Arabian Journal of Geosciences (2024) 17:99
https://doi.org/10.1007/s12517-024-11908-5

ORIGINAL PAPER

# Exploring the impact of socioeconomic factors on land use and cover changes in Dar es Salaam, Tanzania: a remote sensing and GIS approach

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Received: 30 June 2023 / Accepted: 8 February 2024 / Published online: 21 February 2024


## Abstract
Comprehending the interactions between humans and their environment necessitates modeling human–environment interactions. This study employs time-series satellite imagery from Landsat Thematic Mapper (1995 and 2009) and Landsat 8 Operational Land Imager (2022) to examine land use/land cover (LULC) change in Dar es Salaam, Tanzania, after image pre-processing with the Google Earth engine code editor, while random forest machine learning in R classified LULC. Geographically weighted regression (GWR) correlates LULC changes to socioeconomic factors spatially. Analysis reveals a dynamic LULC transformation between 1995 and 2022, with a 14.9% increase in built-up areas and a 14.6% decline in bushland. Out of the total LULC, 65.8% experienced gains and losses, while 34.2% remained stable. The GWR model, surpassing the ordinary least squares (OLS) model, achieves an $R^2$ value of 0.73, indicating a strong relationship between LULC changes and socioeconomic factors, explaining 73% of the variation. The influences of these factors exhibit variations across different LULC change types. Population density and proximity to the city center significantly contribute to LULC changes, while the impacts of gross domestic product and distance to roads are comparatively less significant. Poverty does not drive LULC changes significantly. The findings indicate that urbanization and urban sprawl, influenced by population density and distance from the city center, significantly impact land use and cover changes. Effective urban planning strategies should be prioritized to address this, considering factors such as population density and distance from the city center to mitigate the considerable effects on land use and cover changes in the study area.

**Keywords** Land cover change · Spatial data analysis · Geographically weighted regression · Ordinary least squares · GWR

## Introduction

Rapid urbanization poses a global threat as metropolitan areas witness escalating population concentrations, leading to consequential land use and land cover (LULC) changes (Rana and Sarkar 2021). Projections suggest that the world's urban population will increase from 55 to 68% by 2050, adding 2.5 billion people to urban areas, with 90% of this growth concentrated in less developed nations, and as of 2022, the world's urban population has already risen to 57% of the total population (United Nations 2019a; Demographia 2022). Projections indicate that sub-Saharan African countries are expected to represent over 50% of the global population by 2050 (United Nations 2019b), making inevitable land use and land cover changes particularly pronounced in developing nations.Typically, people migrate from rural areas to cities for employment and economic opportunities, increasing the demand for land for settlement and development (Firozjaei et al. 2019; Grigoraș and Urițescu 2019). Consequently, increased land demand exacerbates LULC change, ultimately increasing the likelihood of natural ecosystem deterioration (Dimobe et al. 2015).

The migration of people from rural to urban areas intensifies the demand for land, propelling rapid urban expansion and exacerbating LULC changes, posing a substantial threat to natural environments (Rana and Sarkar 2021). This phenomenon is evident in megacities like Dar es Salaam,

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Tanzania, where urban land cover has expanded by 6% per year over the last three decades (Mkalawa 2016). The complex relationship of socioeconomic variables influencing these LULC changes, including population growth, land-use demands, infrastructure development, and agricultural expansion, remains insufficiently understood (Betru et al. 2019; Rasool et al. 2021).

While existing research has provided valuable insights into the general dynamics of LULC changes in Dar es Salaam, it predominantly relies on nonspatial methods, overlooking the nuanced spatial relationships between socioeconomic variables and these changes (Mkalawa and Haixiao 2014; Kibassa and Shemdoe 2016; Mkalawa 2016; Manyama et al. 2019; Igulu and Mshiu 2020; Masao 2020; Mnyali and Materu 2021). While previous studies exploring spatial aspects have primarily focused on the distribution of driving factors, creating a gap in understanding the varying influence of these factors on different types of LULC changes.

This study employs advanced geospatial techniques, specifically geographically weighted regression (GWR), to comprehensively investigate the impact of socioeconomic factors on various categories of LULC changes in Dar es Salaam. This research aims to unveil localized patterns and relationships often obscured in traditional global analyses by conducting a spatially explicit analysis. Additionally, the study seeks to quantitatively assess the contributions of various socioeconomic variables to LULC changes.

The primary research objectives are to (i) investigate the temporal patterns of LULC changes in Dar es Salaam from 1995 to 2022, (ii) assess how socioeconomic variables affect LULC in Dar es Salaam using Ordinary Least Squares (OLS) and GWR models, (iii) identify the major driving factors for LULC changes in the region, and (iv) examine how GWR coefficients vary across different LULC change types. The comprehensive analysis of the impact of socioeconomic factors on various LULC changes provides valuable insights for spatial planning and management, addressing the challenges posed by rapid urbanization and environmental degradation, with a specific focus on Dar es Salaam, Tanzania.

## Materials and methodology

### Description of the study area

Dar es Salaam Metropolitan City (DMC) is the largest commercial city in Tanzania, located on the country's southern coast and bordering the Indian Ocean. The city is divided into five administrative districts: Temeke, Kinondoni, Kigamboni, Ubungo, and Ilala, with a total area of 1654 $km^2$ and a population of 5,383,728 people as of the 2022 census. Its urban population grows by ~5.67% annually (Peter and Yang 2019). DMC is Tanzania's primary port of entry and a transportation hub. Additionally, DMC is subdivided into the central business district (CBD), existing city, and future city, which are its three main development initiatives. A city's commercial and business district is known as the CBD. The existing city acts as the framework for the development of the new city, and the future city is a location for the future urban growth of the metropolitan area (United Republic of Tanzania 2018). Figure 1 shows the location map of the study area.

DMC exhibits a modified equatorial climate with two rainy seasons, averaging 1000 mm of annual rainfall and maintains a consistently hot and humid environment throughout the year due to its proximity to the equator and the warm Indian Ocean (Kibassa and Shemdoe 2016). The relative humidity remains high throughout the year and typically varies from 55 to ~100% (Baruti et al. 2020), with morning and afternoon levels peaking at ~96% and 67%, respectively (Kibassa and Shemdoe 2016). Consequently, DMC is one of the warmest regions in Tanzania, with an average yearly temperature of 25.9 °C. Monthly temperatures typically exceed 25 °C for most of the year, except between June and September (Kabanda and Kabanda 2019). Figure 2 shows the rainfall and temperature trends of the study area.

### Land use/land cover change data

Three images were obtained for assessment in this study for the years 1995 (source: Landsat 5), 2009 (source: Landsat 5), and 2022 (source: Landsat 8). All images were acquired from the US Geological Survey geoportal (https://earthexplorer.usgs.gov). The attributes of the satellite images used are shown in Table 1.

### Image pre-processing and classification

Image pre-processing was done using the Google Earth Engine open-source code function (Ermida et al. 2020), including clouds masking and gap filling, stacking individual bands, and clipping to the study area. The final pre-processed images were exported as GeoTIFF. Supervised classification, employing random forest machine learning in R software, was utilized to map distinct land cover classes. On-screen digitization and integration of higher-resolution images from diverse sources facilitated the establishment of training sites for each land cover class within QGISS 3.18 software. Subsequently, post-classification procedures were implemented, and the land use and land cover (LULC) were categorized into seven primary categories, aligning with the framework established by the National Forest Monitoring and Assessment of Tanzania (NAFORMA 2015). These primary land cover classes include agriculture, bare soil, built-up area, bushland, forest, grassland, and water (Table 2).

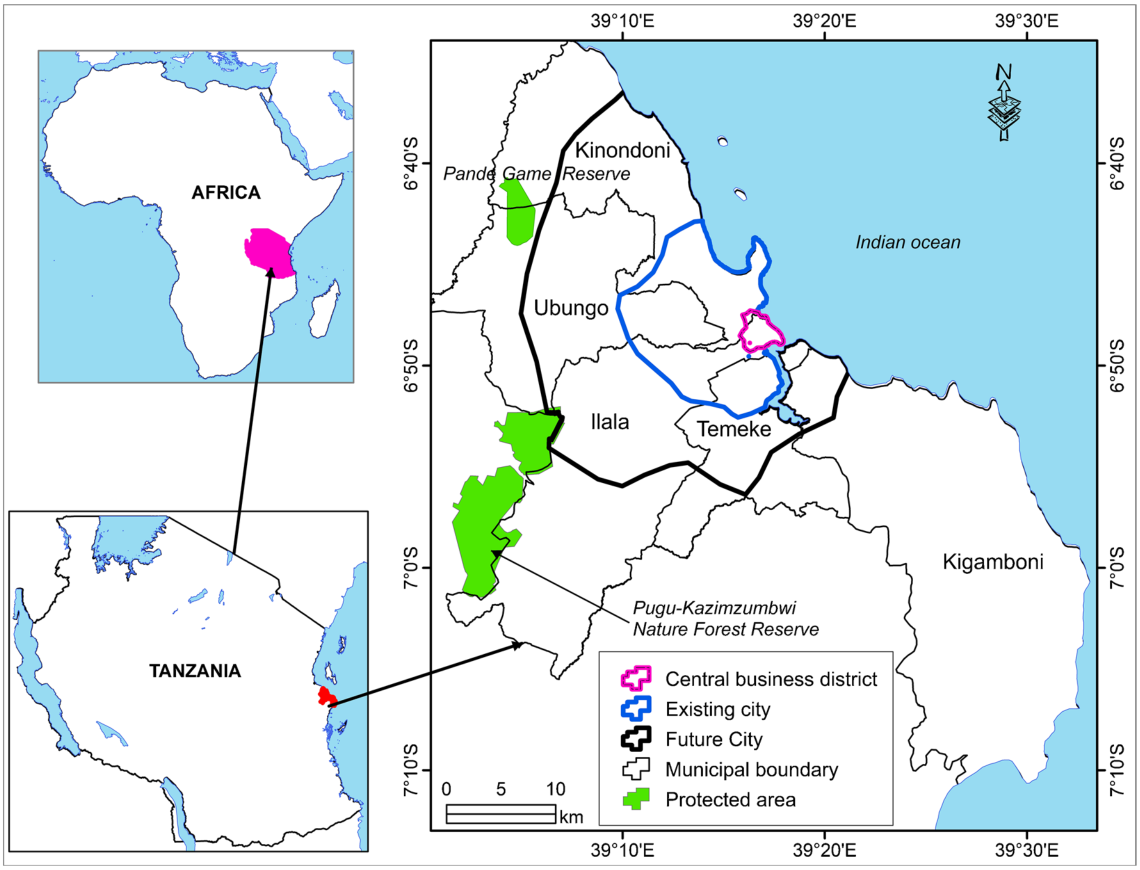
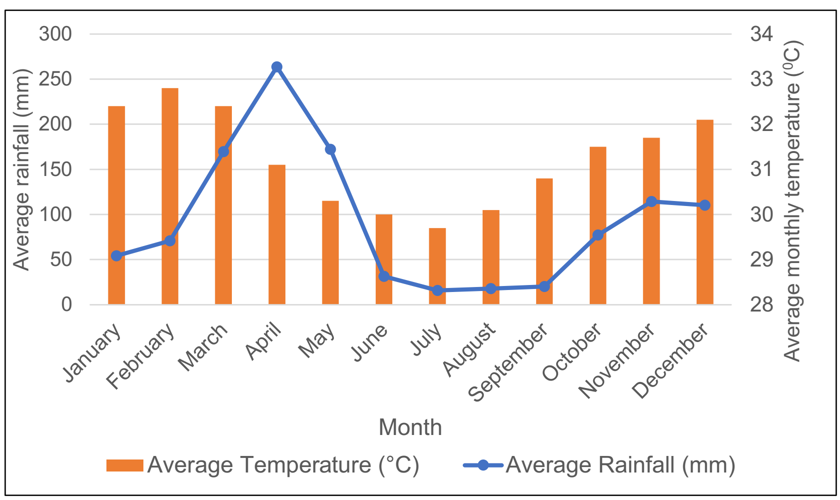



Fig. 1 Location of the study area

Fig. 2 Rainfall and temperature trends for Dar es Salaam, 1991–2020. Data source: https://en.wikipedia.org/wiki/Dar_es_Salaam




## Accuracy assessment

During the fieldwork, 265 training points were collected: 90 for agriculture, 14 for bare soil, 59 for built-up land, 35 for bushland, 41 for forest, 18 for grassland, and 8 for water bodies. The accuracy was evaluated by comparing the collected samples and the classified results. The accuracies were 81.40%, 88.42%, and 81.51%, and the Kappa coefficients were 0.7686, 0.8585, and 0.7688 in 1995, 2009, and 2022, respectively. As per Kayombo et al. (2020), agreements are classified as strong (> 0.80 or 80%), moderate (0.40–0.80 or 40–80%), and poor (< 0.40

**Table 1** Satellite image attributes of used satellite images

| Year | Data type | Sensor type | Path/row | Acquisition date | Spatial resolution (meter) | Season |
|---|---|---|---|---|---|---|
| 1995 | Landsat 5 | Thematic Mapper (TM) | 166/65 | 25 June | 30 | Dry |
| 2009 | Landsat 5 | Thematic Mapper (TM) | 166/65 | 01 July | 30 | Dry |
| 2022 | Landsat 8 | Operational Land Imager (OLI) | 166/65 | 03 June | 30 | Dry |

Source: USGS 2022

**Table 2** Land use/land cover classes and their descriptions (Source: NAFORMA 2015)

| ID | LULC class | Definition |
|---|---|---|
| 1 | Forest | Humid montane, lowland, mangrove, plantation |
| 2 | Bushland | Bushland, thicket, with scattered cultivation |
| 3 | Grassland | Grassland |
| 4 | Agriculture | Wooded crops, grain, and other crops, scatteres settlements |
| 5 | Built-up area | Settlements and urban areas |
| 6 | Bare Soil | Bare soil, rock outcrop, coastal sands |
| 7 | Water | Inland water and ocean |

or 40%). This categorization indicates good accuracy for both periods.

## Social-economic data collection

Five socioeconomic variables were selected to identify the impact of each independent variable on LULC in DMC: poverty, GDP, population density, distance from the city center, and roads. These variables reflect population dynamics, urbanization, economic and industrial development, social investment, technical advancement, and external traffic conditions, which could influence LULC.

The driving factors were determined based on specific criteria. DMC, Tanzania's largest city and economic hub, is crucial in various sectors, including trade, finance, manufacturing, services, and tourism. It accommodates important businesses, government institutions, and international organizations, while its port is a vital gateway for imports and exports, contributing significantly to the country's economy. Although GDP indirectly influences land cover change, it contributes to urban development and land use patterns. Economic growth, as measured by GDP, often leads to increased urbanization and infrastructure development, resulting in changes to land cover.

Furthermore, the distance to the city center and roads was selected as the primary driver of LULC changes in DMC. This choice was influenced by the fact that 62% of the city's population relies on public transportation for travel in and out of the city (Tengecha and Mwendapole 2021). Despite efforts to improve transportation in the city, it remains a significant challenge for the residents of DMC. Factors such as residents' behavior, proximity to transportation options, land use, and population density in their communities contribute to these challenges (Mkalawa and Haixiao 2014). The city's high population density, poverty, and uncontrolled urban growth further complicate the government's provision of adequate transportation services and infrastructure, leading to limited mobility. Living closer to the city center offers greater access to public transportation, reducing transportation time and costs.

These data were obtained from different sources, including population data from the Tanzania National Bureau of Statistics (https://www.nbs.go.tz/), GDP data from the World Bank Geocoded Research databases (AidData 2017), poverty data from world population health and development indicators (Noor et al. 2008), and roads from the Tanzania National Roads Agency (*TANROADS*). Based on these data, the socioeconomic-caused changes in land use can be analyzed.

## Relationship between land use/land cover and socioeconomic indicators

The relationship between LULC and socioeconomic indicators was determined using a GWR model.

## Ordinary least square and geographically weighted regression models

### Ordinary least square (OLS)

OLS is predicated on the assumption that the sample regression model is the one that most closely matches the data. In spatial modeling using OLS regression, the coefficients or statistical model parameters are assumed constant over the entire research area. As a result, the model projected the same value for dependent variables throughout the region. This limitation is significant because the spatial variation in the data may not be accurately captured, leading to biased or incorrect results (Simon et al. 2022). The OLS coefficient matrix was calculated according to Eq. 1:

$$y = X\beta + \varepsilon \tag{1}$$

where $y$ is the estimated dependent variable, $x$ is the estimator, and $\varepsilon$ is the model error or deviation when estimating $\beta$ or model coefficients (Kashki et al. 2021).

### Geographically weighted regression (GWR)

The relationship between a dependent variable and its explanatory variables at each sample point is calculated using the non-stationary local regression method known as geographically weighted regression (GWR) (Kashki et al. 2021). This model varies from previous regression models in that one or more geographic characteristics are included to explain geographical variation (Ahmadi et al. 2018). Equation (2) is a representation of the GWR model.

$$y_i = \beta_0\left(u_i, v_i\right) + \sum_{i=1}^{n} \beta_n\left(u_i, v_i\right)x_{in} + \theta_i \tag{2}$$

where $y_i$ is the observed variable; $\beta_0\left(u_i, v_i\right)$ is the regression constant of the sample point at $\left(u_i, v_i\right)$; $\beta_n\left(u_i, v_i\right)$ is the regression parameter, which depends on the variable's location $n$ at the sample point geographically; $n$ is the number of factors; $x_{in}$ is the value of the independent variable $x_n$ at the sample point; and $\theta_i$ is the random error. The geographic distance between an observation point and a specific point defines an observation's weight, with observations closer to the provided location having a higher weight than those farther away (Simon et al. 2022).

## Spatial sampling data

For regression analysis, it is essential to establish the data points' locations ($x$ and $y$ coordinates) and identify the dependent and independent variables involved. Initially, only the LULC change and poverty variables were in raster layers, and the other variables were in vector format. To transform raster to vector and tabular data, ArcGIS was used. The regular grid sampling method was used to generate sample points. The study area was divided into 1 × 1 km regular grids in ArcGIS, considering the original data size and reducing spatial autocorrelation at the megacity level (Zhao et al. 2018; Birhanu et al. 2021). These steps were followed to derive the values for each dependent and independent variable:

i. The Bayesian interpolation method converted GDP and population density data to the raster format.
ii. Distance variables were calculated as the Euclidean distances from roads and the city center.
iii. Values for poverty, distance from roads, city center, and population density rasters were generated by taking the average mean values inside each grid using the zonal statistics function in ArcGIS 10.8 software.
iv. The value of land cover change was calculated as the ratio of the summarized area of LULC changes inside a grid to the area of the grid.

Lastly, the rasters were entirely transformed into the vector and tabular data through spatial analysis, as required by the R-based GWR, where the GWR model retained ~ 1680 data points.

## OLS and GWR statistical analyses

The spatial relationships between LULC change, the dependent variable, and the socioeconomic factors of population density, poverty, GDP, and distance from roads and the city center were used here as the predictor variables for the OLS and GWR models. First, a correlation analysis was performed to determine whether the statistical significance of the predictor variables was statistically significant for GWR modeling (Gregorich et al. 2021). To this end, a variance inflation factor (VIF) was established to avoid multicollinearity among the socioeconomic variables (Zhi et al. 2020). Then, the VIF values of the explanatory variable, which were > 7.5, were regarded as highly correlated and removed from the regression models (Li et al. 2010). All analyses were conducted using the R-4.2.1 software build for Windows, the GWR *sugar* package, and ArcGIS 10.8.

Ultimately, the aim is to obtain the coefficients of the GWR model by analyzing the local relationships between LULC changes and the driving factors at the data points. The crucial aspect is to examine the specific relationships between LULC changes and the driving factors within the study area. This analysis will help identify which factors are responsible for LULC changes, either for all types or specific types, and determine how the influence of these factors varies across different locations.

## Coefficient of determination

The coefficient of determination ($R^2$) is used to assess the model's goodness of fit. $R^2$ was calculated by comparing the estimated and observed values. The $R^2$ values ranged from 0 to 1, where larger values indicated a better fit, representing the variance in the dependent variable explained by the independent variable(s) (Li et al. 2010).

### Akaike information criterion

The Akaike information criterion (AIC) is a statistical method employed to evaluate the suitability of a model by balancing its precision and complexity to find a compromise. A smaller AIC value indicates that the model's predicted value is nearer to the actual value or reality (Li et al. 2010; Kashki et al. 2021).

### Spatial autocorrelation by the global Moran's *I* index

The global Moran's *I* index was employed to ensure independence among explanatory variables (i.e., no spatial autocorrelation). The index can be categorized as positive, negative, or lacking spatial autocorrelation. In cases of positive spatial autocorrelation, comparable values tend to cluster in space, whereas similar values tend to disperse in issues of negative spatial autocorrelation. A value of 0 implies perfect randomness.

## Results

### Spatial distribution and dynamic changes in LULC

Figure 3 shows the spatial distribution of different land uses across DMC from 1995 to 2022. Agriculture was predominantly concentrated along the river plains, including the Msimbazi, Mzinga, Kizinga, and Mbezi Rivers, paralleling the major trunk roads connecting DMC to neighboring regions. Additionally, agriculture was observed in areas adjacent to the existing city. At the same time, bushland was distributed in almost all peri-urban areas of the city, mainly in the study area's southeast, west, and northwest regions. Forests were primarily found in protected areas (such as the Pande Game Reserve northwest of the study area), mangrove forests along the coast, and all military base areas in DMC.

Furthermore, forests were found in high-altitude and hilly areas, such as the area around the University of Dar es Salaam and areas adjacent to the Pugu-Kazimzumbwi nature forest reserves in the western part of the study area. Water bodies were mainly distributed in the eastern coastal areas of the study. Built-up land was distributed sporadically in central coastal areas, especially in the city's CBD, along all major roads.

LULC analysis showed that the extent of land cover classes varied annually. From 1995 to 2022, the study area generally showed an overall decrease in bushland, forest, and bare soil, a considerable increase in built-up and agricultural land, and anal most constant area of water bodies (Table 3). The substantial increase in built-up areas was followed slightly by increased agricultural land, while the percentage areas of bushland, forest, and bare soil decreased. The significant expansion of the built-up area can be attributed to the rapid increase in construction land that occurred mainly after 2015. Grassland also showed a slightly decreasing trend between 1995 and 2009 before a slight rise between 2009 and 2022.

### Land use/land cover transition

From 1995 to 2022, the study area experienced significant LULC changes, as shown in Table 4. The total affected area was 1089 km$^2$, accounting for 64.3% of the total study area. The most significant change in LULC was from bushland to agriculture (274 km$^2$ or 25.7% of the total change). The

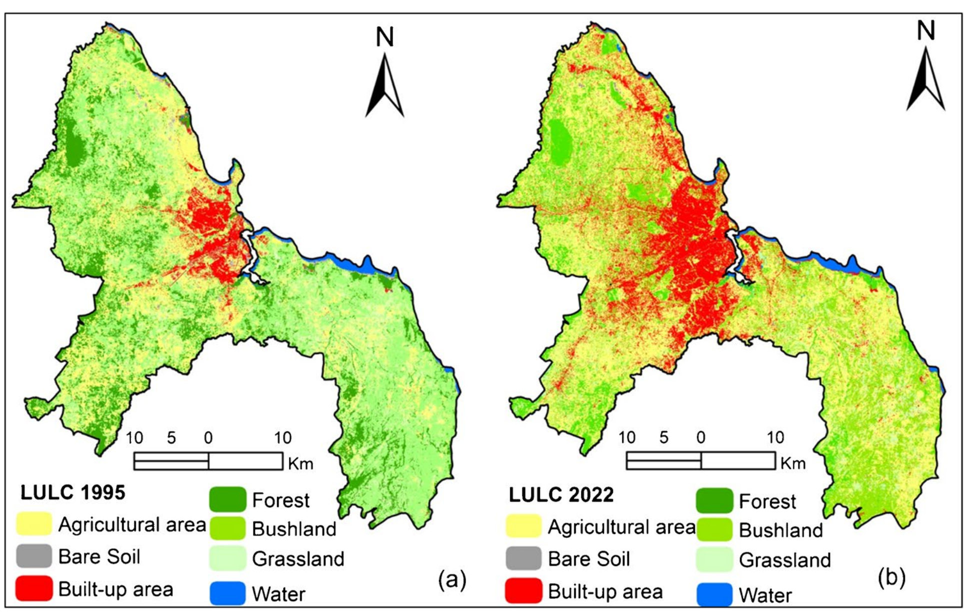



**Fig. 3** Land cover dynamics of the main land use/land cover classes in the Dar es Salaam Metropolitan City for 1995 and 2022

**Table 3** LULC classification results for 1995, 2009, and 2022

| LULC classes | 1995 | | 2022 | | LULC change 1995–2022 | |
|---|---|---|---|---|---|---|
| | $km^2$ | % | $km^2$ | % | $km^2$ | % |
| Agriculture | 396.70 | 24.00 | 471.36 | 28.48 | 74.66 | 4.48 |
| Bare soil | 17.38 | 1.03 | 11.28 | 0.67 | −6.1 | −0.36 |
| Built-up | 72.55 | 4.41 | 318.77 | 19.29 | 246.22 | 14.88 |
| Bushland | 668.97 | 40.45 | 428.26 | 25.88 | −240.71 | −14.57 |
| Forest | 296.09 | 17.90 | 248.14 | 14.99 | −47.95 | −2.91 |
| Grassland | 178.58 | 10.82 | 149.54 | 9.07 | −29.04 | −1.75 |
| Water | 23.58 | 1.45 | 26.48 | 1.57 | 2.9 | 0.12 |
| Total | 1,654 | 100 | 1,654 | 100 | 74.66 | 4.48 |

**Table 4** Transition matrix showing LULC change in Dar es Salaam Metropolitan City between 1995 and 2022

| Area ($km^2$) | | 2022 | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | AL | BSL | BUA | BL | FL | GL | WB |
| 1995 | AL | 179 | 2 | 92 | 63 | 26 | 29 | 0 |
| | BSL | 4 | 2 | 9 | 1 | 0 | 0 | 1 |
| | BUA | 4 | 1 | 61 | 4 | 1 | 1 | 0 |
| | BL | 274 | 1 | 68 | 197 | 51 | 68 | 0 |
| | FL | 101 | 0 | 20 | 69 | 81 | 20 | 1 |
| | GL | 82 | 1 | 18 | 42 | 9 | 24 | 0 |
| | WB | 0 | 0 | 1 | 0 | 0 | 0 | 21 |
| Percentage (%) | | AL | BSL | BUA | BL | FL | GL | WB |
| 1995 | AL | 45.78 | 0.51 | 23.53 | 16.11 | 6.65 | 7.42 | 0.00 |
| | BSL | 23.53 | 11.76 | 52.94 | 5.88 | 0.00 | 0.00 | 5.88 |
| | BUA | 5.56 | 1.39 | 84.72 | 5.56 | 1.39 | 1.39 | 0.00 |
| | BL | 41.58 | 0.15 | 10.32 | 29.89 | 7.74 | 10.32 | 0.00 |
| | FL | 34.59 | 0.00 | 6.85 | 23.63 | 27.74 | 6.85 | 0.34 |
| | GL | 46.59 | 0.57 | 10.23 | 23.86 | 5.11 | 13.64 | 0.00 |
| | WB | 0.00 | 0.00 | 4.55 | 0.00 | 0.00 | 0.00 | 95.45 |

*AL* agriculture, *BSL* bare soil, *BUA* built-up area, *BL* bushland, *FL* forest, *GL* grassland, *WB* water

second most prominent change was from forest to agriculture (101 $km^2$ or 9.4% of the total LULC change), while the shift from agriculture to built-up area accounted for 8.6% (92 $km^2$) of the total change. In comparison, the total LULC change was 7.6% (82 $km^2$) from grassland to agriculture, 69 $km^2$ (6.4%) from forest to bushland, and 68 $km^2$ (6.3%) from forest to bushland. The remaining LULC changes comprised less than 6.0% of the whole area. Generally, bushland, forest, and grassland showed a decreasing trend, while built-up areas and agriculture showed an increasing trend.

## Land use/land cover change data for modeling

LULC changes were extracted from the two sets of polygons (1995 and 2022). The LULC classes were coded as text as AL, BSL, BUA, BL, GL, FR, and WB for agriculture, bare soil, built-up area, bushland, grassland, forest, and water, respectively. The attributes of polygons indicate which type of change arises. For example, AL-BL means the transformation from agriculture to bushland, and FL-BUA means the conversion from forest to built-up area. The changed polygons were dissolved into 42 polygons, with a total area of 1089 $km^2$, which accounts for 64.3% of the total area of the study area. Among the 42 types of LULC changes, nine types were chosen because they accounted for almost 80% of the changes in the study area, including bushland to agriculture (BL-AL, 26.9%), forest to bushland (FL-BL, 9.2%), agriculture to the built-up area (AL-BUA, 8.4%), forest to agriculture (FL-AL, 7.6%), grassland to agriculture (GL-AL, 6.7%), agriculture to bushland (AL-BL, 6.6%), bushland to grassland (BL-GL, 6.5%), bushland to forestland (BL-FL, 6.3%), and bushland to the built-up area (BL-BUA, 4.4%). Among the eight types, almost 84% were natural vegetation loss and forest degradation. Concentrating on these significant LULC changes makes the subsequent analysis more

**Table 5** OLS regression coefficients between LULC change and driving factors

| | Population | Poverty | Distance from the city center | GDP | Distance from road |
|---|---|---|---|---|---|
| *Correlation* | 0.0000016 | −0.134100 | −0.000006 | −0.01145 | −0.000019 |
| *VIF* | 1.543299 | 6.061805 | 4.160220 | 3.667774 | 1.386293 |
| *std error* | 0.00000035 | 0.07008 | 0.000001 | 0.001038 | 0.000007 |
| t value | 4.526 | −1.914 | −5.294 | −11.026 | −2.625 |
| Pr(>\|t\|) | 0.00000643*** | 0.05576 | 0.00000013*** | <2e−16 *** | 0.00874** |
| *Intercept* | 848,300, <2e−16*** | | | | |

*Significance level* (*p-value*): ***$p<0.001$; **$p<0.01$; *$p<0.05$

**Table 6** Model fitting of all types of LULC changes

| Residual sum of squares | The effective number of parameters | AICc | Sigma | $R^2$ | $R^2$ adjusted |
|---|---|---|---|---|---|
| 1.05882E+11 | 0.589259 | 41.9005 | 273,959.7922 | 0.73290 | 0.8107 |

targeted and efficient, enhancing the model's explanatory power and accuracy.

## GWR and OLS analysis of driving factors of land use/land cover changes

### OLS analysis of driving factors

The regression parameters of LULC change established by OLS are indicated in Table 5. Notably, the OLS results were less than ideal, producing an $R^2=0.1425$ and Moran's *I* index = 0.2531.

From this table, the following conclusions can be drawn.

- The VIF values of all explanatory variables were < 7.5, indicating the lack of collinearity among these variables.
- From the perspective of the significance tests, the influences of the variable population, GDP, distance from the road, and distance from the city center on LULC changes are statistically significant at 0.001. However, the effect of the poverty variable is insignificant. Therefore, poverty was excluded from GWR modeling due to a lack of statistical significance.
- The signs of the coefficients indicate that the population variable positively influences LULC changes. In contrast, the poverty, GDP, distance from the road, and distance from city center variables adversely affect LULC changes.

### Geographically weighted regression analysis of driving factors

The spatial variation in LULC change was analyzed using the GWR model and four socioeconomic variables (after excluding poverty due to lack of statistical significance). Table 6 presents a summary of the analysis. The corrected Akaike information criterion (AICc) value was lower (41.9005) than that of the OLS (46220.7779), indicating that the values predicted by the GWR model were closer to those observed using the OLS model. As the cells were distributed regularly and consistently throughout the region, a fixed-kernel method was employed, producing a coefficient of determination $R^2$ value between LULC change and the socioeconomic parameters of 0.73.

**Table 7** Global Moran's index spatial autocorrelation summary between OLS and GWR

| | *OLS* | *GWR* |
|---|---|---|
| *Moran's index* | 0.2532 | 0.0284 |
| *Expected index* | −0.000593 | −0.000593 |
| *Variance* | 0.002550 | 0.002551 |
| *z-score* | 5.044315 | 0.573741 |
| *p-value* | 0.000000 | 0.566143 |

### GWR and OLS, as well as spatial autocorrelation analysis using the global Moran's *I* index

The spatial autocorrelation analysis of the global Moran's *I* index using the OLS and GWR models is presented in Table 7. Here, the OLS model exhibited higher Moran's *I* values (0.2532) than the GWR model (0.0284), implying potential spatial dependence in OLS errors. The lower Moran's *I* in GWR suggests its better ability to capture and address spatial patterns, making it potentially superior for handling spatial dependencies in the data compared to OLS.

The z-score values were 5.044315 (OLS) and 0.573741 (GWR). The higher z-score for OLS indicates a substantial departure from spatial randomness, implying pronounced spatial autocorrelation in its residuals. The lower z-score for GWR suggests that this model is more effective at handling spatial dependencies in the data. Furthermore, the variance values of 0.002551 at a 5% significance level indicate significant spatial heterogeneity in the relationships between the socioeconomic variables and LULC change. The study concluded that changes in LULC over the DMC are unlikely due to chance; therefore, it rejected the null hypothesis.

## The influences of driving factors on specific types of land use/land cover changes

This section examines the interactions between LULC types and driving factors. The dependent variable is the ratio of the specific LULC change area to the sampling unit area. In contrast, the independent variables include population density, GDP, distance from roads, and distance to the city center (excluding poverty due to lack of statistical significance). GWR models are employed to analyze the data. The study considers eight significant types of LULC changes, which account for approximately 80% of the total changes in the study area. The model fitting results and coefficients, organized by their corresponding areas, are presented in Tables 8 and 9. The analysis reveals that the interactions between the eight LULC change types and the factors vary across different classes. Six types exhibit moderate fitting degrees, with adjusted $R^2$ ranging from 0.3 to 0.5 (BL-AL, FL-BL, AL-BUA, FL-AL, BL-GL, and BL-FL), while GL-AL and AL-BL have fitting degrees below 0.3 adjusted $R^2$. Theoretically, the six types with moderate fit degrees can be reasonably explained by the driving factors, whereas the two types with lower fitting degrees cannot be adequately explained.

i) GDP and LULC changes

- GDP coefficients exhibit varying significance across LULC change types.
- Statistically significant influence on six types (BL-AL, FL-BL, GL-AL, AL-BL, BL-GL, and BL-FL).
- Positive coefficients suggest GDP's facilitation of transitions from forestland to bushland (FL-BL) and agricultural land to built-up areas (AL-BUA).
- Negative coefficients indicate that GDP may inhibit agriculture expansion and certain land conversions.

ii) Population density and LULC changes

- Population density coefficients are statistically significant for all LULC change types.

**Table 8** Model fitting of specific types of land use/land cover changes

| LULC change type | Residual sum of squares | Sigma | AICc | $R^2$ | Adjusted $R^2$ |
|---|---|---|---|---|---|
| BL-AL | 1,227,577.108 | 99,253.5340 | 5530.6907 | 0.6845 | 0.4708 |
| FL-BL | 1,356,829.724 | 104,348.0529 | 5551.7135 | 0.6099 | 0.3458 |
| AL-BUA | 379,779.0859 | 55,206.07857 | 5284.3168 | 0.6967 | 0.4913 |
| FL-AL | 566,586.6168 | 67,430.22906 | 5368.3253 | 0.6297 | 0.3789 |
| GL-AL | 302,417.2681 | 49,263.517 | 5236.4832 | 0.4780 | 0.1245 |
| AL-BL | 183,164.137 | 38,339.1128 | 5131.1837 | 0.4737 | 0.1173 |
| BL-GL | 203,631.2455 | 40,424.40573 | 5153.4282 | 0.5922 | 0.3161 |
| BL-FL | 379,821.4457 | 55,209.15844 | 5284.340212 | 0.689136 | 0.478613 |

**Table 9** The coefficients for specific types of LULC changes

| LULC change type | Intercept | Population density | GDP | Distance from road | Distance from the city center |
|---|---|---|---|---|---|
| BL-AL | 179,574.6945* | 0.4491* | −3885.9516* | −16.8484* | −0.3690 |
| FL-BL | 10,188.2460 | −0.9807* | 1114.5461* | 24.1931* | 2.8245* |
| AL-BUA | 7908.2348 | 1.2939* | 153.3691 | −5.6467* | −0.8758* |
| FL-AL | 40,169.4535* | −0.8142* | −92.8626 | −13.4897* | 2.4285* |
| GL-AL | 59,793.5750* | 0.3056* | −1718.5436* | −0.3558 | −1.0675* |
| AL-BL | 11,744.3431* | 0.4874* | −454.4984* | 0.2105 | 0.4396* |
| BL-GL | 36,882.0057* | −0.1918* | −839.3617* | 1.9754 | 0.6724* |
| BL-FL | −36,373.60976* | 1.1672* | −442.4071* | −9.1369* | 1.6000* |

*An asterisk beside a number indicates a statistically significant $p$-value ($p < 0.01$)

- Positive influence on several conversions, including agriculture expansion and certain land cover transitions.

iii) Road proximity and LULC changes

- Coefficients for relationships between roads and LULC changes vary in significance.
- Some positive correlations exist between distance to roads and specific LULC changes (e.g., FL-BL, AL-BL, BL-GL).
- However, these findings lack statistical significance.

iv) Distance from the city center and LULC changes

- Positive and negative correlations exist between the distance from the city center and various LULC changes.
- Proximity to the city center influences land conversions, with closer areas experiencing different changes than farther away.

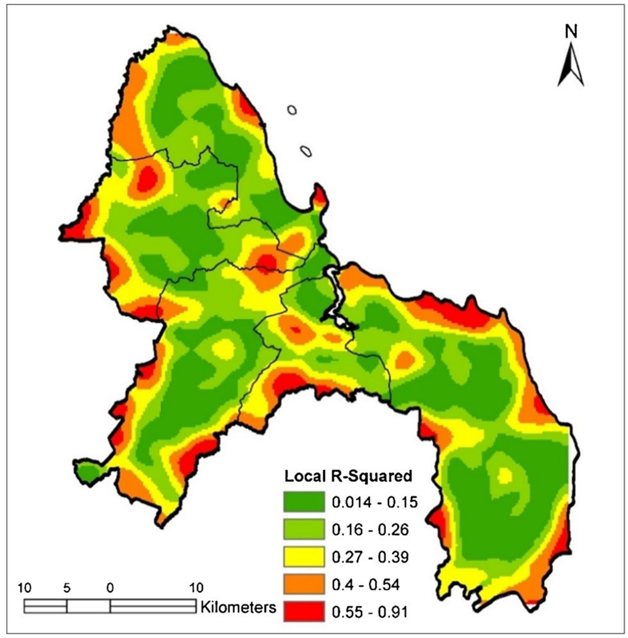



**Fig. 4** The spatial distribution of the GWR local $R^2$

## Spatial distribution of the GWR estimation

The OLS model explains only 14% of the variance in LULC change values in DMC. This percentage is significantly lower than the 73% obtained through the GWR coefficient of determination $R^2$, for example, in Fig. 4, the mapped GWR local $R^2$ values reveal some interesting findings. The local $R^2$ values range from 0.14 to 0.91, showing spatial variation. Local $R^2$ values indicate that only specific local models provided a better fit than the OLS model. Notably, there is an apparent pattern in the spatial distribution of $R^2$ values in Fig. 4. The central areas, including the Mabibo, Makuburi, and Tabata wards, along with the eastern Somangila ward, northern (Kunduchi and Mbezi wards), southern (Mianzini and Toangoma wards), and western (Kibamba, Kwembe, and Pugu wards), exhibit higher $R^2$ values. Higher $R^2$ values suggest that the regression model effectively captures the relationships between socioeconomic factors and LULC changes in these areas.

## Spatial distribution of local regression intercepts

The visualization analysis presented in Fig. 5 offers valuable insights into the patterns and interactions between land use and land cover (LULC) changes and socioeconomic factors within the study area. The local intercept in the geographically weighted regression (GWR) model represents the expected value of the dependent variable when all independent variables are zero for a specific geographic location. Notably, as observed in the spatial distribution of local intercepts in Fig. 5, an apparent trend emerges: LULC changes gradually increase with the growing distance from the central business district (CBD). Within this GWR model, negative signs are evident in the CBD and existing city areas. In contrast, they are more pronounced in the peri-urban areas of the city. This observed pattern implies a spatial variation in the relationship between socioeconomic factors and land use and cover changes. Negative signs in the urban core areas suggest a potential decrease in predicted land use and cover changes when other factors are held constant, potentially influenced by established land use patterns, stringent land use planning regulations, or limited available space for substantial changes. Conversely, higher positive signs in the peri-urban areas indicate increased predicted land use and cover changes in these outskirts when other factors are constant. This increase could be attributed to factors such as urban expansion, population growth, or economic activities that drive land use changes in the peri-urban. zones.

## Coefficients of socioeconomic factors and LULC changes

The spatial distribution of geographically weighted regression (GWR) local coefficients, depicted in Fig. 5, highlights four influential factors (population density, gross domestic product, distance from roads and distance from city center). Examining the signs of the coefficients for each socio-economic variable yields the following observations:

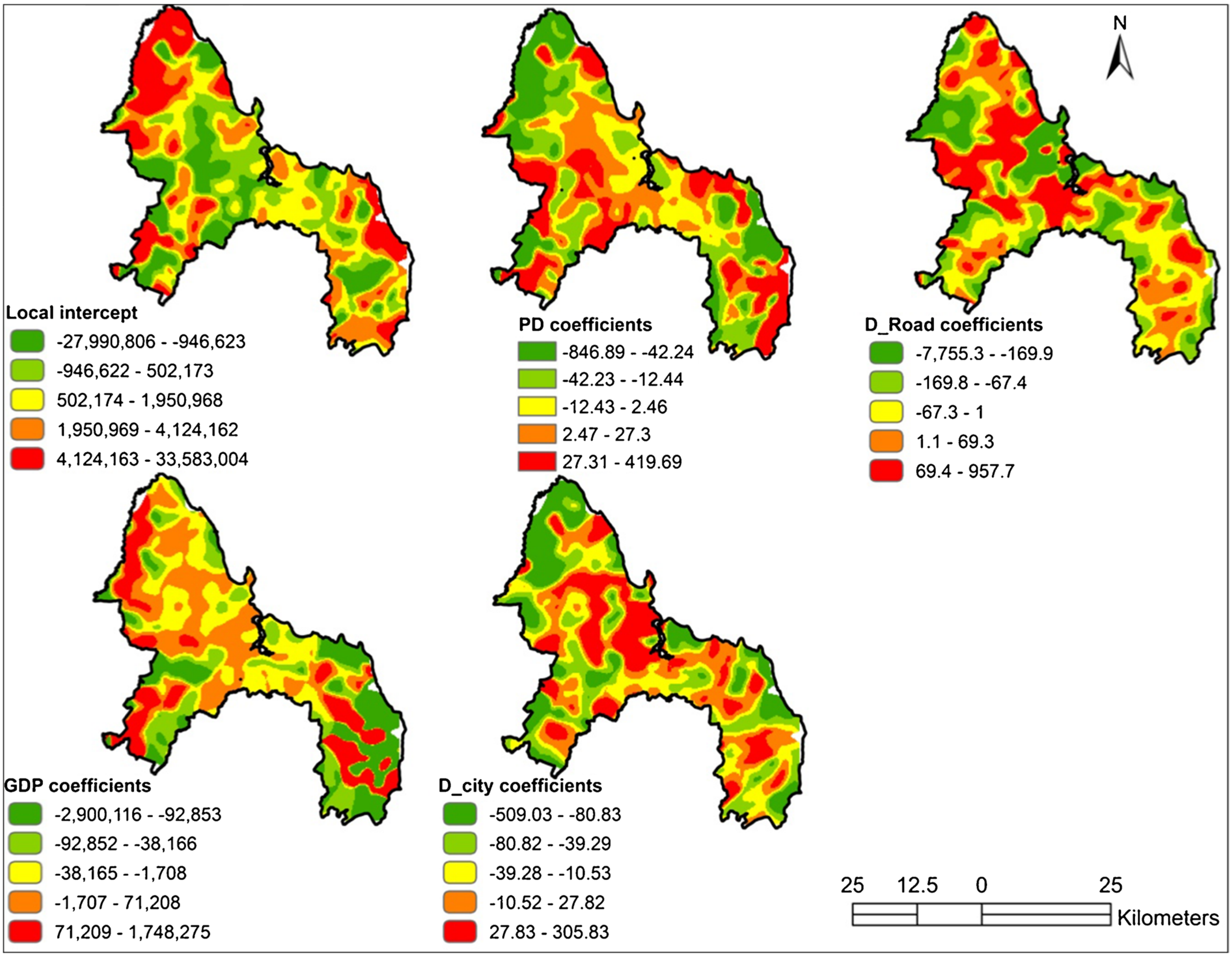



**Fig. 5** The spatial distribution of GWR local coefficients has four influencing factors. Note: PD, population density; GDP, gross domestic product; D_Road, distance from roads; D_city, distance from city center

- **Population density (PD) coefficients:** Spatial variability is evident. Certain municipalities like Ilala, Temeke, and parts of Kinondoni exhibit higher positive coefficient estimates, indicating the significance of population in driving LULC changes in these areas.
- **Distance from roads (D_Road) coefficients:** Higher estimates are observed along major roads. Higher estimates observed along major roads suggest that urban areas expand and commercial or residential activities develop near these corridors due to improved accessibility and connectivity.
- **GDP coefficients:** Distinct patterns are noted, with higher estimates in peri-urban areas such as Kinondoni, Kigamboni, and southwestern parts of Dar es Salaam City Council. This reflects the impact of these regions' economic activities, urbanization, industrialization, and infrastructure expansion.
- **Coefficients between LULC and distance from the city center:** Positive effects are observed in the CBD, adjacent areas, and along major roads, indicating a strong relationship between proximity to the city center and LULC change. The CBD is a focal point for economic, commercial, and residential activities, while roads influence land use patterns along their routes.

## Discussion

### Spatial distribution and dynamic changes in land cover

The spatial distribution of land cover change in Dar es Salaam reveals an unexpected surge in agriculture, as highlighted in Table 3. This departure from the anticipated trend of more significant growth in populated urban areas adds a compelling dimension to our analysis. Despite the more noticeable increase in built-up areas (14.88%) compared to agriculture (4.48%), the dynamics of agricultural expansion are interesting. Urban agriculture practices, including urban gardening, vacant plots, verges, balconies, and container cultivation, contribute to this unexpected trend. Moreover, the large-scale conversion of land from bushland and forest to agriculture (Table 4) and the inclusion of scattered settlements—sometimes challenging to distinguish due to image resolution—adds to the spatial complexity of the agriculture category.

Significantly, it is vital to highlight that the upswing in agriculture is not solely a consequence of changes in built-up areas. Instead, it signifies a clear indication of population growth and an escalating demand for land resources to support the expanding population, particularly in transforming bushland and forest areas into agriculture zones. The study's findings also depict a significant decrease in forest and bushland areas alongside a noteworthy increase in built-up and agricultural areas. The findings align with previous research highlighting substantial urban growth in the Dar es Salaam Metropolitan Area, resulting in environmental quality degradation, slum expansion, and a decline in green infrastructure(Kibassa and Shemdoe 2016; Mzava et al. 2019). Contributing factors include illegal deforestation, domestic land use, subsistence farming, and challenges in spatial development planning control (Malekela and Nyomora 2019; Mligo 2020; Msuya et al. 2021). This trend is consistent with observations in other global cities, such as Pabna Municipality (Rana and Sarkar 2021), Bangladesh; Tabriz, Iran (Rahimi 2016); Daqahlia Governorate, Egypt (Hegazy and Kaloop 2015); Delhi Metropolitan City, India (Shahfahad et al. 2022); Bucharest, Romania (Grigoraș and Urițescu 2019); and Kandy City, Sri Lanka (Dissanayake et al. 2019). They emphasize shared challenges in urbanization, environmental conservation, and sustainable land use planning, underscoring the need for thoughtful strategies on a global scale.

## Driving factors of land use/land cover changes

These results highlight the relationship between socioeconomic variables and the dynamics of urban land, highlighting the varying degrees of effect in various study areas. Understanding these spatial variations is essential for well-informed urban planning and programs for sustainable development customized to each locality's unique features. The study's observed land use and land cover (LULC) changes demonstrate a complex network of linked influencing forces. The following summarizes the key variables driving these changes:

i. **Population density dominance:** Population density is the most influential factor impacting LULC changes. The substantial population increase in the DMC between 2002 and 2022 (Msuya et al. 2021; United Republic of Tanzania, Ministry of Finance and Planning, Tanzania National Bureau of Statistics and President's Office—Finance and Planning, Office of the Chief Government Statistician 2022) drives the demand for land, particularly for housing and infrastructure (Mkalawa and Haixiao 2014). This surge underscores the pivotal role of population density in reshaping the region's landscape.

ii. **Distance to the city center:** Proximity to the city center is the second most influential factor in LULC changes. Areas located farther from the city center exhibit reduced accessibility and attractiveness for development, directly influencing land cover changes within the region.

iii. **Distance from roads:** The distance from roads represents the third most prominent influence on LULC alterations. A negative correlation between road proximity and land cover change indicates that areas closer to roads undergo a higher transformation rate. Living near roads provides improved access to public transportation despite transportation challenges for many of DMC's inhabitants (Tengecha and Mwendapole 2021).

iv. **Limited influence of GDP:** Compared to population density, city center proximity, and road accessibility, gross domestic product (GDP) exhibits a relatively subdued impact on LULC changes. Surprisingly, an increase in GDP correlates negatively with LULC changes, suggesting a shift toward more efficient land-use practices as the city experiences economic growth. Furthermore, according to Malekela and Nyomora (2019), agricultural activities in the city are primarily for subsistence farming.

The current study's findings align with a study conducted in Ethiopia by Hishe et al. (2020), emphasizing population increase as a key driver of LULC changes and underscoring the role of demographic factors in urban development. However, these findings contradict the conclusions of previous research by Li and Li (2019) and Li et al. (2020). Li and Li (2019) proposed that population density, GDP per capita, and industrial structure were the primary factors contributing to urban sprawl in China. In contrast, Li et al. (2020) found that LULC changes in Gansu, China, were primarily influenced by natural forces, with negligible effects from socioeconomic highlighting the context-specific nature of land use dynamics and the multifaceted factors influencing these changes.

### The influences of socioeconomic driving factors on land use/land cover changes

The analysis uncovers diverse influences of various factors on different types of LULC changes. GDP and population density significantly impact specific conversions, while the relationship between road proximity and land changes lacks statistical significance in certain cases. The distance from the city center reveals a notable trend in land transformations, reflecting the global pattern of urban densification closer to city centers, with peri-urban areas dominated by agricultural land.

Understanding these correlations is crucial for informed land management and urban planning decision-making. Recognizing the multifaceted influences on diverse LULC changes assists in developing sustainable strategies that balance urban development with ecological preservation, particularly in regions like DMC, where interactions between human activities and natural processes drive varied land transitions.

### Spatial distribution of the GWR estimation

Analyzing the spatial distribution of the GWR estimation reveals a substantial improvement in explaining LULC change variance compared to the OLS model. While the OLS model only accounts for 14% of the variance, the GWR model achieves a much higher explanatory power with a coefficient of determination ($R^2$) of 73%.

Mapped GWR local $R^2$ values exhibit spatial variability, indicating variations in the model's effectiveness across different DMC areas. Specific regions, including central and various wards in the north, south, east, and west, display higher $R^2$ values, suggesting that the regression model effectively captures the relationships between socioeconomic factors and LULC changes in these areas.

In contrast, factors like climate or biophysical elements in other areas may significantly influence LULC changes more than the socioeconomic factors considered in the regression model. This spatial variation underscores the significance of localized modeling approaches, like GWR, in comprehending region-specific LULC dynamics for more precise and context-sensitive analyses and predictions.

### Spatial distribution of local regression coefficients

The coefficients of the four significant socioeconomic factors exhibit considerable spatial variability within the studied region. The spatial distribution of population density (PD) coefficients reveals specific municipalities, including Dar es Salaam City Council, Temeke, and Kinondoni, displaying higher positive coefficient estimates. This observation underscores the pivotal role of population in driving land use and land cover (LULC) changes in these areas, highlighting the complex interplay between demographic factors and urban development.

In addition, the coefficients associated with distance from roads (D_Road) unveil higher estimates concentrated along major road networks, implying that socioeconomic activities tend to concentrate and prosper in areas adjacent to these transportation corridors. This phenomenon suggests that urban areas expand, and commercial or residential activities develop along these roads, capitalizing on improved accessibility and connectivity to the transportation infrastructure offers.

The gross domestic product (GDP) coefficients exhibit a distinct pattern, with higher estimates predominantly found in peri-urban areas such as Kinondoni, Kigamboni, and the southwestern parts of Dar es Salaam City Council. This pattern reflects the profound impact of economic activities and development on LULC change dynamics, indicating the presence of rapid urbanization, industrialization, and infrastructure expansion in these regions.

Furthermore, the coefficients that pertain to the relationship between LULC and distance from the city center demonstrate positive effects in specific areas, including the central business district (CBD), adjacent regions, and along major roads. The higher coefficient values in these areas signify a robust relationship between proximity to the city center and LULC changes. This observation suggests that the CBD is a focal point for economic, commercial, and residential activities. At the same time, the presence of roads significantly influences land use patterns and developmental trends along their routes.

Understanding these coefficient values offers valuable insights for policymakers and urban planners, providing them with essential information to make informed decisions concerning land use, sustainable development, and conservation efforts across different regions within the study area. These insights underscore the necessity of region-specific strategies and policies to address each area's unique dynamics and requirements, ensuring sustainable and balanced urban development while preserving ecological integrity.

Generally, the implications of these findings are profound for urban planning and policy development in DMC. Policymakers and urban planners must recognize the diverse impacts of population growth, distance from the city center, and road accessibility when devising strategies for sustainable urbanization and environmental conservation. The study's insights offer a foundation for evidence-based decision-making, guiding the formulation of policies tailored to the unique challenges and opportunities of different areas within the city. Moreover, these findings also emphasize the importance of balancing urban development with environmental preservation, urging authorities to implement strategies that safeguard green spaces and natural habitats amid urban expansion.

## Conclusion

This study comprehensively examines the relationships between LULC changes and driving factors, focusing on spatial variability. The findings contribute to both methodological and practical aspects of the research. Methodologically, the study highlights the influence of spatial variability on the relationships between LULC changes and driving factors. The coefficients, significance, and fitting degrees vary significantly across different spatial locations, indicating the substantial impact of underlying drivers on LULC changes.

From a practical standpoint, the study comprehensively investigates the relationships between LULC changes and socioeconomic driving factors. By considering factors such as GDP, poverty, population density, and distance from roads and the city center, the study uncovers diverse results for LULC changes. Population density and distance from the city center emerge as the most influential factors, although with varying significance across locations. At the same time, poverty does not significantly influence LULC changes in the study area. In addition, distance to roads and the city center is identified as a significant driver along major roads due to easy accessibility. Finally, GDP affects many peri-urban areas, potentially due to industrial, manufacturing, or agricultural investment opportunities.

The use of GWR in this study reveals the local variations in the relationships between driving factors and LULC changes. This model accounts for spatial proximity and employs local data to capture the spatial heterogeneity of the associations, elucidating the importance of considering spatial variation in understanding LULC change and its socioeconomic drivers. Furthermore, the GWR analysis emphasizes the significance of local factors such as proximity to roads and population density in shaping LULC change, suggesting the need for more effective approaches to land use planning and management strategies; the spatial variability of LULC changes and underlying socioeconomic drivers are critical for promoting sustainable city management and environmental conservation. These strategies should balance economic development with environmental protection and address the negative impacts of urbanization on natural resources and ecosystems.

This study underscores the role of socioeconomic factors as a primary driver of urban land expansion. It emphasizes the potential environmental strain caused by rapid urbanization and the depletion of natural lands. However, future research should employ space–time methods and more comprehensive time series data spanning 30 years to analyze further and model these influences, incorporating climatic and biophysical drivers of LULC change into future research and considering the long-term implications for sustainable development.

**Acknowledgements** The authors thank the National Aeronautics and Space Administration (NASA), the US Geological Survey (USGS), the National Bureau of Statistics of Tanzania, the World Population Health and Development Indicator, and the World Bank for their respective contributions to Landsat imagery, population data, poverty data, and GDP data, respectively.

**Funding** This study was partially funded by the RCMRD/GMES and Africa Scholarship Grant.

**Data availability** The datasets generated by the current study are available from the corresponding author upon reasonable request.

## Declarations

**Conflict of interest** The authors declare no competing interests.

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