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Spatial relationship between urban expansion and distribution of healthcare facilities in Morogoro municipality, Tanzania

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Abstract
Background: The majority of the world's uninsured population, 1.3 billion individuals, reside in developing countries. Location disparity is a characteristic of the distribution of healthcare facilities in metropolitan regions of developing countries like Tanzania. Spatial variation in urban expansion and population growth are critical factors influencing *the* establishment and distribution of healthcare facilities in urban areas.
Methods: Statistical regression techniques can be used to describe the relationship between the variables. To achieve the study's goal, a variety of techniques were used to evaluate the spatial relationship between urban growth and the distribution of healthcare services. Remote sensing data provides massive amounts of spatial data on urban expansion. Population projection and population density indexes were used to determine population growth. Using Morogoro Municipality as a case study, Geographically Weighted Regression was applied to facilitate efficient spatial assessment of the relationship between urban expansion and distribution of healthcare facilities.
Results: The result shows that from 1990 to 2020 built-up increased from 3.9% to 18.9% of the total urban area of Morogoro Municipality while non-build class decreased from 96.1% to 81.9% of the total urban area of Morogoro Municipality. The overall coefficient determination R^2 was 0.599, 0.34 and 0.07 for the study period 2010-2020, 2000-2010 and 1990-2000 respectively showing that the explanatory power of variables urban expansion and population density was increasing with time.
Conclusion: The spatial relationship link of urban expansion and distribution of healthcare facilities in Morogoro Municipality within 30 years' study period implies that there has been a progressive relationship between urban expansion and distribution of healthcare facilities during 1990-2000 there was a weak relationship same for 2000-2010 while 2010 -2020 exhibited a moderate relationship

Keywords: Urban expansion, Healthcare facilities, Distribution, Relationship, Geographically Weighted Regression

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Introduction

Urban expansion and its consequences on infrastructure provision in cities of developing countries have drawn the attention of many scholars due to various reasons. Informal urban expansion is characterized by lack of service infrastructure such as health care, poor physical accessibility to water supply (Acheampong *et al.,* 2017). The underlying fear is how a government can mobilize resources to meet the rapidly growing demand. Urbanization is the process by which settlements grow in population, size, and economic activity over time (Jacobs, 1969). The emergence and growth of cities and big regions have historically been attributed to the concentration of population and economic activities or agglomeration theory (Henderson, 2002).

One of the most significant results of population agglomeration in urban centers is urban growth (Sumari *et al*., 2019). Rapid and often unplanned urbanization leads to conditions that affect human health in a negative way (Rezaee, et al., 2021). Poverty, environmental problems and increasing population demands that outstrip available service capacity are some of these conditions (Moore et al., 2003). Urban expansion in developing countries leads to increased pressure on existing healthcare facilities if additional facilities are not provided for the growing population. However the investment in healthcare infrastructure has been historically low (Reddy *et al.,* 2011).The distribution of most healthcare facilities in urban areas of developing countries is characterized by location disparity and concentrated in one location than the other. Various studies have already been done on urban expansion and distribution of healthcare facilities for decision making in different sectors (Ntuli *et al*., 2020; Acheampong *et al*., 2017).

However little has been done on assessment of urban expansion and population in relation to growth of health facilities to overcome location disparity and geographic inequities within urban areas to strengthen health service delivery. Spatial variation in urban expansion and population growth are critical factors influencing establishment and distribution of healthcare facilities in urban area, (Sumari *et al.,*2020). The importance of healthcare infrastructure allocation is often undermined and overlooked leading to slow progress of the healthcare sector in most developing countries (Travis *et al.,* 2004). Statistical regression and correlation approaches have traditionally been used to describe the relationship between variables (Yang *et al.,* 2006; Zhang *et al.,* 2006).

So it very importance to assess the spatial relationship among these variables urban expansion and distribution of healthcare facilities so as to know variations in distribution of health service. Thus, health resources are allocated to meet the demands of urbanisation and population increase. Recently, there have been significant advancements in geospatial technology-based techniques that allow urban planners and managers to study and monitor urban conditions and growth (Sumari *et al*., 2020). Several techniques for analyzing urban expansion include spatial index (SI), annual expansion rate (AER), urban expansion twitter model (UET), landscape expansion index (LEI)), urban expansion intensity index (UEII) and urban expansion differentiation index (UEDI) (Terfa *et al*., 2020). These are among the recent techniques for urban expansion determination (Jiao *et al*., 2015, 2018; Liu *et al*., 2010; Viana *et al*., 2019).

Several techniques have been used to analyse the relationship among different aspects concerning spatial visualization, including geographically weighted regression (GWR) and ordinary least square (OLS) regression (Brunsdon *et al*., 2012; O'Sullivan, 2003). GWR has the capability of spatially displaying the parameter estimates and coefficient of determination regarding all variables in a raster surface and vector map respectively for easy and quick visual interpretation of relationships and detected spatial patterns (Fotheringham, 2009). For example, used the Geographically Weighted Regression (GWR) which is a spatial statistical technique that shows variations in relationships between predictors and outcome variable over space (Lu *et al*., 2014).

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The authors used the model to establish relationships between urban expansion and population .This model has revealed the growth relationship among three variables e.i urban expansion, population density and healthcare facilities. Despite the importance of knowing the relationship among urban expansion, population density and healthcare facilities, little has been done on assessment of urban s expansion and population in relation to growth of health facilities to overcome location disparity and geographic inequities within urban area to strength better health service delivery in Tanzania regions including Morogoro region. The purpose of this study was to therefore to assess the spatial relationship between urban expansion and distribution of healthcare facilities within a 30 year study period in Morogoro Municipaliy.

Materials and methods

Description of study area

The study area was Morogoro Municipality which is one of the nine districts in Morogoro Region including Kilosa, Ifakara, Kilombero, Malinyi, Mvomero, Gairo, Ulanga, Morogoro municipality and Morogoro Rural. Morogoro region occupies 221492 populations that are approximately 13.7% of the total populations of Morogoro region. The municipality is the capital of Morogoro region and it covers 540 km^2 which has 28 Wards (URT, 2012).

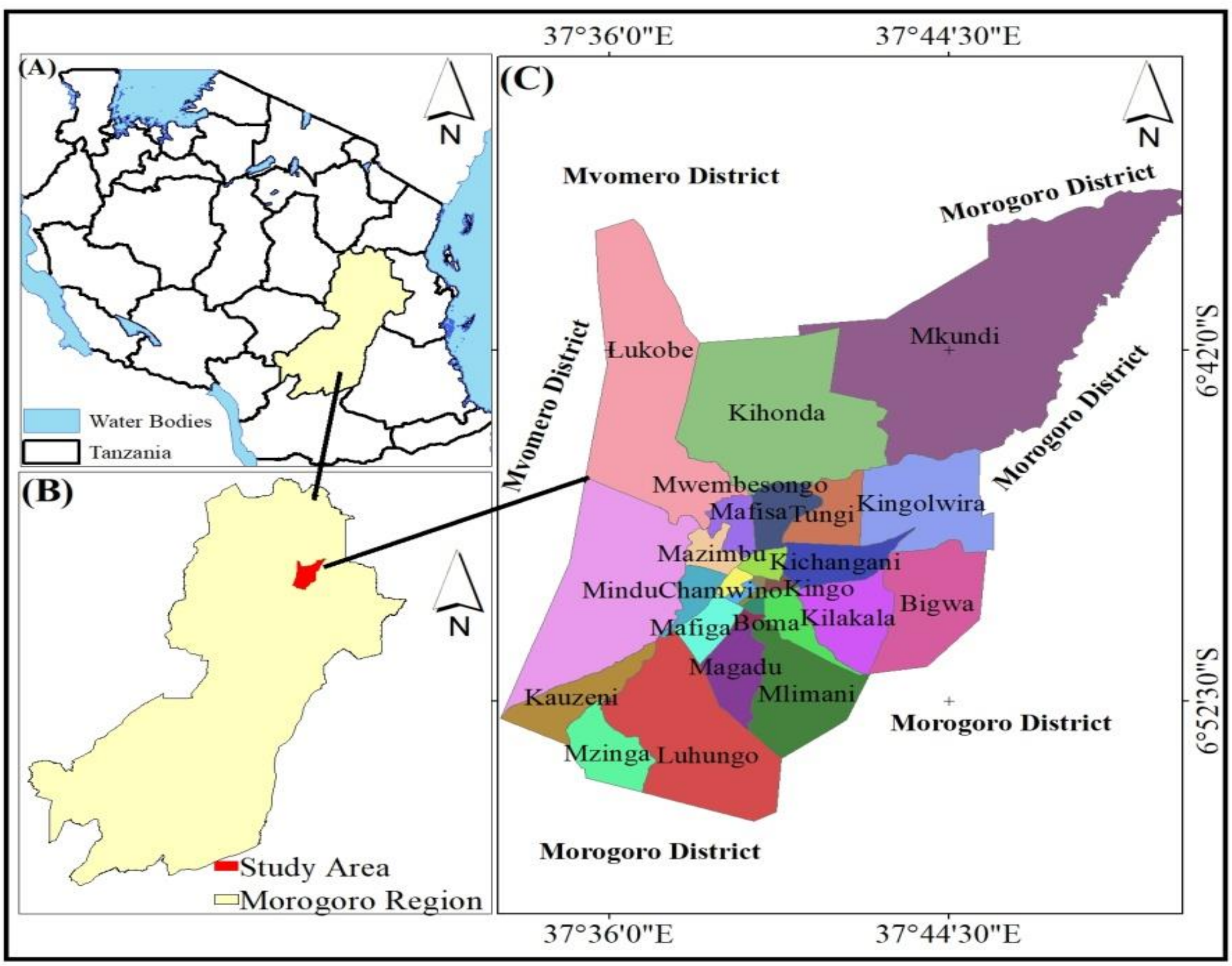

Figure 2.1: Location Map of Morogoro Municipality

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Data collection and analysis procedures.
The data collected and analysis of this study will base within 30 years period from 1990 to 2020.

Image acquisition and processing.
The images of the study area and respective dataset were acquired from the United States Geological Survey Earth-Explorer (USGS EE) website. Data sets included Landsat collection 1 level 1, Landsat 4-5 TM C1 Level 1, Landsat 7 EMT+C1 Level 1 and Landsat 8 OLI/TIRS C1 Level 1. Downloaded images had several bands which were composed by using Arc GIS Software, whereby Landsat 4-5 TM C1 Level1, Landsat 7 EMT + C1 Level band 1 to band 7, and Landsat 8 OLI/TIRS C1 Level 1 bands 1 to band 7 and band 10 were combined together by using Composite Bands tool in ArcGIS Program. The composed images were then clipped based on the study area and processed together to create a single raster dataset so that they can be managed, viewed, and queried as show in Figure 2.2.

The Landsat images were acquired for 1990 (TM data), 2000 (ETM+ data), 2010 (ETM+ data), and 2020 (OLI data). All Landsat images were obtained from http://earthexplorer.usgs.gov/ website of United States Geological Survey (USGS)) from the path/row number 167/065. ENVI version 5.3 was used for image classification, with ERDAS Imagine version 2014 for accuracy assessments and ArcGIS version 10.3 for image data processing, visualization, and map generation. All images were registered to UTM coordinate system with WGS 84 datum zone 37 South for consistency, after that the images were clipped based on the boundary of the study area.

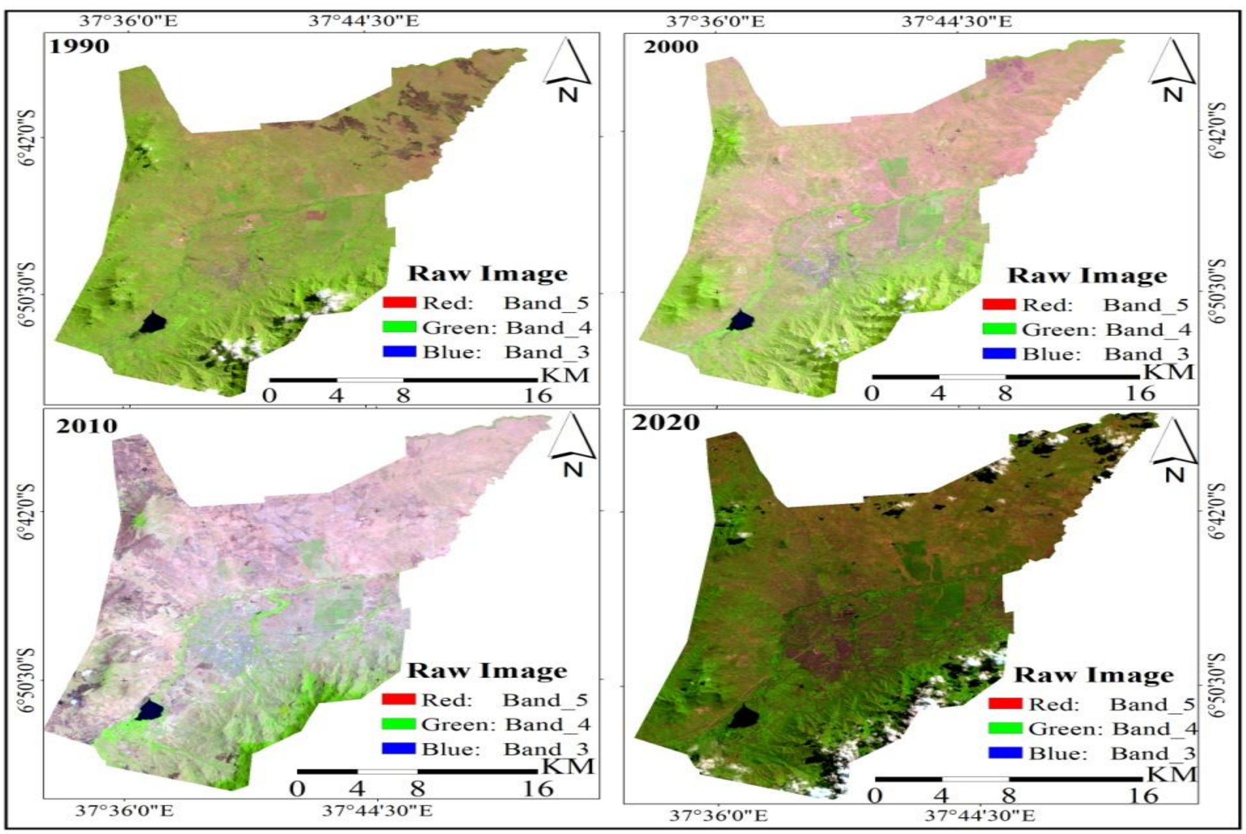

Figure 2.2: Clipped raw images from 1990 to 2020 of the study area

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Image classification

The technique of categorizing all pixels in an image or raw remotely sensed satellite data to get a particular set of labels or land cover themes is known as image classification (Gómez-Chova et al., 2017; Weng and Lu, 2009). According to Lu et al. (2004), the major steps of image classification may include Choice of a suitable classification method. In this study supervised classification method was selected for classifying images of different periods from 1990-2000, 2000-2010 and 2010-2020 (10 years in each category) in to two categories, i.e., built-up area and un-built up area classes. Ten years for each category is considered appropriate as it is virtually impossible to determine urban expansion.

Geographically weighted regression

Geographically Weighted Regression (GWR) is a spatial statistical technique that shows variations in relationships between predictors and outcome variable over space (Lu et al., 2014; Mennis, 2006). This technique was developed by Cleveland (1979). Other techniques for the analysis of spatial relationships also have recently emerged (Oshan et al., 2019). The GWR model can be expressed as;

$$y_i = \beta_{IO} + \sum_{k=1}^{m} (\beta_{ik} x_{ik} + \varepsilon_i) \qquad \text{……………………………………………………….. (1)}$$

Where: y_i is the dependent variable at location i; χ_{ik}, is the k^{th} independent variable at location i; m is the number of independent variables; β_{io}, is the intercept parameter at location i; β_{ik}, is the local regression coefficient for the independent variable at location i; and ε_i is the random error at location.

The weight field allows some features to be more important in the model calibration process than others. Primarily useful when the number of samples taken at different locations varies, values for the dependent and independent variables are averaged, and places with more samples are more reliable (should be weighted higher). The number of samples is used as weight field so that locations with more samples have a larger influence on model calibration than locations with fewer samples (Khayyun *et al*., 2019).

In this study, urban expansion and population density were used as independent variables, and were determined within 30 years from 1990 to 2020 in three categories of 10 yearly intervals. Healthcare facilities were thus used as a dependent variable and weighted 1-3, with hospital being weighted as 3, health centre as 2 and dispensary as 1. So each urban expansion category was analysed with 3 weighted fields (hospital, health centers and dispensary).The first experiment involved the use of a single variable, urban expansion as the only explanatory variable for the regression analysis whilst for the second experiment the second explanatory variable, population density of individual wards was added. This technique was applied in GIS environment whereby the spatial statistic tool in ArcGIS 10.5 was used to analyze the relationship between urban expansion and distribution of healthcare facilities.

Population data

Population data was very important in calibration of the GRW model where population density was used as an independent variable in the second test experiment. In this study population data was projected for the years 1990-2000, 2000-2010 and 2010-2020 based on the 1988 and 2012 population and growth rate date from National Bureau of statistics and was used to calculate population density in the study area. Sarker (2001) used the discrete model with modification of the growth rate which is not constant. They the population of Bangladesh for the period 1976-2093 and obtained a parabolic profile. In many cases, for a small population one may use the discrete model as:

$$p\,t = p\,0\,(1 + r)t \qquad \text{…………..……........................... (2)}$$

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Where $p\ 0$ = current population; $p\ t$ = population after time t; r = growth rate.
Population density is a measurement of the number of people in an area. Population density is calculated by dividing the number of people by the area. Population density is usually shown as the number of people per square kilometre (Shawky, 2016). The formula for population densityis expressed as:

$$Dp = \frac{N}{A} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Whereby Dp = population density N= total population A= total land area covered by population

Ethical considerations
Ethical clearance was obtained from Morogoro region commission (Ref. No: AB.175/245/01/98) and Morogoro district commission (Ref.No.AB210/249/01/163) .The permission to conduct the study at all health facilities in Morogoro municipality was obtained from Morogoro Municipal director department of health (Ref. No R.10/MMC-99/167). All of health officers in each health facilities received information about the study while on duty, and they were provided with information on the potential risks and benefits of participating.

Results

Urban expansion
Spatial distribution of the built-up extent and urban growth from 1990 to 2020 are depicted in (Figure 3.1). Built-up growth tended to expand outward towards all directions but mainly in the north-west.

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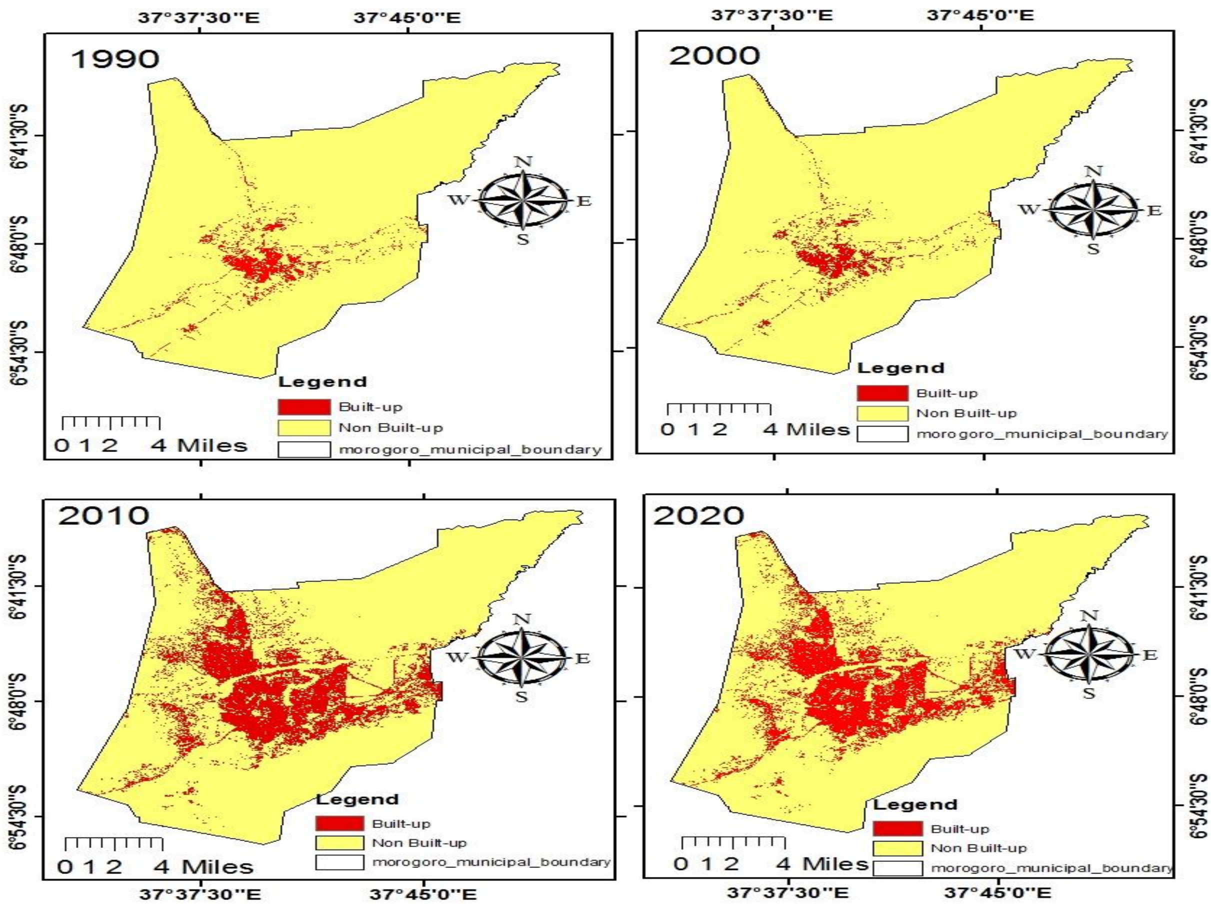

Figure 3.1: Urban expansion in Morogoro Municipality from 1990 to 2020

Table 3.1: Percentages of Urban expansion of Morogoro Municipality from 1990 to 2020

LAND CLASSES	1990 %	2000 %	2010 %	2020 %
Built-up	3.9	4.8	6.6	18.1
Non Built-up	96.1	95.2	93.4	81.9

Result of Geographically Weighted Regression (GWR)

Table 3.2 shows the results the first experiment show that the sum of residual squares for 2000-2010 study period was 8.68, meaning that the model in 2000-2010 time period fits best to explain the impacts of the explanatory variable.

Table 3.2: Estimation results of the first experiment of the GWR model

Parameters	Study Period			
	1990-2020	2010-2020	2000-2010	1990-2000
Intercept	1.462993	0.359536	0.37457	0.884869
UEII	0.05368	4.74364	1.20196	-0.37818
Standard Error	1.082025	1.340375	0.34003	0.767835

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Local R^2	0.000002	0.12174	0.0196	0.001669
R^2	0.190326	0.172987	0.01967	0.00177
Adjusted R^2	0.066255	0.121235	-0.01814	-0.0367
Bandwidth	0.091704	0.188664	2.65453	2.654526
Residuals Squares	99.561045	76.17383	8.68293	23.3871

A new variable (Population density) was added in the second experiment for the analysis of the urban expansion and distribution of the healthcare facilities in Morogoro Municipalilty to check for the relative strength of the variable. In this study, population density of individual wards referred to the total number of residents in a particular ward per unit area of that ward in square meters. Table 3.3 shows the results for the estimation of healthcare facilities in Morogoro Municipality using a combination of two variables, i.e, population density and urban expansion intensity index of the individual wards.

Table 3.3: Estimation results second experiment of the GWR model

Parameters	Study Period			
	1990-2020	**2010-2020**	**2000-2010**	**1990-2000**
Intercept	-0.855557	-1.81851	-0.0988	1.228856
UEII	0.14514	4.4483	1.78074	-0.68966
Population Density	-0.03897	0.17084	0.06856	-0.06464
Standard Error	0.132302	0.107593	0.13071	0.59598
Local R^2	0.06314	0.193746	0.17858	0.064879
R^2	0.552046	0.598565	0.35564	0.065146
Adjusted R^2	0.349671	0.414784	0.17108	-0.09782
Bandwidth	0.091704	0.091704	0.14965	2.654526
Residuals Squares	55.082297	36.97507	5.70721	21.90229

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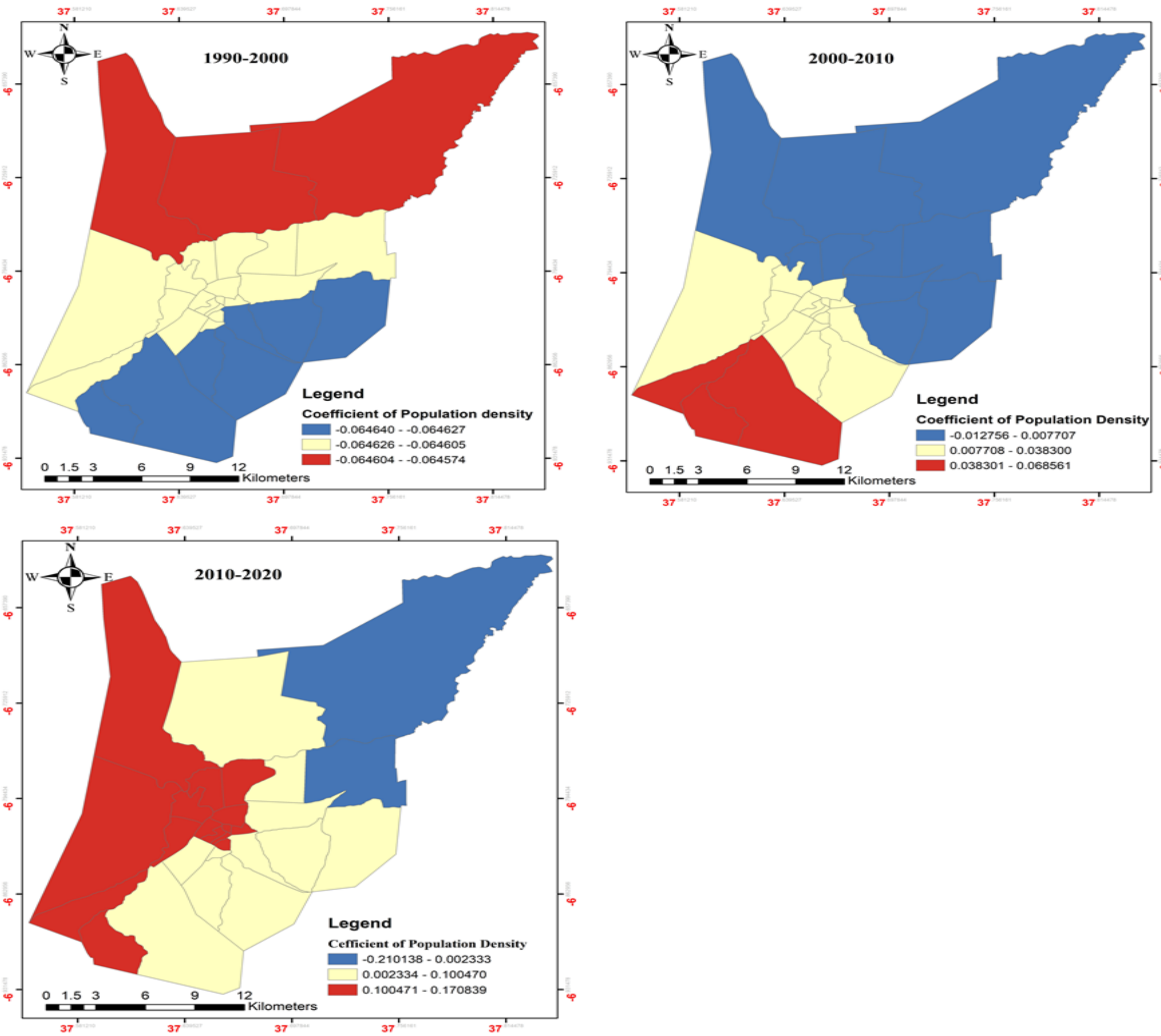

Figure 3.1: Regression coefficients of population density and healthcare facilities for different time periods

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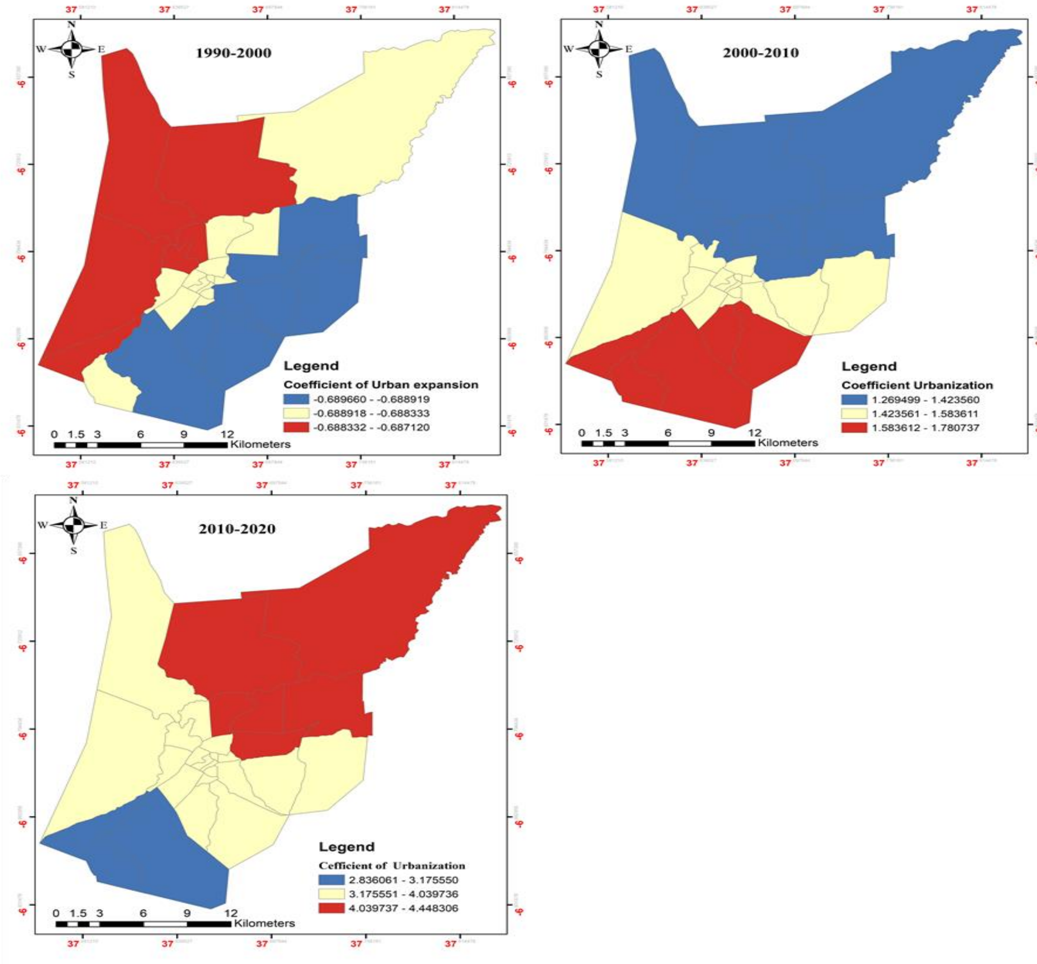

Figure 3.2: Regression coefficients of urban expansion and healthcare facilities for different time periods

As for the urbanization in **Figure 3.3** below, the greatest regression coefficients of urban expansion for the three study periods are -0.689, 1.7807 and 4.448 for the 1990-2000, 2000-2010 and 2010-2020 study periods respectively. This output implies that the impact/explanatory power of urbanization on the development of health facilities is increasing progressively

Discussion

Urban expansions

Morogoro Municipality has experienced tremendous and very rapid urbanization. In 1990 to 2020 built-up increased from 3.9% to 18.9% of the total urban area of Morogoro municipality while non built up LULC class decreased from 96.1% to 81.9% of the total urban area of Morogoro municipality (Table 3.1). Spatial distribution of the built-up extent and urban growth from 1990 to 2020 are depicted in (Figure 3.1). Built-up growth tended to expand outward towards all directions but mainly in the north-west

Geographically Weighted Regression model

The first experiment for the estimation of healthcare facilities in Morogoro Municipality using the explanatory variable urban expansion intensity index for different study periods from 1990 to 2020. From the table 3.2 GWR gives the coefficients of determination of Morogoro Municipality in the

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different study periods. The coefficients of determination which is for the entire 1990-2020 study period was 0.19. In this study coefficients of determination for the estimation using urban expansion as an explanatory variable are 0.17, 0.019 and 0.0017 for the time periods 2020-2010, 2000-2010 and 1990-2000 respectively, which shows that the explanatory power of urban expansion on the distribution of healthcare facilities is increasing over time. Residual Squares are the sum of residual squares of difference between the observed y and the estimated y in our GWR model.

The overall coefficients of determination for this prediction were 0.599, 0.36 and 0.07 for the time periods 2010-2020, 2000-2010 and 1990-2000 respectively indicating that the explanatory power of the variables urban expansion and population density on the distribution of healthcare facilities has been increasing over the years for the study period. Using urban expansion intensity index and the population density of individual wards as the explanatory variables, the resultant model fits the best for the 2000-2010 time periods which has only 5.71 residual squares (the lowest number among the time periods). Sumari *et al*. (2019) explains the significant relationship between urban expansion of Morogoro Municipality and population increase.

In second experiment The GWR model gives the results of regression coefficient of each explanatory variable for each ward in Morogoro Municipality considering their spatial distribution. The coefficient of determination of population density in the three time periods showed a slow increase y from 1990-2000 to 2000-2010 (-0.06457 to -0.01275) but rose exponentially in 2010-2020 (-0.21013) (Fig. 3.2). This shows that the explanatory power of population density on the development of the healthcare facilities constructions was increasing with time during the study period. This output implies that the explanatory power of urban expansion on the development of healthcare facilities is increasing progressively.

Rahman and Smith (2000) only a handful of academic location and allocation studies in developing nations have claimed implementation of their results since location decision are usually taken by local elected leaders or government officials. Therefore it is essential that we consider national healthcare policies and guidelines while attempting to bridge the gap in spatial distribution of healthcare infrastructures. However, central and local governments have often been negligent in the development of healthcare facilities (Patel *et al.,* 2003) which led to weak relationship between urban expansion and distribution of healthcare facilities. In order to balance the supply and demand for healthcare facilities, there is need for concerted effort to alleviate the service quality and distribution concern about the existing situation (Rahman and Smith, 2000).

Also has been observed that in developing countries healthcare facilities in urban area 27% of the population concentration about 75% of healthcare infrastructure and other health resource (Patil *et al*., 2002).The GWR model gives the results with the regression equation and coefficient of each explanatory variable for each ward in Morogoro municipal considering their spatial location. The greatest coefficient of population density in the three study periods was increasing slowly from 1990-2000 to 2000-2010 (-0.06457 to 0.068561) but rise exponentially in 2010-2020 (0.170839) (Figure 3.2). This shows that the impact/explanatory power of population density on the development of the health instructions is increasing with the time in the study period.

Conclusion

In this study GWR model was experimented twice to explain the spatial relationship between urban expansion and distribution of healthcare facilities in Morogoro Municipality. The GWR tool produces a variety of outputs. In the first experiment coefficients of determination for the estimation using urban expansion as an explanatory variable were 0.17, 0.019 and 0.0017 for the time periods 2020-2010, 2000-

2010 and 1990-2000 respectively, which shows that the explanatory power of urban expansion on the distribution of healthcare facilities is increasing over time.
In the second experiment where an additional variable (population density) was included, the overall coefficients of determinations for this prediction were 0.599, 0.34 and 0.07 for the time periods 2010-2020, 2000-2010 and 1990-2000 respectively indicating that the explanatory power of variables urban expansion and population density was increasing with time over the years of the study period. This implies that during 1990-2000 there was weak relationship same for 2000-2010 while 2010-2020 experienced moderate relationship. Within the 30 year study period it's shown that there is progressive growth of relationship between variables i.e., urban expansion and distribution of healthcare facilities from weak in 1990 to moderate relationship in 2020.

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