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Detecting land-use landcover changes in a protected area conservancy using geospatial technology

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Abstract

This paper analyses the present and future changes in land-use landcover of the Midlands Rhino Conservancy which is a protected area with mining activities. A GIS and Remote Sensing approach was used for detecting change in the protected area. A thirty-year time of 1980-2020 shows a major land use change, with agricultural activities increasing within the protected area. The projected results help to detect the future changes that might occur under the same case scenario in the protected area. Agricultural activities increased with 20%., Alternatively, there is a decrease in vegetation cover from 60% to 15%, built up increased from 0.03% to 0,08%. The reasons for the change detection such as (for monitoring habitat disturbance among others) have been discussed.

Keywords: Land-use; Landcover change; Mining; Prediction; Simulation; Vegetation; Agriculture

1 Introduction

Monitoring of land use/landcover (LULC) change using geotechnology has become a central component in current strategies for managing natural resources and environmental change. There is wide use of remote sensing data in the provision of LULC information for environmental conservation(Naikoo et al. 2020).

A combination of GIS and remote sensing detects and control land use/cover change in a way which is easier and faster than the traditional methods of monitoring land use/cover change (Elagouz et al. 2020, Koko et al. 2020).This study focused on spatiotemporal assessment of the dynamics that occur in a protected area landscape where there is a combination of wildlife activities, agriculture and mining. Understanding these changes in a protected area setup has potential to improve land use planning and avert environmental challenges including biodiversity loss and species extinction. Information of land use /landcover is required for a wide range of planning purposes(Elagouz et al. 2020, Koko et al. 2020). Land use planning was understood and still is a social process that aims at a sustainable land use and balance of interests in protected areas and some other territories (Naikoo et al. 2020). The environmental condition of Midlands Black Rhino conservancy was very health before the advent of mining and agricultural activities. The protected area was endowed with vast wetlands, rich forest scenic beauty diversity of wildlife among others, hence the main motivating driver to carrying out this research.

Geotechnology(GIS and Remote Sensing) have proved to be a very important tool in the ecology of the landscapes as well as in the mapping of disturbance zones in the ecosystem, quantifying the impacts on biodiversity as well as detecting change of land use/landcover in time and space(Naikoo et al. 2020, Wolters and Steel 2020). To understand the cause and effect of disturbance on habitats there is need of a spatiotemporal assessment of landcover change(Tang et al. 2020). Previous studies have proved that the biodiversity of the terrestrial ecosystems is expected to be mainly

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affected by anthropogenic changes within the next century (Ge et al. 2019, Tang et al. 2020). Wolters and Steel (2020) also came up with research that helped much in addressing the issue of landcover /land use change within the context of global environment. For the past decades the research addressed a drastic and continuous change in the regional and climate variables such as temperature, rainfall, cloud cover among others(Homer et al. 2012). Upon this background the question remains on how the ongoing changes affect the global ecosystems, biodiversity, land cover changes. The collective impact of land cover changes is regarded as the most important aspect of global environmental change despite the local and site-specific nature of the changes. Another researcher ascertained that; human beings are the key players regarding the dominant force behind global environmental change (Hackmann et al. 2014). The research went on to address that the use of land by human beings has effects which amounts to 40% of net primary production globally and locally and this alters ecosystem services on terrestrial ecosystems (Hackmann et al. 2014). Midlands Black Rhino conservancy is a protected area in Zimbabwe where there is extensive mining of chrome which has been practiced for over a decade. In a disturbed environment like that, landscape patterns have a tendency of fluctuating widely over time in response to the interplay between disturbance and natural regeneration leading to change in biodiversity. The extensive mining of chrome in the protected area is changing the environment, land use potential and the aesthetic value of the landscape. There is damage over a large area due to mining although farming is another factor. Therefore, it is of great importance to do a geo-technological assessment of land use landcover change in the area in order to address the extent of damage by these anthropogenic activities. Most of the studies which were done on mining focused on the post mining environments outside protected areas as well as in urban areas, so there in need to assess the damage caused by mining activities during the activities other than after the damage.

1.1 Land use/landcover change detection.

Land use is defined as a series of operations undertaken on land by human beings mainly for gaining the services provided by the land (Naikoo et al. 2020. Land use can also be defined as the purpose saved by specific land (not the specific cover of the land), for instance agriculture, habitats, recreation among others (Knoke et al. 2020). Contrarily, landcover is defined as anything that occupy the ground, for instance, vegetation or man-made constructions. Bare rock, ice, water gravel, sand among other similar surfaces they all can be count as landcover. In other words, land cover can refer to the surface cover on the ground and the use of land normally depends on the type of cover of that particular land (Tang et al. 2020).

Change detection is a process that measures how the attribute of a particular area have changed over time (between two or more-time periods) (Elagouz et al. 2020, Gandhi et al. 2015) . Change detection can also be defined as the process of identifying state of an environmental phenomenon through observing it at different time periods. It involves comparing satellites imagery taken at different times. It has been widely used for the assessment of natural disasters like cyclones, impact of earthquakes, land use landcover shifts among others over time(Gandhi et al. 2015, Hegazy and Kaloop 2015).

2 Material and methods

2.1 Description of the study area

Midlands Black Rhino Conservancy (MBRC) was formed in 1987 to move the Black Rhino from the borders (Zambezi valley) which were being slaughtered by mainly cross border poachers. The idea was to make it difficult for the poacher to get to the animals. The area originally set up for this purpose was 63000ha which consisted of farmland and forestland.

MBRC is lying between 18 ° 58, 31 ° S and 030 ° 06, 62 ° E bounded by Munyati River and Mvuma-kwekwe road on the north and south respectively. The conservancy lies in Zimbabwe's agroecological region 3 which is a semi-intensive farming region that receives a total annual rainfall of between 650- 800 mm characterised by mid-season dry spells and high temperatures with annual average minimum and maximum of 11.9 and 27.5^{o}C respectively, and an annual average of 21.1^{o}C (Makaure and Makaka 2013). The region is generally suitable for drought-tolerant crops, livestock, and semi-intensive farming. The map below shows the study area including the boundaries of original farms.

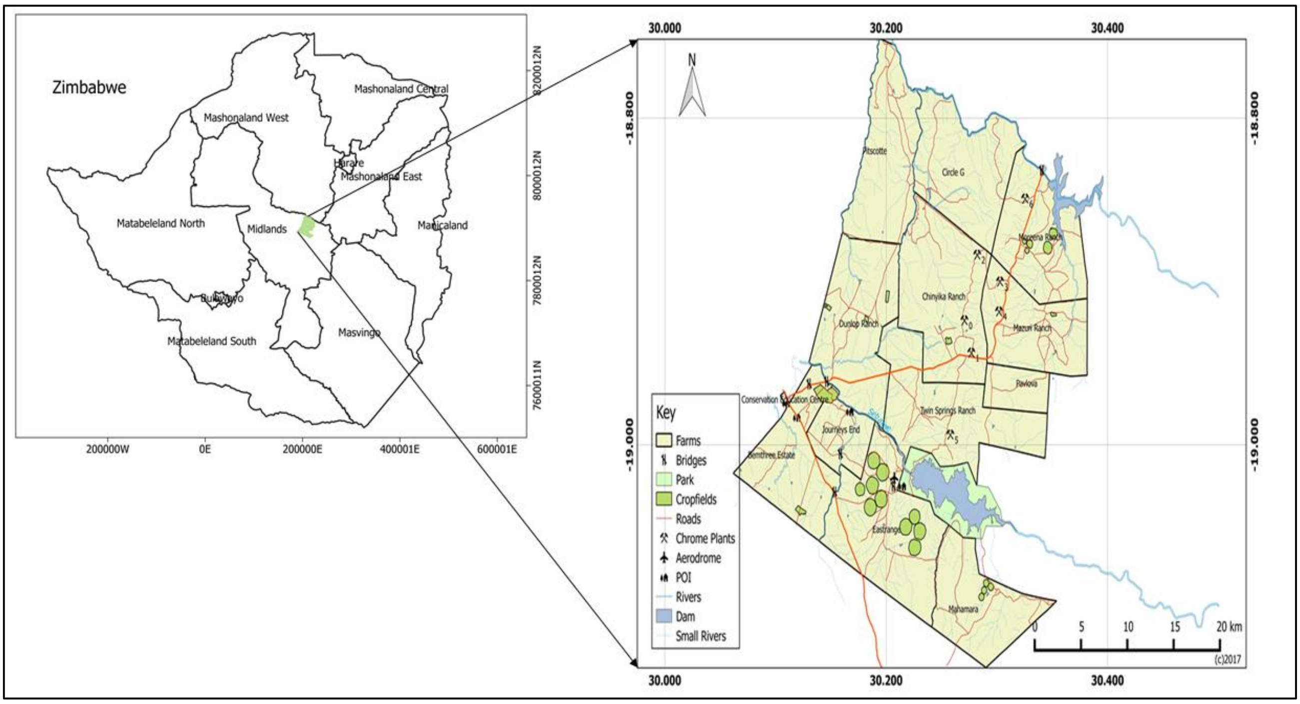

Figure 1 Study area map of Midlands Black Rhino conservancy

2.2 Methods

2.2.1 Pre-processing and description of data

Firstly, the available Landsat-5, Landsat-7 Landsat 8 summer images for 1980 to 2020 were collected of 30m resolution. The images were collected based on the scene quality as well as the phenology thus based on minimum cloud cover as well as better plant or vegetation cover. The Landsat data was pre-processed and reprojected to Universal transverse Mercator (UTM) using the World Geodetic Datum (WGS 84 zone 36). All the data were resampled to 30m resolution using the cubic convolution interpolation approach which is a new technique used for resampling of discrete data (Alhedyan 2021, Li et al. 2017, Ma et al. 2020). The pre-processing of data was done through image mosaicking, radiation calibration, atmospheric corrections, image enhancement before the classification of the images using ILWIS (The Integrated Land and Water Information System) and ENVI tool (Image Processing and Analysis Software Solution)(Keys 1981). To obtain high quality satellite images, data fusion was done through the use of STF (Spatio-temporal data fusion) method which is a type of methodology for fusing satellite images from two sensors**,** with sensor one having high frequency but coarse spatial resolution such as MODIS and AVHRR, and sensor two having very high spatial resolution but lower frequency such as Landsat and Sentinel-2.) (Li et al. 2017, Ma et al. 2020).

2.2.2 Land cover classification and accuracy assessment

For the mapping of habitat disturbance, the research borrowed some of the procedures from the terrestrial habitat classification schemes developed by the United Kingdom especially the color codes (and revised in 2016). It provides a common language through which data can be stored and gathered(Jung et al. 2020).

For the images the research used Landsat images which were pan sharpened or fused before the habitat classification is done. The study used a series of five decadal images from 1980, of disturbance habitats 1990, 2000,2010 and 2020, to do a trend analysis to check on the patterns of habitats over a 40-year period. This helps to reflect the changes that may have occurred over time in a changing environment (Maybe due to climate or due to mining activities). The analysis of data was firstly done in ArcMap for the development of DEM, slope Map Aspect and proximity maps (nearest to the road map and near to the river map). Then the second part was done in TERRSET and lastly in QGIS 3.10.

2.2.3 Accuracy assessment

To assess the accuracy of the classified images for the period of study, validation data based on ground truthing was set. The validation data was comparable to the measures derived from the remotely sensed images. The procedure followed the random generation of 250 points that were uniformly distributed across each land use landcover map which were later cross checked with the reference data. The overall accuracy greater than 85 % was accepted suitable for this study. Kappa coefficient and the overall accuracy assessments reports are shown on table 1 below.

Table 1 Accuracy assessment for land use landcover change for the year 1980 -2020

High resolution images were used as reference images from google earth and visual i

Year	1980	1990	2000	2010	2020
Overall accuracy(%)	95.28	92.3	94.87	93.57	90.47
Kappa coefficient	0.89	0.88	0.85	0.90	0.86

interpretation was done using Landsat images as the reference images. The overall accuracy is higher than 92% which is followed by the kappa coefficients higher than 85%. Hence an important requirement for this research.

2.2.4 Modelling the Prediction of land use landcover change

Cellular automata_ Markov (CA-Markov) in IDRISI (under TERRSET 2020) was used to predict the land use Landcover information in Midlands Black Rhino conservancy. The model has a potential to accurately simulate land use Landcover changes in time and space through a combination of its ability to do chain prediction long time series and can precisely help in simulation of land use landcover change in time and space (de Almeida et al. 2003, Singh 2003). This model is a stochastic model mainly used for the modelling of land use landcover change (Gandhi et al. 2015). Theoretically, the use Cellular Automata-Markov model for prediction means that the simulated period is equal to the inter-annual interval between the base and the end images used for the prediction (Li et al. 2017,Keshtkar and Voigt 2016, Santé et al. 2010). The model helps to describe the land use change over time as well as predicting the future trends in landcover change (Goetz 2009, Gross, Goetz, and Cihlar 2009). Cellular Automata has an advantage as a model in that it is simple and easy. It performs spatial dynamics, and time explicitly and it can be considered as analytical engine of GIS. Raster GIS with map algebra can be integrated with enhanced capabilities(Gross, Goetz, and Cihlar 2009, Sui and Zeng 2001).

Cellular Automata Markov model the following parameters and steps in predicting land use Landcover Change. These are data format conversion and reclassification to obtain fixed land use types, the state probability matrix and the transfer, area matrix were obtained as well as transition image were all set. This research used a 5*5 filter which is a matrix space composed of 5*5 cells around each central cell. Following this, this research used Kappa coefficient as an error matrix in assessing the accuracies of prediction according to the actual images.(Anderson 1976, Baker 1989, Usha et al. 2012). This research is mainly focused on detecting and predicting land use landcover change and CA Markov is very useful in that it has high prediction abilities other than any other software. The base land use image of 2020 is used as the starting point for change simulation.

3 Results and discussion

3.1 Land use landcover change detection.

The landcover change analysis generated was based on supervised classification in IDRISI using maximum Likelihood classification. Supervised classification is a type of classification that use prior knowledge of the study area to direct the analysis(Lu et al. 2019, Mishra and Rai 2016). Then the criteria for class groupings are determined by the signature class which is derived from the creation of training areas(Azizi et al. 2016, Fathizad et al. 2015). Based on the mentioned criteria, five main classes were mapped, and these are Water, Forest, Bare land, Agriculture and Built-up. These are summarized in table 2 below.

The results for the landcover classification are shown on figure 1. The area of each landcover category was calculated based on the classified results and the distribution of each landcover category is shown on table 2. From the results, one can note that the dominant landcover in 1980 is forest followed by vegetation then water, agricultural land and built-up. Bare land area decreases from 1980 to 1990 and most of the bare areas were occupied by vegetation in 1990. The reason behind the positive change is because of the time which was given to the park to regenerate after independence and 1980 drought. During the war the conservancies were also at risk and under much disturbance since they were the hiding places for the war fighters. These results concur with the findings of a research which was conducted in North China in 2004 where the study saw a decline in forest land and an increase in bare land because of seasonal variability.

Table 2 Land use/landcover change from 1980 to 2020.

	1980		1990		2000		2010		2020	
Class	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%
Water	300	0.5	500	0.84	1000	1.87	3000	5.02	5000	0
Forest	35107	60	40224	67	15560	29	23865	40	13799	23
Bare land	23712	40	18533	31	35873	67	28654	48	30314	51
Agriculture	415	0.7	426	0.71	1000	2	4202	7	10676	18
Built-up	20	0.03	30	0.05	35	0.07	40	0.07	50	0.08

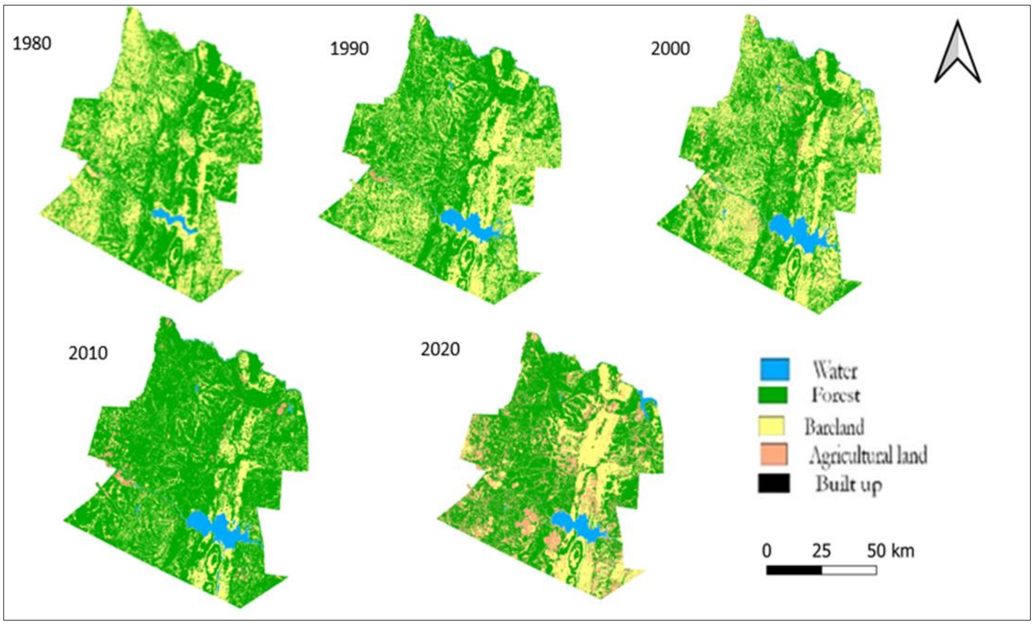

Figure 2 Land use/landcover change maps from 1980 to 2020

The above is a representation of a transition from 2000 to 2010 in Midlands Black Rhino Conservancy which is a protected area where mining is a business. The dominant landcover in 2000 is bare land followed by shrinking patches of vegetation. Maybe the reason behind that is the drought which occurred in 1999/2000 season which left most parts of the conservancy bare. The landcover changed in 2010 with most of the bare parts found on rocks along the mountain range. The rest of the conservancy is covered with vegetation and the lake has increased with 5%. This is because of the better 2009/2010 season which saw increased amount of rainfall in the country and the region of study. The bare areas away from the mountain range where there are few rocks describe the presence of mining areas. The agricultural plots have slightly increased and some of the areas that were agricultural areas in 2000 have turned to bare land. These results concur well with the study which was done in Simla Netherlands in 2003 which saw the decrease in vegetation patches in the study area due to occurrence of droughts(Razavi 2014). The is a remarkable increase in bare land between 1990 and 2000. 67% of the landcover in 2000 is bare land maybe because of the drought which occurred during the 1999/2000 season. The hazard increased the bare land cover and the conservancy saw an increase in agricultural land and the few patches of forest. There is an abrupt transition in land use landcover change from 2000 to 2010. There is a 40% vegetation cover in 2010 maybe because the area received a lot of rainfall during the 2009/2010 season and since the study area is a protected area the regeneration of vegetation is much quicker even if it had experience drought in the past season. The bare areas outside the mountain range again explains the existence of abandoned farming areas as well as mining areas in the conservancy. There is also remarkable transition from 2010 to 2020 in land use landcover change (Figure 3). The transition saw an increase in the area covered by agricultural land covering at least 18% of the area. There is also an increase in the area covered by bare land outside the mountain range which marks the presence of mining areas in the conservancy. Vegetation is mainly in patches and has decreased in cover throughout the conservancy. Some of the areas close to the water storages such as rivers and dams have been cleared for agricultural purposes and it shows from the map that its mostly irrigation since the farms are close to the water storages.

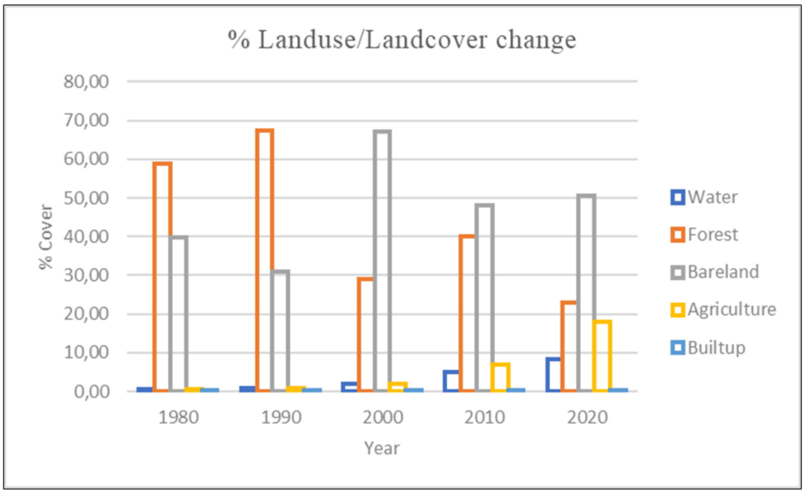

Figure 3 % Land use landcover change over the years

Figure 4 represents the trends of environmental phenomena change over time. Forest which is a focus in the conservancy is showing a decreasing trend which is a sign of the presence of environmental degradation within the conservancy. The vegetation is changing over time because of factors such as farming and mining . Bare land is increasing as illustrated on the line graph followed by a remarkable increase in agriculture.

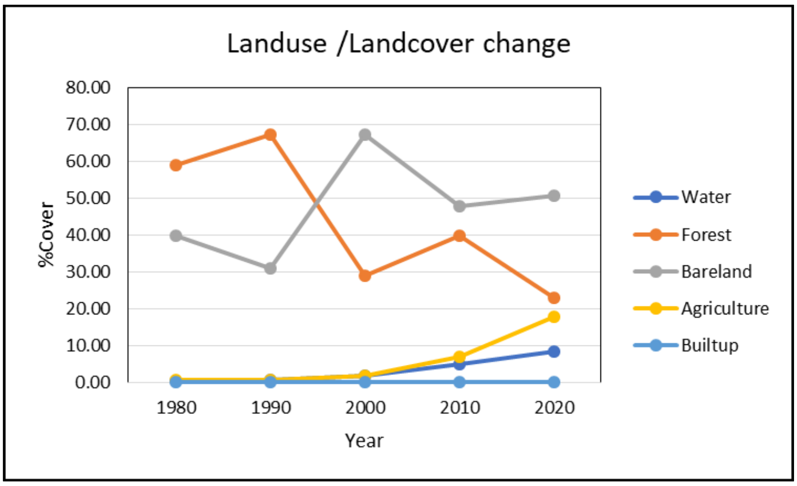

Figure 4 Land use landcover change per category over the years

3.2 Modelling land use landcover change

There is a significant change indicated by the simulated results in Midlands Rhino Conservancy. The vegetation cover has decreased from 35107ha in 1980 to10397ha projected for 2030. Bare land is increasing in a rapid way from 23712ha in 1980 to 40567 ha in 2030.The area covered by water is expected to increase slightly by 5.4 % in the year 2030 as shown below (table 3).

The results of the simulation and prediction done in Idrisi indicate an expected increase in bare land and a decrease in forest land as well as an increase in agricultural land. Maybe it could be as a result of the simulation model in Markov. Given the condition that the factors that affect change such as climatic events political interventions among others have not changed over the years, they are likely to affect the predicted outcome of land use/landcover change in the area. The Markov model uses the contiguity rule which suggest that a pixel near to an environmental phenomenon is likely to be classified under the same (neighborhood analysis). The validity of the simulation using a multiple base resolution statistical algorithm which measure the agreement and disagreement between the images (Fathizad et al. 2015, Lu et al. 2019, Razavi 2014). The Kappa statistics with accuracy exceeding 90% (table 1). The predicted maps for Midlands Black Rhino conservancy were produced based on the land use/landcover maps of 1980-2020, and the later year was used for validation and comparison. There is a high agreement between the predicted 2020 map and the actual map as shown on figure 5, hence revealing that CA-Markov is one of the proper models for future land use/landcover prediction.

Table 3 Projected land use/landcover change.

	1980		1990		2000		2010		2020		projected 2030	
Class	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%
Water	300	0.5	500	0.84	1000	1.87	3000	5.02	5000	0	3670	5.4
Forest	35107	60	40224	67	15560	29	23865	40	13799	23	10397	15
Bare land	23712	40	18533	31	35873	67	28654	48	30314	51	40567	59
Agriculture	415	0.7	426	0.71	1000	2	4202	7	10676	18	13788	20
Built-up	20	0.03	30	0.05	35	0.07	40	0.07	50	0.08	57	0.08

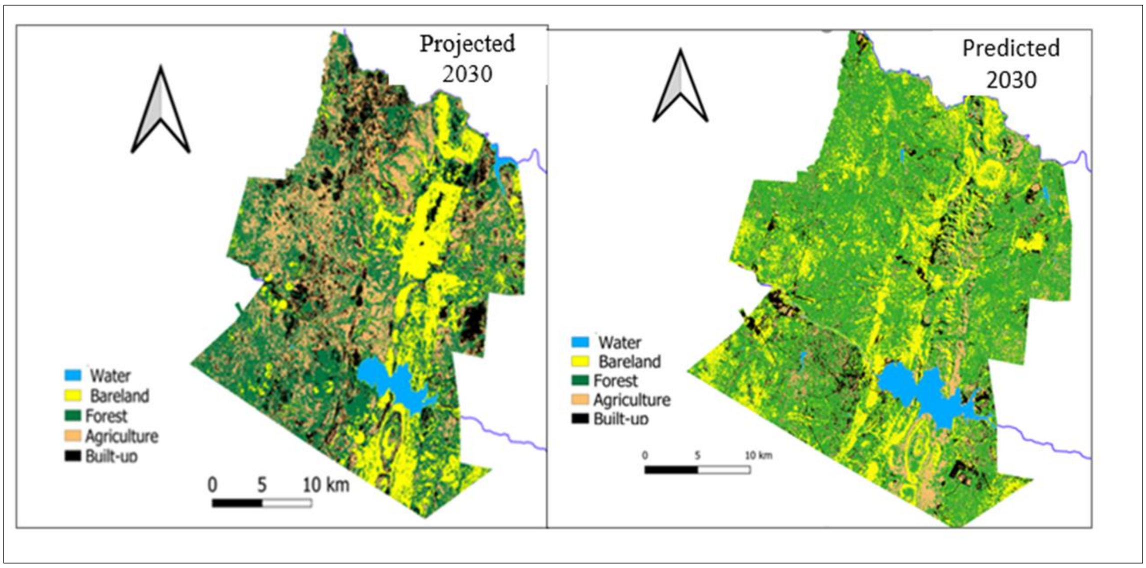

Figure 5 Projected and predicted maps for 2030

These results concur with the predictions and projected maps that were done in a research on land use landcover change in Ningxia North China, where the findings of the research were proving Markov to be the most appropriate model for land use landcover change (Abd El-Hamid et al. 2021, Gidado et al. 2019). The landcover of bare land has been increasing, forest cover decreasing, agricultural land increasing as well as water in the future projected land use landcover for the year 2030. Increased population and expanding mining activities may be the main reasons behind the increase in bare land and agricultural activities in the conservative. The decrease in forest or vegetation cover maybe attributed by expanding residential area as well as need for agricultural expansion (figure 5).

4 Conclusion

The Midlands Black Rhino conservancy has experienced significant forest loss due to landcover changes which occurred between 1980 and 2020. The major drivers of forest degradation were anthropogenic development mostly mining, agriculture opening of new crop fields and infrastructure development in the conservancy. The accelerated deforestation rates in the conservancy quest for mining and agriculture by the citizens of Zimbabwe. This saw a large influx of new small-scale farmers occupying the conservancy, and in the process clearing large areas of forests for different farm-related activities amongst crop farming and settlement. Forests have been lost persistently throughout the study period. This is negative feedback since the country is working towards reducing carbon emission. Forest management through REDD+ programs is one way Zimbabwe can reduce atmospheric carbon through carbon sequestration by vegetation. Forests in the Midlands Black Rhino Conservancy are facing a risk of clearance if the current socio-economic development activities are not harmonized with the country's climate change mitigation policies particularly policies to reduce carbon emission and forests conservation.

Recommendations

The study recommends the harmonization of the socio-economic development activities in the protected area with the national policies and legislations that are aiming to reduce carbon emissions.

The study also recommends the continuous call for sustainable land and ecosystem management for sound provision of all the ecosystem services rendered by the biota.

Compliance with ethical standards

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Disclosure of conflict of interest

There is no conflict of interest.

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