegetation cover. Built-up appeared as the main land use patterns that guided the dynamics of the landscape of Ouagadougou. The change in LULC has led to more emission of CO_2 than absorption due to the important forest loss area compared to forest gain. The expansion of built-up at the detriment of savanna vegetation affects the land surface properties, such as the increase of the land surface temperature, which is likely to impact the urban dwellers. Housing sprawling towards the peri-urban area is a common feature of the West African cities and raises the issue of provision of goods and services to the citizens. The study pointed out the problem of land use planning in Ouagadougou, and it calls for climate change mainstreaming into the city's master plan or land use policies. Afforestation activities, through tree planting campaigns, should be promoted to reinforce carbon sequestration potential by vegetation over the municipality. The findings of our study can be used to address sustainable land use planning in Ouagadougou. Moreover, the results can contribute to the country's National Determined Contribution (NDC), and they provide key arguments to meet REDD+ targets.

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