Selected Driver Variables for the Simulation of Land-Use and Land-Cover Change for the Republic of Djibouti: A Study from Semi-Arid Region

Santa Pandit[1], Sawahiko Shimada[1], Timothy Dube[2]

[1] Department of Bioproduction and Environment Engineering, Tokyo University of Agriculture, Sakuragaoka, Setagaya, Tokyo, Japan (razs.san@gmail.com/ shima123@nodai.ac.jp)
[2] Institute for Water Studies, The University of the Western Cape, Cape Town, South Africa (tidube@uwc.ac.za)

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Abstract

This study aims to integrate driver variables with a land use change model (LCM) to explore their impact on the natural environment within the context of land-use changes in the Republic of Djibouti, considering possible Business-as-usual scenarios. Secondary data from 1990 and 2012 on land use land cover (LULC) were analyzed, with a 2022 map generated by adopting the same method of secondary data used (random forest classification in Google Earth Engine (GEE)) for validation. Eight key driver variables were utilized to model plausible future land cover (2035) for Djibouti. Statistical outputs and change maps from the LCM were compared to gauge historical change estimates and simulated scenarios. Analysis from 1990 to 2022 highlights significant land use and cover changes spurred by urbanization, environmental factors, and economic development. Barren land and bushland dominated, while built-up areas and water bodies expanded notably. Urbanization, agriculture, and climate change contributed to vegetation degradation, with declines in mangroves and increases in built-up areas. Water bodies also expanded during this period. Projections from the 2035 LULC map anticipate further urban expansion, underscoring the need for sustainable land management practices. In conclusion, comprehensive land-use planning, interdisciplinary approaches, and stakeholder engagement are deemed critical for addressing Djibouti's socio-economic and environmental challenges and steering towards a sustainable future. These simulated results offer valuable insights for regional governments to frame strategic policies and assess management actions for resource utilization amidst urbanization and population growth trends.

1. INTRODUCTION

Land use and land cover change (LULCC) is a complex process that involves transforming land from one use or cover type to another and has a significant global environmental issue. The driving factors for LULCC can be broadly categorized into natural and anthropogenic factors. Natural factors include climate change and other environmental conditions, while anthropogenic factors include economic development, the social environment, and population changes. This phenomenon was explained in a study by Liu et al. (2010). Among the natural factor, climate change plays a vital role in LULCC (Samson and Elangovan, 2015), which in turn has been exacerbated by strong interaction between anthropogenic activities and the natural environment (Wang et al., 2005; Tang et al., 2008). The current trend of world population change has resulted in unprecedented demographic diversity across regions and countries (Cohen, 2003), and both the substantial population increase and its decline have become serious concerns. There is no doubt the current rate of population expansion is placing stress on the natural environment due to the extreme resource consumption and the earth's surface modifications; on the contrary, depopulation in term leads to an underuse of resources—is also recognized as a significant threat to biodiversity loss (Duraiappah et al., 2012). It can be evident from various numbers of existing literature that the former demographic change has exerted pressure on the natural systems, often leading to a non-linear transformation of its mosaic landscapes (Morgado et al., 2014; You et al., 2018) where Africa, Asia, and Middle East regions are experiencing these issues (Nelson et al., 2006) whereas East Asia and Europe are experiencing the latter change as the growth has slowed down. In light of this, it is important to note that exponential population growth and depopulation both have profound implications for land use and land cover change. For example, the less human intervention in the usage of the socio-ecological landscapes led to the deformation of ecosystem characteristics, an increase in soil erosion, depreciation in landscape aesthetics, and an increase in human-wildlife conflicts (Beilin et al., 2014; Katayama et al., 2015; Mauerhofer et al., 2018). In such cases, re-establishing human-nature relationships by utilizing the country's natural capital more can offer one possible direction to reduce the impact of population decrease (Hashimoto et al., 2018).

According to the IPCC (2018), arid and semi-arid regions are highly susceptible to extreme weather events like heatwaves (Fu and Feng, 2014) and droughts (Greve et al., 2014; Spinoni et al., 2020). They are also more likely to experience rapid land and environmental degradation because they have fewer natural water resources (Dregne, 2002; Glantz, 2019). The driving factors of LULCC in arid regions are diverse and can be classified into two main categories: human and natural factors. These driving factors are interrelated and can have cascading effects on the environment and human well-being. In a recent study, Spinoni et al. (2021) examined how the expansion of arid areas will affect croplands, pastures, forests (land use), and people. Understanding these factors is crucial for developing effective policies and strategies to manage LULCC and promote sustainable development in arid regions. Over the years, there has been significant progress in quantifying land use land cover (LULC) varying from remote sensing, GIS, and traditional methods (field data collection) (Li et al., 2004; Turner et al., 2007), which can be further simulated predicted applying various drivers of change, land use policies (Shade and Kremer, 2019).

The Land Change Modeler (LCM) is a software developed by Clarks Lab, Clark University USA, used for assessing and predicting land cover change (Clark Labs, 2009). It focuses on change analysis, transition potential, change prediction, and planning actions. LCM also supports REDD projects and evaluates future emissions. Transition potentials are generated using sub-models with driver variables, which can be static or dynamic. Static variables are unchanging over time, while dynamic variables are time-dependent and recalculated during prediction. LCM includes six model types for prediction: Multi-Layer Perception (MLP) neural network, Decision Forest machine learning, Logistics Regressions, Weighted Normalized Likelihood (WNL), Support Vector Machine (SVM), and a SimWeight procedure (Clark Labs, 2009).

During the process, various direct factors that can accelerate the changes can be considered depending on the geographical nature of the proposed study sites with the inclusion of policy interventions (such as land policies or urban expansion policy). Depending on how directly these variables would affect any future changes—which could be static or dynamic—they could be part of the same set or different. Static variables are appropriate for the transition under study and remain constant throughout time, whereas dynamic variables vary over time and are reassessed during the prediction process.

In this research, we utilize the MPL model mainly because it is a robust model that is capable of handling complex non-linear relations with the variables (Hashimoto et al., 2018; Mishra et al., 2014). This approach of LCM-MPL and remote sensing could be beneficial for countries like Djibouti, where the geographical position of the country is most sophisticated in the world by the state-of-the-art port complexes. As of 2019, 78.2% of the people in Djibouti lived in urban areas, making it the most urbanized nation in sub-Saharan Africa (Yeboua, 2023). From 76% in 1990, this percentage has grown, and it is anticipated to do so in the future. However, if this expansion is not well controlled, it may result in several problems like unemployment, poverty, environmental degradation, ill health, and squalor (Yeboua, 2023). Moreover, to achieve the UN 2030 agenda and the African Union agenda 2063, the country's master plan 2024, and its vision 2035 - which aims to boost economic transformation and diversification - it is essential to conduct comprehensive research, have a clear understanding of the challenges that may negatively impact the country's geography, and ensure the future sustainability of development (World Bank 2014; Yeboua, 2023). In addition to mitigating climate change and natural disasters such as flooding, practical and good urban planning could contribute to fostering an inclusive economy. It is, therefore critical to understand how the rising population trend in Djibouti might influence future socio-ecological landscapes at a regional level for better policy interventions at the earliest possible.

Thus, this study aims to identify the spatio-temporal patterns and driving factors of LULCC between 1990 and 2012. The primary objective is to predict a business-as-usual future scenario of transition between different LULC classes within the region, which quantitatively describes the role of natural or anthropogenic activities in the major transition processes. It can be used as a preliminary step for more advanced LULCC analysis and highlights the positive and negative impact of government policies that occurred within this time frame.

2. STUDY AREA AND METHODOLOGY

2.1 Study Area: Djibouti is geographically located on the easternmost projection of the African continent within the Horn of Africa, uniquely positioned on the southern side of the Gulf of Aden (372 km) along the world's busiest shipping routes. Its longitudes are between 41°8' and 43°4' E, and its latitudes are between 10°9' and 12°7' N, with a total land area of 23,200 km^2 (Fig. 1). The country shares its borders with Eritrea to the north, Ethiopia to the west and south, and Somalia to the southeast. Djibouti is located in the Horn of Africa. The terrain is mostly made up of desert-like plains, with some intermediate mountain ranges near the eastern border. The country is divided into five regions: Ali Sabieh, Dikhil, Obock, Tadjourah, and Arta. The capital city, also named Djibouti, holds a special status. According to the World Bank, the country's population is estimated to be 1.12 million, with a growth rate of 1.4% per annum.

Djibouti has a semi-arid climate, which is characterized by high temperatures and high evaporation throughout the year. The country experiences two seasons: a dry season from May to October and a relatively cool season from November to April. The temperatures range from warm during December, January, and February (with average temperatures between 23 – 29°C) to extremely hot in July (31 – 41°C), with oppressive humidity adding to the uncomfortable conditions. Djibouti receives an average annual rainfall of approximately 147mm, which occurs between November and March. High-elevated coastal areas receive higher rainfall (Dabar et al., 2022).

Djibouti's main natural asset is probably its strategic location, which is at the southern entrance to the Red Sea, marking a bridge between Africa and the Middle East and adjacent to some of the World's busiest shipping lanes (between Asia and Europe). As a result, Djibouti hosts a multitude of foreign military bases.

2.2 Data Acquired and Land Use Land Cover (LULC)

LULC maps are the essential input data for predicting future land-use changes in any region. The spatial data sets of LULC generated by SATREPS generated data (Tokyo University of Agriculture) for the years 1990 and 2012 were used as the two base year maps, while for validation purposes, the 2023 LULC map was generated by following a similar process in the Google Earth Engine platform using random forest classification method. The major classes identified by utilizing Landsat 30m resolution images were mangroves, bushes, farmland, built-up areas, water bodies, barren land, and salt. The three-year input LULC data (1990, 2012, and 2023) were employed for business scenarios LULC development.

Driver variables play a crucial role in the land change modeling process within the TerrSet IDRISI software, particularly in the Land Change Modeler module. The dataset of eight driver variables was used; seven of them were acquired from different freely available online sources, whereas one geology map was utilized from SATREPS-generated data. The seven driver variables were DEM, slope acquired from SRTM https://earthexplorer.gov/, the population density was acquired from https://data.humdata.org/dataset/highresolutionpopulationdensitymaps-dji, the annual temperature was acquired from https://www.worldclim.org/data/worldclim21.html, annual precipitation was acquired from https://chrsdata.eng.uci.edu/, distance from river data was acquired from https://geoportal.icpac.net/layers/geonode%3Adji_water_lines_dcw, and distance from roads was acquired from https://datacatalog.worldbank.org/search/dataset/0041424/Djibouti-Major-Roads.

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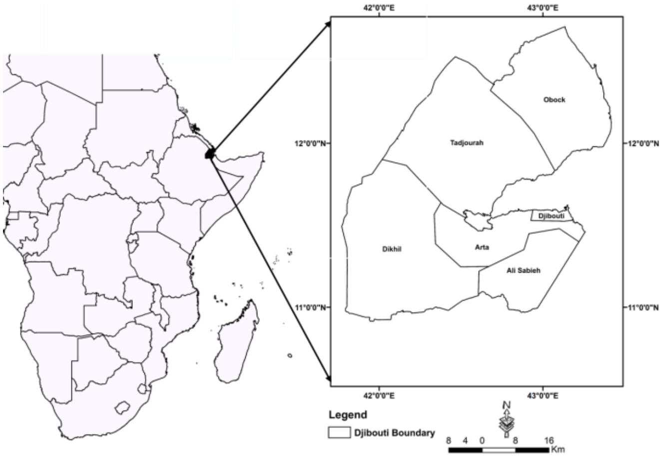


Figure 1. Map showing the study area

2.3 Land Change Model for Scenarios Development

The Land Change Modeler (LCM) is an integrated software developed to project future land-use changes for the Republic of Djibouti. In recent years, LCM has gained popularity mainly due to the adequate explanation and trial materials offered by the developer (Mas et al., 2014; Mirhosseini et al., 2016) and combined with IDRISI GIS and Image processing software package (Eastman, 2016). The LCM is categorized into five main modules: analyzing past land-use change, modeling the change (transition potential), predicting future change, assessing implications for biodiversity, and planning interventions (Cerreta and De. P. 2012).

To analyze the past land-use change pattern, two time period LULC maps of 1990 and 2012 were used in the change analysis module. In this panel, the transition of one class to another was evaluated by the gain, loss, and unchanged values. Since this study considers the possible driver variables as population dynamics and geology, our transition of interest was that class where humans have a high impact on their change and geology affected by human or natural processes (climate change). The transition of interest, as mentioned in the statement, focuses on areas where human activities have a high impact on land cover changes and where geological features are influenced by both human and natural processes, such as climate change. By examining these specific classes, the study aims to gain insights into the complex interactions between human activities, natural processes, and land cover dynamics within the study area. Thus, the individual transitioning model derived from both variables was included for the prediction of the LULC map.

The second step is to create a transition potential map which was changed over those two time periods. LCM offers the transition of the model by an inbuilt Multi-Layer Perceptron neural network, which develops a multivariate function that estimates the transition potential based on the values of input driver variables (Shoyama et al., 2018). An evidence likelihood raster was also created for each transition that occurred and added as a driver variable. These variables represent the factors that influence land use and land cover changes, such as environmental conditions, socio-economic factors, infrastructure developments, topography, and agricultural expansion. By incorporating eight driver variables into the modeling process, researchers can better understand the relationships between these factors and land cover changes, allowing for more accurate predictions of future land use scenarios, and thus the model structure was executed. For this modeling, we choose those transitions that are directly affected by human interaction, which means the most transition taking into built-ups and farmland. Thus, there were seven transitioned models. For every transition selected for this modeling, a random sample of cells was generated by the neural network. Additionally, it builds a network of weighted neurons. These weights are used to determine the training error, modify the weight, and raise accuracy. The RMS error drops as the weight changes. Approximately 80% is regarded as an acceptable accuracy rate (Eastman, 2006). In this study, the MLP has finished 10000 iterations (default) of training and testing with an accuracy of more than 70% to 95 %. Then, seven transition potential maps were obtained, where we changed the training parameter's learning rate as recommended in the TerrSet manual.

2.4 Markov Chain Modeling

A Markov Chain is a random process that calculates the expected land cover transition from a later date to a predicted date, using earlier and later land cover maps. This process creates a transition probabilities file, a matrix that records the probability of each land cover category changing to another. Markov Chains produce a transition matrix, transition area matrix, and conditional probability image by analyzing 1990 and 2012 LULC images. The prediction year 2035 was chosen with the consideration of vision Djibouti 2035, where the government has envisioned an optimistic scenario or reference scenario to achieve strong and sustainable growth to increase the Gross Domestic Product (GDP) and reduce the unemployment rate from 50% to 10% (Republic of Djibouti, 2015). This prediction is based on the Markov chain analysis (Eastman, 2016). The Markovian process is a method in which a forecast can be estimated based on the findings of past change analysis and transition potential, i.e., how much area would be expected to change from 1990 to 2035 based on prior change experience. In this process, the manipulation of the transition probability matrix can be performed from the edit option provided in the change demand modeling panel if you can predict each land use class based on any policy intervention. However, in our case, we did not make any changes as we did not find any supporting national documents that define future land use; hence, we opted to use the current trend scenario based on historical change periods (1990-2012).

2.5 LCM Model Validation

Model validation is considered one of the crucial steps as it gives the accuracy of the stimulated map against the reference map. The LULC maps for 1990 and 2012 were utilized to stimulate the 2022 LULC map. Then, the comparison of the predicted map was done with the actual map using cross-tabulation in a 3-way comparison between the later land cover image (2012), the predicted land cover image (2022) image, and the actual land cover map (2023). This module helps statistically assess the quality of the predicted 2035 map.

The result of the modules shows "hits" for accurate prediction, "false alarm" where the model predicted change but actually did not occur, and "misses" where the model was unable to predict it but areas are changing in reality. However, while the kappa coefficient is computed between the predicted and actual maps, it does not discriminate between the location erroneous and the quantification (Leta et al., 2021). The validate module can be utilized for this purpose, as it provides dependent K-indices such as *Kno* (Kappa for no information) for the total agreement between the predicted and real image, Kappa for location, or *Klocation*; for the spatial accuracy of the overall land categories, Kappa for standard, or *Kstandard*; the ratio of incorrectly assigned by chance to correctly assigned, and *KlocationStrata*; an indicator of the spatial accuracy within the predefined strata (Eastman, 2020). Additionally, the validate module provides several metrics to quantify the strength of the agreement between the simulated and reference maps, including AgreementQuantity, AgreementChance, AgreementGridCell, DisagreementGridCell, and DisagreementQuantity.

2.6 Analysis of Land Use Land Cover

Using the LCM approach, we calculated the change in LULC assessment. The LCM identifies loss and gain, net change, and net persistence experienced by each LULC class. The classed maps (1990, 2012, and 2022) and predicted LULC (2035) were used to depict the pattern of changes. The numerical values retrieved from the categorized images were used to examine the LULC dynamics throughout each research period. To obtain the change pattern, images from consecutive periods were cross-tabulated and compared.
Furthermore, the change percentage and rate of change (Arfasa et al., 2010) for LULC categories were calculated using Equations (1) and (2) to assess the amount of change experienced between the periods of the various LULC categories.

$$\text{Percent of Change} = (Ay-Ax)/Ax*100 \quad (1)$$

$$\text{Rate of Change} = (Ay-Ax)/T*100 \quad (2)$$

where Ax = the area of LULC (km^2) of an earlier LULC map
Ay = the area of LULC (km^2) of a later LULC map
T = Time Interval between Ax and Ay in years

3. RESULTS

3.1 LULC Change of Three Time Periods

The secondary data acquired for the two base years (1990 and 2012) and the same methodology adopted, the random forest classification at the GEE platform for 2022 images were evaluated through the gains, losses, and the net change between the identified classes for the period 1990, 2012, and 2022 (Figs. 2 and 3). The kappa statistics and the overall accuracy of obtained secondary data were 90% and 0.92, whereas, for the year 2022 image, the kappa was 95% and overall accuracy was 0.91.

3.2 LULC Change Analysis

The LULC analysis was conducted to evaluate the gains, net changes, and losses experienced by different categories. This was achieved through the use of the change analysis tool in LCM. Spatial and temporal changes between various classes during the period from 1990 to 2012 and 2022 were analyzed (Table 1).
Given the climatic region, the predominant land use and cover (LULC) category in Djibouti is barren land, accounting for 75.2%, 87%, and 80.75% of the total in 1990, 2012, and 2022 respectively. Following this category is bush, which exhibited a declining trend from 1990 to 2012 (23.68%, 11.63%) but experienced an increase in 2022 (17.55%). Therefore, throughout the study period, the majority of the changes have been seen in these two classes (Fig. 2). However, the large area of more than 3,214 km^2 bushland has been lost for both two study periods (1990-2012, 2012-2022) with the net change of -2,601.28 km^2 and -1322.66 km^2. Likewise, barren land lost over 674 km^2 between 1990-2012 and more than 2089 km^2 between the years 2012 and 2022, with a net change of 2547.2 km^2 and 1198 km^2. Nonetheless, there has been a notable increase in other significant land categories, such as built-up and water bodies, which account for less than 1% of the total land area (21.90 to 66.6 km^2, 156.86 to 242.8 km^2). The result shows that the built-ups have gained nearly 30 km^2 and 47 km^2 in these two time periods, while water bodies have gained nearly 50 km^2 and 103 km^2 in between 1990-2012- and 2012-2022-time frame. On the other hand, a modest reduction in the area used for farming and salt deposition was noted (11.15 to 10.6 km^2, 52.03 to 51.7 km^2), where the loss of farmland accounts for the nearly 7.5 km^2 between 1990-2012 and 9 km^2 between 2012-2022 with the net change higher in between earlier time frame of -3.5 km^2.

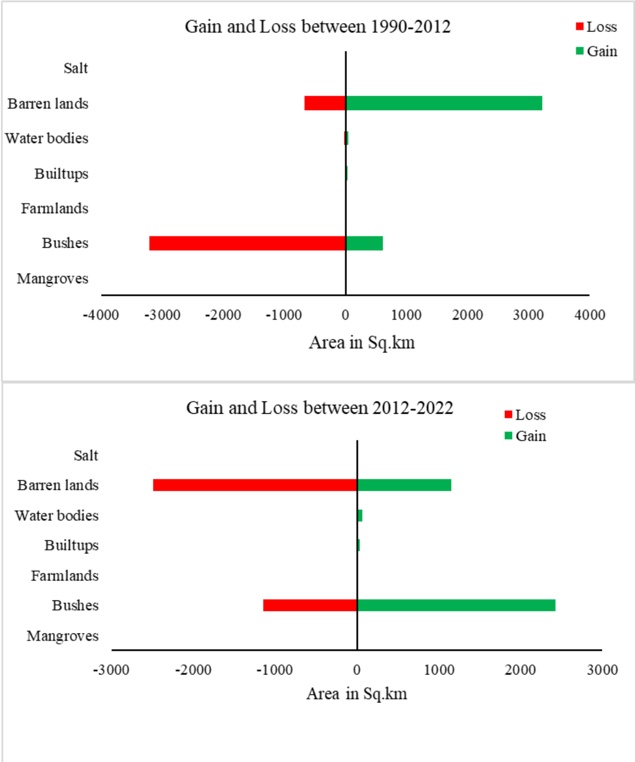
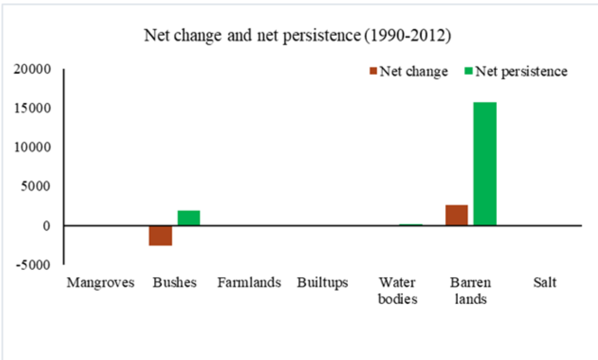


Figure 2. Gain and loss area of the LULC between 1990-2012 and 2012-2022



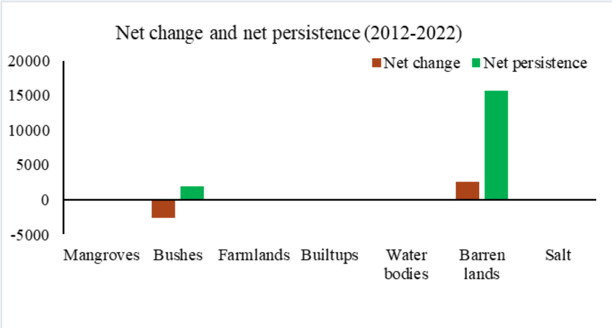


Figure 3. Net change and net persistence area of LULC class between 1990-2012 and 2012-2022

Furthermore, the rate of change (Table 1) for the two-time frame depicts that 119.57 km^2/yr barren land has increased while 122.1 km^2 area of bush cover was lost per year between 1990 and 2012. Similarly, from 2012 to 2022, the increment rate for the same categories was found to be 139.29 km^2/yr and 132.09 km^2/yr. Likewise, the built-up area has increased at a rate of 1.20 km2/yr (between 1990-2012), while nearly 2 km2/yr was increased from 2012-2022. On the contrary, farmland was found to decrease with the change rate of 0.16 and 0.31 km2/yr for the two different periods. Surprisingly, the water body was also observed to be increased for three consecutive years, where the rate of change was found to be 32.05 km2/yr and 5.39 km2/yr between 1990-2012 and 2012-2022.

Overall, between 1990 and 2022, the areas covered by bush and farmland have decreased at a rate of 42.67 and 0.0016 km^2 per year, respectively. On the other hand, the built-up areas, water bodies, and barren land have increased at rates of 1.4, 2.69, and 38.68 km^2 per year, respectively. Additionally, mangroves and salt areas have also decreased at a small noticeable rate.

	Area (km^2)			Change					
LULC Types	1990	2012	2022	1990-2012		2012-2022		1990-2022	
	Area	Area	Area	Area	Rate of change (km^2/year)	Area	Rate of change (km^2/year)	Area	Rate of change (km^2/year)
Mangroves	7.10 (0.03)	6.01 (0.02)	6.97 (0.03)	-1.09 (-15.36)	-0.05	1.06 (17.65)	0.11	-0.03 (-0.42)	-0.001
Bushes	5279.22 (23.68)	2592.85 (11.63)	3913.13 (17.55)	-2686.37 (-50.89)	-122.11	1320.93 (50.95)	132.09	-1365.44 (-25.86)	-42.670
Farmlands	11.15 (0.05)	7.53 (0.03)	10.64 (0.05)	-3.61 (-32.42)	-0.16	3.10 (41.18)	0.31	-0.51 (-4.59)	-0.016
Builtups	21.90 (0.10)	48.28 (0.22)	66.5 (0.30)	26.38 (120.42)	1.20	18.28 (37.85)	1.83	44.65 (203.86)	1.395
Water bodies	156.86 (0.70)	188.92 (0.85)	242.02 (1.09)	32.05 (20.43)	1.46	53.88 (28.52)	5.39	85.93 (54.78)	2.685
Barren lands	16764.30 (75.20)	19394.84 (87)	18000.9 (80.75)	2630.54 (15.69)	119.57	-1392.90 (-7.18)	-139.29	1237.64 (7.38)	38.676
Salt	52.03 (0.23)	54.13 (0.24)	51.7 (0.23)	2.10 (4.04)	0.10	-2.46 (-4.55)	-0.25	-0.36 (-0.69)	-0.011
Total	22292.56	22292.56	22292.0						

Table 1 The area of LULC, percent, and rate of change in Djibouti between 1990-2022

3.3 The transition probability matrix of LULC change between 1990-2022 and the driver variables used

The transition matrix (Table 2) shows the changes in land use and land cover (LULC) types from 1990 to 2012 and from 2012 to 2022 for Djibouti. The column represents the LULC types in the initial year, and the row represents the LULC types in the final year. The diagonal elements of the matrix represent the areas that remained unchanged in each LULC type, while the off-diagonal elements represent the areas that changed from one LULC type to another in km^2.

From 1990 to 2012, the total area of mangroves decreased from 7.10 km^2 to 6.00 km^2, mainly due to conversion to barren lands (0.73 km^2). The total area of bushes decreased from 5279.30 km^2 to 2592.78 km^2, mainly due to conversion to barren lands (625.78 km^2). The total area of farmlands decreased from 11.15 km^2 to 7.53 km^2, mainly due to conversion to bushes (4.87 km^2). The total area of builtups increased from 21.90 km^2 to 48.27 km2, mainly due to the conversion from barren areas and bushes (24.37 km^2, 4.47 km^2). The total area of water bodies increased from 156.81 km^2 to 188.69 km^2, indicating a possible rise in sea level or erosion of land. The total area of barren lands increased from 16764.22 km^2 to 19394.29 km^2, mainly due to conversion from bushes (3304.48 km^2). The total area of salt increased from 52.03 km2 to 54.13 km^2, mainly due to expansion within the same LULC type (50.44 km^2).

Likewise, from 2012 to 2022, the total area of mangroves increased from 6.00 km^2 to 6.97 km^2, mainly due to conversion from water bodies (1.23 km^2). The total area of bushes increased from 2592.78 km^2 to 3913.13 km^2, mainly due to conversion from barren lands (2502.38 km^2). The total area of farmlands increased from 7.53 km^2 to 10.64 km^2, mainly due to conversion from bushes (4.19 km^2). The total area of builtups increased from 48.27 km^2 to 66.50 km^2, mainly due to expansion within the barren and bush LULC type (21.43 km^2 and 5.68 km^2). The total area of water bodies increased from 188.69 km^2 to 242.02 km^2, mainly due to expansion within the same LULC type (177.84 km^2). The total area of barren lands decreased from 19394.29 km^2 to 18000.78 km^2, mainly due to conversion to bushes (1164.61 km^2). The total area of salt decreased from 54.13 km^2 to 51.67 km^2, indicating the recovery from bushland (1164.61 km^2).

LULC Types		1990							
		Mangroves	**Bushes**	**Farmlands**	**Builtups**	**Water bodies**	**Barren lands**	**Salt**	**Total**
2012	**Mangroves**	**4.97**	0.15	0.00	0.00	0.16	0.73	0.00	6.00
	Bushes	0.04	**1959.86**	4.87	1.96	0.28	625.78	0.00	2592.78
	Farmlands	0.00	1.16	**3.41**	0.08	0.00	2.87	0.00	7.53
	Builtups	0.16	4.47	0.54	**17.52**	1.22	24.37	0.00	48.27
	Water bodies	0.93	8.98	0.00	0.21	**137.44**	41.03	0.10	188.69
	Barren lands	1.00	3304.48	2.32	2.13	14.68	**16068.21**	1.48	19394.29
	Salt	0.00	0.00	0.00	0.00	2.90	0.79	**50.44**	54.13
	Total	7.10	5279.30	11.15	21.90	156.81	16764.22	52.03	22292.50
LULC Types		**2012**							
		Mangroves	**Bushes**	**Farmlands**	**Builtups**	**Water bodies**	**Barren lands**	**Salt**	**Total**
2022	**Mangroves**	**4.47**	0.06	0.00	0.01	1.23	1.19	0.00	6.97
	Bushes	0.03	**1404.83**	3.02	2.30	0.56	2502.38	0.02	3913.13
	Farmlands	0.00	4.19	**2.82**	0.08	0.00	3.55	0.00	10.64
	Builtups	0.05	5.68	0.36	**37.15**	1.84	21.43	0.00	66.50
	Water bodies	0.08	13.42	0.00	0.16	**177.84**	50.08	0.43	242.02
	Barren lands	1.36	1164.61	1.34	8.58	6.33	**16815.05**	3.51	18000.78
	Salt	0.00	0.00	0.00	0.00	0.89	0.61	**50.17**	51.67
	Total	6.00	2592.78	7.53	48.27	188.69	19394.29	54.13	22292.0

Table 2. Transition area (km^2) between 1990-2012 and 2012-2022

3.4 Validation of the Model

The Validation Module used to assess the agreement between the two categorical maps that we used in our study was the predicted land cover map generated by the model, and the other map was the actual land cover map obtained from satellite imagery (2022). Validation is a crucial step to check the accuracy of the model and to determine how well it reflects reality. The largest difference is observed for bushes, which increased, while the smallest difference is observed for mangroves. Table 3 below provides the summary of the result for the reference image and the predicted image. The table provides a useful comparison of the land cover changes for the validation module used.

	Projected		Actual		difference
Land covers	Area	%	Area	%	Area
Mangroves	5.88	0.03	6.97	0.03	1.09
Bushes	2589.91	11.62	3913.13	17.55	1323.22
Farmlands	7.18	0.03	10.64	0.05	3.46
Builtups	63.79	0.29	66.50	0.30	2.71
Waterbodies	187.18	0.84	242.02	1.09	54.84
Barren lands	19383.64	86.95	18000.78	80.75	-1382.86
Salt	54.13	0.24	51.67	0.23	-2.46
Total	22292		22292		

Table 3 Validation of the Model

The results of the validation process are summarized in Table 4, which shows the achieved k-indices. A k-index greater than 82% indicates good agreement between the projected and actual LULC map, indicating a good overall agreement and projection ability of the model.

Index	Value
kno	0.881
Klocation	0.878
KlocationStrat a	0.878
Kstandard	0.821

Table 4 K-indices values of the stimulated LULC map of 2022

The validation result analysis shows the agreement and disagreement component values for the LCM process, as shown in Table 5 below. The agreement chance value of 0.125 indicates that there is a low probability of random agreement between the observed and simulated land cover maps. The agreement quantity value of 0.296 implies that the overall quantity of each land cover class is well simulated by the LCM model. The agreement gridcell value of 0.475 suggests that the LCM model can capture the spatial distribution of land cover classes at the gridcell level. The disagree gridcell value of 0.066 represents the proportion of gridcells that have different land cover classes in the observed and simulated maps. The disagree strata value of 0.000 indicates that there is no disagreement between the observed and simulated maps at the strata level. The disagree quantity value of 0.038 reflects the difference in the quantity of each land cover class between the observed and simulated maps.

	Value	Value %
AgreementChance	0.125	12.5
AgreementQuantity	0.296	29.58
AgreementStrata	0.000	0
AgreementGridcell	0.475	47.5
DisagreeGridcell	0.066	6.6
DisagreeStrata	0.000	0
DisagreeQuantity	0.038	3.8

Table 5 The Validation Result Analysis (Agreement/Disagreement component values)

3.5 Future LULC Prediction

The future changes in land use and land cover (LULC) have been predicted for the year 2035. A transition probabilities matrix was used to analyze the probability percentages of changes in LULC between the periods of 2022-2035. The Markov chain provides the quantity of change, while the MLP neural network helps determine the spatial distribution, which together provide the LULC prediction in LCM. The simulated future LULC images of the country can be seen in Figure 4, and Table 6 provides the area coverage. The changes in LULC increase or decrease have been represented in Figure 6.

Based on the result obtained, the Land Cover Mapping (LCM) process for the prediction of Land Use and Land Cover (LULC) for Djibouti from 2022 to 2035 indicates several changes. The area of mangroves is predicted to decrease from 7 km^2 in 2022 to 5.9 km^2 in 2035. Similarly, the area of bushes is expected to decrease from 3913.1 km^2 in 2022 to 2589.9 in 2035 km^2. The farmlands also show a slight decrease from 10.6 km^2 in 2022 to 8.18 in 2035 km^2. In contrast, the area of built-ups is projected to increase from 66.5 km^2 in 2022 to 72.24 km^2 in 2035. The area of waterbodies shows a decrease from 242.02 km^2 in 2022 to 187.18 km^2 in 2035. The largest land cover, barren lands, is expected to increase slightly from 18001.8 km^2 in 2022 to 19374.7 km^2 in 2035. The area of salt also increases from 51.7 km^2 in 2022 to 54.13 km^2 in 2035.

Land covers/Years	**1990**	**2012**	**2022**	**2035**
Mangroves	7.13	6.01	6.97	5.98
Bushes	5279.22	2592.85	3913.13	2589.97
Farmlands	11.15	7.53	10.64	8.18
Builtups	21.90	48.28	66.50	72.24
Waterbodies	156.86	188.92	242.02	187.18
Barren lands	16764	19394.84	18000.78	19374.64
Salt	52.03	54.13	51.67	54.13
Total	22292	22292	22292	22292

Table 6. Area of predicted LULC and its comparison with the previous study period

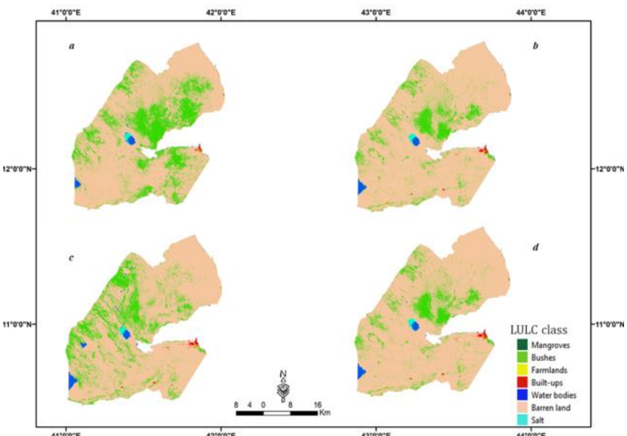
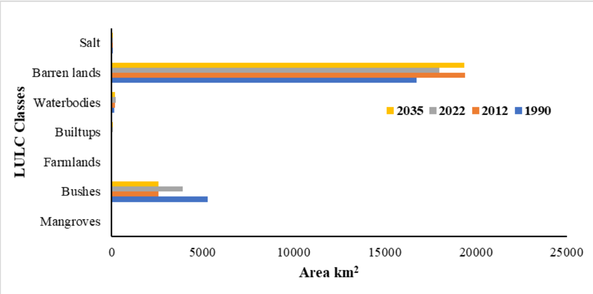


Figure 4: LULC maps of Djibouti; (*a*) for 1990, (*b*) for 2012, (*c*) for 2022, and (*d*) for 2035

Figure. 6. Land use land cover change from 1990-2035



4. DISCUSSIONS

4.1 Land use land cover analysis and simulation

The results obtained from the random forest classification and the LCM change analysis showed that Djibouti experienced significant changes in its LULC patterns from 1990 to 2022; specifically, barren land and bushland were the most prevalent and dynamic classes, while built-up and water bodies increased their area significantly, although they were still minor classes. The data provides quantitative information on the gains, losses, and net changes of different land cover categories over time and space.

In the first time period, the most noticeable changes were the decrease of bushes and the increase of barren lands. This indicates a large-scale degradation of vegetation cover due to various factors such as urbanization, agriculture, and climate change. The area of mangroves also decreased by 0.1 km^2, which may have negative impacts on biodiversity and coastal protection, whereas the area of builtups increased by 17.36 km^2, reflecting the expansion of human settlements and infrastructure. The area of water bodies increased by 31.88 km^2, mainly due to the increase of salt by 1.38 km^2 and the conversion of barren lands to water bodies by 41.03 km^2.

From 2012 to 2022, the trends of LULC changes were similar to the previous period but with some differences. The area of bushes continued to decrease by 679.65 km^2 but at a lower rate than before. The area of barren lands also increased by 1393.51 km^2 but at a higher rate than before. The area of mangroves increased by 0.97 km^2, which may indicate some recovery of this ecosystem. The area of builtups increased by 18.23 km^2, showing a faster growth of urbanization. The area of water bodies increased by 53.33 km^2, mainly due to the increase of salt by 3.73 km^2 and the conversion of barren lands to water bodies by 50.08 km^2.

Based on the historic LULC changes, the predicted 2035 land cover map showed the most significant changes are expected to occur. The bushes will decline by 32.78%, from 3913.8 km^2 to 2589.97 km^2, due to overgrazing, deforestation, and drought. The waterbodies will shrink by 22.88%, from 242.8 km^2 to 187.18 km^2, as a possible result of reduced rainfall, increased evaporation, and water diversion (World Bank, 2021). The builtups will expand by 8.47%, from 66.6 km^2 to 72.24 km^2, reflecting the rapid urbanization and population growth in the country. However, this percentage is likely to increase due to ongoing projects and government development strategies. The barren lands will increase by 7.63%, from 18000.9 km^2 to 19374.64 km^2, indicating the loss of soil fertility and vegetation cover. The mangroves, farmlands, and salt will have minor fluctuations but will remain relatively stable. The mangroves will decrease by 1.12%, from 7.1 km^2 to 5.98 km^2, due to coastal erosion and human disturbance. The farmlands will decrease by 2.42%, from 10.6 km^2 to 8.18 km^2, due to land degradation and urban encroachment. The salt will increase by 4.69%, from 51.7 km^2 to 54.13 km^2, due to increased salinization of soils and water sources. These changes reflect the impacts of urbanization, desertification, and climate change on the natural and human systems of the country. The LCM process provides a useful tool for planning and management of land resources, as well as for assessing the environmental and socio-economic implications of land cover changes.

Also, the overlaid maps of the predicted LULC and geology shape file revealed that the builtup areas are suitable under the middle-aged basalt new era rock types, followed by a sedimentary rock before sinking, volcanic rock basalt while for farmland, middle-aged basalt is suitable occupies a maximum of the areas (CERD, 2015).

4.2 Comparison with similar studies and validation

In contrast to tropical and subtropical regions, comparatively few previous investigations have been carried out in semi-arid regions. Nonetheless, our analysis of changes in land cover and land use in the Republic of Djibouti is consistent with findings from a number of other recent studies carried out in comparable environments utilizing RF modeling and Landsat data. A study conducted by Amini et al. (2022) in Isfahan, Iran; Sexana et al. (2024), in Rajasthan, India; Keshavarzi et al. (2022), in northeastern Iran; Kadri et al. (2023) in Tunisia; and Abubakar et al. (2023) in northern Nigeria have shown strong performance of the RF classifier in Google Earth Engine, achieving over 90% overall classification accuracy for different land use categories and crop types. Another study conducted by Rash et al. (2023) showed that the RF algorithm produced the most accurate maps for the three-decadal study period, acquiring a high kappa coefficient (0.93–0.97) compared with the SVM, ANN, KNN, and XGBoost algorithms in Iraq. In contrast, research by Rozentein and Karnieli (2011) and Li et al. (2018) discovered that combining supervised and unsupervised algorithms can improve performance even with limited training data and the capacity to apply across a large territory.

In recent years, LCMs have been widely employed in diverse geographical contexts to assess the impacts of human activities, climate change, and policy interventions on landscapes due to their robust capabilities in spatial modeling and analysis. However, there has been limited research exploring the potential of this model in semi-arid regions. Appiagyei et al. (2023) stimulated the possible LULC scenarios (2029 and 2039) for Northwest Algeria and obtained the simulation at a skill measure of > 0.50. Likewise, a study conducted in the Nashe watershed area of Ethiopia, which is a neighboring country of Djibouti, showed a good agreement measure between the actual map and the predicted (92.81%) and concluded the result shows the model has a higher ability to predict the LULC changes in location than in quantity. (Leta et al., 2021). Comparably, the study carried out in Iran produced results that were comparable to ours, with an average accuracy of 84.89% (Shafie et al., 2023); in fact, our results were superior to theirs. Another study in Saudi Arabia, which utilized the LCM MLP-NN algorithm to predict LULC for 2040, resulted in an overall accuracy of 88% (Alqadhi et al., 2021). The other research conducted by Ghonchepour et al. (2023) in the Gorganrud River basin, Iran, obtained higher validation results for the 2040 LULC map and correlated with the predicted population as a main driving force in such changes. They further concluded that other driver variables should be considered to identify the driving forces behind such a transition so that effective management strategies can be utilized.

4.3 An Amplification of the Findings

The changes that have occurred, as shown in this study, have many implications, both complex and manifold. On one hand, the increase in mangroves and salt may have a positive effect on biodiversity, ecosystem services, and coastal protection. Conversely, the decrease in bushes and farmlands may have negative impacts on food security, livelihoods, and carbon sequestration. Furthermore, the increase in water bodies may pose challenges for adaptation and resilience to climate change, particularly in coastal areas, as well as for water quality and availability. Compared with some of the existing reports and research, the increase in barren land could be possibly due to the degradation of vegetation cover caused by drought (World Bank, 2021) and overgrazing (Shimada et al., 2019). The increase in built-up areas was mainly due to the urbanization and development of infrastructure in the country.
During the transition from the 1990s to the 2000s, Djibouti's construction sector emerged as a significant instrument for leveraging its geographic and economic strengths. Significant initiatives, ranging from urban regeneration projects to the building of new transportation networks, energy infrastructure, and water facilities, have been supported by various private enterprises, non-governmental organizations, China, and the US. (GFDRR, 2011; Republic of Djibouti, 2015; JICA, 2014). Furthermore, the government of Djibouti's policy for the year 2035 focuses on these industries, with a major focus on boosting GDP development and increasing job prospects (the Republic of Djibouti, 2015). These changes have important implications for the environmental and socio-economic conditions of Djibouti, as they affect the ecosystem services, biodiversity, and livelihoods of the local population. However, the increase in builtups may entail trade-offs between economic growth and environmental sustainability, as well as social issues such as inequality, congestion, and pollution. Nonetheless, to mitigate urbanization's impact on biodiversity sustainably, the comprehensive land-use planning of green spaces within urban zones, incorporating green infrastructure elements, collaborative governance, green transportation, and community engagement is crucial.
The study also discussed the implications of these changes for the socio-economic and ecological well-being of Djibouti. For example, the loss of bushes could affect the livelihoods of pastoralists and farmers who depend on them for fodder and fuelwood. The USAID report shows that nearly 20% (USAID/OFDA, 2004) of Djibouti's population depends on pastoralism. In the region of Djibouti, it is recommended that agro-pastoralism be adopted as a viable means of livelihood, particularly in light of the diverse climatic phenomena that have impacted the area. Agro-pastoralism refers to a mixed farming system that combines crop cultivation with livestock raising. This system is particularly beneficial for rural communities that have access to water for irrigation or seasonal rainfall that is adequate for crop cultivation. By adopting agro-pastoralism, communities in Djibouti can develop a sustainable and diversified livelihood strategy that is resilient to the challenges posed by the region's climatic conditions.
For the validation of our predicted map, we obtained 0.82 Kappa statistics, which is acceptable for remote sensing applications. However, the TerraSet developers suggest one should focus on the MLP statistics output, which includes very important information about the explanatory power of the independent variables such as skill measure (a Pierce Skill Score) rather than a % accuracy. A skill score accounts for chance agreement and provides you with a baseline. A skill score would assess the level of random chance to be a skill of 0, with the range going from -1 to +1. A reasonable skill level would be 0.5, which should be achievable. In this research, we obtained a 0.01 to 1 score for the seven transitions model (mainly for Builtups and farmlands conversions). The low skill score of the selected transitions model could be recognized as a very difficult process at a pixel level. At the pixel level, there are an enormous number of factors over which one has no control or proper information. For example, you have no way to know that a particular farm changed land cover because it was sold in a particular year. This is the phenomenon of indeterminacy, so one should carry out the assessment at a coarser scale.
Similarly, the pixel level agreement was 47.5%, whereas the chance agreement was 12.5% (Table 5). It appears to be a better outcome, given indeterminacy. However, taking into account this shift in the agreement value also implies that it may be too much to include seven transitions modeling at once. Nevertheless, from this study, we recommend two points. First, to increase the skill score, modeling a single transition at a time or concentrating just on the most significant transitions that are relevant is highly recommended. Multiple transitions are difficult for even the most advanced machine learning processes. Second, the number of explanatory variables is also important while running the MLP. One should remember that more explanatory variables are not always better than fewer. If the model consists of a lot of variables, it again makes the modeling challenging. However, it's often the case that with many variables, there is multicollinearity (correlations between variables). That leads to redundancy, unintended weighting of correlated variables, and confusing relationships. If you really want to consider many variables, use Principal Component Analysis (PCA) to remove collinearity. The use of a Standardized PCA will allow us to check inter-correlations. The resulting components are left to be independent, where the %Variance is well explained by keeping only the lowest PCAs that account for the majority of variance and discarding the rest. However, our hypothesis considering the most possible driver variables, such as population dynamics and geology, which can be affected by climate change in the future, are reasonably proven to be justified.
These findings suggest that the LCM model accurately replicates the process of land cover change, but it needs to improve in capturing the heterogeneity and variability of land cover classes at smaller scales.

5. CONCLUSION

This study aimed to analyze the past and projected land use and land cover patterns in the period between 1990 and 2035. An integrated method that utilized remote sensing, GIS, and a system assimilated with MLP and CA-Markov chain model in LCM was used to comprehend the spatiotemporal dynamics of LULC and predict future changes in LULC in the Republic of Djibouti.
The analysis of Djibouti's land use and land cover changes spanning from 1990 to 2022 reveals a dynamic landscape shaped by urbanization and environmental factors. Notably, barren land and bushland have undergone significant alterations, reflecting the consequences of urban expansion, agricultural practices, and climate change. Concurrently, built-up areas and water bodies have experienced noticeable growth, albeit still representing minor land cover classes. These transformations carry profound implications for biodiversity, food security, and livelihoods in Djibouti. The decline in bushland, for instance, affects pastoralists and farmers who rely on it for fodder and

fuelwood, underscoring the importance of agro-pastoralism in rural communities. Additionally, the expansion of urban areas and water bodies may exacerbate challenges related to urbanization, such as infrastructure strain and environmental degradation. Addressing these complexities requires a multi-faceted approach, including sustainable land use planning, investment in green infrastructure, and active community engagement. Moreover, refining modeling techniques by employing skill measures like the Pierce Skill Score and simplifying the analysis process can enhance accuracy and inform more effective decision-making. Looking ahead to 2035, projected changes suggest the continued dominance of urbanization and its associated impacts, emphasizing the urgency of adopting sustainable land management practices to ensure the resilience and well-being of Djibouti's ecosystems and population.

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