

Strengthening forest landscape restoration through understanding land use dynamics: case study of Tchamba Prefecture (Togo)

Kossi Hounkpati, Kossi Adjonou, Hamza Moluh Njoya, Atsu K. Dogbeda Hlovor, Harison K. Kipkulei, Stefan Sieber, Katharina Löhr, Kouami Kokou

Angaben zur Veröffentlichung / Publication details:

Hounkpati, Kossi, Kossi Adjonou, Hamza Moluh Njoya, Atsu K. Dogbeda Hlovor, Harison K. Kipkulei, Stefan Sieber, Katharina Löhr, and Kouami Kokou. 2024. "Strengthening forest landscape restoration through understanding land use dynamics: case study of Tchamba Prefecture (Togo)." *Journal of the Indian Society of Remote Sensing* 52 (5): 1117–34. <https://doi.org/10.1007/s12524-024-01862-w>.

Nutzungsbedingungen / Terms of use:

CC BY 4.0

Dieses Dokument wird unter folgenden Bedingungen zur Verfügung gestellt: / This document is made available under these conditions:

CC-BY 4.0: Creative Commons: Namensnennung

Weitere Informationen finden Sie unter: / For more information see:

<https://creativecommons.org/licenses/by/4.0/deed.de>





Strengthening Forest Landscape Restoration through Understanding Land Use Dynamics: Case Study of Tchamba Prefecture (Togo)

Kossi Hounkpati^{1,2}  · Kossi Adjonou¹  · Hamza Moluh Njoya^{2,3,4}  · Atsu K. Dogbeda Hlover¹ · Harison Kiplagat Kipkulei^{2,3,5}  · Stefan Sieber^{2,3}  · Katharina Löhr^{2,6}  · Kouami Kokou¹ 

Received: 21 August 2023 / Accepted: 27 March 2024 / Published online: 20 April 2024
© The Author(s) 2024

Abstract

Land use and land cover (LULC) change remains a major concern in many countries. To examine how land is used for increased actions on forest landscape restoration (FLR) issues, this study analyses LULC changes from 1991 to 2022 and predict future patterns for the years 2050 in Tchamba Prefecture, Togo, using remote sensing and the Cellular Automata-Markov modelling technique. Results show that dense forests and gallery forests (18.85%), open forest/woodland (20.17%), and tree and shrub savannah (50.04%) were the predominant classes of the landscape in 1991. However, by 2022, most tree and shrub savannah had been converted to mosaic crop/fallow land (52.27%), open forest/woodland (19.32%), and plantation (7.09%). Thus, between 1991 and 2022, forest area decreased from 89.87% to 48.96%; a 45.52% reduction in coverage. Predictions are that open forest/woodland, tree and shrub savannah will decline, while mosaic crop/fallow land will increase (51.66%). However, slight increases were recorded in plantation (9.43%) and a slight balance in dense forests/gallery forests (16.17%). Consequently, forest area will slightly change between 2022 (48.96%) and 2050 (47.41%). These changes in LULC are associated to socio-economic pressures and political instability in the 1990s. So, the return to stability, the promotion of community forests as a key restoration model, and the valorisation of agroforestry species allows for the stabilisation of dense forests/gallery forests areas and an increase in plantation. Thus, it is therefore for all stakeholders involved in restoration processes to consider this information when planning FLR activities.

Keywords Remote sensing · Land use · Land change prediction · Key restoration model · Forest landscape restoration

Introduction

Since the 1990s, tropical forest landscapes have undergone significant changes, resulting in the degradation and modification of about 930 million hectares (ha) in tropical regions (ITTO, 2020). Within the region, the estimated annual deforestation rate between 2015 and 2020 is 10 million ha. During the 2010s, the largest net losses were recorded in South America and Africa (FAO, 2022). Africa alone has experienced an annual loss of around 3.9 million ha of forest (FAO & UNEP, 2020). Worse still, Africa's forests, farmland, and pastureland continue to face degradation (Pasiiecznik & Reij, 2020). Many anthropogenic pressures are driving these changes, mainly unsuitable agricultural practices, urbanization and industrialization, combined with natural hazards resulting from climate change (Haque & Basak, 2017). These increase the regressive dynamics of land cover, soil degradation, and compromised ecosystem services (Gbedzi et al., 2022; Tsegaye, 2019). Other consequences of land use

✉ Katharina Löhr
Katharina.Loehr@zalf.de

¹ Laboratoire de Recherche Forestière (LRF), Centre de Recherche sur le Changement Climatique (CRCC), Université de Lomé, 1515 Lomé, Togo

² Sustainable Land Use in Developing Countries (SusLAND), Leibniz Centre for Agricultural Landscape Research (ZALF e.V.), 15374 Müncheberg, Germany

³ Department of Agricultural Economics, Humboldt-Universität zu Berlin, 10099 Berlin, Germany

⁴ Department of Rural Socio-Economics and Agricultural Extension (SERVA), Faculty of Agronomy and Agricultural Sciences, University of Dschang, 222 Dschang, Cameroon

⁵ Department of Geomatic Engineering and Geospatial Information Systems, Jomo Kenyatta University of Agriculture and Technology (JKUAT), P.O Box 62, Nairobi 000-00200, Kenya

⁶ Division Urban Plant Ecophysiology, umboldt-Universität zu Berlin, 14195 Berlin, Germany

and land cover (LULC) include biodiversity loss (Hansen et al., 2004) and disruption of biogeochemical cycles (Ramachandra, 2014). Thus, changes in LULC have substantial impacts on the environment and people's livelihoods (Munthali et al., 2022). In Africa, LULC problems are exacerbated by high population pressure and over-reliance on land resources for livelihoods and food, agricultural activities, and illegal logging. As data and insights provided by LULC dynamics are essential for the management of sustainable land resources, examining past changes as well as future trends in LULC of the concerned landscapes are essential to improve sustainable planning, governance, and monitoring (Bunyangha et al., 2021), as well as adopting measures to mitigate climate change (Reddy et al., 2017). LULC reviews are critical elements that can support the implementation of different measures and approaches, such as forest landscape restoration (FLR). The examination of land use to support processes like FLR is critical for effective planning. As per Nedd et al. (2021), studies conducted since 2000 typically acknowledge the need to enhance knowledge of LULC. The studies include, among others, the typology of LULC, the direct and indirect changes associated to LULC, as well as the challenges and knowledge gaps relating to LULC (Nedd et al., 2021). Despite these studies have been carried out to increase awareness of LULC change issues, most FLR initiatives are launched with limited land-use assessments and frequently lack analyses of future trends. Thus, the consideration of successful local practices is often marginalized in planning, which hinders effective FLR action. Hence, it is crucial to evaluate LULC to ensure the sustainability of FLR efforts.

In Togo, the LULC has undergone significant transformations, driven mainly by population growth, urbanization, and agricultural expansion. Agriculture is the main land use in Togo, employing 60% of the country's population (MAEH, 2017). Smallholder farmers practice traditional slash-and-burn agriculture, which involves clearing forests, burning vegetation, and planting crops. These factors are compounded by logging, charcoal production, and overgrazing, which significantly contribute to deforestation and land degradation in Togo. Despite Togo's limited forest cover, which stands at 24.24% (MERF/GIZ, 2016), the country experiences an annual deforestation rate of 0.42% and significant land degradation, estimated at 4.14% between 2000 and 2010 (MERF, 2018, 2020).

To address these issues, Togo has implemented several policies and programs promoting sustainable management practices. The National Land Use Planning Program (PNAT) seeks to promote sustainable land use, including integrated watershed management, sustainable agriculture, and ecosystem-based approaches to natural resource management. Furthermore, Togo has launched several management initiatives to restore degraded forest landscapes. These initiatives

include the National Investment Plan for Environment and Natural Resources (PNIERN) (MERF, 2010), the National Reforestation Programme (PNR) (MERF, 2017), the adoption of forest policy matched with a National Forestry Action Plans, which envisages increasing the national forest cover from 24.24% in 2016 to 25%, 26%, and 30% in 2025, 2030, and 2050, respectively. The initiatives have a clear objective to enhance forest governance, increase reforestation to 1 billion trees, and restore 1.4 million ha by 2030 (MERF, 2017, 2021). Additionally, the initiatives aim to restore degraded forest ecosystems in line with the New York Declaration on Forests, the Bonn Challenge, and the AFR100 initiative.

In addition, Togo has implemented several approaches for FLR, including the “community forest management” approach in Tchamba prefecture. This approach aims to give local communities the rights and responsibilities to manage their forests. This is how Tchamba, a district in Togo's central region that is considered a biodiversity hotspot, is a key beneficiary of several projects that aim to address the negative effects of LULC to better implement FLR, such as the Forests4Future (F4F) project. This project is based on the achievements of the Preparation for REDD+ and Forest Rehabilitation programme in Togo (ProREDD) and the International Waldpolitik (IWP) programme. These programmes support community forest management, socio-economic characterisation of households, and Tchamba Prefectoral Forest Inventory (IFP) to assess the potential for timber and non-timber products (DFS/GOPA, 2016; IWP/AFR100/GIZ, 2020a, b).

However, despite numerous initiatives operating at different levels and scales, investigations into landscape dynamics have remained relatively limited. Thus, information available on the landscape of this area is incomplete. Besides the limited knowledge of LULC in the area, there is a lack of studies focusing on the forecasting of future trends. As temporal changes in land use are an equally important component for any planning (Gülersoy, 2014) and as FLR is a lengthy process, it is essential to examine historical land use. Restoration actions and sustainable management of natural resources require a critical understanding of LULC and their impacts on natural resources (Munthali et al., 2022). Against this background, the aim of this study is to (i) analyze changes in LULC in Tchamba Prefecture from 1991 to 2022; and (ii) predict future trends for the 2050s to increased action on FLR issues.

To achieve these objectives, landscape dynamics are investigated using Geographic Information Systems (GIS) and Remote Sensing (RS) (Forkuo et al., 2021). Landsat satellite images are analyzed to achieve the study objectives. The images are proven to provide important radiometric and geometric qualities for LULC analysis. In addition, these images provide a long-term archive of satellite data for historical analysis (Gutman & Masek, 2012). The historical

LULC analysis is integrated with the Cellular Automata-Markov modelling to understand the future LULC patterns. Findings inform policymakers and practitioners on land implementation programs, helping them to understand the current state of LULC. As pointed out by Leta et al. (2021), this knowledge can be useful for improving land use policies with a view to long-term land use planning to cope with future changes. The results will also contribute to a greater pool of data on LULC dynamics that can feed into the global data set, thus strengthen ongoing positive actions and properly guiding FLR activities to the benefit of all.

Materials and Methods

Study Area

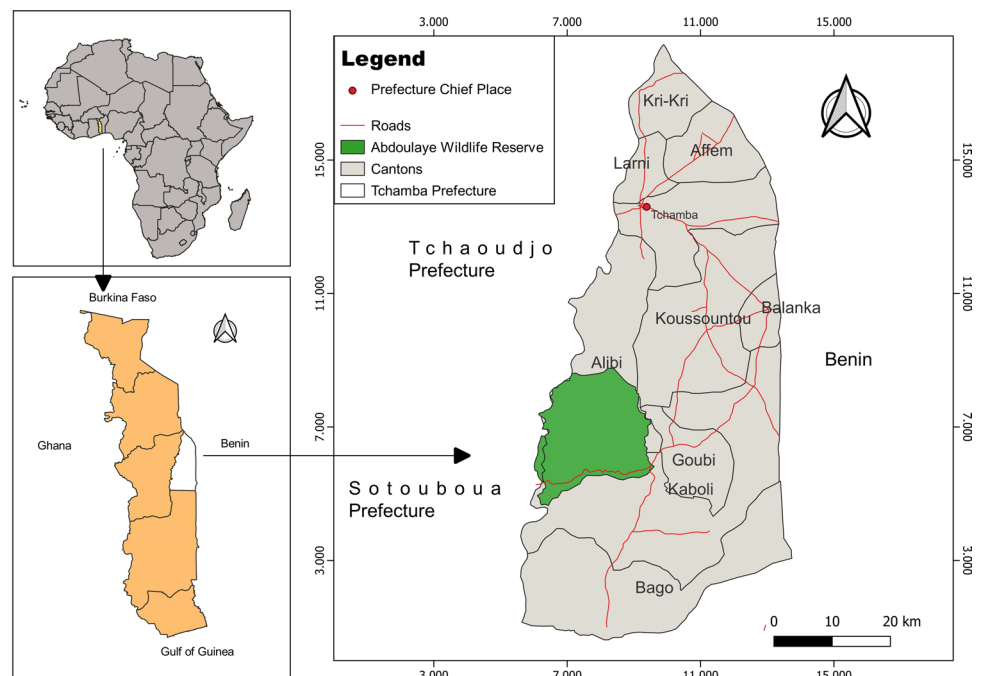
The district of Tchamba is situated in the central region of Togo, located between latitudes 8°22' N and 9°20' N and longitudes 1°15' E and 1°38' E. It is approximately 300 km from the capital city (Fig. 1). It is bounded to the South by Est-Mono prefecture, on the North and East by Benin Republic, and on the West by Sotouboua and Tchaoudjo Prefectures. The study area covers about 3,166 km², i.e. 20% of the Central Region's surface area. The Prefecture is administratively divided into ten (10) cantons (Tchamba, Larini, Alibi, Adjéidè, Affem, Koussountou, Balanka, Kaboli, Goubi, and Bago) grouped in three (3) municipalities (Tchamba 1, Tchamba 2, and Tchamba 3) (INSEED, 2011). The climate in this region is characterized as Sudano-Guinean. It experiences a rainy season that typically lasts

from April to October, with an average annual rainfall of 1100 to 1300 mm. The dry season runs from November to March and, during this time, there is a continental north-east trade wind known as harmattan, which blows from November to February. It is a hydrographic system formed by 94 rivers and streams, with Mono and its tributary Ogou being the main streams (IWP/AFR100/GIZ, 2020a). At the Prefectural level, the population is estimated at 156,814 people, with a density of 49 people/Km² (IWP/AFR100/GIZ, 2020a). The main activities in the districts are agriculture (food crops), livestock (poultry, small ruminants and large livestock), trade (general foodstuffs, cash crops, especially cashew nuts, building materials, etc.), crafts (weaving, sculpture, carpentry, pottery, hairdressing, sewing, etc.), transport (taxis and motorbike taxis), and timber exploitation (timber, energy wood, service wood). This prefecture was selected because of its status as the country's largest forest area, covering a total of 93,287 ha. It has a great ecosystem diversity comprising the Abdoulaye Wildlife Reserve (30,000 ha), Community Forests (Affem Boussou, Alibi 1, Bago, Goubi, and Koussountou) (MERF/GIZ, 2016) and sacred forests (Hounkpati et al., 2022; Lynch et al., 2018). It not only benefits from several support programs and initiatives, but it is also a target of the "Forests4Future" project, hosting the pilot phase in Togo.

Data Collection

This study combines the use of (i) satellite data and (ii) ground survey data collected using a handheld Geographical Positioning System (GPS) instruments to evaluate the

Fig. 1 Location of the study area



current LULC. The ground survey data enable the creation of a training and evaluation database for the RS classification algorithm. Ground survey data are crucial in understanding land use dynamics and to perform the statistical evaluation of different land use categories (Regasa & Nones, 2022). Landsat data with complete spatial and spectral resolution (30 × 30 m) from the United States Geological Survey (USGS) website (<https://earthexplorer.usgs.gov/>) were captured during the end of the dry season (January to February) and has less than 5% cloud cover. Multispectral data from Landsat 4–5 (Thematic Mapper), Landsat 7 (Enhanced Thematic Mapper Plus), and Landsat 8 (Operational Land Imager/Thermal InfraRed Sensor) (Bunyangha et al., 2021) were used (Table 1). From the data, the spectral bands used to classify the images are Blue, Green, Red, Near- Infra-Red, Short Wave Infra-Red 1 and 2 (Gyamfi-Ampadu et al., 2020). The bands provide a spatial resolution of 30 m, sufficient to monitor forest dynamics (García-Álvarez et al., 2022). In addition to the data acquisition, Landsat images offer corrected geometric and radiometric data to analyze land use change (Yang & Lo, 2002).

Data Analysis and Processing

Image Processing and Classification

The Landsat images used in the study provide Level 1 terrain-corrected data, which had already undergone both geometric and radiometric corrections (Bunyangha et al., 2021)

Table 1 The Metadata on the satellite images acquired

Satellite	Sensor	Year	Acquisition Date	Spatial resolution
Landsat 8	OLI/TIRS	2022	January 23	30 m
Landsat 7	ETM+	2012	January 4	30 m
Landsat 5	TM	2002	February 2	30 m
Landsat 4	TM	1991	January 10	30 m

Table 2 LULC classes and their description

LULC types	Description
Dense forests and gallery forests	Area with enclosed formations, tall trees and enclosed formations of dense forest along the watercourses
Open forest and woodland	Area with mixed forest formations, open stands and whose tree tops are less joined or form a clear canopy
Tree and shrub savannah	Area with formations in which trees and shrubs are spread out among the grass cover or shrubs only among the grass cover
Plantation	Area with tree plantation as <i>Anacardium occidentale</i> , <i>Gmelina arborea</i> <i>Vitellaria paradoxa</i> <i>Khaya senegalensis</i> <i>Tectona grandis</i> ...
Mosaic crop and fallow land	Crop areas or fields previously cropped, abandoned or overgrown with exogenous species or recovering savannah
Built-up	Area covered by urban and rural settlements, roads, industries, infrastructures

and were used directly as inputs in the classification process. However, as the images were acquired on different dates and with different sensors, it was necessary to harmonize them in order to apply a multitemporal approach. For classification, it was necessary to establish a reference that defines how the target land cover types appear on the images. Thus, a definition of the reference points (land use classes) was made by using the high resolution images accessible on Google Earth for the year 2022 (Zhao & Zhu, 2022). Based on the training plots, the images were classified for the four selected dates using verified target land cover types. The satellite images were projected into the WGS 84/UTM 31 N coordinate system prior to classification. Supervised classification using the RandomForest (RF) algorithm, developed by Breiman (2001) was applied to the satellite images. This algorithm was chosen for its good predictive capabilities for LULC (Gislason et al., 2006) and in the case of temporal analysis. It is a non-parametric supervised classification algorithm that combines the decision tree algorithm with an aggregation technique. In order to create multiple small classification trees, this algorithm randomly selects a sample of observations and variables multiple times, according to Breiman (2001) and Grinand et al. (2013). The small trees are then combined and a majority voting rule is applied to determine the final classification category, as per Grinand et al. (2013). Subsequently, validation of the classification was carried out based on 1/3 of the ground survey points taken in the field. Once the classification and validation were done on the 2022 reference map, the same operations were performed on the other scenes. The pre-determined classes delineated were dense forests/gallery forests, open forest/woodland, plantation, tree and shrub savannah, mosaic crop/ fallow land, and built-up (Table 2).

Accuracy Assessment

Image accuracy assessment is one of the crucial steps in classification. As stated by Bunyangha et al. (2021), no LULC classification process can be considered complete without a thorough accuracy assessment. Assessing the

accuracy of the classification provides a certain level of confidence in the results, in the detection of changes, and in the representativeness of the ground features on the corresponding classified image (Leta et al., 2021). For accuracy in this study, it was necessary to establish a reference that defines how target land cover types appear on the images. The reference definition was made based on Google Earth high-resolution images for the year 2022. The kappa index was employed to evaluate the classification accuracy (Jia et al., 2018). By comparing the total corrected and total samples, the overall precision provides an overview of the number of correctly classified sites. The Kappa coefficient, a measure of agreement, compares actual and expected agreement with reference data (Bunyangha et al., 2021). When its value is close to 1, the classification is known as accurate and not accurate when the value is close to 0 (Regasa & Nones, 2021). In this research, the Kappa coefficient was computed using Congalton (1991) equation.

$$K = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} * x_{+i})} \quad (1)$$

where, K = Kappa Coefficient, r = number of rows/columns in the error matrix, N = total number of samples, x_{ii} = sum of correctly classified samples, x_{i+} = row i total, while x_{+i} = column i total.

Land Use and Land Cover Change Detection

The method used to detect changes in LULC is Post Classification Comparison (PCC). This method implies the comparison of sequentially and independently classified images by an overlay to establish how the LULC classification at the initial date has evolved toward a different category at the final date. The matrix rows produced indicate the land use at the initial date (t₁) and the columns represent the land use at the later date (t₂) (Table 4). The vectors in the rows illustrate the evolution of the land use type between date t₁ and t₂, while the vectors in the columns describe the land use type at t₁ that has converted to the land use type at t₂. The data on the diagonal represent areas where LULC remains consistent. In this study, changes for each of the six LULC categories were calculated using 6 × 6 transition matrices.

Annual Rate of Land Use and Land Cover

The annual rate of change measures the extent of change in occupancy classes per year. This variable serves to identify the LULC conversion rate (Bunyangha et al., 2021). In this study, the Puyravaud (2003) formula was used to calculate the annual rate of change (r) in different LULC classes (C₁, C₂) at specific times (t₂, t₁).

$$r = \left[\left(\frac{1}{t_2 - t_1} \right) * \ln(C_2/C_1) \right] * 100 \quad (2)$$

where: r = rate of change (%); C₁ = area of the class at date t₁; C₂ = area of the class at date t₂ and t = years between the two dates with t₂ > t₁. A positive value for the rate of change indicates an increase, while a negative value indicates a decrease, and when the value approaches zero, it means an equilibrium in the land use class (Eastman, 2009; Leta et al., 2021).

Future Prediction of LULC

TerrSet Geospatial Monitoring and Modeling System software, specifically the Land Change Modeler (LCM), was used to predict future LULC patterns for the years 2030 and 2050, using historical satellite images classified in this study. This model is proven to have a high capacity for dynamic projection, a deep calibration and the capability to simulate several types of land cover (Eastman, 2009; Leta et al., 2021). Using two dates, t₁ as the initial date and t₂ as the final date, LCM examines the variation in land use, calculates the modifications, then anticipates the future evolution of the land use (t₃, t₄) based on the relative transition potential maps (Qacami et al., 2023).

The LCM model produces transition potential maps through three approaches: multi-layer perceptron neural network (MLP), logistic regression, and machine learning via similarity-weighted instances (SimWeight) (Eastman, 2016; Mishra & Rai, 2016). The MLP model is characterized by the use of a minimal number of parameters, it is more accessible and has been improved to offer an automatic mode (Regasa & Nones, 2022). Indeed, three main units make up the MLP neural network: the input layer, the hidden layer containing computing nodes, and the output layer (Eastman, 2009). To model transitions, these units are used. For each transition from one land use type to another, a potential change model is generated as a transition sub-model. In cases where multiple transitions share similar underlying variables and depend on the vulnerability of the LULC to change to other land use types, these sub-models are grouped together. This creates a composite change potential map, also known as transition adequacy, for this land use category (Bunyangha et al., 2021).

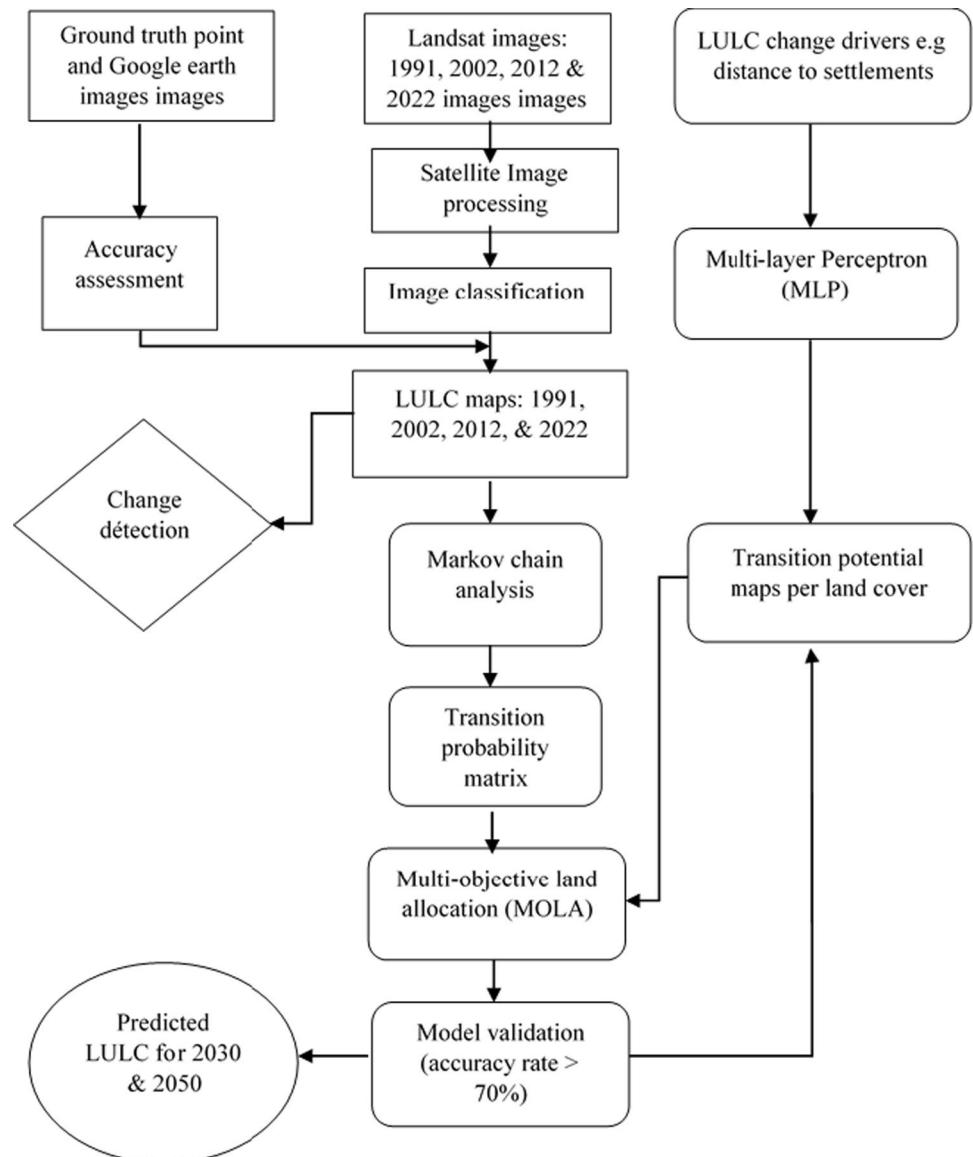
For predicting the future LULC scenarios, it is necessary to have access to historical LULC maps and a set of driving forces as input data (Regasa & Nones, 2021, 2022). In this study, the following driving variables were considered for the LULC Change Model (LCM) simulations: the distance from disturbance, the distance from the stream, the distance from urban areas, the distance from the road, and the evidence likelihood. All of these variables are dynamic and differ from static variables like elevation and slope (Regasa & Nones, 2021, 2022). The LCM simulations in this study

considered several factors that can affect driving, such as the distance from disturbances, streams, urban areas, and roads, all of which are dynamic variables unlike elevation or slope. This information was provided by Regasa and Nones (2022). The study analysed the changes LULC trends for the years 1991, 2002, 2012, and 2022 in order to predict future LULC changes for 2030 and 2050. The modelling in this study was based on a business-as-usual scenario, which assumes that future land use patterns will follow the trends observed in the past (Clerici et al., 2019).

Future trends in LULC will follow the same pace as historical and recent trends in the region, being driven by influencing factors similar as mentioned by Bunyangha et al. (2021). To assess the predictive performance of the LCM model for future LULC, a map of predicted LULC for 2022 was generated from data for 1991, 2002, and

2022. The multiple objective land allocation (MOLA) and the Cellular automata integrated into the LCM model were used to spatially assign Markov transitions. To validate the Markov model, we compared the simulated land LULC map for the year 2022 with the classified LULC map of the same year (Kundu et al., 2017). The Kappa variations as a basis for comparison was used. The study design is summarized in Fig. 2 below.

Fig. 2 Overview of the methodology used for the detection and prediction of LULC



Results

Spatio-temporal Dynamics of LULC in Tchamba Prefecture

The results of LULC classification for 1991, 2002, 2012, and 2022 of Tchamba prefecture were obtained with Kappa values of 0.92, 0.83, 0.81, and 0.85, respectively. The results show that, in 1991, dense forests/gallery forests covered 6026.85 ha, which translates to 18.85% of the Prefecture (Table 3, Fig. 3). Open forest/ woodland, and tree and shrub savannas covered 64,496.66 ha (20.17%) and 159,965.14 ha (50.04%), respectively, of the total area of the prefecture. Plantation occupied the least area of 2577.18 ha (0.81%). Considering these classes, the forested area covered 287,306.83 ha (89.87%) of the prefecture with tree and shrub savannah being the predominant class of the forested zones. The non-forest area comprising mosaic crop/ fallow land and built-up areas cover 29,505.14 ha (9.23%) and 2877.02 ha (0.90%), respectively.

The results further show that, in 2002, there were several changes in the composition of the LULC. Most of the classes decreased slightly except open forest/ woodland, which declined by 32,325.52 ha. This area is more than half of the open forest/woodland coverage in 1991 (Table 3). With an annual loss rate of 6.32%, open forest/ woodland decreased to 32,171.14 ha (10.06%). Similarly, dense forests/gallery forests recorded an annual decline rate of 1.30%, decreasing to 52,223.83 ha (16.34%), i.e. a decline of 8043.93 ha. Tree and shrub savannah, however, increased slightly to 179,845.65 ha (56.26%), which is a net gain of 198,880.51 ha and remained the predominant land class. Plantation, mosaic crop/fallow land, and the built-up area also increased slightly to 3512.13 ha (1.10%), 44,888.82 ha (14.04%), and 7047.37 ha (2.20%), respectively. The forest area continued to cover a large part of the area; although it decreased to 267,752.81 ha (83.75%).

LULC coverage in 2012 reveals that dense forests/gallery forests registered an annual loss rate of 1.51% and decreased slightly to 44,893.48 (14.04%), which was a decline of 7330.41. Also, Tree and shrub savannah decreased significantly to 151,732.74 ha (47.46%), a decline of 28,112.90 ha. However, the open forest/ woodland increased by 13,818.29 ha. With an annual rise of 3.29%, the area of open forest/woodland increased to 44,688.91 ha (13.98%). Also, mosaic crop/fallow land and plantation increased significantly. The plantation increased to 6160.47 ha (+ 1.93%) which was a net gain of 2648.34. This translates to an annual rate of 5.6% over the period. On the other hand, mosaic crop/fallow land

increased to 63,410.51 ha (19.84%), translating to a net gain of 89,395.24 ha and an annual positive rate of 3.45%. Built-up area land increased slightly to 8802.89 (2.75%). All these conversions led to a decrease in forest area to 247,475.59 (77.41%) (Table 3, Figs. 3 and 4).

2022 was marked with the most significant conversions. The LULC dynamics indicated that dense forest/gallery forest stabilised at 43,808.8 ha (13.70%), which translated to a decline of 0.24% from the previous epoch. However, tree and shrub savannas declined by 16.5% per year, i.e. a drastic decrease of 122,663.10 ha to a coverage of 29,069.64 ha (9.09%). Open forest/wooded land slightly increased to 58,507.20 ha (18.30%), translating to a net gain of 12,517.76 ha and a positive annual rate of 2.69%. In the same period, there was a significant increase in forest plantations and crop/fallow. Forest plantation recorded a net gain of 18,989.13 ha to reach 25,149.60 ha (7.87%). This translates to an annual rate of 14.07%, i.e. crops/fallow recorded a net gain of 89,395.24 ha to coverage of 152,805.74 ha (47.80%). The annual gain rate in this case was 8.80%. However, the built-up area revealed a varied trend. The increase in their surface area remains slight at 10,347.96 ha (3.24%). In terms of forest dynamics, forest area declined from 89.87% to 48.96%, a decrease of a 45.52% between 1991 and 2022.

Composite analysis of the conversion matrix shows that tree and shrub savannah have experienced the highest conversion, followed by open forest/woodland and then dense forest/gallery forest at decreases of 5.50%, 1.03%, and 0.31%, respectively between 1991 and 2022 (Tables 3 and 4). Indeed, 86.05% of Tree and shrub savannah were completely converted to 52.27% of mosaic crop/fallow land, 19.32% of open forest/woodland, 7.03% of dense forests/gallery forests, 7.09% of plantation, and a mere 2.33% of built-up (Table 4, Fig. 5). The matrix shows that 79.40% of open forest/woodland was converted mainly into mosaic crop/fallow land (45.67%), dense forests/gallery forests (20.28%), and forest plantation (7.87%). As for dense forests/gallery forests, the matrix reveals that 66.42% of this class was converted to mosaic crop/fallow land (37.37%), open forest/woodland (18.78%), and forest plantation (5.21%). Although the conversion of dense forests/gallery forest, open forest/woodland and tree/shrub savannah was significant, the matrix shows that in 2022 dense forest/gallery forest and open forest/woodland retained a significant part of their area respectively at 45,625.59 ha. However, tree and shrub savannah have totally disappeared, i.e. 26,150.67 ha instead of 158,590.8 ha in 1991. The mosaic crop/fallow land, and forest plantation classes, however, have increased significantly, i.e. 153,845.19 ha instead of 29,706.11 ha and 26,234.37 ha instead of 2693.61 ha in 1991 (Tables 4).

Table 3 LULC composition and change trend of Tchamba Prefecture from 1991 to 2022, Area in ha and %, Change and annual change rate in %

LULC type	1991		2002		2012		2022		Change detected (ha)			Rate of change per annum (%)			
	ha	%	ha	%	ha	%	ha	%	1991–2002	2002–2012	2012–2022	1991–2002	2002–2012	2012–2022	1991–2022
Dense forest/gallery forests	60,267,85	18,85	52,223,88	16,34	44,893,48	14,04	43,808,85	13,70	-8043,96	-7330,41	-1084,63	-1,30	-1,51	-0,24	-16,459,00
Open forest/woodland	64,496,66	20,17	32,171,14	10,06	44,688,91	13,98	58,507,20	18,30	-32,325,5	12,517,76	13,818,29	-6,32	3,29	2,69	-5989,46
Tree and shrub savannah	159,965,14	50,04	179,845,65	56,26	151,732,74	47,46	29,069,64	9,09	19,880,51	-28,112,9	-122,663,10	1,06	-1,70	-16,5	-130,895,5
Plantation	2577,18	0,81	3512,13	1,10	6160,47	1,93	25,149,60	7,87	934,95	2648,34	18,989,13	2,81	5,62	14,07	22,572,42
Mosaic crop/fallow land	29,505,14	9,23	44,888,82	14,04	63,410,51	19,84	152,805,74	47,80	15,383,67	18,521,69	89,395,24	3,81	3,45	8,80	123,300,60
Built-up	2877,02	0,90	7047,37	2,20	8802,89	2,75	10,347,96	3,24	4170,35	1755,52	1545,07	8,14	2,22	1,62	7470,94
Total	319,688,99	100,00	319,688,99	100,00	319,688,99	100,00	319,688,99	100,00							

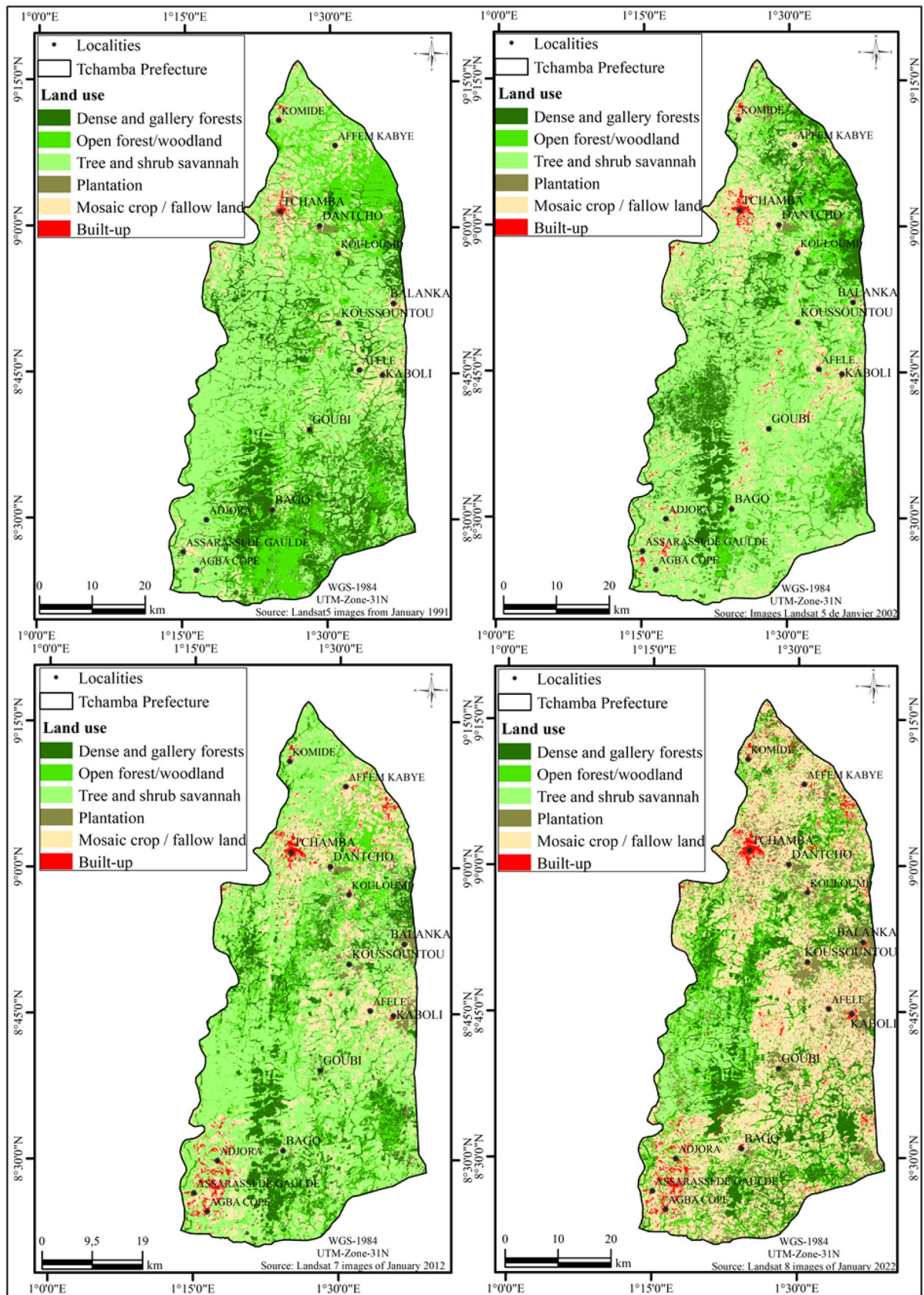


Fig. 3 Classified LULC maps from 1991 to 2022

Fig. 4 Trend of LULC in Tchamba Prefecture from 1991 to 2022

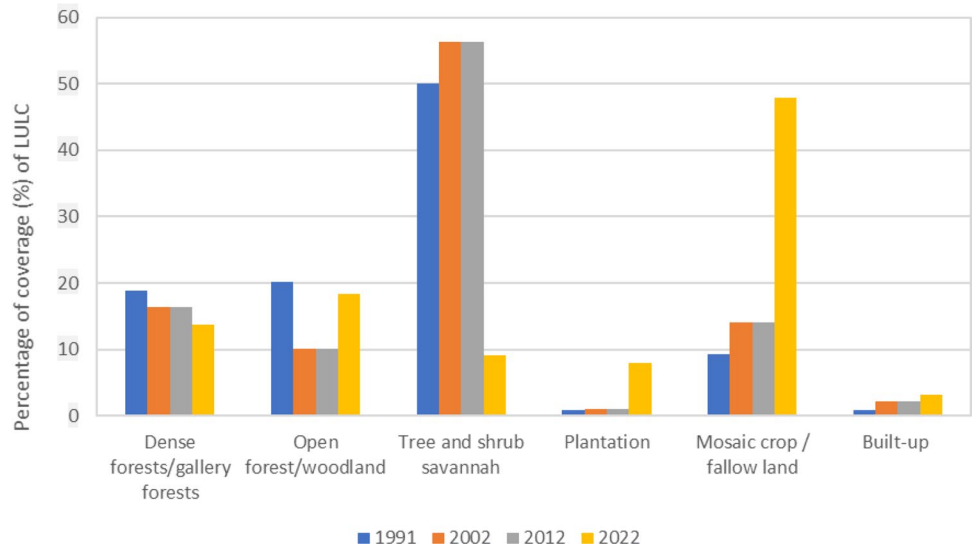
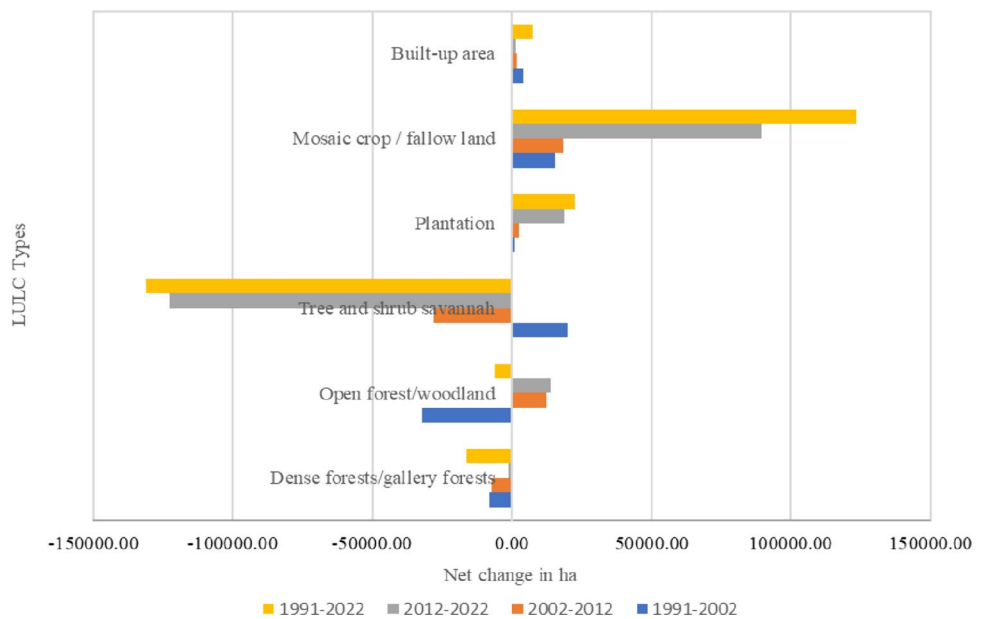


Table 4 LULC transition matrix from 1991 to 2022, Area in ha

LULC types	Dense forests/ gallery forests	Open forest/woodland	Tree and shrub savannah	Plantation	Mosaic crop / fallow land	Built-up	Total 1991
Dense forests/gallery forests	20,347.47	11,384.28	1396.17	3160.62	22,772.97	1544.67	60,606.18
Open forest/woodland	13,188.96	13,388.4	2042.01	5120.1	29,689.02	1575.09	65,003.58
Tree and shrub savannah	11,150.91	30,649.05	22,116.15	11,245.5	79,724.61	3704.58	158,590.8
Plantation	206.91	167.22	55.35	712.44	1301.49	250.2	2693.61
Mosaic crop / fallow land	711	2738.61	503.73	5620.5	18,595.71	1452.33	29,706.11
Built-up	20.34	146.88	37.26	375.21	1761.39	747.63	3088.71
Total 2002	45,625.59	58,474.44	26,150.67	26,234.37	153,845.19	9274.5	319,688.99

Fig. 5 Net change for each LULC category from 1991 to 2022



Validation of Future LULC Prediction

To assess the reliability and robustness of the prediction algorithm, LULC in 2022 was predicted based on historical LULC maps from 1991, 2002, and 2012 using the LCM model. The results were then compared to the actual LULC maps in 2022 (Fig. 6). The results reveal that, from a spatial perspective, there are virtually no differences between projected and observed land use maps. The Kappa index is

estimated to be 0.91, while the overall error between predicted and actual land use is only 0.001% (Table 5). These values assume that the model and comprehensive LULC maps are well suited to predict future LULC. The slight non-significant overestimates observed in the land cover classes, except for open forest/woodland, tree and shrub savannah, mosaic crop/fallow land, did not affect the reliability and general acceptability of the prediction of future land use and cover conditions using this method.

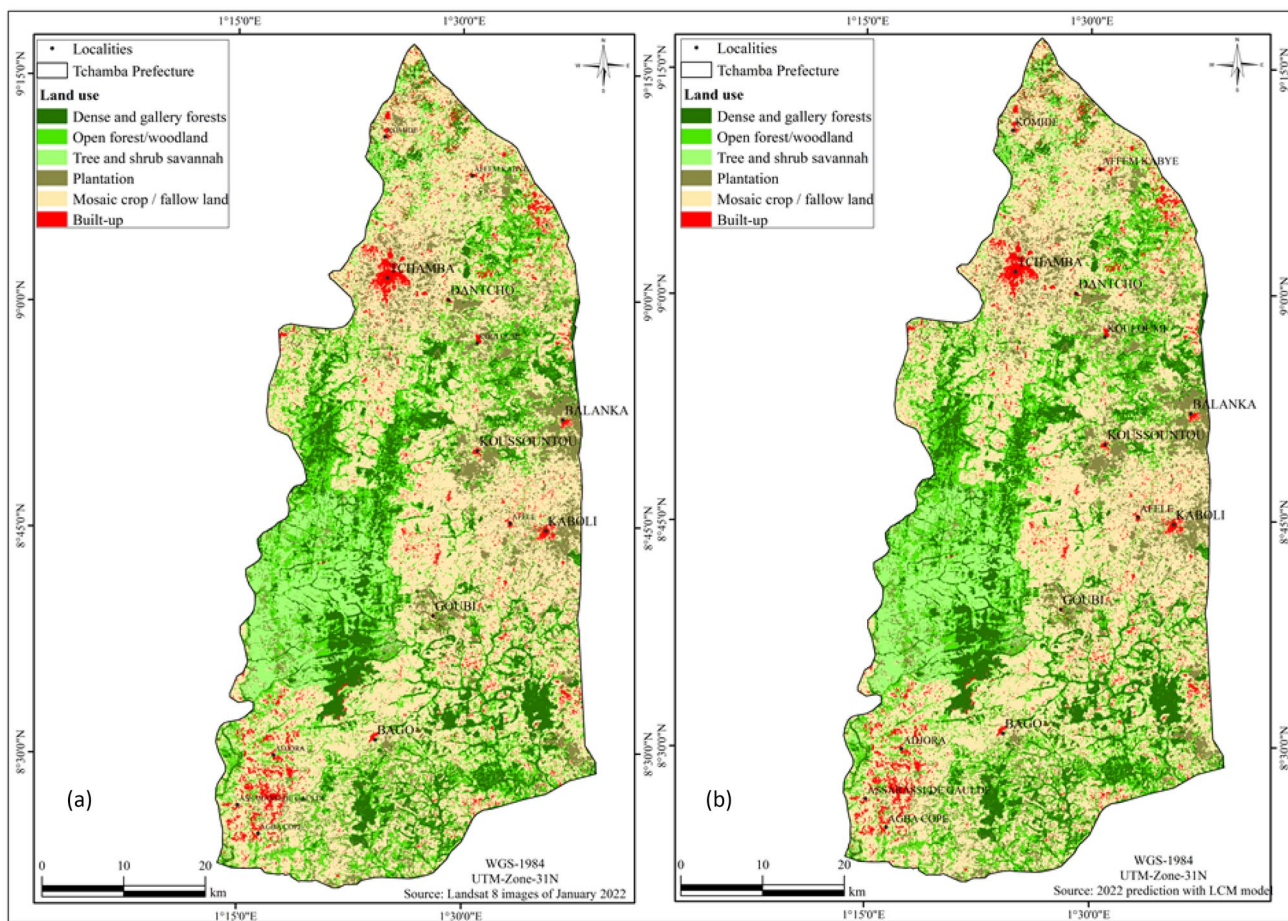


Fig. 6 Predicted and actual land use and cover map in 2022, (a) predicted LULC map by the model, (b) actual LULC map

Table 5 Validation of the LULC prediction based on the actual and simulated 2022 LULC image

LULC type	Actual		Projected		
	Area (ha)	Area (%)	Area (ha)	Area (%)	
Dense forests and gallery forests	43,808.85	13.70	45,747.52	14.31	0.04238
Open forest and woodland	58,507.20	18.30	57,903.21	18.11	-0.01043
Tree and shrub savannah	29,069.64	9.09	26,939.01	8.43	-0.07909
Plantation	25,149.60	7.87	26,834.50	8.39	0.06279
Mosaic crop and fallow land	152,805.74	47.80	151,847.75	47.50	-0.00631
Built-up	10,347.96	3.24	10,421.98	3.26	0.00710
Total	319,688.99	100.00	319,693.97	100.00	0.001%

Future LULC Prediction

Future changes in LULC in Tchamba Prefecture were predicted for 2030 and 2050. The probable percentages of changes in landscape units for 2022–2030 and 2030–2050 were analysed using the transition probability matrix. The coverage highlights the changes observed from the simulated future images between 2022 and 2050, the percentage and the rate of change in the area occupations. The results show significant changes in mosaic crop/fallow land from 47.80% in 2022 to 49.26% in 2030 and 51.66% in 2050. Mosaic crop/fallow land will be the predominant LULC type. The rate of increase observed between 2030, i.e. 3.05% and 2050, i.e. 4.88% shows that mosaic crop /fallow land will increase significantly between 2022 and 2030 compared to changes between 2030 and 2050. Dense forests/gallery forests will slightly stabilise at 13.70% in 2022 and 13.23% in 2030. However, a significant increase will be observed in Dense forests/gallery forests in 2050 with a coverage of 16.17%, which is a rate of 22.24%. On the other hand, a continuous increase in plantation land cover will be observed. Plantation land cover is expected to increase significantly from 7.87% in 2022 to 9.10 in 2030 and slightly to 9.43 in 2050. Additionally, built-up is expected to increase slightly from 3.24% in 2022 to 3.40%. However, Open forests/woodland, as well as tree and shrub savannah, will continue to decline. Open forest/woodland will decline from 18.30% in 2022 to 16.92% in 2030 and 13.36% in 2050. Tree and shrub savannah will decrease from 9.09% in 2022 to 8.16% in 2030 and 5.97% in 2050 (Table 6, Fig. 7). In terms of forest dynamics, forests change only slightly between 2022 (48.96%) and 2050 (47.41%).

The transition matrix analysis provides the transition probabilities of each land cover class to transform into other classes over 2022–2050. The results show a negative trend for open forest/woodland, i.e. 26.99%, in favour of dense forests/gallery forests and tree and shrub savannah and mosaic crop/fallow land (Table 7, Fig. 8). As for the tree and shrub savannah, they transform at a rate of -34.35% to mosaic crop/fallow land, built-up and plantation. Finally, mosaic crop/fallow land, plantation and built-up will continue to increase at 19.89%, 8.08%, and 5.13%, respectively.

Discussion

The study integrates RS approaches and GIS to analyse LULC changes from 1991 to 2022 and predicts future trends through 2050 using the Cellular Automata-Markov modelling technique. The RandomForest algorithm is applied for classification (Breiman, 2001), integrating determining factors relating to dynamic and static variables to enhance the precision of the projections (Regasa & Nones, 2022). The

Table 6 Area coverage of LULC, percent, and rate of changes between 2022 and 2050

LULC type	Area		Change detected			
	2022	2030	2022–2030	2030–2050	2022–2050	%
	ha	ha	ha	ha	ha	%
Dense forests/gallery forests	43,808.85	42,298.00	-1510.85	9405.09	7894.24	18.02
Open forest/woodland	58,507.20	54,076.00	-4431.20	-11,358.67	-15,789.87	-26.99
Tree and shrub savannah	29,069.64	26,091.00	-2978.64	-7007.51	-9986.15	-34.35
Plantation	25,149.60	29,090.00	3940.40	1062.99	5003.39	19.89
Mosaic crop / fallow land	152,805.74	157,470.00	4664.26	7683.44	12,347.70	8.08
Built-up	10,347.96	10,664.00	316.04	214.66	530.70	5.13
Total	319,688.99	319,688.99	100	100	100	100

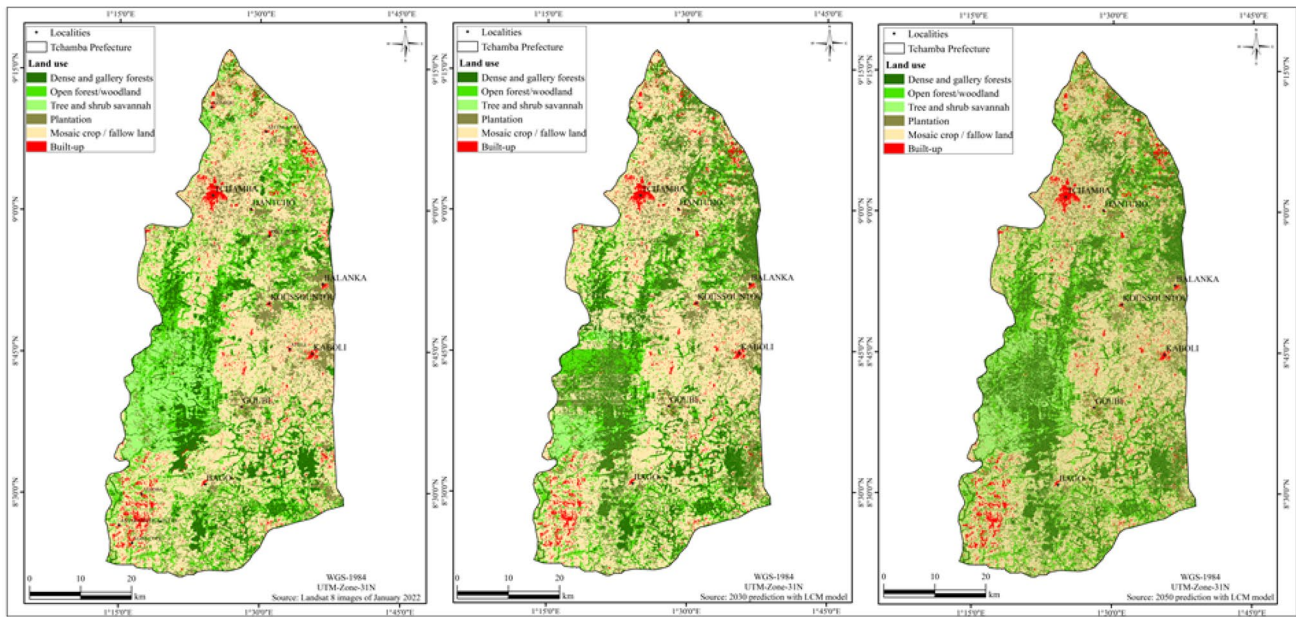
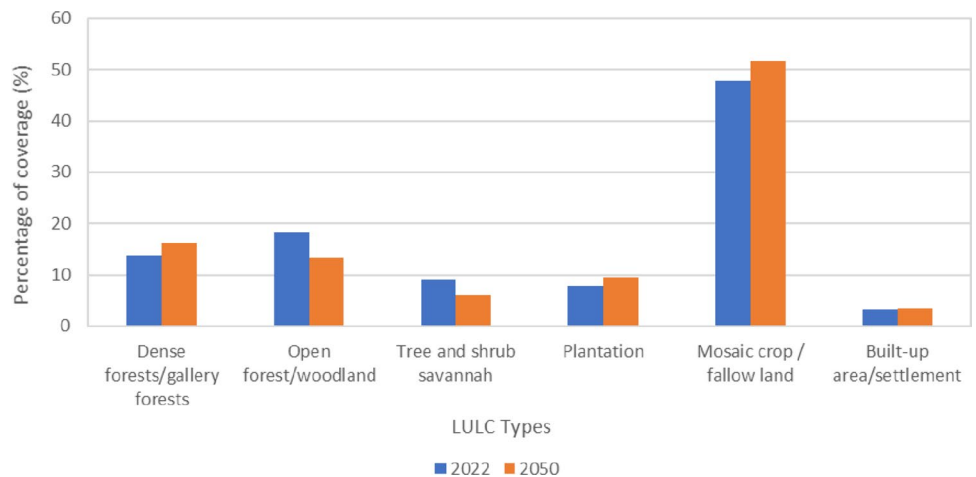


Fig. 7 Future trends in LULC from 2022 to 2030 and 2050

Table 7 LULC transition matrix from 2022 to 2050, Area in ha

LULC types	Dense forests/ gallery forests	Open forest/woodland	Tree and shrub savan- nah	Plantation	Mosaic crop / fallow land	Built-up	Total 2022
Dense forests/gallery forests	25,207.54	12,022.53	69.97	1440.17	4215.20	853.45	43,808.85
Open forest/woodland	14,010.61	17,779.93	1091.60	2700.06	27,736.94	867.89	58,507.20
Tree and shrub savannah	8330.79	98.11	14,806.58	62.91	34.33	57.11	29,069.64
Plantation	1199.40	206.41	179.05	15,161.78	6323.44	2079.52	25,149.60
Mosaic crop / fallow land	2730.04	12,350.45	2529.75	10,081.07	122,656.70	2457.73	152,805.74
Built-up	224.70	259.92	406.56	707.02	4186.82	4562.94	10,347.96
Total 2050	51,703.09	42,717.33	19,083.49	30,152.99	165,153.44	10,878.66	319,688.99

Fig. 8 Trends in LULC of 2022 and 2050 in Tchamba Prefecture



historical analysis of the LULC dynamics was obtained with Kappa values of 0.92, 0.83, 0.81, and 0.85 for the four dates. The quality of the classification confirmed by the Kappa index values is considered statistically acceptable as the image analysis results with a Kappa value above 0.50 are considered good (Pontius, 2000). Similarly, the supervised classification used in this study is among the most appropriate methods for studying LULC by remote sensing because it involves using verification zones (Masoud & Koike, 2006; Nagendra et al., 2006). Regarding the simulation, the value of the kappa index was 0.91, exceeding 80%, and the error was around 0.001%, thus illustrating a solid agreement between the simulated and real LULC maps (Li et al., 2020). Our model's results show high accuracy and are supported by the few additional studies on Togo as well as be explained by socio-political factors.

Over the past 31 years, the analysis of LULC indicates a gradual decline in dense forests/gallery forests, open forest/woodland, and tree and shrub savannah. Meanwhile, there is an increase in plantation, mosaic crop/fallow land, and built-up areas. The conversion matrix analysis reveals that tree and shrub savannah underwent the highest conversion, followed by dense forests/gallery forests and open forest/woodland. Notably, the most significant losses in dense forests/gallery forests and open forest/woodland occurred between 1991 and 2012. These findings align with regional studies, reflecting similar changes (Adjonou et al., 2010; Kombate et al., 2020). Findings can largely be attributed to socio-political challenges in Togo during the 1990s, leading to the cancellation of international cooperation programs. Additionally, political instability negatively impacted the economy and transactional capacities, contributing to a precarious socio-political climate (Aisen & Veiga, 2013; Bunyangha et al., 2021; Dalyop, 2019). This has affected natural resource management, particularly in protected areas like the hot spot of Abdoulaye Wildlife Reserve (RFA), which experienced degradation due to population invasion and non-conservative agricultural practices (UICN/PACO, 2008). The studies by Adjonou et al. (2010) in the area of the reserve indicates a decrease in forest formations in favour of mosaic crop/fallow land and bare soil between 1972 and 2000. The reasons lie in the non-participatory way these classified areas were created and their management system, which was often based on repression (UICN/PACO, 2008). Additionally, the rise in charcoal and high wood energy production (1000 to 1500 tones of wood per month) in the region, intensified agricultural activities, while the exploitation of river banks further contributes to forest degradation in Tchamba Prefecture (Adjonou et al., 2010; Kaina et al., 2021; Kombate et al., 2020).

However, between 2012 and 2022, dense forests/gallery forests almost stabilised, while open forest/woodland increased to 18.30%, nearing 1991 levels. Political stability,

demonstrated by involving local communities in forest management since 2008, can explain these positive changes. The revision of Abdoulaye Faunal Reserve leading to the retrocession of certain parts of the reserve to the communities and vice versa to the recognition of the reserve's state status and the creation of community forests (Alibi-I and Bago) with the retroceded parts of the reserve (MERF, 2016) showcase successful community-based forest management, offering insights for landscape-level restoration in the Prefecture of Tchamba. Through the creation of community forests, the state is accorded legal status to the communities by making them responsible for managing their forest. This model of community forest management, now used as a key restoration model, has allowed for managing several conflicts related to land management and preserving several vegetation resources at the landscape level in the Prefecture. Tchamba remains a successful case where there is at least one community forestry initiative per canton (Issifou et al., 2022). These examples of community forestry have been proven to bring important lessons and insights to the field of FLR and, in particular, to restoration efforts targeted at rural communities (Niraula et al., 2013; Paudyal et al., 2017), as is the case in Tchamba Prefecture.

Between 2012 and 2022, there was a significant decline in tree and shrub savannah, alongside an increase in mosaic crop/fallow land and plantation. Restricted access to the Abdoulaye Wildlife Reserve and community forest areas led to farmers to convert tree and shrub savannah to mosaic crop/fallow land for farming. According to Issifou et al. (2022), to access the new land, over 82% of the farmers clear the forest and even the shallows. The rise in plantations, particularly cashew trees (*Anacardium occidentale*), is driven by economic value and the cultivation of various plant species (shea (*Vitellaria paradoxa*), African locust (*Parkia biglobosa*), Kapok (*Bombax costatum*), Black Plum (*Vitex doniana*)) is prioritized for economic, religious, and cultural reasons in the Prefecture (Kokou et al., 2015). Further, Gmelina (*Gmelina arbore*), Teak (*Tectona grandis*), and Albizia (*Albizia ferruginea*) are increasingly being planted by the people following their promotion by restoration programmes in the area.

The modelled results indicate that mosaic crop/fallow land, the predominant LULC, is expected to dominate in 2050, showing a more significant increase until 2030. This rise is associated with the continued trend of decreasing tree and shrub savannah, open forest/woodland, as shown by the current dynamics in this study and other studies in the region (Adjonou et al., 2010; Kokou et al., 2015; Kombate et al., 2020). This increase is probably linked to ongoing Togolese legislation and the persistent demand for arable land, given the Prefecture of Tchamba's high agricultural potential, attracting people from surrounding areas. The increase in land for agriculture is reported in

similar studies in Uganda (Bunyangha et al., 2021), Ethiopia (Leta et al., 2021), Kenya (Kipkulei et al., 2022), Ghana (Kleemann et al., 2017), and many other countries (Phartiyal et al., 2023).

It is remarkable to underline that dense forests/gallery forests are projected to slightly increase in 2050, likely due to the continued rise of the population for the status of the main reserve of the Prefecture and conservation efforts. Community forests initiatives and current resource management policy may contribute to this positive trend through 2050. The rise in planted land reflects a strong commitment to economically viable tree plantations, supported by ongoing restoration projects that contribute to income generation and provide ecological benefits. Changes in land use should not only be considered from a negative perspective but rather how these changes can impact positively upon planning actions, especially in FLR. Trends in LULCs, whether in favour of agricultural land use (Stanturf et al., 2015) or not, always provide learning opportunities that can be used to better plan actions in the FLR context. Moreover, it is critical that barriers to FLR implementation and their understanding are addressed before restoration initiatives are scaled up to meet national and international commitments (McLain et al., 2021).

LULC analysis is a valuable tool for FLR efforts. The continuous expansion of mosaic crop/fallow land shows the need for targeted restoration, particularly agro-ecological innovations, to avoid total degradation. This study underscores the significance of commercial tree plantations for future FLR activities, offering environmental benefits and promoting equity (McLain et al., 2021). The evaluation of restoration success, especially based on the community forest restoration model, should be put at the centre of future actions for scaling up throughout the prefecture and beyond its borders. This will allow for consideration of the socio-economic and technological contributions of local communities (Nielsen-Pincus & Moseley, 2013) that are often neglected in the case of FLR. Yet, participatory processes, including community forest-based restoration models, play a crucial role in achieving faster and more successful FLR implementation at the local level (Fleming & Fleming, 2009; Sayer et al., 2013). While Landsat imagery, with a spatial resolution of 30 m, offers long-term image availability, high-resolution imagery should be used to accurately assess the restoration efforts of local communities. In addition, a complete analysis should incorporate an examination of socio-economic data and scenarios that outline and spatialise various potential futures. These components, combined with a temporal analysis of LULC, as suggested by Bunyangha et al. (2021), are essential for a thorough understanding of the drivers of change in LULC.

Conclusion

LULC is crucial for effective landscape restoration initiatives. This study reveals spatiotemporal changes in LULCs since 1991, with predicted trends for 2050 using the Cellular Automata-Markov modelling technique. Historical analysis identifies two phases. In the first phase, forest lands were converted to farmlands due to socio-economic pressures in the 1990s, with mosaic crop/fallow land dominating the LULC changes. The second phase is marked by the stabilization of dense forests/gallery forests decline through participatory management and community forest recognition. Community forests became a key model for landscape restoration, with the active participation of the population in reforestation, especially in agroforestry plantations. The results of the predictions for 2050 indicate continued dominance of mosaic crop/fallow land due to rich soil attracting agricultural practices. While mosaic crop/fallow land intensifies, there is a conservation of dense forests/gallery forests and an increase in plantation, reflecting policy awareness and local community efforts. These findings inform restoration planning, supporting local communities and ecological integrity. These results provide information for policy makers designing reforms for natural resource preservation and guide stakeholders in prioritizing restoration efforts for sustainable management. The scientific community and other actors can use these results to enrich assessments and achieve FLR objectives.

Acknowledgements The authors thank the anonymous reviewers for their comments that helped in improving the manuscript. The authors express their gratitude to the United State Geological Survey (USGS) for making free available of Landsat images. The authors acknowledge the Leibniz Centre for Agricultural Landscape Research (ZALF) for providing support to carry out this research work. The authors acknowledge the « Laboratoire de Recherche Forestière, Centre de Recherche sur le Changement Climatique (CRCC), Université de Lomé » that further supported this study.

Author Contributions Conceptualization, methodology, validation, investigation, resources, original draft preparation: Kossi Hounkpati; Resources, writing, review editing and supervision: Kossi Adjonou; Resources, writing, review and editing: Hamza Moluh Njoya; Methodology, software, formal analysis: Atsu K., Dogbeda Hlovor; Resources, review and editing: Harison Kiplagat Kipkulei; Funding acquisition, resources, writing, review, editing and supervision: Stefan Sieber; Funding acquisition, resources, writing, review, editing and supervision: Katharina Löhr; Resources, writing, review, editing and supervision: Kouami Kokou.

Funding Open Access funding enabled and organized by Projekt DEAL. Open Access funding enabled and organized by Projekt DEAL. The research leading to these results received financial support from the German Federal Ministry for Economic Cooperation and Development (BMZ) commissioned and administered through the global project on forest landscape restoration and good governance in the forest sector (Forests4Future) of the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ). The contents of this study are the

sole responsibility of the author(s) of this publication and can under no circumstances be regarded as reflecting the position of GIZ or BMZ.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Adjonou, K., Djiwa, O., Kombate, Y., Kokutse, A. D., & Kokou, K. (2010). Etude de la dynamique spatiale et structure des forêts denses sèches reliques du Togo : Implications pour une gestion durable des aires protégées. *International Journal of Biological and Chemical Sciences*. <https://doi.org/10.4314/ijbcs.v4i1.54242>
- Aisen, A., & Veiga, F. J. (2013). How does political instability affect economic growth? *European Journal of Political Economy*, 29, 151–167. <https://doi.org/10.1016/j.ejpoleco.2012.11.001>
- Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5–32.
- Bunyanga, J., Mwanjalolo, J. G., Majaliwa, A. W., Muthumbi, N. N., & Gichuki, A. E. (2021). Past and future land use/land cover changes from multi-temporal Landsat imagery in Mpologoma catchment, eastern Uganda. *The Egyptian Journal of Remote Sensing and Space Science*, 24(3), 675–685. <https://doi.org/10.1016/j.ejrs.2021.02.003>
- Clerici, N., Cote-Navarro, F., Escobedo, F. J., Rubiano, K., & Villegas, J. C. (2019). Spatio-temporal and cumulative effects of land use-land cover and climate change on two ecosystem services in the Colombian Andes. *Science of the Total Environment*, 685, 1181–1192. <https://doi.org/10.1016/j.scitotenv.2019.06.275>
- Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 37(1), 35–46. [https://doi.org/10.1016/0034-4257\(91\)90048-B](https://doi.org/10.1016/0034-4257(91)90048-B)
- Dalyop, G. T. (2019). Political instability and economic growth in Africa. *International Journal of Economic Policy Studies*, 13(1), 217–257.
- DFS/GOPA. (2016). Evaluation du potentiel de restauration des paysages forestiers au Togo. https://tg.chmcbd.net/implementation/docs/evaluation-du-potentiel-de-restauration-des-paysages-forestiers-autogo/download/fr/1/160903-DFS_Etude_MEOR_Togo_revised.pdf.
- Eastman, J. R. (2009). IDRISI Taiga guide to GIS and image processing. *Clark Labs Clark University, Worcester, MA, Manual Version*, 16(02), 325.
- Eastman, J. R. (2016). *Eastman: TerrSet geospatial monitoring and modeling system*. <https://clarklabs.org/wp-content/uploads/2016/10/Terrset-Manual.pdf>.
- FAO and UNEP. (2020). The state of the world's forests 2020. *FAO and UNEP*. <https://doi.org/10.4060/ca8642en>
- FAO. (2022). The State of the World's Forests 2022. <https://doi.org/10.4060/cb9360en>
- Fleming, B., & Fleming, J. P. (2009). A watershed conservation success story in Nepal: Land use changes over 30 years. *Waterlines*, 28(1), 29–46.
- Forkuo, E. K., Biney, E., Harris, E., & Quaye-Ballard, J. A. (2021). The impact of land use and land cover changes on socioeconomic factors and livelihood in the Atwima Nwabiagya district of the Ashanti region. *Ghana. Environmental Challenges*, 5, 100226.
- García-Álvarez, D., Olmedo, M. T. C., Paegelow, M., & Mas, J. F. (Eds.). (2022). *Land Use Cover Datasets and Validation Tools: Validation Practices with QGIS*. Springer International Publishing. <https://doi.org/10.1007/978-3-030-90998-7>
- Gbedzi, D. D., Ofosu, E. A., Mortey, E. M., Obiri-Yeboah, A., Nyantakyi, E. K., Siabi, E. K., Abdallah, F., Domfeh, M. K., & Amankwah-Minkah, A. (2022). Impact of mining on land use land cover change and water quality in the Asutifi North District of Ghana, West Africa. *Environmental Challenges*, 6, 100441.
- Gislason, P. O., Benediktsson, J. A., & Sveinsson, J. R. (2006). Random forests for land cover classification. *Pattern Recognition Letters*, 27(4), 294–300.
- Grinand, C., Rakotomalala, F., Gond, V., Vaudry, R., Bernoux, M., & Vieilledent, G. (2013). Estimating deforestation in tropical humid and dry forests in Madagascar from 2000 to 2010 using multi-date Landsat satellite images and the random forests classifier. *Remote Sensing of Environment*, 139, 68–80. <https://doi.org/10.1016/j.rse.2013.07.008>
- Gülersoy, A. E. (2014). Temporal change of land use in seferihisar (1984–2010) and proposals for optimal land use. *Süleyman Demirel Üniversitesi Fen-Edebiyat Fakültesi Sosyal Bilimler Dergisi*, 2014(31), 31.
- Gutman, G., & Masek, J. G. (2012). Long-term time series of the Earth's land-surface observations from space. *International Journal of Remote Sensing*, 33(15), 4700–4719. <https://doi.org/10.1080/01431161.2011.638341>
- Gyamfi-Ampadu, E., Gebreslasie, M., & Mendoza-Ponce, A. (2020). Mapping natural forest cover using satellite imagery of Nkandla forest reserve, KwaZulu-Natal, South Africa. *Remote Sensing Applications: Society and Environment*, 18, 100302. <https://doi.org/10.1016/j.rsase.2020.100302>
- Hansen, A. J., DeFries, R. S., & Turner, W. (2004). Land Use Change and Biodiversity: A Synthesis of Rates and Consequences during the Period of Satellite Imagery. In G. Gutman, A. C. Janetos, C. O. Justice, E. F. Moran, J. F. Mustard, R. R. Rindfuss, D. Skole, B. L. Turner, & M. A. Cochrane (Eds.), *Land Change Science: Observing, Monitoring and Understanding Trajectories of Change on the Earth's Surface* (pp. 277–299). Springer Netherlands. https://doi.org/10.1007/978-1-4020-2562-4_16
- Haque, Md. I., & Basak, R. (2017). Land cover change detection using GIS and remote sensing techniques: A spatio-temporal study on Tanguar Haor, Sunamganj, Bangladesh. *The Egyptian Journal of Remote Sensing and Space Science*, 20(2), 251–263. <https://doi.org/10.1016/j.ejrs.2016.12.003>
- Hounkpati, K., Adjonou, K., & Kokou, K. (2022). Distribution and cultural identity of sacred groves in Togo. *International Forestry Review*, 24(2), 163–174. <https://doi.org/10.1505/146554822835629550>
- INSEED. (2011). TOGO - Recensement Général de la Population et de l'Habitat (2009–2011), Quatrième Recensement Générale au Togo. <http://160.242.193.218:8082/nada/index.php/catalog/2>
- Issifou, A., Fousseni, F., Kombate, B., Atakpama, W., Komlan, B., Koffi, K., & Koffi, A. (2022). Cartographie participative des terroirs riverains De La Réserve De Faune D'abdoulaye Au Togo. *Rev. Écosystèmes Et Paysages*, 2, 83–97.
- IWP/AFR100/GIZ. (2020a). Rapport de Cartographie Participative de la Préfecture de Tchamba. Technical No. Provisoire. Internationale

- Waldpolitik (IWP)—Deutsche Gesellschaft für Internationale Zusammenarbeit GmbH (GIZ), Sokoté, Rép. Du Togo.
- IWP/AFR100/GIZ. (2020b). Inventaire Forestier Préfectoral (IFP)—Préfecture de Tchamba. Rapport Technique Provisoire. Internationale Waldpolitik (IWP) – Deutsche Gesellschaft für Internationale Zusammenarbeit GmbH (GIZ), Sokoté, Rép. Du Togo.
- ITTO. (2020). *Guidelines for forest landscape restoration in the tropics*. (ITTO Policy Development Series International Tropical Timber Organization (ITTO), Yokohama, Japan, 1–No. 24.). https://www.itto.int/direct/topics/topics_pdf_download/topics_id=6511&no=1&disp=inline
- Jia, Z., Ma, B., Zhang, J., & Zeng, W. (2018). Simulating spatial-temporal changes of land-use based on ecological redline restrictions and landscape driving factors: A case study in Beijing. *Sustainability*, 10(4), 1299. <https://doi.org/10.3390/su10041299>
- Kaina, A., Dourma, M., Folega, F., Diwziga, B., Kpérkouma, W., & Akpagana, K. (2021). Localisation des bassins de production de bois énergie et typologie des acteurs de la filière dans la région centrale du Togo.
- Kipkulei, H. K., Bellingrath-Kimura, S. D., Lana, M., Ghazaryan, G., Boitt, M., & Sieber, S. (2022). Modelling cropland expansion and its drivers in Trans Nzoia County. *Kenya. Modeling Earth Systems and Environment*, 8(4), 5761–5778. <https://doi.org/10.1007/s40808-022-01475-7>
- Kleemann, J., Baysal, G., Bulley, H. N. N., & Fürst, C. (2017). Assessing driving forces of land use and land cover change by a mixed-method approach in north-eastern Ghana, West Africa. *Journal of Environmental Management*, 196, 411–442. <https://doi.org/10.1016/j.jenvman.2017.01.053>
- Kokou, K., Kamana, P., Ganiou, T., Kossi, A., Yendouhame, K., Aoufoh, D. K., Ouro-Yodou, T., Abdou-Kérim, B. I., & Kokou, F. (2015). Impacts assessment of success stories in natural resources management in Togo (West Africa) (pp. 25–50)
- Kombate, B., Dourma, M., Foussemi, F., Atakpama, W., Wala, K., & Koffi, A. (2020). Spatio-temporal dynamics and habitat fragmentation within a central region of Togo. *Agricultural Science Research Journal*, 10, 291–305.
- Kundu, S., Khare, D., & Mondal, A. (2017). Landuse change impact on sub-watersheds prioritization by analytical hierarchy process (AHP). *Ecological Informatics*, 42, 100–113. <https://doi.org/10.1016/j.ecoinf.2017.10.007>
- Leta, M. K., Demissie, T. A., & Tränckner, J. (2021). 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*, 13(7), 3740. <https://doi.org/10.3390/su13073740>
- Li, K., Feng, M., Biswas, A., Su, H., Niu, Y., & Cao, J. (2020). Driving factors and future prediction of land use and cover change based on satellite remote sensing data by the LCM model: A case study from Gansu province. *China. Sensors*, 20(10), 2757.
- Lynch, L., Kokou, K., & Todd, S. (2018). Comparison of the ecological value of sacred and nonsacred community forests in Kabolli. *Togo. Tropical Conservation Science*, 11, 1940082918758273.
- Masoud, A. A., & Koike, K. (2006). Arid land salinization detected by remotely-sensed landcover changes: A case study in the Siwa region, NW Egypt. *Journal of Arid Environments*, 66(1), 151–167.
- MAEH. (2017). *Programme National d'Investissement Agricole, de Sécurité Alimentaire et Nutritionnelle*. https://agriculture.gouv.tg/wp-content/uploads/2020/06/PNIASAN-_apres-atelier-de-validation-_11_01_2018.pdf
- McLain, R., Lawry, S., Guariguata, M. R., & Reed, J. (2021). Toward a tenure-responsive approach to forest landscape restoration: A proposed tenure diagnostic for assessing restoration opportunities. *Land Use Policy*, 104, 103748. <https://doi.org/10.1016/j.landusepol.2018.11.053>
- MERF. (2010). Programme National d'Investissements pour l'Environnement et les Ressources Naturelles au Togo (PNIERN). <https://tg.chm-cbd.net/implementation/docs/programme-national-d-investissements-pour-l-environnement-et-les-ressources>
- MERF. (2016). Aire Protégée d'Abdoulaye: Plan d'Aménagement et de Gestion.
- MERF. (2017). Programme National du Reboisement au Togo 2017–2030 Phase 1 2017–2021 FAO TCP/TOG/3502. <https://faolex.fao.org/docs/pdf/tog198334.pdf>
- MERF. (2018). Programme de Définition des Cibles Nationales de la Neutralité en Matière de Dégradation des Terres (PDC NDT) au Togo. https://www.unccd.int/sites/default/files/ldn_targets/Togo%20LDN%20TSP%20Country%20Report.pdf
- MERF. (2020). Niveau de référence pour les Forêts (NRF) du Togo. https://redd.unfccc.int/files/nrf_togo_06_1_20_rev_18_08_20_finale.pdf
- MERF. (2021). Politique Forestière du Togo. [https://environnement.gouv.tg/wp-content/uploads/files/2018/Septembre/POLITIQUE%20FORESTIERE%20DU%20TOGO%20\(PFT\)%202011-2035.pdf](https://environnement.gouv.tg/wp-content/uploads/files/2018/Septembre/POLITIQUE%20FORESTIERE%20DU%20TOGO%20(PFT)%202011-2035.pdf)
- MERF/GIZ. (2016). *Rapport Inventaire Forestier National du Togo*. <https://docplayer.fr/225363887-Rapport-inventaire-forestier-national-du-togo.html>
- Mishra, V. N., & Rai, P. K. (2016). A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. *Arabian Journal of Geosciences*, 9(4), 249. <https://doi.org/10.1007/s12517-015-2138-3>
- Munthali, M. G., Davis, N., Adeola, A. M., & Botai, J. O. (2022). The impacts of land use and land cover dynamics on natural resources and rural livelihoods in Dedza District. *Malawi. Geocarto International*, 37(6), 1529–1546.
- Nagendra, H., Pareeth, S., & Ghate, R. (2006). People within parks—Forest villages, land-cover change and landscape fragmentation in the Tadoba Andhari Tiger Reserve, India. *Applied Geography*, 26(2), 96–112.
- Nedd, R., Light, K., Owens, M., James, N., Johnson, E., & Anandhi, A. (2021). A synthesis of land use/land cover studies: definitions, classification systems, meta-studies, challenges and knowledge gaps on a global landscape. *Land*, 10(9), 994. <https://doi.org/10.3390/land10090994>
- Nielsen-Pincus, M., & Moseley, C. (2013). The economic and employment impacts of forest and watershed restoration. *Restoration Ecology*, 21(2), 207–214. <https://doi.org/10.1111/j.1526-100X.2012.00885.x>
- Niraula, R. R., Gilani, H., Pokharel, B. K., & Qamer, F. M. (2013). Measuring impacts of community forestry program through repeat photography and satellite remote sensing in the Dolakha district of Nepal. *Journal of Environmental Management*, 126, 20–29. <https://doi.org/10.1016/j.jenvman.2013.04.006>
- Pasiecznik, N., & Reij, C. (2020). Restoring African Drylands.
- Paudyal, K., Baral, H., Putzel, L., Bhandari, S., & Keenan, R. J. (2017). Change in land use and ecosystem services delivery from community-based forest landscape restoration in the Phewa Lake watershed. *Nepal. International Forestry Review*, 19(4), 88–101. <https://doi.org/10.1505/146554817822330524>
- Phartiyal, B., Mohan, R., Chakraborty, S., Dutta, V., & Gupta, A. K. (2023). *Climate Change and Environmental Impacts: Past Present and Future Perspective*. Springer Nature.
- Pontius, R. G. (2000). Quantification error versus location error in comparison of categorical maps. *Photogrammetric Engineering and Remote Sensing*, 66(8), 1011–1016.

- Puyravaud, J.-P. (2003). Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management*, 177(1), 593–596. [https://doi.org/10.1016/S0378-1127\(02\)00335-3](https://doi.org/10.1016/S0378-1127(02)00335-3)
- Qacami, M., Khattabi, A., Lahssini, S., Rifai, N., & Meliho, M. (2023). Land-cover/land-use change dynamics modeling based on land change modeler. *The Annals of Regional Science*, 70(1), 237–258. <https://doi.org/10.1007/s00168-022-01169-z>
- Ramachandra, T. V. (2014). Hydrological responses at regional scale to landscape dynamics. *Journal of Biodiversity*, 5(1–2), 11–32. <https://doi.org/10.1080/09766901.2014.11884748>
- Reddy, C. S., Singh, S., Dadhwal, V. K., Jha, C. S., Rao, N. R., & Diwakar, P. G. (2017). Predictive modelling of the spatial pattern of past and future forest cover changes in India. *Journal of Earth System Science*, 126(1), 1–16.
- Regasa, M. S., & Nones, M. (2021). *Historical and future land use and land cover changes in the Fincha watershed, Ethiopia* [Preprint]. In Review. <https://doi.org/10.21203/rs.3.rs-978807/v1>
- Regasa, M. S., & Nones, M. (2022). Past and future land use/land cover changes in the ethiopian fincha sub-basin. *Land*. <https://doi.org/10.3390/land11081239>
- Sayer, J., Sunderland, T., Ghazoul, J., Pfund, J.-L., Sheil, D., Meijaard, E., Venter, M., Boedhihartono, A. K., Day, M., Garcia, C., van Oosten, C., & Buck, L. E. (2013). Ten principles for a landscape approach to reconciling agriculture, conservation, and other competing land uses. *Proceedings of the National Academy of Sciences*, 110(21), 8349–8356. <https://doi.org/10.1073/pnas.1210595110>
- Stanturf, J. A., Kant, P., Lillesø, J.-P. B., Mansourian, S., Kleine, M., Graudal, L., & Madsen, P. (2015). *Forest landscape restoration as a key component of climate change mitigation and adaptation* (Vol. 34). International Union of Forest Research Organizations (IUFRO) Vienna, Austria. [http://curis.ku.dk/ws/files/161428268/Stanturf et al 2015 IUFRO World Series vol 34 FLR adaptation mitigation.pdf](http://curis.ku.dk/ws/files/161428268/Stanturf%20et%20al%202015%20IUFRO%20World%20Series%20vol%2034%20FLR%20adaptation%20mitigation.pdf).
- Tsegaye, B. (2019). Effect of land use and land cover changes on soil erosion in Ethiopia. *International Journal of Agricultural Science and Food Technology*, 5(1), 26–34.
- UICN/PACO. (2008). *Evaluation de l'efficacité de la gestion des aires protégées : Aires protégées du Togo*. <https://papaco.org/fr/wp-content/uploads/2015/07/RAPPAM-Togo.pdf>
- Yang, X., & Lo, C. P. (2002). Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area. *International Journal of Remote Sensing*, 23(9), 1775–1798. <https://doi.org/10.1080/01431160110075802>
- Zhao, Y., & Zhu, Z. (2022). ASI: An artificial surface Index for Landsat 8 imagery. *International Journal of Applied Earth Observation and Geoinformation*, 107, 102703. <https://doi.org/10.1016/j.jag.2022.102703>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.