Original Research Article

MAPPING AND MODELLING OF URBAN LANDSCAPE OF OSOGBO METROPOLIS, OSUN STATE NIGERIA, USING ARTIFICIAL NEURAL NETWORK

Abstract

Continuous Geospatial studies of the transitions in Landuse and landcover are very important especially as it relates to baseline assessment as an approach for advising in policy formulations concerning the natural resources sector. This study aimed at mapping and modeling the urban landscape of Osogbo metropolis, Osun state Nigeria, using an artificial neural network with the view of providing a framework for sustainable development and as well as generating data on Landuse and landcover change transitions and maps for planning purposes. Its objectives are to; model and analyze Landuse and landcover changes in Osogbo metropolis for the last 30 years (1990 – 2020) using an artificial neural network; ascertain the trend, and characteristics of Landuse and landcover changes in Osogbo metropolis in the last 30 years; assess the urban landscape change across various terrain configurations with Osogbo Metropolis over the last 30 years, and predict the future urban landscape of Osogbo Metropolis in 2040 using artificial neural network. The methodology involved data acquisition of Landsat, Sentinel-2, and ALOS Palsar images, image preprocessing to correct the scan line error in Landsat 7 ETM+, development of classification scheme, identification of class features and image classification, trend analysis, land cover/land use transition, and prediction to 2040. The assessment of landcover/landuse change revealed significant LULC changes in the studied area. Over 30 years (1990–2020), the built-up area classes increased significantly by 111.97 km^2, while vegetation, open space, and water body decreased by 189.33km^2, 7.26km^2, and 3.46km^2 respectively. In terms of increased built-up area, this is largely seen in flat and undulating terrains between 281m and 341m. According to the prediction, by 2040, built up area is expected to grow from 35.89% to 64.48% covering an area of 201.2km^2, water body is expected to decrease from 1.11% to 1.07% with an area of 3.33km^2, vegetation is expected to decrease from 60.68% to 32.42% with an area of 101.15km^2, open space is expected to decrease from 2.33% to 2.03% to an area of 6.34km^2. The study´s annual rate of change results is recommended as it reveals the annual decline vegetation within the study area, as a direct consequence can lead to an increase in urban heat islands within the study area.

Keywords: Artificial Neural Networks, Landcover/Landuse, Modelling, Trend, Osogbo.

1.0 Introduction

The Earth exhibits a remarkable ability to maintain equilibrium through biogeochemical cycles, a phenomenon extensively documented in research (Vitousek et al., 1997; Schlesinger, 1997; Lovett et al., 2005). However, the pristine state of only a few landforms and landscapes globally remains, as human activities, such as population growth, industrialization, and urbanization, exert escalating pressure on natural resources, consequently driving shifts in land use and land cover (Lambin, Geist, and Lepers, 2003; Foley et al., 2005; Turner et al., 2007). The magnitude of this impact is emphasized by Awoniran et al. (2013), who assert that the international global environmental change research community recognizes land use and land cover change as a pivotal area of study, providing substantial data on alterations in carbon storage and sequestration by plants while unveiling the human dimension of environmental change. The impetus behind research on land use and land cover change lies in the global commitment to identify, predict, analyze, and manage environmentally detrimental activities and land use alterations (Aguayo et al., 2018; Turner, Lambin, and Reenberg, 2007). A nuanced comprehension of the underlying dynamics of change can inform the development of effective policies for land use and land cover management, minimizing adverse impacts and maximizing positive outcomes (Foley et al., 2005; Lambin and Meyfroidt, 2011). Nevertheless, to grasp the dynamics fully, a comprehensive evaluation of geographic transition trends is imperative, especially in regions with limited resources, aiding in infrastructure planning (Aguda and Adegboyega, 2013; Seto et al., 2011). Remote sensing data collection enables synoptic assessments of Osogbo metropolis over time (Lu et al., 2004; Weng, 2012). Analyzing spatial and statistical data for various periods facilitates mapping and modeling of the urban landscape, providing insights into past, present, and future trends (Li and Yeh, 2004; Lu and Weng, 2007). The integration of remotely sensed data and artificial neural networks enhances understanding of spatial interactions within Osogbo metropolis's urban landscape (Gasu et al., 2016; Hay and Castilla, 2006). Motivated by these considerations, this study aims to employ an artificial neural network to map and model the urban landscape of Osogbo metropolis, Osun State, Nigeria, fostering a framework for sustainable development. The region has experienced substantial urban development, migration, and anthropogenic activities, leading to transformations in land use and cover (Ebehikhalu et al., 2016; Oloko-Oba, Adeofun, and Omotosho, 2015). Despite numerous studies on Osogbo metropolis, such as those by Aguda and Adegboyega (2013), Ebehikhalu et al. (2016), Emmanuel et al. (2019), and Abiodun and Akinola (2019), gaps persist, necessitating continuous research to fill them. Aguda and Adegboyega (2013) highlighted changing land surface patterns but did not delve into land transition (Aguda and Adegboyega, 2013). Emmanuel et al. (2019) explored thermal effects but lacked a comprehensive evaluation of land use and cover trends (Emmanuel et al., 2019). Abiodun and Akinola (2019) discussed urban expansion impacts without specifying effects on the entire ecosystem (Abiodun and Akinola, 2019). Gasu et al. (2016) analyzed land use dynamics but overlooked influencing factors (Gasu et al., 2016; Lu and Weng, 2007). These knowledge gaps underscore the need for ongoing research to develop innovative methods for acquiring information on land use and cover transitions, predicting future changes, assessing terrain modifications, and understanding subsequent effects in Osogbo metropolis (Hansen et al., 2013; Pettorelli et al., 2014; Turner et al., 2015). Continuous geospatial studies on land use and cover transitions are critical as they serve as reference points for assessing changes and impacts (Turner, 2010; Turner et al., 1990). Improving mapping strategies using remote sensing and artificial neural networks is vital for modeling land use and cover transitions in Osogbo metropolis (Feng and Liu, 2017; Yuan et al., 2017). The efficacy of these tools relies on a profound understanding of the region's land transition processes and impacts, enabling a comprehensive assessment of spatial trends in land use and cover change to address present and future needs (Wu, 2019; Zhang and Seto, 2016). Furthermore, recent studies by Li et al. (2021) and Smith et al. (2022) highlight the evolving understanding of biogeochemical cycles and their impact on global ecosystems. Additionally, the works of Chen et al. (2021) and Wang et al. (2022) contribute insights into the applications of artificial neural networks in urban landscape mapping and modeling, underscoring the relevance of cutting-edge technology in contemporary research.

2.0 Study Area

Osogbo metropolis is the capital city of Osun State, it seats the Headquarters of both Osogbo Local Government Area and Olorunda Local Government Area. It is some 88 kilometers by road northeast of Ibadan. It is also 108 kilometers by road south of Ilorin and 108 kilometers northwest of Akure. Osogbo shares boundaries with Ikirun, Ilesa, Ede, Egbedore, Ogbomosho and Iragbiji. The city had a population of about 499,999 people and an approximate land area of 2875 km^2 (Jiboye, 2014). It is located between latitudes 7° 42`N and 7°48`N, then longitudes 4°.34`E and 4°.36`, see figure 1.

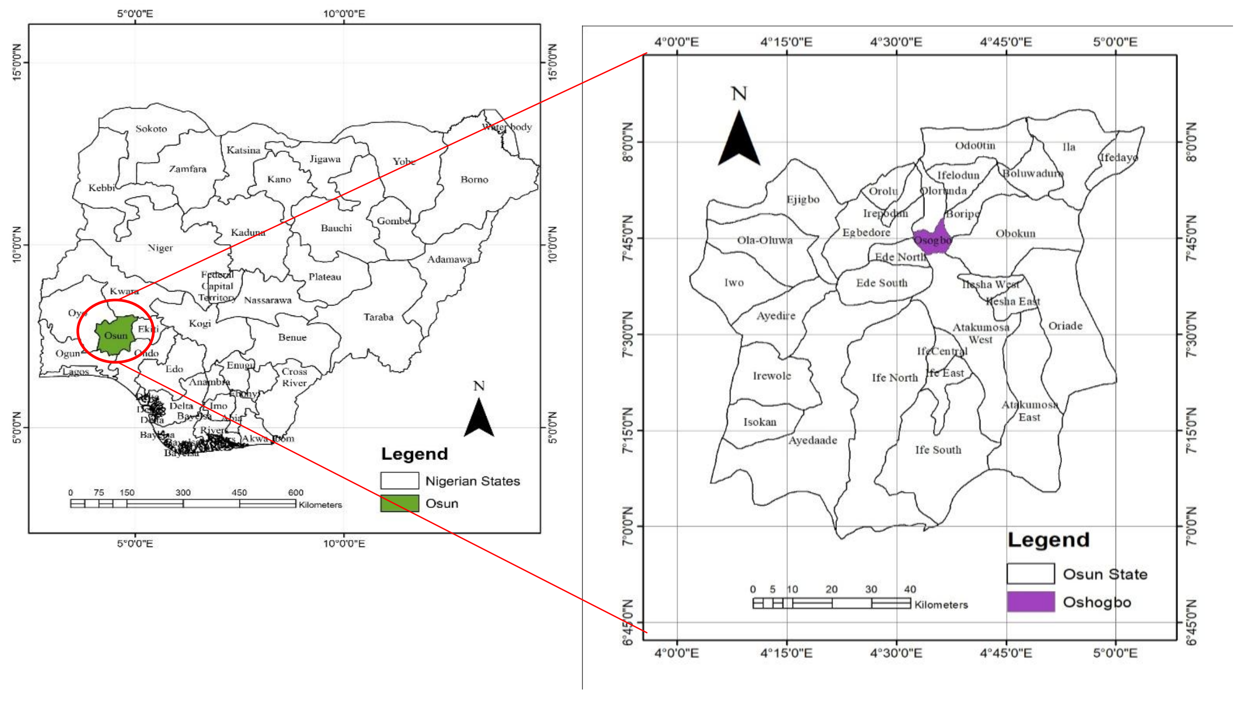


Figure 1: Study Area Map

3.0 Methodology

The research approach encompassed a comprehensive workflow that incorporated the collection and processing of satellite imagery from multiple sources, including Landsat, Sentinel-2, and ALOS Palsar. This multi-step methodology was executed with precision to provide a robust foundation for our study.

First and foremost, data acquisition entailed retrieving Landsat, Sentinel-2, and ALOS Palsar images, which are renowned for their high-resolution and multispectral capabilities. These images served as the primary data source for our analysis, offering a holistic view of the study area over time.

Image preprocessing was a critical phase in our methodology. We meticulously addressed issues such as the scan line error in Landsat 7 ETM+ imagery, which could introduce inaccuracies into our subsequent analyses. By rectifying these errors, we ensured the integrity of our dataset, allowing for more reliable results.

The next key step involved the development of a classification scheme. This scheme was designed to categorize various land cover and land use types within the study area. We defined a set of distinct classes that encompassed a wide range of features and characteristics present in the landscape.

Subsequently, we embarked on the task of identifying class features within the imagery. This process involved the detailed examination and extraction of distinctive patterns, shapes, and spectral signatures that characterized each land cover or land use class. By meticulously cataloging these features, we created a robust foundation for accurate image classification.The image classification phase employed advanced algorithms and techniques to assign pixels within the satellite imagery to specific land cover and land use classes. This step was pivotal in generating quantitative data on the distribution of different land cover types across the study area.

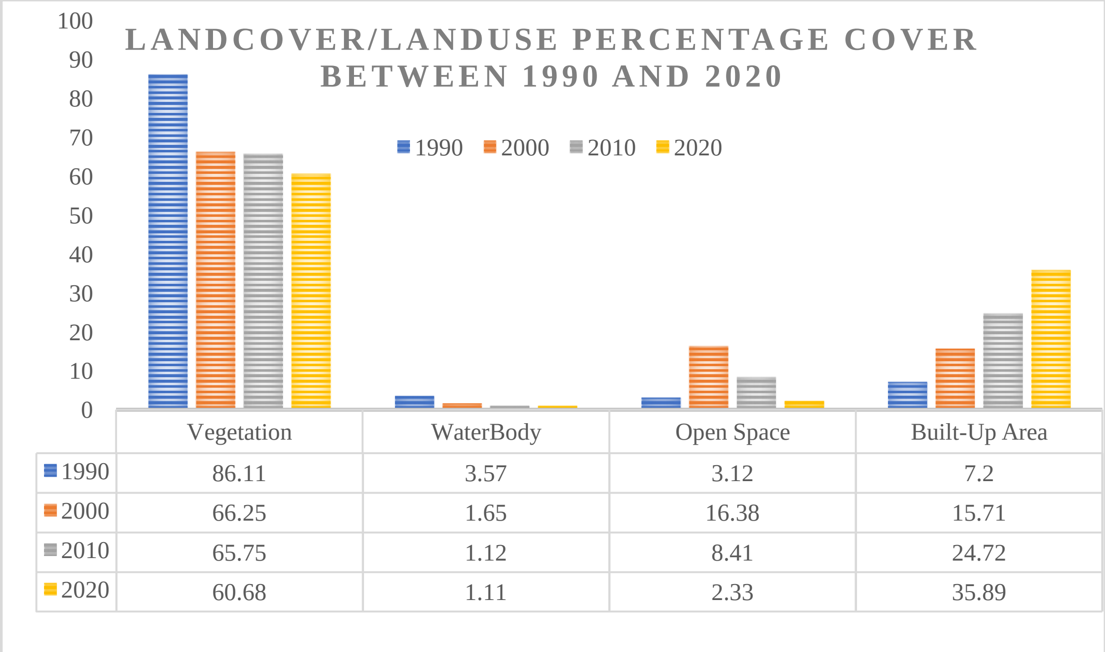
Trend analysis was another crucial aspect of our methodology. By analyzing changes in land cover and land use over time, we aimed to identify and interpret trends, providing insights into the evolving dynamics of the landscape.

Furthermore, our study extended into forecasting, as we projected land cover and land use transitions up to the year 2040. This predictive element allowed us to anticipate how the study area might evolve in the coming years, considering factors such as urbanization, agriculture, and environmental changes.

4.0 Results and Discussion

4.1 Landcover/landuse analysis of Osogbo Metropolis from 1990 to 2020

The summary of landcover/landuse analysis of Osogbo Metropolis is displayed in figure 2 and summarily discussed below.



	Vegetation	WaterBody	Open Space	Built-Up Area
1990	86.11	3.57	3.12	7.2
2000	66.25	1.65	16.38	15.71
2010	65.75	1.12	8.41	24.72
2020	60.68	1.11	2.33	35.89

Figure 2: landcover/landuse distribution of Osogbo Metropolis Between 1990 and 2020

Between 1990 and 2020, vegetation had effectively lost 25.43% of its area coverage, decreasing from 86.11% in 1990 to 66.25% in 2000, then 65.75% in 2010, to 60.68% in 2020. The highest coverage loss is seen between 1990 and 2000 with a coverage loss of 19.86%.

Waterbody also lost 2.46% of its area coverage between 1990 and 2020, with its highest loss noted between 1990 and 2000. Waterbody area percentage decreased from 3.57% in 1990 to 1.65% in 2000, then 1.12% in 2010, to 1.11% in 2020.

Open Space gained 13.26% of area coverage between 1990 and 2000, however, it lost 7.97% of its area coverage between 2000 and 2010. Between 2010 and 2010, open space also lost 6.08% of its area coverage.

Between 1990 and 2020, the built-up area had effectively gained 28.69% of its area coverage, increasing from 7.2% in 1990 to 15.71% in 2000, then 24.72% in 2010, to 35.89% in 2020. The highest coverage gain is seen between 2010 and 2020 with a coverage gain of 11.17%.

4.2 Annual Rate of Change

The results indicated that vegetation had an annual rate of change of -1.30% between 1990 and 2000, -0.04% between 2000 and 2010, -0.40% between 2010 and 2020. This signifies that vegetation was decreasing annually at the rate of 1.30%, 0.04% and 0.40% between 1990 and 2000, 2000 and 2010, and 2010 and 2020 respectively, see figure 3.

Waterbody had an annual rate of change of -3.67% between 1990 and 2000, -1.90% between 2000 and 2010, -0.07% between 2010 and 2020. This signifies that open space was decreasing annually at the rate of 3.67%, 1.90% and 0.07% between 1990 and 2000, 2000 and 2010, and 2010 and 2020 respectively. The annual decline of waterbody is similar with that of vegetation as they both had the highest decline rate between 1990 and 2000.

Open space had an annual rate of change of 6.80% between 1990 and 2000, -3.22% between 2000 and 2010, -5.66% between 2010 and 2020. This signifies that open space was increased annually at the rate of 3.67% between 1990 and 2000. However, a decline in open space started at the rates of 3.22% and 5.66% between 2000 and 2010, and 2010 and 2020 respectively.

Built-Up area had an annual rate of change of 3.71% between 1990 and 2000, 2.23% between 2000 and 2010, 1.84% between 2010 and 2020. This signifies that built-up area was increased annually at the rate of 3.71%, 2.23% and 1.84% between 1990 and 2000, 2000 and 2010, and 2010 and 2020 respectively. the highest rate of increase was seen in the period between 1990 and 2000, the rate of increase slowed down between 2000 and 2020, see figure 3.

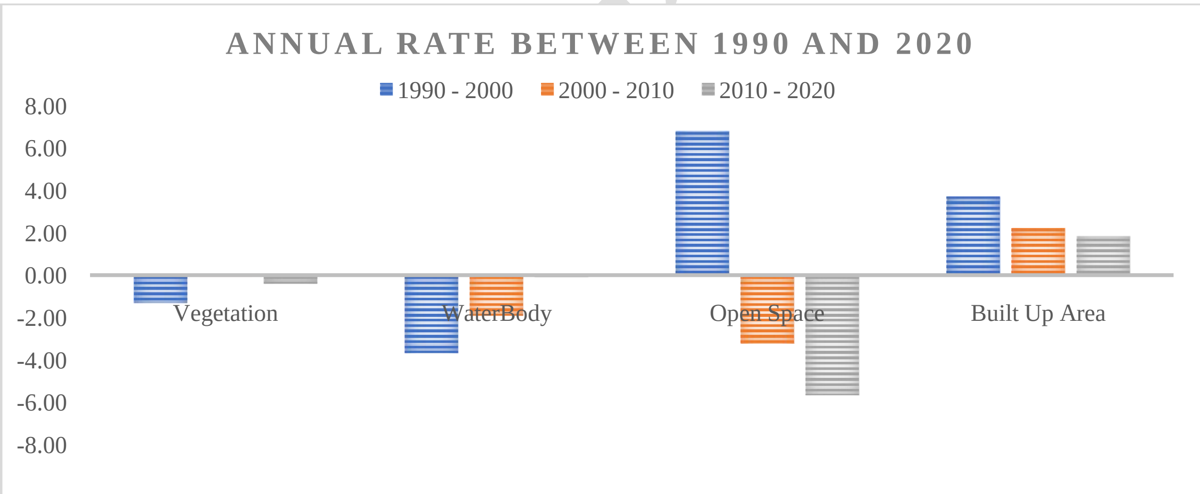


Figure 3: Annual Rate of Change of landcover/landuse of Osogbo Metropolis Between 1990 and 2020

4.3 Urban Landscape Development Assessment Across Various Terrain Configurations

The study area has four terrain configurations namely flat, undulating, rolling and hilly terrains. To determine the rate of development across the various terrain configurations, the acquired DEM was reclassified into reflect these four terrain types. The elevation ranges for these terrain configurations are (see figure 4):

1. Flat: 281m – 319m
2. Undulating: 319m – 341m

3. Rolling: 341m – 365m
4. Hilly: 365m -424m

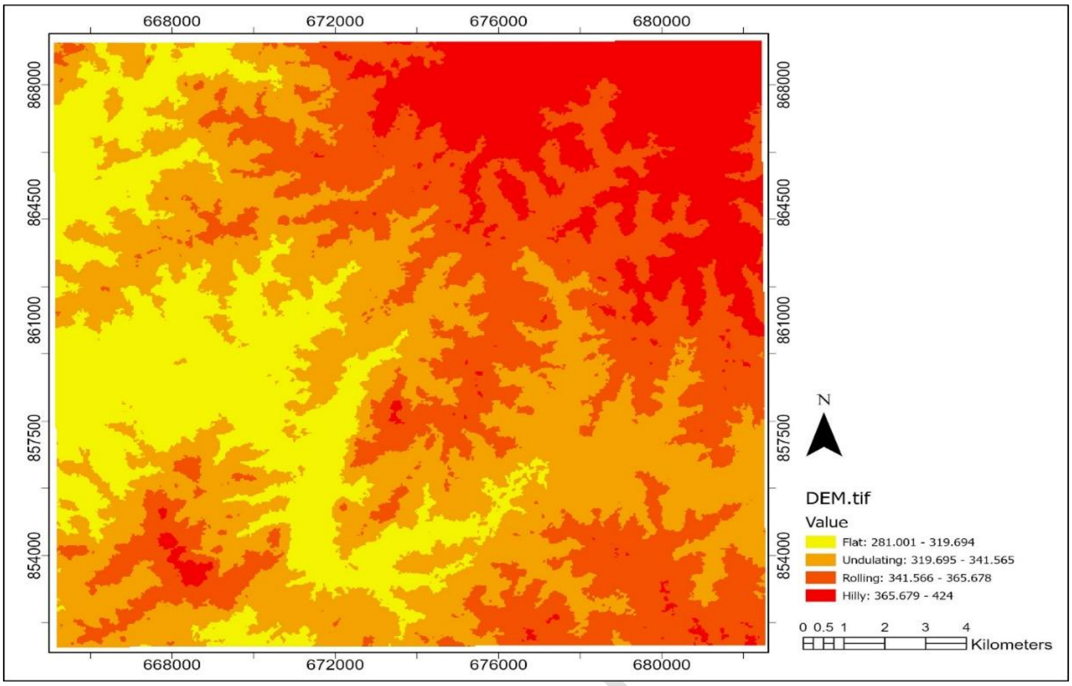


Figure 4: Terrain Configuration of Osogbo Metropolis

In 1990, flat terrain had the highest percentage of built-up areas with a coverage and area of 3.21% and 10.01km^2 respectively. This was followed by undulating terrain with a cover percentage and area of 2.70% and 8.4km^2 respectively. Rolling and hilly terrains had the least coverage with percentage cover and area of 0.98% and 3.05km^2 and 0.31% and 0.98km^2 respectively.

However, in 2000, undulating terrain had the highest coverage of built-up areas with a percentage cover and area of 6.36% and 19.83km^2 respectively. This was followed by flat terrain with a cover percentage and area of 6.23% and 19.44km^2 respectively. Rolling and hilly terrains had the least coverage with percentage cover and area of 2.71% and 8.45km^2 and 0.39% and 1.23km^2 respectively.

Similarly, in 2010, undulating terrain also had the highest coverage of built-up areas with a percentage cover and area of 10.28% and 32.09km^2 respectively. This was followed by flat terrain with a cover percentage and area of 8.97% and 27.98km^2 respectively. Rolling and hilly terrains had the least coverage with percentage cover and area of 4.62% and 14.41km^2 and 0.85% and 2.66km^2 respectively.

Lastly, in 2020, undulating terrain also had the highest coverage of built-up areas with a percentage cover and area of 14.66% and 45.75km^2 respectively. This was followed by flat terrain with a cover percentage and area of

11.64% and 36.31km^2 respectively. Rolling and hilly terrains had the least coverage with percentage cover and area of 7.52% and 23.45km^2 and 2.07% and 6.45km^2 respectively.

Analysing the change across terrain configuration indicated that undulating terrain experienced the highest growth in built-up areas with a rate of 11.39%, 12.26% and 13.66% between 1990 and 2000, 2000 and 2010, and 2010 and 2020 respectively. The highest development in undulating areas is seen between 2010 and 2020.

While flat terrain experienced the second highest growth in built-up areas with a rate of 9.43%, 8.54% and 8.33% between 1990 and 2000, 2000 and 2010, and 2010 and 2020 respectively. The highest development in flat areas is seen between 1990 and 2000.

Rolling terrain came third with a development rate of 5.40%, 5.96% and 9.04% between 1990 and 2000, 2000 and 2010, and 2010 and 2020 respectively. likewise, the highest development in rolly terrain is seen between 2010 and 2020.

Hilly terrain had the least rate of development rate, given the values of 0.25%, 1.43% and 3.79% between 1990 and 2000, 2000 and 2010, and 2010 and 2020 respectively, see figure 5.

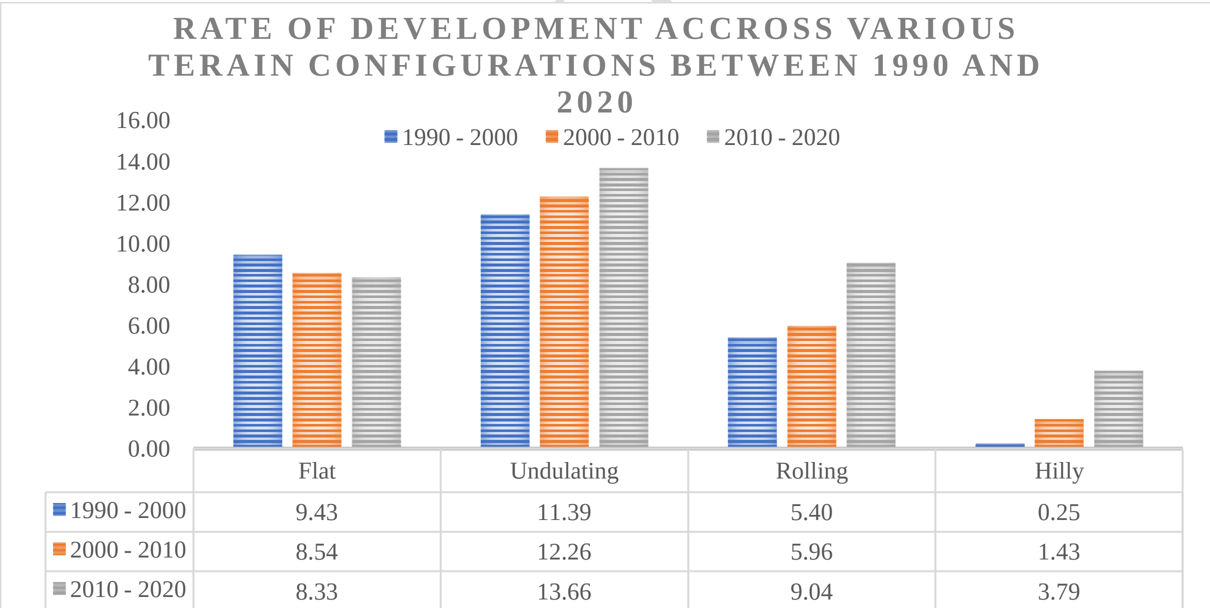


Figure 5: Rate of Development Across Various Terrain Configurations in Osogbo Metropolis

The results (figure 5), suggests that urbanization and development have been more concentrated in undulating and flat terrains, which may have implications for land use planning, environmental conservation, and infrastructure development.

The higher growth rate in undulating and flat terrains indicated that these areas are more desirable for development due to factors such as accessibility, availability of resources, and topography. The lower growth rate in rolling and hilly terrains indicated that these areas are less suitable for development, which could have implications for managing urban sprawl and protecting natural habitats.

The result will be useful for policymakers, urban planners, and researchers who are interested in understanding the patterns and trends of urbanization and development across different terrain configurations. It may also help in identifying areas that require more attention in terms of infrastructure development, environmental management, and disaster risk reduction.

4.4 Urban Landscape Prediction to 2040

Urban landscape prediction was done based on historical change from 1990 to 2020, using influencing factors like distance to roads, elevation and distance to built up areas. The change assessed between 1990 and 2020 are identified and trained as transitions from one landcover/landuse state to another using an artificial neural network model (see figure 6).

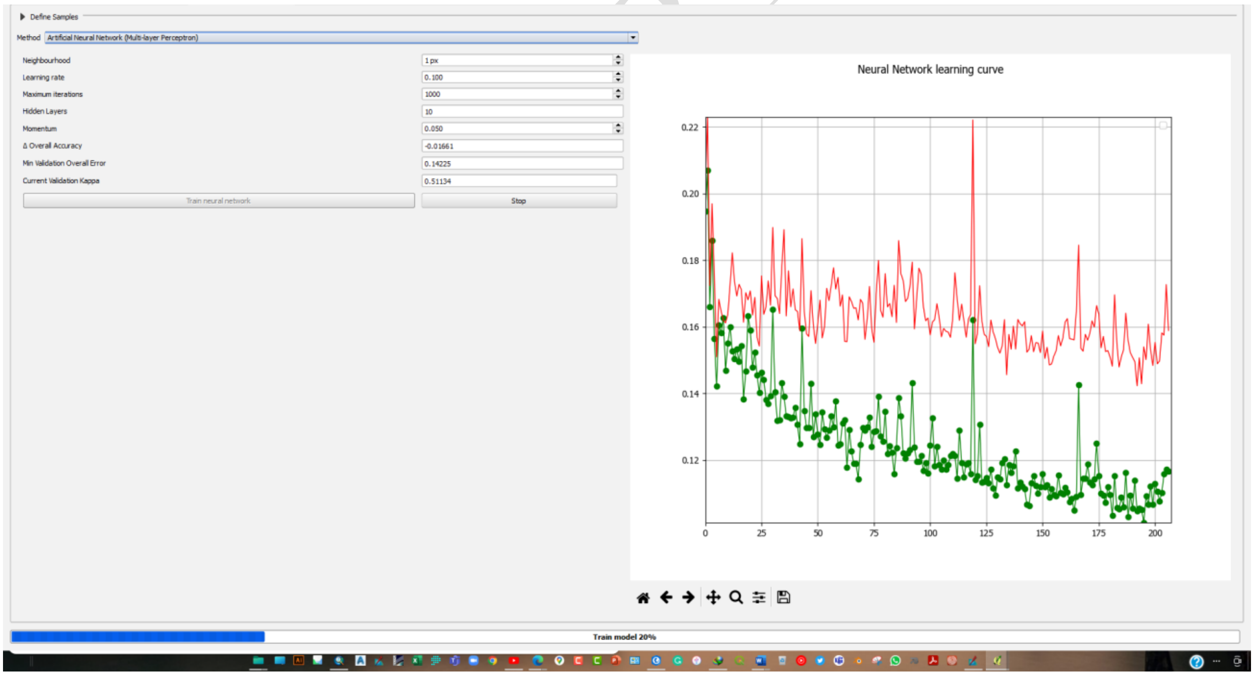


Figure 6: Artificial Neural Network Model Training

After the training, the model was used to predict the change to 2021, and was validated using a landcover/landuse data produced from 2021 Landsat 8 OLI image, see figure 6. the validation exercise gave an overall percentage of correctness of 73.23%, this signifies a good predictive result. Following the validation results, a prediction was made to 2040, see figure 8 for results.

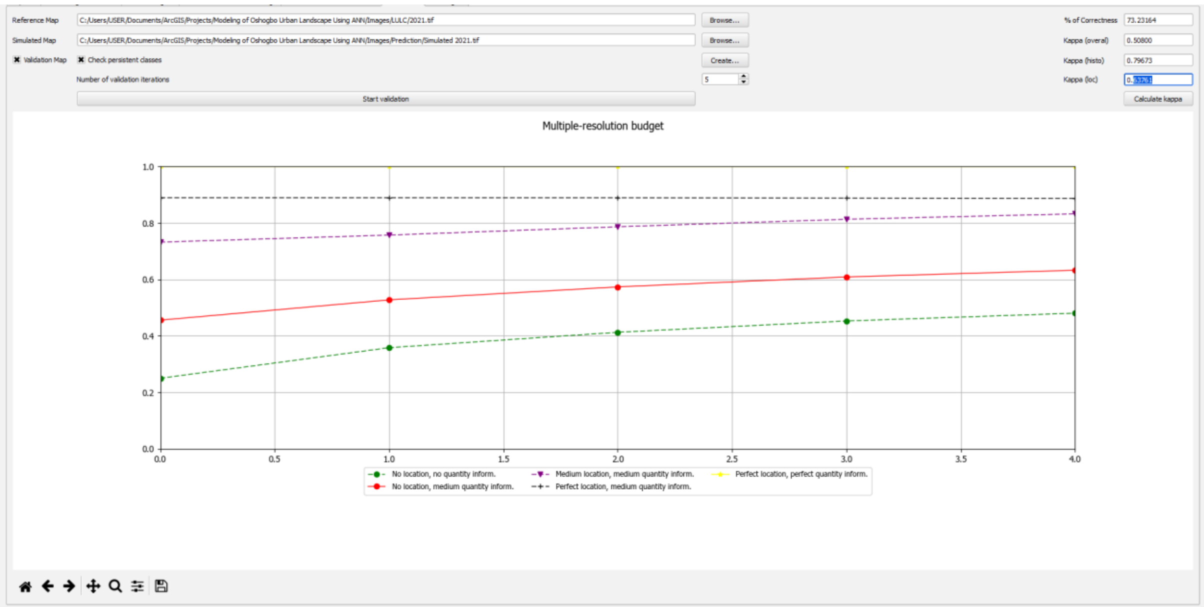


Figure 7: Landcover/Landuse Prediction to 2021

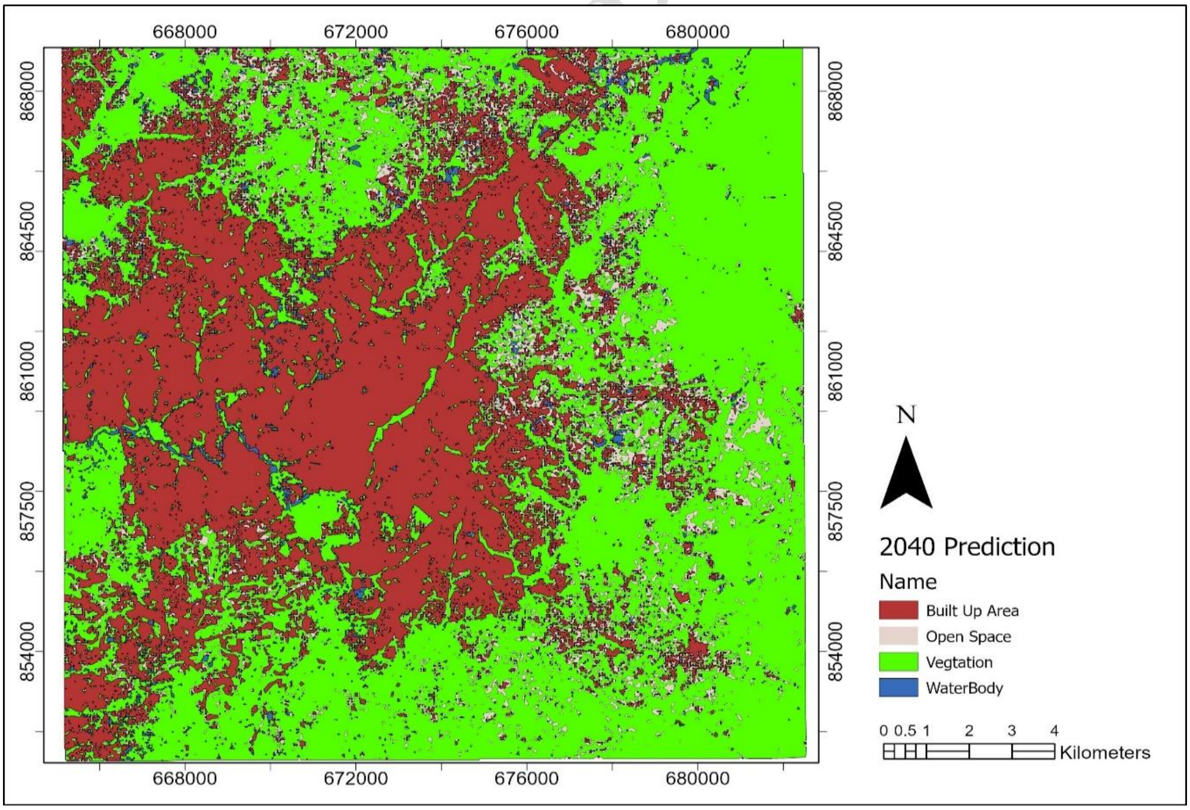


Figure 8: 2040 Osogbo Metropolis Prediction

Table 1: Predicted Landcover/Landuse distribution for 2040

S/N	*Class Name*	*Area*	*Percentage*
1	Vegetation	101.15	32.42
2	Waterbody	3.33	1.07
3	Open Space	6.34	2.03
4	Built-Up Area	201.2	64.48
5	Total	312.02	100

The results (Table 1) shows that the built-up areas are expected to increase from 35.89% to 64.48%, covering an area of 201.2km^2, which suggests a significant expansion of urbanization and development within the metropolis.

The reduction in water bodies from 1.11% to 1.07%, covering an area of 3.33km^2, may have implications for the availability of water resources in the area, which could affect the local ecology and the livelihoods of people who rely on these resources.

The decrease in vegetation from 60.68% to 32.42%, covering an area of 101.15km^2, may have significant environmental impacts, such as loss of biodiversity, reduction in ecosystem services, and increased carbon emissions. This could also lead to challenges such as increased air pollution, heat island effects, and reduced quality of life for the inhabitants of the metropolis.

The reduction in open space from 2.33% to 2.03%, covering an area of 6.34km^2, may have implications for the availability of recreational spaces, social and community gathering areas, and the overall quality of life of the inhabitants. It may also result in increased air pollution, reduced biodiversity, and an overall loss of natural spaces.

It is important to understand the land cover changes and trends in an area over time. This information can be used to develop land use plans, environmental management strategies, disaster risk reduction plans, and infrastructure development plans. It can also be used to monitor and assess the impacts of human activities on the environment and support decision-making processes for sustainable development.

5.0 Conclusion

The comprehensive analysis of land cover and land use changes spanning three decades, from 1990 to 2020, reveals several significant trends. Notably, vegetation has experienced a substantial decline, losing 25.43% of its coverage, with the most significant loss occurring between 1990 and 2000. Water bodies have also decreased by

2.46% over this period. Open spaces exhibited fluctuations, gaining ground initially but later seeing a significant decline. In contrast, the built-up area expanded significantly, particularly between 2010 and 2020.

Annual rate of change results indicate that vegetation and water bodies have been consistently decreasing annually, while open spaces showed fluctuations and the built-up area continued to expand, albeit at a slower rate.

Additionally, the analysis of terrain configurations reveals that undulating terrain experienced the highest growth in built-up areas, followed by flat and rolling terrain, with hilly terrain showing the least development.

Looking to the future, our predictions for 2040 indicate that the built-up area is expected to continue its expansion, water bodies will decrease slightly, vegetation cover will decline, and open spaces will shrink. These findings have the following implications for environmental conservation, urban planning, and sustainable development in the study area.

a. The significant decline in vegetation underscores the urgent need for environmental conservation and measures to counter deforestation and land degradation.

b. The decrease in water bodies calls for improved water resource management and conservation efforts to ensure water availability for the future.

c. Fluctuations in open spaces highlight the importance of adaptable land use policies to preserve green areas within urban environments.

d. The projected expansion of built-up areas emphasizes the necessity of sustainable urban planning to accommodate growth while maintaining quality of life for residents.

e. Terrain-specific growth patterns should inform local land use planning and development strategies to maximize the benefits of different terrain types.

In conclusion, the findings of this study offer crucial insights into the changing landscape and provide a foundation for informed decision-making to address the observed trends and plan for the future in the study area.

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