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Identifying the Rates and Drivers of Spatiotemporal Patterns of Land Use and Land Cover Changes in the Hurungwe District, Zimbabwe: A GIS and Remote Sensing Approach

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Abstract

Identifying spatiotemporal patterns of land use and land cover changes (LULCC) and their impacts on the natural environment is essential in policy decisions for effective, sustainable natural resource management solutions. This study employed supervised image classification in Google Earth Engine (GEE) cloud-based platform to assess the land cover land use changes for the past 30 years (1989-2020), as well as predict the land cover states and the risk of future forest loss in the next ten years, using TerrSet 20 software in Hurungwe district, Zimbabwe. The study findings revealed a net forest area and shrub loss of 32% and 10%, while croplands, water bodies, and bare lands have increased by about 171%, 7%, and 119% between 1989 and 2020, respectively. Croplands are the major contributor to the net change in forests, particularly tobacco farming. The predictive model estimated that by 2030 the district would lose approximately 7% of the current forest cover area, most likely converted into croplands, shrubs, and settlements. The results reinforce the importance of bridging the gap between socioeconomic activities and institutional policies to ensure proper natural resource management. Integrating institutional policy and socioeconomic goals is indispensable to ensure sustainable development.

Keywords

Land Use and Land Cover Change, Cellular Automata-Markov, Tobacco Farming, Drivers of Deforestation, Geographic Information System

1. Introduction

Extreme environmental concerns, such as global warming and pressures of rapid population growth, have overseen a growing interest in land use and land cover changes (LULCC) studies in different parts of the globe, with a particular interest in developing countries [1] [2] [3]. Given the greater demands for natural resources in the present and the near future, a better understanding of LULCC is fundamental in designing sustainable and robust land management strategies and policy decisions [4] [5]. The continuous monitoring and assessment of LULCC provide essential information on the patterns of change in natural resources. It also lays the foundation for effective management and mitigation measures for sustainable natural resource planning.

Unfortunately, most developing countries have insufficient documentation of land use and land cover changes (LULCC) driven by human activities. These anthropogenic activities include agriculture, urban development, deforestation, and other socioeconomic activities such as mining and brickmaking. Land use land cover change is also one of the primary causes of biodiversity loss and rising CO_2 emissions. It can accelerate global climate change and land degradation, reducing ecosystem services and functions [6] [7]. In the context of global warming, deforestation is notably the most significant contributor to anthropogenic carbon emissions. It accounts for 10% of the world's greenhouse gas emissions [8], and the IPCC predicts an upsurge in the concentration of CO_2 in the coming years due to increased anthropogenic activities [9]. Consequently, deforestation is a genuine concern and threat in many parts of the world, particularly developing countries [10]. In light of this, quantifying LULCC and identifying the rates and causes of deforestation is fundamental in designing practical land management policy instruments and incentives for programs such as Reduced Emissions from Deforestation and Forest Degradation (REDD) [4] [5] [11] [12].

Rapid LULCC directly impacts humanity and the environment [13]. Deforestation, due to LULCC, is a severe environmental and socioeconomic problem occurring at all scales (global, regional, and local). Several studies have applied GIS and remote sensing data to quantify LULCC from remotely sensed data in Zimbabwe. It is also used to predict the extent and rates of deforestation, especially over large areas [1] [14] [15] [16] [17]. Remote sensing is an effective tool for managing the earth's surface and monitoring LULCC by providing spatiotemporal information on land use land cover (forest, grassland, settlement, water, and cropland) [18] [19] [20].

Located in the northwestern part of Zimbabwe, Hurungwe district, over the past few decades (1989-2020), has been experiencing rapid modification and alterations in the LULC through increased anthropogenic activities such as agriculture, fuel wood extraction, mining, and other socioeconomic activities [1] [15] [21] [22]. Deforestation due to expanding agricultural activities to meet a fast-growing agro-based population is also prevalent [23]. Agricultural activities, particularly tobacco farming, have been identified as the primary drivers responsible for LULC transformation, given the area's favorable farming conditions, good soil quality, specialization in crop farming, and intensive livestock rearing [15] [24]. Furthermore, following the agrarian and land reform programs initiated in 1999/2000, there has been a considerable increase in farmlands and settlement development [25] [26] [27]. However, the croplands' continued expansion and the forest degradation for fuel wood to cure tobacco and other socioeconomic activities are not in line with the country's ever-growing population [23]. There is also a lack of awareness among key stakeholders (policymakers and civil society) to account for the multiple and often interacting drivers and impacts of LULCC in fostering sustainable land and environmental management.

Despite the growing environmental concerns about tobacco farming and LULCC on sustainable development and local environmental changes [24] [28]-[36], studies on LULCC in the Hurungwe district are nonexistent. Most studies on LULCC in Zimbabwe are spatially concentrated in major cities, focusing on the urban sprawl dynamics [16] [37] [38]. However, natural resource availability, dynamics, and management differ temporarily and spatially. Likewise, factors driving LULCC depend on humans' exact conditions and environments [16] [39] [40]. The magnitude and dynamics of these changes have not been extensively studied in the study area. Little is known about the spatiotemporal dimensions of the LULC changes that have modified and shaped the Hurungwe district. There is little research work quantifying and predicting LULC changes and forest cover loss over time in the region. More evidence is required to understand the human or climate-induced changes of a subtropical landscape, the present status of the landscape, the extent and rate of change, and the impact of the reported changes.

To address this scarcity in literature, the integration of remote sensing (RS) and geographical information system (GIS) data will provide great potential for monitoring and predicting LULCC and future forest cover loss [41] [42]. Therefore, it is of utmost importance to investigate LULCC so that the impact can be detected and corrective measures for sustainable land use planning can be devised [16] [37]. The present study will attempt to identify and predict the spatiotemporal pattern of LULCC for Hurungwe district using geospatial data to enable decision-makers to understand the dynamics of the changing environment and ensure sustainable development. Therefore, based on remote sensing data, this research aims to quantify land-cover change processes and generate land-cover change projections using the Markov-based model to predict the risk of future forest loss in Hurungwe district and its drivers for successive Landsat imageries of the study period (1989 - 2020).

2. Materials and Methods

2.1. Description of the Study Area

The study was conducted in the Hurungwe district, situated in the north-western part of Zimbabwe and is one of six districts that make up Mashonaland West. It is the largest district in the area, with a total area of 19,678.34 km^2, and lies between 16˚S and 17˚S and 29˚E and 30˚E (**Figure 1**). Zimbabwe is divided into five agroecological regions based on biophysical, climatic conditions and different agricultural productivity potentials. The quality and fertility of the soil and precipitation regimes decline from region I to V, respectively [43]. Our study area is located within [41] zone II, with an average annual precipitation of 750 mm-1000 mm [42]; the site is predominantly under smallholder farming. The main crops grown in the area include flue-cured tobacco, maize, cotton, wheat, soybeans, sorghum, and groundnuts [42] Hurungwe district was selected because it has one of the highest forest loss rates in Zimbabwe. According to Global Forest Watch (GFW), from 2001 to 2021, Hurungwe lost 3.52 kha tree cover, corresponding to a 100% decrease since 2000 and 12% of the global total [44]. Additionally, the Hurungwe district was chosen because this is where large-scale farming is most viable, given the favorable biophysical and climatic conditions relative to most places of the country.

2.2. Methods

Google Earth Engine (GEE) was used to map out temporal and spatial changes

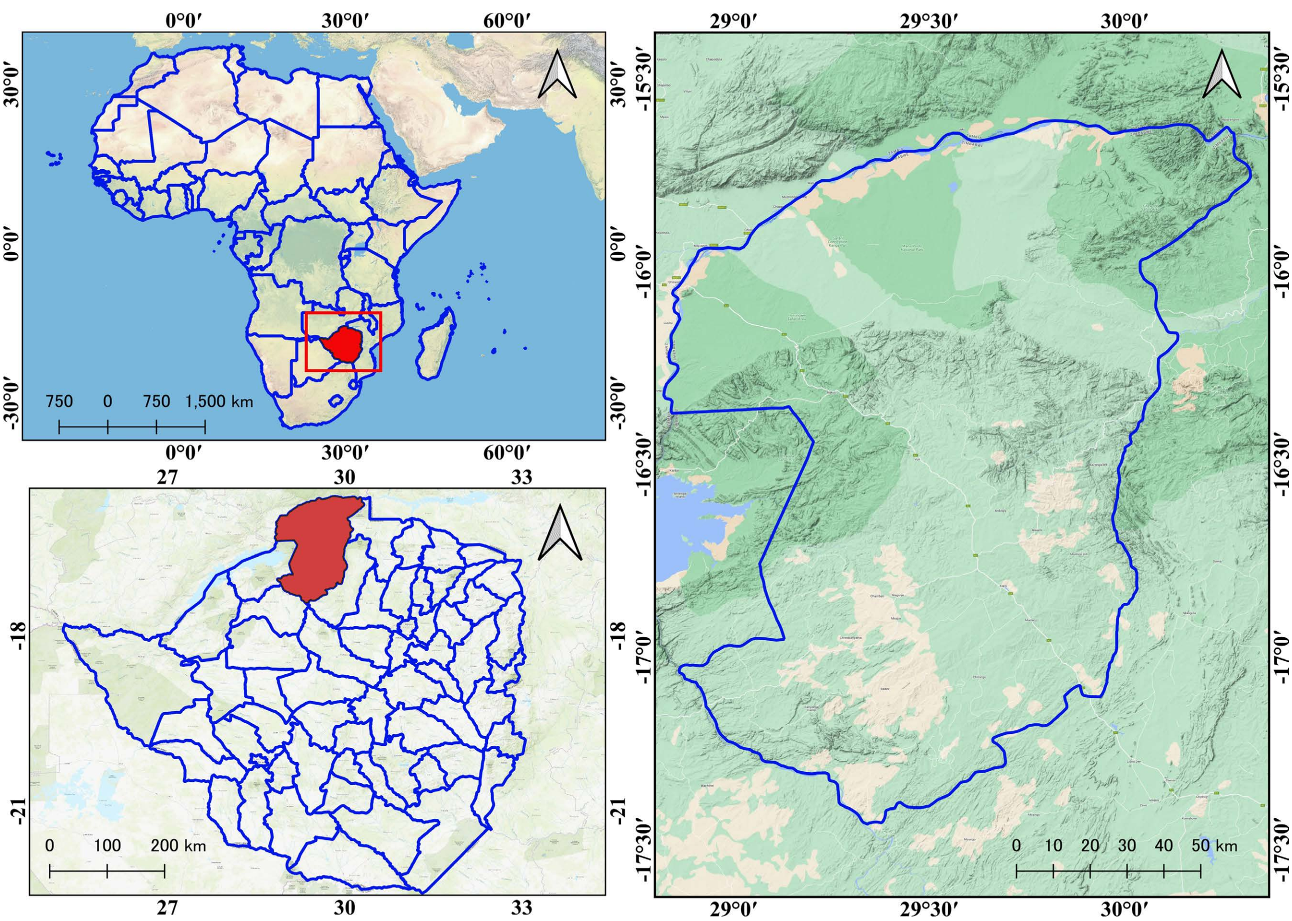

Figure 1. Hurungwe district location.

in the study area during 1989 - 2020. Google Earth Engine is an open-access cloud-based geospatial processing platform that enables researchers and practitioners to detect changes, map trends, and quantify differences using remote sensing (RS) data [45] [46] [47] [48] Specifically, in this study, GEE was used to perform image collection, supervised classification, and accuracy assessment using machine learning algorithms (**Figure 2**).

The CA-Markov chain model in IDRISI GIS in TerrSet 2020 was then used to simulate and predict the future land cover states of different land cover classes. Land use and land cover (LULC) maps of 2002 and 2010, digital elevation model

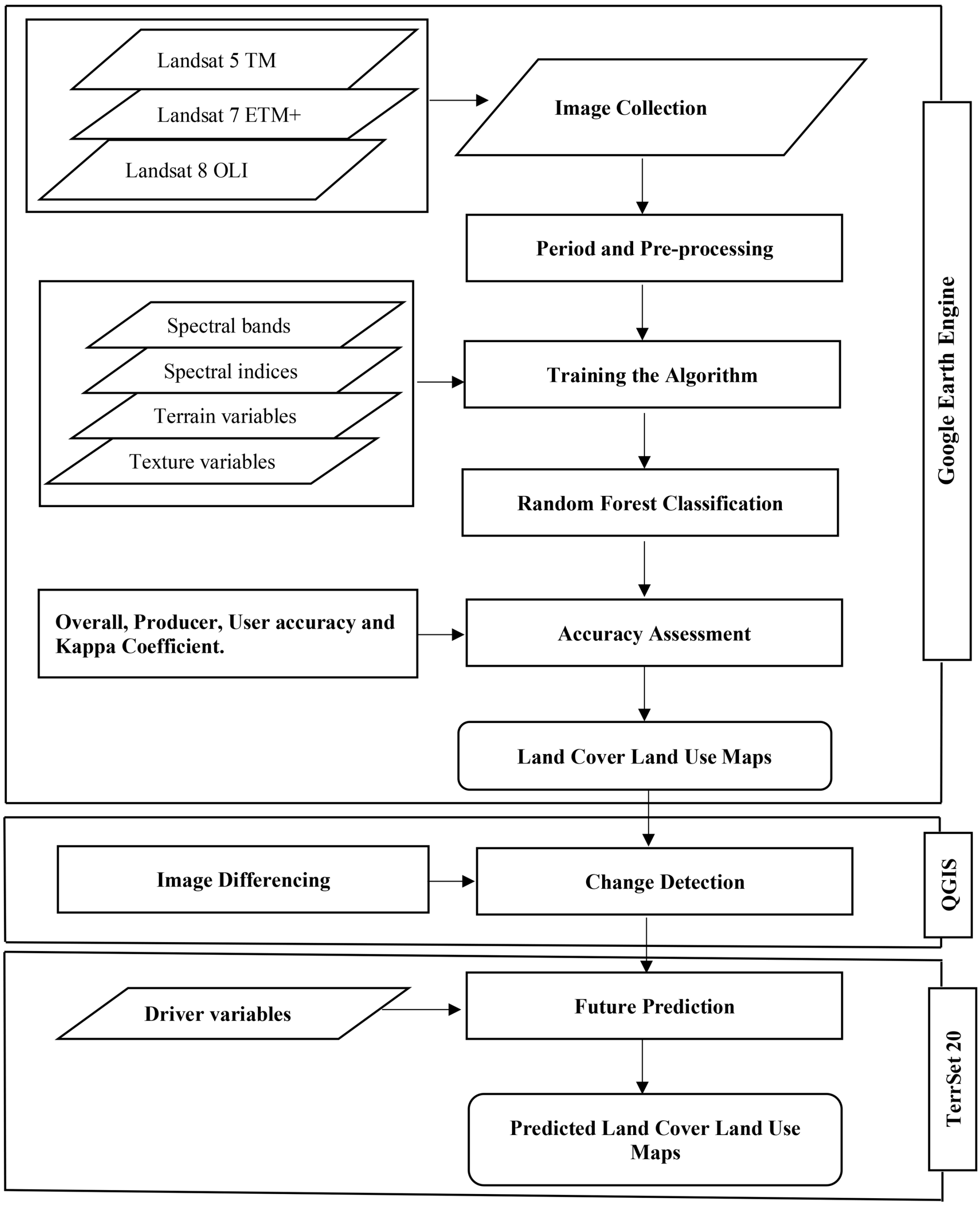

Figure 2. Methodological flowchart.

(DEM), distance from roads, forest disturbance map 2010, and rivers were among the spatial driver variables used to run the simulation and prediction processes. LULC maps of 2002 and 2010 were used to generate a transitional matrix using the Markov change modeler, while slope, road, and elevation maps were used to create potential transitional maps. Both datasets were combined to predict future forest loss using the CA-Markov chain model (**Figure 2**).

2.3. Image Collection

This study used Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) image collections with 30 m spatial resolution (**Table 1**) to generate LULC maps. All images consist of tier 1 Landsat collections scenes with the highest available data quality. Classifications were performed annually, with individual scripts and datasets for each year (**Table 1**).

2.4. Image Pre-Processing

The satellite images for 1989, 2002, 2010, and 2020 were used in this study (**Table 1**). The assessment was based on a 10-year interval trend analysis. The time interval was based on image availability, institutional and policy changes in Zimbabwe, and the assumption that the specified trend analysis would provide quantifiable and noticeable differences. Therefore, limiting the time frame of the image collections to post-rainy, thus between April to July (**Table 1**); given that during this period, there is less cloud cover interference, and the vegetation density is the highest; therefore, images of these months could enhance the spectral separability between complicated land cover classes such as shrubland, cropland, and bareland. Finally, the images were orthorectified to a Universal Transverse Mercator (UTM) projection using the World Geodetic System (WGS) 84 datum. The study area is spread over 4 Landsat images with the Path/Row 171/71-2 (**Table 1**). The pre-processed images were mosaicked and clipped to remain within the area of interest for image classification.

Table 1. Image collection details.

Year	Sensor	Path/Row	Resolution (m)	Period of collection
1989	Landsat 5 Thematic Mapper (TM)	171/71-72	30	10/05/89-10/06/89
2002	Landsat 7 Enhanced Thematic Mapper (ETM+)	171/71-72	30	16/05/02-30/07/02
2010	Landsat 5 Thematic Mapper Plus (TM)	171/71-72	30	10/04/10-05/05/10
2020	Landsat 8 Operational Land Imager (OLI)	171/71-72	30	20/04/20-30/04/20

2.5. Image Classification, Classification Features, Accuracy Assessment, and Change Detection

It is important to include the most optimal features in the classification to obtain highly accurate LULC maps [46] [49]. Based on our pilot classification analysis, we could identify classification input features that significantly improved the accuracy levels of the classified maps for the study area. The features listed in **Table 2** (23 features in total) have the highest potential to discriminate various land cover classes and, thus, were used in this study. Spectral bands and indices, terrain variables and Gray-Level Co-occurrence Matrix texture features of the images were used in the training random forest classifier in GEE (**Figure 2**). For instance, the Normalized Difference Vegetation Index (NDVI) is the most noteworthy feature for identifying vegetation, an essential characteristic of forest and non-forest discrimination [50] [51] [52].

Classifications were performed annually, with individual scripts and datasets for each year. Furthermore, the pilot classification revealed spectral confusion challenges within selected classes (**Table 3**). The problem of within-class variability in the classification was addressed by subdividing classes according to similar spectral characteristics, and the subclasses were later merged. For example, shrubs were wrongly classified as cropland, while bare land areas were misclassified

Table 2. Image collection details Features applied to the classifications in this study.

Satellite	Feature	Name of Feature
Thematic Mapper (TM)	Spectral bands	B1 (Blue), B2 (Green), B3 (Red), B4(NIR), B5 (SWIR1), B7 (SWIR2)
	Spectral indices	NDVI, NDWI, SAVI, SR, NDBI, EVI, and BSI.
	Terrain features	Slope and Digital Elevation Model
	GLCM texture features	Angular Second Moment, Entropy, Dissimilarity, Contrast, Correlation, Variance, Cluster Shade, and Inverse Difference Moment
Enhanced Thematic Mapper Plus (ETM+)	Spectral bands	B1 (Blue), B2 (Green), B3 (Red), B4(NIR), B5 (SWIR1), B7 (SWIR2)
	Spectral indices	NDVI, NDWI, SAVI, SR, NDBI, EVI, and BSI.
	Terrain features	Slope and Digital Elevation Model
	GLCM texture features	Angular Second Moment, Entropy, Dissimilarity, Contrast, Correlation, Variance, Cluster Shade, and Inverse Difference Moment
Operational Land Imager (OLI)	Spectral bands	Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 5 (NIR), Band 6 (SWIR1), Band 7 (SWIR2)
	Spectral indices	NDVI, NDWI, SAVI, SR, NDBI, EVI and BSI.
	Terrain features	Slope and Digital Elevation Model
	GLCM texture features	Angular Second Moment, Entropy, Dissimilarity, Contrast, Correlation, Variance, Cluster Shade, and Inverse Difference Moment

B: Band, NIR: Near Infrared, SWIR: Shortwave Infrared; NDWI: Normalized Difference Water Index; NDVI: Normalized Difference Vegetation Index; SAVI: Soil Adjusted Vegetation Index; NDSI: Normalized Difference Soil Index; SR: Simple Ratio; EVI: Enhanced Vegetation Index; BSI: Bare Soil Index; GLCM: Gray-Level Co-occurrence Matrix.

Table 3. Definitions of the land cover classes mapped in this research.

Land cover class	Description
Forest	All wooded areas with 5% - 20% tree canopy cover. This class includes riverine vegetation with sparse grass cover, mainly perennial species.
Cropland	This class includes areas currently under crop, orchards, and fallow, and in addition land under irrigation, cultivated land or land being prepared for raising crops. Physical boundaries are broadly defined to encompass the main areas of agricultural activity.
Water	Streams, rivers, ponds, dams, and reservoirs.
Shrubs	Sparse woodland or scattered trees about 100 m apart, giving a canopy cover of about 2% - 10% with a tree height greater than 5 m. This class also includes a varying density of small shrubs and bushes about 2 m in height. The grass cover is well developed and continuous due to the low canopy cover. Grazing land is also included in this class.
Bareland	Non-vegetated areas such as artificial structures or areas with minimal vegetation cover. bare natural soil, sand, rocky areas, temporary bare land, and settlements.

as dry cropland or vice versa.

2.6. Classification

To map LULC temporal and spatial changes, supervised classification was applied using the random forest classifier based on an extensive literature review and used in Google Earth Engine [46] [47] [53] [54]. Random forest was used due to its high classification accuracy and stability [45] [55]. The five thematic classes adopted in the classification were 1) forest; 2) cropland; 3) water; 4) shrubs mixed with bush and grassland; 5) bareland, including bare natural soil, sand, rocky areas, temporary non vegetated areas, and settlements were identified from the images. The classification scheme (**Table 3**) is based on the Zimbabwe Forestry Commission's vegetation and non-vegetation guidelines, high-resolution data from Google Earth Pro, Forest Cover Change (GFCC) Hansen (2000, 2005, 2010 and 2020), aerial photos and field observation of the study area. Considering that the primary objective of this study was to quantify forest loss over the years; therefore, the adopted classes were broad. The decision to use a broad classification scheme is supported by [56], who argued for using more general categories when trying to meet predetermined accuracy standards (**Table 3**). An overall accuracy higher than 85% was accepted as adequate for this study, following Anderson, Hardy, Roach, and Witmer (1976) [57].

2.7. Change Detection

Change detection assessment was conducted for all the classified maps to quantify the changes in LULC in the Hurungwe district over 30 years. Differences were detected based on statistics from 1989 to 2002, 2002 to 2010, 2010 to 2020, and 1989-2020 in QGIS 3.26.1. (**Figure 2**). The change analysis was carried out to determine the multi-temporary differences in land cover classes and how the transformations in each land cover class drove forest cover loss in the study area.

2.8. Expert and Smallholder Farmers Interviews

Questionnaire surveys were designed to assess critical informants' perceptions of the causes of deforestation and LULCC. A literature review and policy document analysis were done to identify the key stakeholders in Zimbabwe's tobacco farming sector. Based on this list, key experts from different stakeholders were contacted for interviews. Based on consent and availability, fifty-three experts from tobacco purchasing companies, civil society, government officials, academic experts, consulting firms, and NGOs were interviewed (**Table 4**). To undertake the household survey, we contacted the Department of Agricultural Technical and Extension Services (Agritex) and the Tobacco Industry Marketing Board (TIMB) to collect information related to tobacco production rates and the number of farmers in the district. After collecting the farmers' lists, we selected the sample size according to Cochran's formula [58]. Hurungwe district had a total of 33,451 registered tobacco farmers in 2021. Per the formula, the sample size determined for this study is presented;

$$n = \frac{z^2 pq}{e^2} = \frac{2.6^2 (0.5)(0.5)}{0.10^2} = 169$$

where n is the sample size, z represents the critical value 2.6% at a 99% confidence interval, and p is the proportion of the smallholder farmers participating in tobacco farming. According to Cochran (1977) [58], if this proportion is not known with certainty, it must be assumed to be half of the population. Therefore $p = 0.5$ while $q = 1 - 0.5 = 0.5$, which is the proportion of smallholder farmers not participating in tobacco farming. e is the allowable error equal to ±10%.

The final respondents comprised two hundred seventy-three smallholder tobacco and non-tobacco farmers. The respondents were chosen because we believed they have information and knowledge that others do not possess (e.g., forest policies, institutional changes, tobacco farming, and its environmental impacts, causes of forest loss, and deforestation. Subsequently, their perceptions were compared with the land-cover changes observed from the remote sensing imagery (**Table 4** and **Table 5**).

Table 4. Expert informants' details.

Key informant group	Harare (Head office)	Hurungwe district
Tobacco purchasing companies	4	7
Civil society	4	19
Government officials	3	2
Academic experts	3	6
Consulting firms and NGOs	6	2
Total (n)	20	33

Table 5. Characteristics of expert interview respondent.

Organization	Department	Position
Government		
Tobacco Industry Marketing Board (Main)	Research, Monitoring and Evaluation	Principal Research Officer Senior Research Officer
Environmental Management Agency	Environmental Management Services Department—EMS	Chief Programme Officer
Forestry Commission Zimbabwe	Research and training	REDD+ Knowledge Management/ Stakeholder Consultation Specialist
Ministry of Lands, Agriculture, Water, Climate and Rural Resettlement	AGRITEX	Extension officers
Zimbabwe Farmers Union (ZFU)	Field and Operations	Director
Department of The Surveyors General	GIS and Mapping	Director
Rural District Councils	District Attorney's Office	Deputy District Attorney
Technical companies/licensed buying companies		
Zimbabwe Leaf Tobacco Company (ZLTC)	Extension and Contract farming	Technical Trainer
Northern Tobacco (NT)	Contract farming	Project leader
Premium	Operations Department	Project Manger
Tian Ze	Contract farming	Buyer
Shasha	Extension	Buyer
Research institutions		
The University of Zimbabwe	Department of Agricultural	Research Scientist
Tobacco Research Board	Research and Extension Services	Agricultural Economist
CSOs/NGOs		
Environmental Buddies, Zimbabwe	Field Operations	Field staff
Rift Valley	Operations Department	Project Manger

2.9. Land Use and Land Cover Change Simulation and Prediction

This study used Cellular Automata-Markov Chain Model (CA-Markov model) to predict future LULC changes. The CA-Markov model was chosen based on a systematic literature review [1] [15] [59] [60]. The primary objective of the prediction was to assess the magnitude of forest loss in 2030 relative to other LULC classes evaluated in the study area. The CA-Markov model is a robust approach for predicting land use change, given that the hybrid model can simultaneously estimate spatial and temporal components, thus a powerful model best suited to deal with complex processes and changes in land use planning and management.

The 2002 and 2010 classified maps were used as input datasets to generate a transition probability matrix using the CA-Markov model, and then transition potential maps were produced. The 2002 and 2010 classified maps were the initial and final state land cover inputs in building the model. Additional spatial driver variables used to predict the future LULC maps consisted of the following data: (1) slope, (2) main roads, (3) 2010 forest disturbance, (4) digital elevation model, and (5) rivers (Figure 3).

The transition probability matrix was used to forecast the area change of LULC. A conditional transition matrix showed the potential of each land use category to change into another class for the predicted time. All the driver variables were used to simulate the 2020 LULC map and predict the 2030 LULC map. Given that the focus was to predict the risk of forest cover loss over the next decade (2020 to 2030), only transitions from forest to other classes were included in the sub-model to be predicted (Table 6). The Multi-Layer Perception (MLP) neural network technique was employed to generate the transition potential of the chosen sub-model. As a result of this process, four suitability maps were generated, indicating the transition probabilities of pixels changing between classes for each transition selected in the sub-model. After that, a cellular automata simulation of the 2020 land cover ensued and was followed by model validation using the observed 2020 LULC map. The validated model was then used to predict the land cover for 2030 (Figure 3)

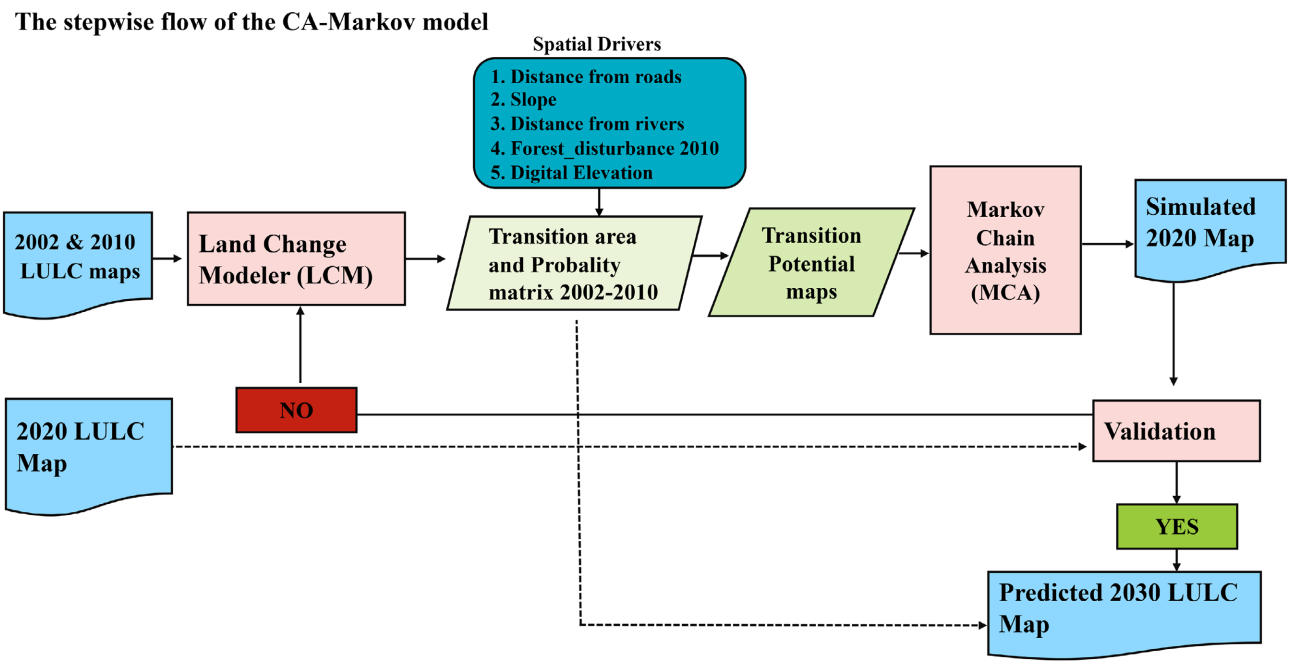

Figure 3. Prediction methodological flow chart.

Table 6. Transition sub-models used for simulation of land use and land cover.

From	To	Sub-model name
Forest	Cropland	Forest loss
Forest	Water	Forest loss
Forest	Shrubs	Forest loss
Forest	Bareland	Forest loss

3. Results

3.1. LULCC Mapping and Classification Accuracy Assessment

The land cover land use maps from the image classification are shown in Figure 4. The maps reveal the major land cover classes in the Hurungwe district for three decades, *i.e.*, 1989, 2002, 2010, and 2020. Five predominant land cover classes were identified. The overall accuracy levels of the four classified maps are

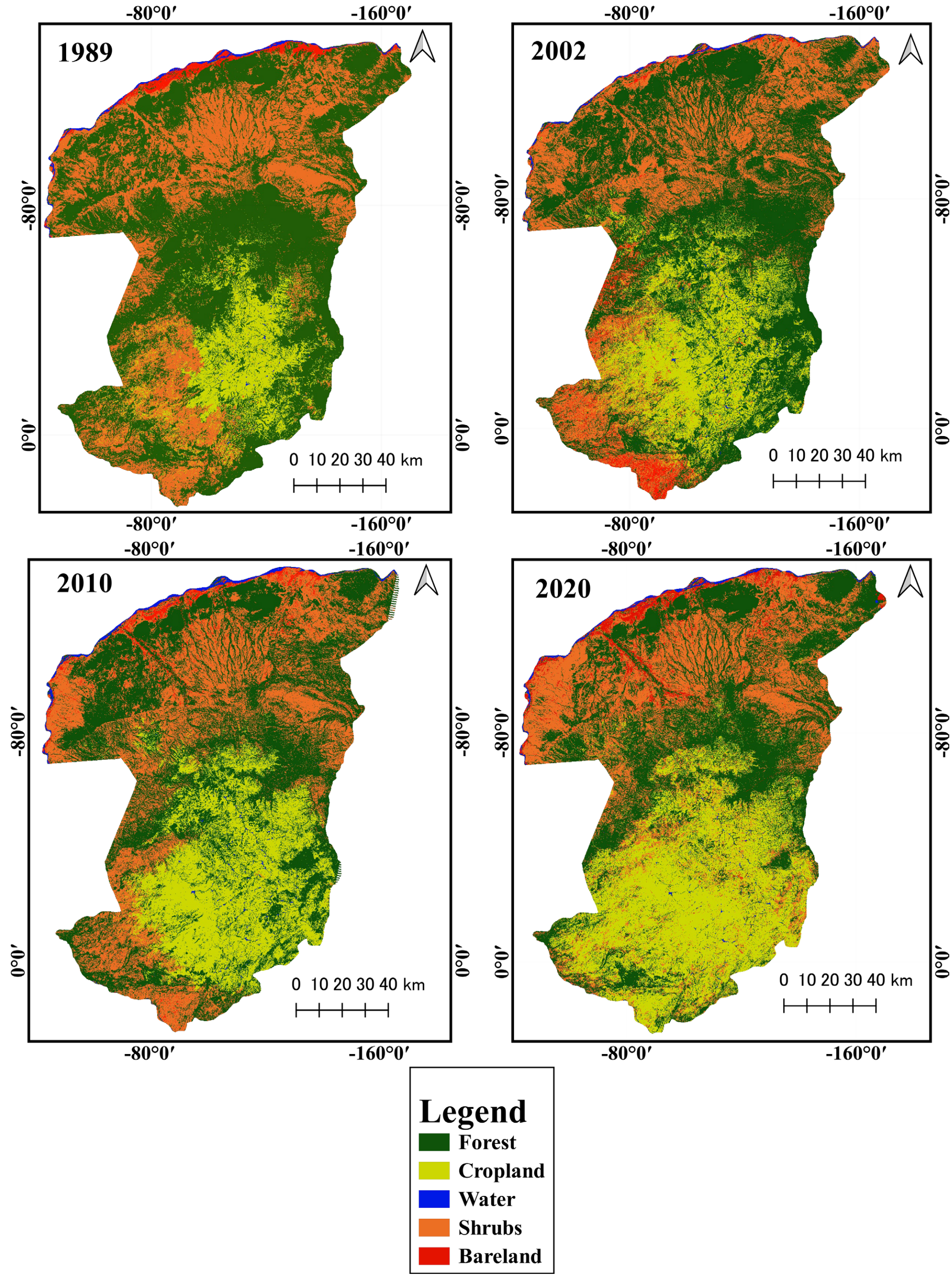

Figure 4. LULC maps of the study area for 1989, 2002, 2010, and 2020.

93.3%, 87.1%, 92.1%, and 89.6%, respectively, with Kappa values of 0.881, 0.835, 0.890, and 0.864, showing almost perfect agreement (Table 7).

At the beginning of the study period, the forest (woodland) was the dominant land-cover class in the study area, covering 55.8% of the area, followed by shrubs at 30.9%, cropland (11.1%), water, and bareland both (0.6%), respectively (Table 8). The total forest areas that changed for 1989-2002, 2002-2010, and 2010-2020 were 11,060.60 km^2, 10,255.73 km^2, 8989.48 km^2, and 7564.42 km^2, respectively (Table 8). These changes denoted net area time-series changes of −7.3%, −12.3%, −15.9%, and an overall 30-year forest area loss of −31.6%, respectively. On the contrary, cropland increased by 171.2% during the study period (1989-2020) (Table 9), expanding from 11.1% to 30.2% of the total land area of the Hurungwe district. Cropland continuously gained area throughout the study period, with 1560.57 km^2 between 2010 and 2020 than any other class; this was also the highest gain over the 30 years. During the study period, shrubs fluctuate up and down; the analysis reveals a total area loss of 640.35 km^2, which is a 10.4% decrease in the area comparing the initial and final states of the class. There are minimal changes in both water and bareland classes (Table 8). Over the study period, cropland gained more area, and forest lost more area, followed

Table 7. Accuracy assessment (PA: Producer's Accuracy; UA: User's Accuracy; K: Kappa).

Land-Cover Class	1989		2002		2010		2020	
	PA	UA	PA	UA	PA	UA	PA	UA
Forest	98.8	97.8	90.9	88.8	93.8	88.3	91.8	94.1
Cropland	94.4	79.0	91.5	84.2	96.4	94.9	92.5	89.7
Water	100.0	99.1	98.6	100.0	97.6	100.0	100.0	96.8
Shrubs	99.6	99.7	86.8	77.4	83.9	84.8	80.6	79.7
Bareland	88.9	20.0	71.8	90.7	79.4	96.4	81.0	88.2
Overall	93.3		87.1		92.1		89.6	
Kappa	0.881		0.835		0.890		0.864	

Table 8. Area per land-cover class in 1989, 2002, 2010, and 2020.

Class	1989		2002		2010		2020	
	Area (Km^2)	(%)	Area (Km^2)	(%)	Area (Km^2)	(%)	Area (Km^2)	(%)
Forest	11,060.60	55.8	10,255.73	51.8	8989.48	45.5	7564.42	38.2
Cropland	2205.48	11.1	3582.07	18.1	4421.28	22.4	5981.86	30.2
Water	127.25	0.6	106.89	0.5	177.78	0.9	136.52	0.7
Shrubs	6128.43	30.9	5291.20	26.7	5758.05	29.2	5488.07	27.7
Bareland	294.08	1.5	580.10	2.9	401.47	2.0	645.13	3.3
Total	19,815.83	100.0	19,815.99	100.0	19,748.06	100.0	19,815.99	100.0

Table 9. Net change of the LULC by class area extent (km^2) and percentage (%).

Class	1989-2002		2002-2010		2010-2020		1989-2020	
	Area (Km^2)	(%)	Area (Km^2)	(%)	Area (Km^2)	(%)	Area (Km^2)	(%)
Forest	−804.87	−7.3	−1266.25	−12.3	−1425.06	−15.9	−3496.19	−31.6
Cropland	1376.59	62.4	839.21	23.4	1560.57	35.3	3776.38	171.2
Water	−20.36	−16.0	70.89	66.3	−41.26	−23.2	9.27	7.3
Shrubs	−837.22	−13.7	466.85	8.8	−269.98	−4.7	−640.35	−10.4
Bareland	286.02	97.3	−178.63	−30.8	243.66	60.7	351.05	119.4

*Negative values mean a decrease in the size of the land cover class over 30 years, and positive values indicate an increase in the size over the study period.

by shrubs, while there are slight gains in bareland and almost no changes in water bodies (Table 9). Image analysis results (Table 9) reveal that within each land cover type, there were losses and gains over the study period.

3.2. Patterns of Land Cover Change during the Study Period 1989 - 2020

Forests were the most dominant land-cover class category in 1989, covering 11,060.60 km^2 (Table 10). However, only 7564.41 km^2 (55.8%) of the area remained in 2020, while 3496.19 km^2 (38.2%) of the area converts to other land-cover types. Of this, the most significant proportion of the forest class converted to cropland (2454.92 km^2) and shrubs (2170.71 km^2) during the study period (Table 10). A closer look at the time-series change dynamics reveals that the forest class changes to cropland or shrubs. For example, during 2002-2010, forests lost 1166.13 km^2 to cropland and 1634.05 km^2 to shrubs amounting to 11.4% and 16.0%, respectively. From 2010-2020, a similar trend occurred, with the forest class losing 1004.61 km^2 and 1654.30 km^2 to cropland and shrubs, respectively, 11.2% and 18.4% of the forest area. Throughout the time-series analysis, cropland had the highest gain of 62.4% between 1989 and 2002 and 35.3% in 2010-2020. Cropland expanded by 3776.37 km^2 (171.2%) from 1989-2020. However, the forest area also recorded a net gain of 1079.75 km^2 from shrubs, while the shrubs experienced a net loss of 640.35 km^2 during the study period. Over the study period, the water and bareland classes had minimal changes, and the forest class had the highest loss, as highlighted by the image differencing results in Table 10.

3.3. LULCC and Drivers of Deforestation in Hurungwe District

3.3.1. Land Use and Land Cover Changes

Land cover refers to the biophysical characteristics of the earth's surface, including the distribution of vegetation, water, soil, and other physical features of the land. Land use refers to how the land has been used by humans and their habitat, usually emphasizing the functional role of land for economic activities.

Table 10. Landscape change matrices for 1989 - 2002, 2002 - 2010, 2010 - 2020, and the overall 1989 - 2020. All values are area (in km²). The matrix shows the dynamics of LULC changes. For each of the three periods and summarized time series of the study area, the column totals represent the areal extent in the final state, while row totals are values in the initial state. The coinciding values between each class in the initial state and class in the final state are the land cover type into which the former changed into the latter. The diagonal values (**in bold**) of each matrix or the intersection of the same class from the initial and final states denote unchanged land.

		Final State (2002)					
		Forest	Cropland	Water	Shrubs	Bareland	Total
Initial Stage (1989)	Forest	**8053.90**	1040.20	13.13	1829.48	123.89	11,060.60
	Cropland	432.25	**1633.90**	4.11	97.87	37.35	2205.48
	Water	19.10	2.46	**82.61**	4.39	18.69	127.25
	Shrubs	1702.71	899.92	1.93	**3192.49**	331.38	6128.42
	Bareland	47.75	5.59	5.00	166.98	**68.75**	294.08
	Class Total	10255.72	3582.07	106.77	5291.20	580.07	19815.83
	Class Changes	3006.70	571.58	44.64	2935.93	225.32	
	Image Difference	−804.88	1376.59	−20.48	−837.22	286.00	
		Final State (2010)					
		Forest	**Cropland**	**Water**	**Shrubs**	**Bareland**	**Total**
Initial Stage (2002)	Forest	**7378.30**	1166.13	25.60	1634.05	13.33	10,217.40
	Cropland	301.04	**2964.78**	2.12	306.10	8.02	3582.06
	Water	1.56	0.56	**104.46**	0.00	0.01	106.58
	Shrubs	1265.15	243.76	9.22	**3463.06**	281.39	5262.58
	Bareland	43.43	46.06	36.39	354.84	**98.72**	579.43
	Class Total	8989.48	4421.28	177.78	5758.05	401.47	19,748.06
	Class Changes	2839.10	617.28	2.13	1799.52	480.72	
	Image Difference	−1227.92	839.22	71.20	495.47	−177.96	
		Final State (2020)					
		Forest	**Cropland**	**Water**	**Shrubs**	**Bareland**	**Total**
Initial Stage (2010)	Forest	**6305.89**	1004.61	4.31	1654.30	20.37	8989.48
	Cropland	267.20	**3778.51**	0.56	329.21	45.81	4421.28
	Water	11.57	5.87	**127.50**	4.92	27.92	177.78
	Shrubs	930.07	1162.04	0.61	**3454.14**	211.20	5758.05
	Bareland	3.15	29.79	1.93	37.25	**329.35**	401.47
	Class Total	7517.87	5980.81	134.91	5479.82	634.66	19,748.05
	Class Changes	2683.59	642.77	50.28	2303.91	72.12	
	Image Difference	−1471.61	1559.53	−42.87	−278.24	233.19	

Continued

		Final State (2020)					
		Forest	**Cropland**	**Water**	**Shrubs**	**Bareland**	**Total**
Initial Stage (1989)	Forest	**6342.96**	2454.92	18.44	2170.71	73.57	11,060.60
	Cropland	108.24	**1926.67**	4.28	143.07	23.22	2205.48
	Water	10.70	5.01	**95.45**	4.00	12.08	127.25
	Shrubs	1079.75	1583.84	2.87	**3112.57**	349.41	6128.43
	Bareland	22.75	11.41	15.35	57.72	**186.85**	294.07
	Class Total	7564.41	5981.85	136.38	5488.07	645.12	19,815.83
	Class Changes	4717.64	278.81	31.80	3015.86	107.23	
	Image Difference	−3496.19	3776.37	9.13	−640.35	351.04	

LULCC is the conversion of different land use types and is the result of complex interactions between humans and the physical environment.

3.3.2. Expert Interviews

The experts interviewed included academics, researchers, government officials, smallholder farmers (non-tobacco and tobacco), tobacco companies, business institutions, and non-governmental organizations. All the respondents have either lived through the study period or had relevant, expert knowledge of the study area, tobacco farming, forestry, and settlement planning. Like other districts in Zimbabwe, Hurungwe district is experiencing significant LULCC. A cross-reference with expert and household interviews indicated several changes and identified the dominant land-cover types and their drivers of change in the Hurungwe district in the last 30 years. The drivers of change are categorized into socio-economic and environmental, as highlighted on Table 11.

Several drivers have influenced LULCC in the study area. Figure 5 depicts the drivers linked to farmland expansion, government land policy, population pressure, investments, deforestation, and climatic changes to be the major causes behind the LULCC.

The district also falls within region II, which specializes in agriculture and livestock rearing, and receives a high amount of rainfall, thus attracting many people and driving the changes perceived. Despite 91% of the respondents describing tobacco as a lucrative high, generating income cash crop, the interviewed farmers cited, tobacco farming-related deforestation as the primary driver of LULCC. Of the 273 respondents, 88 % correctly mentioned forest as the dominant land cover at the beginning of the study period, 76% of the interviewees correctly ranked shrubs as second, and 70% perceived cropland as the third most dominant class type in the Hurungwe district. This suggests that respondents correctly perceive historic land-cover patterns dominated by forests, grasslands, and croplands. During the study period, all respondents correctly perceived a significant increase in the cropland area and a decrease in the forest

Table 11. Drivers of LULC Changes as cited by expert and household interviews.

Environmental changes (natural)	Socio-economic changes (human-induced)
• Droughts increased • Drying up of dams • Hectares of land reduced due to droughts	• Increased tobacco farming • Deforestation for development and tobacco production • Overpopulation increasing pressure on available resources • Increased veld fires • High Migration • No grazing lands for animals • Paddocks encroachment • Land size reduced because of over population • People have adapted to other forms of agriculture such as Pfumvudza

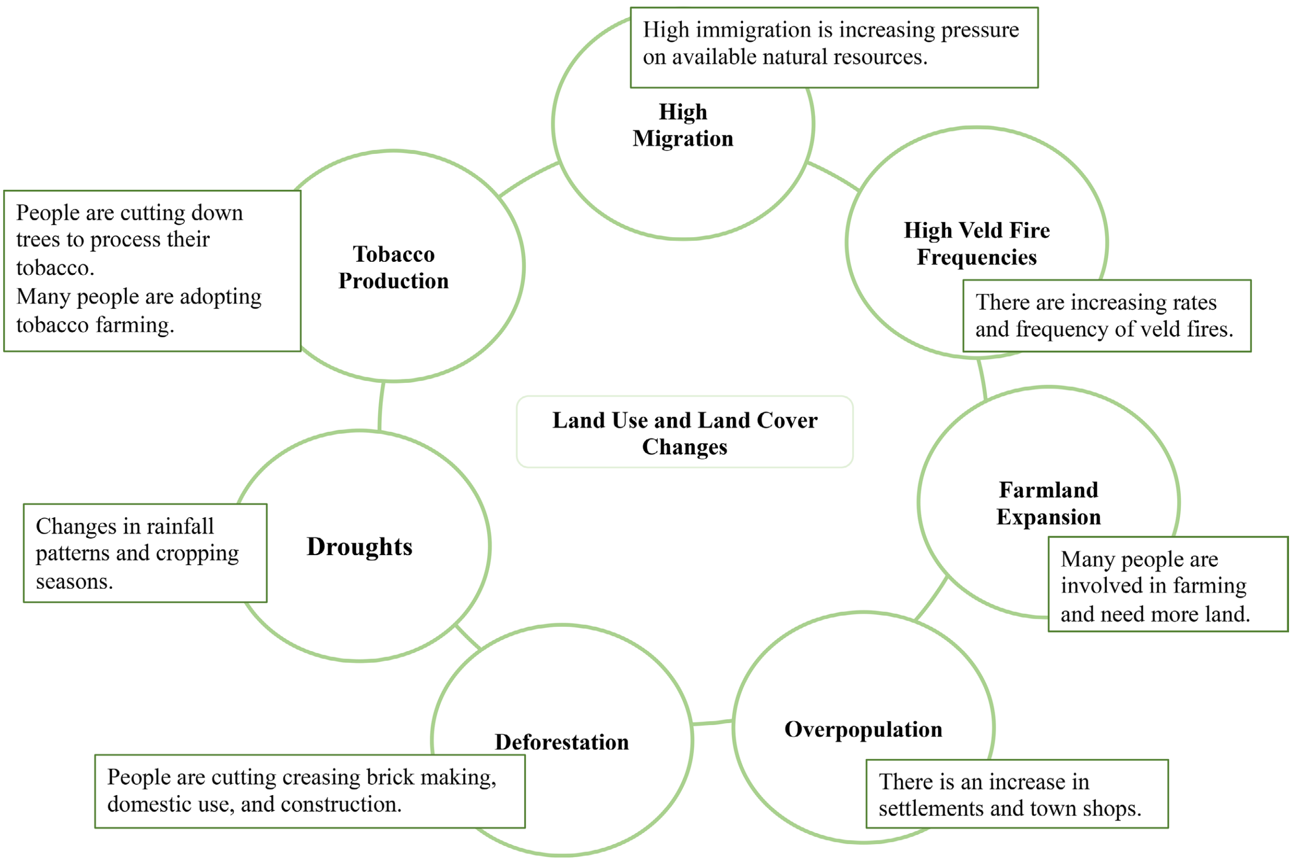

Figure 5. Key Drivers of LULC changes (n = 273).

area. The respondents' perceptions of water and bareland land cover classes varied between a decrease and no change, which is consistent with the slight changes observed in both classes in the remote sensing analysis.

3.4. Drivers of LULCC and Deforestation in Hurungwe District

Survey analysis shows that the proximate drivers of LULCC and deforestation result from increased agricultural activities, particularly tobacco farming (Figure

6). 41% of the respondents cite the cutting down of indigenous by tobacco farmers to cure tobacco harvests (Figure 7). 19% identify domestic use and brick making as the second leading causes of landscape changes and deforestation in the Hurungwe district (Figure 7).

Document analysis and interviews reveal that the incentivized agrarian and development policy changes have increased small-scale tobacco farmers from 975 in the 1989/90 season to 166,959 registered tobacco growers for the 2019/20 season. The growth in tobacco growers is also increasing the demand for farmland hence increasing deforestation as more and more people are clearing forests in search of new farms and settlements. Moreover, during one of the most severe droughts, this policy change hit Zimbabwe (from 2000 to 2001). Hence, the informants added that changing rain patterns and veld fires as other catalysts

Figure 6. Fuel wood for tobacco curing (photo by author, 15 September 2022).

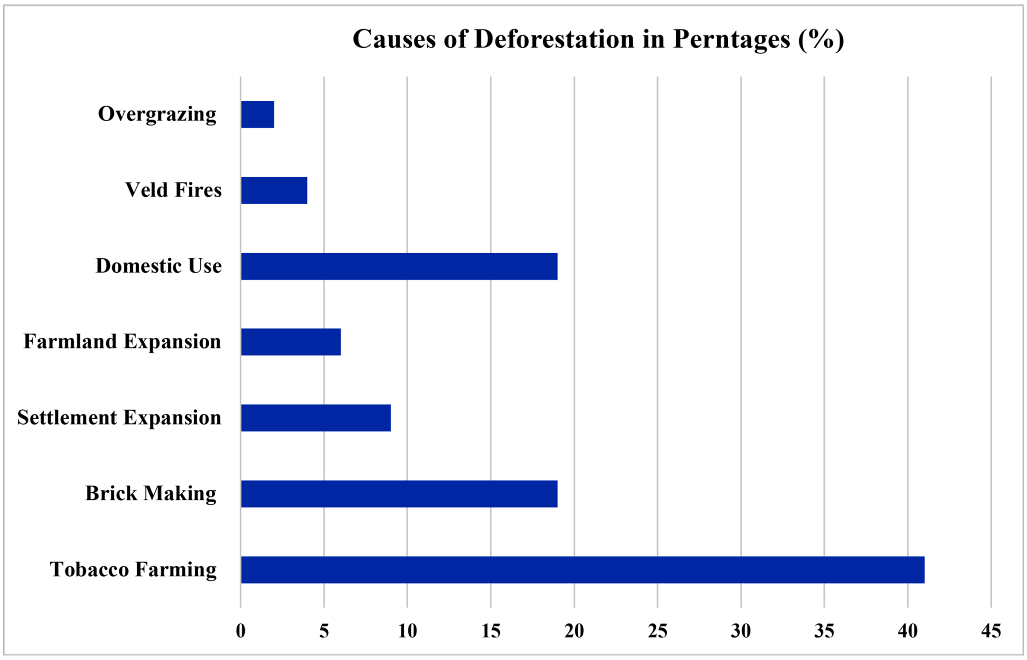

Figure 7. Drivers of deforestation (n = 273).

exacerbating the clearing of forests during this period, as the affected farmers began to come up with other sources of income generation, like brickmaking, and fuel wood extraction, to buy food and overcome its impacts.

Additionally, since food crops such as cereals have low final returns, tobacco became the core cash crop in Hurungwe District. Most people use tobacco farming because it is more profitable than other crops and is a high foreign currency (US$) earner. Some informants also cited that Hurungwe produces good quality tobacco recommended on the market floors, and this sector has thus gained a lot of support and funding. Hurungwe district presently has about 24 companies that provide extension services by funding farmers (MTC, Shasha, Voedsell, Premium Tobacco) with inputs such as seeds, fertilizers, chemicals, and expertise in agronomy services. Farmers also receive money to cover the harvesting expenses, making it easier for them to continue engaging in tobacco cultivation as they are provided with almost everything they need right at their doorstep.

However, some respondents highlighted that people do not have other survival means and only end up going for tobacco production, giving them higher returns over a short period. Consequently, deforestation levels have increased, as identified by the survey results and remote sensing image analysis in areas such as Chundu, Kazangarare, Chikuti, and Magunje, the hotspots.

3.5. Land Use and Land Cover Prediction

The predicted scenarios for 2030 using a CA-Markov model (**Figure 8**) showed some relevant results. The predicted maps had the MLP model accuracy of 99.96%, whereas the prediction accuracy of each class was as follows: forest 80.9%, cropland 94.1%, water 69.8%, shrubs 65.4%, and bareland 67.5%. The overall individual class accuracies indicate a good agreement between observed and predicted results. **Figure 8** shows 2020 simulated and 2030 predicted maps for the study area. The simulations suggest that the forest area will continue a downward trend, decreasing by 7.9%. The cropland and shrub area are predicted to increase by 3.4%, with minimal to no change for water and bareland in 2030 (**Table 12**).

4. Discussion

4.1. Classification Accuracies

The accuracy results of the classified maps of 1989, 2002, 2010, and 2020 consisted of high overall accuracies; however, users' and producers' accuracies of shrubs and bareland had low accuracies in 1989, 2002, and 2020 respectively (**Table 7**). The low accuracy levels can be attributed to spectral signature confusion between cropland/shrubs and harvested cropland/bareland, which were similar. Initially, the accuracies were extremely low. However, the results improved by subdividing each class while collecting training and validation samples. The sub-divisions were done due to differences in signatures within a class

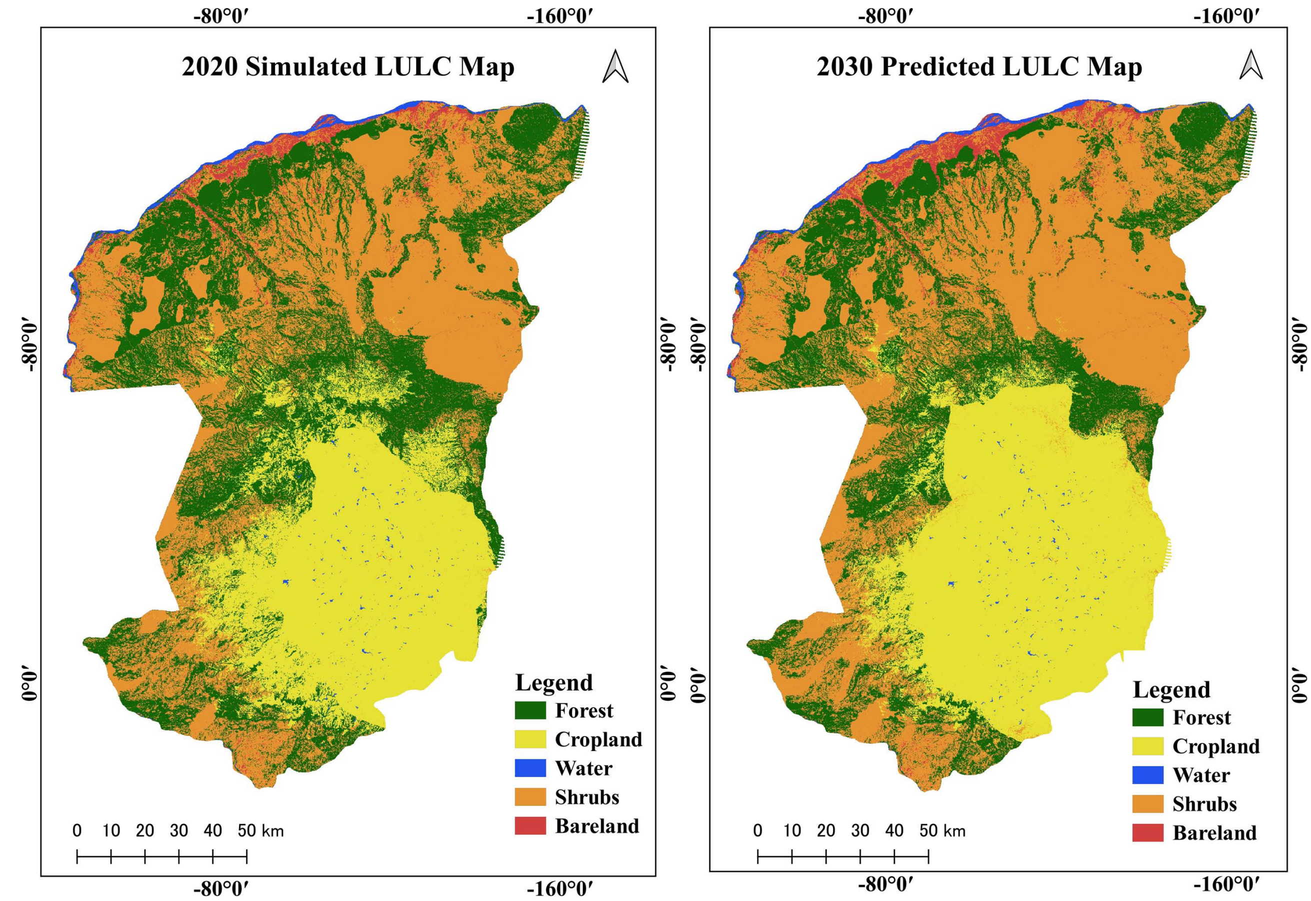

Figure 8. LULC prediction maps.

Table 12. Predicted results of area extent and accuracy for 2030.

Land-cover class	2020 Reference Data		2030 Predicted Data		Percentage Change %	Prediction Accuracy %
	Area (km²)	%	Area (km²)	%		
Forest	6120.37	31.9	4744.92	24.0%	−7.9	80.9
Cropland	5626.70	28.5	6297.71	31.9	3.4	94.1
Water	177.78	0.9	177.78	0.9	0.0	69.8
Shrubs	7387.66	37.4	8010.07	40.6	3.2	65.4
Bareland	435.55	2.2	517.58	2.6	0.4	67.5
Multi-Layer Perception (MLP) accuracy 99.96%						

across the study area and were later merged.

Furthermore, the inclusion of Gray-Level Co-occurrence Matrix (GLCM) textural features improved the accuracy levels, as shown in Table 7. The overall accuracy results meet the United States Geological Survey (USGS) benchmark of 85%, as cited in [21] [57]. The results for the individual land-cover class accuracy levels are provided in Table 7. These values indicate that the maps were sufficiently accurate for further analysis.

4.2. Land Use Land Cover Change Patterns and Forest Cover Loss

The time-series assessment of Landsat satellite images reveals a changing mosaic of five LULC classes between 1989 and 2020 in the study area (**Figure 4**). Although there are several case studies in Zimbabwe quantifying LULC changes and the driving forces behind the changes, mainly the deforestation of indigenous miombo woodlands [15] [17] [37] [61] [62] [63], fewer studies have applied Google Earth Engine time-series method to quantify the dynamics of LULCC [64]. Existing literature is constrained to comparing two periods rather than a time-series analysis explored in this study. The longitudinal analysis adopted in this study shows complex changes in land cover types within the study area over the three time periods examined (1989 - 2002, 2002 - 2010, and 2010 - 2020). For example, changes in the shrub areas (losses and gains) were inconsistent and asymmetrical from one period to the next. This results from adding intermediate periods to LULC analysis, which often results in contrasting scenarios but provides more precise information on change dynamics in the study area [65].

In detail, this study shows a decrease in the forest cover area in the Hurungwe district due to increased anthropogenic socio-economic activities. Previous studies in different parts of Zimbabwe show similar findings [15] [16] [66]. The analysis indicates that the highest forest loss occurred between 2010-2020 and 2002-2010, respectively. The extensive forest cover loss between the two decades (2002-2020) is a result of policy changes and various socio-economic drivers, such as increased agricultural activities [66], settlement development, wood harvesting, and veld fires [15] [16] [17] [33]. The growth of tobacco farming is tied to the increased levels of deforestation in the district. Between 2000 and 2019, smallholder tobacco farmers in Hurungwe increased from 600 to 98,447. Most of the new smallholder farmers use indigenous woodland to cure tobacco. Areas previously covered with forest were cleared for cropping, and vast areas of forest were cleared for tobacco curing and building of houses for resettled smallholder farmers. According to the Forestry Commission, every year, Zimbabwe loses more than 300,000 hectares of forests to deforestation, and 15 percent of the forest cover loss is attributable to tobacco farming [32]. A combination of expert interviews, focus group discussions and household surveys affirm that forest areas are being cut down for agricultural activities and wood cleared for tobacco curing since tobacco production increased in the district from 2000 onwards. Geist, (1999) [24], quantifying the forest cover loss rates linked to tobacco farming in Zimbabwe, found identical findings.

Forest cover loss in the Hurungwe district during the 2000 - 2020 period follows a global phenomenon occurring in many different parts of the world. According to the Global Forest Watch (GFW) reports, from 2001 to 2021, Hurungwe lost 3.52 kha, a decrease equivalent to a 4.7% loss in forest cover [44].

Between 1989 - 2002 and 2010 - 2020, the cropland area expanded significantly at the expense of the forest area. Throughout the study period, the cropland area continued an upward trajectory, with a 171% increase in size over 30 years.

The forest and shrubs classes were being converted to cropland. The bareland and water areas experienced minimal changes, while the shrubs fluctuated throughout the study. The fluctuations in shrub areas can be explained by the forest cover losses occurring in the study area. The findings of this assessment are consistent with previous studies on deforestation rates and drivers in Upper Manyame Sub-Catchment, where extensive deforestation was between 2000 - 2020 [15]. During the same period, the forest area was lost at the expense of croplands and settlements. The conversion was driven by policy changes, specifically the Fast Track Land Reform Program (FTLRP) between 2000 and 2008 [26] [27] [66]. The FTLRP transferred land ownership from a small number of large-scale commercial farmers to millions of black, indigenous smallholder farmers. The drastic policy change resulted in increased smallholder farmer participation leading to massive conversion of forest area to agricultural purposes at a national, particularly in areas such as Hurungwe district. Case studies assessing the impact of the land reform program on land cover indicate that forest areas were cleared for cropland and settlement upon implementing the FTLRP [67].

High population growth is another factor cited as a primary driver for forest cover loss in the Hurungwe district. Population growth leads to high land demand for infrastructure development and pasture, leading to increased LULCC and deforestation. Given the high land demands for settlement and farming, fuel wood and other socio-economic activities such as mining and brickmaking are associated with a growing human population. Throughout the study period, the Hurungwe district population grew at an annual rate of +2.6%, thus, a decrease in forest area is accompanied by population growth [23]. Also included among the drivers of forest loss are adverse climatic conditions combined with difficult economic circumstances resulting in veld fires and persistent energy cuts in the country, respectively. More and more people depend on wood as the primary energy source, thus exacerbating extensive forest harvesting due to the frequent load shedding experienced in Zimbabwe.

5. Conclusions

Hurungwe is experiencing significant forest cover loss due to LULC changes occurring in the district. The major drivers of forest cover loss are primarily socioeconomic, specifically tobacco farming, cropland expansion, and settlement development. Natural factors such as veld fires and changing climatic conditions are also driving forest cover loss in the Hurungwe district. Policy intervention such as the Fast-Track Land Reform and Resettlement Programme (FTLRP) implemented during the 2000/1 season is one of the primary drivers of forest cover loss and LULCC in most local contexts in Zimbabwe. The implementation of FTLRP changed the landscape dynamics of Zimbabwe. This land ownership transfer, accompanied by the redistribution act, accelerated the clearing of large areas of forests for different farm-related activities amongst tobacco curing, brick making, domestic use, and settlement. Forests have been lost persistently throughout the study period. This is negative feedback since the country is working towards reducing carbon emissions. Forest management through REDD+ programs is one way Zimbabwe can reduce atmospheric carbon through carbon sequestration by vegetation. Hurungwe district forests risk clearance if the current socioeconomic development activities contradict the country's climate change mitigation policies, particularly policies to reduce carbon emissions and forest conservation. Without robust environmental control legislation and substantial financial support for its enforcement, the goal of reducing tobacco-related deforestation will remain elusive.

Therefore, this study argues that the success of socioeconomic and ecological regulations in the study area and country-level context fundamentally depends on governments' capacities to coordinate and integrate socioeconomic and ecological policy regulations. Enforcement of forest conservation and recovery projects in Zimbabwe, including growing eucalyptus plantations for tobacco curing, promotion of clean energy alternatives, new barn technology, and production of alternative crops with similar financial returns to tobacco farming, could be an essential catalyst between tobacco farming and forest sustainability reform objectives and reform results. The study illustrates the critical importance of country-level efforts to ensure policy coherence amongst its different government sectors consistent with global environmental and tobacco control measures.

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Avoid the stilted expression, "One of us (R. B. G.) thanks..." Instead, try "R. B. G.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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