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ASSESSMENT OF LAND COVER CHANGE ANALYSIS IN CHIKWAWA DISTRICT, MALAWI USING CA-MARKOV CHAIN MODEL

By J.Khendlo, R.Beeharry and R.Goodary

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ABSTRACT

Chikwawa District has experienced significant urban development, agricultural expansion, and population growth over the years. The study analysed Landsat Satellite images from 1979, 1995, 2009, and 2023 to assess land use and land cover changes. The CA-Markov chain model, a spatially explicit model that integrates cellular automata and Markov chains, was applied to predict future LULC scenarios for 2035, 2045, and 2065. The Spearman rank correlation coefficient (ρ) was used to assess the statistical significance of changes in land cover classes. The results show that the Random Forest classification method yielded the highest accuracy, with Kappa values of 85%, 86%, 86%, and 90%, and overall accuracy of 88%, 90%, 90%, and 93% for the years 1979, 1995, 2009, and 2023, respectively. Over a 44-year period, land cover changes revealed a 21% decrease in forest, 3% in vegetation, and 0.3% in water bodies, while built-up areas and bare land increased by 22% and 16%. Predicted future changes indicate further decreases in forest cover (-28.6%, -33.8%, and -51%), vegetation (-12.9%, -19.8%, and -24.7%), and water (-28.2%, -12.3%, and -14%), with increases in built-up areas (+23.2%, +22.2%, and +22.8%) and bare land (+13%, +15.3%, and +37.1%) for the periods 2035-2023, 2045-2035, and 2065-2045, respectively. The CA-Markov model validated the predictive results, demonstrating a good too perfect agreement with the actual data for the years 2009, 2011, and 2023. The decline in vegetation and water bodies exacerbates the potential for environmental degradation, which could lead to greater vulnerability to climate change impacts, such as floods and droughts. This underscores the necessity for policy interventions to regulate land conversion, promote sustainable agricultural practices, and implement effective land-use planning frameworks.

KEY WORDS CA-Markova Chain model, GIS, Land Use Land Cover, Random Forest , Remote sensing

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1. INTRODUCTION

Climate change, biodiversity loss, and environmental degradation are a few of the unprecedented, cascading, and interconnected socio-economic and environmental issues facing the world today (Grima, 2020). In recent studies, the ongoing global loss of biodiversity has been described as “biological annihilation.” The primary drivers of terrestrial biodiversity decline are detrimental changes in land use and land management (Christian, 2023). Over the past 300 years, land use activities, primarily agricultural expansion and timber extraction, have led to a net loss of 11 million square kilometres of forest worldwide (Christian, 2023; Cabernard, Pfister and Hellweg, 2024). According to a FAO report, 2022 an estimated 289 million hectares of forests will be deforested by 2050. Deforestation is the intentional clearing out of forests and trees. It plays a significant role in global warming and subsequent shifts in climate patterns, as a substantial amount of the carbon stored in trees is released into the atmosphere as carbon dioxide during deforestation, thereby contributing to climate change.

According to a report by DGB Group (2023), approximately four million hectares of African forests, primarily located in Zambia, Angola, Tanzania, and the Democratic Republic of Congo, are deforested annually due to unsustainable logging practices, agricultural expansion, grazing activities, and settlement establishment (Solomon, 2023). Within local ecosystems, forests play a crucial role in hydrological regulation by acting as natural sponges that absorb rainfall from tropical storms, thereby stabilizing soil conditions and gradually releasing water. However, deforestation disrupts this function, leading to increased surface runoff, elevated river levels, and heightened flood risks for downstream communities, urban areas, and agricultural lands. Additionally, deforested regions experience prolonged droughts, which adversely affect river navigation, agricultural productivity, and industrial operations during dry seasons (Seth et al., 2023).

Between 2001 and 2023, Malawi experienced a substantial decline in forest cover, losing approximately 224,000 hectares, equivalent to a 15% reduction in its total tree cover. This deforestation resulted in an estimated emission of 94.0 metric tons of CO_2 (Skole et al., 2021) . The Malawian economy is heavily dependent on agriculture and related sectors such as forestry and fisheries, making the nation particularly vulnerable to climate change. The reliance on rain-fed agriculture, coupled with exposure to both flooding and droughts, exacerbates this vulnerability (Pizzorni, Innocenti and Tollin, 2024). Furthermore, approximately 85% of Malawi’s population resides in rural and marginalised areas, with nearly 80% directly dependent on natural resources for subsistence, household income, and overall livelihoods. This heavy reliance on natural ecosystems exerts considerable pressure on land, forests, and water resources, accelerating environmental degradation and contributing to widespread deforestation (Hodgson, 2020) Empirical studies have identified multiple key drivers of deforestation in Malawi, including uncontrolled firewood collection, infrastructure development, agricultural expansion, illegal charcoal production, shifting cultivation, urbanization, high population density, and the extensive use of wood for tobacco curing by both smallholder farmers and large-scale estate owners (Lencucha et al., 2020). The exacerbation of wood energy demand is further compounded by the limited access to electricity, with only 6% of the urban population and a mere 2% of the predominantly rural populace having access to expensive and rationed power supply, thereby perpetuating unsustainable reliance on biomass energy sources (Agoundedemba, Kim and Kim, 2023).

To address challenges related to land use and land cover (LULC) changes, several international organizations, including the Food and Agriculture Organization (FAO), Global Land Cover Facility, Living Atlas, Esri World Land Cover, and NASA USGS, have developed advanced LULC mapping tools and datasets with global, national, and regional coverage (Zhang and Li, 2022; Wang et al., 2023). While these datasets serve as valuable resources, their applicability at the local level is often constrained by methodological inconsistencies, variations in spatial and temporal resolution, and discrepancies in geographic reference systems (Liu et al., 2024). Consequently, localised assessments of LULC dynamics are crucial, as they provide precise insights into land use trends, rates of change, and the underlying socio-economic and environmental drivers influencing these transformations. This study aims to bridge this critical gap by conducting a localised, high-resolution assessment of LULC changes in Malawi, focusing on the spatial and temporal dynamics of deforestation and its associated socio-economic drivers. By integrating advanced geospatial techniques, remote sensing analysis, and community-based environmental assessments, this research seeks to provide precise, policy-relevant insights into land cover transformations. The study’s findings will be instrumental in informing evidence-based policy decisions, supporting sustainable land management strategies, and strengthening climate adaptation frameworks at both local and national levels. Furthermore, by generating a more nuanced understanding of deforestation patterns and their underlying causes, this research will contribute to broader global efforts aimed at mitigating climate change, conserving biodiversity, and promoting sustainable development (Xie et al., 2023).

1.1. Literature review

Recent studies have extensively analysed spatiotemporal land-use/land-cover (LULC) changes and their environmental impacts using various modelling approaches. (Wang *et al.*, 2022)the competition for space in land-use conversion is getting fierce. The Wuhan metropolitan area, as one of the main areas of modern agriculture and manufacturing, has been significantly affected by urbanization, industrialization, and national development policies, resulting in regional man-land contradiction. In this complex region, scientifically measuring the land-use/land-cover (LULC employed a logistic-MCE-CA-Markov model and GIS to assess LULC dynamics in Wuhan, China, from 1990 to 2015, identifying a decline in arable land and woodland due to urban expansion, with projections for 2015–2025 indicating increased landscape fragmentation. Similarly, Abbas *et al.*, (2021) a CA-ANN model was used in QGIS to examine LULC changes in the Greater Bay Area, China, from 1980 to 2020. Their findings revealed rapid urban expansion, increasing built-up areas from 4.75% to 14.75% at the expense of cropland, grassland, and forests, with projections (2030–2050) indicating continued urban growth and further land cover alterations. Yang *et al.*, (2024) investigated LULC dynamics in the Loess Plateau, China, utilising transfer matrix analysis, land use dynamics, and geodetector techniques. Their study revealed significant declines in cropland, grassland, and bare land, coupled with an increase in woodland and built-up land, particularly after 2000. Human activities were the primary drivers of change in southeastern agricultural areas, while reforestation policies played a crucial role in the central region, and vegetation responses were strongly influenced by temperature and precipitation in arid northwestern areas. Meanwhile, Jiang *et al.*, (2020)we conducted a quantitative analysis of urban growth on the impact on precipitation in Shanghai, China. We considered four periods of LULC data in 1979, 1990, 2000 and 2010, in addition to the long-term (1979–2010 analysed LULC changes and precipitation trends in Shanghai from 1979 to 2010, demonstrating a strong correlation between urban expansion and increased annual and extreme precipitation in core urban areas, while outskirt and suburban regions experienced declining precipitation trends.

In Kathmandu District, Nepal Wang *et al.*, (2020) , a study on land use and land cover change over a period of 20 years, reveals that the district lost 9.8% of its forest, 9.80% of its agricultural land and 77% of its water bodies due to land cover changes. Gedefaw *et al.*, (2020) A study on land cover change detection in Gozamin, Ethiopia, reveals a decline in cropland, grassland and bare land by 10.5%, 5.7% and 2.49% respectively. On the other hand, forest, built-up area, shrubs/vegetation and water bodies expanded by 13.4%expanded by 13.4%4.09%, 0.98% and 0.25% respectively. Ackom, Adjei and Odai, (2020) A study in Ghana revealed a decline in the open forest, bare land and closed forest areas due to the increase in urban expansion.

Studies on Land Use and Land Cover (LULC) dynamics (Olorunfemi *et al.*, 2020; Tsegaye, 2021; Sameer and Hamid, 2023; Seyam, Haque and Rahman, 2023)and it can undermine environmental health as well. Therefore, this study was aimed at understanding land use and land cover change in Kersa district over the last 30 years. Time-series satellite images that included Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS, which covered the time frame between (1990-2020 have documented a significant transformation in land use patterns, often with adverse environmental and socio-economic consequences. The expansion of commercial agriculture, both large- and small-scale, alongside urbanisation and extractive activities, has been identified as a major driver of LULC changes (Seyam, Haque and Rahman, 2023). These transformations are typically characterized by the conversion of forests, wetlands, and other ecologically significant landscapes into agricultural fields, urban settlements, and industrial zones, leading to habitat fragmentation, biodiversity loss, and climate-related vulnerabilities.

Studies like these and others (Li et al., 2020; Nguyen et al., 2020; Rana and Venkata Suryanarayana, 2020; Sarker, 2021) indicate a significant increase in land-use conversion, often with profound environmental and socio-economic consequences. The expansion of commercial agriculture—both large- and small-scale—along with rapid urbanization and extractive activities, has emerged as a primary driver of LULC transformations (Bonye, Aasoglenang and Yiridomoh, 2021). Researchers have employed unsupervised classification methods, such as Iterative Self-Organising Data Analysis (Lemenkova, 2021 Vimala, 2020; Lemenkova, 2021), and supervised classification methods, including the Maximum Likelihood Classifier (Abbas and Jaber, 2020; Basheer et al., 2022), support Vector machine learning classifier (Tamirat, Argaw and Tekalign, 2023; Xie et al., 2023) and Random forest classifier (Amini et al., 2022; Shih et al., 2022; Svoboda et al., 2022). These methods, among others, have demonstrated varying degrees of accuracy in LULC classification, contributing to a more precise assessment of land-use dynamics. They facilitate the quantification of land-use change rates and support the development of predictive models for future LULC scenarios. Through advanced model analysis and spatial simulations, key driving factors influencing LULC transformations can be identified, enabling more reliable projections of future land-use patterns. Such predictive capabilities are essential for informing sustainable land management strategies, mitigating environmental degradation, and guiding policy interventions aimed at balancing development and ecological conservation (Khawaldah et l., 2020).

Several predictive approaches have been employed in Land Use and Land Cover (LULC) studies to analyse spatial-temporal changes and predict future trends. These include Cellular Automata (CA) models (Nguyen *et al.*, 2020; Khawaldah *et al.,* 2020; Shih *et al.*, 2022; Akdeniz *et al.,* 2023)2015, and 2018 was employed to analyze and predict the spatial distributions of LULC categories. The Random Forest (RF, Artificial Neural Networks (Chambers *et al.*, 2023), Bayesian Networks (Nascimento *et al.*,

2020) and Logistic Regression Models (Pradana *at al.,* 2023)a multivariable method for modeling the relationship between multiple independent variables and a categorical dependent variable, and 2. Each of these models exhibits distinct methodological strengths and limitations, influencing their performance in simulating land-use dynamics and forecasting LULC transitions (Tessema *et al.,* 2020; Lukas *et al.,* 2023)the land use and land cover change and its impacts are revealing on different natural resource and man-made systems. This study attempted to examine the land use and land cover (LULC.

While several LULC studies have been conducted in specific regions of Malawi (e.g. Munthali *et al.*, 2020; Djenontin *et al.,* 2022; Nyirenda, 2022; Pangapanga-Phiri *et al.*, 2022; Nazombe and Nambazo, 2023)animal feed and fuel. Rising incomes lead to dietary changes, from staple crops, towards commodities with greater land requirements, e.g. meat and dairy products. Despite yield improvements partially offsetting increases in demand, agricultural land has still been expanding, causing potential harm to ecosystems, e.g. through deforestation. We use country-level panel data (1961-2011, comprehensive assessments of LULC changes in the study area remain limited.

This study employed four distinct image classification methods and systematically evaluated their accuracies to identify the most optimal approach for Land Use and Land Cover (LULC) classification. Additionally, the Cellular Automata (CA)-Markov chain model was applied to simulate and predict future LULC scenarios. The integration of the CA-Markov model in LULC change prediction offers several advantages, primarily due to its robust spatial simulation capabilities and ability to effectively capture transition probabilities between land use classes. This model is particularly advantageous for analysing spatial data, enabling efficient detection of land cover transitions while providing a structured framework for forecasting future landscape dynamics with enhanced precision (Nguyen *et al.*, 2020; Ait *et al.,* 2023). The robustness of the CA-Markov Model over other simulation models was the reason why the model was used for this study.

1.2. Study objectives

The study was guided by the following objectives:

- To analyze historical land use and land cover (LULC) changes in the study area from 1979 to 2023 using geospatial techniques.
- To develop an updated and accurate land cover map of the district for current spatial planning and management.
- To model and predict future land use and land cover dynamics using the CA-Markov Chain model.

2. MATERIALS AND METHODS

2.1. Area of study

Chikwawa District is situated in Malawi's southern area, a nation in Sub-Saharan Africa. Its northern, eastern, southern, and western boundaries are shared by the districts of Mwanza, Blantyre, Thyolo, Nsanje, and the international border of Mozambique. Geographically speaking, it is located at 16 10 and 34 45. The district is located along the Shire River's flat basin, which is along the Great Africa Rift Valley's meandering course. (GoM, 2022). The district covers an area of 4892 km2. The entire region experiences tropical weather, with wet and dry seasons. The inter-Tropical convergence zone oscillations, which greatly influence the district's climate, are where the zonal Congo air mass, the meridian south-eastern trade winds, and the monsoonal north-eastern winds connect. The Lengwe, Majete, and Elephant Marsh national parks make up the majority of the district's forest cover, which is split into two groups by the district's terrestrial ecology (GoM, 2020). The district encounters unpredictable and diverse precipitation patterns, ranging from a minimum of 96.7mm to a maximum of 170mm. It is inhabited by a population of 564,684 individuals, resulting in a density of 116 persons per square kilometre, and most of the residents rely on agriculture for their livelihoods(NSO, 2018).

This study focuses on assessing land use and land cover (LULC) changes in Chikwawa District, including historical trends, current dynamics, and future projections. The choice of 1979 as the base year is justified by the availability of reliable satellite imagery (Landsat MSS), which provides a consistent and comparable historical baseline for analysing LULC changes over more than four decades. This long-term perspective is critical for identifying gradual transformations in land use patterns driven by demographic growth, agricultural expansion, and policy interventions. The projection years of 2035, 2045, and 2065 were selected to align with medium- and long-term planning horizons relevant for policy and development. The year 2035 corresponds to near-term targets for Malawi's national development strategies and global sustainable development goals (SDGs). The year 2045 provides a medium-term outlook, useful for assessing the impacts of demographic pressures, agricultural demands, and climate change adaptation efforts. Finally, the year 2065 allows for a long-term scenario analysis, offering insights into the cumulative impacts of current land use practices and enabling the design of forward-looking strategies for sustainable land management, biodiversity conservation, and climate resilience.

By combining historical analysis with future projections, the study scope provides a comprehensive understanding of LULC dynamics in Chikwawa, thereby informing both immediate interventions and long-term planning for sustainable development

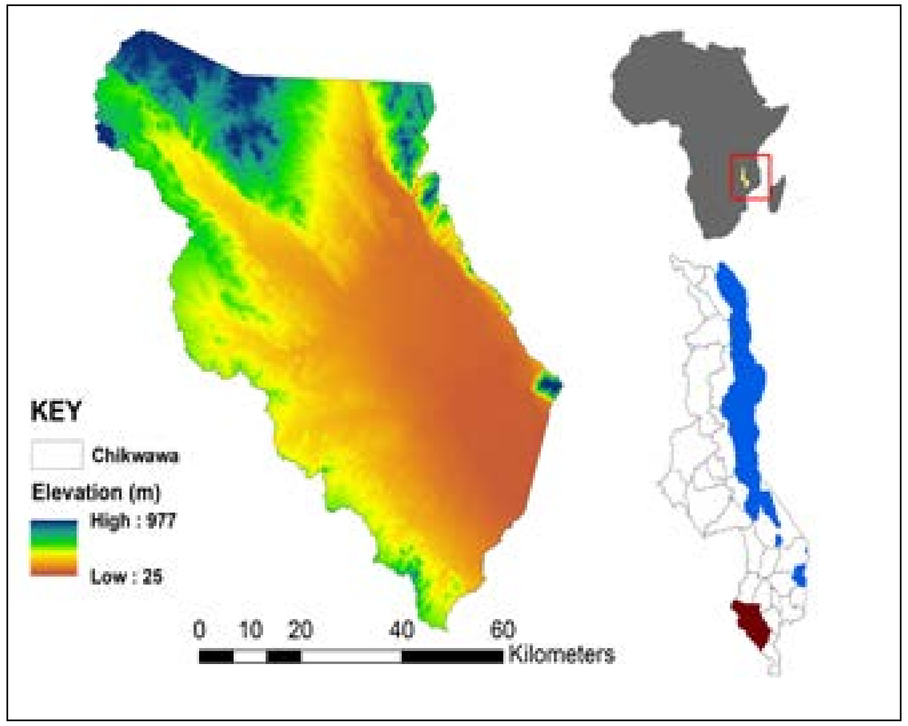


Figure 1. Study Area (Source: Author)

2.2. Data sources and Image processing

Remotely sensed Landsat OLS/TM/ETM+ spectral data are frequently used for regional-scale LULC classification due to their relatively low cost, long historical record, and high archival frequency (Potapov et al., 2022). Landsat images were acquired during the dry season (between September and November) for the years 1979, 1995, 2009, and 2023 in order to fully comprehend the long-term changes in land cover throughout time. Landsat 3 (MSS), Landsat 5 (TM), Landsat 7 (ETM+) and Landsat 8 (OLI &TIRS), which were downloaded from EarthExplorer (usgs.gov). All downloaded images had a cloud cover of less than 9% to prevent cloud obstruction of land surface features. Table 1 below provides the details of the acquired images and the spectral resolution of each band within the images.

They were then resampled to a uniform spatial grid with a 10-meter resolution using the nearest neighbour technique to mitigate distortions caused by sensor misalignment and variations in satellite altitude. The root-mean-square errors for both image resampling and re-projection were determined to be less than 0.5 pixels, ensuring high geometric accuracy. Furthermore, a composite multispectral band image was generated using the spatial analysis tools in ArcGIS, integrating multiple spectral bands for enhanced analytical capabilities. To ensure precise geometric alignment of the images, a basic edge detection method was employed for image registration. Furthermore, the Geo-processing clipping tool was employed to extract satellite images within the boundary of the study area.

During the classification process, each classification method utilized 1000 training samples and 560 test data sets. A training sample is a region that has been classified according to a specific classification scheme (ESRI, 2022). Some studies (Ge et al., 2020 ;Liu, 2022) have indicated that the size of the training sample for each class should be 10 to 30 times larger than the total number of bands in the image. The land cover classes categories were based on (FAO, 2016) classification, namely: Water, Vegetation, Built up, Bare land and Forest as stipulated in Table 1. The analysis process has been summarised in the flow chart in Figure 2.

Table 1: Table 1: Land cover classification Source: FAO, 2016)

Land cover type	Description of each Land cover type
Forest	Natural forest and plantation area with mainly planted eucalyptus trees. Areas covered by trees (eucalyptus) forming closed or nearly closed canopies; forest; plantation forest; dense (50%-80% crown cover) predominant species like Juniperus procera

Land cover type	Description of each Land cover type
Vegetation	Land covered with natural grass and cropland, or dominated by grass, includes areas used for communal grazing as well as bare land that is seasonally grass-covered
Built-up area	Areas are mainly scattered rural settlements and rural institutions such as schools and clinics.
Bare land	Areas of land which are not covered by any type of vegetation due to erosion, overgrazing and cultivation. Areas without any vegetation due to either erosion or mismanagement (especially overgrazing); also covered by bare soil and exposed rocks.
Water bodies	Permanent rivers and freshwater (rivers, streams, intermittent ponds and canals). It also includes wetlands, which dry up during the dry season.

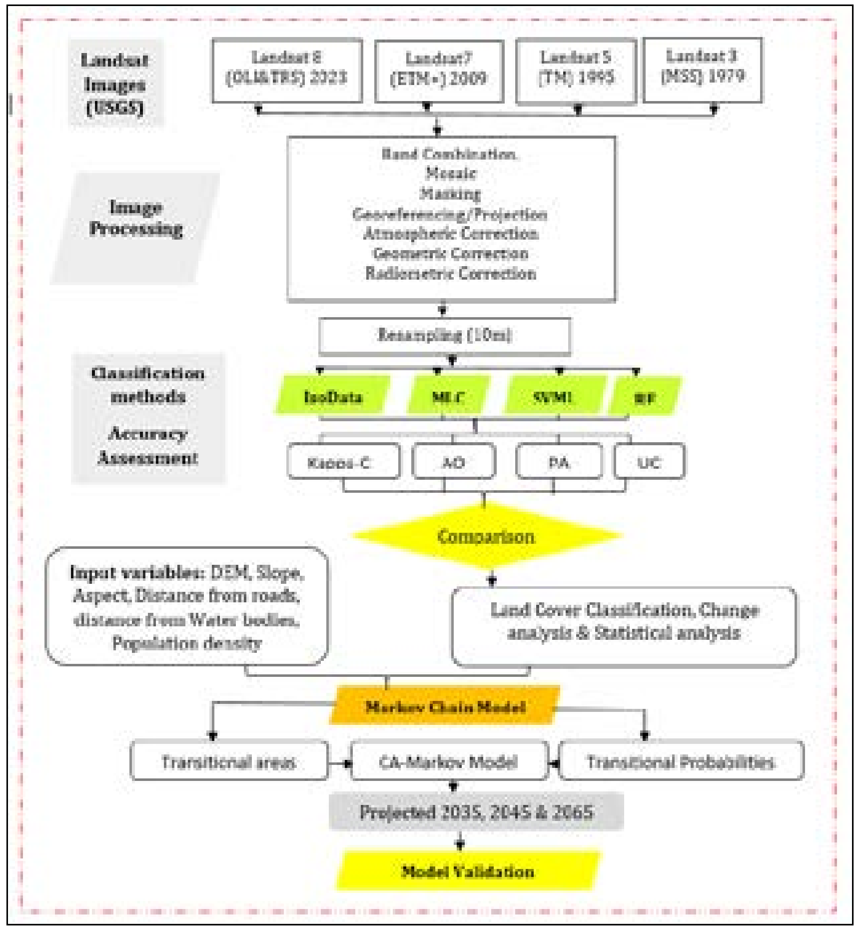


Figure 2. Research conceptual framework (Source:Author)

Table 2. Landsat images and explanatory variables

Satellite	Sensor	Acquisition date	Path	Row	Bands	Spatial resolution	Data Source
Landsat 8	OLI & TIRS	2022/11/29	167/167/168	071/072/071	Visible (B2, B3, B4) ; NIR (B 5);SWIR (B 6, B7), Thermal (B10, B11) Panchromatic (8)	30m 30m;100m 15m	USGS
Landsat 7	Enhanced Thematic Mapper (ETM+)	2009/11/04	168/168/167	072/071/071	Visible (B1, B2, B3); NIR (B4); SWIR (B5, B7); Thermal (B6); Panchromatic	30m 30m;60m 15m	USGS
Landsat 5	Thematic Mapper (TM)	1995/11/23	162/168/167	072/071/071	Visible (B1, B2, B3); NIR (B4);SWIR (B5, B7)	30m 30m; 60m	USGS
Landsat 3	Multispectral scanner (MSS)	1979/08/30	180/179/179	071/071/072	Visible (B4, B5); NIR (B6, B7)	80m	USGS

(Source: Author)

2.3. Assessing LULC classification methods

The study evaluated the accuracy of both supervised and unsupervised classification methods using the kappa coefficient, producer accuracy, user accuracy, and overall accuracy. Several factors can influence the accuracy of image classification, including the type of sensor, the quality of training and validation data, the number of land cover classes, and the chosen classification method. Selecting an appropriate algorithm is essential to achieving an optimal balance between classification accuracy and computational efficiency (Houng Thi Thanh Nguyen et al., 2020). To compare the accuracy of image classification results, four classification methods were employed, including one Iterative Self-Organising Data Analysis (ISODATA) unsupervised classification method (Lemenkova, 2021; Vimala, 2020; Lemenkova, 2021) and three supervised classifications namely Maximum likelihood classifier (Feudjio et al., 2023; Tamirat, Argaw and Tekalign, 2023; Chen et al., 2025), support Vector machine learning classifier (Tamirat, Argaw and Tekalign, 2023) and Random forest classifier (Amini et al., 2022; Shih et al., 2022; Svoboda et al., 2022). The assessment was done using Kappa-coefficient, over all accuracy, producer accuracy and User accuracy (Islami et al., 2022; Nicolau, Dyson and Saah, 2024).

2.4. Accuracy assessment

The kappa coefficient is calculated as;

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i + x_{x+1})}{N^2 - \sum_{i=1}^{r}(x_{ii} X x_{+1})}$$

(1)

where N = total number of observations, r = number of rows and columns in the error matrix (pixels)

X_{ii} =observation in row I and column 1,

Xi+ = marginal total of row *i*, and X+i= marginal total of column i

A Kappa Coefficient of 1 denotes perfect agreement, whereas a value close to zero suggests that the agreement is only somewhat better than would be expected by chance (Version and Raadt, 2020).

The overall accuracy is given as;

$$OA = \frac{\sum_{i=1}^{n} S_i \sum_{j=1}^{k} \alpha_{ij}\beta_{ij}}{\sum_{i=1}^{n} S_i}$$

(2)

where k is the number of classes and n is the total number of segments, α_(ij) is 1 if the reference label for segment i is j and 0 otherwise, β_ij is 1 if the map label of segment i is j true classification of segment i is indicated by $\sum_{j=1}^{k} \alpha_{ij}\beta_{ij} = 1$, where the reference and map classes for segment I are equal. For area-based metrics, Si is the area of segment i, for count-based metrics, Si is 1 (Brinkhoff et al., 2020).

The producer's accuracy provides the likelihood that a class *j* object will be accurately classified, and it is represented as;

$$OA = \frac{\sum_{i=1}^{n} S_i \sum_{j=1}^{k} \alpha_{ij}\beta_{ij}}{\sum_{i=1}^{n} S_i}$$

(3)

The user's accuracy determines the possibility that an object actually belongs to class j, which is expressed as;

$$OA = \frac{\sum_{i=1}^{n} S_i \sum_{j=1}^{k} \alpha_{ij}\beta_{ij}}{\sum_{i=1}^{n} S_i}$$

(4)

2.5. Predicting future land dynamics.

2.5.1. CA-MARKOVA CHAIN MODEL

Cellular Automata (CA)-based models are a type of Spatially Explicit Model (SEM) that operate on the principle that the future state of a land cover type is influenced by historical local interactions among various land cover classes (Saganeiti *et al.*, 2020).The CA-Markov model integrates the spatial dependencies of cellular automata with the temporal dependencies of the Markov model by combining the transition rules of CA with the transition probabilities of the Markov process (Asif *et al.*, 2023). This approach quantifies land cover changes using transition matrices and spatially distributes these changes based on the computed probabilities. The Markov process models temporal dynamics by estimating transition probabilities between different land cover states over discrete time steps, while spatial dynamics are governed by CA rules, which consider either neighbourhood configurations or transition probabilities (Ouadif *et al.,* 2023). The Markov chain, a stochastic model for predicting categorical changes, calculates the likelihood of transitions between two time steps (Hasan and El, 2025). As a discrete, random process in both time and state, it enables the forecasting of land use change trends. The simulation framework primarily generates a probability transition matrix and a land use area transfer matrix to model these dynamics (Merhej, Ali and Thabeet, 2022). The prediction of land use changes is mathematically formulated in Equation (5).

$$S(t, t+1) = Pij \times S(t)$$

(5)

Pij is the transition probability matrix in a state, which is determined as, where S(t) is the system status at the time of t, S(t+1) is the system status, the s at the time of t+1, and is calculated as;

$$P = ||P_{ij}|| = \begin{Vmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,N} \\ P_{2,1} & P_{2,2} & \dots & P_{2,N} \\ \dots & \dots & & \dots \\ P_{N,1} & P_{N,2} & \dots & P_{N,N} \end{Vmatrix}$$

(6)

$$\sum_{j=1}^{n} P_{ij} = 1 \quad (7)$$

$$(0 \le P_{ij} \le 1) \quad (8)$$

Where P is the probability of a transition, *Pij* is the likelihood that the current state *i* will change to state j the next time, and PN is the probability of any state at any time. The likelihood of a low transition will be close to (0), whereas the probability of a high transition will be close to (1).

The acquisition of a primary matrix and a matrix of transition probability is the crucial stage in the Markova model (Pij) (Kumar, Radhakrishnan and Mathew, 2014). Following that, the Markova forest model is given as;

$$P_{(n)} = P_{(n-1)} \qquad P_{ij} = P_{(0)} P_{ij}^{n}$$

(9)

The Markov chain calculates precisely how much land would be expected to change between the most recent data and the anticipated date. The output of this operation is a matrix called a transition probability file, which records the likelihood that each class of land cover change will change over every other class. The study of the two separate dates of LULC images generates transition matrices, a transition area matrix, and a set of conditional probability images using the Markov chain modeling method (Al *et al.*, 2021).

2.5.2. LAND USE CHANGE MODELER (LCM)

The Land Change Modeler (LCM) module in TerrSet is designed to analyze land use and land cover (LULC) changes and project potential future transformations. This model integrates Artificial Neural Networks (ANN), Markov Chain matrices, and transition suitability maps, which are developed through the training of multilayer perceptron (MLP) or logistic regression models (Akdeniz *et al,* 2023) a rapid tourism-related development occurs depending on the investments in tourism, which causes a dramatic land use/land cover (LULC. By utilizing classified images from two distinct time periods, the model generates an initial estimation of land cover changes, providing insights into historical trends and enabling future scenario predictions (Jalayer *et al.*, 2022; Ait *et al.,* 2023)2014, and 2021 to produce LULC maps of the Chalus watershed. In this study, the transition potential maps and the transition probability matrices between LULC types were provided by the support vector machine algorithm and the Markov chain model, respectively, to project the 2021 and 2040 LULC maps. The achieved K-index values that compared the simulated LULC map with the actual LULC map of the year 2021 resulted in a Kstandard = 0.9160, Kno = 0.9379, Klocation = 0.9318, and KlocationStrata = 0.9320, showing good agreement between the actual and simulated LULC map. Analysis of the historical LULC changes depicted that during 2001-2021, the significant increase of agricultural land (14317 ha. (Jalayer et al., 2022; Ait et al., 2023).

2.5.3. SPATIAL VARIABLES

Spatial variables, or driving forces, are factors that influence future land use changes based on their current state (Gharaibeh *et al.*, 2020)spatial, and environmental variables (slope, distance to road, distance to urban centers, distance to commercial, density, elevation, and land fertility. Topographic and distance-based variables have been widely employed in land cover change simulations across various studies (Leta, Demissie and Tränckner, 2021; Classes, Change and Algorithms, 2023). Drawing from previous research, the key spatial variables identified for this study include elevation, slope, aspect, proximity to roads, proximity to water bodies, and population density (Nguyen *et al.*, 2020; Khawaldah *et al.,* 2020; Jalayer *et al.*, 2022; Shih *et al.*, 2022; Ait *et al.,* 2023)2015, and 2018 was employed to analyze and predict the spatial distributions of LULC categories. The Random Forest (RF. The selection of these driving variables was guided by a comprehensive review of existing literature (Al *et al.*, 2021; Leta, Demissie and Tränckner, 2021b) as well as the specific geographical and environmental characteristics of the study region. The selected variables are presented in Figure 3 and Table 3 below.

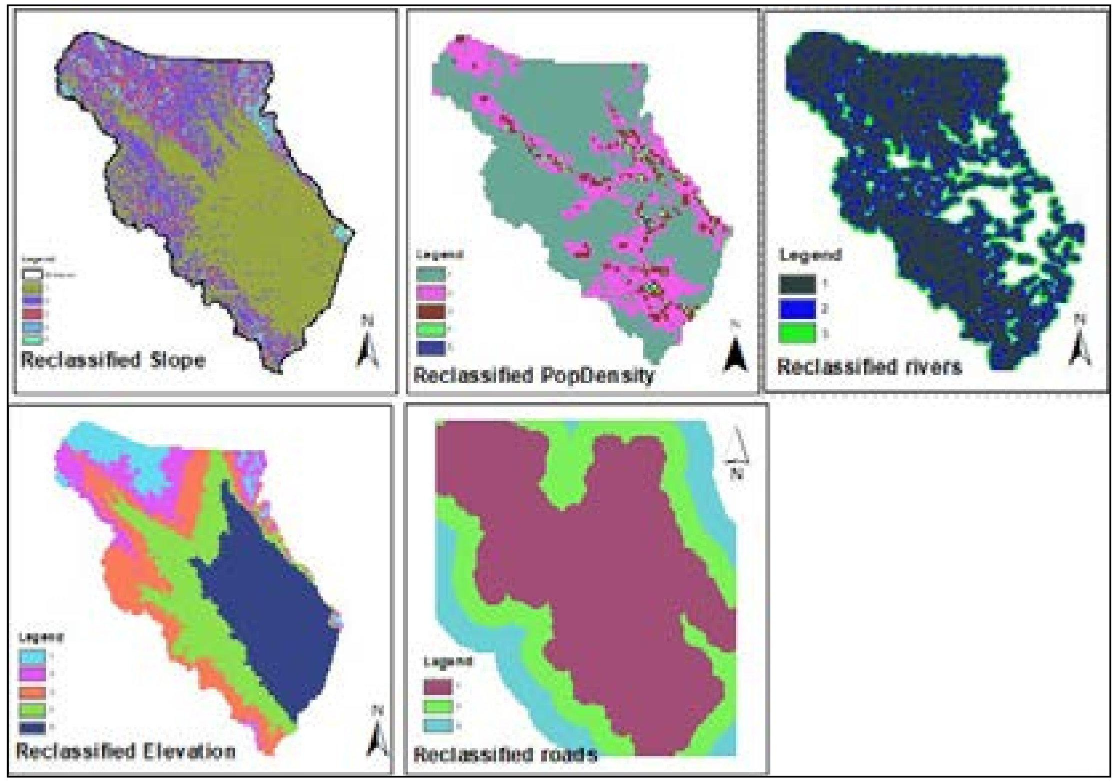


Figure 3: Spatial variables

Tabl e3: Spatial variables

Variable	Effects/influence	Range	Score	Reference
Distance from road (m)	Facilitates access	0-100	5	(Asif et al., 2023)
		100-200	4	
		200-500	3	
		500-1000	2	
		>1000	1	
Distance from Water bodies (m)	Agriculture, settlement patterns	0-25	1	(Supriatna et al., 2022)
		25-50	2	
		>50	3	
Elevation (m)	Temperature Precipitation Vegetation type	0-200	5	(Supriatna et al., 2022)
		200-500	3	
		500-3000	2	
		>3000	1	

Variable	Effects/influence	Range	Score	Reference
Slope (%)	Soil erosion, Water runoff	0-3	4	(Asif et al., 2023)
		3-16	3	
		16-40	2	
		>40	1	
Population density (People/km2)	Affects urban expansion	0-50	1	(Jalayer et al., 2022)
		50-200	3	
		200-500	4	
		>500	5	

(Source:Author)

2.5.4. MODEL VALIDATION

Validation of the model involved calculating the Kappa coefficient, the most commonly used metric for measuring a model's predictive accuracy (Lukas *et al.,* 2023). The Kappa index was computed by comparing the model's simulated images with the reference data (classified maps) for the same date (Ahmad *et al.*, 2023; Ait *et al.,* 2023). The predicted LULC for 1979, 1995, 2009, and 2023 was compared with the classified images from those same years using the validation model in IDRISI Selva Software (Alshari and Gawali, 2022; Avtar *et al.*, 2022; Lukas, Melesse and Kenea, 2023)Fiji, through a combination of remote sensing with a geospatial-based modeling approach. Land use classification was performed using Landsat 7 and Landsat 8 imageries of the years 2000 and 2020; then, cellular automata and artificial neural network (CA-ANN. Kappa values above 0.40 are considered acceptable, and values exceeding 0.75 are regarded as almost perfect agreement.

3. RESULTS

3.1. Land cover

The results of the image classifications for all the years 1979, 1995, 2009 and 2023 using all four classification methods showed varying level of accuracy as shown in Figure 2 below;

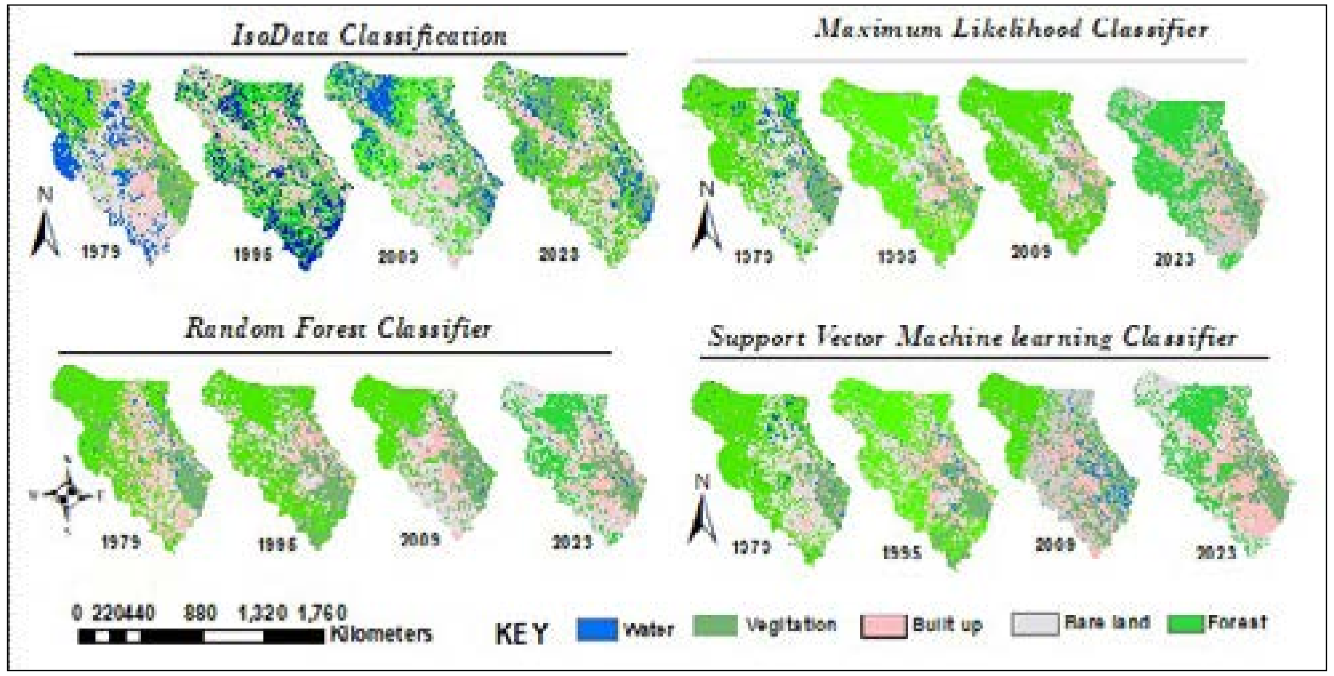


Figure 4: Classified images using IsoData, MLC, SVM and RF for 1979, 1995, 2009 and 2023

3.2. Accuracy assessment of Classification methods

The accuracies of the classification methods were assessed using the Kappa Coefficient, Overall Accuracy, Producer accuracy and User accuracy. The results indicate that Random Forest classification had the highest both Kappa coefficient and overall accuracies value for all the years with 82% in 1979, 86% in 1995, 86% in 2009 and 90% in 2023, and the overall accuracy values were 88% in 1979, 90% in 1995, 90% in 2009 and 93% in 2023. The results also show that Producer and User accuracies for Random Forest classification were within a range of 84% to 96% for all classified images. Random Forest classified images were used for quantifying the changes in land use and land cover, and also for the prediction of future land use. Table 4 and Table 5 below shows the results of the accuracy assessment.

Table 4: Kappa Coefficient and overall accuracy

	Kappa-Coefficient				Overall Accuracy			
	1979	1995	2009	2023	1979	1995	2009	2023
RF	0.88	0.90	0.90	0.93	0.88	0.90	0.90	0.93
SVM	0.87	0.90	0.87	0.92	0.87	0.90	0.87	0.92
MLC	0.76	0.86	0.87	0.89	0.76	0.86	0.87	0.89
IsoData	0.45	0.37	0.45	0.55	0.45	0.37	0.67	0.58

Where RF is Random Forest, SVM is Support vector machine, MLC is Maximum Likelihood Classifier and IsoData is Iterative self-organising data

Table 5: Producer and User accuracy

		1979		1995		2009		2023	
Classification Method	**Land Class**	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)
Random Forest Supervised classification	**Water**	85	82	94	89	86	96	89	97
	Vegetation	81	82	97	85	97	93	97	94
	Built up	87	95	87	94	80	89	88	97
	Bare land	81	86	93	81	91	89	95	92
	Forest	82	98	93	98	97	93	93	94
Support Vector Machine Supervised classification	**Water**	65	64	87	60	65	86	81	87
	Vegetation	54	77	80	67	80	78	86	88
	Built up	68	61	51	74	53	86	87	93
	Bare land	69	70	86	79	95	85	78	82
	Forest	57	80	81	82	98	83	95	87
Maximum likelihood Supervised classification	**Water**	65	14	86	63	92	49	79	82
	Vegetation	65	58	90	66	87	83	78	94
	Built up	54	89	39	72	55	76	58	70
	Bare land	68	78	84	79	87	98	78	83
	Forest	56	87	76	95	98	95	90	81
Iterative Self-organising DATA unsupervised classification	**Water**	27	26	26	10	49	78	57	96
	Bare land	60	48	30	46	80	55	86	54
	Forest	38	57	30	71	74	62	75	89
	Built up	38	64	57	39	67	85	69	82
	Vegetation	52	27	29	20	53	56	76	68

3.3. Quantities for Land cover changes

The results of areas covered by each land class has been summarized in Figure 4 below.

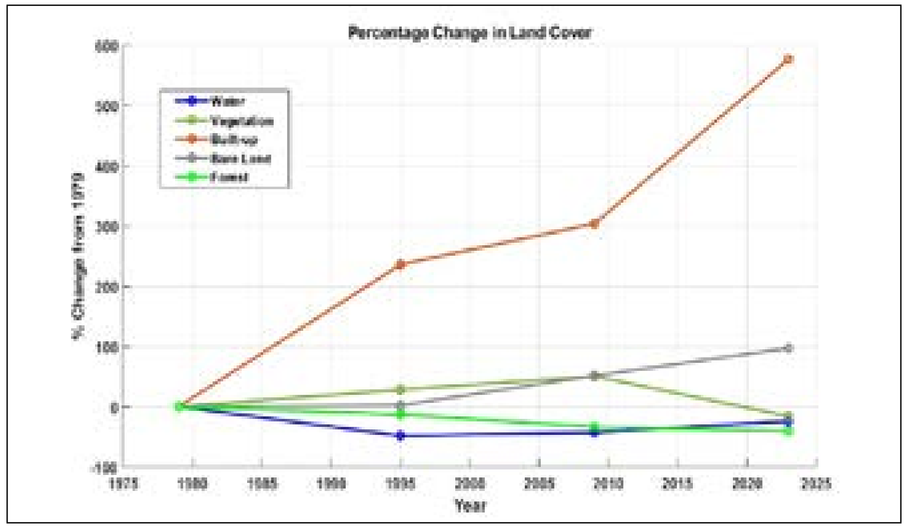


Figure 5: Percentage changes in the Land cover classes

From 1979 to 1995, the forest cover area decreased by 14.28%, water bodies decreased by 0.23%, whereas vegetation, built-up areas and Bare land increased by 4.85%, 9.07%, and 0.86%, respectively. Between 1995 and 2009, forest cover decreased by 13.73%, water bodies decreased by 0.35%, while vegetation, built-up areas, and bare land increased by 3.15%, 2.75%, and 7.90% respectively. Lastly, during the period between 2009 and 2023, forest cover decreased by 4.54%, and vegetation increased by 11.24%, while bare land, water bodies, and built-up areas increased by 5.19%, 0.36%, and 10.44% respectively. The results have been shown in Figure 3 below;

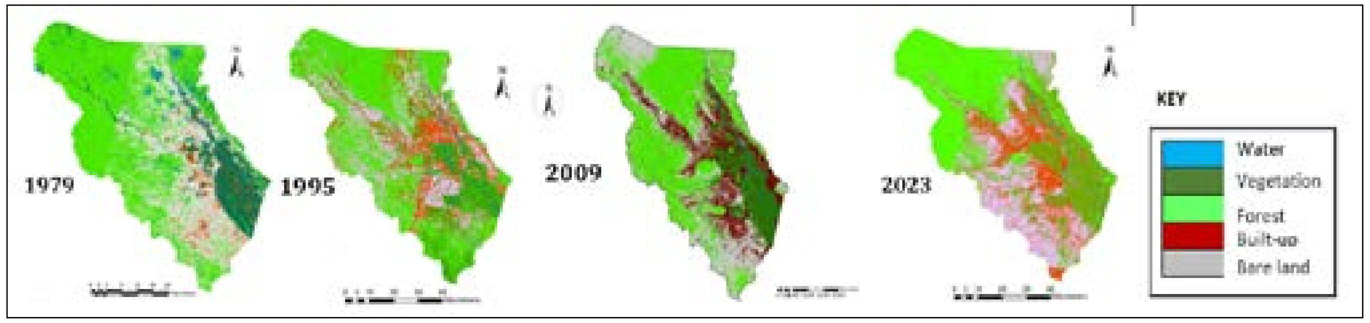


Figure 6: Random Forest Classified images

3.4. Land Cover prediction

3.4.1. ASSESSING SPATIAL VARIABLES ASSOCIATION USING CRAMER'S V

Cramer's V was used to assess whether a particular driver variable is appropriate for predicting changes in land use and land cover (LULC). Cramer's V ranges from 0 to 1. According to (Jin et al., 2013; Karakus et al., 2015), values close to or exceeding 0.4 are deemed suitable for prediction, while values below 0.4 indicate a weak predictive capability for a driver variable. However, Cramer's V does not ensure robust model performance, as it cannot account for the mathematical specifications of the modeling approach or the complexity of the relationships involved (Ghosh et al., 2017; Akdeniz et al., 2023). Cramer's V is used to assess whether a specific driver variable should be included in predicting LULC changes. Cramer's V for the variable is introduced in Table 6 below. The Cramer's V for all variables ranges between 0.75 to 1 and hence all the variables were used in creating sub-models and hence incorporated in the prediction of future land cover classes.

Table 6: Spatial variable association assessment

Variable	Cramer's V	X^2	Degrees of freedom	P-Value
Distance from road	0.736	10.833	8	0.2113
Distance from Water bodies	1	20	4	4.99E-04
Elevation	1	20	4	4.99E-04
Slope	1	20	4	4.99E-04
Population density	1	20	4	4.99E-04

3.4.2. PREDICTED LAND COVER CHANGES

The predicted land cover changes suggest significant environmental and socio-economic challenges for the study area. The decline in water bodies by 28.2% (2035), 12.0% (2045), and 14.0% (2065) could exacerbate water scarcity, affecting both domestic and agricultural water supplies. Given the district's reliance on rain-fed and irrigated farming, reduced water availability may threaten crop yields and livestock farming, leading to food insecurity and economic instability, particularly for smallholder farmers and community's dependent on subsistence agriculture. The predicted vegetation loss of 12.9% (2035), 19.8% (2045), and 24.7% (2065), coupled with a 28.6% (2035), 33.8% (2045), and 51.0% (2065) decline in forest cover, signals severe ecological consequences. Deforestation and vegetation loss will likely result in increased soil erosion, declining soil fertility, and altered microclimatic conditions, all of which pose a direct threat to agricultural productivity. Furthermore, deforestation reduces the district's natural ability to regulate flooding, which is critical given Chikwawa's vulnerability to extreme flood events. The destruction of forests and vegetation may also accelerate desertification, limiting the region's long-term agricultural potential.

The projected expansion of built-up areas by 23.2% (2035), 22.2% (2045), and 22.8% (2065) indicates rapid urbanization, which could lead to increased demand for infrastructure, housing, and services. While urban expansion may provide economic opportunities, it also raises concerns about unplanned settlements, inadequate waste management and increased pressure on existing water and energy resources. The growth of bare land by 13.0% (2035), 15.3% (2045), and 37.1% (2065) is particularly alarming, as it suggests increasing land degradation, which could make the district more prone to droughts and extreme weather conditions. From a tourism perspective, the loss of forests and vegetation, coupled with the decline in water bodies, could negatively impact wildlife habitats, particularly in areas like Majete Wildlife Reserve. Reduced biodiversity and habitat degradation may lower the district's appeal as a tourist destination, potentially affecting revenue streams from eco-tourism.

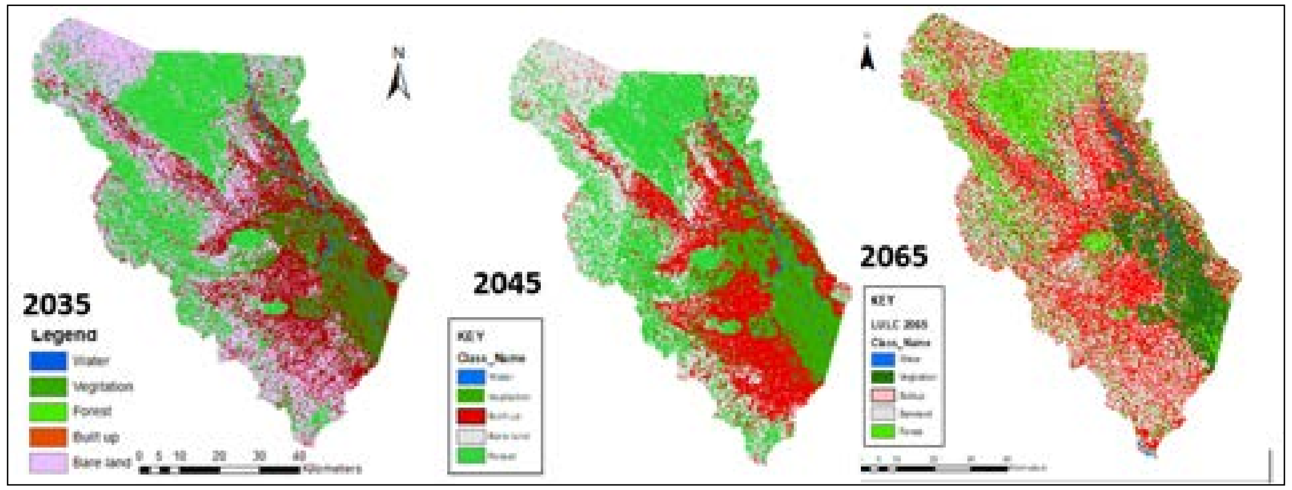


Figure 7: Predicted Land cover classes

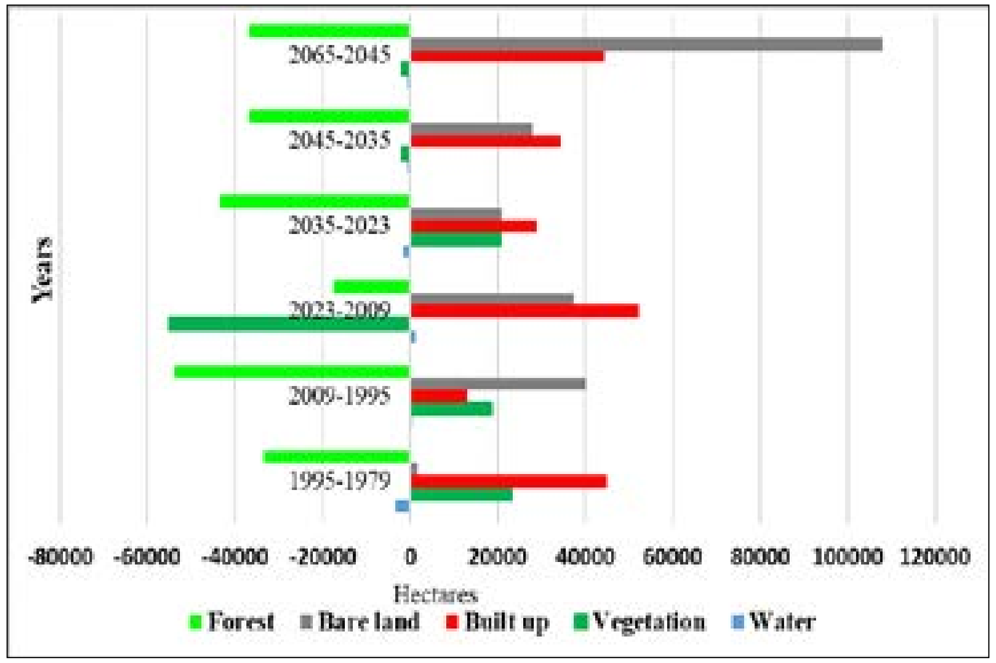


Figure 8: Land cover gain and loss 1979 through 2065

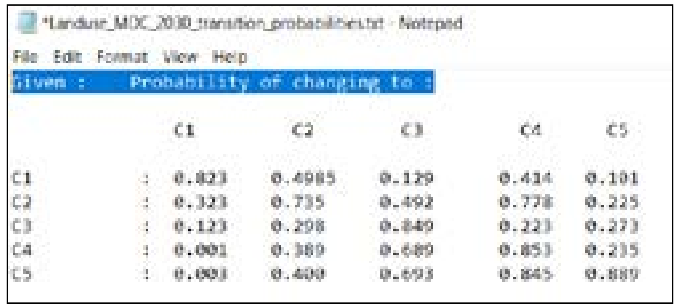
3.4.3. VALIDATION OF CA-MARKOVA MODEL

The CA-Markov model is a widely used spatial modelling approach that integrates Cellular Automata (CA) and Markov Chain analysis to predict future land use and land cover (LULC) changes based on historical trends. The Markov Chain component establishes transition probabilities between different land cover classes over time, while Cellular Automata incorporate spatial interactions and neighbourhood effects, ensuring that transitions follow logical spatial patterns (Gebresellase *et al.*, 2023). This integration enables the model to capture both temporal trends and spatial dependencies, making it an effective tool for simulating complex land use dynamics (Gasirabo *et al.*, 2023).

3.4.4. MODEL PARAMETERS AND IMPLEMENTATION

To assess LULC changes and project future scenarios, the CA-Markov model was applied using historical Landsat satellite imagery from 1979, 1995, 2009, and 2023. The model was configured with key parameters essential for accurate simulation. The Transition Probability Matrix was derived from past land cover changes, quantifying the likelihood of each land class transitioning into another. Additionally, the Transition Area Matrix estimated the expected extent of change for each category.

This matrix displays the probability of land cover changing on a scale from 0 to 1, where 0 indicates that the change is impossible and 1 indicates that the change is certain to occur. The results are displayed in figure 5 below; where C1 is water, C2 is Vegetation, C3 is Built up area, C4 is Bare land and C5 is Forest.


File Edit Format View Help

Given : Probability of changing to :

	C1	C2	C3	C4	C5
C1 :	0.823	0.4985	0.129	0.414	0.101
C2 :	0.323	0.735	0.492	0.778	0.225
C3 :	0.123	0.298	0.849	0.223	0.273
C4 :	0.001	0.389	0.689	0.853	0.235
C5 :	0.003	0.400	0.693	0.845	0.889

Figure 9: Transition Matrix

A 5×5 neighbourhood filter was employed within the Cellular Automata framework, allowing spatial interactions to influence land transitions, ensuring spatial coherence and realistic land use evolution (Long, Zhang and Tu, 2021). Furthermore, constraint factors, such as protected areas and water bodies, were incorporated to restrict certain land conversions, maintaining ecological and regulatory integrity (Sharma *et al.*, 2020).

3.4.5. VALIDATION OF THE CA-MARKOV MODEL

To ensure the robustness of the CA-Markov predictions, model validation was performed using the Kappa Index and the Confusion Matrix, both widely recognized methods for evaluating classification accuracy. The Kappa Index, including its variants (Kno, Klocation, and Kstandard), was employed to measure the level of agreement between observed and predicted LULC maps. The model demonstrated good to perfect agreement, with Kappa values exceeding 80% for the testing years 2009, 2011, and 2023. These high values indicate strong predictive performance and reliability in modelling future land cover scenarios (Atef and Ahmed, 2024).

In addition to the Kappa Index, a Confusion Matrix was used to compare predicted and actual land cover distributions, quantifying classification accuracy and identifying misclassifications. The combination of these validation methods provides a rigorous assessment of the CA-Markov model's reliability (Chen *et al.*, 2025).

Table 8: Accuracy assessment for model validation

Maps used for simulation	Maps used for validation		Degree of compatibility	Kappa Index		
Observed LULC			**Validation of simulation**			
(RF Classified)	Simulated LULC	(RF Classified)	CA-Markova %	Kno	Klocation	Kstandard
1979-1995	2009	2009	83.4	0.79	0.81	0.81
1995-2009	2011	2011	82.7	0.81	0.79	0.82
1979-2009	2023	2023	81.6	0.80	0.84	0.83

Where RF is Random forest classified images, kno is over accuracy (measures overall agreement between the simulated and observed maps), klocation is the Location kappa (measures the agreement considering the location of the changes) and kstandard is the Standardized Kappa (standardized Kappa index that accounts for the chance agreement)

3.5. Trend analysis

The analysis of land cover changes over time reveals significant trends, particularly in forest cover, bare land, built-up areas, vegetation, and water bodies. Spearman's rank correlation coefficient (ρ) was employed to assess the statistical relationships between these land cover classes and time, providing insights into their long-term dynamics.

The results indicate a perfect negative correlation for forest cover (ρ = −1.000, P-Value = 0.0004) with the regression equation *y*=−2663x+5530194.33. This strong inverse relationship confirms a continuous and substantial decline in forest cover over time, aligning with findings from previous studies on deforestation and land degradation in rapidly urbanizing regions (Aguiar *et al.*, 2024). The sharp reduction in forest area is likely attributed to agricultural expansion, urban development, and increasing demand for land resources (United Nations, 2024). Conversely, bare land and built-up areas exhibit perfect positive correlations (ρ = 1.0000, P-Value = 0.0004) with the regression equation *y*=2668x−5228411. Similarly, the built-up area also exhibits a perfect positive correlation (ρ = 1.0000, P-Value = 0.0004) with the regression equation *y*=2571x−5073683, respectively. These results suggest a continuous increase in these land categories over time, consistent with global urbanization trends and land conversion processes(Tuan, 2022). The strong positive correlation highlights rapid infrastructure expansion and land-use change, often driven by population growth and economic activities (Bon *et al.*, 2023). Vegetation cover demonstrates a very weak negative correlation (ρ = -0.1071, P-Value = 0.8397) with the regression equation y=−145.51x+387365, indicating relative stability over time. This weak correlation suggests that while localized fluctuations may occur, the overall vegetation extent has not undergone significant change, possibly due to conservation efforts or natural regeneration in certain areas (Rahman and Chandio, 2023). Water bodies show a strong negative correlation (ρ = -0.7500, P-Value = 0.0663) with the regression equation y=−32.42x+69579, implying a notable decline over time. This trend aligns with research highlighting the impact of climate change, increased water extraction, and land-use alterations on water resources (Kuehn and Longo, 2021).

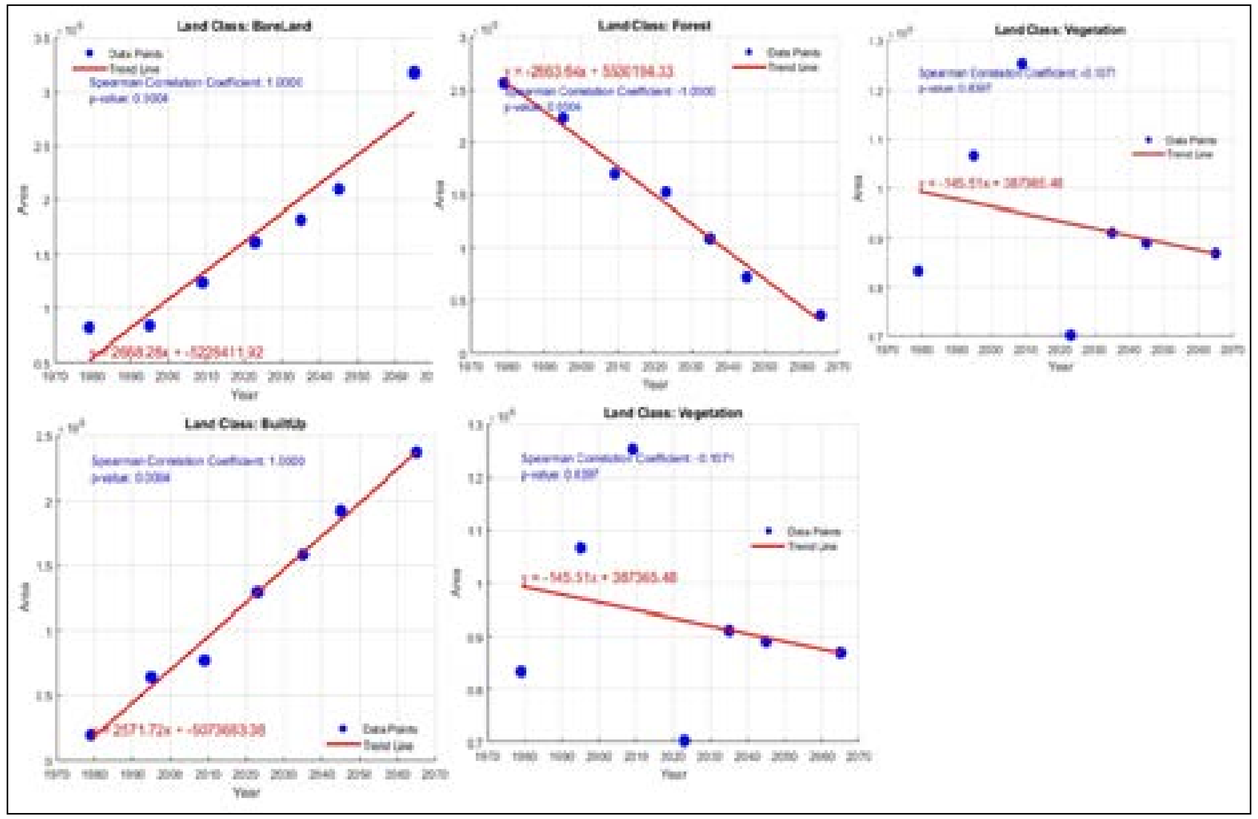


Figure 10: Trend analysis results

4. DISCUSSION

The findings of this study reveal substantial socio-economic and environmental implications of land use and land cover (LULC) changes in Chikwawa District, particularly affecting agriculture, water resources, and tourism. Rapid LULC transformations are driven by population growth, economic activities, and weak policy enforcement. Expanding human settlements and agricultural land conversion have accelerated deforestation, habitat loss, and soil degradation. Subsistence farming, large-scale estates (notably sugarcane), and charcoal production are the principal drivers of environmental change, often exacerbated by poverty and high energy demands. These practices diminish soil fertility, reduce biodiversity, and increase the vulnerability of farmlands to droughts and erratic rainfall patterns (Atef & Ahmed, 2024; Wang & Liu, 2023). Water resources are under growing strain as vegetation loss disrupts hydrological cycles. Forests play a critical role in groundwater recharge and erosion control, but their degradation heightens water scarcity, undermines irrigation, and increases sedimentation in the Shire River. This not only reduces water availability for domestic and agricultural use but also threatens hydropower generation and aquatic ecosystems (Stoutjesdijk, 2022).

Tourism and biodiversity conservation are also significantly affected. Chikwawa hosts Majete and Lengwe National Parks, which serve as ecotourism hubs and sources of local employment. However, continued habitat destruction threatens wildlife populations and undermines tourism revenue. Furthermore, local communities are losing access to wild food sources, worsening food insecurity (Marsh, 2023; GoM, 2020). Overall, the district's heavy reliance on agriculture and natural resources heightens its vulnerability to environmental degradation. The interlinkages between land cover change, agricultural productivity, water resource sustainability, and biodiversity highlight the urgent need for integrated land management and conservation strategies.

5. CONCLUSION

This study underscores that land cover changes in Chikwawa District are driven by demographic pressures, unsustainable agricultural practices, and weak policy enforcement, with profound consequences for agriculture, water resources, tourism, and biodiversity. The findings demonstrate that deforestation and land degradation threaten soil fertility, water availability, and ecosystem services, while simultaneously undermining economic opportunities linked to tourism and ecotourism. If unaddressed, these dynamics will exacerbate food insecurity, water scarcity, and biodiversity loss, further jeopardizing community livelihoods and resilience. It is therefore imperative that land management strategies move beyond short-term interventions toward long-term, integrated, and community-driven solutions. The evidence from this study contributes to the wider discourse on sustainable land use in Sub-Saharan Africa and highlights the importance of balancing environmental conservation with socio-economic development.

6. RECOMMENDATIONS

Based on the findings, several recommendations are proposed to mitigate the negative impacts of land use and land cover (LULC) changes in Chikwawa District. First, reforestation and agroforestry initiatives should be promoted to restore degraded landscapes and enhance ecological resilience. Planting multi-purpose tree species would not only improve soil fertility and reduce erosion but also generate alternative income through timber and non-timber forest products (Sahoo et al., 2020). Second, strengthening community-based natural resource management (CBNRM) is essential to empower local communities in participatory forest management. Experiences from other parts of Sub-Saharan Africa demonstrate that such approaches can enhance biodiversity conservation while diversifying livelihoods (Biswas & Pakhira, 2023). Third, the protection and restoration of riparian buffer zones along major rivers should be prioritized to stabilize banks, reduce sedimentation, and minimize flood risks. Replanting native vegetation in flood-prone areas would further strengthen ecosystem resilience (Calow, Mason & Tanjangco, 2021). Fourth, sustainable urban and agricultural land use planning must be enforced through strict zoning regulations and the integration of green infrastructure in urban areas. Climate-smart agriculture practices such as conservation farming, crop diversification, and precision irrigation should also be promoted to optimize productivity while limiting environmental degradation (Chen & Dong, 2024).

Fifth, there is a need to strengthen policy implementation and enforcement. While Malawi has policies aimed at environmental management, their effectiveness remains limited by weak governance and inadequate funding. Stronger enforcement mechanisms are required to curb illegal deforestation and unsustainable land use practices (GoM, 2020). Finally, future research should focus on examining the socio-economic drivers of land cover change, including land tenure and population dynamics, while also assessing the long-term effects of climate change on land use patterns. Additionally, research should monitor the effectiveness of conservation interventions over time to inform adaptive management strategies.

Authors declaration

The author declares that the is no conflict of interest in the research as any data source has been duly cited

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7. REFERENCES

Abbas, Z. and Jaber, H.S. (2020) 'Accuracy assessment of supervised classification methods for extraction land use maps using remote sensing and GIS techniques', *IOP Conference Series: Materials Science and Engineering*, 745(1). Available at: https://doi.org/10.1088/1757-899X/745/1/012166.

Abbas, Z., Yang, G., Zhong, Y. and Zhao, Y. (2021) 'Spatiotemporal change analysis and future scenario of lulc using the CA-ANN approach: A case study of the greater bay area, China', *Land*, 10(6). Available at: https://doi.org/10.3390/land10060584.

Ackom, E.K., Adjei, K.A. and Odai, S.N. (2020) 'Monitoring land-use and land-cover changes due to extensive urbanization in the Odaw River Basin of Accra, Ghana, 1991–2030', *Modeling Earth Systems and Environment*, 6(2), pp. 1131–1143. Available at: https://doi.org/10.1007/s40808-020-00746-5.

Agoundedemba, M., Kim, C.K. and Kim, H.G. (2023) 'Energy Status in Africa: Challenges, Progress and Sustainable Pathways', *Energies*, 16(23). Available at: https://doi.org/10.3390/en16237708.

Aguiar, D., Pi, J., Rußwurm, M., Hughes, L.H., Lenczner, G., See, L. and Wegner, J.D. (2024) 'Mapping drivers of tropical forest loss with satellite image time series and machine learning OPEN ACCESS Mapping drivers of tropical forest loss with satellite image time series and machine learning'.

Ahmad, H., Abdallah, M., Jose, F., Elzain, H.E., Bhuyan, M.S., Shoemaker, D.J. and Selvam, S. (2023) 'Evaluation and mapping of predicted future land use changes using hybrid models in a coastal area', *Ecological Informatics*, 78(May), p. 102324. Available at: https://doi.org/10.1016/j.ecoinf.2023.102324.

Ait El Haj, F., Ouadif, L. and Akhssas, A. (2023) 'Simulating and predicting future land-use/land cover trends using CA- Markov and LCM models', *Case Studies in Chemical and Environmental Engineering*, 7(March), p. 100342. Available at: https://doi.org/10.1016/j.cscee.2023.100342.

Akdeniz, H.B., Sag, N.S. and Inam, S. (2023) 'Analysis of land use/land cover changes and prediction of future changes with land change modeler: Case of Belek, Turkey', *Environmental Monitoring and Assessment*, 195(1), pp. 1–28. Available at: https://doi.org/10.1007/s10661-022-10746-w.

Al, Abdulla, Huda, N., Subramanyam, G., Faisal, A.-, Uddin, N., Al, Abdullah and Akter, M. (2021) 'Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka , Bangladesh', *Environmental Challenges*, 4(March), p. 100084. Available at: https://doi.org/10.1016/j.envc.2021.100084.

Alencar, A., Shimbo, J.Z., Lenti, F., Marques, C.B., Zimbres, B., Rosa, M., Arruda, V., Castro, I., Ribeiro, J.P.F.M., Varela, V., Alencar, I., Piontekowski, V., Ribeiro, V., Bustamante, M.M.C., Sano, E.E. and Barroso, M. (2020) 'Mapping three decades of changes in the brazilian savanna native vegetation using landsat data processed in the google earth engine platform', *Remote Sensing*, 12(6). Available at: https://doi.org/10.3390/rs12060924.

Alexander, P., Rounsevell, M.D.A., Dislich, C., Dodson, J.R., Engström, K. and Moran, D. (2015) 'Drivers for global agricultural land use change: The nexus of diet, population, yield and bioenergy', *Global Environmental Change*, 35, pp. 138–147. Available at: https://doi.org/10.1016/j.gloenvcha.2015.08.011.

Alshari, E.A. and Gawali, B.W. (2022) 'Modeling Land Use Change in Sana'a City of Yemen with MOLUSCE', *Journal of Sensors*, 2022. Available at: https://doi.org/10.1155/2022/7419031.

Amini, S., Saber, M., Rabiei-Dastjerdi, H. and Homayouni, S. (2022) 'Urban Land Use and Land Cover Change Analysis Using Random Forest Classification of Landsat Time Series', *Remote Sensing*, 14(11), pp. 1–23. Available at: https://doi.org/10.3390/rs14112654.

Asif, M., Kazmi, J.H., Tariq, A., Zhao, N., Guluzade, R., Soufan, W., Almutairi, K.F., Sabagh, A. El and Aslam, M. (2023) 'Modelling of land use and land cover changes and prediction using CA-Markov and Random Forest', *Geocarto International*, 38(1), p. Available at: https://doi.org/10.1080/10106049.2023.2210532.

Atef, I. and Ahmed, W. (2024) 'Future land use land cover changes in El-Fayoum governorate : a simulation study using satellite data and CA-Markov model', *Stochastic Environmental Research and Risk Assessment*, 38(2), pp. 651–664. Available at: https://doi.org/10.1007/s00477-023-02592-0.

Avtar, R., Rinamalo, A.V., Umarhadi, D.A., Gupta, A., Khedher, K.M., Yunus, A.P., Singh, B.P., Kumar, P., Sahu, N. and Sakti, A.D. (2022) 'Land Use Change and Prediction for Valuating Carbon Sequestration in Viti Levu Island, Fiji', *Land*, 11(8). Available at: https://doi.org/10.3390/land11081274.

Basheer, S., Wang, X., Farooque, A.A., Nawaz, R.A., Liu, K., Adekanmbi, T. and Liu, S. (2022) 'Comparison of Land Use Land Cover Classifiers Using Different Satellite Imagery and Machine Learning Techniques', *Remote Sensing*, 14(19), pp. 1–18. Available at: https://doi.org/10.3390/rs14194978.

Batty, M., Wang, S. and Corcoran, J. (2019) 'Modelling urban change with cellular automata : Contemporary issues and future research directions'. Available at: https://doi.org/10.1177/0309132519895305.

Biswas, S. and Pakhira, R. (2023) 'The Role of Agroforestry-Based Farming in Sustainable Agriculture', (November).

Bon, B., Simonneau, C., Denis, E. and Delville, P.L. (2023) 'Ordinary changes in land use linked to urbanisation in the global South Housing , capitalisation , agricultural changes To cite this version : Ordinary changes in land use linked to urbanisation in the global South'.

Bonye, S.Z., Aasoglenang, T.A. and Yiridomoh, G.Y. (2021) 'Urbanization, agricultural land use change and livelihood adaptation strategies in peri-urban Wa, Ghana', *SN Social Sciences*, 1(1). Available at: https://doi.org/10.1007/s43545-020-00017-1.

Brinkhoff, J., Vardanega, J. and Robson, A.J. (2020) 'Land cover classification of nine perennial crops using sentinel-1 and -2 data', *Remote Sensing*, 12(1), pp. 1–26. Available at: https://doi.org/10.3390/rs12010096.

Cabernard, L., Pfister, S. and Hellweg, S. (2024) 'Biodiversity impacts of recent land-use change driven by increases in agri-food imports', *Nature Sustainability*, 7(November). Available at: https://doi.org/10.1038/s41893-024-01433-4.

Calow, R., Mason, N. and Tanjangco, B. (2021) 'Nature-based solutions for flood mitigation Discussion Paper', (March).

Celio, E., Koellner, T. and Grêt-Regamey, A. (2014) 'Modeling land use decisions with Bayesian networks: Spatially explicit analysis of driving forces on land use change', *Environmental Modelling and Software*, 52(February), pp. 222–233. Available at: https://doi.org/10.1016/j.envsoft.2013.10.014.

Chambers, F., Cruz, C., Di, G., Serugendo, M., Chambers, F., Cruz, C., Di, G. and Serugendo, M. (2023) 'Agent-based modelling of urban expansion and land cover change : a prototype for the analysis of commuting patterns in Geneva , Switzerland To cite this version : HAL Id : hal-04146986'.

Chen, M., Samat, N., Javad, M., Tilaki, M. and Duan, L. (2025) 'Land use / cover change simulation research : A system literature review based on bibliometric analyses', *Ecological Indicators*, 170(August 2024), p. 112991. Available at: https://doi.org/10.1016/j.ecolind.2024.112991.

Chen, Z. and Dong, H. (2024) 'Results in Engineering Exploring urban and agricultural land use planning', *Results in Engineering*, 24(July), p. 103093. Available at: https://doi.org/10.1016/j.rineng.2024.103093.

Chikwawa District Council (2020) 'Chikwawa District Physical Development Plan', (August).

Christian, H.-M. (2023) 'The Main Drivers of Biodiversity Loss: A Brief Overview', *Journal of Ecology & Natural Resources*, 7(3). Available at: https://doi.org/10.23880/jenr-16000346.

Classes, C.M., Change, R. and Algorithms, A. (2023) 'Simulation and Prediction of Urban Land Use Change Considering Multiple Classes and Transitions by Means of Random Change Allocation Algorithms'.

Degerickx, J., Roberts, D.A. and Somers, B. (2019) 'Enhancing the performance of Multiple Endmember Spectral Mixture Analysis (MESMA) for urban land cover mapping using airborne lidar data and band selection', *Remote Sensing of Environment*, 221(August 2018), pp. 260–273. Available at: https://doi.org/10.1016/j.rse.2018.11.026.

DGB GROUP (2023) 'Deforestation in Nigeria: causes, effects, and solutions'. Available at: https://www.green.earth/blog/deforestation-in-nigeria-causes-effects-and-solutions.

Dhriti Rudrapal and Mansi Subhedar (2015) 'Land Cover Classification using Support Vector Machine', *International Journal of Engineering Research and*, V4(09). Available at: https://doi.org/10.17577/ijertv4is090611.

Djenontin, I.N.S., Zulu, L.C. and Richardson, R.B. (2022) 'Smallholder farmers and forest landscape restoration in sub-Saharan Africa: Evidence from Central Malawi', *Land Use Policy*, 122(August), p. 106345. Available at: https://doi.org/10.1016/j.landusepol.2022.106345.

Du, P., Liu, S., Liu, P., Tan, K. and Cheng, L. (2014) 'Sub-pixel change detection for urban land-cover analysis via multi-temporal remote sensing images', *Geo-Spatial Information Science*, 17(1), pp. 26–38. Available at: https://doi.org/10.1080/10095020.2014.889268.

ESRI (2022) 'Overview of image classification—ArcGIS Pro | Documentation', *Esri - ArcGIS Pro* [Preprint]. Available at: https://pro.arcgis.com/en/pro-app/2.8/help/analysis/image-analyst/overview-of-image-classification.htm.

FAO (2016) 'in fulfilling the mandates of many United'.

Feudjio, L., Franklin, I., Yanick, B., Mounmemi, H., Delanot, A., Nkondjoua, T., Nguetsop, F. and Zapfack, L. (2023) 'Trees , Forests and People Predicting land use / land cover changes in the Santchou Wildlife Reserve (Santchou , West-Cameroon) using a CA-Markov model', *Trees, Forests and People*, 14(September), p. 100438. Available at: https://doi.org/10.1016/j.tfp.2023.100438.

Gasirabo, A., Xi, C., Hamad, B.R. and Edovia, U.D. (2023) 'A CA – Markov-Based Simulation and Prediction of LULC Changes over the Nyabarongo River Basin , Rwanda'.

Ge, G., Shi, Z., Zhu, Y. and Yang, X. (2020) 'Land use / cover classi fi cation in an arid desert-oasis mosaic landscape of China using remote sensed imagery : Performance assessment of four machine learning algorithms', *Global Ecology and Conservation*, 22, p. e00971. Available at: https://doi.org/10.1016/j.gecco.2020.e00971.

Gebresellase, S.H., Wu, Z., Xu, H. and Muhammad, W.I. (2023) 'Scenario-Based LULC Dynamics Projection Using the CA – Markov Model on Upper Awash Basin (UAB), Ethiopia'.

Gedefaw, A.A., Atzberger, C., Bauer, T., Agegnehu, S.K. and Mansberger, R. (2020) 'Analysis of land cover change detection in Gozamin district, Ethiopia: From remote sensing and DPSIR perspectives', *Sustainability (Switzerland)*, 12(11). Available at: https://doi.org/10.3390/su12114534.

Gharaibeh, A., Shaamala, A., Obeidat, R. and Al-Kofahi, S. (2020) 'Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model', *Heliyon*, 6(9), p. e05092. Available at: https://doi.org/10.1016/j.heliyon.2020.e05092.

Ghosh, P., Mukhopadhyay, A., Chanda, A., Mondal, P., Akhand, A., Mukherjee, S., Nayak, S.K., Ghosh, S., Mitra, D., Ghosh, T. and Hazra, S. (2017) 'Application of Cellular automata and Markov-chain model in geospatial environmental modeling- A review', *Remote Sensing Applications: Society and Environment*, 5, pp. 64–77. Available at: https://doi.org/10.1016/j.rsase.2017.01.005.

Gislason, P.O., Benediktsson, J.A. and Sveinsson, J.R. (2006) 'Random forests for land cover classification', *Pattern Recognition Letters*, 27(4), pp. 294–300. Available at: https://doi.org/10.1016/j.patrec.2005.08.011.

Di Gregorio, A. (2016) *Land Cover Classification System: Classification Concepts*, *October*. Available at: https://www.fao.org/3/x0596e/x0596e00.htm%0Ahttp://www.fao.org/docrep/003/x0596e/x0596e00.htm.

Hamad, R., Balzter, H. and Kolo, K. (2018) 'Predicting land use/land cover changes using a CA-Markov model under two different scenarios', *Sustainability (Switzerland)*, 10(10), pp. 1–23. Available at: https://doi.org/10.3390/su10103421.

Häme, T., Sirro, L., Kilpi, J., Seitsonen, L., Andersson, K. and Melkas, T. (2020) 'A hierarchical clustering method for land cover change detection and identification', *Remote Sensing*, 12(11). Available at: https://doi.org/10.3390/rs12111751.

Han, H., Yang, C. and Song, J. (2015) 'Scenario simulation and the prediction of land use and land cover change in Beijing, China', *Sustainability (Switzerland)*, 7(4), pp. 4260–4279. Available at: https://doi.org/10.3390/su7044260.

Hasan, J. and El, A. (2025) 'Modelling of land use and land cover changes and prediction using CA-Markov and Random Forest'. Available at: https://doi.org/10.1080/10106049.2023.2210532.

Heydari, S.S. and Mountrakis, G. (2018) *Effect of classifier selection, reference sample size, reference class distribution and scene heterogeneity in per-pixel classification accuracy using 26 Landsat sites*, *Remote Sensing of Environment*. Available at: https://doi.org/10.1016/j.rse.2017.09.035.

Hodgson, F.W. (2020) 'Layout and design', *Modern Newspaper Practice*, pp. 94–119. Available at: https://doi.org/10.4324/9780080885728-12.

Islami, F.A., Tarigan, S.D., Wahjunie, E.D. and Dasanto, B.D. (2022) 'Accuracy Assessment of Land Use Change Analysis Using Google Earth in Sadar Watershed Mojokerto Regency', *IOP Conference Series: Earth and Environmental Science*, 950(1). Available at: https://doi.org/10.1088/1755-1315/950/1/012091.

Jalayer, S., Sharifi, A., Abbasi-Moghadam, D., Tariq, A. and Qin, S. (2022) 'Modeling and Predicting Land Use Land Cover Spatiotemporal Changes: A Case Study in Chalus Watershed, Iran', *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 15, pp. 5496–5513. Available at: https://doi.org/10.1109/JSTARS.2022.3189528.

Jiang, Q., He, X., Wang, J., Wen, J., Mu, H. and Xu, M. (2020) 'Spatiotemporal analysis of land use and land cover (Lulc) changes and precipitation trends in Shanghai', *Applied Sciences (Switzerland)*, 10(21), pp. 1–21. Available at: https://doi.org/10.3390/app10217897.

Jin, S., Yang, L., Danielson, P., Homer, C., Fry, J. and Xian, G. (2013) 'A comprehensive change detection method for updating the National Land Cover Database to circa 2011', *Remote Sensing of Environment*, 132(December), pp. 159–175. Available at: https://doi.org/10.1016/j.rse.2013.01.012.

Karakus, C.B., Cerit, O. and Kavak, K.S. (2015) 'Determination of Land Use/Cover Changes and Land Use Potentials of Sivas City and its Surroundings Using Geographical Information Systems (GIS) and Remote Sensing (RS)', *Procedia Earth and Planetary Science*, 15, pp. 454–461. Available at: https://doi.org/10.1016/j.proeps.2015.08.040.

Kaya, I.A. and Görgün, E.K. (2020) 'Land Use and Land Cover Change in Tuticorin Coast Using Remote Sensing and Geographic Information System Land Use and Land Cover Change in Tuticorin Coast Using Remote Sensing and Geographic Information System', *Environ Monit Assess*, (January), p. 18.

Khawaldah, H.A., Farhan, I. and Alzboun, N.M. (2020) 'Simulation and prediction of land use and land cover change using GIS, remote sensing and CA-Markov model', *Global Journal of Environmental Science and Management*, 6(2), pp. 215–232. Available at: https://doi.org/10.22034/gjesm.2020.02.07.

Kuehn, C. and Longo, I.P. (2021) 'Tipping point dynamics in global land use Tipping point dynamics in global land use'.

Kumar, S., Radhakrishnan, N. and Mathew, S. (2014) 'Land use change modelling using a Markov model and remote sensing', *Geomatics, Natural Hazards and Risk*, 5(2), pp. 145–156. Available at: https://doi.org/10.1080/19475705.2013.795502.

Lemenkova, P. (2021) 'Evaluating land cover types from Landsat TM using SAGA GIS for vegetation mapping based on ISODATA and K-means clustering', *Acta agriculturae Serbica*, 26(52), pp. 159–165. Available at: https://doi.org/10.5937/aaser2152159l.

Lencucha, R., Moyo, T., Labonte, R., Drope, J., Appau, A. and Makoka, D. (2020) 'Shifting from tobacco growing to alternatives in Malawi? A qualitative analysis of policy and perspectives', *Health Policy and Planning*, 35(7), pp. 810–818. Available at: https://doi.org/10.1093/heapol/czaa057.

Leta, M.K., Demissie, T.A. and Tränckner, J. (2021a) 'Modeling and prediction of land use land cover change dynamics based on land change modeler (Lcm) in nashe watershed, upper blue nile basin, Ethiopia', *Sustainability (Switzerland)*, 13(7). Available at: https://doi.org/10.3390/su13073740.

Leta, M.K., Demissie, T.A. and Tränckner, J. (2021b) 'Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed , Upper Blue Nile Basin , Ethiopia', (March). Available at: https://doi.org/10.3390/su13073740.

Li, Q., Qiu, C., Ma, L., Schmitt, M. and Zhu, X.X. (2020) 'Mapping the land cover of africa at 10 m resolution from multi-source remote sensing data with google earth engine', *Remote Sensing*, 12(4), pp. 1–22. Available at: https://doi.org/10.3390/rs12040602.

Liu, G.R. (2022) 'Unsupervised Learning Techniques', *Machine Learning with Python*, pp. 585–624. Available at: https://doi.org/10.1142/9789811254185_0017.

Liu, X. jie, Jin, X. bin, Luo, X. li and Zhou, Y. kang (2024) 'Identifying and quantifying local uncertainty and discrepancy in the comparison of global cropland extent through a synergistic approach', *Applied Geography*, 162(April 2023), p. 103164. Available at: https://doi.org/10.1016/j.apgeog.2023.103164.

Long, H., Zhang, Y. and Tu, S. (2021) 'Land Use Transitions: Progress, Challenges and Prospects'.

Lukas, P., Melesse, A.M. and Kenea, T.T. (2023) 'Prediction of Future Land Use/Land Cover Changes Using a Coupled CA-ANN Model in the Upper Omo–Gibe River Basin, Ethiopia', *Remote Sensing*, 15(4). Available at: https://doi.org/10.3390/rs15041148.

Manandhar, R., Odehi, I.O.A. and Ancevt, T. (2009) 'Improving the accuracy of land use and land cover classification of landsat data using post-classification enhancement', *Remote Sensing*, 1(3), pp. 330–344. Available at: https://doi.org/10.3390/rs1030330.

Marsh, T.E. (2023) 'June, 2023'.

Merhej, O.A., Ali, M.K. and Thabeet, A. (2022) 'Using CA-Markov Model to Predict Land Use/Land Cover Changes in Bayer and al-Bassit region, Latakia, Syria', 27(April 2021), pp. 50–58. Available at: https://doi.org/10.53541/jams.vol27iss2pp50-58.

Mondal, I., Srivastava, V.K., Roy, P.S. and Talukdar, G. (2014) 'Using logit model to identify the drivers of landuse landcover change in the lower gangetic basin, India', *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, XL–8(1), pp. 853–859. Available at: https://doi.org/10.5194/isprsarchives-XL-8-853-2014.

Munthali, K.G. and Murayama, Y. (2011) 'Land use/cover change detection and analysis for Dzalanyama forest reserve, Lilongwe, Malawi', *Procedia - Social and Behavioral Sciences*, 21, pp. 203–211. Available at: https://doi.org/10.1016/j.sbspro.2011.07.035.

Munthali, M.G., Mustak, S., Adeola, A., Botai, J., Singh, S.K. and Davis, N. (2020) 'Modelling land use and land cover dynamics of Dedza district of Malawi using hybrid Cellular Automata and Markov model', *Remote Sensing Applications: Society and Environment*, 17(November 2019), p. 100276. Available at: https://doi.org/10.1016/j.rsase.2019.100276.

Nascimento, N., West, T.A.P., Biber-Freudenberger, L., Sousa-Neto, E.R. d., Ometto, J. and Börner, J. (2020) 'A Bayesian network approach to modelling land-use decisions under environmental policy incentives in the Brazilian Amazon', *Journal of Land Use Science*, 15(2–3), pp. 127–141. Available at: https://doi.org/10.1080/1747423X.2019.1709223.

National Statistical Office (2019) 'MALAWI POPULATION AND HOUSING CENSUS REPORT-2018 2018 Malawi Population and Housing Main Report', (May). Available at: http://www.nsomalawi.mw/images/stories/data_on_line/demography/census_2018/2018 Malawi Population and Housing Census Main Report.pdf.

Nazombe, K. and Nambazo, O. (2023) 'Monitoring and assessment of urban green space loss and fragmentation using remote sensing data in the four cities of Malawi from 1986 to 2021', *Scientific African*, 20. Available at: https://doi.org/10.1016/j.sciaf.2023.e01639.

Nguyen, Houng Thi Thanh, Doan, T.M., Tomppo, E. and McRoberts, R.E. (2020) 'Land Use / Land Cover Mapping Using Multitemporal Sentinel-2 Imagery and Four Classification', *Remote Sens*, 12, pp. 1–27. Available at: www.mdpi.com/journal/remotesensing.

Nguyen, H. T.T., Pham, T.A., Doan, M.T. and Tran, P.T.X. (2020) 'Land use/land cover change prediction using multi-temporal satellite imagery and multi-layer perceptron markov model', *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 54(3/W1), pp. 99–105. Available at: https://doi.org/10.5194/isprs-archives-XLIV-3-W1-2020-99-2020.

Nicolau, A.P., Dyson, K. and Saah, D. (2024) *Accuracy Assessment : Quantifying Classification Quality*. Springer International Publishing. Available at: https://doi.org/10.1007/978-3-031-26588-4.

Van Niel, T.G., McVicar, T.R. and Datt, B. (2005) 'On the relationship between training sample size and data dimensionality: Monte Carlo analysis of broadband multi-temporal classification', *Remote Sensing of Environment*, 98(4), pp. 468–480. Available at: https://doi.org/10.1016/j.rse.2005.08.011.

Norovsuren, B., Tseveen, B., Batomunkuev, V., Renchin, T., Natsagdorj, E., Yangiv, A. and Mart, Z. (2019) 'Land cover classification using maximum likelihood method (2000 and 2019) at Khandgait valley in Mongolia', *IOP Conference Series: Earth and Environmental Science*, 381(1). Available at: https://doi.org/10.1088/1755-1315/381/1/012054.

Nyirenda, H. (2022) 'Changes in tree structure, composition and soil in different disturbance categories in Miombo and agroecosystems in Malawi, central Africa', *Heliyon*, 8(9), p. e10664. Available at: https://doi.org/10.1016/j.heliyon.2022.e10664.

Of, T.H.E.S. (2022) 'In Brief to The State of the World's Forests 2022', *In Brief to The State of the World's Forests 2022* [Preprint]. Available at: https://doi.org/10.4060/cb9363en.

Olorunfemi, I.E., Fasinmirin, J.T., Olufayo, A.A. and Komolafe, A.A. (2020) *GIS and remote sensing-based analysis of the impacts of land use/land cover change (LULCC) on the environmental sustainability of Ekiti State, southwestern Nigeria*, *Environment, Development and Sustainability*. Springer Netherlands. Available at: https://doi.org/10.1007/s10668-018-0214-z.

Pangapanga-Phiri, I., Mungatana, E.D., Pangapanga, L. and Nkoka, F.S. (2022) 'Understanding the impact of sustainable land-scape management practices on farm productivity under intensifying tropical cyclones: Evidence from Southern Malawi', *Tropical Cyclone Research and Review*, 11(4), pp. 265–276. Available at: https://doi.org/10.1016/j.tcrr.2023.02.002.

Parker, D.C., Berger, T. and Manson, S.M. (2001) 'Agent-Based Models of Land-Use and Land-Cover Change - Report and review of an international workshop October 4 - 7, 2001, Irvine, California, USA', (6).

Phillips, P.M. and João, E. (2017) 'Land use planning and the ecosystem approach: An evaluation of case study planning frameworks against the Malawi Principles', *Land Use Policy*, 68(November 2016), pp. 460–480. Available at: https://doi.org/10.1016/j.landusepol.2017.08.006.

Pizzorni, M., Innocenti, A. and Tollin, N. (2024) 'Droughts and floods in a changing climate and implications for multi-hazard urban planning: A review', *City and Environment Interactions*, 24(June), p. 100169. Available at: https://doi.org/10.1016/j.cacint.2024.100169.

Potapov, P., Hansen, M.C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X.-P., Baggett, A., Kommareddy, I. and Kommareddy, A. (2022) 'The Global 2000-2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results', *Frontiers in Remote Sensing*, 3(April), pp. 1–22. Available at: https://doi.org/10.3389/frsen.2022.856903.

Pradana, A.N., Djuraidah, A. and Soleh, A.M. (2023) 'Land Use Change Modelling Using Logistic Regression, Random Forest and Additive Logistic Regression in Kubu Raya Regency, West Kalimantan', *Forum Geografi*, 37(2), pp. 149–163. Available at: https://doi.org/10.23917/forgeo.v37i2.23270.

Profile, S. (2017) 'ON THE COVER Chikwawa District Council Office TABLE OF CONTENTS LIST OF ACRONYMS XIII FOREWORD XVII EXECUTIVE SUMMARY XIX ACKNOWLEDGEMENT XXI', (September 2020).

Pullanikkatil, D., Palamuleni, L. and Ruhiiga, T. (2016) 'Assessment of land use change in Likangala River catchment, Malawi: A remote sensing and DPSIR approach', *Applied Geography*, 71, pp. 9–23. Available at: https://doi.org/10.1016/j.apgeog.2016.04.005.

Pullanikkatil, D., Palamuleni, L.G. and Ruhiiga, T.M. (2016) 'Land use/land cover change and implications for ecosystems services in the Likangala River Catchment, Malawi', *Physics and Chemistry of the Earth*, 93, pp. 96–103. Available at: https://doi.org/10.1016/j.pce.2016.03.002.

R, V. (2020) 'Unsupervised ISODATA algorithm classification used in the landsat image for predicting the expansion of Salem urban, Tamil Nadu', *Indian Journal of Science and Technology*, 13(16), pp. 1619–1629. Available at: https://doi.org/10.17485/ijst/v13i16.271.

Rahman, G. and Chandio, N.H. (2023) 'Urban expansion impacts on agricultural land and thermal environment in Larkana , Pakistan', (March), pp. 1–14. Available at: https://doi.org/10.3389/fenvs.2023.1115553.

Rana, V.K. and Venkata Suryanarayana, T.M. (2020) 'Performance evaluation of MLE, RF and SVM classification algorithms for watershed scale land use/land cover mapping using sentinel 2 bands', *Remote Sensing Applications: Society and Environment*, 19(July), p. 100351. Available at: https://doi.org/10.1016/j.rsase.2020.100351.

Rodriguez-Galiano, V.F., Ghimire, B., Rogan, J., Chica-Olmo, M. and Rigol-Sanchez, J.P. (2012) 'An assessment of the effectiveness of a random forest classifier for land-cover classification', *ISPRS Journal of Photogrammetry and Remote Sensing*, 67(1), pp. 93–104. Available at: https://doi.org/10.1016/j.isprsjprs.2011.11.002.

Rossiter, D.G. and Loza, a (2008) 'Technical Note: Analyzing land cover change with logistic regression in R', *ITC, Enschede, The Netherlands*, pp. 2008–2012. Available at: http://www.itc.nl/personal/rossiter/teach/R/R_LCC.PDF.

Saganeiti, L., Mustafa, A., Teller, J. and Murgante, B. (2020) 'Modeling Urban Sprinkling with Cellular Automata'.

Sahoo, G., Wani, A., Sharma, A. and Rout, S. (2020) 'Agroforestry for Forest and Landscape Restoration', (September).

Sameer, M.K. and Hamid, A.M. (2023) 'Remote Sensing and GIS Techniques in Monitoring Land Use Land Cover Change', *International Journal of Sustainable Construction Engineering and Technology*, 14(1), pp. 13–20. Available at: https://doi.org/10.30880/ijscet.2023.14.01.002.

Sarker, I.H. (2021) 'Machine Learning: Algorithms, Real-World Applications and Research Directions', *SN Computer Science*, 2(3), pp. 1–21. Available at: https://doi.org/10.1007/s42979-021-00592-x.

Seth, A.-O., Kwaku, K.M., Michael, O.A. and Owusu, A. (2023) 'Tragedy of urban green spaces depletion in selected sub-Sahara African major cities', *Journal of African Studies and Development*, 15(3), pp. 46–61. Available at: https://doi.org/10.5897/jasd2023.0682.

Seyam, M.M.H., Haque, M.R. and Rahman, M.M. (2023) 'Identifying the land use land cover (LULC) changes using remote sensing and GIS approach: A case study at Bhaluka in Mymensingh, Bangladesh', *Case Studies in Chemical and Environmental Engineering*, 7(December 2022), p. 100293. Available at: https://doi.org/10.1016/j.cscee.2022.100293.

Sharma, N., Kappas, M., Garg, P.K. and Sensing, R. (2020) 'CA MARKOV MODELING OF LAND USE LAND COVER CHANGE PREDICTIONS AND EFFECT OF NUMERICAL ITERATIONS , IMAGE INTERVAL (TIME STEPS) ON', XLIII, pp. 713–720.

Shih, H. chien, Stow, D.A., Chang, K.C., Roberts, D.A. and Goulias, K.G. (2022) 'From land cover to land use: applying random forest classifier to Landsat imagery for urban land-use change mapping', *Geocarto International*, 37(19), pp. 5523–5546. Available at: https://doi.org/10.1080/10106049.2021.1923827.

Shivakumar, B.R. and Rajashekararadhya, S. V. (2018) 'Investigation on land cover mapping capability of maximum likelihood classifier: A case study on North Canara, India', *Procedia Computer Science*, 143, pp. 579–586. Available at: https://doi.org/10.1016/j.procs.2018.10.434.

Skole, D.L., Samek, J.H., Mbow, C., Chirwa, M., Ndalowa, D., Tumeo, T., Kachamba, D., Kamoto, J., Chioza, A. and Kamangadazi, F. (2021) 'Direct measurement of forest degradation rates in malawi: Toward a national forest monitoring system to support redd+', *Forests*, 12(4), pp. 1–30. Available at: https://doi.org/10.3390/f12040426.

Solomon, B.D. (2023) 'Forestry', *Dictionary of Ecological Economics: Terms for the New Millennium*, p. 233. Available at: https://doi.org/10.4337/9781788974912.F.21.

Stoutjesdijk, J. (2022) 'FOR OFFICIAL USE ONLY Report No : PAD4790 PROJECT APPRAISAL DOCUMENT ON A PROPOSED CREDIT IN THE AMOUNT OF SDR 99 . 7 MILLION (US $ 134 MILLION EQUIVALENT) TO THE FOR THE SHIRE VALLEY TRANSFORMATION PROGRAM - PHASE 2 Water Global Practice Eastern and So'.

Svoboda, J., Štych, P., Laštovička, J., Paluba, D. and Kobliuk, N. (2022) 'Random Forest Classification of Land Use, Land-Use Change and Forestry (LULUCF) Using Sentinel-2 Data—A Case Study of Czechia', *Remote Sensing*, 14(5). Available at: https://doi.org/10.3390/rs14051189.

Tamirat, H., Argaw, M. and Tekalign, M. (2023) 'Support vector machine-based spatiotemporal land use land cover change analysis in a complex urban and rural landscape of Akaki river catchment, a Suburb of Addis Ababa, Ethiopia', *Heliyon*, 9(11), p. e22510. Available at: https://doi.org/10.1016/j.heliyon.2023.e22510.

Teluguntla, P., Thenkabail, P., Oliphant, A., Xiong, J., Gumma, M.K., Congalton, R.G., Yadav, K. and Huete, A. (2018) 'A 30-m landsat-derived cropland extent product of Australia and China using random forest machine learning algorithm on Google Earth Engine cloud computing platform', *ISPRS Journal of Photogrammetry and Remote Sensing*, 144(February), pp. 325–340. Available at: https://doi.org/10.1016/j.isprsjprs.2018.07.017.

Tessema, N., Kebede, A. and Yadeta, D. (2020) 'Modeling land use dynamics in the Kesem sub-basin, Awash River basin, Ethiopia', *Cogent Environmental Science*, 6(1). Available at: https://doi.org/10.1080/23311843.2020.1782006.

Tokar, O., Vovk, O., Kolyasa, L., Havryliuk, S. and Korol, M. (2018) 'Using the random forest classification for land cover interpretation of landsat images in the prykarpattya region of Ukraine', *International Scientific and Technical Conference on Computer Sciences and Information Technologies*, 1(November), pp. 241–244. Available at: https://doi.org/10.1109/STC-CSIT.2018.8526646.

Tsegaye, N. (2021) 'Land Use and Land Cover Change Analysis Using GIS and Remote Sensing in The Case of Kersa District, Jimma Zone, Oromia Region, Ethiopia', *International Research Journal of Agricultural Science and Soil Science*, 10(5), pp. 1–9. Available at: http://www.interesjournals.org/IRJESTI.

Tuan, N.T. (2022) 'Urbanization and land use change : A study in Vietnam Environmental & Socio-economic Studies Urbanization and land use change : A study in Vietnam', (June). Available at: https://doi.org/10.2478/environ-2022-0008.

Ulbricht, K.A., Teotia, H.S. and Civco, D.L. (1993) 'Supervised Classification to Land Cover Mapping in Semi-Arid Environment of NE Brazil Using Landsat-TM and SPOT Data', *International Archives of Photogrammetry and Remote Sensing*, 29, pp. 821–821. Available at: http://www.isprs.org/proceedings/XXIX/congress/part7/821_XXIX-part7.pdf.

United Nations (2024) 'The Sustainable Development Goals Extended Report 2024 (Goal-7: Affordable and Clean Energy)', (April). Available at: https://unstats.un.org/sdgs/report/2024/extended-report/Extended-Report_Goal-7.pdf.

Usman, H. and Khan, A. (no date) 'Land Use and Land Cover Simulation', pp. 1–22.

Version, D. and Raadt, D. (2020) 'Comparison studies on agreement coefficients with emphasis on missing data Comparison studies on agreement coefficients with emphasis on missing data Alexandra de Raadt'. Available at: https://doi.org/10.33612/diss.136232170.

Wang, Q., Wang, H., Chang, R., Zeng, H. and Bai, X. (2022) 'Dynamic simulation patterns and spatiotemporal analysis of land-use/land-cover changes in the Wuhan metropolitan area, China', *Ecological Modelling*, 464(December 2021), p. 109850. Available at: https://doi.org/10.1016/j.ecolmodel.2021.109850.

Wang, S.W., Gebru, B.M., Lamchin, M., Kayastha, R.B. and Lee, W.K. (2020) 'Land use and land cover change detection and prediction in the kathmandu district of nepal using remote sensing and GIS', *Sustainability (Switzerland)*, 12(9). Available at: https://doi.org/10.3390/su12093925.

Wang, X. and Liu, L. (2023) 'The Impacts of Climate Change on the Hydrological Cycle and Water Resource Management', *Water (Switzerland)*, 15(13), pp. 2–5. Available at: https://doi.org/10.3390/w15132342.

Wang, Y. and Lu, D. (2017) 'Mapping Torreya grandis spatial distribution using high spatial resolution satellite imagery with the expert rules-based approach', *Remote Sensing*, 9(6). Available at: https://doi.org/10.3390/rs9060564.

Wang, Yanzhao, Sun, Y., Cao, X., Wang, Yihan, Zhang, W. and Cheng, X. (2023) 'A review of regional and Global scale Land Use/Land Cover (LULC) mapping products generated from satellite remote sensing', *ISPRS Journal of Photogrammetry and Remote Sensing*, 206(November), pp. 311–334. Available at: https://doi.org/10.1016/j.isprsjprs.2023.11.014.

Wu, G., Zhong, B., Si, H., Wei, B., Wu, Q. and Song, C. (2007) 'Agent-based modeling in land use and land cover change studies', *Geoinformatics 2007: Remotely Sensed Data and Information*, 6752, p. 675232. Available at: https://doi.org/10.1117/12.761292.

Xie, G., Xie, G., Learning, M., Use, L. and Cover, L. (2023) 'Machine Learning methods and Land Use / Land Cover (LULC) in the coastal Pays de Brest To cite this version : HAL Id : tel-04217323'.

Yang, L., Shi, L., Li, J. and Kong, H. (2024) 'Spatio-temporal pattern change of LULC and its response to climate in the Loess Plateau, China', *Scientific reports*, 14(1), p. 23202. Available at: https://doi.org/10.1038/s41598-024-73945-0.

Zhang, C. and Li, X. (2022) 'Land Use and Land Cover Mapping in the Era of Big Data', *Land*, 11(10). Available at: https://doi.org/10.3390/land11101692.

Zhang, J., Pan, Y., Yi, C., Ma, Q. and Xu, C. (2008) 'An integrated approach using ISODATA and SVR to land cover classification: an example of wheat', *Geoinformatics 2008 and Joint Conference on GIS and Built Environment: Classification of Remote Sensing Images*, 7147(2006), p. 71470C. Available at: https://doi.org/10.1117/12.813212.