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Research paper

# Perceptions of drivers of land use–land cover change in the Bangweulu Wetland and surrounding areas, Zambia

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Wetlands are vital to healthy ecosystems as they control floods and perform other important roles. Globally, the primary cause of wetland degradation is land use–land cover (LULC) change, a situation that also applies to Zambia. This research investigated LULC changes in the Bangweulu Wetland and its perceived drivers, using remote sensing, geographic information systems (GIS), questionnaires, and key informant interviews. The land was categorized into five types: settlements, grassland, cropland, water, and forest. The results showed a decline in forest (from 45 298.93 km$^2$ to 33 233.52 km$^2$), grassland (from 32 557.91 km$^2$ to 26 418.19 km$^2$), and water (from 2 410.72 km$^2$ to 2 278.31 km$^2$) between 1990 and 2020. In contrast, settlements grew from 356.69 km$^2$ to 2 210.38 km$^2$, and cropland expanded from 165.27 km$^2$ to 5 108.13 km$^2$. The perceived drivers of this change were also identified. Population growth was the most significant (3.76/5), followed by settlement expansion (3.66/5), declining ecosystem services (3.57/5), and forest loss (2.64/5). Minor perceived drivers included the built environment (2.21/5), recreation (1.54/5), and industry (1.34/5). Underlying causes involved agricultural development and energy needs, driven by market demands for charcoal and cash crops, which accelerate farming and deforestation. Understanding these local perspectives is essential for creating effective land management strategies and sustainable policies to conserve the Bangweulu Wetland's ecological functions.

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## INTRODUCTION

Wetlands play a crucial role in supporting biodiversity and various water-related activities (Alikhani et al., 2021). These unique ecosystems offer a multitude of ecosystem services that benefit both humans and the environment (Mandishona and Knight, 2022). They provide important functions such as flood control, groundwater recharge and water quality regulation (Liu et al., 2004). The Ramsar Convention, an international treaty, aims to promote the sustainable use of wetlands for both environmental preservation and the livelihoods of communities dependent on them (Secretariat of the Convention on Wetlands, 2007). However, wetlands face threats due to global climate change and land use change, which have negative impacts on freshwater resources, biodiversity and flood regimes (Nachtergaele et al., 2016). Land use–land cover (LULC) change is commonly driven by human activities that modify the natural landscape for different purposes (Maitima et al., 2010), with drivers such as population growth being a major contributor to current land use change in wetlands (Phethi and Gumbo, 2019). Accurately assessing and monitoring land use changes over time is essential for understanding wetland ecosystem dynamics (Banda et al., 2023) and formulating effective management policies and land use planning strategies (Jamal and Ahmad, 2020).

Munthali et al. (2019), in their study in Malawi, identified a decline in forested, agricultural, wetland and water areas, accompanied by an increase in built-up and barren land. The local communities ranked firewood collection, charcoal production, population growth and poverty as drivers of LULC dynamics. Notably, education levels significantly influenced perceptions of these drivers (Munthali et al., 2019). Similarly, research by Assefa et al. (2021) unveiled a significant reduction in wetlands and water bodies over a 35-year period in Bahir Dar City, primarily attributed to expansion of built-up and cultivated areas. Cai et al. (2022) also discovered that human actions are crucial in determining the fate of wetlands across the globe, potentially leading to future challenges, and flagged climate change and rapid agricultural expansion as key drivers.

Regrettably, the world has witnessed a substantial decline in wetlands, with more than 50% vanishing since the early 1900s (Davidson, 2014). This degradation has resulted in reduced freshwater supply, diminished biodiversity and detrimental effects on traditional wetland-based livelihoods, flood control and carbon storage (Secretariat of the Convention on Biological Diversity, 2015). Human activities, such as increased agriculture, grazing, urban infrastructure development and water diversion, stand as the primary culprits driving global wetland degradation (Secretariat of the Convention on Wetlands, 2014). The loss of wetlands has led to adverse consequences for biodiversity, as evidenced by the decline in populations of freshwater species (McLellan et al., 2014). Watersheds across the globe are wrestling with negative impacts stemming from residential and commercial land use, as well as agricultural practices (Akhtar et al., 2011). Identifying the perceived drivers that influence the changes in LULC offers a detailed understanding of the connection between human actions and alterations in the environment (Garg et al., 2019). However, there have been limited studies on the importance of assessing the drivers of land use change in Zambian wetlands in general and the Bangweulu Wetland in particular. Hence, additional evaluations are necessary within wetland regions to ensure the continuity of conservation efforts, as understanding how socio-economic activities influence the dynamics of LULC is essential in

developing sustainable policies for effective land use and resource management (Banda et al., 2023).

The main aim of the study was to assess LULC changes in the Bangweulu Wetland and surrounding areas. The specific objectives of the study were to: (i) assess LULC change between 1990 and 2020 using Landsat satellite images; (ii) identify the perceptions of drivers of observed changes in the wetland; and (iii) determine the factors that influence the perceived changes in LULC in the Bangweulu Wetland and surrounding areas.

## MATERIALS AND METHODS

### Description of study area

The Bangweulu Wetland, located in Zambia's Luapula, Central and Northern Provinces, is among the largest and most diverse wetland systems in southern Africa (Kamweneshe, 2000; Secretariat of the Convention on Wetlands, 2002). The study area encompasses a sub-catchment covering a total area of about 75 158 km$^2$ (Fig. 1). This region includes both the Bangweulu Wetland itself, which is about 30 000 km$^2$ (Secretariat of the Convention on Wetlands, 2002), and the surrounding territories, amounting to 35 158 km$^2$. The wetland has three distinct seasons, namely winter, summer and the rainy season, with annual average rainfall ranging from 1 100 mm to 1 500 mm (Beilfuss, 2017) (Fig. 2) and annual maximum and minimum temperatures ranging from 6°C to and 37°C (Fig. 3). The primary soil types in the wetland are arenosols, gleysols and histosols, with varying nutrient retention capacities and saturation levels (Spaargaren, 2008). The main lake, Bangweulu, is approximately 72 km long and 38 km wide. The regional vegetation is predominantly grassland, with open evergreen forest and termite mounds near the margins of the wetland. Land cover includes major lakes, papyrus swamps, floodplains and man-made canals (Hughes and Hughes, 1992).

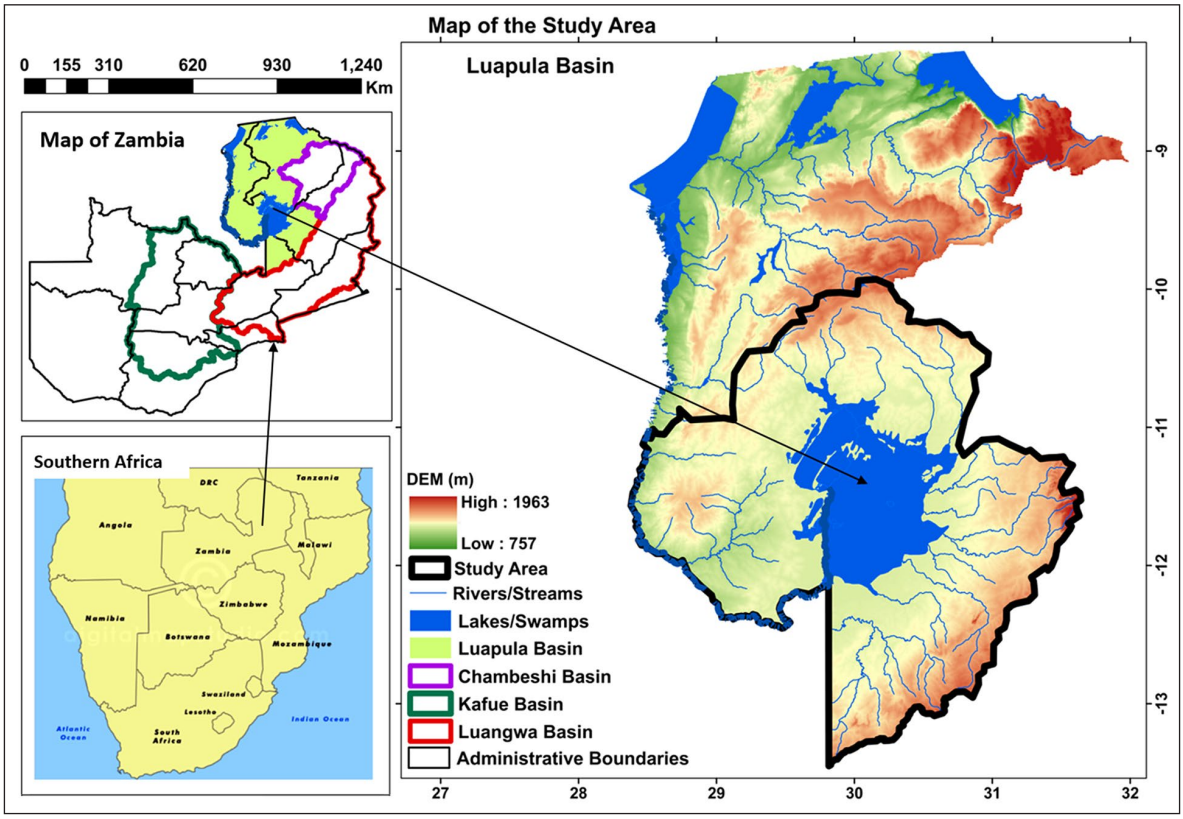


**Figure 1.** Map showing the location of Bangweulu Wetland and surrounding areas, Zambia (Source: Chundu et al., 2024)

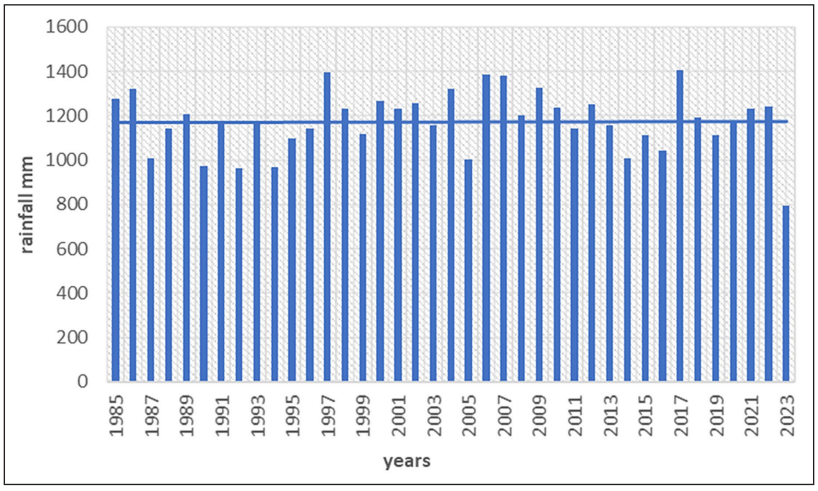


**Figure 2.** Historical rainfall trends of Bangweulu Wetland and surrounding areas, Zambia

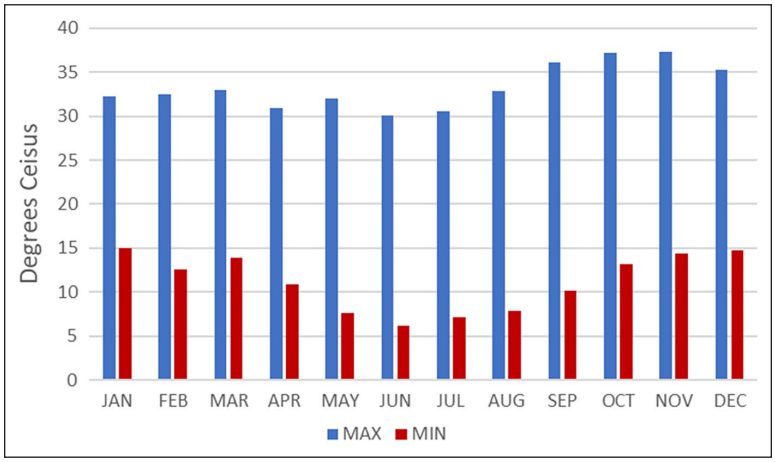


**Figure 3.** Annual maximum and minimum temperatures of the Bangweulu Wetland and surrounding areas of Zambia (Sparks, 2018); MAX = maximum temperature; MIN = minimum temperature

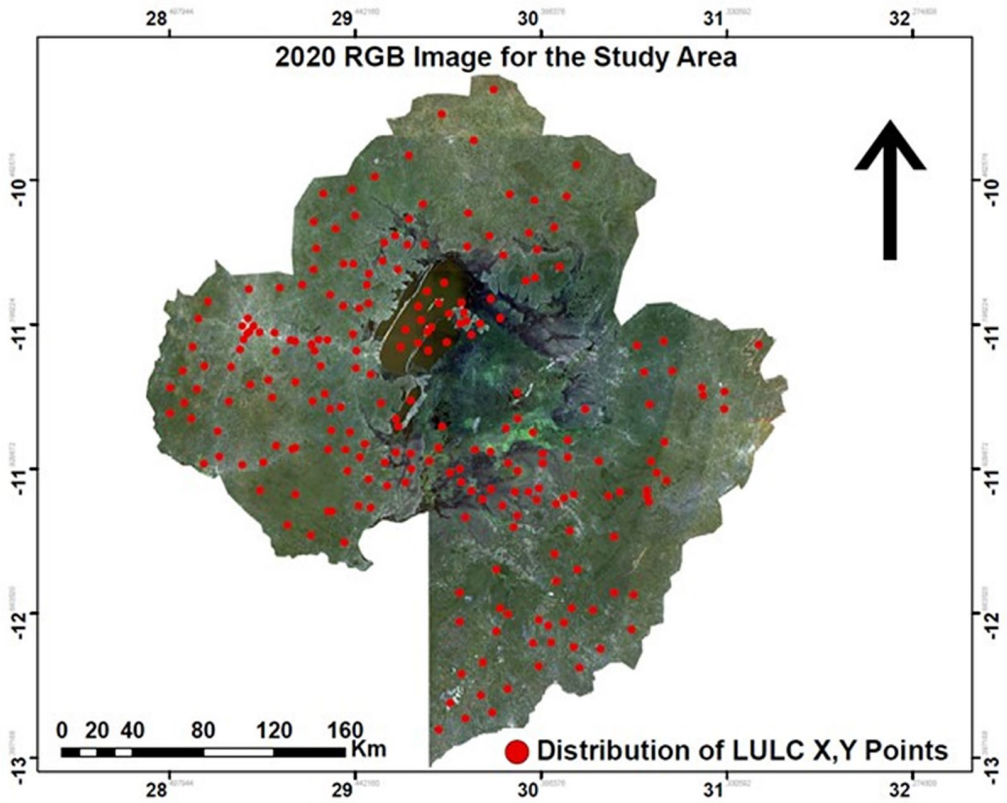


**Figure 4.** Distribution of the training sample points

## Sampling design and data collection

### *Field and spatial data*

Ground control points (250 points) consisting of different LULC features and their location points were recorded using a global positioning system (GPS) instrument (Fig. 4). The full latitude/longitude locations of the training points are provided in Table A1 (Appendix). Pre-processed Landsat 5 (1990, 2000, and 2010 images) and Landsat 8 (2020 image) images with 4 bands (near-infrared, red, green, and blue) of the Bangweulu Wetland and the surrounding areas were downloaded from Climate Engine (Climate Engine, 2017). Climate Engine (ClimateEngine.org) is a web-based application that overcomes many computational barriers users face by employing Google's parallel cloud computing platform, Google Earth Engine, to process, visualize, download and share climate and remote-sensing datasets in real-time (Huntington et al., 2017). It leverages cloud computing to quickly produce ready-to-use outputs, saving significant time and computational resources. This makes Climate Engine a more efficient and accessible option for downloading satellite and climate images (Chundu et al., 2024; Huntington et al., 2017). The shapefile of the study area was overlaid with imagery data downloaded from a climate engine. By overlaying the imagery data with the shapefile, it was possible to create a visual representation of the imagery data for the study area.

### *Social survey*

In order to assess data obtained from satellite imagery, similarly to other studies (Aldrich et al., 2006; Endfield, 2009), a social survey was conducted, which involved the use of household questionnaires and key informant interviews. The survey aimed to gather information on the perceived drivers of LULC change in the study area. A total of 300 household questionnaires were administered to randomly selected households and 5 key-informant interviews

were conducted with individuals who were available and had relevant knowledge and expertise (Table 1). The selection of villages for the social survey was based on their proximity to the lake and the wetland (Fig. 5), ensuring that the collected social data could be compared and aligned with the ecological survey data, particularly regarding agricultural land cover (Wang et al., 2023).

The methodology for data collection involved the use of household questionnaires and semi-structured interviews to obtain insights into LULC change and perceived drivers in the study area (Munthali et al., 2019), specifically the Bangweulu Wetland and its surrounding areas. Household questionnaires were administered to the heads of each household, where Tanzania National Bureau of Statistics, (2011) defines a household as a group of individuals who share meals and accommodation. The head of the household, as the primary decision-maker, provided responses to the questionnaires.

The questionnaires also helped gather information on the main economic activities of the households and other relevant details. In addition, interviews were conducted with various stakeholders who possessed extensive knowledge or were involved in specific projects or topics related to LULC change (Wilson, 2014). These interviews aimed to tap into the informants' expertise and gather more information about the perceived drivers of LULC change in the study area.

## Data analysis

### *Image analysis*

Landsat Bands 4, 3, and 2 were used during the training phase of the maximum likelihood classification, primarily to support visual interpretation and aid in the identification and delineation of training sites for each LULC class. This is because these bands correspond to the red, green, and blue wavelengths, respectively, which collectively produce true-colour images resembling human vision, thereby providing critical spectral information that differentiates different LULC types (Nyamekye et al., 2021). The classification was performed in ArcGIS 10.7.1 using 5 classes: water, grassland, settlements, cropland and forest. The accuracy of land cover categorization was evaluated using a confusion matrix and Kappa Index (KI) based on the ground truthing data. The kappa coefficient ($k$) is expressed mathematically as:

$$k = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i G_i)}{N^2 - \sum_{i=1}^{n}(G_1 G_i)} \quad (1)$$

where: $i$ = class number; $N$ = total number of classified pixels; $m_{i,i}$ = number of pixels in Ground Truth Class $i$ correctly classified as $i$; $G_1$ = total number of pixels classified as $i$; $G_i$ = total number of pixels in Ground Truth Class $i$ (Munthali et al., 2019).

**Table 1.** Sampled districts and interviewed key informants in the Bangweulu Wetland and surrounding areas

| No. | District | Households per district | Key informant interviews conducted |
|---|---|---|---|
| 1. | Serenje | 37 | District Agriculture Coordinator |
| 2. | Samfya | 62 | District Agriculture Coordinator, Forestry Coordinator |
| 3. | Mansa | 42 | District Agriculture Coordinator; Forestry Coordinator; Land Husbandry Coordinator; Department of Water Resources Development (DWRD) |
| 4. | Mwense | 10 | |
| 5. | Chifunabuli | 51 | |
| 6. | Chilubi | 50 | District Agriculture Coordinator |
| 7. | Chembe | 27 | District Agriculture Coordinator |
| 8. | Chitambo | 21 | |
| | Total | 300 | |

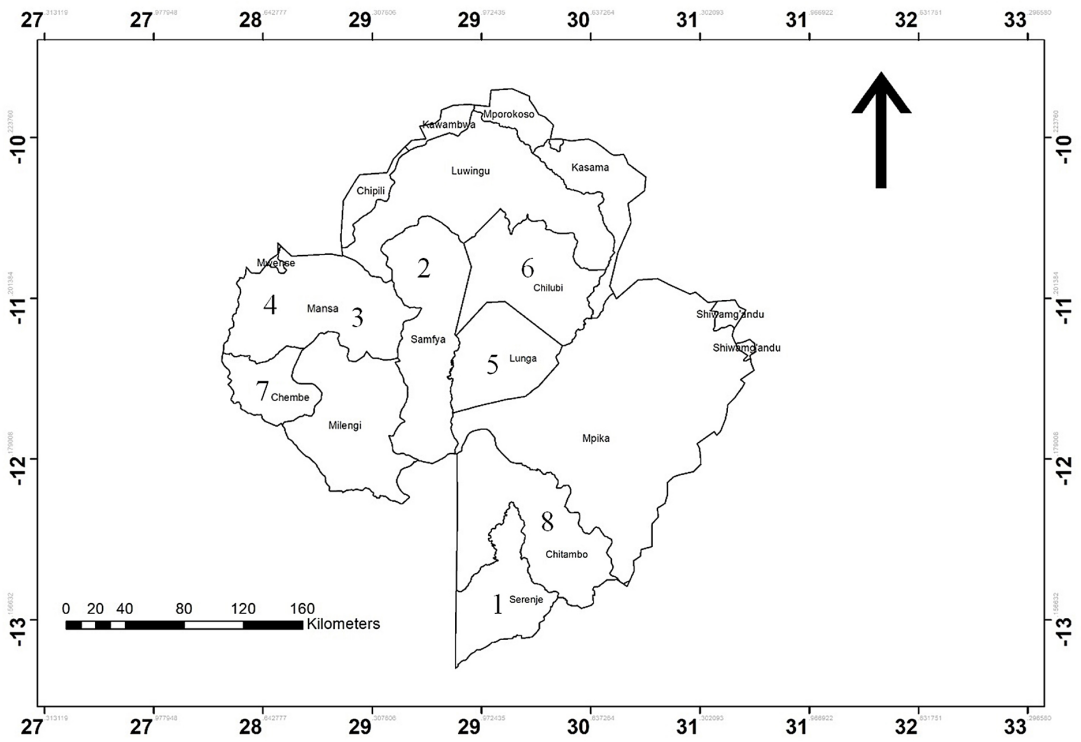


**Figure 5.** Distribution of the sampled areas in the Bangweulu Wetland and surrounding areas

### *Quantitative data analysis*

In this study, the quantitative data obtained from the field were analysed using the Statistical Package for the Social Sciences (SPSS 26) software (Rahman and Muktadir, 2021). Descriptive statistics and regression analyses were conducted. These statistics allowed for a clear understanding of the distribution and patterns of the perceived drivers of land use change as well as the observed land use change patterns, while the logistic regression helped investigate the variables that contributed to changes in LULC change at the household level in the Bangweulu Wetland and surrounding areas (Lesschen et al., 2005).

To enhance the presentation and visualization of the data, tables and graphs were created. These graphical representations facilitated a more comprehensive and accessible interpretation of the findings (Prybutok and Ott, 1989). They provided a visual summary of the key trends and relationships within the data, aiding in the identification of significant patterns and insights (Richmond, 2006). Furthermore, the study utilized the Pearson correlation coefficient to assess the strength and direction of the association between the perceived drivers of land use change and the observed land use change patterns (Chen et al., 2020). This statistical measure allowed for a quantitative assessment of the relationship between these variables, providing valuable insights into the extent to which the perceived drivers influenced the observed land use changes (Pallant, 2016).

A logistic regression analysis was also conducted to investigate variables contributing to changes in LULC change at the household level in Bangweulu Wetland and surrounding areas. The research aimed to determine how respondents' socioeconomic characteristics (independent factors) affected their assessments of the driving reasons underlying LULC change (dependent variables).

## RESULTS AND DISCUSSION

### Accuracy assessment of the LULC classification

The current study had an overall accuracy over 86% and Kappa coefficient values between 0.87 and 0.94 (Table 2). Roy et al. (2015) achieved similar levels of accuracy in their land cover and land use classification, with most classes exceeding 90% accuracy. Muche et al. (2023), for the northeastern highlands of Ethiopia, also reported similar accuracies for 1984, 1991, 2001 and 2021, with overall categorization accuracies ranging from 87% to 91%, revealing a very strong agreement between the categorized images and the ground truthing data. The current findings similarly demonstrate strong agreement between the classified images and the ground truth data.

The kappa coefficient is a measure of the precision or agreement between data from classified imagery and data from ground reference locations (Foody, 2020). Although there are small differences in producer and user accuracies for specific LULC categories, the classification registered a high overall accuracy. These accuracy assessment results provided the basis for subsequent examination of LULC changes.

### Overall trend analysis of LULC change (1990–2020)

The results in Fig. 6 shows the spatial representation of these LULC types. The proportionate coverage area of each of the five classes extracted in the Bangweulu Wetland from 1990 to 2020 is summarized in Fig. 7. The figure indicates that grassland decreased from 32 557.91 km$^2$ in 1990 to 26 418.23 km$^2$ in 2020 and forests shrunk from 45 298.93 km$^2$ in 1990 to 33 233.52 km$^2$, while cropland increased from 165.27 km$^2$ in 1990 to 5 108.13 km$^2$ in 2020 and the settlement area expanded from 356.69 km$^2$ in 1990 to 2 210.38 km$^2$ in 2020. Water cover recorded a decline from 2 410.72km$^2$ in 1990 to 2 278.31 km$^2$ in 2020. These findings are similar to those of Nkolokosa et al. (2023) in Malawi, who observed substantial changes in land cover and land use over a 30-year period. Built-up areas expanded by 209%, while bare land and cropland increased by 10%. In contrast, forest cover, herbaceous vegetation, water bodies and shrubland declined by 30%, 4%, 20% and 20%, respectively. Similarly, Muche et al. (2023) noted an increasing trend in the proportion of cultivated land, built-up areas and barren land, which make up approximately 78.9% of the northeastern highlands of Ethiopia. Similarly, the other three LULC types (forestland, grassland and water bodies) decreased during the study periods, together comprising 21.1% of the total. Furthermore, Mariye et al., (2022) reported similar findings in their study, revealing a significant decrease in forest cover and a notable increase in cultivated land over a period of approximately 45 years in south-central Ethiopia.

Diminishing forest cover, water bodies and grasslands in Ethiopia is reported as concerning by Negese (2021). Their study revealed a decrease in water bodies (10.34%) and natural vegetation (17.21%) over 2 decades. A similar trend of diminishing natural habitats was observed in Ghana by Tuffour-Mills et al. (2020), where analysis of Landsat imagery revealed forest cover loss and conversion to agriculture and settlements.

The current study revealed that the expansion of built-up areas and cultivated lands reflects population growth and agricultural demands. This aligns with the findings of Tsegaye (2019), who studied land-use change in Ethiopia's Afar Region and attributed forest loss (2.4% per decade) to population pressure and agricultural expansion. These findings offer valuable insights into the changing trends of different LULC classes within the study area.

**Table 2.** Accuracy-assessment results for the 1990, 2000, 2010 and 2020 LULC maps

| Class | 2020 | | 2010 | | 2000 | | 1990 | |
|---|---|---|---|---|---|---|---|---|
| | PA | UA | PA | UA | PA | UA | PA | UA |
| Water | 0.97 | 1.00 | 1.00 | 1.00 | 0.97 | 1.00 | 1.00 | 1.00 |
| Forest | 0.81 | 0.97 | 0.86 | 1.00 | 0.91 | 0.97 | 0.88 | 0.97 |
| Grassland | 0.88 | 0.97 | 0.78 | 0.93 | 0.91 | 1.00 | 0.81 | 1.00 |
| Settlement | 0.96 | 0.80 | 1.00 | 0.90 | 1.00 | 0.91 | 1.00 | 0.83 |
| Cropland | 1.00 | 0.83 | 0.91 | 0.67 | 1.00 | 0.92 | 1.00 | 0.83 |
| Overall accuracy | 0.91 | | 0.90 | | 0.95 | | 0.93 | |
| Kappa | 0.89 | | 0.87 | | 0.94 | | 0.90 | |

PA = producer's accuracy; UA = user's accuracy

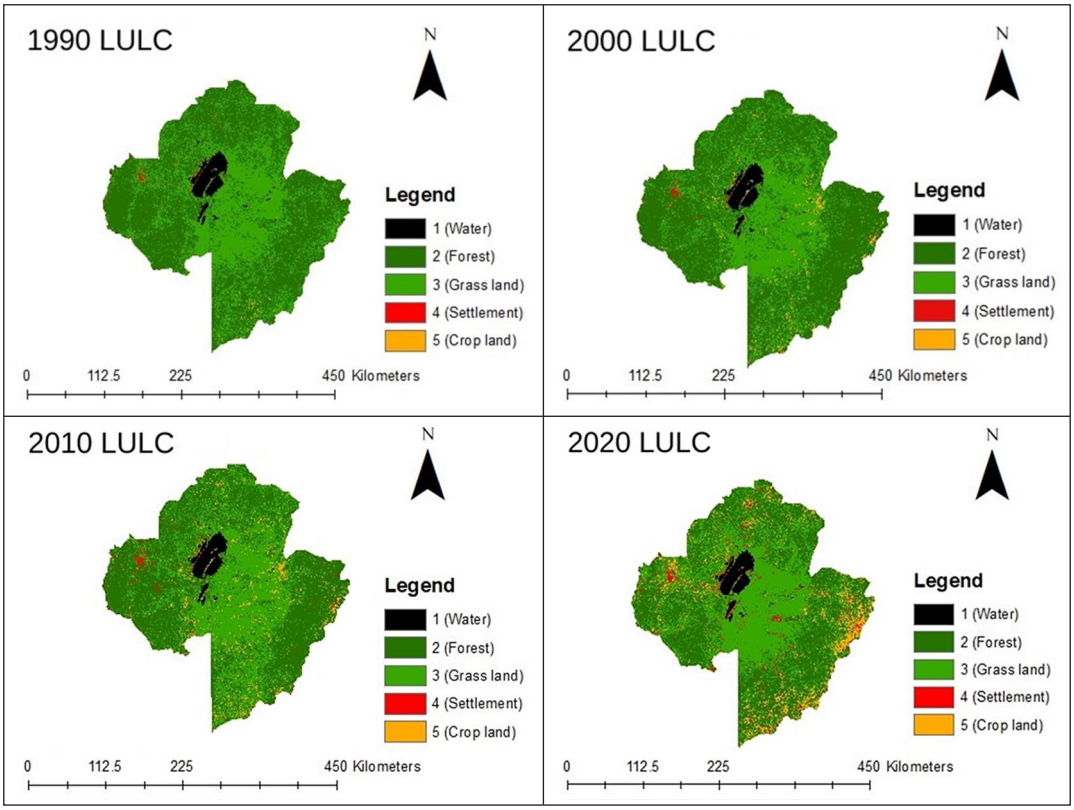


**Figure 6.** LULC Maps for 1990, 2000, 2010 and 2020 in Bangweulu Wetland and surrounding areas

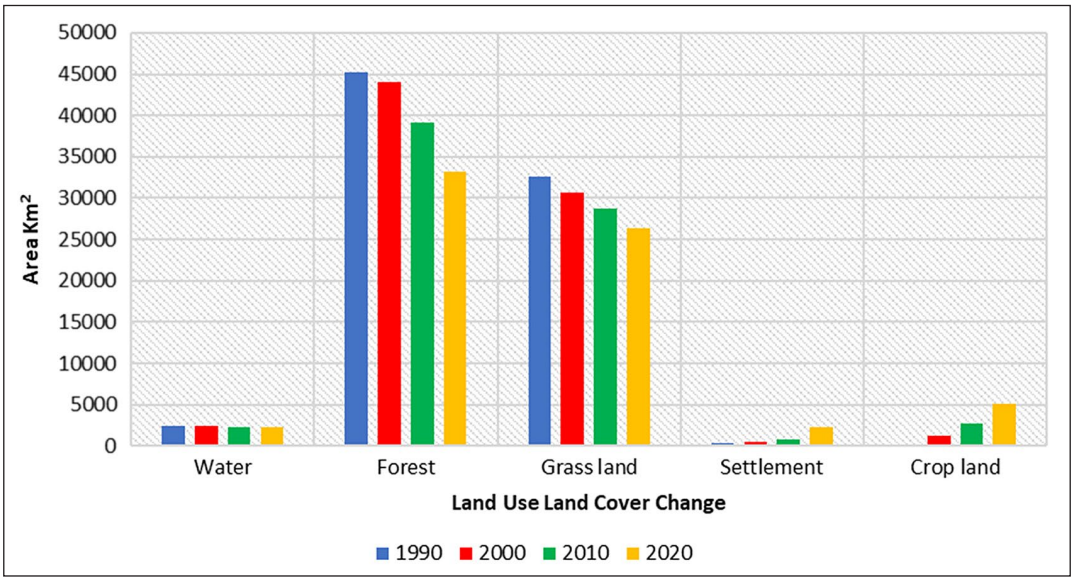


**Figure 7.** Trends of LULC changes in the Bangweulu Wetland and surrounding areas between 1990 and 2020

### Local community perceptions of LULC changes

In order to effectively gather information on various aspects surrounding LULC change in the Bangweulu Wetland and surrounding areas, a household questionnaire was conducted to provide the insights of the local population on observed LULC distribution (Table 3).

This information helped to identify potential connections between land use practices that directly transform land cover, contributing to the transformation of the area within the community. The scoring of these perceived drivers of LULC, conducted on a scale of 1 to 5, revealed the relative significance of each driver. The findings revealed population growth as the most frequently perceived driver with the highest average score of 3.76, while industry had the lowest perceived impact with a mean score of 1.45. The observed land use changes in the Bangweulu Wetland and the surrounding areas were attributed to several factors, as highlighted in red in Fig. 8: population growth, agricultural activities, settlements, forest decline and ecosystem services decline. The assigned scores for each driving force offer valuable insights into how significant these perceived drivers are in influencing the patterns of land use in the specific area being studied.

Population growth, human settlement and economic development are driving land use change in various countries. In Makhitha village, South Africa, this leads to increased agricultural demand and deforestation (Phethi and Gumbo, 2019). In Kenya, human settlement and economic development also influence land

**Table 3.** Descriptive characteristics of the participating households

| Parameter | Category | Percentage of household |
|---|---|---|
| Gender | Male-headed household | 73% |
| | Female-headed household | 27% |
| Household size | >5 people | 51% |
| | 2 to 5 people | 35% |
| | ≤2 people | 14% |
| Age | 18–25 years | 14% |
| | 25–45 years | 41% |
| | ≥45 years | 45% |
| Household status | Migrant | 68% |
| | Indigenous | 32% |
| Education | No formal education | 20% |
| | Primary | 67% |
| | Secondary | 10% |
| | Tertiary | 3% |
| Occupation | Farmer | 49% |
| | Business | 16% |
| | Fishing | 14% |
| | Formal employment | 13% |
| | Craftwork | 5% |
| | Domestic | 2% |
| | Construction | 1% |

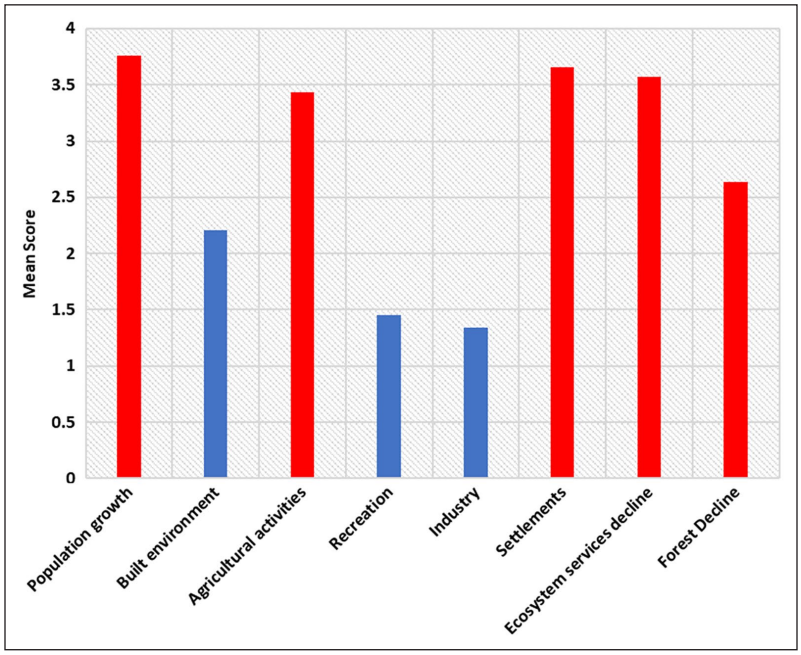


**Figure 8.** Perceived drivers of land use change in the Bangweulu Wetland and surrounding areas

use patterns (Mainuri, 2018). In Ethiopia, human activities, particularly in wetlands, influence land use patterns (Assefa et al., 2021). A study by Chilufya (2011) in Zambia reveals that sustainable agriculture practices like agroforestry and conservation agriculture are crucial to mitigate environmental impacts and ensure food security.

The findings in the current study also align with previous research conducted in the Barotse Floodplain, Zambia. Banda et al. (2023) reported a similar trend – cropland expansion occurring at the expense of forestland. Similarly, Odote (2018), in a study focusing on the Nyando Basin in Kenya, attributed the increased wetland degradation to a combination of factors, including rapid population growth and demand for agricultural land and resources. In their investigation of wetland loss on the Iranian Plateau, Ghajarnia et al. (2020) also identified population growth, along with agricultural expansion and water resource management, as the principal causes.

Similarly, Alikhani et al. (2021) in their study on freshwater wetlands in Finland, attributed fragmentation and habitat loss to increased settlements. These developments lead to changes in lifestyle, consumption patterns and production methods, all of which have an impact on land use. As communities establish settlements, they require land for housing, infrastructure development and other human activities. This demand for land often leads to the conversion of natural habitats, such as wetlands, forests and agricultural areas, into residential zones.

Muche et al. (2023) reported that the expansion of settlements and cultivated land into natural ecosystems, such as forests, water bodies and grasslands, has led to a significant decline in ecosystem services in the northeastern highlands of Ethiopia. Similarly, Assefa et al. (2021), in their study on the impacts of land-use and land-cover changes on wetland ecosystem service values in peri-urban and urban area of Bahir Dar city in northwestern Ethiopia, observed that the unique ecological characteristics of wetland ecosystems, including their diverse biodiversity, water resources and hydrological functions, make wetlands valuable, hence attracting human activities, which in turn influence land use patterns. Zorrilla-Miras et al. (2014), in their study of the Iberian Peninsula, identified various drivers of LULC changes in wetlands, including water diversion, pollution and agricultural intensification. They highlighted how these changes negatively impact ecosystem services such as water purification, carbon sequestration and biodiversity. This aligns with the findings of this study, where a decrease in ecosystem services emerged as one of the perceived drivers of LULC change in the Bangweulu Wetland.

The current study further revealed that expansion of farming and livestock grazing has significantly impacted land cover and land use within the Bangweulu Wetland. Similar findings have been reported by the United Nations Convention to Combat Desertification (UNCCD, 2017) Global Land Outlook, which highlighted that modern crop and livestock management practices often result in soil erosion, declining biodiversity, and reduced water filtration and availability. Chilufya (2011), in his study on sustainable agriculture practices as a remedy for the negative effects of climate change on food security in Zambia, emphasized the need for sustainable agricultural practices, such as agroforestry, conservation agriculture and appropriate land management techniques, to mitigate the negative environmental impacts of agriculture while ensuring food security and preserving the ecological integrity of wetlands. Meyer and Turner II (1992) explored LULC changes in China and showed how agricultural expansion was a major driver of deforestation and the conversion of natural lands to farmland, including wetlands.

Handavu et al. (2019) reported that forest decline was a driver of LULC change, with 79% of the participants in the Miombo woodlands of the Copperbelt Province in Zambia indicating that they had cleared forestland within the past decade. The primary reasons cited for this deforestation were also related to the desire to increase agricultural production. Similarly, Ardiansah et al. (2021), in the Bonehau Watershed, revealed that the decline in forest was greatest in primary forests. This is consistent with the observations made in this study, which showed that forests serve as a reliable source of income for many people and that charcoal burning is a common practice among households, resulting in forest cover loss.

To assess the relationship between land use change and various factors, a Pearson correlation analysis (Table 4) was conducted. The results revealed statistically significant relationships ($p < 0.05$) between the occurrence of land use change and several perceived drivers. Specifically, the *p*-values for the correlation coefficients were 0.000 for forest decline, settlements, ecosystem services decline, and population growth, and 0.041 for agricultural activities. These results demonstrate a statistically significant association between land use change in the wetland and each of the five factors, as all *p*-values fall below the 0.05 threshold.

## Logistic regression analysis of variables of perceived drivers of land use changes

Logistic regression analysis was also performed to investigate the variables that contribute to changes in LULC at the household level in the Bangweulu Wetland and surrounding areas. The coefficient (B) represents the estimated effect of each variable on the outcome. A negative coefficient suggests a negative association with the outcome, while a positive coefficient suggests a positive association. The standard error (SE) provides information about the precision of the coefficient estimate (Bewick et al., 2005). The Wald statistic is used to assess the significance of each variable. The degrees of freedom (df) represent the number of independent pieces of information available for estimating the parameter. The significance level (Sig.) indicates the probability of observing a Wald Statistic as extreme as the one calculated, assuming the null hypothesis that the coefficient is zero (Bewick et al., 2005).

The regression analysis results (Table 5) revealed that length of residence in the wetland had a substantial influence on perceptions of the local community. The amount of time an individual had lived in the neighbourhood, in particular, was found to have a statistically significant ($p < 0.05$) effect on views of population increase and agricultural expansion as perceived drivers of LULC change. The longer someone stayed in the region, the more likely they were to see population increase and agricultural development as major drivers of LULC change. Furthermore, among the key perceived socioeconomic drivers, the study found that having a primary economic activity of farming had a significant effect on views of LULC change and its perceived drivers.

**Table 4.** Statistical significance of Pearson correlation coefficients between LULC and perceived drivers of LULC in Bangweulu Wetland and surrounding areas

| Parameter | Observed land use change | Forest decline | Settlements | Ecosystem services decline | Population growth | Agricultural activities |
|---|---|---|---|---|---|---|
| Sig. (2-tailed) | | 0.000 | 0.000 | 0.000 | 0.000 | 0.041 |
| *r* | 1 | –0.313** | –0.301** | –0.282** | –0.240** | –0.118* |
| *N* | 300 | 300 | 300 | 300 | 300 | 300 |

Correlations are significant at the 0.05 level (2-tailed); *N* – number of participants; *r* – Pearson correlation coefficient

**Table 5.** Results of logistic regression analysis of perceived variables of drivers of land use changes in Bangweulu Wetland and surrounding areas

| Variable | *B* coefficient | SE | Wald statistic | df | *p*-value | Exp(*B*) | 95% C.I. for Exp(B) | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | Lower | Upper |
| How long have you lived in the community? | 2.911 | 0.775 | 14.107 | 1 | 0.000 | 18.37 | 4.022 | 83.898 |
| Farming as main economic activity | 1.559 | 0.752 | 4.3 | 1 | 0.038 | 4.756 | 1.089 | 20.769 |
| Constant | 1.019 | 0.319 | 10.176 | 1 | 0.001 | 2.771 | | |

SE – standard error; df – degrees of freedom; Exp(*B*) – exponentiation of *B* coefficient; CI – confidence interval ratios

These results highlight the importance of considering factors such as duration of residency and economic activities when examining perceptions of LULC at the household level within the Bangweulu Wetland and surrounding areas.

### Factors that influence the perceived drivers of LULC change in the Bangweulu Wetland and surrounding areas

The following conclusions may be drawn about the factors influencing the perceived drivers of land use change in the Bangweulu Wetland and surrounding areas based on the information provided:

#### *Socio-economic status and livelihood strategies*

The results from the household questionnaires revealed that population growth was seen as a perceived driver of LULC change in the study area, with growth mainly attributed to people moving to new areas with the aim of finding new opportunities. The results shown in Fig. 9 indicate that 56% of the participants attributed a significant proportion of the population increase to individuals and families relocating to the wetlands from other areas. Furthermore, 34% of the participants identified a high birth rate as a cause of population growth, indicating that a substantial portion of the population increase can be attributed to natural population growth resulting from a higher number of births. On the other hand, 7% of the participants were unsure about the causes of population growth and 3% indicated that there had been no change in the population. The socioeconomic determinants of the perceived drivers revealed in this study are in agreement with the results of research conducted by Handavu et al. (2019) and Munthali et al. (2019), who showed that migration significantly affected household land use patterns and population growth in the Miombo woodlands of Zambia's Copperbelt Province and in Dedza District, Malawi. Ghosh et al. (2015), in their study on the Sundarbans mangrove forest in India and Bangladesh, emphasized the role of migration and population pressure in contributing to wetland degradation. They highlighted the need to address underlying socioeconomic issues alongside conservation efforts.

The findings observed in this study align with those of Munthali et al. (2019) in Malawi, who attributed population growth to high fertility rates, early marriages, high birth rates, declining mortality rates, polygamy, immigration and illiteracy. Similarly, Ebanyat et al. (2010), working in eastern Uganda, identified several factors that influence land use decisions, including market demand for agricultural products, soil quality, household education level, farming experience and proximity to markets. These socioeconomic factors drive farmers to increase agricultural activities, leading to land use changes as natural habitats are converted for agricultural purposes.

The responses obtained from participants also shed light on the reasons for people moving to the Bangweulu Wetland (Fig. 10). Migration factors, such as employment opportunities and farming, underscore the role of socio-economic factors in influencing individuals' decisions to relocate to the wetland and adopt specific livelihood strategies. The pursuit of economic opportunities and improved living conditions also contributes to the rise in settlements and agricultural activities, resulting in changes to land use patterns.

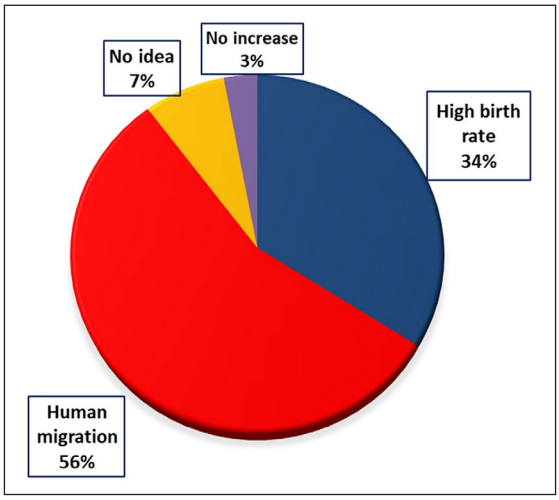


**Figure 9.** Participant responses regarding potential causes of change in the Bangweulu Wetland and surrounding areas

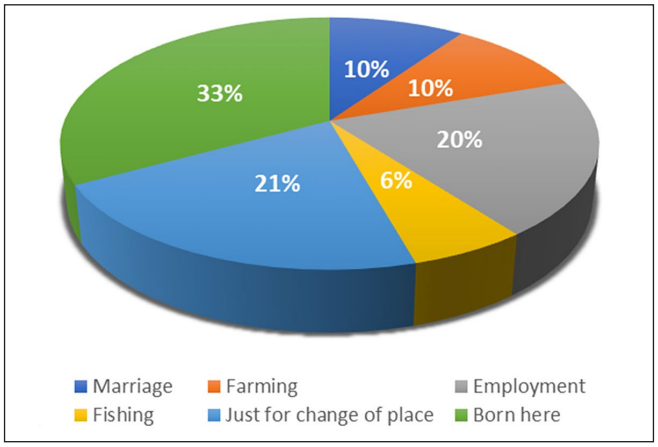


**Figure 10.** Respondents' views on their reasons for migrating to the Bangweulu Wetland and surrounding areas, Zambia

These data were also supported by a report of the Central Statistical Office (2022), which recorded that the population of Luapula in 2022 was 1 514 011, indicating a growth of over 52.6% from the 2010 population of 991 927. Figure 11 shows the population density (2010, 2022) of the sampled districts. Similarly, research conducted by Handavu Chirwa and Syampungani (2019) and Munthali et al. (2019) showed that migrations were an important determinant, capable of substantially influencing households' patterns of land use and also population growth in the miombo woodlands of the Copperbelt Province in Zambia and Dedza District in central Malawi.

### Agricultural development and market demands

The incorporation of traditional and subsistence agricultural methods, coupled with animal grazing, exerts a significant impact on both land cover and land use within wetland areas. The increase in market demand for cash crops such as rice, cassava, groundnuts and maize has been attributed to agricultural development programmes and agrotechnology breakthroughs. This encourages farmers to expand their agricultural operations, which results in land use changes when natural habitats are transformed for agricultural uses. Similarly, Ebanyat et al. (2010) identified several factors that influence land use decisions, including market demand for agricultural products, soil quality, household education level, farming experience and proximity to markets. These socio-economic factors drive farmers to increase agricultural activities, leading to land use changes as natural habitats are converted for agricultural purposes.

The responses of participants when questioned about the primary economic activity in the sampled areas are shown in Fig. 12. Farming was the most popular economic activity, accounting for 49.3% of all replies and the lowest was construction, at 1%. Overall, farming, fishing and business play a dominant role in driving local economies in the surveyed districts.

Similarly, Meijerink and Roza (1971) stated that the distribution of economic activities as presented in Fig. 12 demonstrates the dominant role of farming, fishing and business in driving local rural and urban economies with high levels of poverty in Africa, Latin America, and East Asia. The Food Crop and Seed Project documented by Manintveld et al. (2004) in Zambia reported a similar range of initiatives focusing on crop improvement, conservation farming, natural resource management, social development, the generation of economic opportunities and the development of effective marketing strategies that have helped improve the agricultural industry.

### NGO projects and development programmes

Non-governmental organizations (NGOs) and local authorities are crucial in promoting agricultural development, not only in Luapula Province but the country at large. Projects aimed at enhancing farmers' capacity and capabilities have led to increased

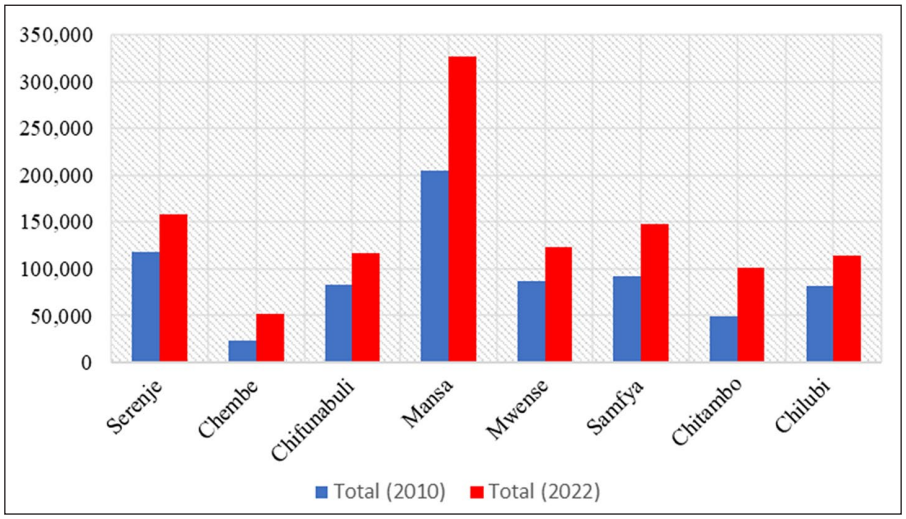


**Figure 11.** Population density (2010, 2022) of Bangweulu Wetland and surrounding areas (Central Statistical Office, 2022)

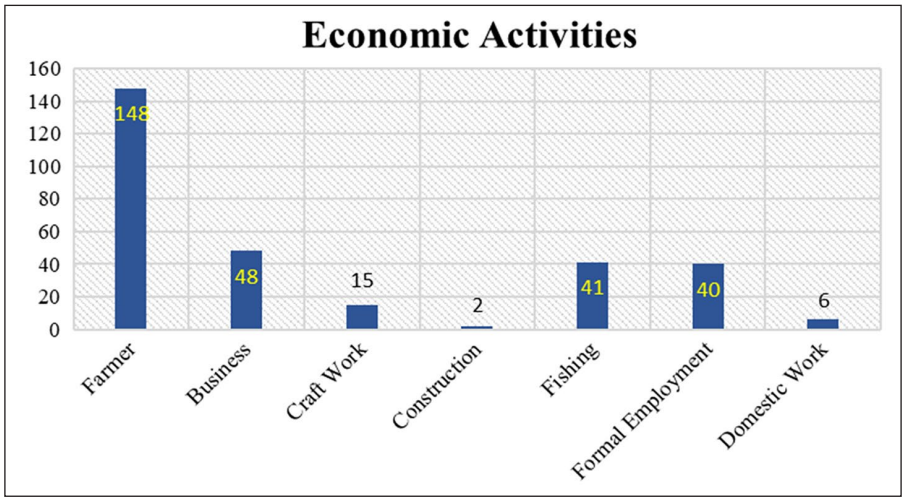


**Figure 12.** Main economic activities in the Bangweulu Wetland and surrounding areas

**Table 6.** Programmes aimed at enhancing farmers' capacity and capabilities that have been undertaken in Luapula Province, Zambia

| No. | Programme |
|---|---|
| 1 | Farmer Input and Response Support Intensive |
| 2 | Promote Sustainability Agriculture, Soil conservation and Water Conservation (2009 to 2011) |
| 3 | Conservation Agriculture Scaling Up (2012 to 2016) |
| 4 | Programme for Luapula Agriculture and Rural Development (2009 to 2015) |
| 5 | Rice Development Programme under JICA (2016 to 2018) |
| 6 | Smallholder Productivity Promotion Programme (2012 to 2018) |
| 7 | Transforming Landscapes for resilience of Development (2018 to date) |

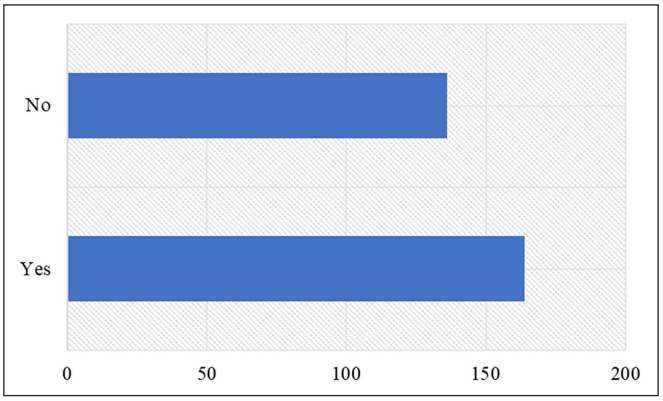


**Figure 13.** Respondents' reported involvement in charcoal burning in Bangweulu Wetland and surrounding areas

engagement in farming activities (Table 6). These initiatives align with socio-economic goals of improving livelihoods, income and food security, influencing land use patterns within the wetland. The study found an increase in market demand for cash crops like rice, cassava, groundnuts and maize in Luapula Province, which was attributed to agrotechnology-supported initiatives. The study also found that Chembe District has achieved self-sufficiency in rice production, a significant milestone for local agricultural development. The implementation of these programmes and projects demonstrates the concerted efforts of various stakeholders, including NGOs and local authorities, to promote agricultural development in Luapula Province.

### Charcoal burning

The decline in forest cover, which is recognized as a factor influencing land use change, is partly attributed to charcoal burning as a main economic activity for households without access to electricity. This indicates that the reliance on charcoal for cooking purposes is driven by limited energy alternatives, affecting the wetland's forest resources (Fig. 13). The socioeconomic factors also shed light on the relationship between energy sources and land use dynamics, with Chidumayo and Savanna (2018), in a study on tropical ecosystems around the world, reporting a significant link between wood fuel use and deforestation.

In summary, factors such as livelihood strategies, agricultural development, NGO projects and energy sources influence the perceived drivers of land use change in the Bangweulu Wetland and surrounding areas. These factors highlight the complex interactions between human activities, economic considerations and environmental changes that shape land use patterns in the region.

## CONCLUSION

Analysis of remote-sensing data revealed a significant decrease in forest coverage and a considerable increase in cropland within the study area over the past 30 years. The study identified 5 LULC categories, where notable changes occurred between 1990, 2000, 2010 and 2020. Forestland decreased from 45 298.93 km$^2$ in 1990 to 33 233.53 km$^2$ in 2020, with an estimated total forest loss of 12 065.42 km$^2$ during this period. Similarly, grasslands decreased from 32 557.91 km$^2$ in 1990 to 26 418.19 km$^2$ in 2020, while the water area decreased from 2 410.72 km$^2$ in 1990 to 2 278.31 km$^2$ in 2020. Conversely, settlement land expanded from 356.69 km$^2$ to 2 210.38 km$^2$ during the study period. The findings indicate that croplands have become the dominant LULC type, increasing from 165.27 km$^2$ in 1990 to 5 108.13 km$^2$ in 2020. Throughout the study period, there has been a consistent trend of increasing cropland and settlement areas at the expense of other land use categories. This highlights the need for effective conservation measures by governmental and non-governmental organizations in the study area.

An analysis of the social survey data reveals that the majority of respondents identified population growth, expansion of settlements, agricultural activities and forest decline as the primary drivers of LULC change in the studied area. These changes are predominantly driven by several essential factors. These factors include the expansion of human settlements due to population growth, advancements in agriculture resulting from amplified demand for specific crops and market dynamics, initiatives undertaken by non-governmental organizations (NGOs) and local authorities and the utilization of energy sources such as charcoal for economic purposes. Population growth stands out as a key catalyst in steering the alterations in land use, as individuals relocate in search of improved living conditions and diverse livelihood opportunities. Moreover, agricultural activities, encompassing cultivation and livestock grazing, significantly contribute to shaping the evolving patterns of land cover. NGOs and local authorities are making noteworthy contributions through their projects, thereby fostering agricultural progress and advocating for sustainable practices among local farmers. Simultaneously, the extraction of charcoal, a substantial economic activity, is closely associated with the decline of forest cover. These multifaceted factors collaboratively determine the land use in the region, ultimately ending in its current transformation.

If this trajectory persists, it could lead to substantial environmental and economic difficulties, negatively impacting local livelihoods. To ensure the sustainability of rural livelihoods, it becomes imperative to implement appropriate policies for land resource management and population strategies based on community-level considerations. These measures are essential to mitigate the rapid conversion of LULC.

## RECOMMENDATIONS

Based on the study's findings, it is recommended that public and non-governmental agencies, along with researchers, focus on sensitizing communities about the importance of sustainable agricultural practices. Comprehensive programmes should be developed to strengthen farmers' capacity in land management and climate-resilient agriculture, while also promoting alternative livelihoods that reduce dependence on forest resources such as charcoal.

In addition, in-depth studies on human–environment interactions should be conducted, taking into account social, economic, and ecological factors – particularly in catchment areas. Promoting sustainable practices such as crop rotation and organic farming is essential for environmental preservation and food security. Collectively, these initiatives aim to enhance agricultural productivity, safeguard natural resources, and improve community well-being, contributing to a more sustainable future.

## AUTHOR CONTRIBUTIONS

Conceptualisation and methodology – Chisanga Lyoba; data collection and fieldwork – Chisanga Lyoba, Greyford Tembo and Misheck Chundu; sample/data analysis – Chisanga Lyoba; interpretation of results – Chisanga Lyoba; writing of the initial draft – Chisanga Lyoba; review and editing – Chisanga Lyoba, Kawawa Banda and Imasiku Nyambe.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

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## REFERENCES

AKHTAR A, RASHID SM, BHAT MS and SHEIKH AH (2011) Impact of land use/land cover dynamics on Himalayan wetland ecosystem. *J. Exp. Sci.* **2** (3) 60–64. https://updatepublishing.com/journal/index.php/jes/article/view/1819

ALDRICH SP, WALKER RT, ARIMA EY, CALDAS MM, BROWDER JO and PERZ S (2006) Land-cover and land-use change in the Brazilian Amazon: smallholders, ranchers, and frontier stratification. *Econ. Geogr.* **82** (3) 265–288. https://doi.org/10.1111/j.1944-8287.2006.tb00311.x

ALIKHANI S, NUMMI P and OJALA A (2021) Urban wetlands: a review on ecological and cultural values. *Water* **13** (22) 1–47. https://doi.org/10.3390/w13223301

ARDIANSAH T, RIJAL S and BARKEY RA (2021) Land use change projection in Bonehau Watershed 2031. *IOP Conf. Ser.: Earth Environ. Sci.* **870** (1) 012028. https://doi.org/10.1088/1755-1315/870/1/012028

ASSEFA WW, ENEYEW BG and WONDIE A (2021) The impacts of land-use and land-cover change on wetland ecosystem service values in peri-urban and urban area of Bahir Dar City, Upper Blue Nile Basin, Northwestern Ethiopia. *Ecol. Process.* **10** (1) 1–18. https://doi.org/10.1186/s13717-021-00310-8

BANDA AM, BANDA K, SAKALA E, CHOMBA M and NYAMBE IA (2023) Assessment of land use change in the wetland of Barotse Floodplain, Zambezi River Sub-Basin, Zambia. *Nat. Hazards* **115** (2) 1719–1737. https://doi.org/10.1007/s11069-022-05589-0

BEILFUSS R, MCCANN K, KAMWENESHE B and ZYAMBO P (2017) Population and distribution of Wattled Cranes, Shoebills, and other large waterbirds in the Bangweulu Swamps, Zambia. Report to the Bangweulu Wetlands Management Board. 31 pp. https://doi.org/10.13140/RG.2.2.26628.32647

CAI W, LIU X, ZHANG D and AKTER F (2022) Impact of land cover changes on the wetland ecosystem water environment using soft computing methods. *Math. Problems Eng.* **2022** 3673758. https://doi.org/10.1155/2022/3673758

CENTRAL STATISTICAL OFFICE (2022) Census of population and housing: preliminary results. URL: https://www.zamstats.gov.zm (Accessed 1 October 2023).

CHEN D, ELHADJ A, XU H, XU H and QIAO Z (2020) A study on the relationship between land use change and water quality of the Mitidja watershed in Algeria based on GIS and RS. *Sustainability* **12** (9) 1–20. https://doi.org/10.3390/su12093510

CHIDUMAYO E and MAKENI S (2018) The environmental impacts of charcoal production in tropical ecosystems of the world: A synthesis. *Energ. Sustain. Dev.* **17** (2) 86–94. https://doi.org/10.1016/j.esd.2012.07.004

CHILUFYA CG (2011) Can sustainable agriculture practices remedy the negative effects of climate change on food security in Zambia? URL: https://searchworks.stanford.edu/view/10171777 (Accessed 10 October 2023).

CHUNDU ML, BANDA K, LYOBA C, TEMBO G, SICHINGABULA HM and NYAMBE IA (2024) Modeling land use/land cover changes using quad hybrid machine learning model in Bangweulu wetland and surrounding areas, Zambia. *Environ. Challenges* **14** 100866 https://doi.org/10.1016/j.envc.2024.100866

CLIMATE ENGINE (2017) Desert Research Institute and University of California Merced. https://app.climateengine.com/climateEngine (Accessed 1 October, 2022).

DAVIDSON NC (2014) How much wetland has the world lost? Long-term and recent trends in global wetland area. *Mar. Freshwater Res.* **65** 934–941. https://doi.org/10.1071/MF14173

EBANYAT P, DE RIDDER N, DE JAGER A, DELVE RJ, BEKUNDA MA and GILLER KE (2010) Drivers of land use change and household determinants of sustainability in smallholder farming systems of Eastern Uganda. *Population Environ.* **31** (6) 474–506. https://doi.org/10.1007/s11111-010-0104-2

ENDFIELD GH (2009) Environmental History. In: Castree N, Demeritt D, Liverman D and Rhoads B (eds) *A Companion to Environmental Geography*. Wiley-Blackwell, Oxford. 238–253. https://doi.org/10.1002/9781444305722.ch14

FOODY GM (2020) Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification. *Remote Sens. Environ.* **239** 111630. https://doi.org/10.1016/j.rse.2019.111630

GARG V, NIKAM BR, THAKUR PK, AGGARWAL SP, GUPTA PK and SRIVASTAV SK (2019) Human-induced land use land cover change and its impact on hydrology. *HydroResearch* **1** 48–56. https://doi.org/10.1016/j.hydres.2019.06.001

GHAJARNIA N, DESTOUNI G, THORSLUND J, KALANTARI Z, ÅHLÉN I, ANAYA-ACEVEDO JA, BLANCO-LIBREROS JF, BORJA B, CHALOV S, CHALOVA A and co-authors (2020) Data for wetland scapes and their changes around the world. *Earth Syst. Sci. Data* **12** (2) 1083–1100. https://doi.org/10.5194/essd-12-1083-2020

GHOSH A, SCHMIDT S, FICKERT T and NÜSSER M (2015) The Indian Sundarban mangrove forests: History, utilization, conservation strategies and local perception. *Diversity* **7** (2) 149–169. https://doi.org/10.3390/d7020149

HANDAVU F, CHIRWA PWC and SYAMPUNGANI S (2019) Socio-economic factors influencing land-use and land-cover changes in the miombo woodlands of the Copperbelt province in Zambia. *For. Polic. Econ.* **100** 75–94. https://doi.org/10.1016/j.forpol.2018.10.010

HUGHES JMR and HUGHES RH (1992) *A Directory of African Wetlands*. IUCN, Gland; UNEP, Nairobi; WCMC, Cambridge, UK. 820 pp.

HUNTINGTON JL, HEGEWISCH KC, DAUDERT KC, MORTON CG, ABATZOGLOU JT, MCEVOY DJ and ERICKSON T (2017) Climate engine: Cloud computing and visualization of climate and remote sensing data for advanced natural resource monitoring and process understanding. *Bull. Am. Meteorol. Soc.* **98** (11) 2397–2409. https://doi.org/10.1175/BAMS-D-15-00324.1

JAMAL S and AHMAD WS (2020) Assessing land use land cover dynamics of wetland ecosystems using Landsat satellite data. *SN Appl. Sci.* **2** (11) 1891. https://doi.org/10.1007/s42452-020-03685-z

KAMWENESHE BM (2000) Ecology, conservation and management of the black lechwe (*Kobus leche smithemani*) in the Bangweulu Basin, Zambia. MSc thesis, University of Pretoria. URL: https://repository.up.ac.za/handle/2263/30551 (Accessed 15 May 2023).

LANDIS JR and KOCH GG (1977) An application of hierarchical kappa-type statistics in the assessment of majority agreement among multiple observers. *Biometrics* **33** (2) 363–374. https://doi.org/10.2307/2529786

LESSCHEN JP, VERBURG PH and STAAL SJ (2005) Statistical methods for analysing the spatial dimension of changes in land use and farming systems. LUCC Report Series No. 7, International Livestock Research Institute, Nairobi, Kenya. 81 pp.

LIU H, ZHANG S, LI Z, LU X and YANG Q (2004) Impacts on wetlands of large-scale land-use changes by agricultural development: The small Sanjiang Plain, China. *AMBIO J. Hum. Environ.* **33** (6) 306–310. https://doi.org/10.1579/0044-7447-33.6.306

MAINURI ZG (2018) Impact of human settlement on land use/land cover changes in the middle river Njoro Sub Watershed in Kenya. *Eur. J. Multidisc. Stud.* **3** (4) 180–188. https://doi.org/10.26417/ejms.v3i4.p180-188

MAITIMA JM, OLSON JM, MUGATHA SM, MUGISHA S and MUTIE IT (2010) Land use changes, impacts and options for sustaining productivity and livelihoods in the basin of Lake Victoria. *J. Sustain. Dev. Afr.* **12** (3) 189–206. URL: https://www.researchgate.net/publication/257657203_Land_use_changes_impacts_and_options_for_sustaining_productivity_and_livelihoods_in_the_basin_of_lake_Victoria (Accessed 19 November 2023).

MANDISHONA E and KNIGHT J (2022) Inland wetlands in Africa: A review of their typologies and ecosystem services. *Prog. Phys. Geogr. Earth Environ.* **46** (4) 547–565. https://doi.org/10.1177/03091333221075328

MANINTVELD K, MULILA-MITTI J and ALMEKINDERS C (2004) Integration of biodiversity aspects in development cooperation – a case study: Food crop and seed project in Zambia. Sida, Stockholm, Sweden. 94 pp. URL: https://cdn.sida.se/publications/files/sida3482en-food-crop-and-seed-project-in-zambia-integration-of-biodiversity-aspects-in-development-cooperation--a-case-study.pdf (Accessed 19 October 2023).

MARIYE M, LI J and MARYO M (2022) Land use land cover change analysis and detection of its drivers using geospatial techniques: A case of South-central Ethiopia. *All Earth* **34** (1) 309–332. https://doi.org/10.1080/27669645.2022.2139023

MCLELLAN R, IYENGAR L, JEFFRIES B, OERLEMANS N, GROOTEN M, GUERRAOUI M and SUNTERS P (eds) (2014) *Living Planet Report 2014: Species and Spaces, People and Places*. WWF International, Gland. 180 pp. URL: https://portals.iucn.org/library/node/45865 (Accessed 10 June 2023).

MEYER WB and TURNER II B L (1992) Human population growth and global land-use/cover change. *Annu. Rev. Ecol. Syst.* **23** 39–61. https://doi.org/10.1146/annurev.es.23.110192.000351

MUCHE M, GETAHUN Y, MOLLA E, WUBETIE A and MUASYA AM (2023) Land use and land cover changes and their impact on ecosystem service values in the north-eastern highlands of Ethiopia. *PLoS ONE* **18** (9) 1–14. https://doi.org/10.1371/journal.pone.0289962

MUNTHALI MG, DAVIS N, ADEOLA AM, BOTAI JO, KAMWI JM, CHISALE HLW and ORIMOOGUNJE OIO (2019) Local perception of drivers of land-use and land- cover change dynamics across Dedza district, Central Malawi region. *Sustainability* **11** (3) 1–25. https://doi.org/10.3390/su11030832

NACHTERGAELE FO, BIANCALANI R, BUNNING S and GEORGE H (2016) Land degradation assessment: the LADA approach. In: *19th World Congress of Soil Science, Soil Solutions for a Changing World*, 1–6 August 2010, Brisbane.

NEGESE A (2021) Impacts of land use and land cover change on soil erosion and hydrological responses in Ethiopia. *Appl. Environ. Soil Sci.* **2021** 6669438. https://doi.org/10.1155/2021/6669438

NKOLOKOSA C, STOTHARD R, JONES CM, STANTON M, CHIROMBO J and TANGENA JAA (2023) Monitoring and simulating landscape changes: how do long-term changes in land use and long-term average climate affect regional biophysical conditions in Southern Malawi? *Environ. Monit. Assess.* **195** (10) 1–16. https://doi.org/10.1007/s10661-023-11783-9

NYAMEKYE C, GHANSAH B, AGYAPONG E, OBUOBIE El, AWUAH A and KWOFIE S (2021) Examining the performances of true colour RGB bands from Landsat-8, Sentinel-2 and UAV as stand-alone data for mapping artisanal and small-scale mining (ASM). *Remote Sens. Appl.: Soc. Environ.* **24** 100655. https://doi.org/10.1016/j.rsase.2021.100655

ODOTE C (2018) Chapter 13. Implications of the ecosystem-based approach to wetlands management on the Kenyan coast. In: Langlet D and Rayfuse R (eds) *The Ecosystem Approach in Ocean Planning and Governance*. 414–442. https://doi.org/10.1163/9789004389984_014

PALLANT J (2016) *SPSS Survival Manual* (6th edn) Open University Press, Maidenhead, UK. 361 pp.

PHETHI MD and GUMBO RJ (2019) Assessment of impact of land use change on the wetland in Makhitha village, Limpopo Province, South Africa. *Jamba: J. Disaster Risk Stud.* **11** (2) 1–6. https://doi.org/10.4102/jamba.v11i2.693

PRYBUTOK VR and OTT L (1989) An introduction to statistical methods and data analysis. *Technometrics* **31** (3) 389–390. https://doi.org/10.2307/3556159

RAHMAN A and MUKTADIR MG (2021) SPSS: An imperative quantitative data analysis tool for social science research. *Int. J. Res. Innov. in Soc. Sci.* **5** (10) 300–302. https://doi.org/10.47772/ijriss.2021.51012

RICHMOND B (2006) Introduction to data analysis handbook. *Academy for Educational Development*, Washington, DC. 27 pp. URL: http://eric.ed.gov/?id=ED536788 (Accessed 25 March 2023).

ROY PS, ROY A, JOSHI PK, KALE MP, SRIVASTAVA VK, SRIVASTAVA SK, DWEVIDI RS, JOSHI C, BEHERA MD, MEIYAPPAN P and co-authors (2015) Development of decadal (1985–1995–2005) land use and land cover database for India. *Remote Sens.* **7** (3) 2401–2430. https://doi.org/10.3390/rs70302401

RUPPERT G, HUSSAIN M and MÜLLER H (2016) Accuracy assessment of satellite image classification depending on training sample. *Austrian J. Stat.* **28** (4) 195–202. https://doi.org/10.17713/ajs.v28i4.522

SECRETARIAT OF THE CONVENTION ON BIOLOGICAL DIVERSITY (2015) Wetlands: meeting the challenges of the future. CBD Press Brief. Convention on Biological Diversity, Montreal. 2 pp. URL: https://www.cbd.int/waters/doc/wwd2015/wwd-2015-press-brief-future-en.pdf (Accessed 3 February 2023).

SECRETARIAT OF THE CONVENTION ON WETLANDS (2002) Information sheet on Ramsar Wetlands (RIS). URL: https://rsis.ramsar.org/RISapp/files/RISrep/DK2051RIS.pdf (Accessed 4 July 2023).

SECRETARIAT OF THE CONVENTION ON WETLANDS (2007) Why conserve wetlands? 8 pp. URL: https://www.ramsar.org/sites/default/files/documents/library/info2007-01-e.pdf (Accessed 23 June 2023).

SECRETARIAT OF THE CONVENTION ON WETLANDS (2014) Wetlands: Why should I care? Ramsar Fact Sheet No. 1. 8 pp. URL: http://www.ramsar.org/sites/default/files/documents/library/factsheet1_why_should_i_care_0.pdf (Accessed 7 August 2023).

SPAARGAREN O (2008) Arenosols. In: Chesworth W (ed.) *Encyclopedia of Earth Sciences Series*. Springer, Dordrecht. 48–49. https://doi.org/10.1007/978-1-4020-3995-9_34

SPARKS AH (2018) Nasapower: A NASA power global meteorology, surface solar energy and climatology data client for R. *J. Open Source Softw.* **3** (30) 1–3. https://doi.org/10.21105/joss.01035

TANZANIA NATIONAL BUREAU OF STATISTICS (2011) Enumerator Manual: NPS 2010 -2011. 254 pp. URL: https://microdata.worldbank.org/index.php/catalog/1050/related-materials (Accessed 3 February 2023).

TSEGAYE G (2019) Land use land cover change analysis using geospatial tools in case of Asayita District , Zone One, Afar Region, Ethiopia. *J. Resour. Dev. Manage.* **54** 1–7. URL https://www.researchgate.net/publication/334575950 (Accessed 16 January 2023).

UNCCD (United Nations Convention to Combat Desertification) (2017) *Global Land Outlook* (1st edn). United Nations Convention to Combat Desertification, Bonn, Germany. URL: https://www.climate-chance.org/en/library/global-land-outlook/ (Accessed 3 February 2023).

WANG Y, RAO Y and ZHU H (2023) Analyzing the land use and cover change inside and outside China's ecological function area. *Land* **12** (7) 1– 14. https://doi.org/10.3390/land12071447

WILSON C (2014) Chapter 2. Semi-structured interviews. In: Wilson C (ed.) *Interview Techniques for UX Practitioners*. Morgan Kaufmann, Waltham. 23–41. https://doi.org/10.1016/B978-0-12-410393-1.00002-8

ZORRILLA-MIRAS P, PALOMO I, GÓMEZ-BAGGETHUN E, MARTÍN-LÓPEZ B, LOMAS PL and MONTES C (2014) Effects of land-use change on wetland ecosystem services: A case study in the Doñana marshes (SW Spain). *Landscape Urban Plann.* **122** 160–174. https://doi.org/10.1016/j.landurbplan.2013.09.013

## APPENDIX

**Table A1.** Locations of the training and validation points

| Point | Longitude | Latitude | LULC type |
|---|---|---|---|
| 1 | 28.69274 | –11.080470 | Forest |
| 2 | 28.67574 | –11.407784 | Forest |
| 3 | 28.57372 | –11.594821 | Forest |
| 4 | 28.90954 | –11.501303 | Forest |
| 5 | 29.12208 | –11.828618 | Forest |
| 6 | 29.09847 | –12.215576 | Forest |
| 7 | 29.97262 | –12.559340 | Forest |
| 8 | 30.17887 | –12.637915 | Forest |
| 9 | 30.37531 | –12.696845 | Forest |
| 10 | 29.98244 | –12.971856 | Forest |
| 11 | 29.97262 | –12.706667 | Forest |
| 12 | 30.09048 | –12.912925 | Forest |
| 13 | 30.57175 | –12.441478 | Forest |
| 14 | 30.65032 | –12.647736 | Forest |
| 15 | 30.78783 | –12.048605 | Forest |
| 16 | 30.85658 | -12.569162 | Forest |
| 17 | 30.84676 | –12.745955 | Forest |
| 18 | 30.37531 | –12.932569 | Forest |
| 19 | 30.54228 | –12.637915 | Forest |
| 20 | 30.45388 | –12.362904 | Forest |
| 21 | 30.15923 | –12.441478 | Forest |
| 22 | 29.41539 | –11.743601 | Forest |
| 23 | 29.32187 | –11.735099 | Forest |
| 24 | 29.42583 | –10.511790 | Forest |
| 25 | 29.54153 | –10.445672 | Forest |
| 26 | 29.34318 | –10.710143 | Forest |
| 27 | 29.86665 | –11.086784 | Forest |
| 28 | 29.80796 | –11.234665 | Forest |
| 29 | 29.23067 | –10.674382 | Forest |
| 30 | 29.24497 | –10.810178 | Forest |
| 31 | 29.1735 | –10.996003 | Forest |
| 32 | 29.05914 | –11.010298 | Forest |
| 33 | 28.64461 | –11.167535 | Forest |
| 34 | 28.61602 | –11.310478 | Forest |
| 35 | 28.56599 | –11.431979 | Forest |
| 36 | 28.60887 | –11.674982 | Forest |
| 37 | 28.50166 | –11.646393 | Forest |
| 38 | 28.50166 | –11.517745 | Forest |
| 39 | 28.6732 | –11.903690 | Forest |
| 40 | 28.75181 | –11.867955 | Forest |
| 41 | 30.30989 | –10.974562 | Forest |
| 42 | 30.19554 | –10.845913 | Forest |
| 43 | 29.44509 | –11.417685 | Forest |
| 44 | 29.57374 | –11.596363 | Forest |
| 45 | 29.50941 | –11.982309 | Forest |
| 46 | 29.38791 | –12.303930 | Forest |
| 47 | 29.21638 | –12.268195 | Forest |
| 48 | 28.95908 | –12.039486 | Forest |
| 49 | 29.50941 | –11.088916 | Forest |
| 50 | 29.43079 | –11.246153 | Forest |
| 51 | 29.50226 | –10.996003 | Forest |
| 52 | 30.50286 | –12.711317 | Forest |
| 53 | 30.43854 | –12.811377 | Forest |

| Point | Longitude | Latitude | LULC type |
|---|---|---|---|
| 54 | 30.13836 | –13.168735 | Forest |
| 55 | 30.93884 | –11.603510 | Forest |
| 56 | 31.05319 | –11.431979 | Forest |
| 57 | 31.01031 | –11.281889 | Forest |
| 58 | 30.87452 | –11.303330 | Forest |
| 59 | 30.48142 | –10.903090 | Forest |
| 60 | 30.45283 | –10.702970 | Forest |
| 61 | 30.35277 | –10.567175 | Forest |
| 62 | 30.51716 | –10.545733 | Forest |
| 63 | 29.39313 | –11.832525 | Forest |
| 64 | 29.25562 | –11.272682 | Forest |
| 65 | 28.89678 | –11.165486 | Settlement |
| 66 | 28.90528 | –11.233500 | Settlement |
| 67 | 30.68961 | –12.844173 | Settlement |
| 68 | 29.82909 | –11.211192 | Settlement |
| 69 | 28.89382 | –11.242317 | Settlement |
| 70 | 28.92528 | –11.204567 | Settlement |
| 71 | 29.60478 | –12.016196 | Settlement |
| 72 | 28.85496 | –11.203865 | Settlement |
| 73 | 28.86019 | –11.216000 | Settlement |
| 74 | 28.84687 | –11.212907 | Settlement |
| 75 | 28.87375 | –11.224567 | Settlement |
| 76 | 28.87946 | –11.229087 | Settlement |
| 77 | 28.88637 | –11.225518 | Settlement |
| 78 | 28.89683 | –11.216238 | Settlement |
| 79 | 28.87471 | –11.186733 | Settlement |
| 80 | 28.86995 | –11.187923 | Settlement |
| 81 | 28.87066 | –11.179833 | Settlement |
| 82 | 28.86876 | –11.176026 | Settlement |
| 83 | 28.94966 | –11.211004 | Settlement |
| 84 | 28.98951 | –11.221759 | Settlement |
| 85 | 28.97738 | –11.223543 | Settlement |
| 86 | 28.99023 | –11.232466 | Settlement |
| 87 | 28.84282 | –11.227826 | Settlement |
| 88 | 28.8496 | –11.241746 | Settlement |
| 89 | 28.88744 | –11.217476 | Settlement |
| 90 | 28.88708 | –11.178572 | Settlement |
| 91 | 28.72468 | –11.195918 | Settlement |
| 92 | 28.74395 | –11.203770 | Settlement |
| 93 | 28.77451 | –11.200772 | Settlement |
| 94 | 31.46081 | –11.821255 | Settlement |
| 95 | 31.45665 | –11.832557 | Settlement |
| 96 | 31.39776 | –11.856352 | Settlement |
| 97 | 30.44231 | –12.568126 | Settlement |
| 98 | 30.43232 | –12.563843 | Settlement |
| 99 | 30.45088 | –12.504357 | Settlement |
| 100 | 30.05553 | –11.701943 | Settlement |
| 101 | 30.06481 | –11.687666 | Settlement |
| 102 | 30.32483 | –11.537570 | Settlement |
| 103 | 30.31198 | –11.554226 | Settlement |
| 104 | 30.42196 | –11.410031 | Settlement |
| 105 | 30.43695 | –11.402178 | Settlement |
| 106 | 30.43981 | –11.395278 | Settlement |
| 107 | 30.4479 | –11.394802 | Settlement |
| 108 | 30.42934 | –11.407889 | Settlement |
| 109 | 30.4172 | –11.415503 | Settlement |

| Point | Longitude | Latitude | LULC type |
|---|---|---|---|
| 110 | 30.38913 | –11.422880 | Settlement |
| 111 | 30.39507 | –11.422880 | Settlement |
| 112 | 30.43928 | –11.374262 | Settlement |
| 113 | 30.44385 | –11.371692 | Settlement |
| 114 | 30.47512 | –11.378259 | Settlement |
| 115 | 30.46584 | –11.378402 | Settlement |
| 116 | 30.24763 | –12.225398 | Grassland |
| 117 | 30.46371 | –12.107536 | Grassland |
| 118 | 30.00208 | –12.176289 | Grassland |
| 119 | 29.92351 | –11.950387 | Grassland |
| 120 | 29.6976 | –11.999496 | Grassland |
| 121 | 30.5521 | –12.834351 | Grassland |
| 122 | 30.75836 | –12.274507 | Grassland |
| 123 | 30.67979 | –11.891456 | Grassland |
| 124 | 29.36863 | –11.616076 | Grassland |
| 125 | 29.28786 | –11.548062 | Grassland |
| 126 | 29.21985 | –11.297263 | Grassland |
| 127 | 29.76102 | –11.291001 | Grassland |
| 128 | 29.71668 | –10.660088 | Grassland |
| 129 | 29.64521 | –10.745853 | Grassland |
| 130 | 29.7953 | –10.788736 | Grassland |
| 131 | 30.13121 | –11.067475 | Grassland |
| 132 | 29.38076 | –11.103210 | Grassland |
| 133 | 29.86677 | –13.254500 | Grassland |
| 134 | 29.6485 | –11.675376 | Grassland |
| 135 | 30.39495 | –11.852169 | Grassland |
| 136 | 30.26727 | –11.940565 | Grassland |
| 137 | 29.97262 | –11.930744 | Grassland |
| 138 | 29.72707 | –11.930744 | Grassland |
| 139 | 29.40295 | –11.940565 | Grassland |
| 140 | 30.17887 | –11.164642 | Grassland |
| 141 | 30.26727 | –11.675376 | Grassland |
| 142 | 30.52264 | –11.783416 | Grassland |
| 143 | 30.52264 | –11.871813 | Grassland |
| 144 | 30.50299 | –12.078071 | Grassland |
| 145 | 30.46371 | –12.500409 | Grassland |
| 146 | 30.5521 | –12.058427 | Grassland |
| 147 | 30.21816 | –11.901278 | Grassland |
| 148 | 29.86458 | –11.822704 | Grassland |
| 149 | 30.26541 | –11.544319 | Grassland |
| 150 | 30.07666 | –11.191984 | Grassland |
| 151 | 30.03261 | –11.248609 | Grassland |
| 152 | 28.79944 | –11.588361 | Grassland |
| 153 | 30.32203 | –12.047654 | Grassland |
| 154 | 30.18991 | –12.116863 | Grassland |
| 155 | 30.26541 | –12.167197 | Grassland |
| 156 | 30.25282 | –12.047654 | Grassland |
| 157 | 30.13328 | –12.035071 | Grassland |
| 158 | 30.08924 | –12.085405 | Grassland |
| 159 | 30.03261 | –12.041363 | Grassland |
| 160 | 29.98228 | –11.997321 | Grassland |
| 161 | 29.8187 | –11.890362 | Grassland |
| 162 | 29.72432 | –11.852612 | Grassland |
| 163 | 29.64882 | –11.846320 | Grassland |
| 164 | 29.90655 | –11.286306 | Water body |
| 165 | 29.88422 | –11.714663 | Water body |

| Point | Longitude | Latitude | LULC type |
|---|---|---|---|
| 166 | 29.98244 | –11.086067 | Water body |
| 167 | 29.77618 | –11.174463 | Water body |
| 168 | 29.69915 | –11.223442 | Water body |
| 169 | 29.67399 | –11.311526 | Water body |
| 170 | 29.8942 | –10.984358 | Water body |
| 171 | 29.80611 | –11.028400 | Water body |
| 172 | 29.76207 | –11.103900 | Water body |
| 173 | 29.81241 | –11.330401 | Water body |
| 174 | 29.72432 | –11.582069 | Water body |
| 175 | 29.6614 | –11.714195 | Water body |
| 176 | 29.97599 | –11.191984 | Water body |
| 177 | 29.61566 | –11.356903 | Water body |
| 178 | 29.5852 | –11.223653 | Water body |
| 179 | 29.72226 | –11.027586 | Water body |
| 180 | 29.70632 | –11.613409 | Water body |
| 181 | 29.67205 | –11.683365 | Water body |
| 182 | 29.70346 | –11.739045 | Water body |
| 183 | 29.85051 | –11.684793 | Water body |
| 184 | 29.86622 | –11.716202 | Water body |
| 185 | 29.8818 | –11.236859 | Water body |
| 186 | 29.91321 | –10.901355 | Water body |
| 187 | 29.91892 | –11.059827 | Water body |
| 188 | 29.64766 | –11.261130 | Water body |
| 189 | 29.61483 | –11.192601 | Water body |
| 190 | 29.6548 | –11.036985 | Water body |
| 191 | 29.30473 | –12.146824 | Cropland |
| 192 | 30.15923 | –12.755776 | Cropland |
| 193 | 30.08066 | –13.079896 | Cropland |
| 194 | 30.00208 | –13.197758 | Cropland |
| 195 | 30.34584 | –12.814707 | Cropland |
| 196 | 30.39495 | –11.901278 | Cropland |
| 197 | 30.61103 | –11.626267 | Cropland |
| 198 | 29.4664 | –11.871126 | Cropland |
| 199 | 29.26661 | –11.407784 | Cropland |
| 200 | 29.30061 | –11.276008 | Cropland |
| 201 | 29.11358 | –11.276008 | Cropland |
| 202 | 29.03281 | –11.237751 | Cropland |
| 203 | 29.71509 | –10.338231 | Cropland |
| 204 | 29.2807 | –10.531439 | Cropland |
| 205 | 29.23067 | –10.917385 | Cropland |
| 206 | 28.9019 | –11.017445 | Cropland |
| 207 | 28.63746 | –11.524892 | Cropland |
| 208 | 30.12407 | –10.745853 | Cropland |
| 209 | 30.01686 | –10.631499 | Cropland |
| 210 | 29.45938 | –12.118105 | Cropland |
| 211 | 29.6595 | –10.917385 | Cropland |
| 212 | 29.58088 | –10.874502 | Cropland |
| 213 | 30.58148 | –12.940026 | Cropland |
| 214 | 30.21698 | –13.047233 | Cropland |
| 215 | 29.92395 | –13.118705 | Cropland |
| 216 | 30.91025 | –11.439126 | Cropland |
| 217 | 31.20328 | –11.517745 | Cropland |
| 218 | 30.36707 | –10.817325 | Cropland |
| 219 | 30.53246 | –12.245042 | Cropland |
| 220 | 30.12976 | –11.842347 | Cropland |
| 221 | 29.31455 | –11.626267 | Cropland |

| Point | Longitude | Latitude | LULC type |
|---|---|---|---|
| 222 | 29.51099 | –10.938740 | Cropland |
| 223 | 29.786 | –10.585154 | Cropland |
| 224 | 29.13776 | –11.488762 | Cropland |
| 225 | 29.03954 | –11.331613 | Cropland |
| 226 | 29.46188 | –11.115533 | Cropland |
| 227 | 29.52081 | –11.449474 | Cropland |
| 228 | 30.37531 | –12.028962 | Cropland |
| 229 | 30.97444 | –11.950387 | Cropland |
| 230 | 31.3182 | –11.626267 | Cropland |
| 231 | 30.94498 | –11.891456 | Cropland |
| 232 | 29.13776 | –11.282503 | Cropland |
| 233 | 29.58956 | –10.781591 | Cropland |
| 234 | 29.70743 | –10.791412 | Cropland |
| 235 | 30.0119 | –10.801234 | Cropland |
| 236 | 30.3262 | –10.732482 | Cropland |
| 237 | 30.05119 | –11.832525 | Cropland |
| 238 | 29.49135 | –11.803060 | Cropland |
| 239 | 29.30473 | –11.832525 | Cropland |
| 240 | 29.52081 | –12.127180 | Cropland |
| 241 | 28.95673 | –11.236026 | Cropland |
| 242 | 28.86865 | –11.204567 | Cropland |
| 243 | 29.91936 | –11.141650 | Cropland |
| 244 | 30.00745 | –11.179400 | Cropland |
| 245 | 28.86865 | –11.909237 | Cropland |
| 246 | 28.97561 | –11.896654 | Cropland |
| 247 | 28.74282 | –11.739361 | Cropland |
| 248 | 28.81203 | –11.412193 | Cropland |
| 249 | 28.85607 | –11.324109 | Cropland |
| 250 | 28.87494 | –11.273776 | Cropland |
| 251 | 29.5922 | –11.896654 | Cropland |