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Predictive Spatio-Temporal Modelling of Urbanization Impacts on Wetlands in Monavale Vlei, Harare, Using Cellular Automata–Markov 2012–2022

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Abstract

Urbanization is a major driver of wetland ecosystems, especially in the rapidly growing city of Harare, Zimbabwe. Monavale Vlei, situated in the Manyame River sub-catchment, is an important component in maintaining ecological and hydrological balance for Harare. This paper uses the Cellular Automata–Markov (CA-Markov) model to evaluate past wetland change dynamics (2012-2022) and forecast future land use and land cover (LULC) change up to 2032. The results show extreme wetland change and conversion due to urban expansion, with water resources projected to decrease by 63.4%, forest cover by 14.9%, and built-up areas to expand by 11.5%. However, some forest recovery (31.2%) and further urban expansion (26.3%) are also expected. These projections confirm the imbalanced effects of urbanization, with its critical hydrological and ecological processes being disproportionately endangered. The results of this study indicate that urban sprawl not only affects biodiversity and groundwater recharge but also affects agricultural and livelihood processes, making the population more susceptible to waterborne diseases. This study stresses the need for urgent conservation and policy measures to address wetland degradation and ensure sustainable urban development in Harare.

Keywords: Land Use/Land Cover (LULC), wetland loss, urbanization, MOLUSCE (Modules for Land Use Change Evaluation)

Introduction

Wetlands are some of the most valuable ecosystems in terms of their ecological services. Wetlands support biodiversity, regulate hydrological cycles, protect against floods, act as water filters, store carbon, and support a wide range of species (Turner, 2021). Unfortunately, wetlands are increasingly threatened by human activities, especially urbanization. Urbanization often takes place in low-lying areas, which are often wetlands, making them highly susceptible to destruction.

In Zimbabwe, the situation in Harare, the capital city, is a case in point. Harare has experienced rapid population growth and urbanization, leading to the encroachment and conversion of wetlands, such as Monavale Vlei, which is part of the Manyame River sub-catchment, a major water source for the city. The loss of wetlands in Harare not only affects the ecological services but also has implications for the livelihoods of people's, including agriculture, fishing, and access to water. In addition, the loss of wetlands makes the city more susceptible to waterborne diseases and environmental problems (Sithole & Goredema, 2013; Feresu et al., 2015). Currently, it has been reported that over 50% of Harare's wetlands have been lost due to the expansion of informal settlements and urbanization (Harare Wetlands Trust, 2021). Understanding the causes and effects of this environmental change requires tracking and measuring wetland loss. Tracking variations in wetland area over time can be effectively accomplished using remote sensing data and geospatial techniques, such as spatial time series analysis. Researchers can identify, quantify, and chart the dynamic processes of wetland conversion and loss through the examination of a series of satellite images or other spatial data.

Analysis of land use and land cover (LULC) change is a vital tool for studying wetland change under urbanization. Land use is the human use of land, while land cover is the physical and biological characteristics of the Earth's surface (Meyer & Turner, 1992; Turner, 2021). Human-induced LULC change, such as the conversion of wetlands into built-up areas, affects the functions of ecosystems and leads to environmental degradation (Amin & Fazal, 2012).

Remote sensing and Geographic Information Systems (GIS) are effective methods for analyzing and measuring LULC change over time. Satellite imagery provides spatial data on land cover at various temporal resolutions, enabling the analysis of conversion patterns and trends (Chuvieco, 2020; Khan et al., 2015). Unlike conventional LULC analysis, which typically involves the comparison of two images at two points in time, predictive models such as Cellular Automata–Markov (CA–Markov) models enable the simulation of future landscape changes based on trends identified in past observations. This method not only helps to determine past wetland conversion but also enables the estimation of the future potential for urban and ecological change.

However, despite global knowledge of wetland degradation, the literature has concentrated on other parts of the world rather than on Africa. In Harare, the wetlands are still under threat from the informal settlements, industries, and population increase. It is important to understand these dynamics to develop sustainable strategies for urban planning and wetland conservation.

Taking these factors into consideration, this research will concentrate on Monavale Vlei in Harare, Zimbabwe, to examine the effects of urbanization on wetland change and predict future changes. In particular, this research will attempt to quantify wetland loss and land cover change in Monavale Vlei from 2012 to 2022, as well as predict future changes in wetland status and urban expansion trends up to 2032 using Cellular Automata–Markov modeling. Furthermore, this research will attempt to evaluate the possible ecological and hydrological effects of wetland conversion due to the continued effects of urbanization. By achieving these research objectives, this study will provide informed insights for decision-makers, urban planners, and environmental managers in Harare to promote sustainable urban development and wetland conservation.

Materials and Methods

Study Area

Monavale Vlei is a wetland situated in the northwestern outskirts of Harare, Zimbabwe, in the Manyame River sub-catchment (roughly 17°47′S latitude and 31°2′E longitude). The wetland is estimated to cover about 120 hectares, making it one of the largest natural wetlands remaining in the Harare municipal area. Monavale Vlei is an important component of Harare's hydrology, recharging groundwater, regulating surface water, and sustaining biodiversity.

The climate in the study area is subtropical with a clear wet and dry season, typical of the highveld climate of Zimbabwe. The area receives an average annual rainfall of 750 mm to 1,000 mm, with the wettest months being November to March, while the dry months are May to August, which are normally cold. This seasonality affects hydrological processes in the wetland and its catchment. Presently, Monavale Vlei is protected by the municipality, but it is not recognized as a Ramsar site. The level of protection afforded to this wetland is only through local government control and management, which seeks to ensure a balance between conservation and the demands of urban development. Even with this level of protection, Monavale Vlei is still facing threats of encroachment by informal settlements, agriculture, and the expansion of urban infrastructure.

The wetland is home to a range of plant and animal species, some of which are indigenous wetland species that rely on the wetland's hydrological role. The importance of Monavale Vlei, both ecologically and hydrologically, and the challenges posed by Harare's rapid growth as an urban centre, make this wetland an important case study for understanding the effects of urbanization on wetland ecosystems.

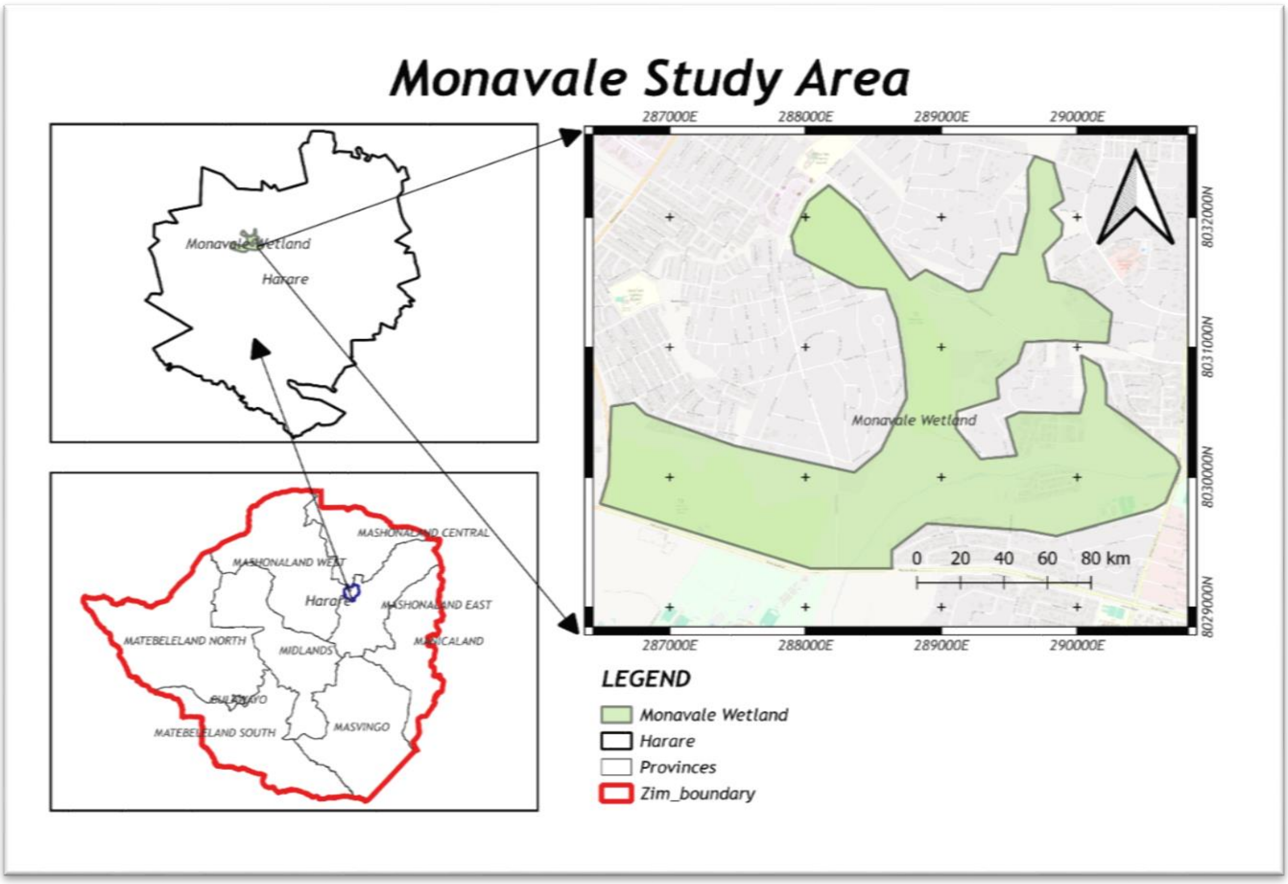


Figure 1: Study Area

To determine the Land Use and Land Cover changes in wetland extent in Monavale.

Data acquisition

To monitor the changes in wetland extent in Monavale, multispectral satellite images were acquired in 2012 and 2022. Both images were downloaded from United States Geological Survey (USGS). The satellite images were chosen based on their quality, focusing on scenes without significant line scan errors. ArcMap was used for classification.

Table 1: Table showing satellite image specifications

Data	Year of acquisition	Bands	Resolution	Cloud cover	Source
LANDSAT 7 ETM	2012	Multi-spectral	30	< 10%	United Sates Geological Survey (USGS)
LANDSAT 8 OLI	2022	Multi-spectral	30	< 10%	United Sates Geological Survey (USGS)

Satellite image pre-processing and classification

The satellite images for 2012 (Landsat 7 ETM+) and 2022 (Landsat 8 OLI/TIRS) were downloaded and analyzed using ArcMap. The images were first georeferenced to enable alignment with the existing geographic coordinates. Landsat 7 ETM+ and Landsat 8 OLI images were analyzed using their respective band combinations. For instance, water features were extracted using Bands 5, 6, 4 for Landsat 7 and Bands 6, 5, 4 for Landsat 8; built-up areas used 6, 3, 2 for Landsat 7 and 7, 4, 2 for Landsat 8; forested areas used 7, 6, 4 for Landsat 7 and 7, 6, 5 for Landsat 8; and bare land used 5, 4, 3 for Landsat 7 and 6, 5, 4 for Landsat 8.

To reduce noise and improve classification accuracy, the Semi-Automatic Classification Plugin (SCP) in ArcMap was used to extract features. The supervised classification was performed by digitizing the training samples as polygons for the four classes of land cover: bare land, water features, built-up areas, and forests. Google Earth Pro was used as the reference material for validatingthe training samples. The final result for each year was a classified raster layer that depicted LULC.

For change detection, a change matrix was developed to detect the transition of classes from 2012 to 2022. For spatial transition modeling, the MOLUSCE plugin was employed to develop a transition potential map, which helped to provide input for predictive analysis on future LULC dynamics.

Accuracy Assessment: The accuracy of classification was assessed using a confusion matrix, which helped to compute the user's accuracy (probability that a pixel assigned to a particular class actually belongs to that class) and producer's accuracy (probability that a reference pixel of a particular class was assigned to that class). The overall accuracy of the classification achieved a Kappa value of 0.899, which revealed very high agreement between the classified map and the reference map. Class-wise accuracy statistics, including producer and user accuracies, were provided for each LULC class.

Table 2: Table showing land use classes on the image classification.

Class Name	**Description**
Water bodies	Rivers, dams, ponds, open water
Forest	Trees, grasslands
Built-up	Settlement, commercial, roads
Bare land	Open areas

Detecting changes in land use was carried out to find out the rate of change that had taken place following the classification and the acquisition of the land use maps. Post-classification change detection was performed by QGIS using a semi-automatic classification plugin (SCP), to quantify the changes that had occurred to the classes of interest. Data from the land use maps was exported to Excel to produce a bar graph representing the changes that had occurred in the land use classes. The Spearman's rho correlation was then used to determine the relation between the degradation of the Monavale Vlei that is the change in LULC, and urbanization.

To analyze the effects of the LULC changes in the wetland.

To analyze the effects of Land Use and Land Cover changes in the Monavale Vlei, a Google Forms yes/no questionnaire was designed to gather insights and observations from the residents living in the areas surrounding the wetland, which are Sherwood Park in the northern part, Meyrick Park in the west, Westlea in the south and Milton Park in the eastern of the wetland. These four areas were used to create the four groups to capture the qualitative data which was then analyzed to determine the effects of urbanization in the wetland. Non-probability sampling/judgmental sampling/purposive sampling were used to choose five respondents from each suburb. This sampling method was used to make sure respondents had long-term knowledge of the wetland and had observed the changes. The questionnaires included observed changes in LULC by the residents, observed ecological impacts and socioeconomic effects of the changes to the residents. SPSS was then used to calculate the statistical relationship between respondents' responses and the effects of LULC changes in the Monavale Vlei.

To predict the future LULC of Monavale wetland in relation to the environment.

To predict the future LULC of Monavale Vlei, the study used machine learning in QGIS. The multi-temporal LULC maps of 2012 and 2022 were loaded into Quantum GIS. A Digital Elevation Model (DEM) was also downloaded. The DEM was used to account for elevation limitations. For example, to enhance prediction accuracy by adding topographic information into LULC changes, since urban development favors flat terrains. The multi-temporal maps and the DEM were checked for their consistency in size, bands, classes, spatial resolution and if they have an aligning coordinate system. The Modules for Land Use Change Evaluation (MOLUSCE) plugin was then used to initiate the prediction process. To check the geometry of the raster layers, the 2012 LULC map was added as the initial map, the 2022 LULC map as the final map and the DEM as the spatial variable. After that, Pearson's correlation was used for evaluating correlation and a class statistics table and a transition matrix were made to create a transition potential map. The transition potential modelling was done using the Artificial Neural Network (Multi-layer Perceptron) and the neural network was trained. The Cellular Automata was then used to create the prediction map of 2032 and to also calculate the percentage of correctness, which was 89.89%, to validate the map.

Results

To determine the change in land use and land cover types in Monavale.

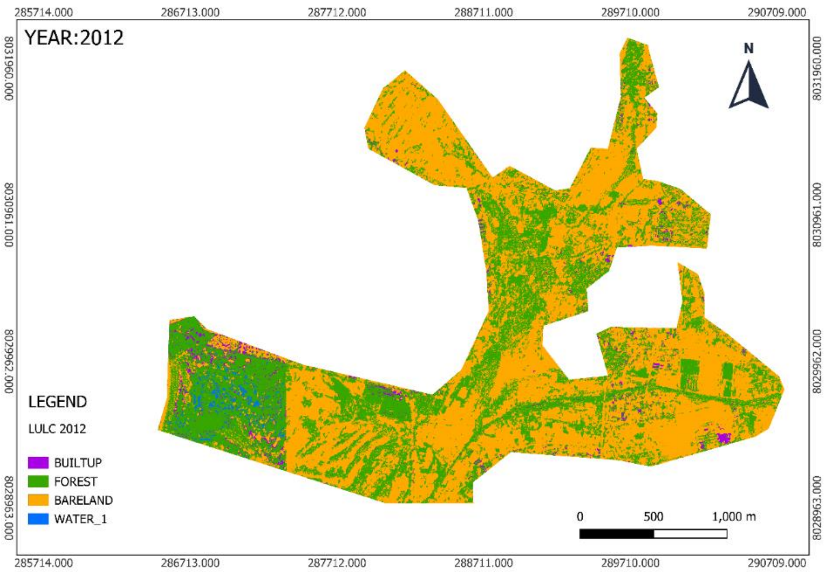


Figure 2: LULC Map for Monavale in 2012

The resultant land use land cover map for 2012 showed that the Monavale Vlei had a total land area of 5.38km^2. Area and percentage cover of individual classes showed that forest had the highest proportion 1.82km^2 which was 46.5% of the total land uses assigned by the supervised classification. Bare land had the second-highest cover at 1.83 km2 (33.8%), followed by Built-up at 0.91 km2 (16.9%), which occupied 16.9% of the wetland. Water bodies accounted for the least, at 7.6% of the area, or 0.41 km2.

Figure 3: LULC Map for Monavale Vlei in 2022

In 2022, bare land had 1.75km^2 (32.5%) taking the highest proportion of the area followed by forest, which covered 31.6% (1.70km^2). The third class had 28.4%(1.52km^2). Water bodies occupied 0.41 km^2, which is 2.9% of the area. Urban development was more concentrated in the South-East of Monavale Vlei.

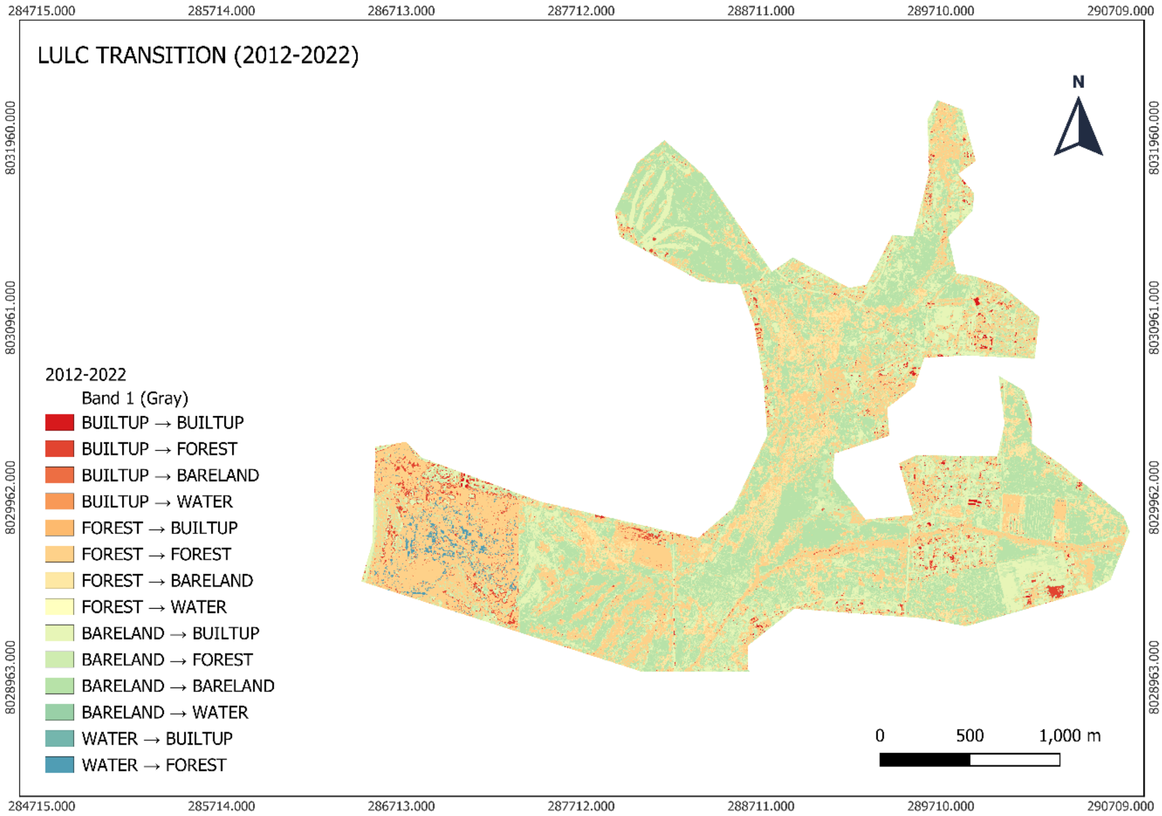


Figure 4:A Monavale Vlei LULC transition potential map from 2012 to 2022

The transition potential map shows LULC changes in square kilometres (km^2) over 10 years that is from 2012 to 2022 showing key trends and pressures on the Monavale wetland ecosystem. It shows the potential losses of each LULC class to another.

Table 3: Change detection matrix from one class to another.

CHANGE 2012-2022	**AREA**
BARELAND-BARELAND	1.688219
BARELAND-BUILTUP	0.898337
BARELAND-FOREST	0.549474
BARELAND-WATER	0.000043
BUILTUP-BUILTUP	0.031562
FOREST-BARELAND	0.694227

FOREST-BUILTUP	0.018877
FOREST-FOREST	1.39178
FOREST-WATER	0.001029
WATER-FOREST	0.03666

The table highlights the quantities of area changes, from one class to another over a decade (2012-2022). The areas correspond to a specific land use transition. Bare land to bare land: 1.688219km^2 of bare land remained bare. This class has the largest persistence, indicating stable bare areas. 0.898337km^2 of bare land transitioned into built-up indicating urbanisation. 0.549474km^2 of bare land also transitioned to forest showing some reforestation efforts or the area was turned into agricultural space. 0.000043km^2 of bare land turned into water. 0.031562km^2 of built-up remained as built-up. 1.39178km^2 of forest remained forest while 0.018877km^2 transitioned into built-up. This shows the occurrence of urban sprawl and 0.694227km^2 of forest turned into bare land due to deforestation. 0.001029km^2 of forest transitioned into water. 0.03666km^2 of water transitioned into forest.

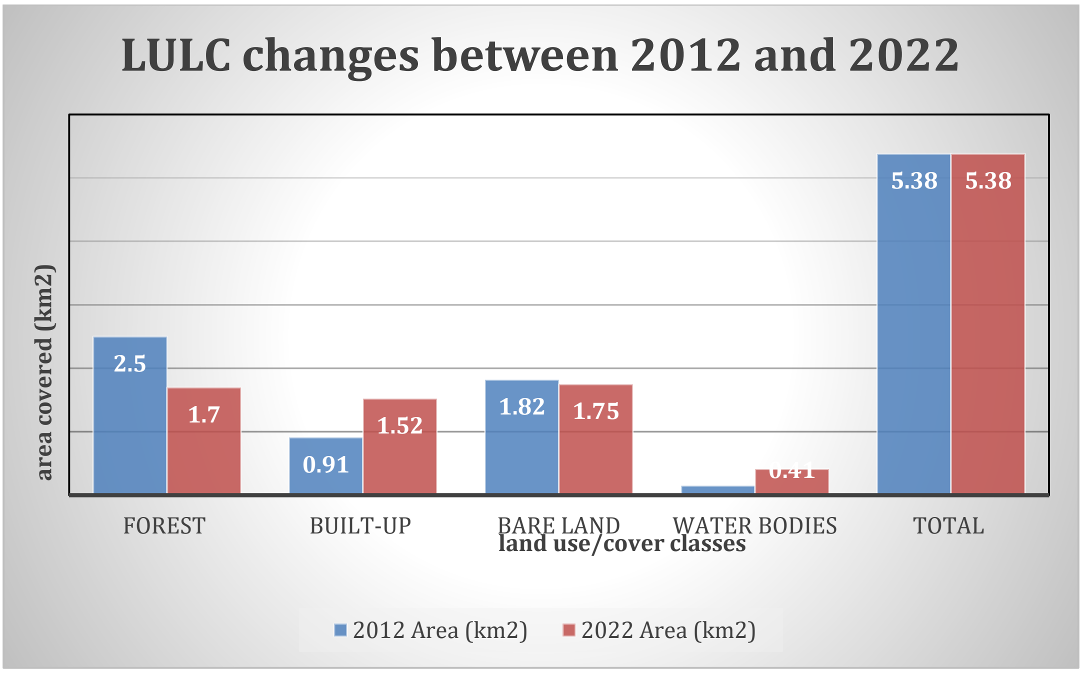


Figure 5: Bar Graph showing LULC changes between 2012 and 2022

The data presents LULC changes between 2012 and 2022, with two sets of numerical values corresponding to each year. The LULC classes include forest, built-up, water bodies and bare land. The first set of values that is of 2012 shows 2.5km^2, 0.91 km^2, 1.82 km^2 and 0.15km^2, while the second set of 2022 displays 1.7 km^2, 1.52 km^2, 1.75 km^2 and 0.41 km^2. The table shows that the forest area in 2012 was 2.50 km^2 which is 46.5% of the total area, and it decreased to 1.70 km^2 (31.6%) in 2022. The area covered by the forest decreased by 0.80 km^2 which is -14.9% relative to 2012. The area covered by built-up was 0.91km^2 (16.9%) in 2012 and it increased to 1.52km^2 (28.4%) in 2022. This is a 11.5% increase in built-up areas. In 2012, bare land was 1.82 km^2 which is 33.8% of the total area. In 2022, bare land decreased to 1.75 km^2 (32.5%). The water bodies in 2012 covered 7.6% of the total area (0.41 km ^{2}) and, in 2022, they covered 2.9% of the total area (0.15 km^2).

Table 4: A table showing the Spearman's Rho Correlation results.

			forest	built-up	bare land	water
Spearman's rho	forest	Correlation Coefficient	1.000	-1.000	1.000	1.000
		Sig. (2-tailed)	.	.	.	.
		N	2	2	2	2
	built-up	Correlation Coefficient	-1.000**	1.000	-1.000	-0.8000
		Sig. (2-tailed)	.	.	.	.
		N	2	2	2	2
	bare land	Correlation Coefficient	1.000**	-1.000**	1.000	-1.000
		Sig. (2-tailed)	.	.	.	.
		N	2	2	2	2
	water	Correlation Coefficient	-1.000**	1.000**	-1.000**	1.000
		Sig. (2-tailed)	.	.	.	.
		N	2	2	2	2

Correlation is significant at the 0.01 level (2-tailed).

Forest cover has a strong negative correlation with built-up areas of -1.000. This shows that as built-up increases, forest cover is lost, indicating that urbanization is causing deforestation in the Monavale Vlei. Forest cover has a positive correlation with bare land of 1.000, meaning that there is also bare land in the forests and this highlights that urban is expanding directly into forests. The correlation of forest and water is positive (1.000). This indicates that as forest cover decreases, the quality and quantity of water also decrease. Built-up and bare land have a correlation coefficient of -1.000, showing a perfect negative correlation. This shows that as built-up increases, bare land decreases indicating that urbanization is expanding and taking up the bare land. There is a strong negative but not perfect correlation between built-up and water. This means that as urbanization increases, the quality and quantity of water are affected and it declines. There is a negative correlation of -1.000 between bare land and water. This indicates that as bare land increases due to deforestation and urbanization, water decreases due to the degradation of wetlands.

To analyze the effects of LULC change on the Monavale wetland

Demographics

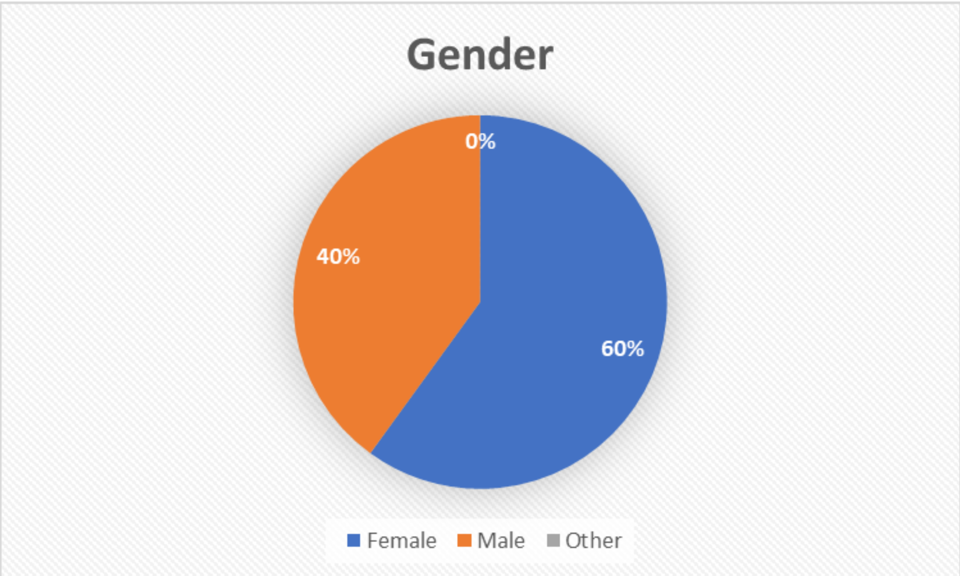


Figure 6: A pie chart showing gender data.

The questionnaire data show a clear gender imbalance among the 20 respondents who answered. Females, highlighted in blue, greatly outnumber males, shown in orange, making up 60% of the responses (12 people), while males make up 40% (8 people). The survey had no responses from gender-diverse or non-binary participants.

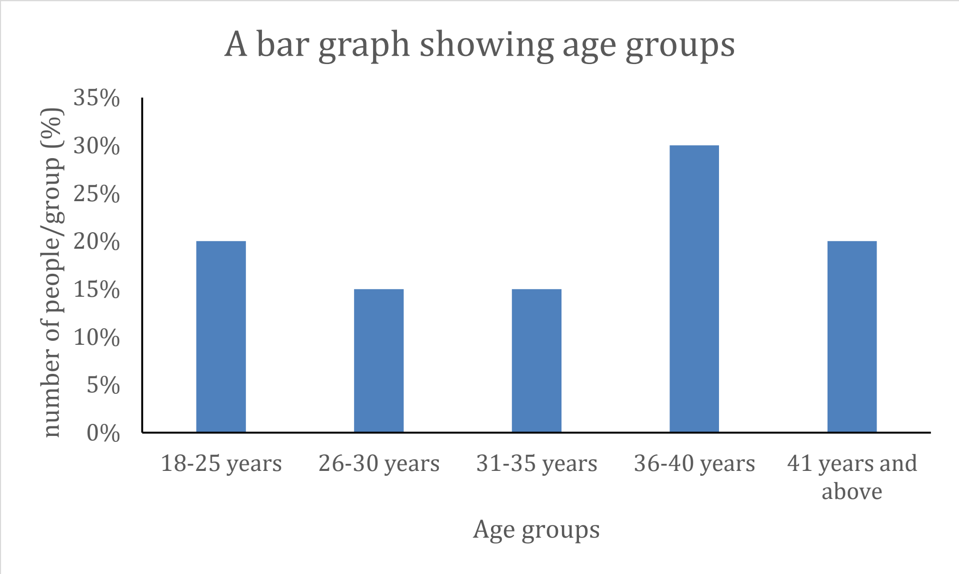


Figure 7: A bar graph showing age groups

The data from the questionnaires presents the age of 20 participants. The most numerous group is 36-40 years (30%, 6 participants), followed by 18-25 years and 41 years and older (20% each, 4 participants). The least numerous groups are 26-30 years and 31-35 years (15% each, 3 participants). The bar graph shows this spread. It is highest for the 36-40 age group and is well distributed across younger and older participants. This shows that the participants are diverse but more middle-aged.

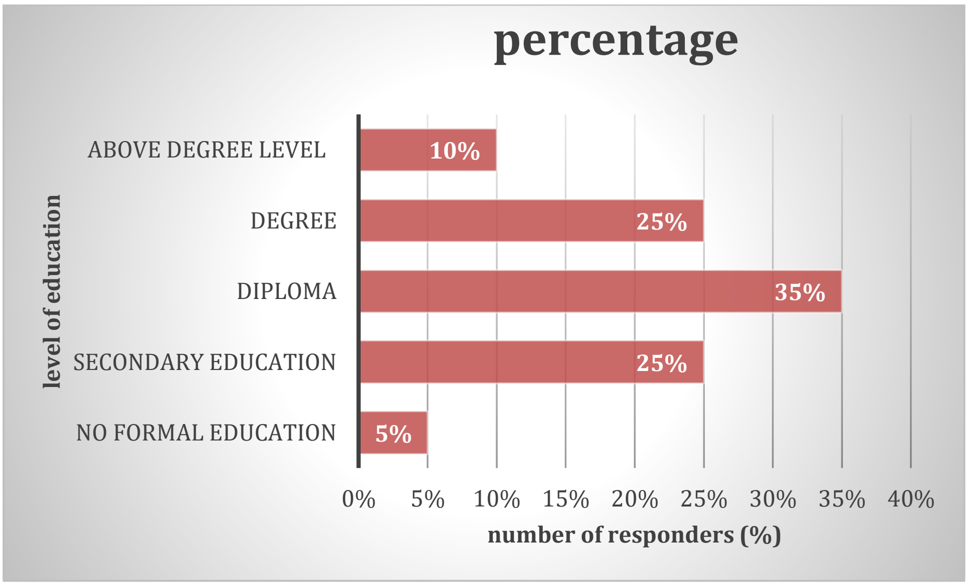


Figure 8: A bar chart showing educational levels.

The data from the questionnaires presents the educational levels of 20 respondents. The most common group is those with Diplomas (35%, 7 people). Secondary and Degree follow, both at 25% (5 people each). Fewer people indicated an above degree level (10%, 2 people). Only 5% (1 person) had No formal education. The bar graph shows this spread, indicating that most individuals have at least a secondary education, with diplomas as the most prevalent qualification. The figures show a grouping of respondents with medium education, with very few at the extremes.

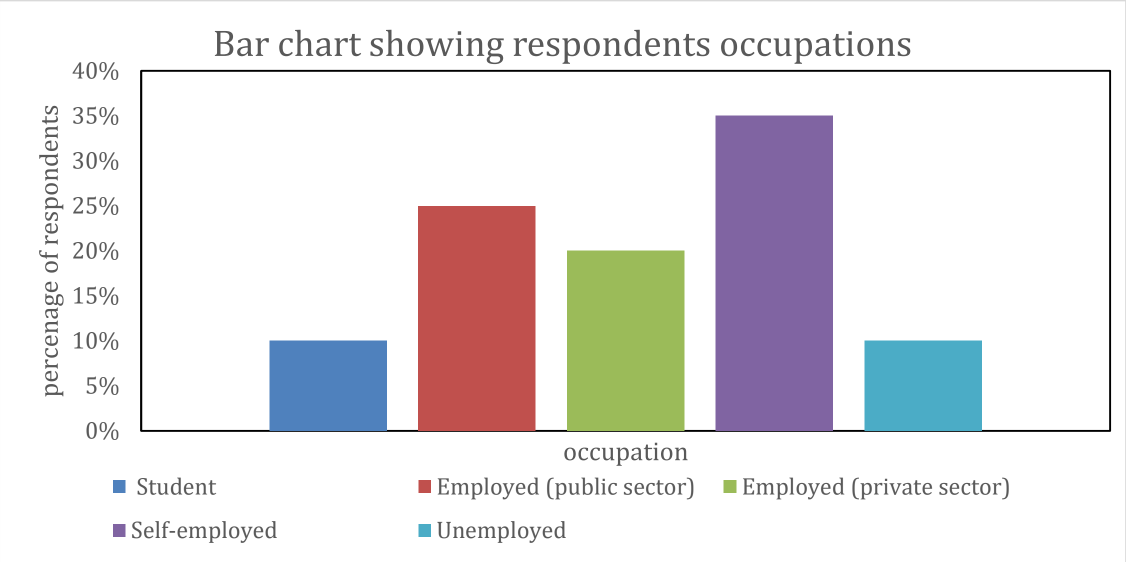


Figure 9: A bar showing respondents occupations.

The occupations of 20 people are reflected in the questionnaire data. The most dominant group is the self-employed (35%, 7 people), followed by employees in the public sector (25%, 5 people) and the private sector (20%, 4 people). Students and the unemployed make up 10% each (2 people). The bar chart illustrates this clearly, highlighting self-employment as the most common occupation. It suggests that the respondents have different employment statuses but most are entrepreneurs.

Table 5: Table showing chi-square tests for the demographics.

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	2.500[a]	3	.475
Likelihood Ratio	3.278	3	.351
N of Valid Cases	20		

Pearson Chi-Square: $\chi^2(3) = 2.500$, $p = 0.475$) as $p>0.05$.

There was no significant relationship between demographics and perceptions of wetland changes. The characteristics of the demographic results did not influence the respondents' responses in any way.

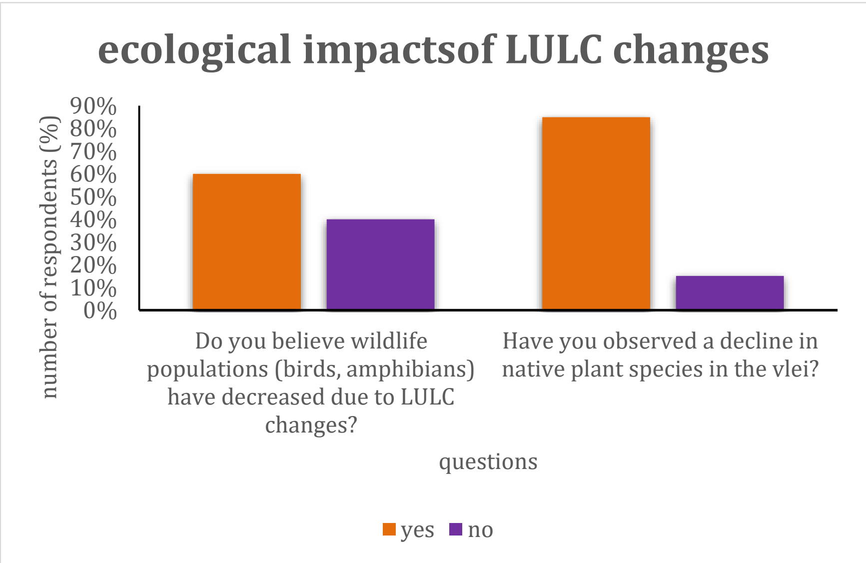


Figure 10: A bar chart showing ecological impacts of LULC.

The survey outcomes indicate widespread community perception of environmental impacts from Land Use/Land Cover (LULC) change in Monavale Vlei. A very high 85% of respondents indicated they had noticed declines in native plant species, indicating widespread visible vegetation degradation. While still elevated, somewhat fewer (60%) believed that wildlife numbers (birds, frogs) had decreased, indicating either fewer visible animal losses or less public awareness of wildlife trends compared to plants. There is a wide range in the variation of plant (85%) and animal (60%) observations.

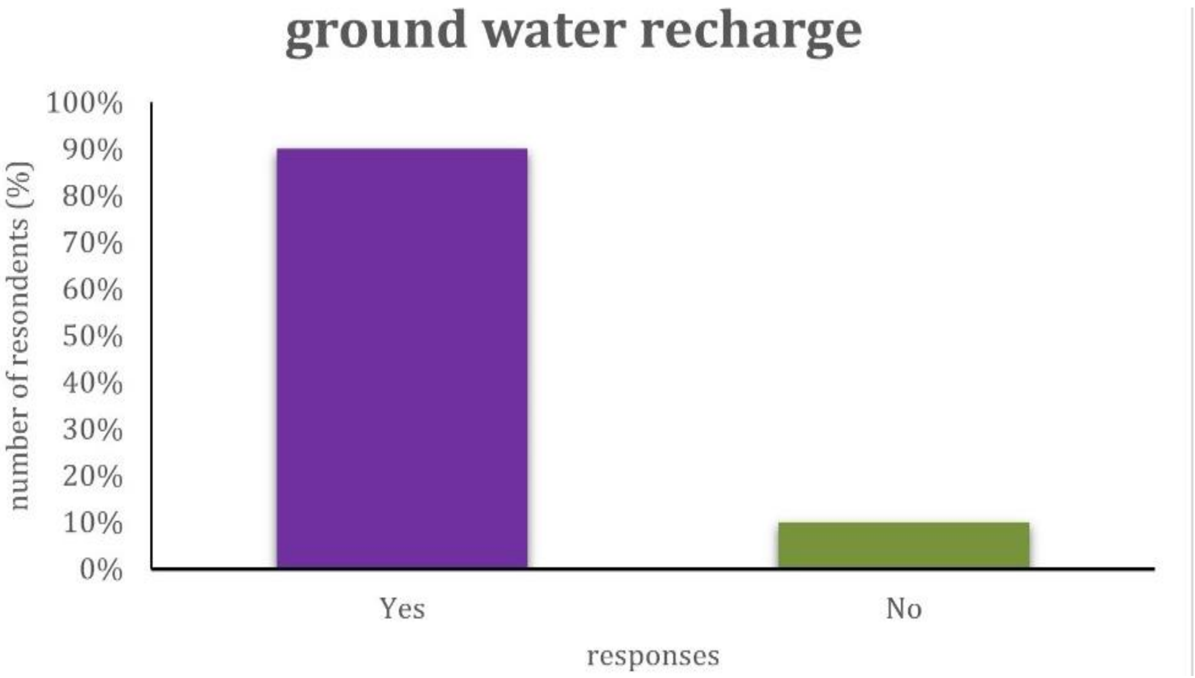


Figure 11: A bar chart showing the effects of LULC on groundwater.

The results of the survey demonstrate that almost all participants share the same opinions regarding the hydrological impacts of Land Use/Land Cover (LULC) changes in Monavale Vlei, with 90% in favor of groundwater recharge being affected and 10% not.

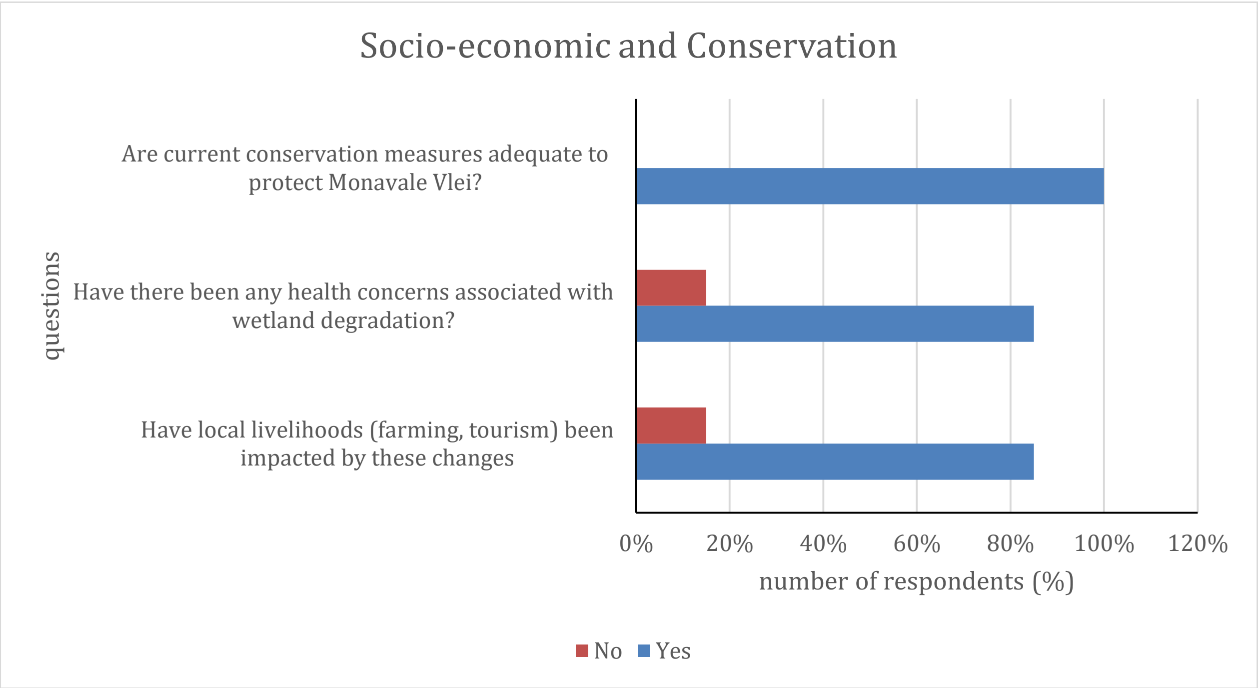
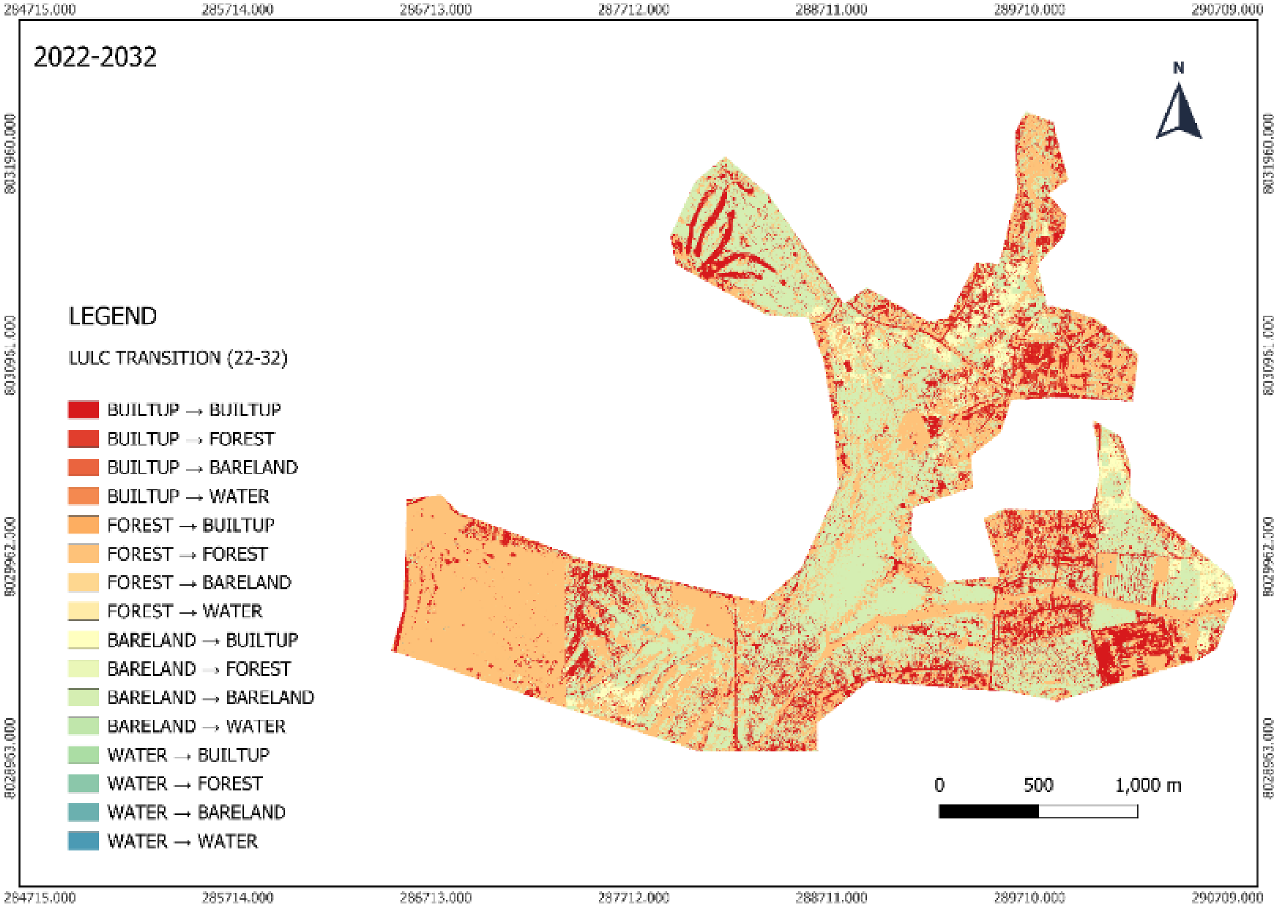


Figure 12: a bar chart showing the socio-economics and conservation efforts.

The survey findings identify key socioeconomic and conservation concerns in Monavale Vlei, with 85% of respondents reporting impacts on local livelihoods (tourism, agriculture) and health problems related to wetland degradation. Notably, 100% believe that current conservation initiatives are insufficient to protect the vlei, indicating broad dissatisfaction with protection efforts to date. The identical 85% rates for both the effect on jobs and health also show that both issues are of equal concern to residents.



To predict the future extent of Monavale wetland in relation to the environment.

Figure 13: A Monavale Vlei LULC transition potential map from 2022 to 2032

This 2022-2032 transition map shows future land use changes based on observed trends, indicating transitions amongland use classes.

Table 6: Table showing class transitions from 2022 to 2032.

CHANGE 2022-2032	**AREA**
BARELAND –BUILTUP	0.295395
BARELAND –FOREST	0.155988
BARELAND -BARELAND	1.828475
BUILTUP -BUILTUP	0.834817
FOREST -BUILTUP	1.987281
FOREST -FOREST	1.987281
FOREST -BARELAND	0.173394
FOREST -WATER	0.000002
WATER_ -FOREST	0.000005
WATER_-WATER	0.001159

1.828475km^2 of bare land will remain constant. 0.155988 km^2 of bare land will transition to forest 0.295395 km^2 of bare land might also change to built-up. 0.834817km^2 of built-up might remain constant. 1.987281 km^2 of forest will remain as forest. 1.987281 km^2 of forest will change to built-up. The forest might lose 0.173394 km^2 of its area to bare land. 0.000002km^2 which is very rare. 0.000005km^2 of water will change to forest while 0.001159km^2 will remain unchanged. Urbanisation will be dominant in bare land and as well as encroaching into forests.

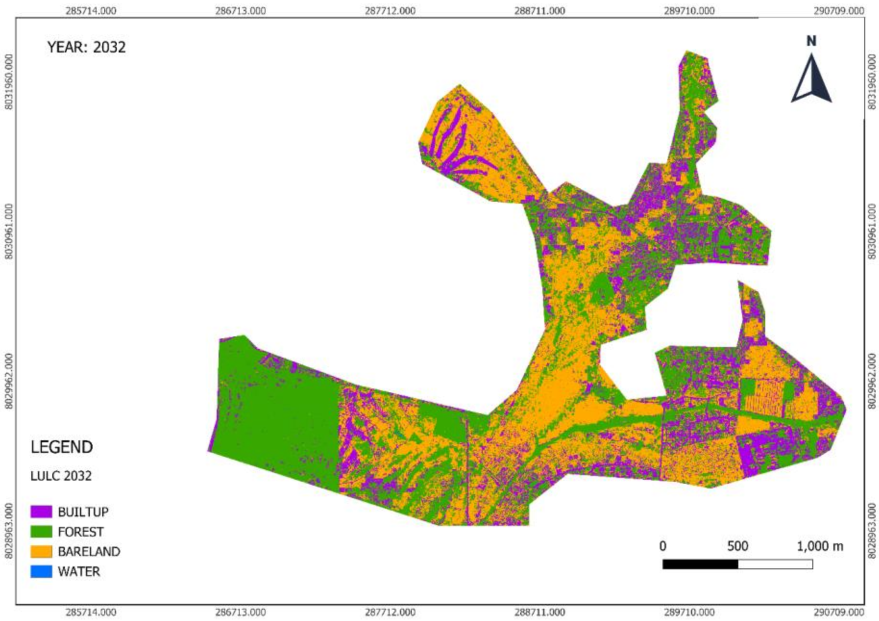


Figure 14: Monavale Vlei predicted LULC map for 2032

Figure 14 is the predicted visualisation of Monavale Vlei LULC changes after a decade from 2022 (2032). This map predicts the 2032 land cover of Monavale Vlei, focusing on four significant classes: Built-up, Forest, Bare land, and Water. Its spatial arrangement displays important trends, including forest regeneration in certain areas (green) and urban growth (red/built-up), whilst bare land (brown) and water (blue) zones may shrink due to urbanisation and/or climatic stresses.

Table 7: Table showing LULC changes from 2022 to 2032

class	2022		2032		Change	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area changed (km^2)	Area changed (%)
Forest	1.70	31.6	2.23	41.4	0.53	31.2
Built-up	1.52	28.4	1.92	35.7	0.4	26.3
Bare land	1.75	32.5	1.14	21.2	-0.61	-34.9
Water bodies	0.15	2.9	0.09	1.7	-0.06	-40
Total	5.38	100	5.38	100		

The 2022-2032 projected land use and land cover map of Monavale Vlei showing changes in land cover. Forests are predicted to increase by 0.53 km^2 (31.2%), raising their share from 31.6% to 41.4% of the total area, indicating that reforestation or natural regrowth is progressing well. Urban areas will also increase by 0.4 km^2 (26.3%), from 28.4% to 35.7%, indicating urban sprawl, likely at the expense of other land-type classes. Bare land will decrease sharply by 0.61 km^2 (-34.9%), from 32.5% to 21.2%. Bodies of water should decrease by 0.06 km^2 (-40%). Overall, the data shows two significant trends: forests are recovering, and cities are spreading out, with bare land serving as the major source for both changes. Total area remains steady at 5.38 km^2 with neither loss nor gain, but within the area, it is dynamic.

Discussion

The results of this research highlight the role of urbanization in the loss of wetlands in Monavale, Harare, as validated by spatial time-series analysis and surveys of communities around the study area. Land use/land cover (LULC) changes between 2012 and 2022 indicated a loss of 14.9% of forest cover and an increase of 11.5% in built-up areas, showing the encroachment of urban development into the wetland ecosystems. Water bodies experienced the most degradation because decreasing by 63.4%, perhaps due to drainage, pollution, and land conversion. These trends align with global patterns in which severe urbanization has led to wetland deterioration, as evidenced by case studies in China and India (Naikoo et al., 2020). The perfect negative correlation (-1.000) between built-up areas and forest cover (Spearman's Rho) also supports urbanization as the main cause of wetland degradation in Monavale. The findings were supported by community survey results, where 90% of the respondents noted LULC changes (Zhou et al., 2024), 85% noted a decrease in wildlife and native plant species, and a further 85% attributed urbanization to decreased groundwater recharge, concurring with the research done by . Significantly, all of the respondents (100%) believed that existing conservation efforts were insufficient and expressed the urgent need for policy intervention similarly to study done in India (Shan et al., 2021).

The CA-Markov predictive modelling as also used by (Ahmad et al., 2017) in analysing LULC in India, predicted recovery of forest cover (31.2%) by 2032 and urbanization will expand by (26.3%) similarly to a research by (Gidey et al., 2017) in Ethiopia. The predictions, however, assume that the existing trends will continue to be unchanged and might not capture unplanned development or climatic variability and sudden policy changes, indicating the model limitations. The effects of these changes are significant. The CA-Markov model demonstrated strong predictive accuracy, with an 89.9% correctness rate and high Kappa agreement values (Kappa location = 0.94, Kappa histogram = 0.94), indicating reliable alignment between simulated and observed land-use changes, though the overall Kappa (0.04) suggests minor discrepancies in class-specific transitions.

Degradation of wetlands has compromised biodiversity, as interview respondents from surveys reported reductions in native vegetation and animals, mirrored by observations from comparable studies in Harare (Kamete, 2018). Flood risk increases as the number of water bodies decreases (Cloke et al., 2017). This is because wetlands lose their natural ability to filter runoff, as seen in other areas that are becoming more urbanised (Faulker, 2004). 85% of those who answered said that the degradation of wetland areas due to construction pollution had negative effects on people's ability to earn a living through activities like farming and tourism.

The same number were also worried about the health risks that came from waterborne diseases, as found out Nyoni et al. (2023). The results are consistent with findings from other research on the effects of continued urbanization in sub-Saharan Africa (Jombo et al., 2017).

The findings of the study highlight the necessity of improved land-use policies that incorporate wetland conservation into urban planning systems, as advocated by Chirisa et al. (2014). Since community awareness is high (90%), participatory strategies that incorporate local individuals into conservation efforts can strengthen policy implementation. Additionally, adopting monitoring technologies, such as real-time GIS and remote sensing, would enable institutions like the Environmental Management Agency (EMA) to track wetland transformation more accurately. However, the study's shortcomings are its reliance on a limited temporal dataset (2012–2022) and potential survey bias towards respondents in their middle age, which present opportunities for future research. The inclusion of previous decades (e.g., 1990–2010) in the analysis would add greater historical context, and the inclusion of climate data would enhance predictive modelling. Generally, this research demonstrates that urbanization is a key driver of wetland degradation in Monavale with great ecological and socioeconomic implications. Although predictive models suggest some scope for forest regeneration, the continued expansion of built-up areas remains a threat. To reduce these effects, policymakers need to prioritize wetland preservation by strengthening land-use regulations, promoting public involvement, and enhancing technological monitoring.

In the absence of such interventions, Harare might lose the remaining wetlands, increasing environmental and public health concerns. The research contributes to an emerging body of scholarship on sustainable urban growth in Zimbabwe and provides actionable recommendations for conservation planning.

Conclusions

This dissertation offers a broader examination of wetland degradation in Monavale Vlei, Harare, attributable to urbanisation. The study employed spatial time series analysis to quantify land use and land cover (LULC) changes, including forest decrease, urban development, and water body depletion, while predictive modelling explained future trends under existing conditions. Community surveys enhanced these findings by documenting local opinions of ecological and socio-economic repercussions, indicating a consensus on the insufficiency of current conservation strategies. The study highlights the essential function of wetlands in preserving biodiversity, enhancing water quality, and mitigating floods, while illustrating how urban development threatens these ecological services. The study addresses a deficiency in localised research regarding wetland loss in Zimbabwe, providing practical insights for policymakers, urban planners, and environmental agencies. The findings, by agreeing with global literature on wetland degradation, enhance broader conversations on sustainable development in urbanising environments. The report ultimately endorses a balanced strategy for urban growth that prioritises environmental sustainability alongside economic development.

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