World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

WJAETS

(Research Article)

Variation of soil organic carbon across different land covers and land uses in the greater Gaborone region of Botswana

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World Journal of Advanced Engineering Technology and Sciences, 2022, 07(02), 097–112

Publication history: Received on 16 October 2022; revised on 28 Novemebr 2022; accepted on 01 December 2022

Article DOI: https://doi.org/10.30574/wjaets.2022.7.2.0115

Abstract

Soils are a potentially viable sink for atmospheric carbon and could contribute to mitigating global climate change. Soil Organic Carbon (SOC) content exhibits considerable spatial variability both horizontally (land use) and vertically (soil profile). Land cover land use (LCLU) is one of the key determinants of SOC stock, hence there is a significant variation of SOC across different LCLUs. This study aimed to investigate the spatial variability of SOC across different LCLUs in the Greater Gaborone region of Botswana. Remotely sensed data used for image classification was obtained from the United States Geological Survey (USGS) Earth Explorer (www.usgs.gov). The imagery used in this study was Sentinel-2A obtained in the month of March with cloud content of less than 10% for easy interpretation. Image classification was done using a supervised classification method based on a Maximum Likelihood classifier. The major LCLU types identified in the area included water bodies, trees dominated, cropland, shrubland, bare land, and built-up. The Walkley and Black method, core method, Bouyoucos hydrometric method and pH meter were used to determine SOC content, bulk density, soil texture and pH, respectively.

Soil bulk density, pH and sand fraction showed a negative correlation with SOC content, while silt and clay showed a positive correlation. The total SOC stock in the study area was estimated to be 4.36 MtC, with trees dominated areas accounting for 1.13 MtC (25.9%), shrubland 2.83 MtC (64.9%), cropland 0.14 MtC (3.2%), built-up 0.22 MtC (5.1%), and bare land 0.04 MtC (0.9%), hence indicating that trees dominated and shrubland were good sequesters of carbon in the Greater Gaborone.

Keywords: Soil organic carbon; Land cover land use; Image classification; Carbon sequestration

1 Introduction

Land-use patterns, influenced by a variety of social processes, often result in changes in land cover that affect biodiversity, water and radiation budgets, and greenhouse gas (GHG) emissions. These factors and other factors when combined can affect the global climate and the biosphere. In Botswana, LCLU changes are primarily driven by human and livestock population pressures, these include rapid urbanization and general development activities such as increased demand for arable and grazing land, tourism, water, and fuel wood [1]. Changes in LCLU have emerged as a key issue within the scientific community concerned with global environmental changes [2], and land use is one of the most important determinants of soil organic carbon (SOC) stock status, as it governs vegetation patterns and the amount of organic matter (OM) that is returned to the soil [2]. Carbon is stored in the living biomass of plants by the process of

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photosynthesis and builds up in soils when dead or decaying biomass is detached from the parent plant. Long-term sequestration of carbon in soils is beneficial to both the environment and agriculture. Changes from one LCLU type to another are responsible for large carbon fluxes in the terrestrial ecosystem [2]. LCLU changes contribute approximately 26% of global GHG emissions (including 13.8% from natural forest conversion) compared to 14.3% and 19% from transportation and industry, respectively [3]. Tree savannah and shrubland are important ecosystems in semi-arid areas and are regarded as carbon sinks and the conversion of these systems into other uses ultimately reduces soil carbon due to soil erosion, decreased plant residue, organic matter input, or soil tillage [3, 4].

Soil is the foundation of terrestrial ecosystems and it provides most of the ecosystem services that benefit mankind [5–7]. It plays a vital role in the global carbon cycle and contains approximately 2344 Pg (1 petagram = 10^{15} grams) of organic carbon [6]. Organic carbon stored in the soil is regarded as one of the most important soil properties, exhibiting not only temporal but also significant spatial variability, both horizontally according to LCLU and vertically within the soil depth [8]. It improves many soil-related functions and services such as the water holding capacity, structural stabilization, retention and release of plant nutrients [9–11]. Also, it contributes significantly to the overall soil health, agriculture, climate change and food security solutions [7]. Excessive depletion of SOC can degrade soil fertility, reduce biomass productivity and adversely affect water quality, food security and further contribute to global climate change [12]. Reducing SOC loss is therefore an effective strategy for food security enhancement and climate change mitigation, hence addressing Sustainable Development Goals (SDG) 2 and 13, respectively.

The Greater Gaborone region has witnessed a significant population growth between 1981 and 2022 primarily driven by rural to urban migration. Its population increased from 72,127 in 1981 to 429,293 in 2022 [13, 14]. According to Keiner and Cavric [15], most of the rural-urban migration that takes place in the country is directed to Gaborone and its neighbouring settlements due to more job opportunities, better infrastructure, social amenities and public services. The growing population coupled with the unprecedented economic and industrial development in and around the city of Gaborone over the past decades have resulted in cropland and shrubland being converted into built-up areas. This has also promoted the expansion of peri-urban satellite settlements, resulting in areas previously occupied by agricultural lands and natural vegetation being converted into built-up areas (such as the Phakalane, Setlhoa and Gaborone North areas) [16].

Even though several studies on LCLU change detection have been conducted in the area over the past years, no studies have been done on SOC stock in the different LCLU types. Therefore, the purpose of this study was to determine how SOC varied spatially among the different LCLUs in Greater Gaborone, Botswana. This included documenting the different LCLU types in the area, estimating the amount of SOC content in the different LCLU types, and examining the relationship between SOC stock and soil bulk density, pH, and soil texture with the objective of providing useful information to policymakers, especially for land use planning purposes.

2 Material and methods

2.1 Description of the Study area

The Greater Gaborone area lies between the Longitude 25^0 45' 17. 76" E and 26^0 11' 01.04" E and Latitude 24^0 41' 15.44" S and 24^0 42' 45.96" S. It covers a surface area of 669 km^2 and has an average elevation of approximately 1000 m above mean sea level. To the east, the area includes the tribal villages of Tlokweng, Oodi and Modipane; to the west, it includes Mogoditshane and Gabane; to the south, it includes Mokolodi; and to the north, Gaborone is bordered by the Bakgatla tribal land (Figure 1). These peri-urban villages have grown with the influence of the city and have attained the status of its suburbs, even though their land tenure remains tribal [13]. Historically, large areas of present-day Gaborone used to be freehold farmland. For example, the area west of the railway line (now known as Gaborone – West) and Broadhurst did not exist until the early 1980s when the government bought freehold farms in those areas to make way for development [13]. Private landholders have also contributed to the expansion of the city. Some farms have been developed into huge townships like Phakalane Estates, Gaborone North and Mokolodi.

The climate is semi-arid, characterized by a hot wet season (November-April), a long dry season (May-October) and a winter season (May-August). The average temperature of the area is 20.6 °C, with average minimum and maximum average temperatures of 12.8 and 28.6 °C, respectively [17]. The annual average rainfall brought by winds from the Indian Ocean averages 500 mm [18]. Prolonged dry spells during rainy seasons are common and rainfall is erratic, highly variable and spatially localized [19].

Agricultural practices in the study area include irrigated, rainfed agriculture and livestock production. Permanent water bodies found in the area include the Gaborone Dam and the water treatment polishing ponds. The vegetation cover mainly consists of Acacia shrubs and tree savanna, with *Acacia tortilis* and *Acacia erubescence* being the most common species [13]. The soil types in the area consist of vertisols, haplic lixisol and eutric regosols [20].

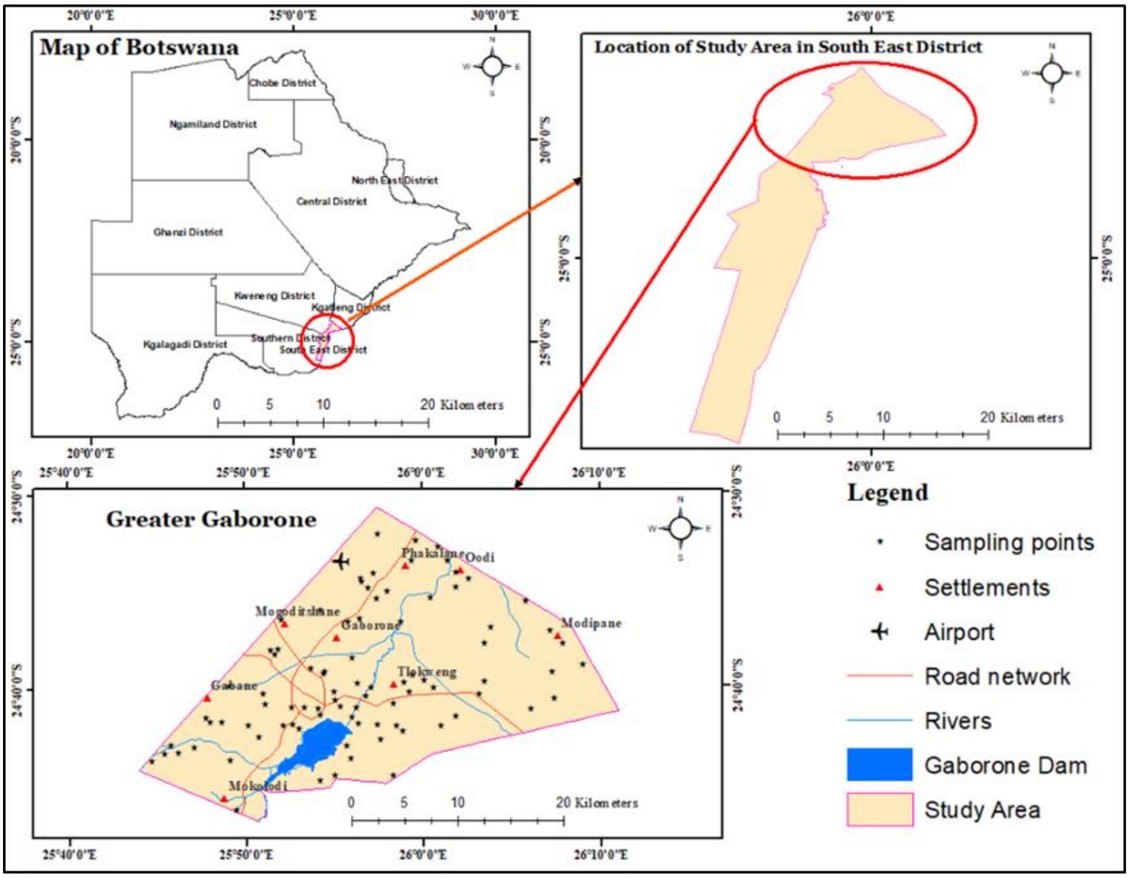

Figure 1 Map of the study area

2.2 Identification of LCLU types in the study area

2.2.1 Data acquisition

This study explored Sentinel-2A Multi-Spectral Instrument (MSI) for 2022 satellite image from the United States Geological Survey (USGS) Earth Explorer (www.usgs.gov). The image under consideration was acquired on 30 March 2022, with a content of less than 10% (for easy interpretation). The area of interest (AOI) was digitized in Google Earth Pro, exported as a KML file and later converted to a shapefile in ArcGIS using the Conversion tool of ArcGIS 10.7. Ground control points (GCP) were collected using a Geographical Positioning System (GPS).

2.2.2 Image pre-processing

Satellite images used for LCLU classification are often affected by atmospheric and topographic/geometric errors, thus requiring correction [21]. Radiometric correction was done by converting digital numbers to radiance. The geometric correction was made possible by orthorectifying the images after projecting them to a common geographic reference system defined by the Universal Transverse Mercator (UTM), specifically, UTM zone 35S coordinate on WGS 1984.

The images were projected to a common geographic reference system defined by the Universal Transverse Mercator (UTM) Zone 35S coordinate on WGS 1984. This correction was possible through the orthorectification process. The study area was covered by two Sentinel-2 image tiles. The two Sentinel images were mosaicked in ArcGIS 10.7 to create a new raster image using the Mosaic to new raster tool under the Data Management tool before extracting the area of interest for classification.

2.2.3 Image classification

In this study, a supervised classification method based on a Maximum Likelihood classifier was adopted because of the ease of implementation to extract the LCLU classes. This classifies pixels based on the highest probability that a pixel belongs to a given class. The validation of classified images was done through ground truthing [22]. Furthermore, this method assumes that the spectral values of the training pixels are normally distributed and compute the probability that the given pixel belongs to a specific class [23]. Training classes were selected through visual interpretation of high-resolution satellite images in Google Earth Pro maps. The training areas of each LCLU class were selected throughout the study area to obtain good representatives [23]. The centres of large patches of LCLU features that were unlikely to contain mixed classes were selected in order to improve the accuracy of the classified image. A minimum of 500 pixels per class were chosen to enable a meaningful calculation of statistics [24]. Based on the characteristics of the image, six major LCLU types were identified in the study area. The identified LCLU classes included water bodies, trees dominated, cropland, shrubland, bare land and built-up. The six classes with their associated descriptions are shown in Table 1.

Table 1 Description of LCLU classes in the study area

	LCLU type	**Description**
1	Waterbody	This includes streams, rivers, dams or reservoirs and ponds.
2	Trees dominated	Woody plants that are taller than 5 meters and have a distinct crown.
3	Cropland	This includes forage, orchards, nurseries, horticultural land, and cultivated land.
4	Shrubland	This includes woody plants less than 5 m tall with no defined crown and a mix of trees and grasses.
5	Bare land	This includes exposed soils, sand, bare rocks, and areas with less than 10% vegetation cover.
6	Built-up	This includes residential, commercial, industrial, transportation and urban areas.

Source: [25]

2.2.4 Post Classification Refinement

A classified image often contains noise caused by the isolated pixels of some classes, within another dominant class, which can form large patches [26]. Post-classification smoothing with a majority filter is essential to reduce unnecessary errors and further improve classification accuracy [26]. Filtering entails conveying isolated pixels to the leading class within which it lies. In this study, tools such as Majority filter and Boundary clean tools integrated within the ArcGIS software were used to smoothen or refine the classified images.

2.2.5 Accuracy Assessment

Accuracy assessment for image classification is essential as it measures the number of ground truth pixels that have been classified correctly – producer accuracy [27] and the expected accuracy when using the created map – user accuracy. In this study, a classification accuracy assessment was performed based on points that were identified on the images and selected to represent the different LCLU classes in the study area. A stratified random sampling method was used to collect a total of 296 reference data from the classified LCLU map of 2022 to ensure that all six LCLU classes were adequately represented based on the proportional area of each class. The data was imported into Google Earth Pro maps to assess the classification accuracy. The ground truth data and the classification data were compared and statistically analyzed using an error matrix to determine if the pixels were grouped to the correct feature class. The Error matrix was then used to compute overall accuracy, Kappa statistic, User accuracy, and Producer accuracy. The overall accuracy, user accuracy and producer accuracy, respectively indicate the accuracy of the entire classification, the likelihood that a pixel classified represents the class on the ground or in reference data, and how well the trained pixels of the given cover type are classified [25]. The following equations were used to compute the user accuracy (UA), producer accuracy (PA) and overall accuracy (OA).

$$OA = \frac{Sum\ of\ diagnal\ (correctly\ classified)}{Total\ number\ of\ sample} \times 100 \ldots\ldots\ldots(1)$$

$$UA = \frac{Samples\ correctly\ identified\ in\ the\ row}{Row\ total} \times 100 \ldots\ldots\ldots\ldots.(2)$$

$$PA = \frac{Samples\ correctly\ identified\ in\ the\ Column}{Column\ total} \times 100 \ldots\ldots\ldots\ldots.(3)$$

Kappa analysis was also carried out. The Kappa coefficient is the measure of reproducibility and assesses the probability of chance agreement between the reference and the image datasets [28]. In this study, the Kappa coefficient was calculated using the equation proposed by Jensen and Cowen [29].

$$\boldsymbol{Kc} = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+} * X_{+i})}{N^2 - \sum_{i=1}^{r}(X_{i+} * X_{+i})} \ldots\ldots\ldots\ldots\textbf{(4)}$$

Where Kc is the Kappa coefficient, N is the total number of observations included in the matrix, r is the number of rows in the error matrix, X_{ii} is the number of observations in row i and column i (on the major diagonal), X_{i+} is the total number of observations in row i (shown as marginal total to the right of the matrix), and X_{+i} is the total number of observations in column i (shown as marginal total at bottom of the matrix).

In Kappa analysis, a Kappa value of 0.80 and above indicates a very strong agreement, a value between 0.40 and 0.80 indicates a good agreement, and a value below 0.4 indicates a poor agreement [30].

2.3 Soil Organic Carbon Stock Determination

Once the LCLUs of the study area had been determined and assessed, the concentration of SOC content in different LCLUs in the study area was investigated to determine how LCLU change influenced SOC content.

2.3.1 Sampling design

The SOC stock was determined through stratified random sampling of the LCLU map. The LCLU types under consideration were trees dominated, shrubland, cropland, built-up land, and bare land. Water bodies were excluded because of the challenges of obtaining soil samples from them. To ensure the sampled data truly represented the SOC stock in the LCLU classes under consideration, Arps and Krause [31] suggested collecting 15 samples per stratum or class to achieve a 95 % confidence interval (CI) with a 5% error margin. Accordingly, 17 sampling points were randomly generated within each LCLU class. A total of 85 sample points were used in this study for soil sample collection. The random points and their geographical coordinates were generated in ArcGIS 10.7 using the Segmentation and Classification tool under Special Analyst tools. The selected points were located in the field using Google maps.

At the sampling points, soil samples were collected from a depth of 30 cm for SOC content, pH, and soil texture determination. Studies have shown that SOC is higher in the topsoil and decreases exponentially with depth [32–34]. In addition, the 30 cm soil depth is considered the most relevant soil depth for SOC estimation because it is the most biologically active layer of the soil [35] and is most affected by land management practices, particularly in the agricultural system (ploughing) [36]. Equally, soil samples were collected from a depth of 15 cm using a core sampler with a known volume (144.32 cm^3) for bulk density determination. This depth was chosen because the bulk density at this depth is not significantly different from that at 15-30 cm. The samples were labelled and packed in sealed plastic bags for easy identification and preservation, as recommended by Pule-Meulenberg [37]. Finally, the samples were transported to the Department of Crop and Soil Sciences Laboratory of Botswana University of Agriculture and Natural Resources (BUAN) for analysis.

2.3.2 Laboratory Analysis

Soil samples (except those for bulk density) were prepared for laboratory analysis by air-drying, crushing, thoroughly mixing and sieving with a 2.00 mm sieve [38]. The parameters determined include SOC content, bulk density, pH and texture.

For bulk density determination, the soil samples collected with the core sampler were oven-dried at a temperature of 105^{o}C for 48 hours [39]. The weight of the oven-dried samples was divided by the core volume to obtain the bulk density as shown in the following equation.

$$Bulk\ density\ (g/Cm^3) = \frac{Oven\ dried\ weight\ of\ sample\ (g)}{Core\ volume\ (cm^3)} \ldots\ldots\ldots\ldots\ldots (5)$$

Soil Organic Carbon Content was determined using the Walkley and Black method [40]. The SOC stock (kg C/m^2) for each sampled depth (30 cm) in the different LCLU types was calculated using the following Equation [41,42].

$$SOC\ stock\ (kgC/m^2) = (OC\ \times BD\ \times D) \times 10 \ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where C is the SOC stock (g/m^2) of a sampled depth, D is the depth at which the soil sample was collected (cm), BD is the bulk density (g/cm^3) of soil at a sampled depth, and OC is the SOC content (%) of a sampled depth.

Soil pH was determined by mixing 10 g of soil sample with 20 ml of distilled water (ratio, 1:2) to form a supernatant solution [43]. The solution was placed in an electric mixer for 30 minutes for thorough mixing. The pH of the solution was then determined using a pH meter (pH-Orion Star A111). The soil texture was determined quantitatively using the Bouyoucos hydrometric method [44, 45]. The soil texture classes were finally determined using a Soil Textural Triangle developed by the United States Department of Agriculture (USDA).

2.3.3 Statistical Analysis

Statistical data analysis was carried out using R statistical software (version 4.21 for Windows) and Microsoft Excel. Statistically significant differences were accepted at $p < 0.05$. One–way ANOVA (analysis of variance) with Post-hoc least significant difference (LSD) was conducted to examine the differences in soil properties (SOC content, bulk density, pH and texture) with LCLU types. Also, the relationships between SOC with bulk density, pH and texture were examined using Microsoft Excel.

3 Results and discussion

3.1 LCLU types in the study area

The Sentinel 2A image obtained from the USGS was analyzed using Supervised classification employing the Maximum Likelihood algorithm. The LCLU map was developed to depict the LCLU types identified in the study area in 2022. The identified LCLU types were water bodies, trees dominated, cropland, shrubland, bare land and built-up land (**Error! Reference source not found.**).

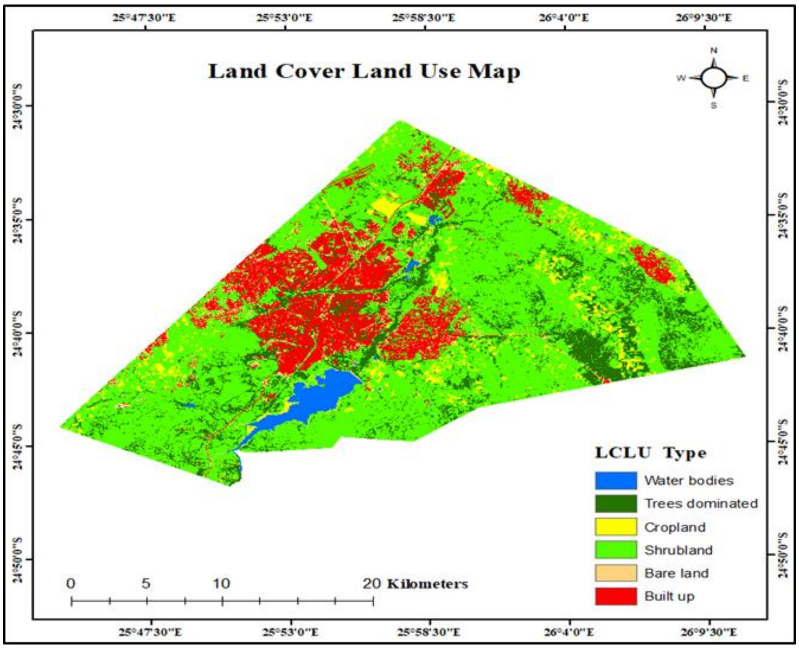

Figure 2 LCLU map of the study area

Accuracy assessment for the LCLU classifications was done by comparing the classification results with ground truth points. An Error matrix was used to compute the user accuracy (UA), producer accuracy (PA), overall accuracy (OA) and the Kappa coefficient (Kc) for the LCLU map. The overall classification accuracy was 94.0%. This value is acceptable as OA statistics normally fall between 85% and 95% [46]. Also, the Kappa coefficient obtained from the classification was 0.93. This value is greater than 0.8, indicating a high level of agreement between image data and ground truth data [30]. The area statistics for the various LCLU types are presented in Table 2. From the result presented in Table 2, it can be deduced that shrubland is the dominant LCLU type in the area occupying an area of 402.57 km^2 (60.18%), while water bodies occupied the smallest area (15.43 km^2, (2.31%)).

Table 2 Area Statistics for LCLU types

LCLU Type	Water bodies	Trees dominated	Cropland	Shrubland	Bare land	Built up	Total
Area (km2)	15.43	96.42	33.47	402.57	21.63	99.41	668.94
Area (%)	2.31	14.41	5.00	60.18	3.23	14.86	100.00

3.2 Soil Organic Carbon Stock

3.2.1 Variation of Soil Parameters with LCLU Types

The mean values of soil parameters in the major LCLU types in the study area are presented in Table 3. The table also includes Post hoc LSD multiple comparison results, which test whether or not significant differences exist in values of soil parameters across different LCLU types.

Table 3 Variation of Bulk density, SOC content, pH and Texture in different LCLU types

LCLU types	BD (g/cm³)	SOC (%)	pH	Sand (%)	Silt (%)	Clay (%)
Bare land	1.56 ± 0.14^{a}	0.32 ± 0.26^{d}	7.64 ± 0.90^{a}	72.59 ± 11.85^{a}	14.24 ± 5.87^{ab}	13.18 ± 7.55^{a}
Built-up	1.55 ± 0.11^{a}	0.42 ± 0.19^{d}	7.44 ± 0.98a	69.90 ± 6.14^{ab}	14.75 ± 3.45^{ab}	13.85 ± 4.90^{a}
Cropland	1.50 ± 0.08^{ab}	0.93 ± 1.04^{c}	6.29 ± 0.59^{b}	70.89 ± 15.46^{ab}	12.67 ± 4.45^{b}	16.84 ± 12.28^{a}
Shrubland	1.44 ± 0.06^{b}	1.40 ± 0.68^{b}	5.82 ± 0.54^{bc}	68.33 ± 12.49^{ab}	14.00 ± 5.77^{ab}	18.78 ± 8.55^{a}
Trees dominated	1.35 ± 0.11^{c}	2.46 ± 1.00^{a}	5.36 ± 0.13^{c}	62.77 ± 18.24^{b}	17.46 ± 6.48^{a}	20.25 ± 14.96^{a}
p-value	0.000***	0.000***	0.000***	0.319	0.162	0.441
$F_{(4, 81)}$	11.46	17.09	25.959	1.196	1.683	0.947

Note: Values are shown as mean ± standard deviation. Means with the same letter in each column are not significantly different ($P < 0.05$).

From the data presented in Table 3 above, it can be deduced that there was a significant difference in soil parameters within the 0 – 30 cm soil depth (except for the clay fraction) in the different LCLU classes in the study area. This suggested that LCLU was the key determinant of soil parameters. We could not have found this difference if geology, climate, and soil type were significant factors for change in these parameters. A detailed analysis of each of the properties is given below.

3.2.2 Bulk density

Soil bulk density varied across the different LCLUs (Figure 3). From the results presented in Table 3, soil bulk density (BD) in bare land (1.55 ± 0.11g/cm³) was significantly higher than in built-up, cropland, shrubland and trees dominated LCLU type ($p < 0.001$), but not significantly different from that in built-up and cropland. Also, the bulk density in cropland was found to be significantly higher than that in shrubland and trees dominated, but not significantly different from that in shrubland ($p < 0.001$).

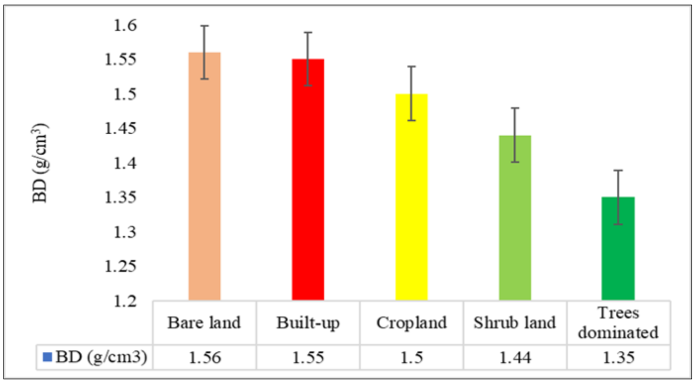

Figure 3 Variation of Bulk density in different LCLU types in the study area

The higher bulk density in cropland compared to shrubland and trees dominated could be attributed to increased soil organic matter decomposition rates as a result of agricultural activities such as tillage. Tillage without crop residue disrupts soil structure, resulting in the loss of soil organic matter, as well as compaction of the surface soil stratum [47]. In addition, the use of heavy machinery contributes to soil compaction, which increases soil bulk density. The higher soil bulk density in shrubland compared to trees dominated may be due to soil compaction caused by animal trampling during grazing since livestock grazing on communal pasture lands is legal. The lowest bulk density in trees dominated compared to other LCLU types may be attributed to the presence of high SOC content, which increases soil volume with no effect on its weight. The findings were consistent with the findings of previous studies conducted globally [3, 48–50].

3.2.3 Soil pH

Analysis of variance (ANOVA) and LSD post hoc results showed a significant difference ($p < 0.001$) in soil pH in different LCLU types in the study area. The pH of soil under trees dominated was found to be significantly lower than that of shrubland, cropland, built-up land, and bare land, but not significantly different from that of shrubland (Table 3 and Figure 4).

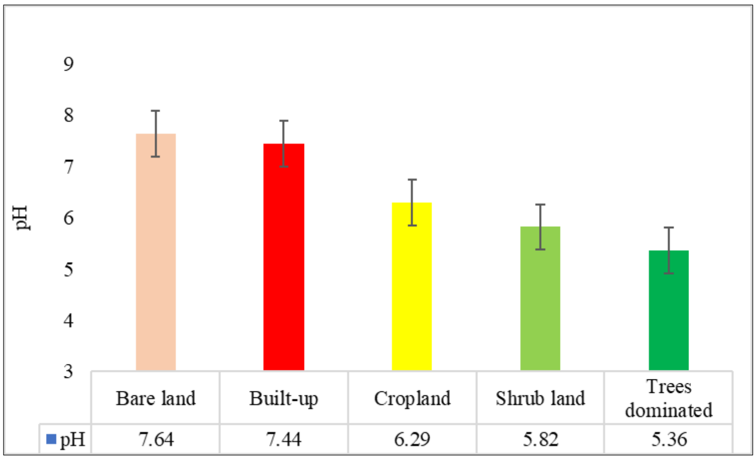

Figure 4 Variation of pH in different LCLU types in the study area

The lower soil pH in trees dominated and shrubland compared to cropland, built-up, and bare land soils could be attributed to the decomposition of more available organic matter (e.g. leaf litter), resulting in the production of hydrogen ions (H^+) that lowered the soil pH [51]. The results of the soil pH obtained in this study were like those reported by Huesken et al. [52] in the Botswana Soil Service and Advisory project of the South East District in 1989.

3.2.4 Soil texture

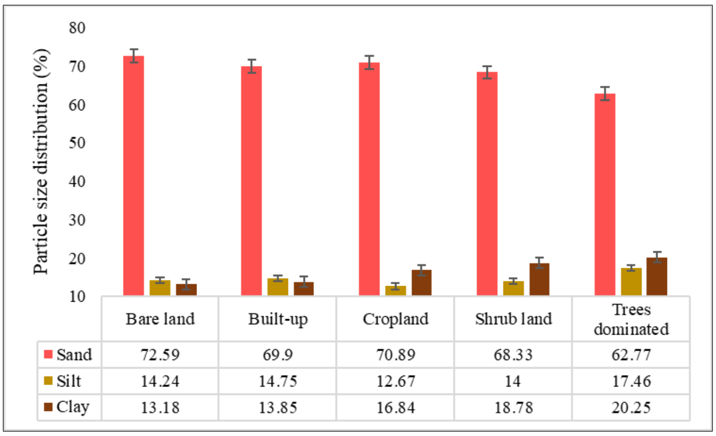

Figure 5 Variation of particle size in different LCLU types in the study area

Soil particle size distribution for the various LCLU types in the study area was also examined (

Figure **5**). The sand fraction under trees dominated was found to be lower than that in other LCLU types (p > 0.05) but was not significantly different from that in shrubland, cropland and built-up (Table 3). The silt fraction was higher under trees dominated and was significantly different from that in the other LCLU types. The clay fraction in tree dominated class was higher than in the other LCLU types but was not significantly different from that in shrubland and cropland.

The high clay and silt content in trees dominated could be attributed to the chemical weathering of the soil due to its high acidic content.

3.2.5 SOC content

SOC content varies significantly across the different LCLUs (Figure 6). Analysis of variance (ANOVA) and *post hoc* multiple comparisons showed that there was a significant difference in SOC content in different LCLU types ($p < 0.001$). Differences in SOC content in different LCLUs supported the hypothesis that different LCLUs have different SOC content.

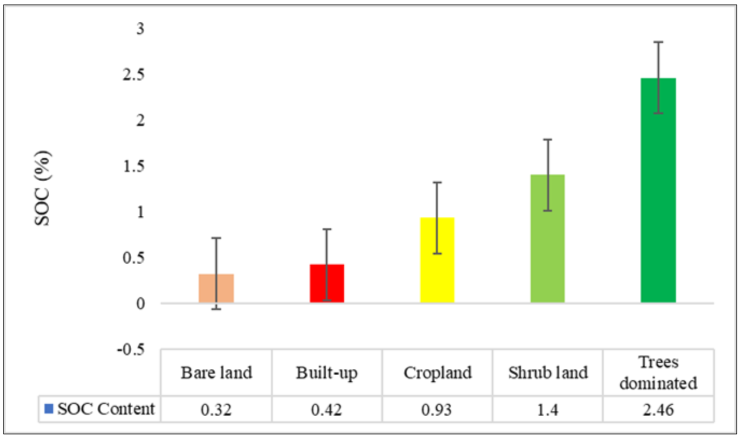

Figure 6 Variation of SOC in different LCLU types in the study area

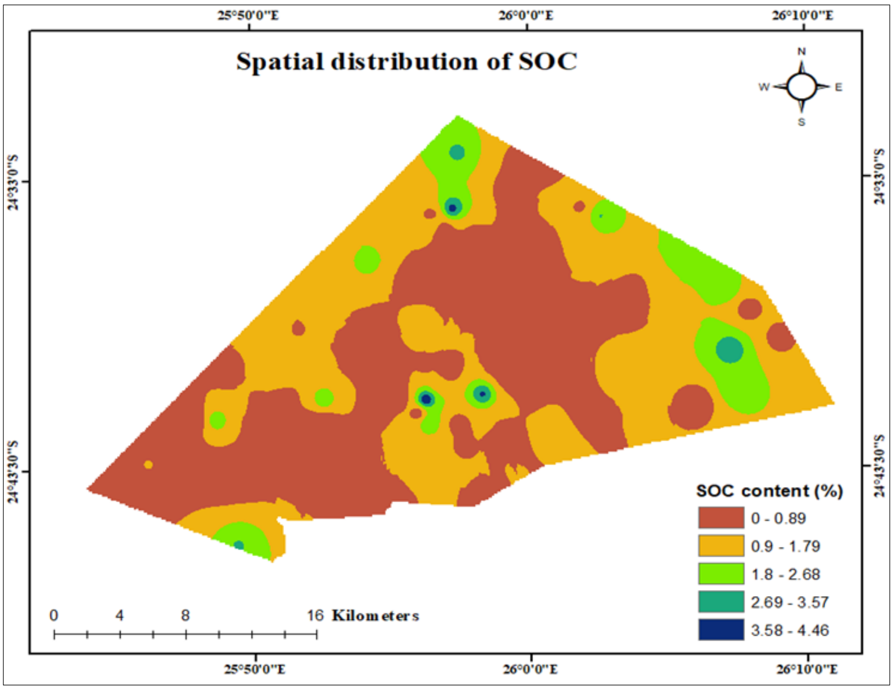

Figure 7 Spatial distribution of SOC in Greater Gaborone

The difference was very strong between bare land (0.32 ± 0.26 %) and trees dominated (2.46 ± 1.00%). The SOC content was significantly higher in soils under trees dominated (2.46 ± 1.00%) and shrubland (1.40 ± 0.68%) compared to cropland (0.93 ±1.04%), built-up (1.95 ± 0.88%) and bare land (0.32 ± 0.26%) (Table 3). Also, the SOC content in built-up was significantly higher than in bare land, but not significantly different. The significantly high SOC content in trees dominated and shrubland compared to the other LCLU classes indicated that there was more supply of litter or return of organic matter to the soil. However, frequent removal of biomass and crop residues from cropland during harvesting and continuous tillage could be the primary reasons for low SOC content in cropland compared to shrubland and trees dominated. Furthermore, continuous tillage or ploughing exposes available SOC to moisture, aeration, and other decomposing agents, allowing for the rapid decomposition of available organic sources, resulting in the reduction of SOC content [47]. Similar findings were reported in studies conducted in Southern Ethiopia by Hailu et al. [53] and Temesgen et al. [54]. These authors found that the SOC content of forest soils was significantly higher than that of open crop fields. This result, therefore, implied that soil under trees dominated and shrubland were good terrestrial sequesters of carbon in Greater Gaborone. The spatial distribution of SOC content in Greater Gaborone is depicted in (

Figure **7**) with the mean SOC content being 0.84%.

In comparison to other Sub-Saharan regions with similar ecosystem characteristics, the mean SOC content in Greater Gaborone was found to be lower than that of Johannesburg (South Africa) and the Birr watershed (Ethiopia). It was, however, slightly higher than in Central Zimbabwe and Central Namibia (Table 4).

Table 4 SOC content in Greater Gaborone compared to similar ecosystems around the Sub-Saharan African regions

Region	SOC (%)	Reference
Birr (Ethiopia)	2.55	[55]
Johannesburg	1.33	[56]
Central Zimbabwe	0.68	[57]
Central Namibia	0.39	[58]
Greater Gaborone	0.84	This study

The SOC stock in the study area was estimated to be 4.36 MtC, with trees dominated accounting for 1.13 MtC (25.9%), shrubland 2.83 MtC (64.9%), cropland 0.14 MtC (3.2%), built-up 0.22 MtC (5.1%), and bare land 0.04 MtC (0.9%) as shown in Table 5. Despite the high SOC content of trees dominated, the majority of the SOC in the study area was stored in shrubland due to its extensive coverage.

Table 5 Total SOC stock in the different LCLUs in the study area

LCLU type	Area (km2)	SOC stock (kgC/m2)	Total SOC Stock (MtC) in LCLU type	% total SOC stock in LCLU type
Bare land	21.63	1.86	0.04	0.9
Built-up	99.41	2.24	0.22	5.1
Cropland	33.47	4.22	0.14	3.2
Shrubland	402.57	7.02	2.83	64.9
Trees dominated	96.42	11.69	1.13	25.9
	653.50		4.36	100.00

3.3 Relationship of SOC content with bulk density, pH and texture in the study area

3.3.1 SOC content and Bulk Density

Many soil factors influence bulk density, one of which is SOC content [59]. Soils with a higher organic carbon content have a lower bulk density [60], indicating that the soil is less compact. This study found a negative relationship between soil bulk density and SOC content (R^2 = 0.995) (Figure 8). For instance, the soil under trees dominated with a bulk density of 1.35 ± 0.11 g/cm^3 had SOC content of 2.46 ± 1.00%, whereas soil under bare land with a bulk density of 1.56 ± 0.14 g/cm^3 had a SOC content of 0.32 ± 0.26 %) (Table 3). The inverse relationship between bulk density and SOC content found in this study was consistent with the findings of several studies conducted globally [2, 51, 61]. This could be explained by the fact that SOC contains a food source for soil organisms, which aids in the breakdown of large and heavy soil aggregates into smaller, more nutritious, and lighter aggregates that are more stable.

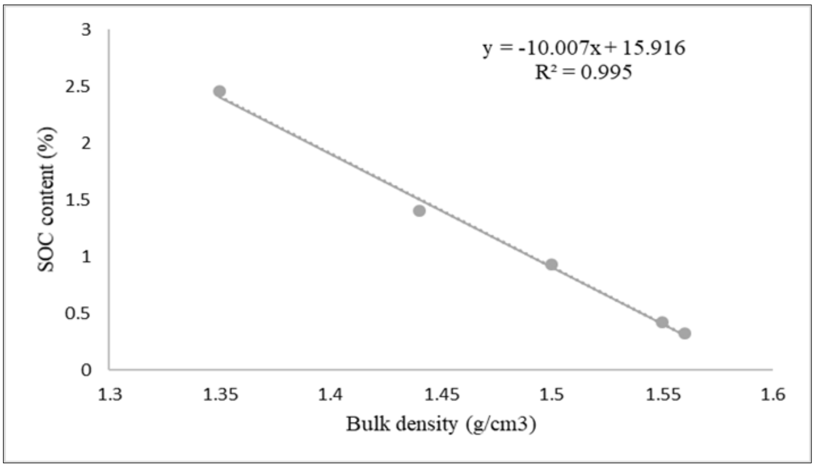

Figure 8 Relationship between SOC content and soil bulk density

Also, soil compaction can inhibit SOC accumulation because it negatively affects soil aggregates by limiting enzyme access to the materials within the soil aggregates and physically maintaining soil organic matter [42, 62].

3.3.2 SOC Content and pH

This study found a negative relationship between soil pH and SOC content (R^2 = 0.8699) (

Figure **9**). Several studies have found that oxidation of organic matter (e.g. leaf litter) produces organic acids in the soil solution that decreases the soil pH [42, 51]. Higher acidity generally inhibits microbial activity and reduces mineralization, resulting in a higher accumulation of SOC [63]. Low pH favours SOC accumulation because the bacteria or organisms most responsible for breaking down the organic matter experience a sharp drop in activity once the pH falls below 6.0 [64]. This explains the significantly higher SOC content in trees dominated (2.46 ± 1.00%) and shrubland (1.40 ± 0.68%) with pH of 5.36 ± 0.13 and 5.82 ± 0.54, respectively, compared to the low SOC content in bare land (0.32 ± 0.26) with high pH (7.64 ± 0.90). Furthermore, low pH (acidic) has the tendency to mechanically weather soil particles [3], thus, explaining the high clay content in soils of trees dominated and shrubland LCLU types than in bare land and built-up LCLU types (Table 3).

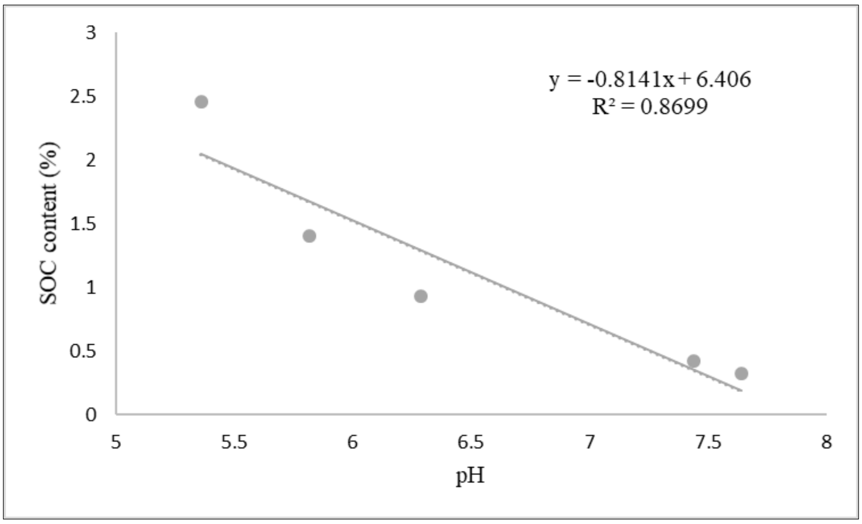

Figure 9 Relationship between SOC content and soil pH

3.3.3 SOC Content and Soil Texture

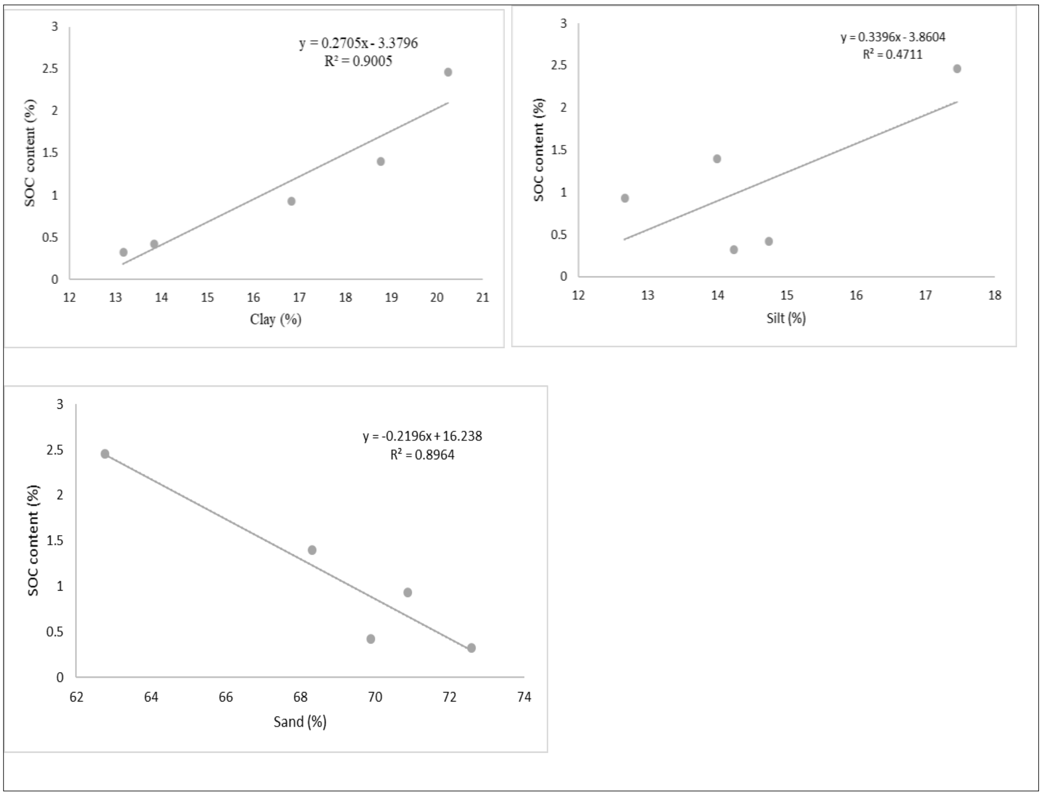

Figure 10 Relationship between SOC content and soil texture

The soil particle size fractions except sand showed a positive relationship with SOC content in the study area (Figure 10). This result was consistent with the findings of several studies conducted globally [17, 51, 64]. Clay and silt positively correlated with SOC content because they help to stabilize soil organic matter [64, 65]. The relationship between SOC content and soil texture has been linked to chemical stabilization of SOC through physicochemical adsorption of SOC on clay soil/mineral surfaces [66]. This relationship demonstrated that clayey soils have a greater potential for SOC storage than sandy soils [67]. This explains why the soil under trees dominated had a significantly higher SOC content than the other LCLU types.

4 Conclusion

This study has demonstrated the potential of land cover and land use to modify soil properties and the status of SOC stock. With the exception of soil texture, SOC, bulk density, and pH were found to differ significantly among the different LCLU types. The total SOC stock found in the study area was estimated to be 4.36 MtC, with the shrubland LCLU type accounting for 2.83 MtC (64.9%) while bare land with the smallest spatial extent stored 0.04 MtC (0.9%). It is thus concluded that soil under trees dominated and shrubland areas are good sequesters of carbon in the Greater Gaborone area. This finding might be important to land planning process given the rapid expansion of built-up areas in Greater Gaborone.

Compliance with ethical standards

Acknowledgments

The authors wish to acknowledge the Mobile of African Scholars for Transformative Engineering (MASTET) for funding this research. They are also grateful to the Department of Crop and Soil Sciences of Botswana University of Agriculture and Natural Resources (BUAN) for providing facilities for soil analysis.

Disclosure of conflict of interest

There are no competing interests in this publication.

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