Chapter

Spatio-Temporal Distribution of the Black Rhino (*Diceros bicornis L.*) in the Midlands Black Rhino Conservancy, Zimbabwe

Blessing M. Mugaviri, Gilbert H. Moyo, Ezra Pedzisai and Cuthbert Maravanyika

Abstract

Geographic Information System (GIS) and Remote Sensing (RS) technologies have many attributes that are beneficial in detecting, mapping, and, monitoring change in Land use/Land cover (LULC). This study used the technology with the aim to evaluate the Spatio -temporal impacts of Land use/Land cover Changes (LULCC) on Black Rhino distribution in Midlands Black Rhino Conservancy (MBRC), Zimbabwe. The study used time series satellite data. Landsat images were downloaded for the month of May at five-year intervals from 2000 to 2020. LULC and Normalized Differences Vegetation Index (NDVI) maps obtained were used in change detection. The images were classified using QGIS software on the maximum likelihood classifier algorithm. Presents and absence data for Black Rhino was used for distribution mapping. Quantum Geographic Information System (QGIS) and, R studio software were used for analysis. Results indicated that, a big percentage cover change was the bare land which increased by over 160%. Woodland decreased by about 46% within the same space of time. LULCC showed a significant positive relationship with black rhino distribution ($p = 0.0381$). MOLUSCE plugin was used for Prediction of LULCC for the year 2030, results indicated the highest increase in bare land 16.59%.

Keywords: biodiversity, habitat, land cover land use changes (LCLUC), Spatio-temporal

1. Introduction

Land Use and Land Cover, Geographic Information System (GIS) and Remote Sensing (RS) technologies have many attributes that would be beneficial in detecting, mapping, and monitoring change in Land use/Land cover (LULC). This study used the technology with the aim to evaluate the Spatio -temporal impacts of Land use/Land cover Changes (LULCC) on Black Rhino distribution in Midlands Black Rhino Conservancy (MBRC), Zimbabwe. The research gives a better understanding of the ecosystem for sustainable management. Remote Sensing using space-borne sensors is a tool, par excellence, for obtaining synoptic observations on the spectral behavior of various environments, for instance, land surface changes (degradation), water quality, soil and, atmosphere [1].

LULC represents an important factor in environmental analysis and spatial planning approaches [2]. When discussing the environment there is a need to understand the existence and importance of each species in an ecosystem and bear in mind that habitat loss threatens the existence of fauna and flora [3]. LULC is a dynamic variable because it reflects the interaction between socio-economic activities and environmental changes, for example, where deforestation has taken place and where land has been cleared due to anthropogenic factors [1]. For this reason, it is necessary to be updated frequently. Integrated GIS and RS have already successfully been applied to map the distribution of several plant and animal species, their ecosystems, landscapes, bio-climatic conditions, and factors facilitating invasions [1, 3–6]. Remote sensing imagery is available for most parts of the world since 1972. The multidate nature of satellite imagery permits monitoring dynamic features of landscape environments and thus provides a means to detect major land cover changes and quantify the rates of change [7]. However, there are inadequate researches that highlight land use impacts on specific species distribution.

The interpretation and analysis of Landsat TM image since 1987, provide comprehensive information regarding the various land uses and the associated environmental problems [8], for example to determine the land-use changes due to new settlements, deforestation, and erosion due to land clearing activities RS techniques have been successfully applied [9]. Due to Advancement in satellite sensors, their analysis techniques are making remote sensing systems fruitful, realistic, and attractive for use in research and management of natural resources [7].

This research was conducted in Midlands Black Rhino Conservancy (MBRC), which consists of privately-owned bush and farmland to evaluate if LULCC have got an impact on Black Rhino distribution. The conservancy supports cattle grazing and game utilization. However, there has been a change in land use in some areas. The clearing of huge tracts of land for mining led to the displacement of many animals, environmental degradation, and the irrecoverable destruction of animal habitat, for example, Black Rhino home ranges. A visit to one of the disused plants of the mining company at Two Springs, deep in the conservancy area, shows furrows and heaps of dumps from mining activities, with no reclamation efforts having been done contributing to habitat loss.

Currently, there have been some changes in land-use practices. Agriculture used to be subsistence farming only but, it is no longer subsistence since they have extended the cropland for better yield. These alterations in land use led to a change in the composition of vegetation diversity thereby, raising a flag to research if, the changes have affected wildlife distribution in the conservancy. Since the area was set aside for cattle and game utilization when the conservancy was formed, there is a need to assess change in land use to quantify the LULCC percentage. Studying trends enables an understanding of changes in land utilization.

The rate of biodiversity loss in MBRC is a serious cause for concern to the ecosystem. Human-induced LULC changes have contributed to the dilapidation of Black Rhino habitat in MBRC, hence the need for an evaluation on LULC change in the important conservancy. It is also unknown to what extent the activities being practiced have impacted the Black Rhino distribution and, also how it will affect the distribution in the future. This article quantified LULC change from 2000 to 2020 and also analyzed the relationship between LULC change and Black Rhino distribution within MBRC for the years 2000 and 2020. Furthermore, it predicted the extent of LULC change in MBRC by 2030.

A major reason for researching historical LULCC is that by understanding the past, we can better understand future trajectories for managers to make informed decisions on the management of the ecosystem [1]. This can be achieved using GIS and RS, and diversity indices to observe land-use change. There is a significant gap in our understanding of the spatial and temporal ecology of biodiversity and ecosystem goods and services. This research seeks to fill the gap by evaluating the spatial and temporal impacts of LULCC on the Black Rhino distribution and uses a model to predict future changes.

1.1 Black rhino (*Diceros bicornis L.*)

Rhinos are large odd-toed ungulates that fall into the Perissodactyla order and the Rhinocerotidae family. The black rhino is a large gray animal that stands 1.4–1.7 m and weighs between 996 and 1362 kg. The black rhino in **Figure 1** has an upper prehensile lip that they use for browsing which is a predominant physiological difference between the two African rhino species. This lip enables them to browse selectively on a diverse array of woody species across their range [10, 11]. They have poor eyesight, which they compensate for with an acute sense of smell and hearing Black Rhino have two continually growing horns that are variable in shape and size with the front horn normally longer than the rear horn. Rhino horn is made up of keratin and is used for predator defense, a stake in encounters with other rhino, and a tool for pulling down hard to reach branches for feeding. The rhino is sensitive to its home range and it is ideal to study the effects of LULCC to its home range.

Figure 1.
Image showing a black rhino.

2. Materials and methods

This research study is on spatio-temporal impacts evaluation of LULCC on Black Rhino distribution in MBRC Zimbabwe. This chapter presents the methodology of this research study. The next important step in any research process after the study of literature and identifying the research questions is deciding on the most suitable methodology. The research methodology is the overall approach to the design process from the hypothetical foundations to the collection of data and analysis adapted for a study [12]. The methodology is therefore how we discover how to go about a task of finding out what we believe to be true [13]. This chapter presents the study area, research method, research design, LULC data acquisition and Rhino distribution data collection.

2.1 Study area

The Midlands Black Rhino Conservancy Trust (MBRC) is situated in the heart of Zimbabwe, located at latitude 18°58’01” S and longitude 30°11’24″ E. The area consists of 63,000 ha (156,000 acres) of bush and farmland bounded by the Munyati River on the northern boundary and the Sebakwe River on the southern boundary with Lake Sebakwe and its Recreational Park in the middle. Agriculturally, Sebakwe is in the country’s Natural Farming Region whose rainfall ranges from 650 to 700 mm per annum [14]. The temperature ranges between 25°C to 28°C. About 70% of the soils are derived from granite, which is loam and light-textured soils. In **Figure 2** Munyati River drains the area to the north and Sebakwe River cuts through the conservancy and drains the study area to the south. Their subsystems which include, among others; Shorai, Nyamaponde, and Zibagwe Rivers also drain the area from South-East to the North-West [15]. Although there is a rich network of rivers, most of them are ephemeral, and annual, animals and cattle rely on pumped water holes.

The ranch has a variety of soil patches including black clays in Vlei, sandy loams, loams, and red soils in uplands particularly the great dyke. The soils are classified as serpentinites and are rich in Chromium and its associated minerals. The topography is generally flat except for the Mazuri- Chinyika boundary which comprises a stretch of the Great Dyke [14]. Wildlife ranching and cattle farming is the predominant land use whilst crop farming and mining are now being practiced. Different woodland types exist in MBRC. These include Miombo, Mopane, Terminalia, Acacia, and mixed species. MBRC has a diverse vertebrate fauna that includes mammals, birds, reptiles, and fish. Mammals include megaherbivores such as Elephants (*Loxodonta africana*) Black rhino (*Diceros bicornis*), Giraffe (*Giraffa camelopardalis*), Wildebeest (*Connochaetes taurinus*), Zebra (*Equus quagga*), Waterbuck (*Kobus ellispiprymus*), Impala (*Aepyceros melampus*) and Eland (*Taurotragus oryx*). The birds include the recent sighting of the ground hornbill, the Gray Lorie, Yellow-billed hornbill to mention only a few [15].

2.2 Research instruments

The instruments that were used were Satellite images, Global Position System, Vehicle, Digital camera, Datasheet, Pen, pencil, ruler, QGIS 3.4, 2.8 and R studio 4.0.2.

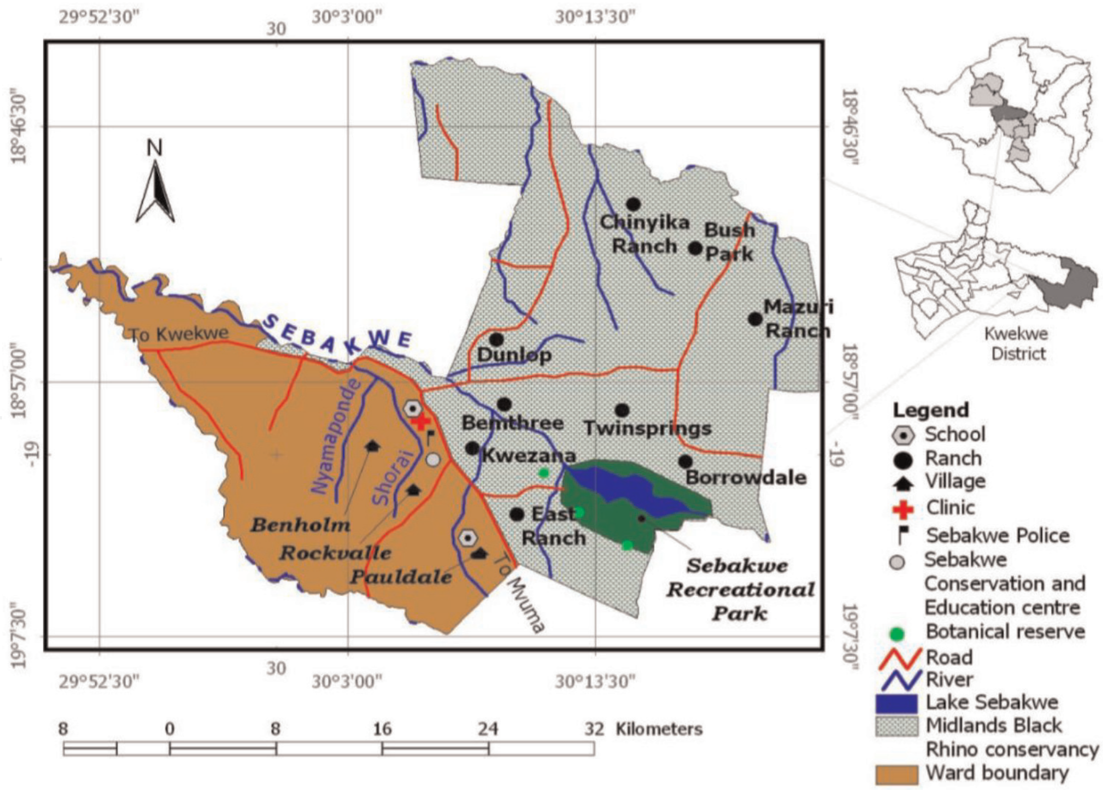

Figure 2.
Map showing midlands black rhino conservancy.

2.3 Research method

In this research study, the researcher adopted a mixed-method research approach. The overall goal of mixed methods research was to combining qualitative and quantitative research components. It also expands and strengthens a study's conclusions and, therefore, contribute to the published literature [13]. In this research study, the use of mixed methods contributed to answering research questions such as the rate of change in LULCC from the year 2000 to 2020 in MBRC, if there is any relationship between LULCC, and Black Rhino distribution within MBRC, and the perceived habitat loss in MBRC by 2030. Qualitative methods were used to explore the phenomena, and generate the conceptual model while quantitative methodologies were used to confirm the validity by testing the hypothesis [16].

2.3.1 Research design

The study included pre-field data collection, field survey and post-field data analysis. Primary data collected during field work and secondary information about the Rhinoceros and the study area were extensively used for the study purpose. To address the research study questions, mixed methods were used, consultations with site farmers, management, and remote sensing were employed as data collection tools. This research study adopted a longitudinal survey approach which refers to an investigation where participant outcomes and possibly treatments or exposures are collected at multiple follow-up times. Longitudinal study generally yields multiple or "repeated" measurements on each subject [17]. Researchers record the information that is present in a population, but they do not manipulate variables [18]. The method is often used to make inferences about possible relationships or to gather preliminary data to support further research and experimentation [19]. Semi-automatic classification plugin in GIS and RS technology were used in detecting, mapping, and investigating the change in LULC. Ground control points were randomly sampled in the study area covering areas with grasslands, cropland, built-up areas, bare land, water bodies, and woodland for ground-truthing [20]. GPS locations for Rhino sightings were collected in the year 2020 and secondary data from year 2000 was used as baseline data.

Landsat images where downloaded from the NASA website (https://earthexplorer.usgs.gov) [21]. Topographic map scale 1:50,000 was used as a guide for interpretation. A digital elevation model of 30 m resolution was used. A statistical sampling methodology based on area frame sampling was adopted for this study. The method relied on satellite imagery, photographs, and maps for data collection [22]. The unaligned area frame sampling scheme was preferred for the area because of the heterogeneous land use cover found in the area. High densification for sample sites where preferred to validate the consistency of the land cover and land use database. Individual land parcels and ground cover classes were identified in each sample segment. The 2030 map was predicted using molusce plugin. Present only and absence data were used to map the Black Rhino distribution.

2.3.2 Rhino distribution data collection

Presence and absence data were collected for spatio-temporal data to plot the distribution of Black Rhino in MBRC on a map. Direct observations of Rhinos and fresh dung were used as present data, furthermore, a handheld Global Processing System (GPS) was used to record the locations of the sightings. Secondary data was also used from the Parks and Wildlife Authority database where sightings and locations are recorded. Secondary data of one hundred, for the year 2000 were used, and 100 sightings for the year 2020 were recorded.

2.3.3 Land use/land cover data acquisition

Satellite images were downloaded from the website (https://earthexplorer.usgs.gov), [21] however, before downloading images to be classified, a pilot survey was conducted to check for images with less cloud cover.It was then observed that for the month of May in each of the following years: 2000, 2005, 2010, 2015, and 2020 the images had less than 10% cloud cover, hence, the images for May were used. The images were georeferenced and fit to the Universal Transverse Mercator (UTM) projection system (zone 45, datum WGS-84). The main steps involved in image classification are determining a suitable classification system, feature extraction, selecting good training samples, image pre-processing and selection of appropriate classification method, post-classification processing, and finally assessing the overall accuracy.

Tiles were obtained in GeoTiff image format for pre-processing. Image composites were generated using images with cloud cover less than 10% from the United States Geological Survey (USGS) archive Landsat–5 Thematic Mapper (TM), Landsat-7 Enhanced Thematic Mapper Plus (ETM+), and Landsat-8 Operational Land Imager (OLI) covering the MBRC area at a spatial resolution of 30 meters, Path 170 and Row 73. Using a shapefile for MBRC the area was clipped from the satellite imagery using Quantum Geographic Information System (QGIS) software version 3.4. Satellite imagery were also pre-processed for radiometric errors. A combination of bands 2, 3, 4, 5, 6, and 7 (**Table 1**) were merged to form composite images for each period under study. Vegetation appears in shades of dark and light green, hot surfaces such as built-up areas and bare land appear in shades of red or yellow. The eligible ranges for candidate images were from 2000 to 2020. Eighty Ground Control Points were collected and a shapefile was created to superimpose on the clipped satellite imagery as reference points for classification.

This research study utilized a supervised classification interpretation approach. According to the research purpose and type of vegetation in the area, six classes including built-up area, cropland, grasslands, bare land, woodland, and water bodies were identified and classified. In this type of classification spectral classes were grouped first, based on the numerical information of the data, and were then matched [23]. Five images were ultimately used to create the image composites for the periods: 2000, 2005, 2010, 2015, and 2020. These images comprised of varying wavelengths separated into wavelength bands (**Table 1**). Band 1 is known as blue as it provides increased penetration of water bodies and also capable of differentiating soil and rock surfaces from vegetation. Band 2 covers the green reflectance peak from leaf surfaces, it separated vegetation (forest, croplands with standing crops) from the soil. In this band barren lands have appeared as brighter (lighter) tones, but forest, vegetation, bare croplands, croplands with standing crops have appeared as dark (black) tones. The third band highlights barren lands. Bands 4 to 7 function in the best spectral regions to distinguish vegetation varieties and conditions in the preceding bands.

Using the QGIS 3.4 maximum likelihood classification, the 4 images were analyzed and processed. Using the raster images, which have values attached to each pixel, training data was created using known sites (Ground Control Points) in the study area, from which the software was able to identify sites with similar cell values. The Maximum Likelihood classification was able to assign each cell in the input raster to the class that it has the highest probability of belonging to, resulting in the creation of 6 land classes: Woodland, mined area, Bare land, Cropland, Built-up Areas, and Water Bodies.

Bands	Wavelength (micrometers)	Resolution (meters)
Band 1-Blue	0.45–0.52	30
Band 2-Green	0.52–0.60	30
Band 3-Red	0.63–0.69	30
Band 4-Near Infrared (NIR)	0.77–0.90	30
Band 5-Shortwave Infrared (SWIR) 1	1.55–1.75	30
Band 6-Thermal	10.40–12.50	60* (30)
Band 7-Shortwave Infrared (SWIR) 2	2.09–2.35	30
Band 8-Panchromatic	.52–.90	15

Source: (Shafri, 2015).
Notes: Colors blue, green, and red indicate the ideal environmental conditions. The color blue indicates water, green is for vegetation, red indicates high reflection (heat), for example from surfaces that are impervious like roads, buildings, etc., bands 4–8 are invisible but affect the intensity of wavelengths in bands 1–3, which then results in varied color shades.

Table 1.
Bands of varying wavelengths separated into wavelength bands as referenced in the study.

2.4 Accuracy assessment

The accuracy of the quantified land cover changes were assessed with the help of reference datasets based on the standard measures for assessing the accuracy of remotely sensed data known as the overall accuracy and the kappa index [24].

The assessment results of the LULC classification for 2000, 2005, 2010, 2015, and 2020 are shown in Tables below. Sixty reference points were used to evaluate the accuracy of the created land use land cover maps. The overall classification accuracy obtained from the error matrix is shown below each table, and the result of Kappa statistic (**Tables 2–6**).

In conclusion, supervised classification was used because the operator can detect errors and correct them although it is time-consuming.

2.5 Data analysis and presentation methods

Spatial statistics is the collection of statistical methods in which spatial locations play an explicit role in the analysis of data [20]. Most often, spatial statistics are used to detect, characterize, and make inferences about spatial patterns, primarily in ecology

Class name	Number of reference pixels	Number of classified pixels	Correctly classified pixels	User's accuracy	Producer's accuracy
Cropland	13	9	8	88.89	61.54
Bare land	7	6	4	66.67	57.14
Water	11	12	11	91.67	100
Grassland	9	12	7	58.33	77.78
Woodland	12	13	10	76.92	83.33
Built up land	8	8	6	75	75
Overall classification accuracy 77% Kappa statistic 0.718.					

Table 2.
Accuracy assessment results for 2000.

Class name	Number of reference pixels	Number of classified pixels	Correctly classified pixels	User's accuracy	Producer's accuracy
Cropland	11	9	7	77.78	63.64
Bare land	9	11	7	63.64	77.78
Water	10	10	10	100	100
Grassland	13	13	8	61.54	61.54
Woodland	9	10	7	70	77.78
Built up land	8	7	5	71.43	62.5
Overall classification accuracy 73% Kappa statistic 0.679.					

Table 3.
Accuracy assessment results for 2005.

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Class name	Number of reference pixels	Number of classified pixels	Correctly classified pixels	User's accuracy	Producer's accuracy
Cropland	10	11	7	63.64	70
Bare land	12	10	8	80	66.67
Water	8	8	7	87.5	87.5
Grassland	9	11	6	54.55	66.67
Woodland	14	11	10	90.91	71.43
Built up land	7	9	5	55.56	71.43
Overall classification accuracy 72% Kappa statistic 0.659.					

Table 4.
Accuracy assessment results for 2010.

Class name	Number of reference pixels	Number of classified pixels	Correctly classified pixels	User's accuracy	Producer's accuracy
Cropland	10	9	6	66.67	60
Bare land	8	12	6	50	75
Water	9	10	8	80	88.89
Grassland	13	13	9	69.23	69.23
Woodland	11	9	8	88.89	72.73
Built up land	9	7	5	71.43	55.56
Overall classification accuracy 70% Kappa statistic 0.639.					

Table 5.
Accuracy assessment results for 2015.

Class name	Number of reference pixels	Number of classified pixels	Correctly classified pixels	User's accuracy	Producer's accuracy
Cropland	11	7	7	100	63.64
Bare land	12	18	12	66.67	100
Water	9	9	8	88.89	88.89
Grassland	8	10	8	80	100
Woodland	10	10	10	100	100
Built up land	10	6	6	100	60
Overall classification accuracy 85% Kappa statistic 0.819.					

Table 6.
Accuracy assessment results for 2020.

and geography. Spatial patterns can be identified using logistic regression analysis [25]. This method measures the mean nearest distance for all points and assumes all points in the study area have been surveyed. Then, the observed mean distance is compared to the expected mean distance under the null hypothesis that the distribution of points is random. Regression is the determination of a statistical relationship between two or more variables. In simple regression there is only two variables independent and dependent variable, Independent Variable is the cause of the behavior of another one [26]. Regression analysis in the R package was used. The relationship between two variables may be one of the functional dependences of one on the other. For change detection analysis, the post-classification change detection technique was adopted. Data was collected and fed into the R package, whereby simple data analysis tools such as frequencies and percentages were used to analyses data. The presentation was done using R, Microsoft Word, and Excel packages in the form of tables, figures, and charts. QGIS 3.4. Logistic regression analysis in R studio was used for analysis to find if there is a significant relationship between LULC change and Rhino distribution. The prediction of LULC map by 2030 was prepared in 3 stages that is: (i) preparation of datasets/raster layer (LULC layers for 2000, 2010, and 2020), and spatial layers using distance from rivers, and DEM layers.(ii) Training model algorithm using MOLUSCE plugin in GIS version 2.8.(iii) Running simulated model to obtain the LULC state for 2030.

A binomial logistic regression model was used to determine and analyze the impact of LULCC on black rhino distribution in MBRC. Logistic regression analysis was performed in R version 4.0.2. LULC was used as an explanatory variable in the logistic regression model. The results of the model indicated that LULC changes have a significant positive relationship with significant impact on black rhino distribution ($p = 0.0381$). The logistic regression expression used takes the form;

$$P = \frac{1}{1 + e^{-1(\beta 0 + \beta 1 X1)}} \tag{1}$$

Where: β_0 = Constant = 0.4677.
β_1 = LULC intercept = 0.04570.
X_1 = LULC map.

3. Results

3.1 Land-use and land cover change

The objective of classification was to group together a set of observational units on the basis of their common attributes. The baseline data for land cover and land use showing 6 different classes, bare land, water body, built-up land, cropland, woodland, and grassland as described in the legend in **Figure 3** were classified (**Tables** 7 and **8**) (**Figure 4**).

To compare the LULC percentage change within the period of 20 years from 2000 to 2020, **Figure 5** above was generated and it showed that from 2000 to 2020 there were increments in percentage cover of the bare lands, water, and croplands classifications while woodland, grasslands and built up land went down. The classification that showed a big percentage cover change was the bare land which increased by slightly over 160% followed by cropland with about 73%. Woodland decreased by

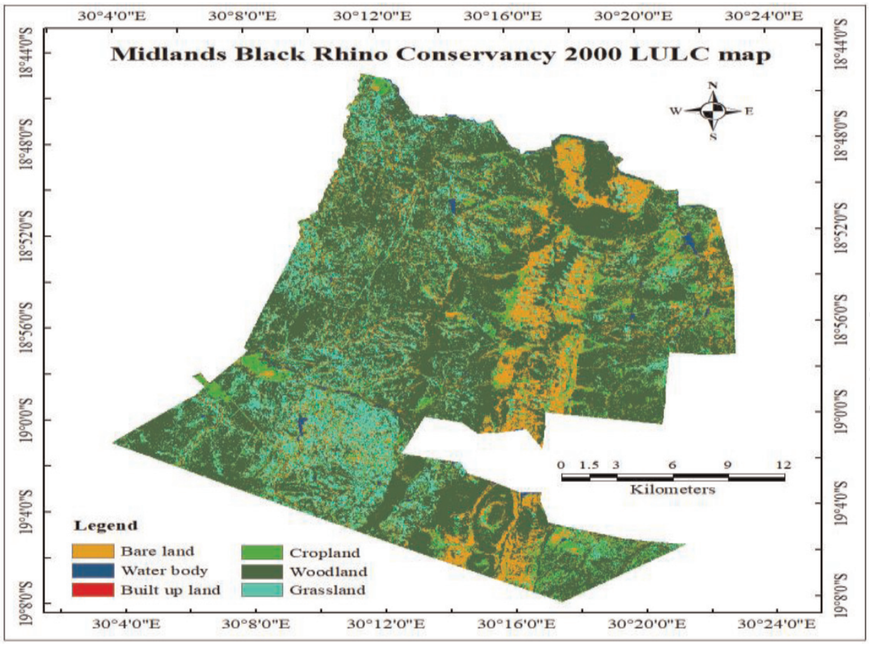


Figure 3.
MBRC LULC map for the year 2000.

Class name	Description
Bare land	This represented virgin land, unoccupied land, and deforested land.
Waterbody	This class included all the dams and other bodies containing clear open water .
Built-up land	These were mainly homesteads.
Cropland	These were mainly planted commercial farms.
Woodland	Included the natural vegetation and shrubs
Grassland	Represented all the areas covered by tall grass and bushes of all types .

Table 7.
Land cover classes.

LULCC(%)	2000	2005	2010	2015	2020
Cropland	13.2	20.75	20.28	10.92	21.56
Water	0.07	14.02	14.29	15.34	20.29
Bare land	12.54	18	23.65	25.98	30.66
Grassland	14.23	10.49	10.91	10.02	7.01
Woodland	35.46	21.1	18.03	20.68	12.17
Built up land	24.5	15.64	12.84	17.06	8.31

Table 8.
Land use land cover change (LULCC) percentage.

about 46% from 2000 to 2020 while built up land also went down by about 39% within the same time. Grasslands percentage cover decreased by about 30% while the water bodies percentage cover increased by over 200%.

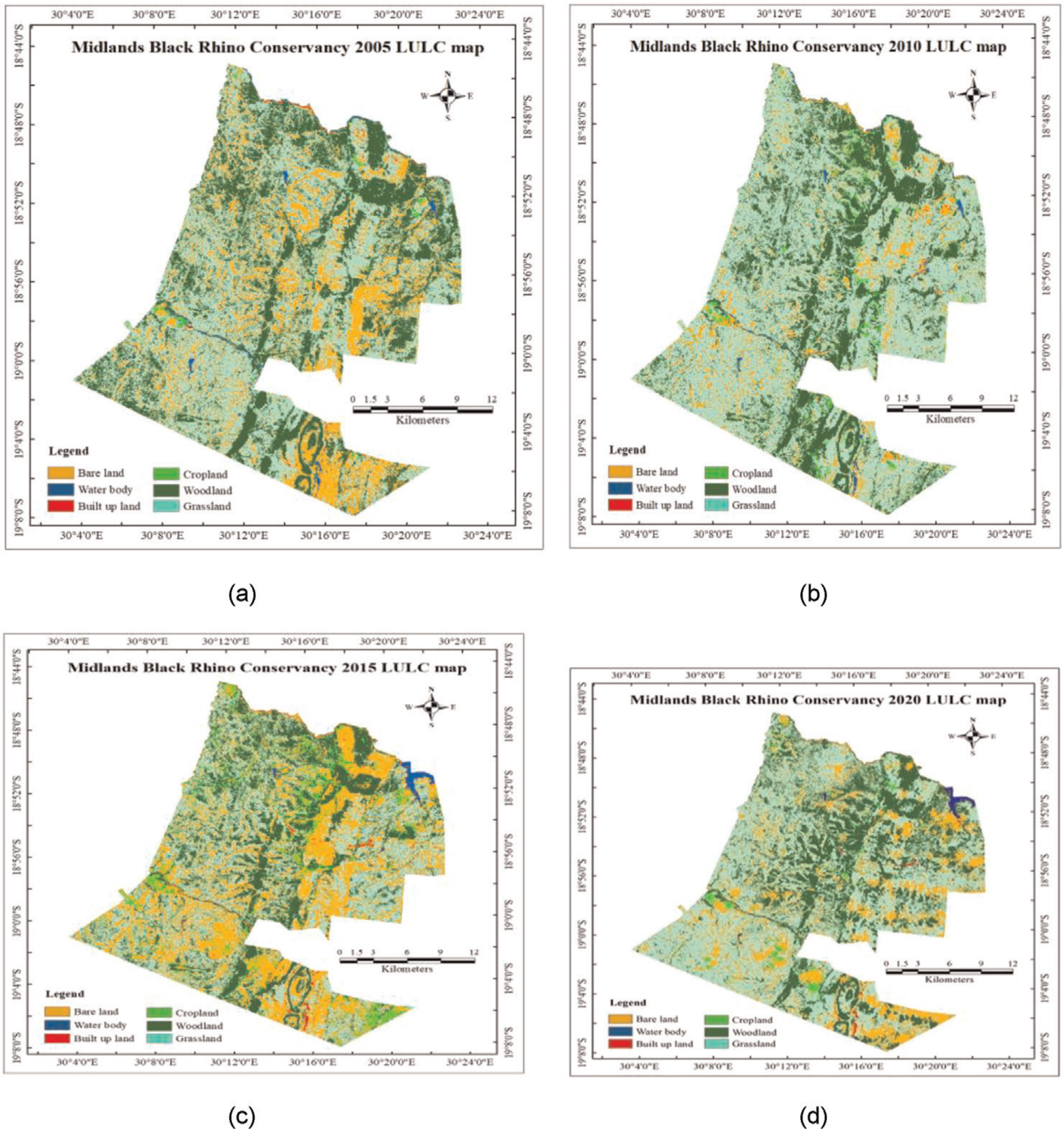


Figure 4.
MBRC LULC map for the year 2005, 2010, 2015 and 2020.

3.2 LULCC, and black rhino distribution

3.2.1 Hypothesis testing

The results of logistic regression analysis were used to test the hypothesis. LULCC may be the major cause of the present pattern of rhino distribution in MBRC, as supported with the statistical analyses (p = 0.0381). Rhino distribution (**Figure 6a**) also illustrates the distribution showing dispersed type of distribution which might be, as a result of browse of woodlands evenly distributed in the southern side of the area in the year 2000. However, possibly in the year 2020 due to LULCC the distribution changed showing Black Rhinos clustered in areas where there is dense woody vegetation and river streams (**Figure 6b**). The black rhino distribution in the MBRC area shows a preference for the wooded land. Factors contributing to this preference may

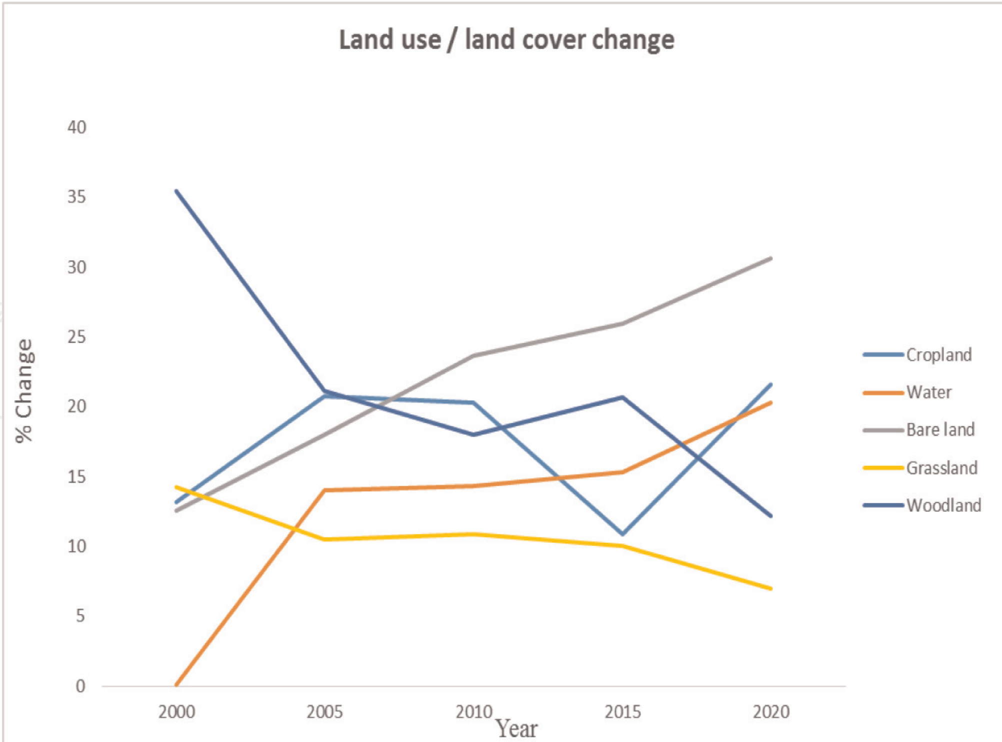
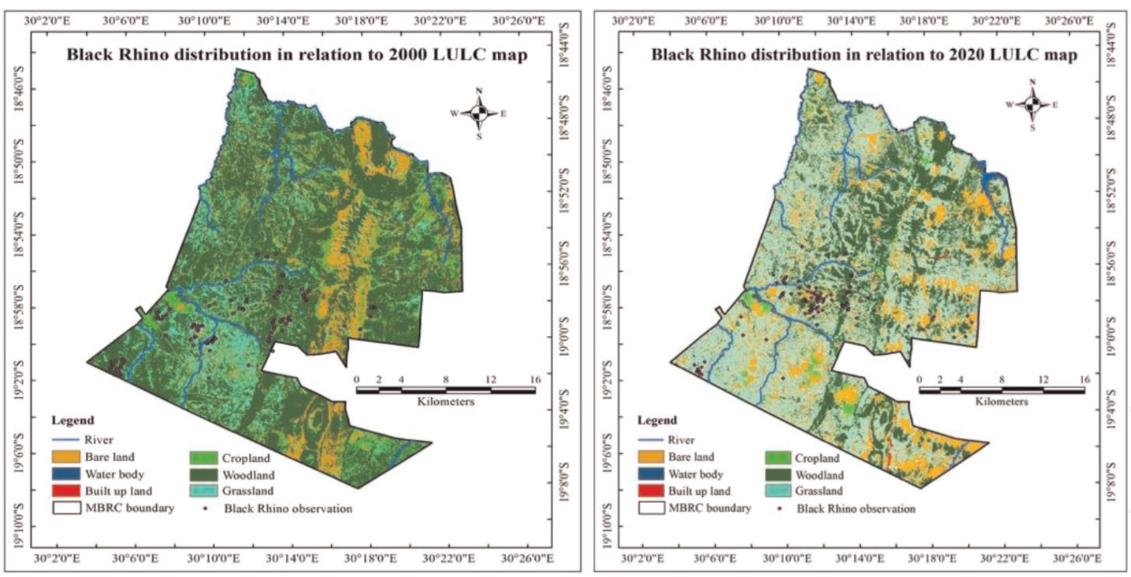


Figure 5.
2000–2020 percentage cover.



(a) (b)

Figure 6.
Black Rhino distribution for the year 2000 and 2020.

be availability of food, cover, and water. Having said that, interspecific competition can play a role in animal distribution [27], not only through competition for resources, as seen in Black Rhino [28] and African elephant [29], but also by the presence of a physically dominating species [30].

Therefore, the hypotheses that, there is no significant impact of LULC change on Black Rhino distribution in MBRC was not supported by the results, hence rejecting the null hypothesis (**Figure** 7).

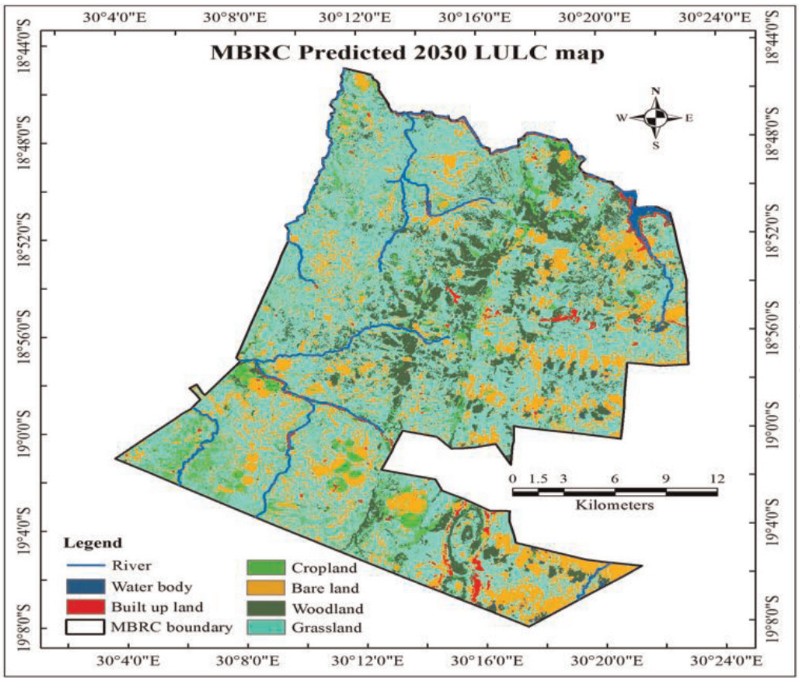


Figure 7.
Predicted map for MBRC by 2030.

Class name	Area (square km)	Percentage
Cropland	60.3585	8.43
Bare land	118.7225	16.59
Water	4.5378	0.63
Grassland	434.2626	60.67
Woodland	87.5151	12.23
Built up land	10.4176	1.46
Total Area 715.8141 square kilometers.		

Table 9.
Predicted 2030 LULC details.

3.3 Prediction of LULCC map by 2030

Prediction of LULCC for the year 2030 was performed in QGIS 2.8 using MOLUSCE plugin. Based on the statistics for the year 2000, 2010, and 2020 it was possible to predict LULCC by 2030.The results predicted an increase in cropland by 8.43%, bareland 16.59%, water 0.63%, grassland 60.67%, woodland, 12.23%, and built up 1.46% as shown in **Table 9** above.

4. Discussion

Damaging human activity continues to encroach on natural environments, thereby destroying the habitats of countless species. As our numbers rise, infrastructure and cropland are growing and merging into each other, fragmenting the remaining habitat and leaving isolated patches for natural populations of plants and animals too small to survive. The increase in bare land is as a result of mining that was done in the area. Mining contributed to lots of deforestation. Furthermore, water cover increased as a result of the open cast mines that were left unclosed hence holding water. Significant increase in cropland experienced may have been triggered by the land reform program since new settlers started to prepare more crop land during the years 2000 to 2005. Agriculture used to be subsistence farming only but, it is no longer subsistence since the farmers have extended the cropland for a better yield. As a result of these anthropogenic factors, land use change has significantly altered the habitat for rhinos in MBRC.

5. Conclusion and recommendations

Quantum GIS and R studio software's made it possible for the formulation of the maps showing the spatial and temporal distribution of Black Rhino furthermore, LULC changes for the month of May year:, 2000, 2005, 2010, 2015, 2020, and modeling of LULCC by 2030 were also made possible. The results predicted an increase in cropland by 8.43% bare land 16.59%, water 0.63%, grassland 60.67%, woodland, 12.23%, and built up 1.46%. Taken together the results, indicated that, LULC changes were significantly impacting Rhino distribution for the period 2000, and 2020. In the year 2000 Rhinos where randomly distributed to the western side of the conservancy however, in the year 2020 Rhinos where found to be clustered in the middle of the conservancy. Furthermore, there is a significant expansion of bare land, and cultivated land noticed. On the other hand there is decrease in woodland area, grasslands area, and built up land area. This study clearly indicated the significant impact of LULC change on Black Rhino distribution. The study also proves that integration of GIS and remote sensing technologies is effective tool for LULCC mapping and modeling. The quantification of LULC changes of MBRC is very useful for environmental management groups, policy makers, and for the academia to better understand the ecosystems.

The researcher recommends constant monitoring of LULCC, and further researches of Black Rhino habitat suitability in MBRC from the management board. The Ministry of Environment, Climate, Tourism, and Hospitality Industry must consider enforcing policies that restricts human encroachment into protected areas set aside for wildlife conservation. The Conservator must introduce re-afforestation of hills and management of woodlands, and grasslands involving both conservation of existing patches of the woodlands and enrichment of degraded grasslands including stream buffering. By linking the cause-effect relations revealed by the analyses, land management prescriptions should be developed for major land use categories in the area. Suitable land use management practices for agricultural land uses should be identified mainly based on their ability to mimic the forest ecosystems.

Author details

Blessing M. Mugaviri[1*], Gilbert H. Moyo[1], Ezra Pedzisai[2] and Cuthbert Maravanyika[1]

1 Scientific Services, Parks and Wildlife Management Authority, Sebakwe Research Station, Kwekwe, Zimbabwe

2 Department of Geography, Bindura University of Science Education, Bindura, Zimbabwe

*Address all correspondence to: mugaviriblessing@icloud.com

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