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Assessing landscape fragmentation and its implications for biodiversity conservation in the Greater Accra Metropolitan Area (GAMA) of Ghana

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Abstract

Context This paper discusses the impact of urban expansion on the environment, including its effects on biodiversity conservation. As urban areas develop, natural habitats such as forests and agricultural lands are transformed into industrial, commercial, and residential uses, which alters landscape patterns and can lead to fragmentation. Fragmentation can have negative impacts on biodiversity, such as deforestation, alteration of watercourses leading to flooding, reduced availability of food, and increased pollution. The objective of this paper is to provide a comprehensive and data-driven analysis of the urban expansion of Greater Accra Metropolitan Area (GAMA) over time, and its effects on biodiversity. The idea is to capture the changes in land cover and landscape patterns in GAMA from 1991 to 2022 and predict the region's landscape patterns for 2030. This was achieved by performing a land cover change analysis of GAMA from 1991 to 2022; capturing the evolution of landscape patterns by calculating landscape metrics; and using multiradial fractal dimension as a transition variable to model and predict the land cover and landscape pattern of GAMA for 2030. The landscape metrics revealed extensive fragmentation of the Vegetation land cover type of GAMA, indicating a negative impact on biodiversity conservation, species movements, ecosystem functioning, and long-term ecological resilience. The trends highlight the importance of considering landscape connectivity, habitat fragmentation and spatial arrangement of land cover types for assessing ecological processes and urban development impacts on the environment. Additionally, multiradial fractal dimension of built-up areas is recommended as an explanatory variable for urban growth modelling.

Keywords Land cover change · Remote sensing · Landscape metrics · Urban growth modelling · Multiradial fractal dimension

1 Introduction

Urbanization is significantly linked to industrialization, modernization, and the sociological process of rationalization, all of which are important factors for regional economies [1]. Measuring the state of urban expansion is crucial to the establishment of a baseline which can aid in appropriate preparations for future occurrences. As urban areas develop, landscape patterns are altered, with forest and agricultural uses being transformed into industrial, commercial, and residential uses [2]. This has significant effects on the ecosystem [3, 4]. According to McGarigal [5], a landscape refers to a varied land area consisting of a collection of interconnected ecosystems that repeat in a similar pattern throughout the

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observed region. As the backdrop for all human activities on earth, landscapes serve as habitats for both human beings and other life forms [6]. Due to the interaction between humans and other living organisms, landscapes are constantly evolving. Gökyer [7] identified five primary factors that contribute to landscape changes, namely socio-economic, political, natural, cultural, and technological advancements. Over the years, there have been several small-scale changes in landscapes aimed at improving the living conditions of humans. Although these changes may seem insignificant when viewed individually, their cumulative impact on the ecosystem is substantial.

Although urbanization may offer improved living standards and access to various services such as education and recreation, it also exposes people to various environmental challenges such as air pollution, noise, water contamination, waste disposal problems, and heat [2, 8]. According to Dong et al. [9], the United Nations' World Charter for Nature from 1982 emphasized the importance of considering the sustainable capacity of ecosystems in long-term economic development plans, to prevent irreversible damage. Effective spatial governance measures must therefore be put in place to promote regional sustainable development while urbanizing. It is also important to monitor the state of urban growth over time to facilitate natural resource management, ecosystem protection, and mitigate unbalanced regional development [9].

In general, a landscape can be modelled as a matrix, corridor, patch, and mosaic [7, 10]. The landscape matrix is typically the most dominant and interconnected land cover type within the landscape. When the landscape composition (i.e., the non-spatial characteristics of the landscape matrix) and the landscape configuration (i.e., the spatial characteristics of the landscape matrix) are changed, the matrix becomes fragmented, a process referred to as fragmentation. Flowers et al. [11] summarized the process of fragmentation into four phases. The four phases are: (a) perforation, which involves the initial formation of small openings that create non-linear areas within the matrix that differ from their surroundings; (b) dissection, which is characterized by larger intrusions of patches, often along with physical features; (c) dissipation, which refers to the spread and merging of patches; and d) shrinkage, which involves a reduction in patch size and attrition. Fragmentation can cause negative impacts such as deforestation, alteration of water courses leading to flooding; reduced availability of food; and increased pollution from automobile usage including exhaust fumes, noise, and dust [6]. While it may not be possible to completely prevent landscape fragmentation due to ongoing human interactions with the environment, understanding the process of fragmentation can help us anticipate and prepare for its effects before they occur. This knowledge can inform the decisions of land use policy makers and authorities, enabling them to act in the best interests of future generations. Since fragmentation is a spatial process that occurs over time, spatiotemporal analysis can be employed to measure it. Simply examining land cover maps is insufficient for measuring fragmentation. Additional quantitative information is required. Such information can be derived from landscape metrics that have been developed to describe landscape patterns.

Landscape metrics are measurable units that allow for the qualitative description and quantification of spatial patterns and ecological processes over time in space. Landscape composition provides the qualitative description of land cover types present in the landscape, while landscape configuration provides a quantitative description of the spatial arrangement of land cover types. Many landscape metrics are strongly correlated, which makes them redundant if they all are chosen for a particular analysis. Selecting a relevant subset from the numerous metrics available, however, can be challenging. According to Turner et al. [12], metrics must be chosen to achieve specific objectives, minimize redundancy, explain pattern variability across the landscape, and cover a substantial portion of the range of their potential values. According to Flowers et al. [11], when utilizing landscape metrics to analyze urban growth patterns, it is recommended to select metrics that capture the characteristics of the landscape area, edge effects, and shape complexity. In this paper, drawing inspiration from previous works on the quantification of landscape patterns for urban growth management, Class Area (CA), Number of Patches (Nump), Edge Density (ED), and Proportion of like Adjacency (PLADJ) have been chosen to quantify the fragmentation process of Greater Accra Metropolitan Area (GAMA) from 1991 to 2022.

The Greater Accra Metropolitan Area (GAMA), which encompasses the administrative capital of Ghana is a vast region measuring 1583.8 km². This area is home to the capital city of Ghana, Accra, as well as the country's most prominent seaport (Tema) and only international airport (Kotoka International Airport), making it a significant economic and political center [13]. It comprises 12 independent municipalities (including Accra Metropolitan Area, Tema Metropolitan Area, Ga South, Ga East, Ga West, Sowutuom, La Dadekotopon, Madina, Adenta, LEKMA, Ashiaman, and Kpone Katamaso), most of which were once rural but have now become part of the built-up area of the Accra Metropolis due to economic and functional changes [14]. Figure 1 is a map of GAMA showing the distribution of the 12 municipalities.

The region's topography exhibits a range of features, including flat and gently undulating lowland areas as well as pockets of inselbergs. The vegetation consists of coastal savannah shrubs intermingled with thickets, coastal scrubs, grassland, and mangrove swamps. Small portions of guinea savannah and moist semi-deciduous forest mainly

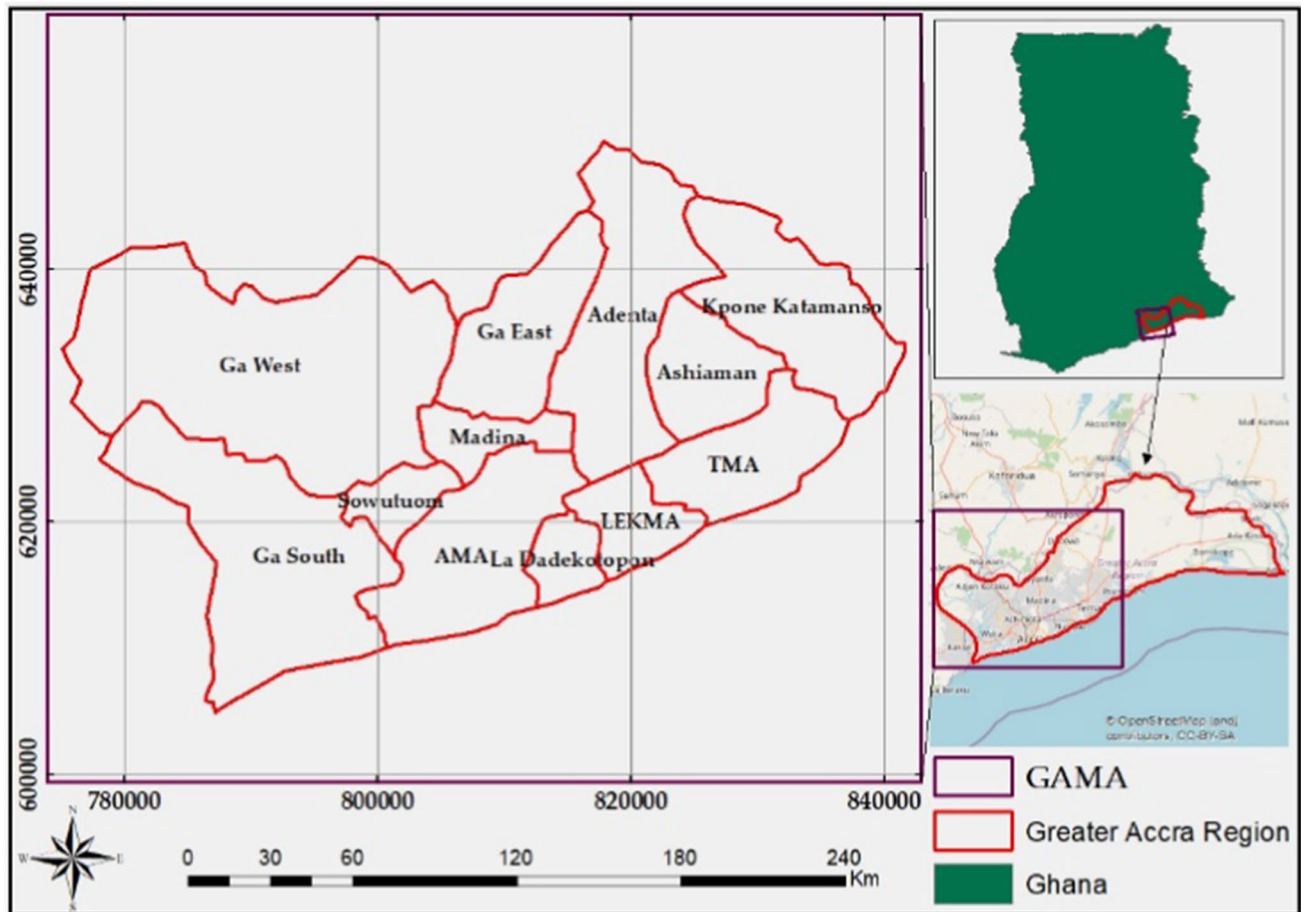


Fig. 1 Map of study area, GAMA

cover the region. The grasses are short, rarely exceeding one meter in height, while the average tree height reaches approximately five meters. Unfortunately, this diverse vegetation is currently facing threats from urban expansion. It is believed that the area was once densely forested, but deforestation caused by climate change and human activities has resulted in its loss [13, 15]. In recent years, the Greater Accra Metropolitan Area (GAMA) has witnessed significant investments in infrastructure and services, both from the public and private sectors [16]. This development has led to increased economic activities, population growth, and pressure on land resource within and around the region, resulting in urban sprawl. This massive urbanization is put into evidence by the normalized difference vegetation index (NDVI) and normalized difference built-up index (NDBI) results shown in Fig. 2a and b. Basically, NDVI represents the extent of vegetation at a given location while NDBI represents the extent of urbanization at a given location. They both range between -1 and $+1$. In the case of NDVI, $+1$ corresponds to strong vegetation, whereas in the case of NDBI, $+1$ corresponds to strong evidence of construction. So it's kind of the reverse. These two indicators were chosen because they complement each other, further confirming what is happening in the study area in terms of land cover change. With respect to biodiversity conservation, it can be observed from Fig. 2a that in 1991 there were a lot of vegetated areas, especially in the northern part of the study area. However, the area covered by vegetation continued to decline as the years progressed. The loss of vegetation is attributed to construction activities as is demonstrated by the results of the NDBI, Fig. 2b. By comparing the NDBI and NDVI results, it is evident that the expansion of the built-up area from 1991 to 2022 at the detriment of vegetation is very alarming.

The objective of this paper is to provide a comprehensive and data-driven analysis of the urban expansion of GAMA over time, and its effects on biodiversity. Using various techniques such as land cover change analysis, landscape metric measurement, and multi-radial fractal dimension calculation, this analysis seeks to utilize information extracted solely from land cover maps generated from freely available satellite images to achieve this objective. The idea is to capture

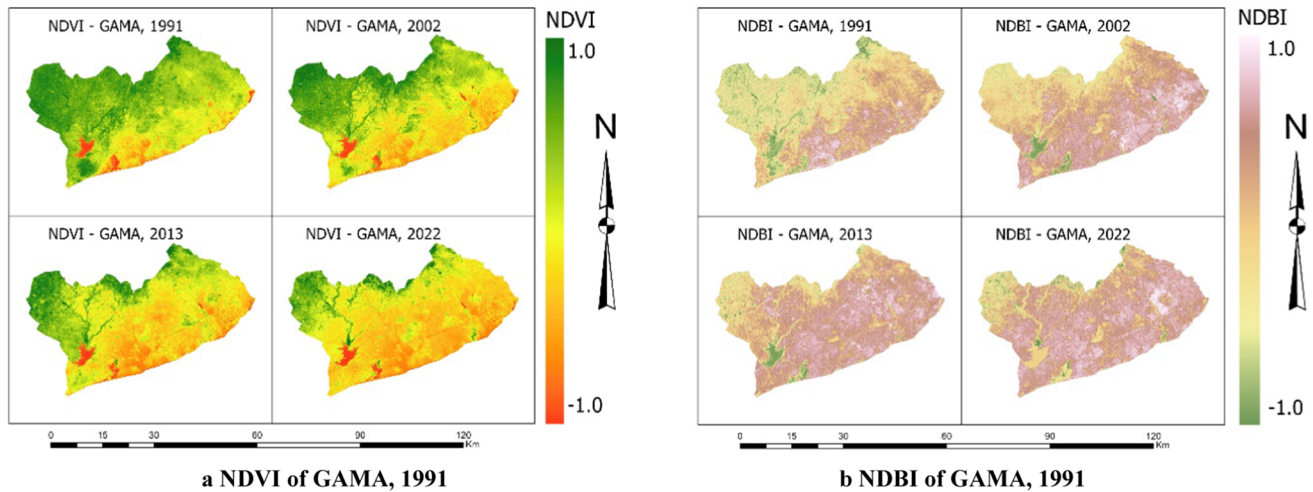


Fig. 2 a NDVI of GAMA, 1991–2022. b NDBI of GAMA, 1991–2022

the changes in land cover and landscape patterns in GAMA from 1991 to 2022 and predict the landscape patterns for 2030. The results of this analysis can be used to understand the drivers and impacts of urban growth in GAMA and to inform urban planning and management strategies for the region’s future development. Additionally, the prediction of future land cover and landscape metrics can provide valuable insights for decision-makers in terms of managing and adapting to the region’s urban growth.

2 Materials and methods

2.1 Materials used

The data and software used in this study are presented in Table 1.

2.2 Methods

The approach utilized in this study consists of three distinct phases. The initial phase involved analyzing the land cover change in GAMA from 1991 to 2022 and determining the rate of urban growth. In the second phase, the land cover for GAMA in 2030 was predicted using a combination of multi-layer perceptron and Markov chain techniques. Finally, the third phase involved calculating the landscape metrics of GAMA from 1991 to 2030.

2.2.1 Land cover change analysis

Land cover maps of GAMA showing four land cover types (Built-up, Vegetation, Transition and Water) from 1991 to 2022 (shown in Fig. 3a–3d) were converted from raster to polygon using ‘From Raster’ from the ‘Conversion Tools’ in the

Table 1 Data and software used

Data used	
Land cover maps of GAMA	1991, 2002, 2013 and 2022
Software used	
ArcMap 10.8	
Fragstats 4.2	
Fractalys 3–0.8.1	
IDRISI 17.0 The Selva Edition	

ArcToolbox. Kappa score was used as the accuracy indicator. It essentially evaluates how well the classification performed as compared to just randomly assigning values to cells, i.e., whether or not the classification did better than randomly assigning values to cells in the image? The kappa score can range from -1 to 1 . A value of 0 indicates that the classification is no better than a random classification. A negative number indicates the classification is significantly worse than a random classification. A value close to 1 indicates that the classification is significantly better than a random classification. The accuracies that were obtained are 0.928 , 0.906 , 0.881 and 0.933 for 1991, 2002, 2013 and 2022 respectively. Built-up area referred to all man-made features such as: buildings, roads, bridges, ports and harbor, etc. Vegetation referred to thick forest cover with trees, dense bushes and grass lands. Transition refers to vegetated areas gradually changing into built-up areas. They represent mixed land cover comprising bare lands, areas cleared for construction purposes, isolated buildings, and shrubs. Water referred to all water bodies such as: streams, lakes, rivers, lagoons etc. To ensure distinct codes for each land cover type, the attribute table was accessed. Next, the 'Dissolve' function from the geoprocessing tab was utilized to merge similar features into a single feature using 'gridcode' as the dissolve field. The different classes were labeled within the attribute table, and the area covered by each class was computed using the 'calculate geometry' option. This process was carried out for all the years under examination, namely 1991, 2002, 2013, and 2022. To identify changes that occurred over time, the 'Intersect' tool from the geoprocessing tab was employed. This operation involved calculating the geometric intersection between consecutive years (1991–2002, 2002–2013, and 2013–2022). The more recent land cover map was superimposed on the previous one, adopting the changes where they occurred while keeping unchanged areas consistent. To facilitate this analysis, a new field named 'Change' with a text data type was added to the attribute table. A VB Script was composed in the field calculator to label the changes according to the format "Change=Land cover type Yr 1 + '-' + Land cover type Yr 2". Additionally, another field named 'Area_Change' with a double data type was created to calculate the area affected by each land cover change. The area calculations were performed using the 'calculate geometry' function within the attribute table. Finally, the attribute table was exported to Excel in order to generate charts illustrating the various changes that occurred over the specified period.

Rate of urban growth: The calculation of urban growth rate involved comparing the land cover classification of a specific area during different time periods. This analysis focused on examining the changes in the extent of land categorized as "Built-up" over time. To determine the rate of urban growth, the area occupied by urban land cover (i.e., Built-up) was

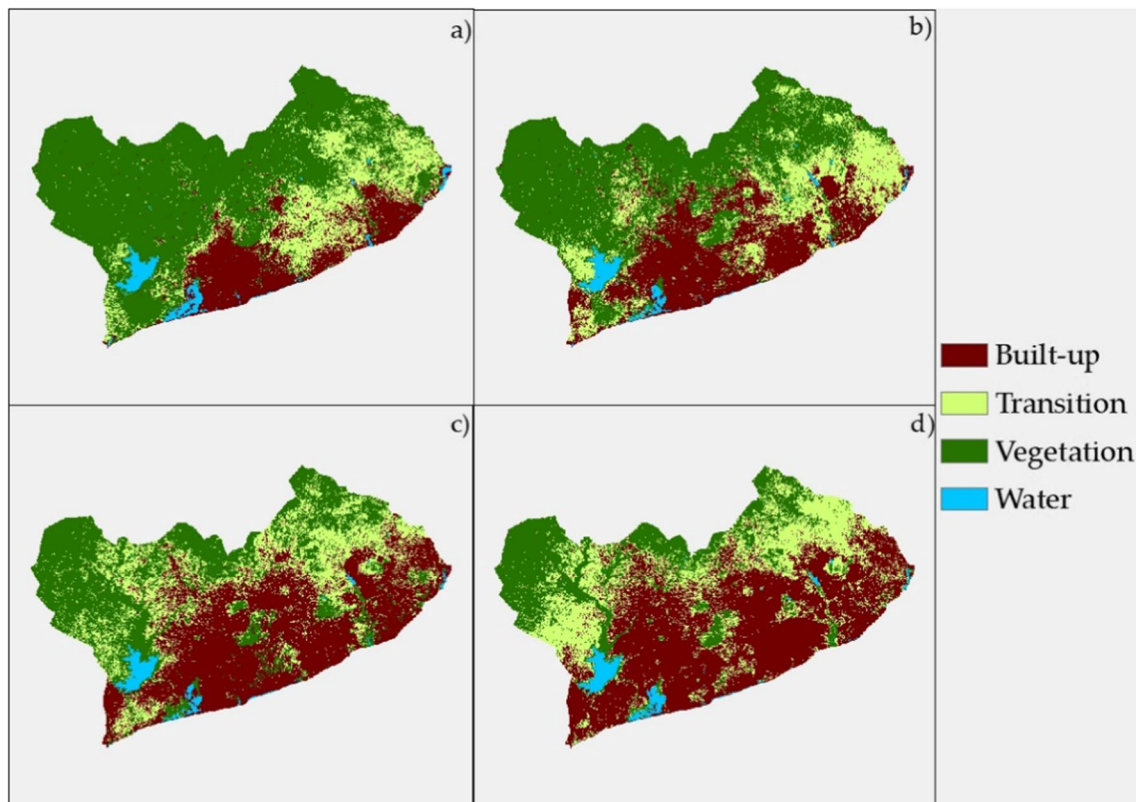


Fig. 3 a–d Landcover maps of GAMA from 1991 to 2022

calculated for each time period. Subsequently, the difference in area between the two time periods was determined. Dividing the change in area by the time period yielded the annual rate of change in urban land cover. Equation 1 was utilized to determine the rate of urban growth.

$$\text{Rate of Morphological Urban Growth} = \frac{((\text{Urban Area}(t_2) - \text{Urban Area}(t_1)))}{\text{Year}(t_2) - \text{Year}(t_1)} \times 0.01 \quad (1)$$

2.2.2 Urban growth modelling of GAMA

The Land Change Modeler (LCM) in Idrisi is a tool used for land change modeling and prediction. It integrates data sources, performs statistical and spatial analysis, and simulates land cover changes over time. LCM follows a stepwise approach, starting with change analysis and transition potential modeling, and progressing to change prediction based on historical data. In change analysis, alterations between two land cover maps are identified as transitions from one state to another. Transition potential modeling groups these transitions into sub-models with transition variables. The transition variables provide valuable information about the conditions and characteristics associated with the transitions between different land cover states. By incorporating transition variables into the modeling process, LCM enables a more accurate representation of the relationships between explanatory factors and land cover change patterns. This process generates a transition potential map indicating change potential at a specific time. The transition sub-models are modeled using the multi-layer perceptron (MLP) neural network, which automatically adjusts parameters and learning rates to improve the model. Markov chain analysis is employed during change prediction to quantify the amount of change in each transition, considering an end date. The resulting models include a hard prediction model that provides a single realization of predicted change based on competitive land allocation, and a soft prediction model that assesses vulnerability to change for selected transitions, offering a comprehensive understanding of change potential. LCM is valuable for land management, urban planning, and environmental assessment purposes. Multi-layer perceptron and Markov chain techniques were chosen as the primary methods for predicting land cover change based on their relevance to the problem, prior success in the field, suitability for our dataset's characteristics, and their demonstrated performance in our experiments. We believe that these methods provide a robust foundation for addressing the complexities of land cover change prediction and contribute to the advancement of this critical area of research.

2.2.2.1 Transition variables This study employed specific transition variables, namely evidence likelihood (evlikelihood), multiradial fractal dimensions (frac), distance from vegetation (Dist_veg), and distance from the central business district (Dist_CBD). These transition variables were derived exclusively from land cover maps created through the classification of freely accessible satellite images.

Evidence likelihood: In IDRISI, the evidence likelihood is obtained by combining a changes map and a land cover map. The changes map represents the transitions between land cover classes over time, while the land cover map shows the initial state of the landscape. Using a probabilistic approach, the conditional probabilities of transitioning between land cover classes are calculated from the changes map. These probabilities are then applied to the land cover map to assign evidence likelihood values to each pixel based on the neighboring pixel's conditional probabilities. This process considers spatial relationships to estimate the likelihood of a pixel belonging to a specific land cover class. The evidence likelihood approach in IDRISI provides a more accurate and probabilistic assessment of land cover classification by incorporating observed changes and their spatial patterns.

Multiradial fractal dimension: Multiradial fractal dimension is a measure used to quantify the complexity or irregularity of a shape or pattern. It is derived from the concept of fractals, which are mathematical objects that exhibit self-similarity at different scales. The multiradial fractal dimension specifically focuses on the dimensionality of a shape or pattern when viewed from different radial directions. In the context of land cover analysis, the multiradial fractal dimension is often applied to quantify the complexity of built-up areas or urban landscapes. By calculating the fractal dimension at multiple radial directions around a point or region, it provides insights into the spatial structure and arrangement of built-up features. Higher values of the multiradial fractal dimension indicate more regular or homogeneous patterns while lower values indicate greater complexity or irregularity in the distribution of built-up areas. The multiradial fractal dimension is a useful tool in understanding urban morphology and spatial patterns, as it captures the inherent complexity and heterogeneity of urban landscapes. It can be employed to analyze the changes in urban form over time, compare different urban areas, or assess the impact of urbanization on the landscape. The multiradial fractal dimension of the

built-up area of GAMA was calculated using Fractalyse 3–0.8.1 after the built-up area was extracted from the land cover map using ArcMap 10.8.

Distance from Vegetation: The distance from Vegetation refers to the spatial proximity from areas with natural or planted vegetation, such as forests, parks, gardens, or green spaces. It is a measure used to understand the relationship between built-up areas and vegetated areas. The distance from vegetation can be an important factor in various environmental and ecological studies. It can provide insights into the availability of green spaces and natural habitats, urban heat island effects, air quality, biodiversity, and overall ecosystem health in urban environments. Analyzing the distance from vegetation can help researchers and policymakers assess the accessibility and distribution of green spaces within a city, identify areas with limited access to nature, and evaluate the potential impacts of urbanization on natural habitats and wildlife. The distance from vegetation was calculated using the Euclidean distance tool in ArcMap 10.8.

Distance from CBD: The distance from CBD refers to the physical distance between a particular location and the central commercial and economic hub of a city or urban area. The CBD is typically characterized by a concentration of commercial activities, office buildings, retail centers, and transportation hubs. The distance from the CBD is an important factor in urban planning, transportation, and land use studies as it can influence various aspects of urban development. The distance from the CBD can impact land values, with properties closer to the CBD often being more expensive due to their proximity to business and employment opportunities. It can also affect transportation patterns, as areas closer to the CBD may experience higher traffic volumes and greater accessibility to public transportation options. Additionally, the distance from the CBD can influence the distribution of land uses and the intensity of development. Typically, areas closer to the CBD tend to have a higher concentration of commercial and residential buildings, while areas farther away may consist of more suburban or rural land uses. Understanding the distance from the CBD is crucial for urban planners, policymakers, and researchers to assess patterns of urban growth, plan transportation networks, allocate resources, and develop strategies to manage urban development effectively. It helps in identifying areas of potential urban expansion, determining the need for infrastructure development, and implementing policies to promote balanced growth and sustainable development across the city or urban area.

2.2.3 Landscape metrics

Fragstats 4.2 was utilized for analyzing the spatial pattern of GAMA's landscape by computing various landscape metrics. The landscape metrics were calculated at class level. These metrics were chosen to assess the evolution of the landscape's structure:

2.2.3.1 Class area (CA) CA is a fundamental measure of landscape composition which indicates how much of the landscape is comprised of a particular patch type. It is the sum of the areas (m^2) of all patches of a particular patch type, divided by 10 000 to convert it to hectares. It is calculated using Eq. 2 [5].

$$CA = \sum_{j=1}^n a_{ij} \left(\frac{1}{10000} \right) \quad (2)$$

where, a_{ij} = area (m^2).

2.2.3.2 Number of patches (NP) A patch could be defined as the four nearest neighbor cells (i.e., horizontal and vertical neighbors only) adjoining the cell or the eight nearest neighbor cells (i.e., horizontal, vertical and diagonal neighbors) adjoining the cell. Based on the definition of a patch by the analyst, NP refers to the total number of patches in the landscape. The number of patches provides valuable information about habitat fragmentation, species diversity, and habitat quality within a landscape. Understanding this metric aids in evaluating the spatial distribution of habitats, assessing the impacts of fragmentation on biodiversity, and guiding conservation and land management decisions to promote ecological integrity and sustainable use of landscapes. It calculated using Eq. 3 [5, 12].

$$NP = N \quad (3)$$

where, N = total number of patches in the landscape.

2.2.3.3 Edge density (ED) ED is the sum of all horizontal and vertical edges between cells of corresponding patch types multiplied by the length unit of the cell divided by the total area of the landscape. Edge density is crucial for assessing landscape structure, habitat fragmentation, and their implications for biodiversity conservation and ecosystem functioning. It aids in making informed decisions regarding land-use planning, habitat restoration, and conservation strategies aimed at maintaining the integrity and ecological value of landscapes. ED is calculated using Eq. 4 [5, 12].

$$ED = \frac{\sum_{k=1}^m e_{ik}}{A} \times 10000 \quad (4)$$

where, e_{ik} = total length of all edges of a particular cover type; A = total landscape area.

2.2.3.4 Proportion of like adjacencies (PLADJ) PLADJ equals the number of like adjacencies involving the focal class, divided by the total number of cell adjacencies involving the focal class; multiplied by 100 (to convert to a percentage). Assessing the proportion of like adjacency is valuable for land management and conservation planning. It helps identify areas with high or low proportions of like adjacency, guiding decisions on habitat restoration, creation of corridors, and prioritization of conservation efforts. By promoting connectivity and appropriate spatial arrangements of land cover types, land managers can enhance habitat quality, maintain ecological processes, and support sustainable land use practices. PLADJ is given by Eq. 5 [5].

$$PLADJ = \left[\frac{g_{ii}}{\sum_{k=1}^m g_{ik}} \right] \times 100 \quad (5)$$

where g_{ii} = number of like adjacencies between pixels of a particular patch type; g_{ik} = number of adjacencies between pixels of different patch types.

3 Results and discussion

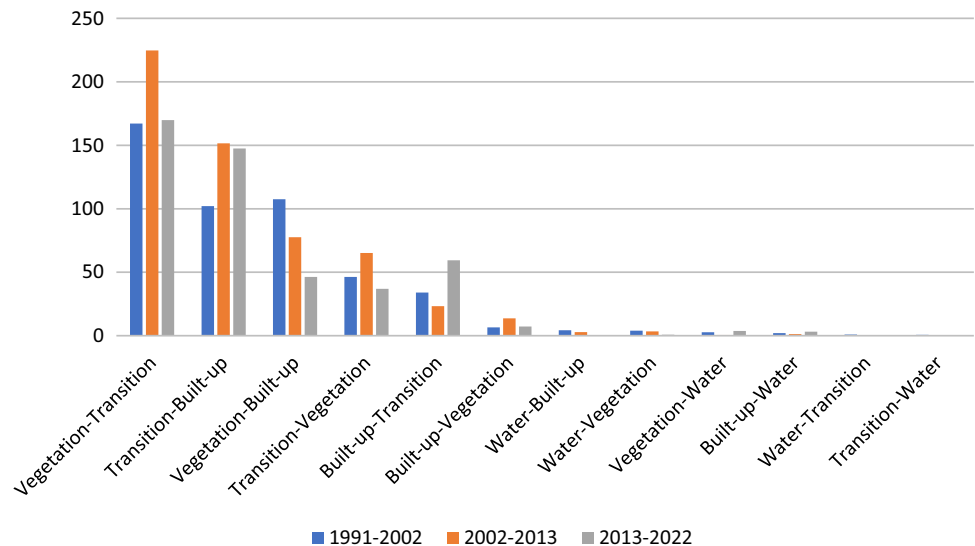
3.1 Land cover change analysis

The trend observed in the land cover changes from 1991 to 2022 indicates several patterns. The most notable change is the increasing trend in the change from Vegetation to Transition, with a peak at 224.79 km² from 2002 to 2013; and a slight decrease to 169.83 km² from 2013 to 2022. This suggests a conversion of Vegetation areas into Transitional land cover during the earlier period, followed by a relatively stable transition in the later years. Similarly, the Transition to Built-up change demonstrates an increasing trend from 102.05 km² from 1991 to 2002 period to 151.54 km² from 2002 to 2013, remaining relatively stable at 147.54 km² from 2013 to 2022. This indicates a consistent growth in Transitioning areas converting into Built-up land cover, which then maintains its extent in the later years. On the other hand, the Vegetation to Built-up change shows a declining trend, decreasing from 107.54 km² from 1991 to 2002 to 77.56 km² from 2002 to 2013 and further decreasing to 46.37 km² from 2013 to 2022. This suggests a reduction in the conversion of Vegetation areas into Built-up land cover over time. The Transition to Vegetation and Built-up to Transition changes exhibit varying patterns with fluctuating values across the three time periods, indicating some level of dynamism and inconsistency in these specific land cover changes. Overall, the trend in land cover changes highlights the dynamic nature of the studied area, with varying rates of changes between different land cover types over the analyzed time span. Figure 4 is chart comparing the land cover changes between 1991 and 2022.

3.1.1 Rate of urban growth

The initial urban area in 1991 measured 271.05 km². Between 1991 and 2002, there was an increase of 169.93 km² in the urban area, corresponding to a growth rate of 0.15% per year. Subsequently, from 2002 to 2013, the urban area expanded by 191.43 km², resulting in a growth rate of 0.17% per year. Between 2013 and 2022, the urban area expanded by 126.28 km², with a growth rate of 0.14% per year. Overall, the rate of urban growth has shown a downward trend, with the period from 2002 to 2013 witnessing the highest growth rate. Table 2 shows the area and the rate of urban growth from 1991 to 2022.

Fig. 4 A chart comparing the various land cover changes between 1991 and 2022



3.2 Urban growth modelling of GAMA

Initially, the required data, including land cover maps of GAMA 1991–2022 (shown in Fig. 3a–d), the transition variables, and excluded areas, were prepared in ArcMap 10.8 and converted to ASCII for easy importation into IDRISI 17.0. The transition variables are shown in Appendix 4. The land cover images of GAMA for 2002 and 2013 were used as inputs to predict the land cover of 2022 using the LCM model, which included modeling transition variables using MLP to determine transition potentials. Two sub-models, namely “urbanization” and “afforestation,” were developed to model land use change. The “urbanization” sub-model accounted for land use changes from Vegetation to Transition, Vegetation to Built-up, and Transition to Built-up. On the other hand, the “afforestation” sub-model represented land use changes from Transition to Vegetation and Built-up to Transition. These changes were the most dominant changes in GAMA from 1991 to 2022 based on the land cover change analysis. The MLP for modelling the transition potential of the 2022 land cover of GAMA produced an accuracy of 93.83% and 85.03% for “urbanization” and “afforestation,” respectively. The MLP results are shown in Appendix 5. Transition potential maps were created and a Markov chain was used to predict the land cover map of GAMA for 2022. The predicted map was compared with the actual land cover map of 2022, resulting in a kappa score of 0.80. Figure 5a and b depict the hard and soft prediction of the land cover map of GAMA 2022. The high kappa score obtained instilled confidence in forecasting the land cover map of GAMA for 2030 using the land cover maps of GAMA in 2013 and 2022. Figure 6a and b showcases the hard and soft predicted land cover maps of GAMA for 2030.

3.3 Landscape metrics GAMA 1991–2030 (predicted)

3.3.1 Class area (CA)

Between 1991 and 2002, there was a significant decrease in the area covered by Vegetation, with a decrease of 221.59 km². At the same time, the Built-up area increased by 169.93 km², which indicates urbanization. The Transition

Table 2 Table showing the rate of urban growth in GAMA from 1991 to 2022

Rate of urban growth		
Year	Area (km ²)	Rate (%)
1991	271.05	
2002	440.98	0.15
2013	632.41	0.18
2022	758.69	0.14

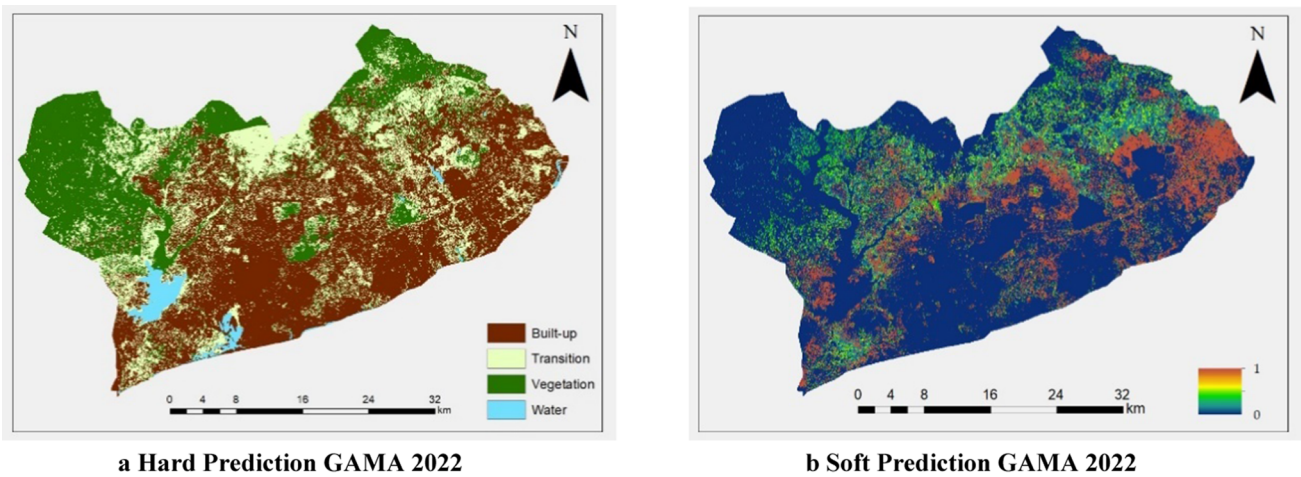


Fig. 5 **a** Hard prediction GAMA 2022. **b** Soft prediction GAMA 2022

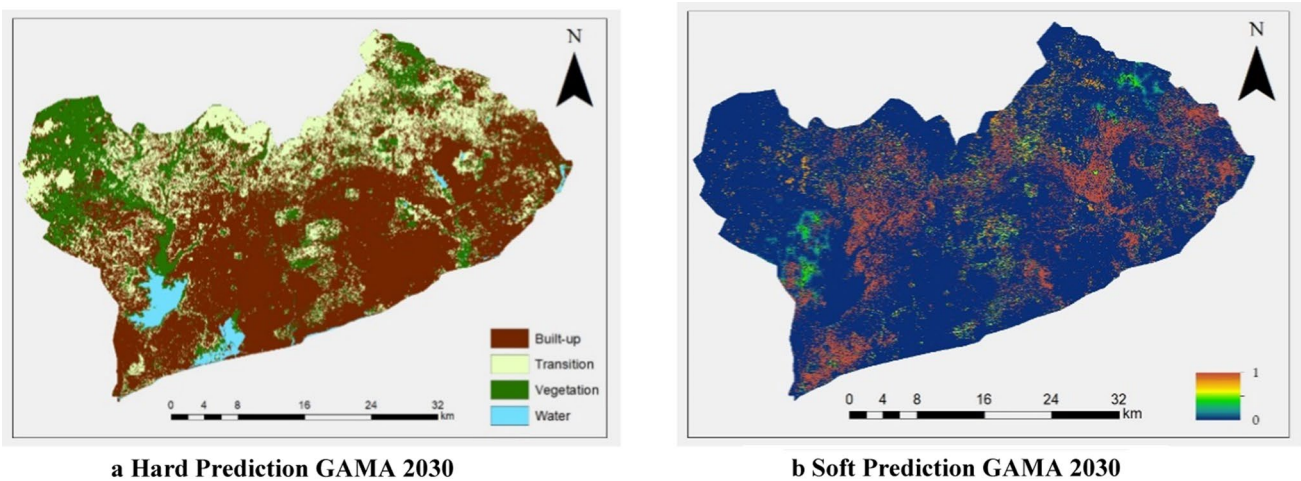
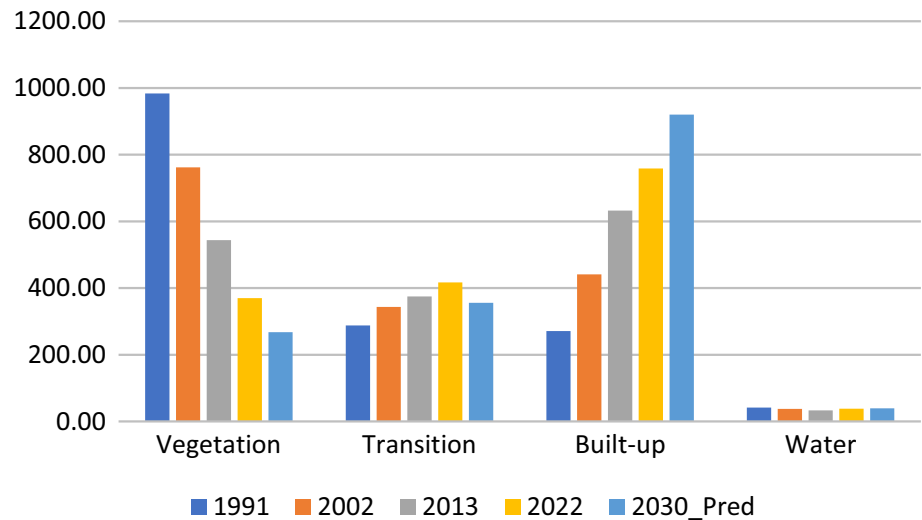


Fig. 6 **a** Hard prediction GAMA 2030. **b** Soft prediction GAMA 2030

area increased by 55.39 km², which could be the result of changes in land use from agricultural or forested land to Built-up. From 2002 to 2013, there was a continuation of the trend from the previous period, with a further decrease of 218.04 km² in Vegetation and an increase of 191.43 km² in the Built-up area. The Transition area also increased by 31.36 km². From 2013 to 2022, there was a further decrease in Vegetation area, but the rate of decrease slowed down significantly. At the same time, the Built-up area continued to increase, but the rate of increase was also slower than in the previous period. The reduced pace of change observed in the areas covered by Vegetation and Built-up suggests that the region may be approaching saturation, which means that there is limited space for substantial changes to occur. The Transition area increased by 42.46 km², which indicates continued changes in land use. The predicted values for 2030 show a further decrease in the Vegetation by 101.74 km², indicating a potential continuation of loss of Vegetation. The Transition class area is predicted to decrease by 61.60 km², indicating a potential shift towards other land cover types such as Built-up. Built-up areas are projected to increase by 161.44 km², suggesting continued urbanization. Water areas are predicted to increase slightly by 1.00 km². Overall, the analysis suggests a trend of decreasing Vegetation class area and increasing Built-up areas over time, indicating potential land cover change associated with urbanization and human activities. The Transition class demonstrates a dynamic nature with both increases and decreases, possibly due to land use changes or natural processes. The slight changes in Water areas indicate relatively stable conditions. However, the predicted values for 2030 suggest a continuation of the observed trends, emphasizing the need for sustainable land management practices to mitigate further land cover changes and promote ecosystem conservation. Table 3 provides information on the class area for the different land cover

Table 3 Showing the area covered by each land cover type and the changes observed

Class area (km ²)	Class area (km ²)				
	1991	2002	2013	2022	2030_Pred
Vegetation	983.40	761.81	543.77	369.56	267.82
Transition	287.98	343.37	374.73	417.19	355.59
Built-up	271.05	440.98	632.41	758.69	920.14
Water	41.46	37.73	32.99	38.46	39.47

Fig. 7 Chart showing the area covered land cover types from 1991 to 2022

types (Vegetation, Transition, Built-up, and Water) for various years (1991, 2002, 2013, 2022, and predicted 2030). Figure 7 is a chart showing the area covered by the various land cover types in GAMA from 1991 to 2030 (predicted).

3.3.2 Number of patches (NP)

Increase or decrease in number of patches causes disruption in the landscape matrix. This is typically as a result of anthropogenic activities. If the number of patches of a landcover increases, it is an indication of fragmentation, whereas if it decreases, it indicates uniformity or a reduction in the area it covers due to land cover change. The data on the number of patches for different land cover types over time reveals several trends and changes in the landscape. Firstly, there was a general increase in the number of patches for Vegetation, Transition, and Built-up areas from 1991 to 2002 and 2013, indicating expansion and fragmentation of these land cover types. However, by 2022, there is a decline in the number of patches, suggesting possible consolidation or merging of these areas. The number of patches for water remains relatively stable throughout the years, with minor fluctuations. This indicates a relatively consistent distribution of water bodies. Additionally, the predicted value for 2030 shows a significant increase in the number of patches, especially for Vegetation, in spite of the decrease in area covered during this period. This could be attributed to the massive fragmentation in the north of the Vegetation land cover as can be observed in Fig. 6a. Overall, the trends in the number of patches reflect changes in land use patterns, urbanization, and ecological dynamics over time. These changes may have implications for habitat fragmentation, biodiversity, and environmental management strategies. Table 4 provides information on the number of patches for different land cover types (Vegetation, Transition, Built-up, and Water) for various years (1991, 2002, 2013, 2022, and predicted 2030). Figure 8 is a chart showing the number of patches of the various land cover types in GAMA from 1991 to 2030 (predicted).

3.3.3 Edge density (ED)

Edge density refers to the amount of edge or boundary between different land cover types relative to the total area. Edge density for different land cover types over time provides insights into the spatial patterns and fragmentation of the

Table 4 Showing the number of patches for each land cover types in GAMA

	Number of patches				
	1991	2002	2013	2022	2030_Pred
Vegetation	7555	7765	9325	6400	19,149
Transition	15,021	20,142	20,963	14,382	16,955
Built-up	8250	10,941	9161	10,618	12,076
Water	440	521	264	311	407

landscape. As landscapes become more and more patchy, the edge density values keep increasing, indicating that the landscape is becoming more fragmented. Several trends were observed during the analysis. Firstly, there was an overall increase in edge density for most land cover types from 1991 to 2013, indicating a higher degree of fragmentation and mixing of land cover types. This suggests that the landscape became more diverse and interspersed with different land cover patches during this period.

However, from 2013 to 2022, there was a significant decrease in edge density for vegetation, and transition, suggesting a reduction in fragmentation and a more consolidated or homogeneous landscape. It is important to note that the predicted value for 2030 shows an increase in edge density for built-up and Vegetation, indicating a potential reversal of the decreasing trend and a possible expansion or further fragmentation of urban areas at the expense of vegetation in the future. The relatively stable edge density for water suggests a consistent spatial pattern, with minimal changes in the boundaries of water bodies over time. Table 5 provides information on the edge density values for different land cover types (Vegetation, Transition, Built-up, and Water) for various years (1991, 2002, 2013, 2022, and predicted 2030). Edge density represents the amount of edge or boundary length relative to the area of a land cover type. Figure 9 is a chart showing the edge density of the various land cover types in GAMA from 1991 to 2030 (predicted).

Fig. 8 Chart showing the number of patches of land cover types from 1991 to 2022

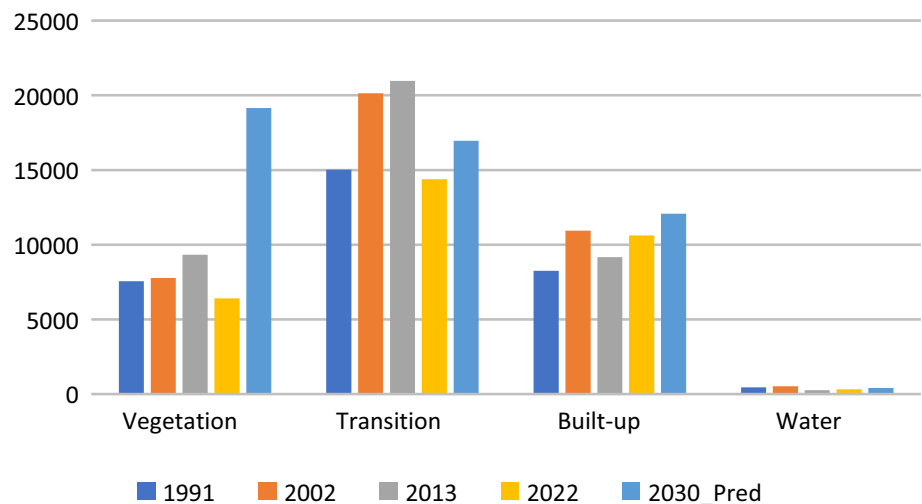


Table 5 Showing the edge density of each land cover type and the changes observed

	Edge density				
	1991	2002	2013	2022	2030_Pred
Vegetation	25.5619	26.2207	28.7652	17.9244	28.7024
Transition	33.6679	38.7118	49.664	42.7035	42.3513
Built-up	17.4832	26.3008	30.9611	30.0044	49.2616
Water	1.2643	1.3352	0.9256	1.0238	1.1471

Fig. 9 Chart showing the edge density of the various land cover types from 1991 to 2022

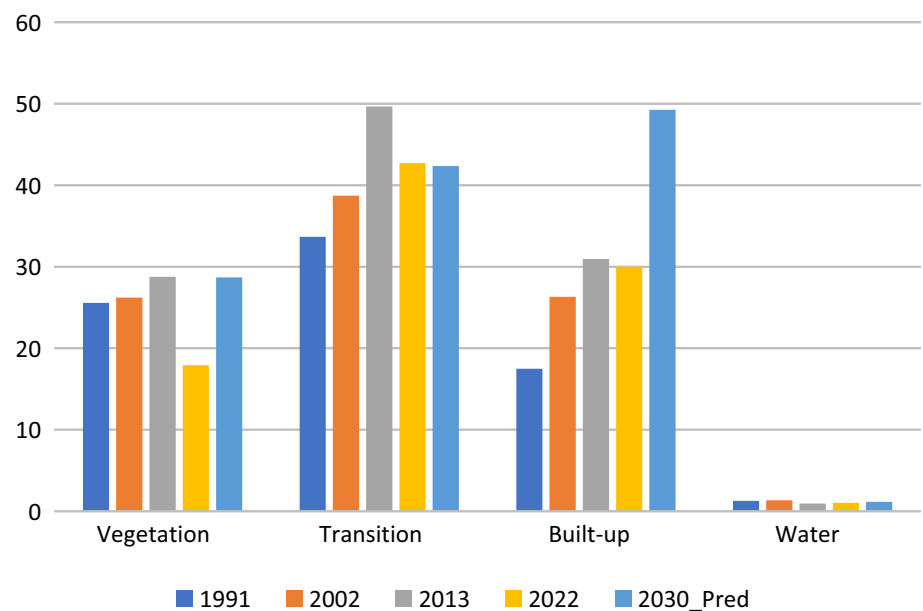


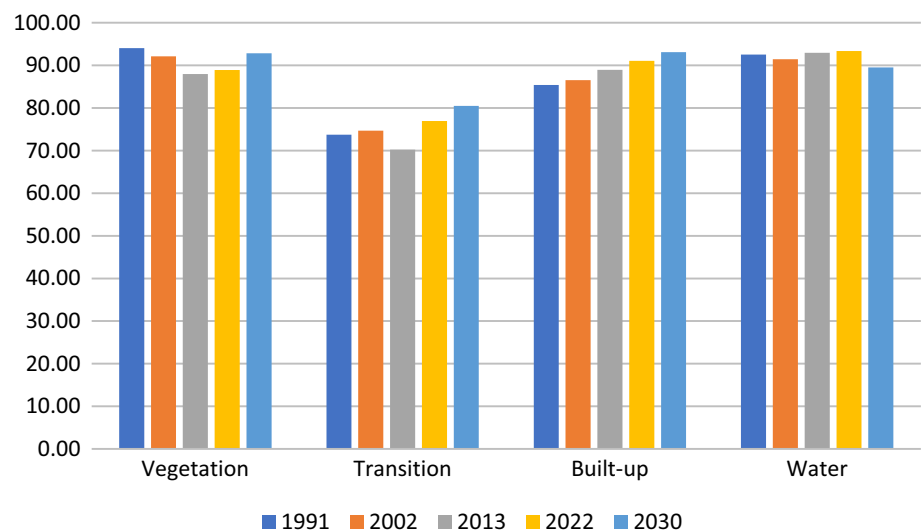
Table 6 Showing the proportion of like adjacency of each land cover type

	Proportion of like adjacency (%)				
	1991	2002	2013	2022	2030
Vegetation	94.05	92.14	87.97	88.91	92.84
Transition	73.74	74.66	70.21	76.96	80.51
Built-up	85.39	86.52	88.94	91.06	93.11
Water	92.55	91.44	92.95	93.36	89.51

3.3.4 Proportion of like adjacencies (PLADJ)

The proportion of like adjacency metric measures the proportion of like adjacent pixels in a given land cover type, with higher values indicating greater clustering of patches. From the results obtained, it can be observed that the proportion of like adjacency varies across the different land cover classes and time periods. In 1991, the highest proportion of like adjacency was observed for Vegetation (94.05%), followed by Water (92.55%), Built-up (85.39%), and Transition (73.74%). However, over the years, there have been fluctuations in these values. Between 1991 and 2013, all land cover classes experienced a decline in the proportion of like adjacency with the exception of Transition, which experienced a slight increase of 0.93% from 1991 to 2002; and Built-up which experienced steady increment throughout the years observed. Vegetation decreased from 94.05% to 87.97%, Transition decreased from 73.74% to 70.21% and Water decreased from 92.55% to 92.95%. However, from 2013 to the projected year of 2030, there is an overall increase in the proportion of like adjacency for all the land cover classes with the exception of Water. From the projections, Vegetation is expected to increase to 92.84%, Transition to 80.51%, Built-up to 93.11%, however, Water is expected to decrease to 89.51%. The results suggest that there have been changes in the spatial configuration of land cover classes within the landscape over time. The proportion of like adjacency provides insights into the degree of aggregation or dispersion of patches of the same land cover class. The fluctuations in these values indicate potential changes in landscape fragmentation, connectivity, and potential impacts on ecological processes and biodiversity. Table 6 provides information on the proportion of like adjacency for different land cover types (Vegetation, Transition, Built-up, and Water) for various years (1991, 2002, 2013, 2022, and predicted 2030). Figure 10 is a chart showing the proportion of like adjacency of the various land cover types in GAMA from 1991 to 2030 (predicted).

Fig. 10 Chart showing proportion of like adjacency of land cover types from 1991 to 2022



4 Conclusion

The study successfully captured the land cover changes and urban growth rate of the GAMA region. The findings revealed a significant transformation in the land cover composition of the region, with the Built-up land cover type now dominating over the previously dominant Vegetation land cover type. The analysis of urban growth rates showed an increase from 0.15% (1991 to 2002) to 0.18% (2002 to 2013), but then a decrease to 0.14% from 2013 to 2022. This decrease suggests a potential saturation of the study area with Built-up land cover, indicating limited room for further urban expansion. The study also captured the landscape patterns of the GAMA region using landscape metrics. The landscape metrics further revealed extensive fragmentation of the Vegetation land cover type, indicating a negative impact on biodiversity conservation, species movements, ecosystem functioning, and long-term ecological resilience. Additionally, the study successfully predicted the land cover and landscape pattern of GAMA for the year 2030 using only freely available satellite imagery. The trends highlight the importance of considering landscape connectivity, habitat fragmentation and spatial arrangement of land cover types for assessing ecological processes and urban development impacts on the environment. Understanding and identifying areas with high fragmentation is crucial for prioritizing conservation efforts. This knowledge can assist landscape planners and managers in making informed decisions regarding land-use planning, habitat restoration, and conservation strategies. By addressing fragmentation in GAMA and promoting habitat connectivity, the integrity and ecological value of the landscapes can be maintained while supporting biodiversity conservation and sustainable ecosystem management. While the research focused on vegetation, a critical component of the natural ecosystem, it is important to note that we did not incorporate data on species richness. Unfortunately, data availability constraints and the scope of our work prevented us from including this valuable aspect in our analysis.

Author contributions Olivier Bonin conceived of the presented idea. Kofi Bonsu performed the analysis and drafted the initial version of the manuscript. All authors contributed to the final manuscript. Supervised by Olivier Bonin.

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Availability of data and materials The land cover maps used can be found at <https://github.com/Kbonsu100/GAMA-Land-cover-maps>.

Declarations

Ethics approval and consent to participate Not applicable.

Competing interests There are no competing interests.

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Appendices

Appendix 1

Area covered by the various land cover changes in GAMA from 1991 to 2002.

Land cover change (1991–2002)	Area (km ²)
Vegetation-Transition	167.15
Vegetation-Built-up	107.53
Transition-Built-up	102.05
Transition-Vegetation	46.35
Built-up-Transition	34.06
Built-up-Vegetation	6.52
Water-Built-up	4.32
Water-Vegetation	4.01
Vegetation-Water	2.70
Built-up-Water	2.09
Water-Transition	0.91
Transition-Water	0.67

Appendix 2

Area covered by the various land cover changes in GAMA from 2002 to 2013.

Land cover change (2002–2013)	Area (km ²)
Vegetation-Transition	224.79
Transition-Built-up	151.54
Vegetation-Built-up	77.56
Transition-Vegetation	65.19
Built-up-Transition	23.29
Built-up-Vegetation	13.72
Water-Vegetation	3.40
Water-Built-up	2.85
Built-up-Water	1.23
Vegetation-Water	0.60
Water-Transition	0.33
Transition-Water	0.09

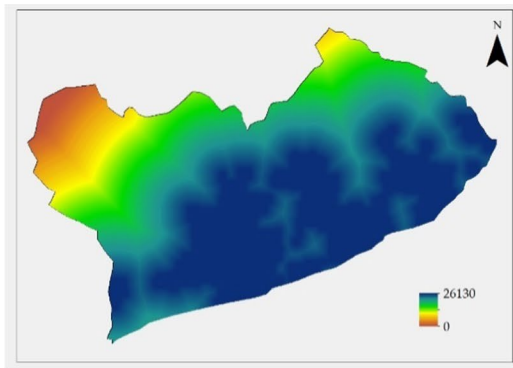
Appendix 3

Area covered by the various land cover changes in GAMA from 2013 to 2022.

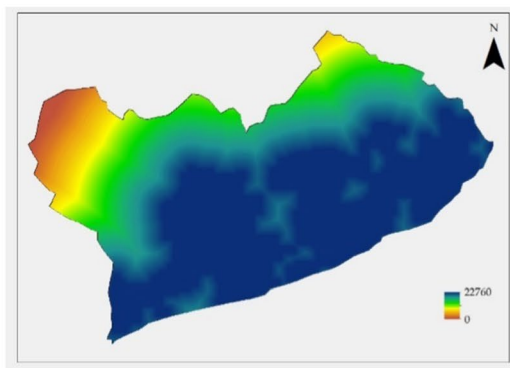
Land cover change (2013–2022)	Area (km ²)
Vegetation-Transition	169.83
Transition-Built-up	147.54
Built-up-Transition	59.38
Vegetation-Built-up	46.37
Transition-Vegetation	36.97
Built-up-Vegetation	7.21
Vegetation-Water	3.70
Built-up-Water	3.13
Water-Vegetation	0.84
Water-Built-up	0.47
Water-Transition	0.12
Transition-Water	0.08

Appendix 4

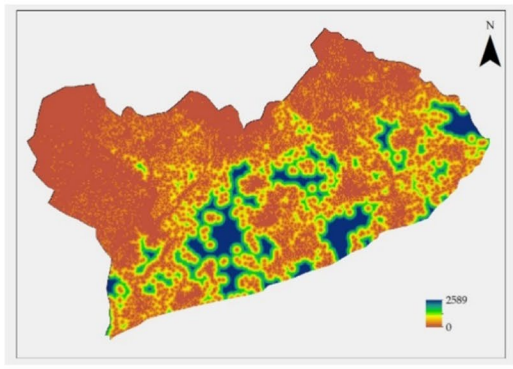
Transition Variables.



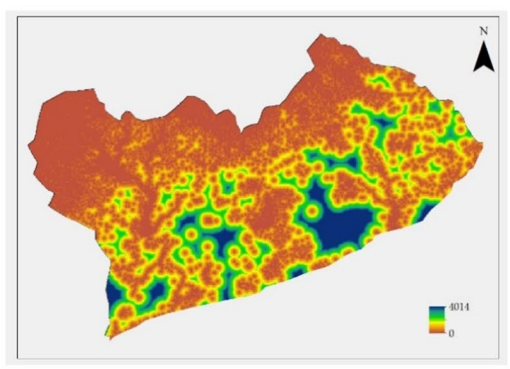
Appendix 4a Distance to CBD 2013



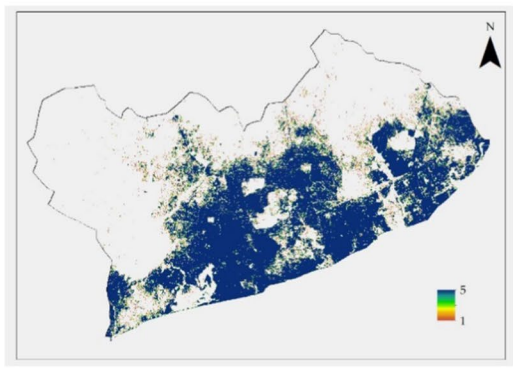
Appendix 4b Distance to CBD 2022



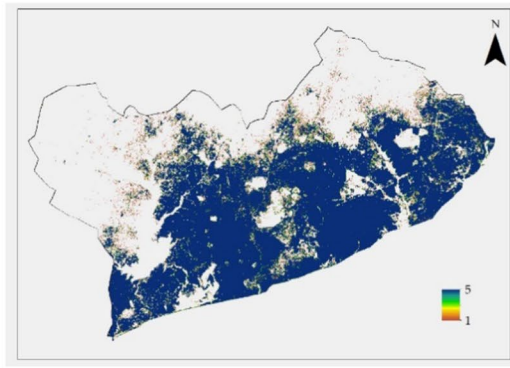
Appendix 4c Distance to Vegetation 2013



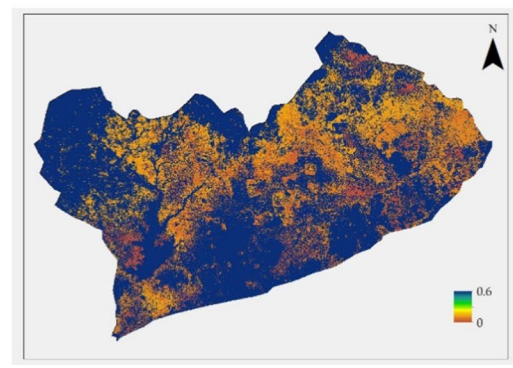
Appendix 4d Distance to Vegetation 2022



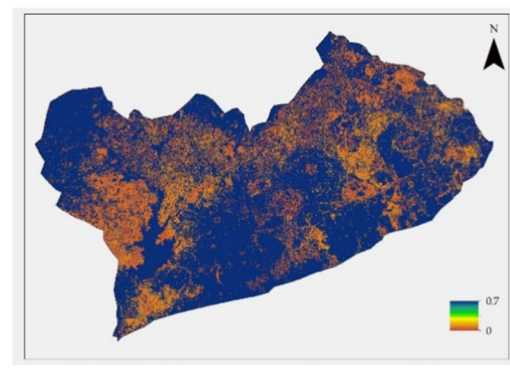
Appendix 4e fractal dimension 2013



Appendix 4f fractal dimension 2022



Appendix 4g Evlielihood 2002-2013



Appendix 4h Evlielihood 2013-2022

Appendix 5

Land change modeler MLP model results

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1. General model information

1) Input files

Independent variable 1	Evlikelihood2002-2013
Independent variable 2	2013_frac
Independent variable 3	Dist_veg_2013
Independent variable 4	Dist_urb_2013
Training site file	ch4_pred_Train_Urbanisation

2) Parameters and performance

Input layer neurons	4
Hidden layer neurons	5
Output layer neurons	5
Requested samples per class	10,000
Final learning rate	0.0000
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10,000
Training RMS	0.2123
Testing RMS	0.2101
Accuracy rate	86.78%
Skill measure	0.8347

3) Model skill breakdown by transition and persistence

Class	Skill measure
Transition: Vegetation to Transition	0.8974
Transition: Vegetation to Built-up	1.0000
Transition: Transition to Built-up	0.7916
Persistence: Vegetation	0.6285
Persistence: Transition	0.8555

2. Weights information of neurons across layers

1) Weights between input layer neurons and hidden layer neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4	h-Neuron 5
i-Neuron 1	-15.0064	11.9790	11.0173	-15.1586	0.5081
i-Neuron 2	-7.3010	-1.0642	1.0303	4.4292	0.1636
i-Neuron 3	-1.6095	0.5460	-1.6145	5.2878	-0.5174
i-Neuron 4	13.4831	-0.6015	-3.3518	-3.4671	3.0182

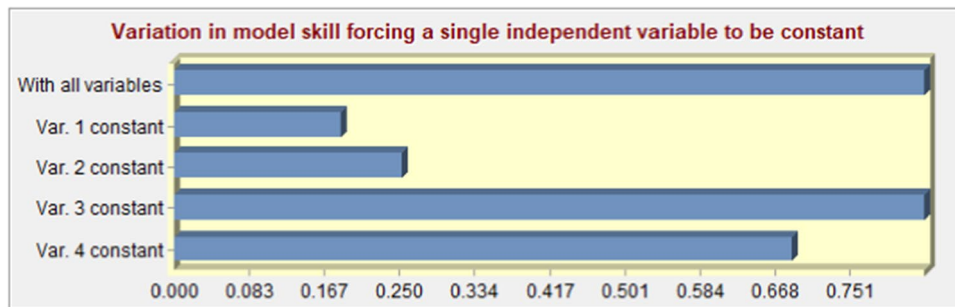
2) Weights between hidden layer neurons and output layer neurons

Neuron	o-Neuron 1	o-Neuron 2	o-Neuron 3	o-Neuron 4	o-Neuron 5
h-Neuron 1	9.7176	8.6705	-11.3918	5.5396	-11.8220
h-Neuron 2	0.3593	-12.9177	2.5852	-3.6545	2.9132
h-Neuron 3	-6.8030	-13.3452	-1.6210	3.0526	4.9523
h-Neuron 4	-12.5072	6.7141	7.2890	-10.7864	-0.2356
h-Neuron 5	-3.9226	-2.4568	-3.5285	-1.7953	-3.0675

3. Sensitivity of model to forcing independent variables to be constant

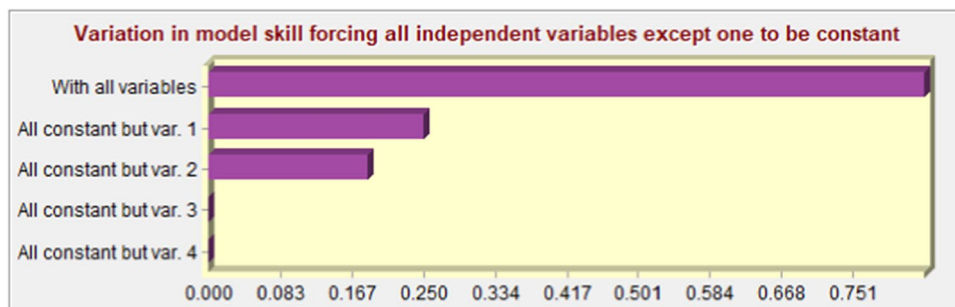
1) Forcing a single independent variable to be constant

Model	Accuracy (%)	Skill measure	Influence order
With all variables	86.78	0.8347	N/A
Var. 1 constant	34.91	0.1863	1 (most influential)
Var. 2 constant	40.33	0.2542	2
Var. 3 constant	86.78	0.8347	4 (least influential)
Var. 4 constant	75.00	0.6876	3



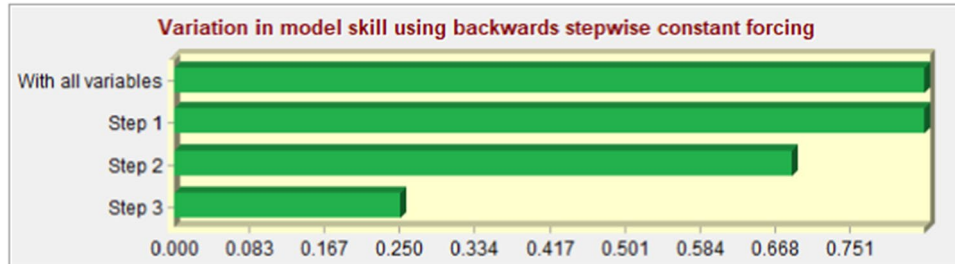
2) Forcing all independent variables except one to be constant

Model	Accuracy (%)	Skill measure
With all variables	86.78	0.8347
All constant but var. 1	40.10	0.2512
All constant but var. 2	34.91	0.1863
All constant but var. 3	20.04	0.0005
All constant but var. 4	12.07	-0.0991



3) Backwards stepwise constant forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	86.78	0.8347
Step 1: var.[3]. Constant	[1, 2, 4]	86.78	0.8347
Step 2: var.[3, 4]. constant	[1, 2]	75.00	0.6876
Step 3: var.[2–4]. constant	[1]	40.10	0.2512



Land change modeler MLP model results

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General model information

1) Input files

Independent variable 1	Evlikelihood2002-2013
Independent variable 2	2013_frac
Independent variable 3	Dist_veg_2013
Independent variable 4	Dist_urb_2013
Training site file	ch4_pred_Train_Afforestation

2) Parameters and performance

Input layer neurons	4
Hidden layer neurons	4
Output layer neurons	4
Requested samples per class	10,000
Final learning rate	0.0001
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10,000
Training RMS	0.2290
Testing RMS	0.2285
Accuracy rate	86.15%
Skill measure	0.8154

3) Model skill breakdown by transition and persistence

Class	Skill measure
Transition: Transition to Vegetation	0.7494
Transition: Built-up to Transition	0.8083

Class	Skill measure
Persistence: Transition	0.7856
Persistence: Built-up	0.9181

2. Weights information of neurons across layers

1) Weights between input layer neurons and hidden layer neurons

Neuron	h-Neuron 1	h-Neuron 2	h-Neuron 3	h-Neuron 4
i-Neuron 1	- 11.0221	- 0.7713	7.4612	1.9104
i-Neuron 2	- 0.9747	- 0.6502	- 3.4820	0.3592
i-Neuron 3	2.8321	- 7.5729	- 15.2060	16.2359
i-Neuron 4	1.2936	8.0707	15.7859	- 17.7950

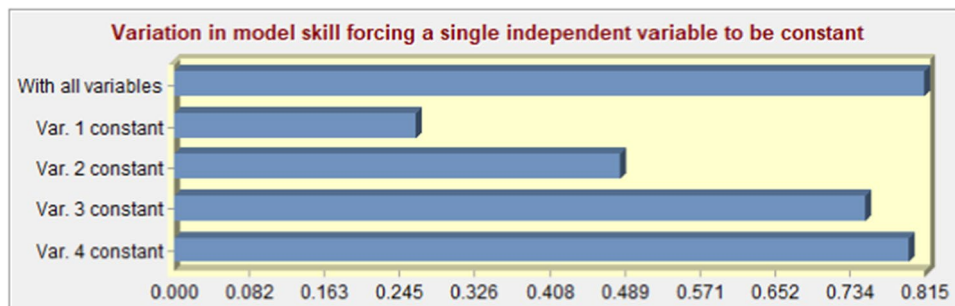
2) Weights between hidden layer neurons and output layer neurons

Neuron	o-Neuron 1	o-Neuron 2	o-Neuron 3	o-Neuron 4
h-Neuron 1	6.7628	8.6903	- 10.0777	- 8.3956
h-Neuron 2	3.2304	- 3.8920	0.5528	- 7.6366
h-Neuron 3	- 0.5786	- 15.8761	7.8819	- 5.2153
h-Neuron 4	- 15.8032	0.1971	- 6.4455	6.5447

3. Sensitivity of model to forcing independent variables to be constant

1) Forcing a single independent variable to be constant

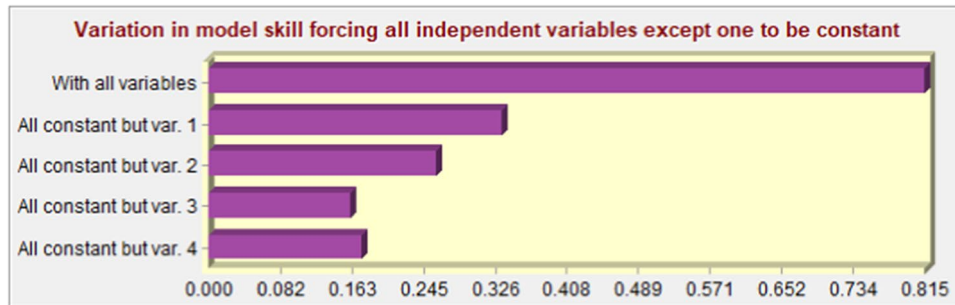
Model	Accuracy (%)	Skill measure	Influence order
With all variables	86.15	0.8154	N/A
Var. 1 constant	44.74	0.2632	1 (most influential)
Var. 2 constant	61.37	0.4849	2
Var. 3 constant	81.37	0.7516	3
Var. 4 constant	84.94	0.7992	4 (least influential)



2) Forcing all independent variables except one to be constant

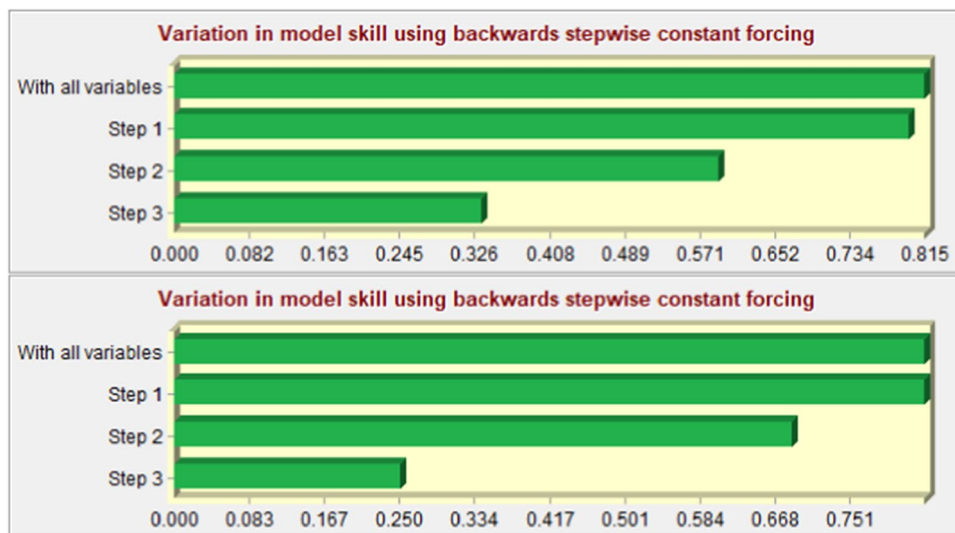
Model	Accuracy (%)	Skill measure
With all variables	86.15	0.8154
All constant but var. 1	50.03	0.3337
All constant but var. 2	44.39	0.2586
All constant but var. 3	37.12	0.1617

Model	Accuracy (%)	Skill measure
All constant but var. 4	38.12	0.1749



3) Backwards stepwise constant forcing

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	86.15	0.8154
Step 1: var.[4]. constant	[1,2,3]	84.94	0.7992
Step 2: var.[4,3]. constant	[1,2]	69.40	0.5920
Step 3: var.[4,3,2]. constant	[1]	50.03	0.3337



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