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ANALYSIS OF LAND USE LAND COVER CHANGE IN THE GLEN VALLEY IRRIGATION SCHEME OF SOUTH-EASTERN BOTSWANA

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ABSTRACT

This study focused on assessing land use land cover (LULC) changes in the Glen Valley Irrigation Scheme of South Eastern Botswana between 2002 and 2022. The study employed remote sensing (RS) and geographic information systems (GIS) tools for analysing LULC changes in the study area during the study period. Landsat 7 ETM+ and Landsat 8 OLI images of 6 February 2002 and 21 February 2022, respectively, were used to detect LULC changes. Image classification was done using a supervised classification approach based on a Maximum Likelihood Classifier. Seven LULC types, namely, Built up, Cultivation, Water body, Sparse vegetation, Moderately dense vegetation, Dense vegetation, and Bare ground, were identified in the area. Post Classification Comparison (PCC) approach was used to detect LULC change during the study period. A pronounced 250 ha increase of cultivated land resulted from 13.2% conversion of sparse vegetation, with adverse implication on greenhouse gas (GHG) emissions and global warming. A noticeable 105 ha increase of Built-up area in the City of Gaborone resulted from 4.3% conversion of sparse vegetation, with implications on land planning process related to rapid urbanization. All changes of LULC types relied on availability of sparse vegetation as a key carbon sink and stabilizer of GHG emissions. Mitigation strategies including conservation agriculture, efficient irrigation and renewable energy are considered necessary.

Keywords: Land Use Land Cover; Image Classification; Change Detection; Conversion; Mitigation.

1 INTRODUCTION

Land-use patterns, influenced by a variety of social processes, often result in changes of land cover that affect biodiversity, water and radiation budgets, and greenhouse gas emissions. These and other factors when combined can affect the global climate and the biosphere. In Botswana, LULC changes are primarily driven by human and livestock population pressures, including rapid urbanization and general development activities such as increased demand for arable and grazing land, tourism, water, and fuel wood [1]. Changes in LULC have emerged as a key issue within the scientific community concerned with global environmental changes [2].

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 [3, 4]. Most of the rural-urban migration taking place in the country is directed to Gaborone and its neighbouring settlements due to more job opportunities, better infrastructure, social amenities and public services [5]. 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 unoccupied by agricultural lands and natural vegetation being converted into built-up areas (such as the Phakalane, Setlhoa and Gaborone North) [6].

In order to supplement insufficient semiarid agriculture for the burgeoning urban population, treated wastewater has been used to produce food, especially vegetables, in the Glen Valley Irrigation Scheme developed over 20 years ago within Gaborone. Nevertheless, adverse effects of irrigation such as soil erosion, water logging, rise in water table and soil salinity, have been reported elsewhere [7, 8]. The focus of studies in the Scheme, over the time, has been to investigate the effects of using treated irrigation wastewater on the quantity and quality of the produce [9, 10]. The parameters necessary to ensure sustainability (e.g. biodiversity) have scarcely been studied. The objective of this study was, therefore, to analyze land use land cover change over the 20-year period under irrigation.

2 MATERIALS AND METHODS

2.1 Features of the Study Area

Glen Valley Irrigation Scheme is situated 10 km northeast of Gaborone, adjacent to Notwane River (Figures 1 and 2). The scheme lies between Latitudes 24°35’23.56’’S and 24°37’01.14’’S and between Longitudes 25°58’ 16.74’’E and 25°58’43.29’’E. The scheme uses secondary treated wastewater. Effluent from the primary ponds in Glen Valley near the Gaborone Wastewater Treatment Plant (WWTP) is pumped by the Irrigation Division of the Ministry of Agriculture & Food Security to secondary ponds for further treatment nearby and pumped back to Glen Valley irrigation scheme to plots of private farmers. The scheme covers about 146 ha of 203 ha of Glen Valley land. Private farmers manage about 47 farms of different sizes (1-10 ha) to produce various arable crops.

The surface soil texture for most Scheme land is characterized as loamy sand to sandy loam with stretches of sandy clay loams. The soils are predominantly sandy loam to sand occurring in an alluvial-cum-colluvial landscape, with patches of vertisolic clayey materials alternating with areas of sandier and, even, gravelly deposits. The soils, mapped on a scale 1:20 000, are classified as luvisols, lixisols, cambisols, calcisols, regosols and arenosols [11]. Soil pH values indicate the soils to be generally slightly acidic to neutral in reaction. The vegetation type is savannah, with tall grasses, bushes and trees.

The Glen Valley Irrigation Scheme has a population of 3132 people made mostly by females [4]. Out of that, 146 are living and working in the farms. The dominant socio –economic activity is horticulture, growing cabbage, rape, butternut, tomatoes, green pepper, maize and fruit trees. Out of the actively cultivated farms, more than 80% are using treated wastewater to irrigate their crops; others use water from Notwane River. It should be noted that most of the currently cultivated farms are adjacent to the river mainly because there is more chance of survival when there is a challenge with the flow of the effluent from the ponds. The alternative source of water is the river.

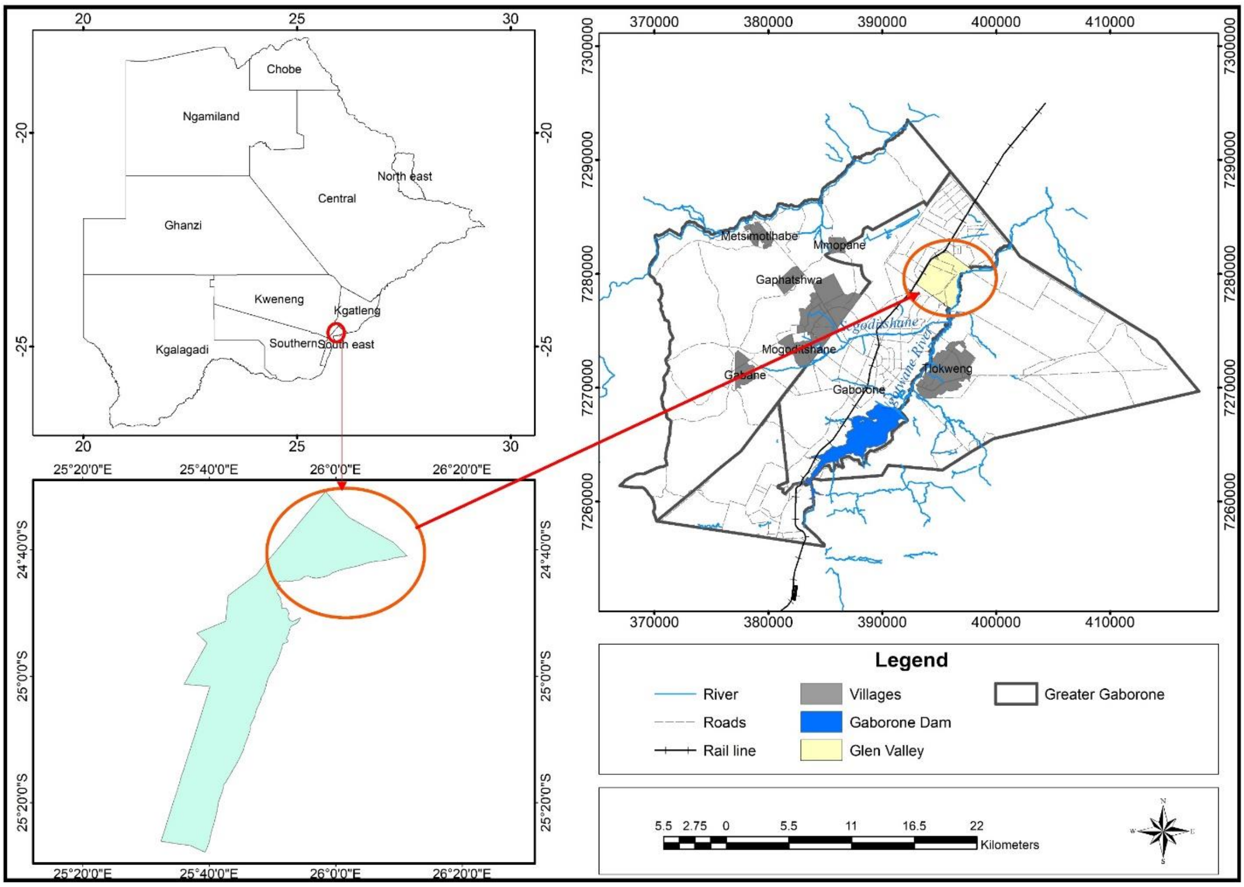

Figure 1: Location of study area

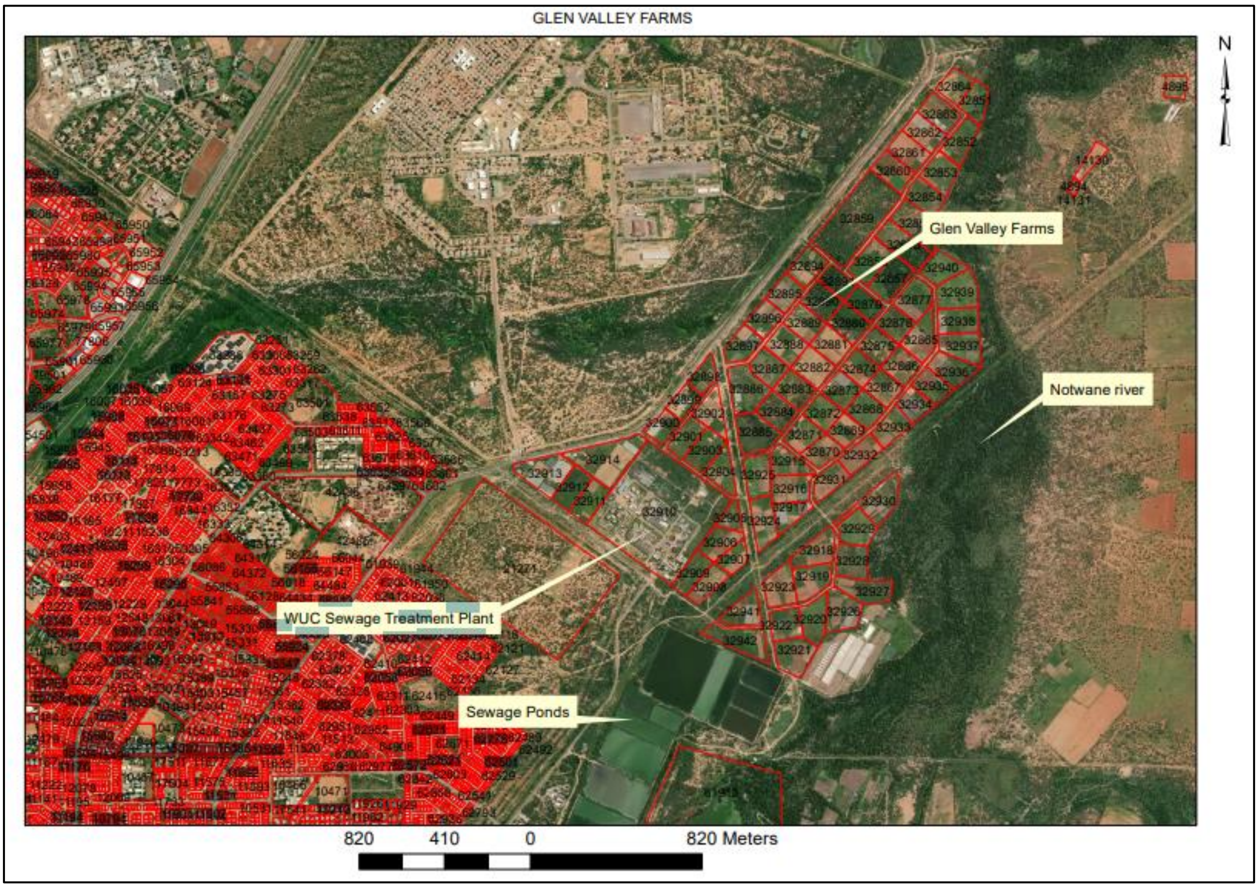

Figure 2: Satellite image of Glen Valley Irrigation Scheme.

2.2 Identification of LULC types in the study area

2.2.1 Data acquisition

The study utilized Landsat 7 ETM+ and Landsat 8 OLI images of 6 February 2002 and 21 February 2022, respectively, which are available freely from https://earthexplorer.usgs.gov. The search criterion for data download was set to only show images which had less than 10% cloud cover to minimize the effects of atmospheric noise on image classification. The area of interest (AOI) was digitized in Google Earth Pro, exported as a KML file and later converted to a shape file 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

Radiometric and atmospheric corrections were carried out to minimize noise from the satellite imageries. Radiometric correction was employed to convert satellite images' digital number (DN) to spectral radiance (at sensor) and reflectance. This process eliminated the effects of differences in illumination geometry hence improving the accuracy of the results obtained from comparison between satellite imageries taken at different dates. On the other hand, atmospheric correction was carried out in Earth Resources Data Analysis System (ERDAS) Image 2022. This process reduced the effects of scattering and absorption on satellite images and hence improving quality of the information extracted from the images. The images were further subjected to images enhancement techniques, the Histogram equalizer. Histogram Equalizer was applied to each band in IDRISI selva. The corrected images were then clipped to area of interest (AOI) in ERDAS Image 2022. The clipped images were later geometrically corrected to a common coordinate system (WGS 1984 Zone 35S) for a better comparison. Layer stacking was then carried out to produce composite images for the year 2002 and 2022.

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 LULC 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 [12]. 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 [13]. Training classes were selected through visual interpretation of high resolution satellite images in Google Earth Pro maps. The training areas of each LULC class were selected throughout the study area to obtain good representatives [13]. The centres of large patches of LULC 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 [14]. Based on the characteristics of the image, seven major LULC types were identified in the study area. The identified LULC classes included Built up (Bu), Cultivation (Cu), Water body (WB), Sparse vegetation (SV), Moderately dense vegetation (MDV), Dense vegetation (DV) and Bare ground (BG).

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 [15]. Post-classification smoothing with a majority filter is essential to reduce unnecessary errors and further improve classification accuracy [15]. 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 [12] 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 LULC classes in the study area. A stratified random sampling method was used to collect a total of 161 reference data from the classified LULC maps of 2002 and 2022 to ensure that all seven LULC 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 analysed 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 [16]. The following equations were used to compute the user accuracy (UA), producer accuracy (PA) and overall accuracy (OA).

$$UA = \frac{Number\ of\ Correctly\ Classified\ Pixels\ in\ each\ Category}{\text{Total Number of Reference Pixels in that Category (The Row Total)}} * 100$$

$$\text{PA} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Reference Pixels in that Category (The Column Total))}} * 100$$

$$OA = \frac{Total\ Number\ of\ Correctly\ Classified\ Pixels\ (Diagonal)}{Total\ Number\ of\ Reference\ Pixels} * 100$$

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 [17]. 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 0.40 indicates a poor agreement.

$$\text{Kappa Coefficient (T)} = \frac{(TSxTCS) - \sum(Column\ Total\ x\ Row\ Total)}{\text{TS2} - \sum(\text{Column Total} - \text{Row Total})}$$

2.2.6 Change detection analysis

Change detection was carried out to assess both the statistical and spatial characteristics of each LULC category. The LULC images were converted from raster to vector data for proper quantification and change detection analysis. A simple intersection was performed in ArcGIS between 2002 and 2022 to obtain a change map. This map shows LULC classes that have experienced positive and negative changes and those that did not change over time. Statistical quantification was then carried out to obtain the changes in ha.

Figure 3 gives a methodological flow chart for the analysis from data acquisition to results.

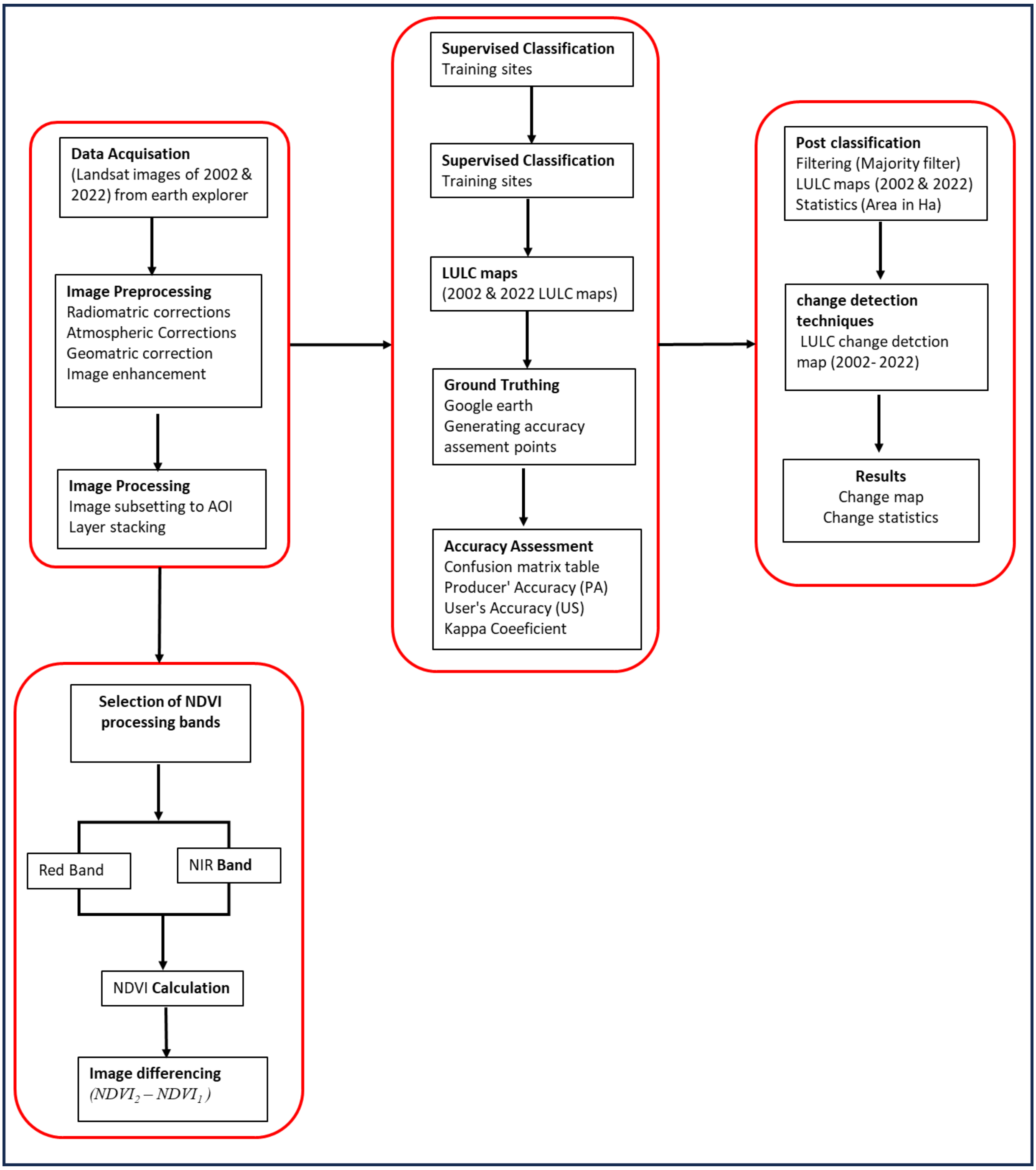

Figure 3: LULC analysis methodology flow chart.

3 RESULTS AND DISCUSSION

3.1 LULC analysis

The performed classification resulted in seven (7) LULC classes shown in Figure 4. The overall accuracy (OA) was 93.0%. This value is acceptable as OA statistics normally fall between 85% and 95% [18]. Also, the Kappa coefficient obtained from the classification was 0.90. This value is greater than 0.8, indicating a high level of agreement between image data and ground truth data [19]. An analysis of these LULC types indicated that sparse vegetation was the dominant LULC class in both periods. A spatial assessment of the LULC types further showed an increase in agricultural land from 2002 to 2022. Most of the cultivation occurred in the southeastern part of the study area.

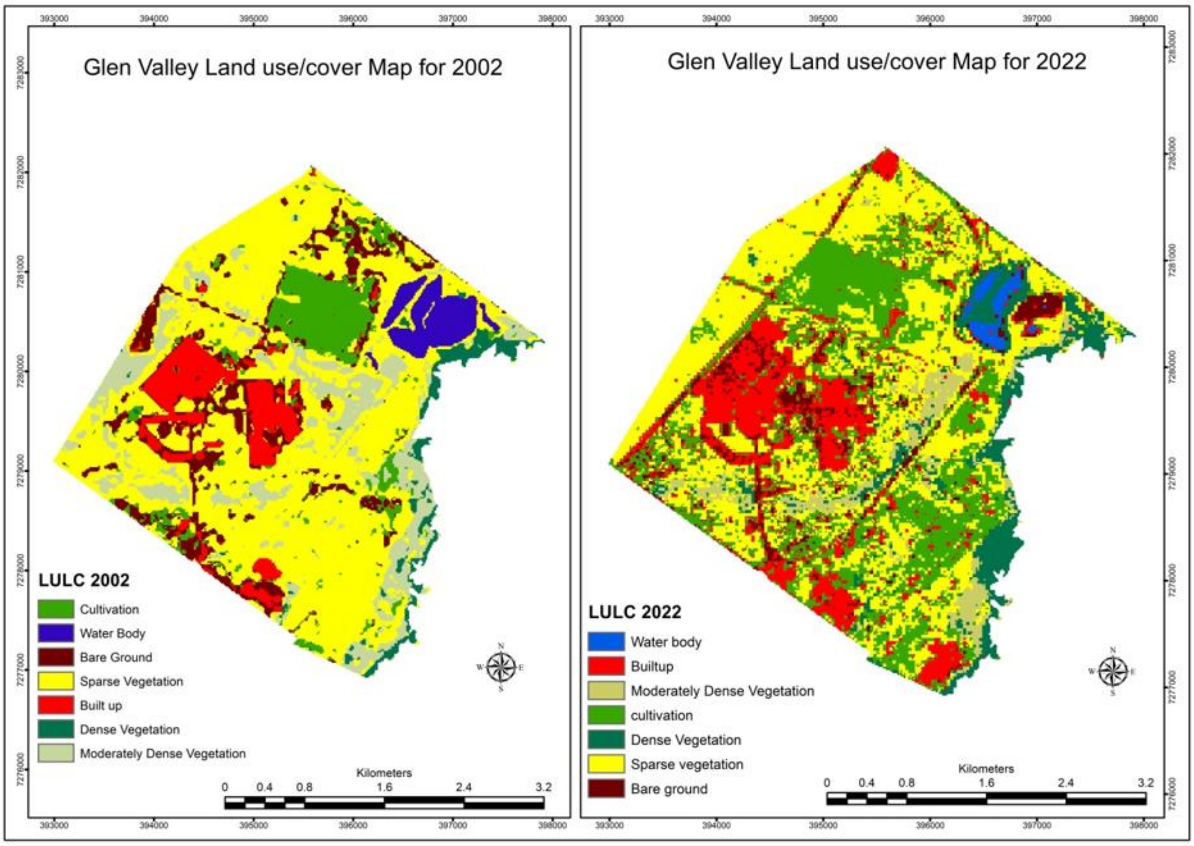

Figure 4: LULC maps for 2002 and 2022.

The analysis also shows a reduction in water body, with more vegegation occuring around the open water sources in 2022. Furthermore, Figure 4 shows an increase of the cultivated area in the eastern to south-eastern parts of the study area, while the same area in 2002 was classified as sparse vegetation. Further scrutiny of the 2022 LULC map on the north-eastern part of the study area shows a dried up open water source which is classfied as bare ground (Figure 4). However, statistics show that there was more bare ground in 2002 compared to 2022 (Figure 5). Figure 5 shows that with the exception of dense vegetation, buildup area and cultivation, the remaining land cover categories were less in area in the year 2022 compared to 2002.

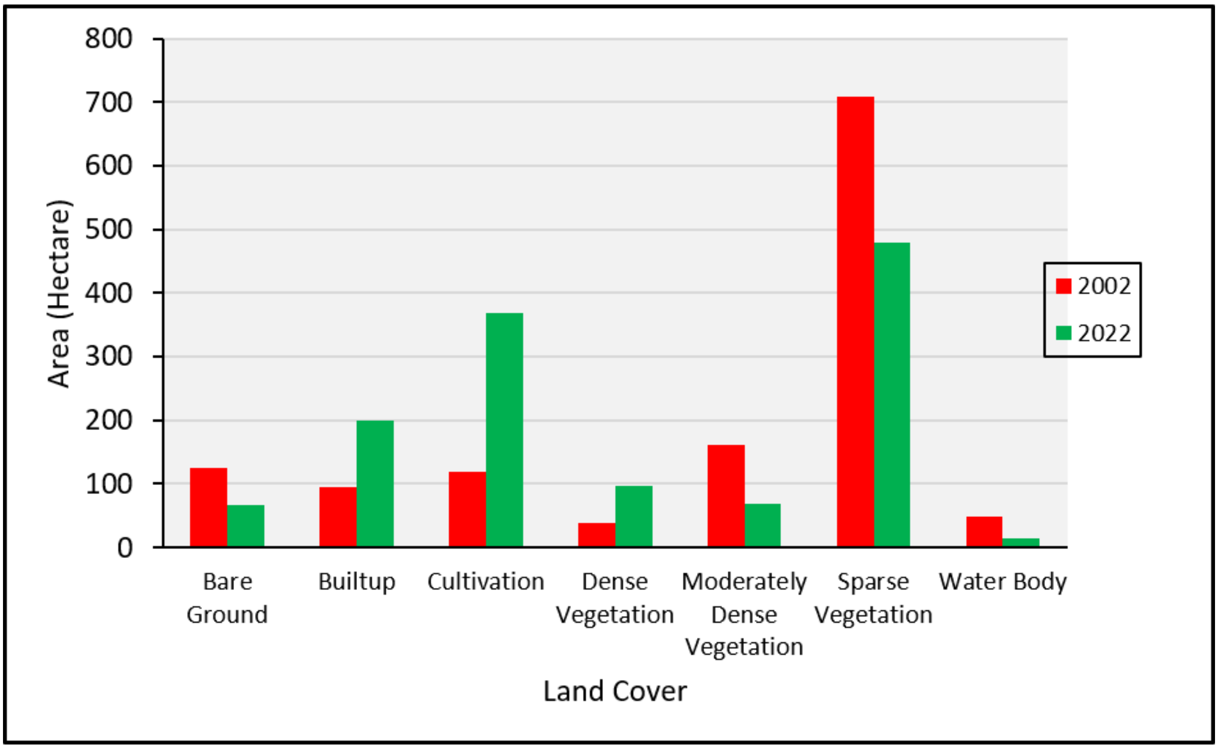

Figure 5: Comparative hectarage of LULC categories between 2002 and 2022.

3.2 Change detection analysis

The change detection analysis shows that three LULC classes (vis. Built up, Cultivation, Dense Vegetation) experienced an increase in area, whereas the remaining four (vis. Bare Ground, Moderately Dense Vegetation, Sparse Vegetation, Water Body) had a decrease during the period 2002 – 2022 (Table 1). Cultivation experienced the largest increase (19.3%) while Sparse Vegetation had the highest decline (17.7%).

Table 1 only indicated if a particular LULC category experienced an increase or a decrease. It did not show where the change happened and to which LULC class it changed to. A further analysis was therefore carried out to visualize the changes that occurred between 2002 and 2022. Figure 6 indicates the transition that occurred from one LULC class to another. The analysis shows that there are notable areas where sparse vegetation was converted to cultivation. About 13.2% of sparse vegetation was converted to cultivation between 2002 – 2022.

Table 1: Magnitude of area change of LULC classes between 2002 and 2022

Class Name	2002(ha)	% Area	2022 (ha)	% Area	Change (ha)	% Change
Bare Ground	124.47	9.60	66.63	5.14	-57.84	-4.46
Built up	95.52	7.36	200.44	15.45	104.91	8.09
Cultivation	118.96	9.17	369.58	28.50	250.62	19.32
Dense Vegetation	38.68	2.98	97.36	7.51	58.69	4.52
Moderately Dense Vegetation	162.14	12.50	69.34	5.35	-92.80	-7.15
Sparse Vegetation	708.06	54.59	479.11	36.94	-228.94	-17.65
Water Body	49.17	3.79	14.46	1.11	-34.71	-2.68
Total	1297.0	100.00	1296.9	99.99		

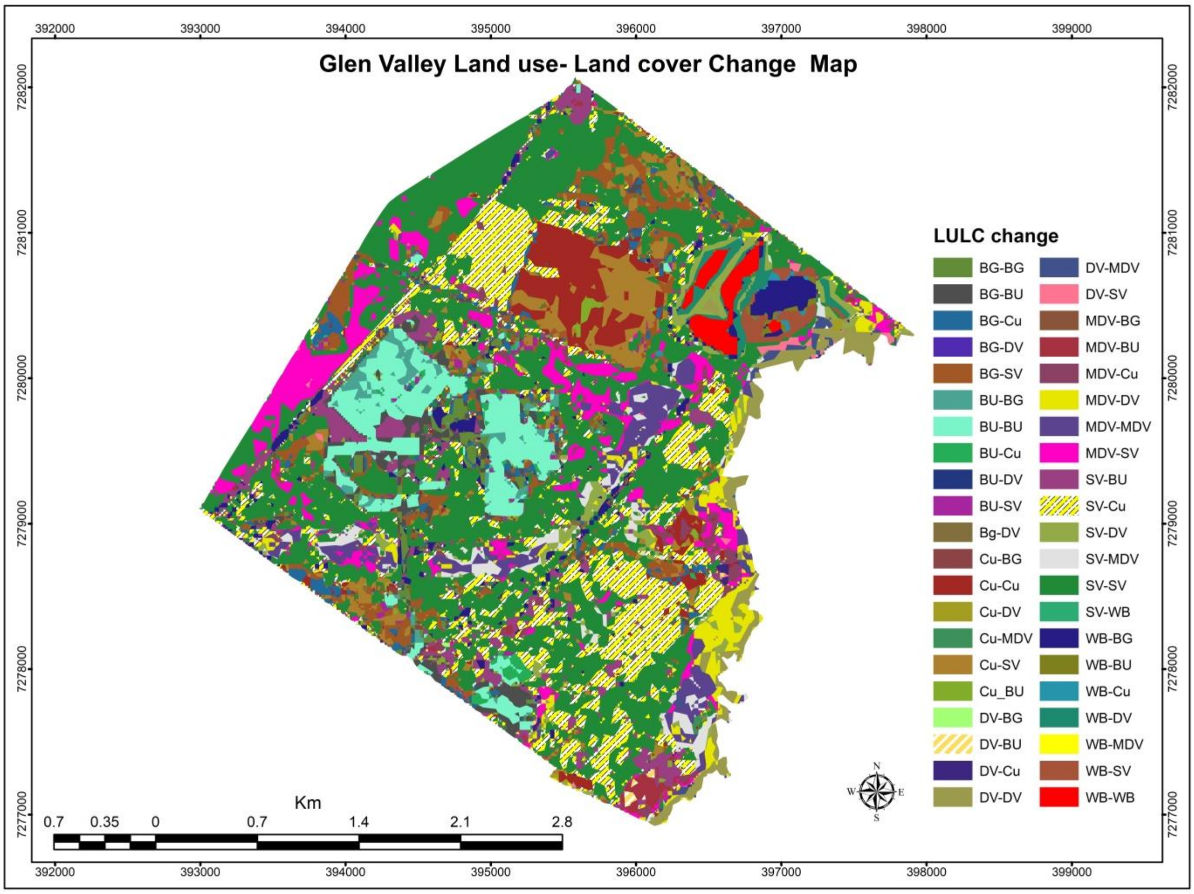

Figure 6. Glen Valley LULC change map: WB = Water body, MDV = Moderately Dense vegetation, BU, Built up, Cu = Cultivation, BG = Bare Ground, Dv = Dense vegetation, SV = Sparse Vegetation.

Although the results show noticebale changes that occurred from sparse vegetation to cultivation, sparse vegetation was still dominant. Figure 7 indicates that at least 31.9% of the area remained unchanged. Similarly, about 5% of built up area remained unchanged. The analysis further shows that a small area (0.405 ha) of land was converted from build up to sparse vegetation, which may not necessarily be the case. This may be due to overgrown vegetation among builtup leading to mistaken identity of pixels.

The first key finding from this study is the 13.2% conversion of sparse vegetation to cultivation during the 20-year span. Changes from one LULC type to another are responsible for large carbon fluxes in the terrestial ecosystem [2]. LULC changes, such as this, contribute approximately 26% of global greenhouse gas (GHG) emissions compared to 14.3% and 19% from transportation and industry, respectively [20].

The second key finding is the 4.3% conversion of sparse vegetation to Built up (BU). 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 sparse vegetation being converted into built-up areas. Tree savannah and sparse vegetation are important ecosystems in semiarid 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 [20]. These findings might be important to land planning process given the rapid expansion of built-up areas in Greater Gaborone.

The third key outcome of this study is the still-dominance of sparse vegetation as 31.9% of its area remained unchanged. Neba et al (2022) also reported a 64.9% of sparse vegetation area dominating in the Greater Gaborone region. They further concluded that tree dominated and sparse vegetation areas are good sequesters of soil organic carbon in the Greater Gaborone area. While cultivation improves food security and wastewater reuse, it comes at the cost of higher GHG emissions unless managed sustainably. Overall, the conversion leads to higher GHG emissions and reduces the natural buffering capacity of semiarid ecosystems, contributing to global warming. The need to maintain an above-average Sparse Vegetation area among LULC types so as to limit GHG emissions at a bearable level is therefore imperative.

Mitigation strategies such as conservation agriculture (e.g. minimal tillage, cover crops, etc.), efficient irrigation (especially drip irrigation) and renewable energy (using solar-powered pumps) may be considered necessary.

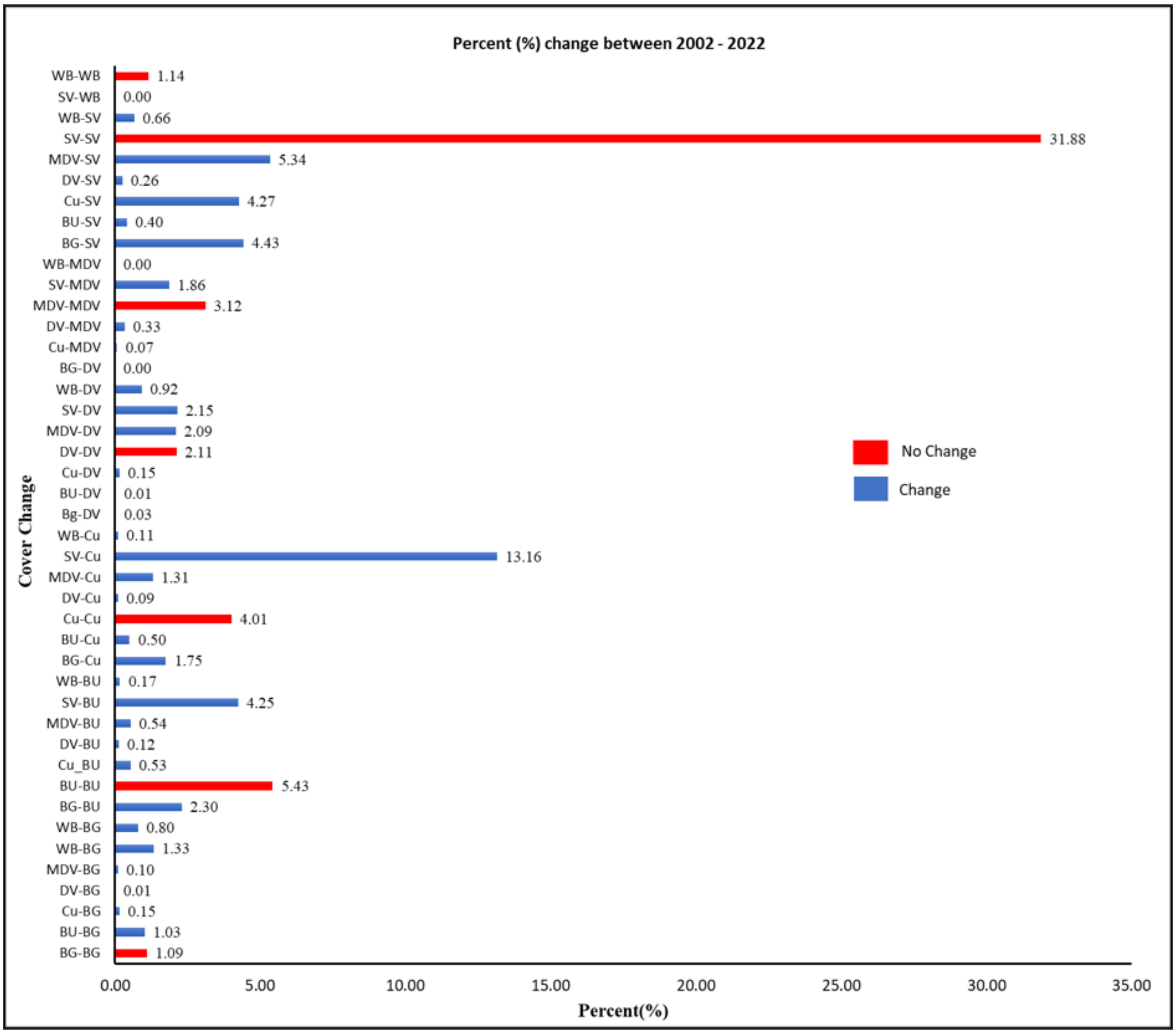

Figure 7: Glen Valley LULC change: WB = Water body, MDV = Moderately Dense Vegetation, BU, Built up, Cu = Cultivation, BG = Bare Ground, Dv = Dense vegetation, SV = Sparse Vegetation.

4 CONCLUSION

The following conclusions are drawn from the study:

- A pronounced 250 ha increase of cultivated land resulted from 13.2% conversion of sparse vegetation, with adverse implication on GHG emissions and global warming;
- A noticeable 105 ha increase of Built-up area in the City of Gaborone resulted from 4.3% conversion of sparse vegetation, with implications on land planning process related to rapid urbanization;
- All key changes of LULC types relied on availability of sparse vegetation as a key carbon sink and stabilizer of GHG emissions;
- Mitigation strategies including conservation agriculture, efficient irrigation and renewable energy are considered necessary.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

We the authors hereby declare that there are no competing interests in this publication.

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