Case Studies on Transport Policy 12 (2023) 100990

Contents lists available at ScienceDirect

Case Studies on Transport Policy

journal homepage: www.elsevier.com/locate/cstp

Assessing and mapping spatial accessibility of peri-urban and rural neighborhood of Durgapur Municipal Corporation, India: A tool for transport planning

Subrata Haldar, Somnath Mandal, Subhasis Bhattacharya, Suman Paul *

Dept. of Geography, Sidho-Kanho-Birsha University, 723104, India

ARTICLE INFO

Keywords:
Urban growth
Transport network
Durgapur Municipal Corporation
Accessibility
Geographical weightage regression

ABSTRACT

The urban growth and its relation to transport network within the *peri*-urban zone were investigated in this paper. Using multi-temporal satellite imageries and road network data, the current study investigates a tool for transport planning and how it creates impact on the growth of built-up area. For the years 2001, 2011 and 2021, Landsat TM and OLI TIRS satellite images were used to create built-up area as well as the network data has been extracted from the different sources and create two 309*309 metrics table for the accessing of accessibility of *peri*-urban and rural neighborhood of Durgapur Municipal Corporation. From the above two metrics table alpha, beta, gamma, pi, grid tree pattern degree of connectivity, average shortest path length, shimbel index, connectivity index etc. have been calculated and mapped. Using the Open Root Service tools, the travel time from the *peri*-urban and rural neighborhood to city center has been also calculated. From the different above index, it has been observed that the along the NH-2, the accessibility is high. On the other hand, to show the built-up characteristics, direction and distance wise the built-up density and built-up expansion intensity index have been also analyzed. The highest expansion rate and intensity has been observed in the WNW, NNW, ESE and SSE direction. The geographical weightage regression also has been applied in this study to show the relation between built-up area and road density. The findings of this study could help regional planners assess the current state of active transportation options and pinpoint areas that need more attention to make them more accessible when allocating new urban facilities or reallocating those that are already there to lessen the negative effects that individual motorized transportation has on urban mobility.

1. Introduction

Peri-urban areas are the region where the urban boundary ends and the rural environment begins, and they have formed as a result of fast population growth and migration (UNESCO, 2014; Hudalah et al., 2007). The *peri*-urban zone is distinguished by a transitional area between agricultural and urban land use, urban characteristics in rural areas, and unplanned growth in the areas surrounding urban bodies, which is facilitated by road extension and the creation of new economic opportunities (Andreaws, 1942; Singh, 1967; Paul and Dasgupta, 2013). The urban core, inner *peri*-urban, outer *peri*-urban and rural neighborhoods are the four zones that make up the *peri*-urban area (Yunus, 2006). Peri-urban zones feature dynamic environments because they have developed from rural regions and will soon become urban areas. Peri-urban expansion is the term used in India to describe the area between the statutory town and the census town (Mondal and Sen, 2020). In India's urban districts, *peri*-urbanization has become a discernible and growing phenomenon during the past few decades. Cities' rapid urbanisation and growth has led to the emergence of *peri*-urban spaces, which act as transitional zones between rural and urban ecosystems (Mondal and Banerjee, 2021). The expansion of the transportation system, changes in the economy, and changes in land use are the key drivers of *peri*-urban growth. The development of the road network is one of the primary causes of the *peri*-urban area (Rajput, 2021). The advancement of any region's transportation infrastructure is essential to that area's social and economic growth (Seliverstov et. al., 2019). The *peri*-urbanization process is significantly impacted by the design of the transportation system. As a result, transportation infrastructure is built where

* Corresponding author.
E-mail addresses: s.haldar90@gmail.com (S. Haldar), mandal.somu1@gmail.com (S. Mandal), suva69eco@gmail.com (S. Bhattacharya), suman.krish.2007@gmail.com (S. Paul).

https://doi.org/10.1016/j.cstp.2023.100990
Received 8 November 2022; Received in revised form 2 February 2023; Accepted 10 March 2023
Available online 21 March 2023

there are numerous settlements or where there is a high rate of migration to metropolitan regions (Hou and Li, 2011). Depending on how accessible and high-quality the road infrastructure is, different economic activities are impacted by the extension and intensity of transportation links (Pablo-Mart and Sánchez, 2017). The constructed transportation infrastructure immediately benefits spatial accessibility at the national and international levels (Fan and Chan-Kang, 2008).

Many scholars have made an effort to assess the efficacy of the road network using various models. Sarkar et al. (2020) utilised the following metrics to assess the accessibility of the road network: Alpha index, Beta index, Gamma index, Pi index, Grid tree pattern, Eta index, Degree of connection, Cyclomatic number, communication matrix, Shimbel index, and Average shortest path length. Sarkar (2013) measures the road network's structure using the Alpha, Beta, Gamma, Cyclomatic, Aggregate Transportation Score, and Road Density. Arif and Gupta (2020) employ the Alpha, Beta, Gamma, Eta, Grid Tree Pattern, Cyclomatic Number, Circuity Index, Degree of Connectivity, Shortest Path Matrix, and Shimbel index to quantitatively analyse the transport network using a graph-based model. The road network of Guwhati city was analysed by Das et al. (2019) using GIS technique and evaluate the shortest route analysis between two sites while taking critical factors like traffic congestion, delays, road accidents, pollution, etc. into consideration. Dinda et al. (19) evaluates the sustainability of urban transportation and its connection to travel behavior using a variety of metrics, including the Alpha index, Beta index, Eta index, Gamma index, Pi index, Theta index, Network density, Landuse land cover change, Transport suitability index (TSI), Analytical hierarchy process (AHP), etc. Ahmed et al. (2017) applied the network analysis on the GIS platform to identify the best route and the closest facility. Chen et al. (2014) applied a spatial–temporal modeling technique to measure connection and accessibility utilising the Alpha index, Gamma index, Beta index, and Cyclomatic number. Using the Origin Destination Matrix, Liu and Zhu (2003) measured accessibility using an integrated GIS platform (OD Matrix). Using GIS and the Grid tree pattern, Tini and Shah (2018) quantify the topological formation of networks. Garrison (1960) assessed the connectedness of the route using graph theory indices. In order to comprehend the road network pattern, some road network indices have been calculated in this study, including the Alpha index, Beta index, Gamma index, Pi index, Eta index, Grid tree pattern, Cyclomatic number, and Degree of connectedness. To measure accessibility using the matrix table, the Connectivity index, Shimbel index, and Average Shortest Path Length has also been examined. The shortest distance and predicted journey time have been examined to measure the duration of travel time in this study area.

Transportation and urban development inextricably linked. In reality, urban development and transportation are interdependent (Aljoufie, 2011). Road networks are crucial components of the infrastructure that support urban integration since they connect various functional sectors. According to factors including capacity, frequency, speed, and trip distance, Mishra et al. (2014) provided a method to determine the line and node level connectivity. Accessibility indexes up to the time of AlMamun and Lownes (2011) research contribution is a composite methodology that scales and adds three indices to produce a final score. They take into consideration the Local Index of Transit Availability (Rood and Sprowls, 1998). Recently, Gu et al. (2022) described accessibility model for spatial network analysis for multimodal urban transportation systems, which evaluates the connectedness and centrality of a land use, population, and transportation network. Variety of metrics used by many researchers to assess the relationship between urban growth and network, including the annual urban spatial expansion index, land use change index, population density index, transport infrastructure expansion index, road density index, road area density index, urban trips density index, and spatial proximity analysis (Aljoufie et al., 2011; Zannat and Choudhury, 2019; Karou and Hull, 2014).

The present study aims to address a RS and GIS based growth and pattern of the *peri*-urban and rural neighborhood of Durgapur Municipal Corporation (DMC) as well as the state of the transportation system today, including the accessibility of the system and the shortest route based on travel time, and to ascertain the relationship between the built-up area and road network. The aforementioned goals have been established using road network indices, accessibility measurements, shortest distance measurements, Kernel density, built-up growth analysis, and geographically weightage regression (GWR) derived from the *peri*-urban and rural neighborhood of DMC, India (Eastern part). This study focuses on the significance of Geographically Weighted Regression (GWR) in understanding the correlation between features and their geographical location. The aim is to investigate the impact of transportation on the evolving urban dynamics and its spatial variability. The findings of this research can assist urban planners globally in identifying the current transportation networks and determining their future growth potential, thereby bridging the gap between urban and rural areas and promoting sustainable development (SDG 10) by reducing inequalities.

1.1. Study area

Asansol Durgapur Development Authority (ADDA, 1980) is in charge of planning and development for this sub-division (Choudhury et al. 2019). After Kolkata (the capital of West Bengal), this development region is the second largest urban area in the state of West Bengal (Ghosh et al. 2015). Population, built-up area to total area in respect of urban, outer and inner *peri*-urban along with rural hinterland has been shown and due to unavailability of 2021 census, dataset between 1991 and 2011 has been calculated **(**Table 1**)**. Four Community Development Blocks (CD Blocks) that surround the Durgapur Municipal Corporation are Kanksa, Faridpur Durgapur, Ondal, and Pandabeswar. Kanksa lies on the eastern side of DMC, Faridpur-Durgapur is on the northern side, Ondal and Pandabeswar are on the western and north-western sides, respectively. In the south and north, the research area is bordered by the Damodar and Ajoy River, as well as the transitional zone between the Jharkhand plateau and the Ganga-Brahmaputra mature delta plain (Ghosh et al. 2015).Due to its advantageous geographic location, this area is also well known for agriculture practice and industrial complex due to the presence of coal and mineral resources within the study area and its surroundings, which is conducive to human habitation and further stimulates urban growth, resulting in the development of various CT, Municipal Corporations, and municipalities, as well as very good infrastructure and well transportation (Fig. 1). The Durgapur region is connected to the rest of India by NH-2 and Eastern railway (Choudhury et al. 2019).

2. Data

Mainly road network data and satellite images data have been used. Road network data has been collected from the Open Street Map and census of India (2011). Road network data have been used for the network analysis and measure the accessibility. In urban transportation research the use of GIS is a unique source of data (Dinda et. al., 2018). The road network data was downloaded from OSM and was rectified and validated using Census map and Google Earth. Then, to remove the error from the junction point, the topology was developed, and the network dataset was generated by the nodes and edges. The network indices were computed using a total of 309 nodes and 740 arcs or edges. For the accessibility measurement, two 309*309 matrices were developed. The satellite images were downloaded from the USGS GLOVIS of last three decades (2001, 2011 and 2021 as this dataset can easily comparable with Census of India Dataset which are basically found in 10 years interval) to conduct the comparative analysis of accessibility with built-up scenario. The characteristics of satellite images are described in Table 3. The satellite images were geometrically corrected after having been downloaded. In the ERDAS Imagine software, geometric correction, radiometric correction, noise correction, and other operations have been

Table 1
Growth analysis of Urban Built-up and population growth.

Categories	Population			Built-up Area [Sq. km]			Area [Sq. km]		
	1991	2001	2011	1991	2001	2011	1991	2001	2011
Urban	0	0	82,288	0	0	12.65	0	0	39.15
Inner Peri-Urban	126,257	272,932	336,319	12.12	33.89	50.53	73.67	148.25	186.40
Outer Peri-Urban	278,227	218,303	186,935	18.94	17.87	25.97	272.96	246.97	302.68
Rural	99,083	81,008	37,313	11.91	8.01	2.59	281.84	233.25	100.24

Source: Computed by the authors.

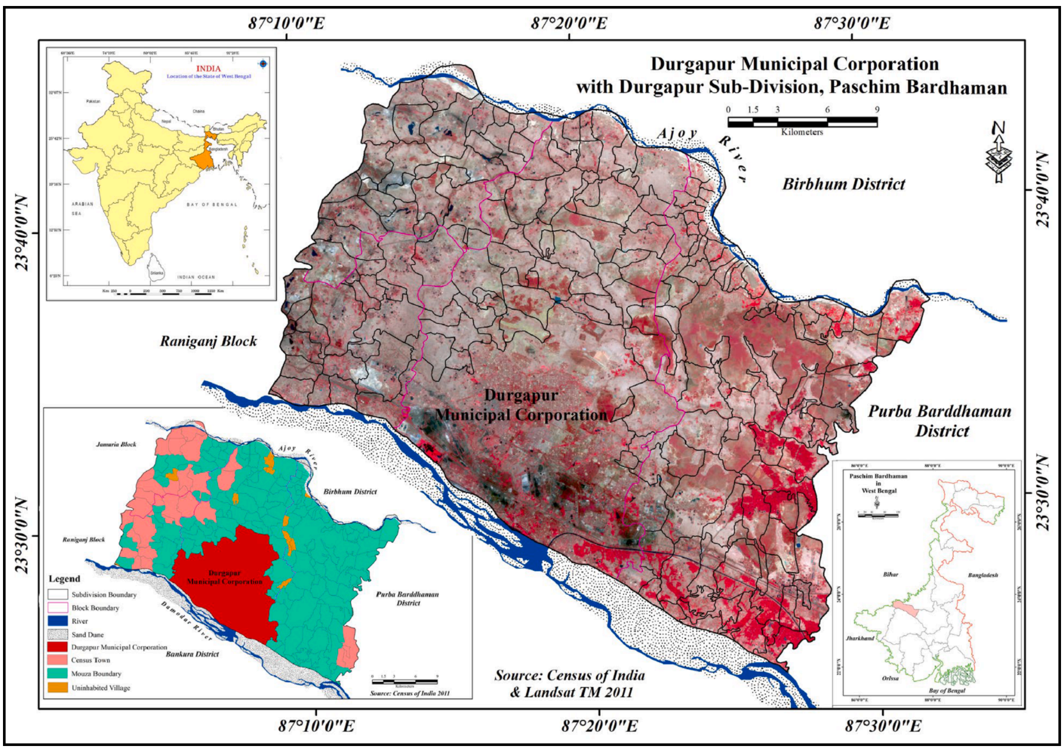


Fig. 1. Location of study Area.

accomplished as required. The built-up area was extracted from satellite images using the Normalized Differenced Built-up Index in this study (NDBI). Geometric correction has been implemented in order to remove the distortion of relative replacement of the features brought on by the sensor. The technique of matching photos between images was applied in this case. The image that was fixed to be the 1991 photograph was discovered by first contrasting it with the Google Earth image, which was then cross-checked with additional images. Overall, not all locations and images require this. It occurs occasionally. Atmospheric effects can be reduced using radiometric correction. To further remove atmospheric effects, the DOS (Dark Object Subtractions) method is used, which turns the DN value into reflectance. It uses a haze removal technique to enhance image interpretation. Haze frequently covers the large industrial belt beneath which this location is situated. Layer stacking and cutting to the area of interest are additional actions. A certain set of techniques are needed for each study field.

The West Bardhaman district (erstwhile known as the Bardhaman district) map from the Census of India 2011 is where the village boundaries are first digitalized. The base map was then created at a scale of 1:50,000 using the scanned topographical sheet. In the ArcGIS software, the scanned topographical sheet was georeferenced using the WGS 1984 UTM zone 45 North coordinate system. ArcGIS techniques were used to digitize and compute the spatial extent of the lengths of each road network, including the National Highway, State Highway, District Road, and other roads. The road network's KML file format was developed from Google Earth satellite image and then converted to a shape file using ArcGIS software. Additional ArcGIS capabilities were utilised to construct a network dataset by adding nodes and arcs to the local road network. After that, the nodes and arcs were meticulously tallied to determine the various indices and level of connection of the area.

3. Methods

3.1. Indices based road network analysis

For any location, improved transportation and communication networks are always economically beneficial (Marr and Sutton, 2007). In this study, connectivity and accessibility were calculated using a matrix table, and network analysis was carried out using graph theory and GIS. Since its first discovery in 1953, the graph theory has been repeatedly rediscovered (Barnes and Harary, 1983). A network's connections are shown symbolically in a graph. Nodes and arcs, which are made up of ordered pairs of numerous nodes, make up a linked graph G = (e, v) (Daniel et. al., 2020). The two components of a road network are junctions and routes. In graph theory, the junction point joins two or more paths and lines and is referred to as a node and vertex (Arif and Gupta, 2019). A node serves as the arcs' point of connection as a result. In this study, various metrics were used to assess the effectiveness of the road network, including the alpha index (***α***), beta index (***β***), gamma index **(γ)**, pi index ***(π)***, eta index ***(η)***, grid tree pattern, cyclomatic number, degree of connection, and others(Table 2). The detail methodology has been shown in the Fig. 2.

3.1.1. Alpha index(α)

The alpha index (α) is one of the most important network indices, and its purpose is to determine the level of connectivity. This is the proportion of the actual circuits to the maximum circuits. The following equation can be used to determine this index:

$$AlphaIndex(\alpha) = \frac{(e - v + p)}{(2v - 5)} \tag{1}$$

The alpha index ranges from 0 to 1, with 0 signifying the least connection and 1 signifying the most connectivity, as well as e denoting the number of edges, v denoting the total number of vertices, and p denoting the number of non-connected nodes in the graph.Table 3

3.1.2. Beta index (β)

The beta index is another essential measure of network connectivity, with the goal of determining the degree of connection of a road network based on the ratio of total nodes to total edges. This index is calculated using the following formula:

$$BetaIndex(\beta) = \frac{e}{v} \tag{2}$$

Where, the total number of edges or arcs is equal to e, and the total number of vertices is equal to v. The resulting value of the beta index ranges from 0 to 3, with higher values indicating higher connections and lower ones indicating lower connectivity.

3.1.3. Gamma index (γ)

The gamma index is a ratio between the observed number of edges and vertices in a given transportation network or a measure of connectivity that evaluates the relationship between the number of observed links and the number of potential links in a particular transportation network. The gamma value ranges from 0 to 1, with 1 indicating a perfectly linked network. This index is calculated using the following equation:

$$GammaIndex(\gamma) = \frac{e}{3(v - 2)} \tag{3}$$

3.1.4. Theta index (θ)

The Theta index is a useful metric in network analysis for determining the length of a route per vertices. This is the proportion of the entire network to the vertices. The lower the value of the Theta index indicates the higher the accessibility, and the higher the value of the Theta index indicates the lower the accessibility, whereas the value of 5.0 represents moderate accessibility in any region (Dayalan, 2020). This index can be calculated by following equation:

$$ThetaIndex(\theta) = \frac{Q}{v} \tag{4}$$

where, Q is the total length of network and v is total number of vertices.

3.1.5. Pi index (π)

The Pi index, which gauges the network's complexity, is determined by dividing the network's overall length by its diam. The value increases along with the complexity of the network and the level of connectivity. This index can be calculated using the following formula:

$$PiIndex(\pi) = \frac{totaldistanceofnetwork(c)}{diatanceofdiam(d)} \tag{5}$$

3.1.6. Eta index (ŋ)

The Eta index is a ratio that measures the utility of a network by comparing the overall length of the network distance to the total number of edges, which is the average length of the network per link. The formula for calculating this index is as follows:

$$EtaIndex(\eta) = \frac{totalnetworkdiatance(M)}{numberofarcs(e)} \tag{6}$$

3.1.7. Grid tree pattern (GTP)

The pattern of the network was identified using this grid tree pattern index. Tree patterns range from 0 to 0.5, grid patterns range from 0.5 to 1, and delta patterns range from 1 to 2. This pattern is calculated by following equation:

$$GridTreePattern(GTP) = \frac{e - v + p}{(\sqrt{v} - 1)^2} \tag{7}$$

3.1.8. Cyclomatic number (μ)

A different method of assessing connectivity is the cyclomatic number. It is based on the idea that once a connected network has enough arcs or links to create a tree, adding any more arcs will result in circuit development. As a result, it can be defined as the number of basic circuits in a graph. The total number of arcs minus the number of nodes

Table 2
Information about Indices based road network analysis.

Indices	Formula	Explanations
Alpha index (α)	(e – v + p) / (2v – 5)	Alpha index (α) is to determine the level of connectivity
Beta Index (β)	e/v	Beta Index (β) is another essential measure of network connectivity
Gamma Index (γ)	e/3 (v – 2)	Gamma Index (γ) evaluates the relationship between the number of observed links and the number of potential links in a particular transportation network
Theta Index (θ)	Q/v	Theta Index (θ) is a useful metric in network analysis for determining the length of a route per vertices
Pi Index (π)	c/d	Pi Index (π) gauges the network's complexity determined by network's overall length by diameter
Eta Index (ŋ)	M/e	Eta Index (ŋ) ratio that measures the utility of a network by comparing the overall length of the network distance to the total number of edges
Grid Tree Pattern (GTP)	$(e - v + p)/(\sqrt{v} - 1)^2$	Grid-tree pattern (GTP) index used to compare road networks with regular road patterns
Cyclomatic Number (μ)	e – v + p	Cyclomatic Number (μ) is very important non ratio measure abstracted from graph theory where greater the cyclomatic number, greater the connectivity of the graph and vice-versa
Degree of Connectivity (DC)	(v (v – 1)/2)/e	DC metric that evaluates the relative position of an observed network connectivity
Connectivity Index (CI)	$\sum_j^n cij$	Connectivity Index measures the degree to which a transportation network is connected
Shimbel Index (SI)	$\sum_{i=1}^n dij$	Shimbel index is being used to measure the network's accessibility
Average Shortest Path Length (ASPL)	$\frac{1}{N(N-1)} \cdot \sum_j^n dist(v_i \cdot v_J)$	ASPL is another important measure for determining the accessibility showing lower result more efficient network is at facilitating movement

Note. *e* denoting the number of edges/ arcs, *v* denoting the total number of vertices, *p* denoting the number of non-connected nodes in the graph, *Q* is the total length of network and v is total number of vertices, c denotes *total distance of network, d denote distance of diameter, M denote total network distance.*

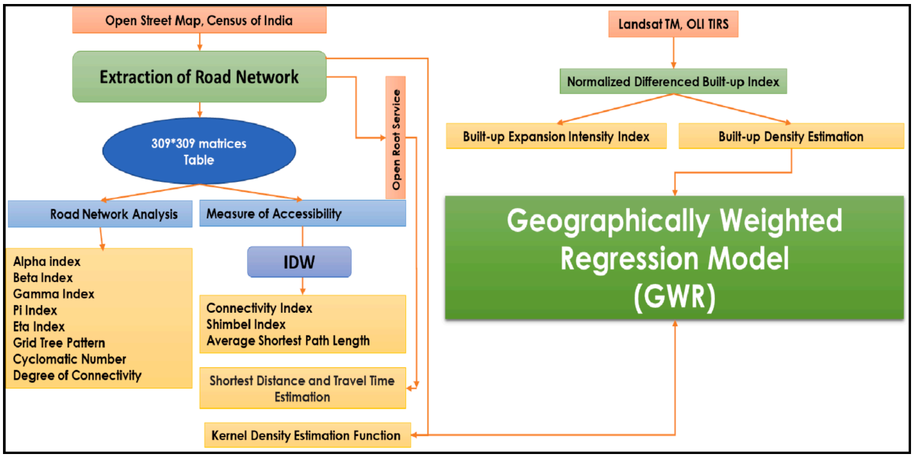


Fig. 2. Methodological workflow of the present Study.

Table 3
Information about Satellite imageries used in the study.

Product	Sensor	Date of Accusation	Path/ Row	Band used	Spatial Resolution
Landsat 5	TM	20.02.2001	139/ 044	Band 4 - Near Infrared Band 5 - Short-wave Infrared	30 m.
Landsat 5	TM	16.02.2011	139/ 044	Band 4 - Near Infrared Band 5 - Short-wave Infrared	30 m.
Landsat 8	OLI_TIRS	27.02.2021	139/ 044	Band 5 - Near Infrared Band 6 - Short-wave Infrared	30 m.

Source: developed by the authors.

equals the number of circuits in a connected system (Raghav, 2014). This can be measured by:

$$CyclomaticNumber(\mu) = (e - v + p) \tag{8}$$

3.1.9. *Degree of connectivity (DC)*

The degree of connectivity may be described as a metric that evaluates the relative position of an observed network's connectivity on a scale restricted by maximum connectivity ratios. The greater score that results indicate a high degree of connectivity. This is measurable by:

$$DegreeofConnectivity(DC) = \frac{\frac{v(v-1)}{2}}{e} \tag{9}$$

3.2. *Measure of accessibility*

Accessibility refers to how easy it is to reach and interact with dispersed locations or activities throughout space. Many different destinations are easily accessible from a location with high accessibility (Farber and Fu, 2017). Network connectivity can be used to determine a region's accessibility (Chen et. al., 2014). Accessibility was measured in this study using various indexes, such as the Connectivity Index (CI), the Shimbel Index (SI) and the Average Shortest Path Length(ASPL) and so on.

3.2.1. *Connectivity index (CI)*

The Connectivity Index measures the degree to which a transportation network is connected. Low connectedness means high isolation and low accessibility, whereas high connectedness means low isolation and high accessibility. Connectivity is a distance-independent measure of accessibility. The connectedness of a node to its nearest node is represented by this matrix. The matrix was constructed using the following criteria: 1 if two nodes are directly connected by an edge or arc, and 0 if two nodes are not directly connected by an edge or arc. The connection index can be calculated as follows:

$$ConnectivityIndex(CI) = \sum\nolimits_{j}^{n} Cij \tag{10}$$

where, Cij denotes a direct link between nodes i and j, and n denotes the number of nodes.

3.2.2. *Shimbel Index(SI)*

The Shimbel index is being used to measure the network's accessibility. The sum of all the shortest paths connecting all the other nodes in the network is used as a measure of accessibility. A lower shimbel index score suggests greater accessibility, and vice versa. This index can be written as follows:

$$ShimbelIndex(SI) = \sum\nolimits_{i=1}^{n} dij \tag{11}$$

where dij denotes the shortest distance between nodes i and j, and n denotes the number of nodes.

3.2.3. *Average shortest Path length (ASPL)*

Average Shortest path length is another important measure for determining the accessibility. The average number of stops required to reach two distant nodes in the graph is a measure of efficiency. The lower result, more efficient network is at facilitating movement (Ducruet and Rodrigue, 2020). This pattern is calculated by following equation:

$$AverageShortestPathLength(ASPL) = \frac{1}{N(N-1)} \sum\nolimits_{ij}^{N} dist(v_i.v_J \tag{12}$$

where, N denotes the total number of nodes, V_i and$V_j$denotes the shortest distance between I and j.

3.2.4. *Kernel density estimation Function(KDE)*

KDE is a key technique for measuring the density of a point or polyline in spatial analysis and determined the process of using a kernel function to estimate an unknown probability density function (Botev et. al. 2010). A kernel density estimate is a function defined as the sum of a kernel function on each data point, whereas a histogram counts the number of data points in random locations (Lichman and Smyth, 2014).

This function is used to find the unit area value and fit each point or line upon a smooth contoured surface (Zhao et. al., 2017). The density of features around each output raster cell is calculated with this function (Xie and Yan 2008). In this research, KDE was used on a road network with weightage according to gradation of road. The national highway has been assigned number four, the state highway has been given number three, the district highway has been assigned number two, and other roads have been allotted number one.

3.3. Shortest distance and travel time estimation (SDTTE)

The Open Root Service (ORS) tool was used in this study to calculate the shortest distance and travel time between different administrative units in the *peri*-urban region using API services. Many services in the field of journey planning can be enabled via the ORS API. This tool can calculate routes, route planning information, find points of interest around or within a particular location, isochrones, time–distance matrices, and more with various travel modes and a wide range of routing alternatives (driving, cycling, walking, and wheelchair) based on the travel interests of the shortest or fastest route while considering the types of roads, road obstacles, and road regulations, among other things (Scandiffio, 2021). The SDTTE have been calculated in this study based on driving by car with shortest distance.

3.4. Inverse distance weightage (IDW)

The inverse-distance weighting (IDW) method is one of the most commonly used prediction models in spatial interpolation. IDW is a deterministic multivariate interpolation method that uses a known distributed set of points. A weighted average of the values available at the known points is used to assign values to unknown points (Lu and Wong, 2008). It might be simple to calculate and interpret. The following is the IDW measurement formula (Ghosh and Das, 2019):

$$Z_P = \frac{\sum_{i=1}^{n}\left(\frac{Z_i}{d_i^P}\right)}{\sum_{i=1}^{n}\left(\frac{1}{d_i^P}\right)} \tag{13}$$

3.5. Normalized differenced Built-up index (NDBI)

For the analysis of built-up area, there are numerous indicators such as the Normalized Difference Built-up Index (NDBI), Enhanced Built-up and Bareness Index (EBBI), Index-based Built-up Index (IBI), Built-up Index (BU) and so on. Using the short-wave infrared and near-infrared bands, the Normalized differenced Built-up Index is most typically used to extract the built-up area, as shown in the equation below.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{14}$$

The short-wave infrared band is SWIR, and the near-infrared band is NIR. The NDBI value ranges from -1 to $+1$. The higher degree of a water body is represented by -1 number, while the higher degree of built-up is represented by $+1$ value. NDBI has been applied to extract the built-up area in this research to find out the built-up expansion and relation to road network.

3.6. Built-up expansion intensity Index(BEII)

The average annual proportion of newly added built-up urban area to all changed area is measured by the BEII (Lu et al., 2014; Akubia and Bruns, 2019) and urban expansion potential is represented by it, which looks at the rate or intensity of urban land-use change through time. The formula for the BEII is given in below (Abdullahi et al., 2017):

$$BEII = BUA_i^{t2} - \frac{BUA_i^{t1}}{TLA_i} X100 \tag{15}$$

Where, BUA_i is built-up area of i^{th} year, t_1 is the base year and t_2 is the final year. The study region's total area is denoted by the $TLA_i$and t is the interval of two time periods.

3.7. Built-up density estimation

The built-up density index is a useful indicator for calculating the ratio of total built-up area to total area. (Akubia and Bruns, 2019). This index can be used to determine the amount of built-up intensity per unit area of total area, as well as the level of urbanization in a particular location. The BUDI was calculated in this study for the years 1991, 2001, and 2011 to determine the Spatio-temporal change of built-up intensity per unit area using the equation:

$$Built-upDensity = \frac{Totalbuilt-uparea}{Totalarea} \tag{16}$$

3.8. Zonal analysis with concentric Rings:

To precisely determine the built-up growth characteristics, the study area was divided into six zones in a clockwise pattern with interval of 45° angle, and the interval of 500 m concentric rings were created from the city centre(Shaw and Das, 2018). These six direction zones are respectively: WNW (West North West), NNW (North-North West), NNE (North-North East), ENE (East-North East), ESE (East-South East) and SSE (South-South East). The direction of administrative units was selected based on the geo-center of units, and buffer rings were integrated with the direction-wise classified administrative units.

3.9. Geographically weighted regression model (GWR)

A collection of statistical techniques called regression analysis is employed to determine the relationship between a dependent variable and one or more independent variables. It can be used to model how strongly variables will be related in the future and to evaluate the strength of that relationship (Zhao et al., 2017). To assess the relationship between the kernel density and built-up density in the Arc GIS platform, a geographically weighted regression model (GWR) has been selected. The kernel density has been regarded as an independent variable, whereas the built-up density has been considered as a dependent variable in this study. The GWR model which is one type of local regression model, commonly used to examine the spatial variables (Brunsdon et al., 2010). When compared to other conventional, widely used linear or nonlinear regression models, the GWR model considerably increased estimation accuracy by including geographic variation to the regression model coefficients (Shi et al., 2019). GWR can implement by the following equation:

$$y_i = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik} + \epsilon_i \tag{17}$$

Where, y_i is the dependent variable which is built-up density, β_0 is the intercept of y, β_k is the coefficient, x_{ik} is the independent variable which is kernel density of road network in this study, and ε_i is the random error term.

4. Results and discussion

4.1. Analysis of road network indices

The most basic properties for analysing the transportation network i. e., the level of connectivity, efficiency, development, and shape of a road network system are measured using network indices (Karimi, 2011; Nagne and Gawali, 2013). The value of the Alpha index was found to be 70%. The Gamma index is at 80%, while the Beta index is at 2.39. The Pi index value was estimated to be 13.27, while the Grid Tree Pattern was found to be 1.56. The Cyclomatic number, Degree of Connectivity, and

Eta index value per vertices were 368, 64.31, and 0.99 km, respectively and the value of Theta index has been obtained 2.39 km per vertices. One of the most essential measurements in network theory is accessibility analysis (see Table 4). In this study, different indexes were measured for accessibility analysis, including Average Shortest Path Length (ASPL), Shimbel Index using a 309*309 matrix of the shortest path, connectivity index using a 309*309 matrix of connectivity, KDE based on road network density, and STTDE using the ORS plug-in. The values of all the indices have been classified into five categories based on natural breaks (Jenks): very high, high, moderate, low, and very low, respectively.

From the Alpha Index value, which is also known as redundancy index, it has been observed that the level of connectivity is high which indicates the maximum options to going from one node to another in this study region (Sarkar, 2013) whereas the Beta Index value is more than 1 which indicates the complicated network pattern (Uy and Nakagoshi, 2007). The result of Gamma index which determines theoretical maximum accessibility of a network has been found 80% network is connected in this region (Grubesic et al. 2008). The circumference of a sphere as well as its diam is generally expressed as a pie index and GTP index indicates the types of network pattern (Dayalan, 2020). From the Pi index it can be interpreted that the study region is characterized with well-connected and complicated as well as the resultant values of GTP indicates the delta network pattern (Sarkar et al., 2020). The Cyclomatic number and degree of connectivity is also high which shows the higher level of connectivity and developed network pattern (Arif and Gupta, 2019). The Eta and Theta index, both have been found as lower value which indicate the higher accessibility have been found in this region (Dayalan, 2020). Therefore, higher road network connectivity in a study area is only possible through the availability of a higher number of nodes and their interconnections. This study clearly shows that an interconnected network offers greater mobility and efficiency for users from *peri*-urban and rural neighbourhoods, resulting in shorter travel distances, reduced congestion, and faster travel times to the DMC. This, in turn, can drive economic growth and encourage development in surrounding areas. Sreelekha et al. (2016) found that increased connectivity in Calicut, India, influenced the spatial structure. In a similar vein, Sarkar et al. (2020) reported that higher connectivity in English bazar, India, facilitated connections with the surrounding area. China has also seen the impact of well-connected road networks on the development of urban areas and economic flows, as evidenced by the findings of Fan and Gao, (2016); Liu and Chen, (2018); Zhang and Fan, (2017).

4.2. Average shortest Path length (ASPL)

The study identified the most accessible zone in the Durgapur Municipal Corporation's peripheral using the ASPL and Shimbel indices. The very high, high, moderate, low, and very low zones, respectively, make up 21.37%, 28.27%, 20.00%, 18.83%, and 10.60% of the entire area, according to the ASPL (Fig. 3a). A zonal unit with a 500 m interval and a village boundary with direction were developed based on the mean value of the ASPL for that specific region. It has been determined how the mean ASPL values vary with direction and distance. While the high region of ASPL has been found at 4.04% area within 5500 m to 16000 m of concentric rings in the periphery of Durgapur Municipal Corporation, the very high region of ASPL value has been found at 7.29% area within 4500 m to 15000 m of concentric rings and the direction of ENE from the city centre of DMC. The very low region of ASPL value has been observed minimum compared to other regions in this same direction, which is found to be 1.44% from 20500 m to 25500 m. The moderate and low regions of ASPL value were found to be 4.81% from 14500 m to 18000 m and 4.80% from 16000 m to 22500 m, respectively. The very high, high, and moderate regions of ASPL value in the periphery regions of Durgapur Municipal Corporation have been observed to be 7.41% from 8000 m to 16000 m, 9.43% from 12500 m to 20500 m, and 0.21% within 18500 m to 20000 m, respectively, of concentric rings in the NNE direction from the city centre of Durgapur Municipal Corporation, whereas the low and very low regions of ASPL value have been observed to be absent. The very high, high, moderate, low, and very low regions of mean ASPL values have been found to be 8.51% within 6500 m to 22500 m, 6.42% within 6000 m to 18000 m, 3.03% within 6500 m to 20000 m, 4.68% within 18000 m to 21500 m, and 2.89% within 19500 m to 23500 m, respectively, of the concentric rings in the direction of NNW from the city centre of Durgapur Municipal Corporation whereas the very high regions of ASPL value have been observed to be absent in the direction of WNW from the city centre of Durgapur Municipal Corporation, and the high, moderate, low, and very low regions have been found 0.83% within 12000 m to 16500 m, 4.42% within 6000 m to 18000 m, 5.72% within 8500 m to 19000 m, and 2.33% within 12500 m to 17000 m of the concentric rings in the periphery of Durgapur Municipal Corporation. The very high region of ASPL value has been observed to be absent in the ESE direction from the city centre of Durgapur Municipal Corporation, whereas the high, moderate, low, and very low regions of ASPL values have been found to be 6.36% within 5000 m to 14500 m, 5.92% within 6000 m to 16000 m, 3.76% within 11000 m to 18500 m, and 3.87% within 17000 m to 21000 m of concentric rings, respectively as well as the very high, high, and moderate regions of ASPL value have been found to be absent in the direction of SSE from the city centre of Durgapur Municipal Corporation, whereas the low and very low regions have been found to be 1.27% within 9500 m to 16000 m and 0.68% within 11500 m to 17500 m of concentric rings in the periphery of Durgapur Municipal Corporation. Based on IDW of ASPL value from node to node, very high, high, and moderate ASPL indexes were found in 12 census towns and 57 villages, 17 census towns and 85 villages, and 14 census towns and 69 villages, respectively, whereas low and very low ASPL indexes were found in 22 census towns and 56 villages, and 20 census towns and 32 villages, respectively.

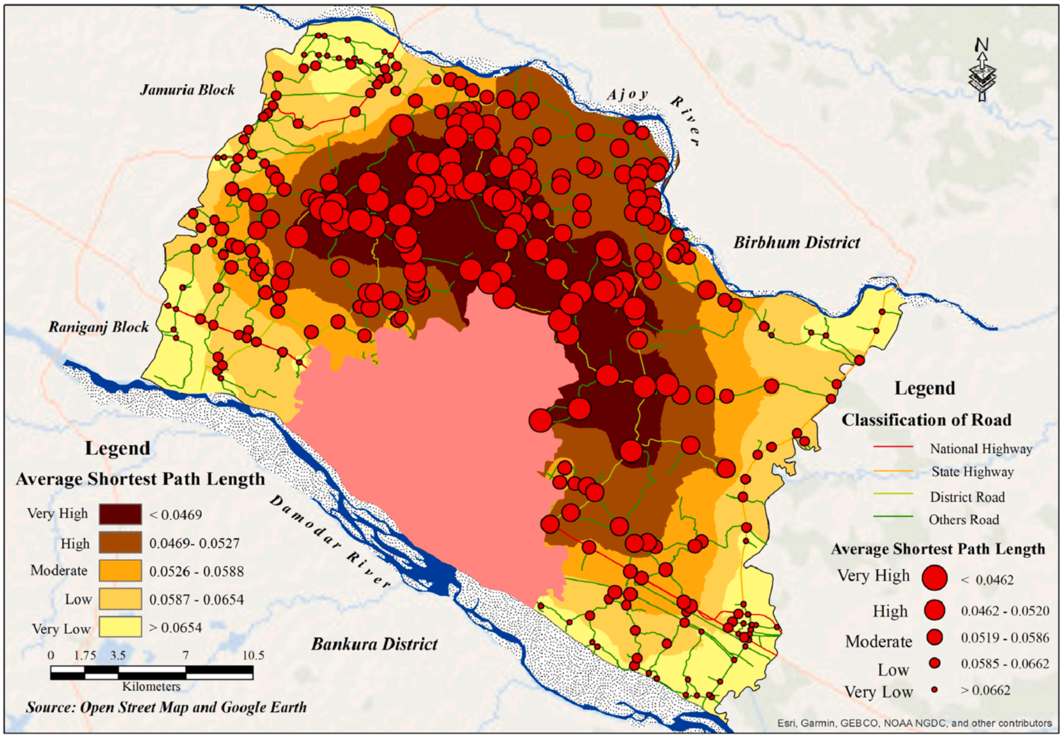
Table 4
Analysis of Road Network Indices.

Road Network Indices	Max	Min	Mean	S.D.	C.V.
Average Shortest Path Length [ASPL]	0.08	0.04	0.05	0.01	0.2
Shimbel Index [SI]	7369.46	3648.36	5151.09	777.51	0.15
Connectivity Index [CI]	7.00	3.00	3.35	0.30	0.09
Kernel Density Estimation [KDE]	0	7.77	1.73	1.30	0.75
Shortest distance and travel time estimation [SDTTE]	0.10	0.66	0.34	0.12	0.35

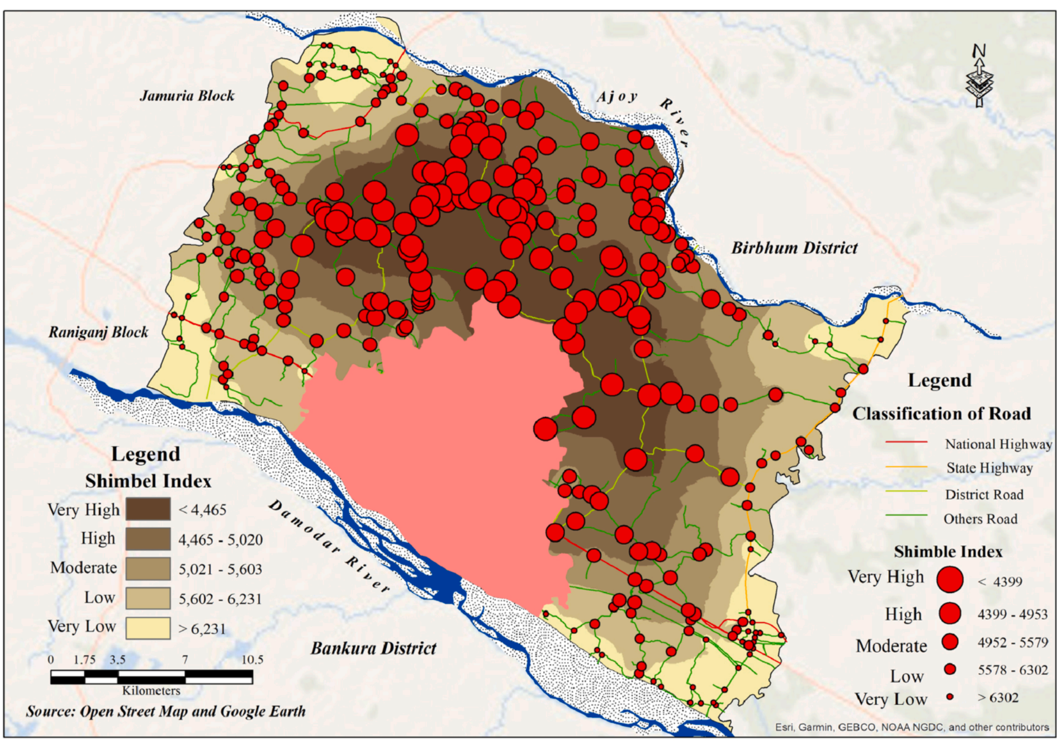
Source: Computed by the authors.

4.3. Shimbel index (SI)

The Shimbel index is another essential measure of accessibility for determining how accessible an administrative unit is. According to the Shimbel index (Fig. 3b), the very high, high, moderate, and low regions are comprised of 17.62%, which are located on the northern side of Durgapur Municipal Corporation and include parts of 10 census towns and 57 villages; 38.08%, which are located on the outskirts of the very high region and include parts of 19 census towns and 107 villages; 22.70%, which includes parts of 19 census towns and 73 villages and is located on the outer periphery of the high region; and 18.72%, which includes parts of 19 census towns and 73 villages, and is also located on the outer periphery of the moderate region whereas The very low regions, which account for 1.83% of the total, are found mostly on the region's outer periphery and include 14 census towns and 13 villages. The very high, high, moderate, and low regions are comprised of 4.23% within 6500 m to 15000 m, 8.39% within 4500 m to 17000 m, 4.93% within 14500 m to 20500 m, and 4.82% within 16500 m to 25500 m of concentric rings in the direction of ENE, respectively, whereas the very low regions are absent in this same direction based on the distance and



(a)



(b)

Fig. 3. (a) Average Shortest Path Length in the study area. (b) Shimbel Index in the study area.

direction-wise analysis from the Durgapur city centre of the mean Shimbel index value on the outskirts of Durgapur Municipal Corporation. The very high region of the mean Shimbel index has been found to be absent in the ESE direction from the Durgapur city centre, whereas the high, moderate, low, and very low zones of the mean Shimbel index were found to be 7.42% within 5000 m to 15000 m, 6.50% within 9000 m to 17000 m, 4.58% within 11500 m to 19500 m, and 1.37% within 18000 m to 21000 m of concentric rings, respectively, from the city centre and in the periphery of Durgapur Municipal Corporation. The very high and high of the mean Shimbel index have been found to be 6.85% within 8000 m to 15000 m and 10.19% within 12000 m to 20500 m of concentric rings from the city centre, and the moderate regions of the mean Shimbel index have been found to be minimum at 18500 m of concentric rings in the direction of NNE from the Durgapur city centre, whereas the low and very low regions have been found to be absent in the periphery region of Durgapur Municipal Corporation. In the direction of NNW, the very high, high, moderate, and low regions of the mean Shimbel index have been found to be 6.63% within 8500 m to 22500 m, 9.05% within 6000 m to 18500 m, 4.18% within 17,000 to 21500 m, and 5.67% within 18500 m to 23500 m of concentric rings, whereas very low regions have been found to be absent in the outskirts of Durgapur Municipal Corporation. In the direction of WNW of the city center, the high, moderate, low and very low regions of mean Shimbel index values have been found to be 1.41% within 6000 m to 16500 m, 6.73% within 7000 m to 18500 m, 4.47% within 8500 m to 19000 m and 0.70% within 15500 m to 17000 m in the concentric rings of the city centre and in the periphery of Durgapur Municipal Corporation, whereas the very high value has been found to be absent as well as in the direction of SSE, the

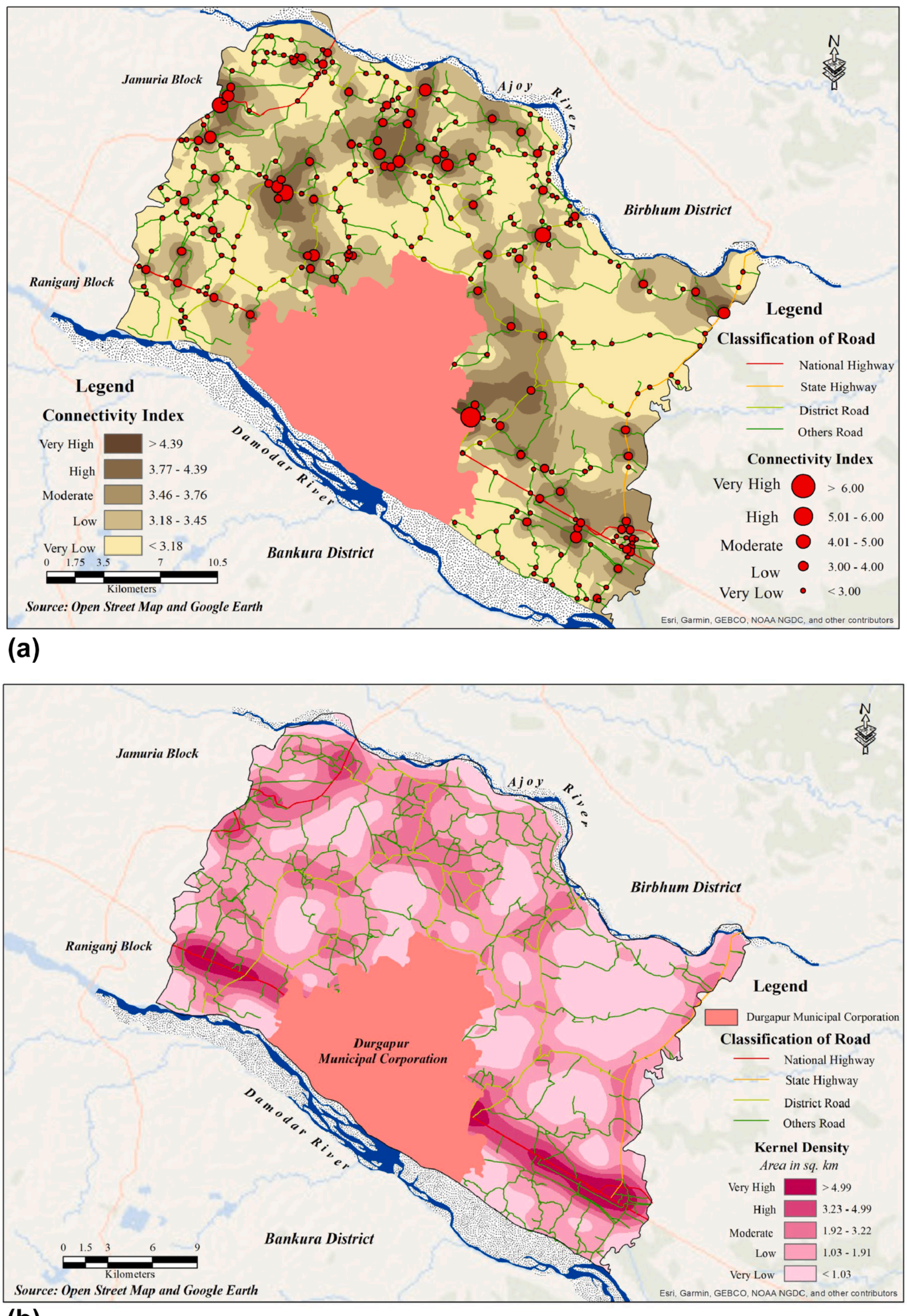


Fig. 4. (a) Connectivity Index in the study area. (b) Road Density in the study area.

mean value of the Shimbel index has been found only as a low region from 9500 m to 17500 m with a concentration of 1.95% of total area.

In order to determine the most accessible region in this study area, the Average Shortest Path Length (ASPL) was used. The most accessible zone can be found in the northern direction and near the DMC, as well as the middle of the study area, as the ASPL value is less than 0.0469, and it gradually decreases from the center to the outer area. In the farthest reaches of the Durgapur Municipal Corporation, the highest ASPL value was found to be 0.77 which indicates the lowest accessible region. The shimbel index also finds the nature of accessibility. The most accessible zone has been observed in the same location as ASPL which has been less than 4465 Shimbel index value and it has been gradually decreased as the Shimbel index value has been increased towards the outer area. These two indices were determined using the 309*309 matrix table, which counts the nodes along the shortest path between sources and destinations. The ASPL and Shimbel index have been shown to be high in the study area's central location because of the numerous connecting roads that connect various NH, state highways, district roads, and other roads (Weber, 2012). From the result of ASPL and SI, it shows that due to present of the interlinking road network, the middle part of the study area experiencing by the better accessibility zone. The phenomenon of higher network coverage has also been observed in the *peri*-urban regions of the English bazar Municipality in Malda district (Sarkar et al., 2020), the *peri*-urban interface of Burdwan City (Arif and Gupta, 2020), and the Thiruvanthapuram corporation of the Indian state of Kerala (Daniel et al., 2020).

4.4. Connectivity index (CI)

The connectivity index was investigated to determine how well one node is connected to another. According to the connectivity index (Fig. 4a), nearly 1.98% and 5.33% of the total area in the periphery of Durgapur Municipal Corporation have very high and high connectivity, respectively, and 18.41% of the total area has moderate connectivity, whereas the low and very low connectivity index have been found to be 37.68% and 35.60% of the total area. The very high, high, moderate, low, and very low categories of mean connectivity index are randomly spread across the peripheral zone of Durgapur Municipal Corporation, both in terms of direction and distance. Very high, high, moderate, low, and very low mean connectivity index regions have been found to be 0.20% within 13500 m to 22500 m, 0.45% within 9000 m to 21500 m, 3.69% within 7500 m to 22000 m, 6.74% within 5500 m to 25500 m, and 11.29% of area within 4500 m to 24500 m of concentric rings from the city centre and in the outskirt region of Durgapur Municipal Corporation at the direction of ENE. In the direction of ESE, very high regions of mean connectivity index were found at 0.34% within 5000 m to 16000 m of buffer rings, high and moderate regions of mean connectivity index were found at 0.57% within 6000 m to 18000 m and 6.07% within 6500 m to 20000 m of buffer rings, as well as low and very low regions of mean connectivity index were found at 8.85% within 7000 m to 21000 m and 4.04% within 7500 m to 19000 m of concentric rings in the peripheral regions of Durgapur Municipal Corporation. At the direction of NNE from the Durgapur city centre, the very high, high, moderate, low, and very low mean connectivity index regions have been found to be 0.31% within 13500 m to 18500 m, 0.38% within 13000 m to 19000 m, 3.27% within 10500 m to 20000 m, 5.43% within 9000 m to 20500 m, and 7.66% within 8000 m to 19500 m, respectively, of concentric rings in the periphery region of Durgapur Municipal Corporation; whereas at the direction of NNW, these sharing areas have been found to be 0.97% within 9000 m to 20500 m, 1.23% within 9500 m to 21500 m, 4.11% within 6500 m to 21000 m, 12.77% within 6000 to 23500 m, and 6.46% of area within 8500 m to 23500 m of concentric rings in the outskirts of DMC respectively. Only the very low region of the mean connectivity index has been identified to be 1.95% within 8500 m to 23500 m of buffer rings in the direction of SSE, whereas in the direction of WNW, the moderate, low, and very low regions of the mean connectivity index have been observed. These are 0.23% within 8500 m to 16500 m, 5.35% within 6000 m to 19000 m, and 7.72% within 8000 to 18500 m of Durgapur Municipal Corporation concentric rings.

The Connectivity Index displays how connected each node is to the others, as well as how many options there are for moving from one node to another. According to the connectivity index map, the western side exhibits stronger connectivity in comparison to the eastern side, and along NH-2, this has also been found to be high. The connectivity has been found to be at the junction points (Lee et al., 2020). The increased connectivity in the western and southern regions of the study area is attributed to the higher number of intersections with National Highways 60 and 2. These intersections provide a direct connection between the interior part of the region and the outside world, thereby promoting the flow of goods and people. This increased connectivity has further facilitated immigration and contributed to urban expansion and development. Previous researchers calculated the connectivity index based on the hypothetical scenario of the geo-centers of villages and their linked road network in India (Arif & Gupta, 2020; Daniel et al., 2020; Sarkar, 2013; Sarkar et al., 2020) as well as in other parts of the World (Fan & Gao, 2016; Gastner& Newman, 2006; Liu & Chen, 2018). However, this study utilizes the current state of the road network across the study area and its connections for measuring connectivity. This approach provides a more accurate representation of the present connectivity levels. The results of this study can help planners globally understand the existing connectivity and determine the future need for road network development to bridge the gap between urban and rural areas.

4.5. Kernel density estimation (KDE)

Kernel density was calculated using the road network to determine the density of the road network based on its priority. From the kernel density, it was determined that the very high region density of the road network was occupied by 4.16% of the whole area of the outskirts of DMC (Fig. 4b), while the high region was occupied by only 6.55% of the total area. The moderate zone accounts for 19.11% of the total periphery area, whereas the low and very low regions are disproportionately large. Both these areas account for 36.76% and 32.48% of the total area, respectively. The kernel density was also investigated in terms of direction and distance. Moderate, low, and very low regions of mean kernel density have been observed in the direction of ENE from the city centre, with 1.56% of the total surrounding area of Durgapur Municipal Corporation within 10000 m to 22500 m, 8.50% within 4500 m to 24500 m, and 12.31% within 5000 m to 25500 m of concentric rings. In the neighborhood of Durgapur Municipal Corporation, the very high, high, moderate, low, and very low regions of mean kernel density have been observed to be 1.01% within 6500 m to 19000 m, 3.39% within 7500 m to 20000 m, 5.08% within 6000 m to 20000 m, 6.93% within 5000 to 20500 m, and 3.49% within 5500 m to 21000 m in the ESE direction. In the direction of NNE from the city centre, the moderate, low, and very low regions have been found to be 3.18% within 11000 m to 18500 m, 9.74% within 8000 m to 19500 m, and 4.13% within 9500 m to 20500 m of buffer rings, whereas in the NNW direction, the high regions of mean kernel density have been observed to be 0.25% only within 18500 m to 19500 m. The moderate, low, and very low regions of mean kernel density have been found to be 8.27% within 7500 m to 21500 m, 10.69% within 6000 m to 22000 m, and 6.31% within 6000 m to 23500 m of concentric rings in the periphery region of Durgapur Municipal Corporation. In the SSE direction from the city centre, low and very low mean kernel density regions have been identified. These are 0.98% for the distance between 14,000 and 17000 m of concentric rings and 0.99% for the distance between 9500 and 17500 m. In the direction of WNW from the city centre, all the five classes of mean kernel density have been identified to be 0.37% within 12000 m to 15000 m, 1.76% within 8500 m to 16500 m, 3.32% within 6000 m to 17000 m, 5.21% within 7000 m to 17500 m, and 2.64% within 8500 m to 19000 m of concentric rings from the periphery of Durgapur Municipal

Corporation.

The study used kernel density with weighted values to reflect the priority and role of roads in the region. The density of roads was calculated based on their relative significance, ranging from national to regional levels. The results showed that the western side of the study region had a significantly higher density compared to the eastern side, due to the presence of National Highway 60, state highways, and district highways. This higher density was also attributed to the higher number and length of roads in the western portion. On the other hand, the eastern part of the region had a low density, despite the presence of state highways, district roads, and other roads, due to the limited number and length of roads in that area. This suggests that merely having state and district highways is not sufficient for higher density, as a higher availability of road numbers and lengths is also required (Gupta and Chatterjee, 2015). It used to study the distribution of different land uses in a city, such as residential, commercial, or industrial areas. This information can be used to guide land use policies and regulations, as well as to determine the distribution of resources and services in a city (Hu et al., 2016).

4.6. Shortest distance and travel time estimation (SDTTE)

In this study, the shortest distance and travel time estimation (SDTTE) method was used to identify most of the accessible regions based on journey time by car (Fig. 5). The lower the SDTTE score value indicates, the more accessible the region is from Durgapur Municipal Corporation's city centre and vice versa. According to the SDTTE, the very high and high accessible zones, which are closest to the city centre, account for 32.59% and 19.11% of the total area, respectively. The moderate, low, and very low regions comprise 16.27%, 20.30%, and 10.81% of the total peripheral area of Durgapur Municipal Corporation, respectively. The SDTTE was also analysed in terms of distance and direction. The very low, low, moderate, high, and very high regions of mean SDTTE in the direction of ENE from the city centre have been observed to be 5.06% within 15500 m to 25500 m, 47.35% within 12500 m to 20500 m, 5.43% within 8500 m to 16500 m, and 3.17% within 4500 m to 15000 m of Durgapur Municipal Corporation's periphery area respectively. The very low and low regions of mean SDTTE have been found to be absent in the direction of ESE from the city centre, whereas the moderate, high, and very high regions of mean SDTTE have been identified as 3.32% within 13000 m to 20500 m, 6.91% within 10500 m to 21000 m, and 9.64% within 5000 m to 16500 m of the concentric rings of Durgapur Municipal Corporation. The very low, low, and moderate regions have been determined to be 5.50% within 16000 m to 20500 m, 9.41% within 8000 m to 18000 m, and 2.13% within 8000 m to 14000 m in the direction of the NNE, whereas the high and very high regions were non-existent. The very low, low, moderate, high, and very high regions have been found to be 2.31% within 16500 m to 23500 m, 8.82% within 9500 m to 23500 m, 6.75% within 8500 m to 20000 m, 4.46% within 6000 m to 16500 m, and 3.19% of the total studied area within 6000 m to 22500 m of distance from the geo-center of Durgapur Municipal Corporation in the direction of NNW. The very low, low, and very high regions of mean SDTTE have been found to be absent in the direction of SSE from the city centre, whereas the moderate and high values have been found to be minimum within 16500 m to 17500 m and 9500 m to 16500 m in the Durgapur Municipal Corporation's surroundings. The moderate, high, and very high regions have been found to be 0.89% within 15000 m to 19000 m, 3.68% within 9500 m to 18500 m, and 8.73% within 6000 m to 17000 m in the direction of WNW from the city centre, whereas the very low and low regions of mean SDTTE have been found to be absent in the periphery of Durgapur.

The results of the study indicate a higher accessibility in terms of shortest distance and travel time to the city center. The city center was found to be highly accessible due to the presence of the National Highway (NH-2), which also connects to other state and district highways. The travel time from the city center to the village geo-center was found to be less than 0.24 h. The next region, which encompasses a very

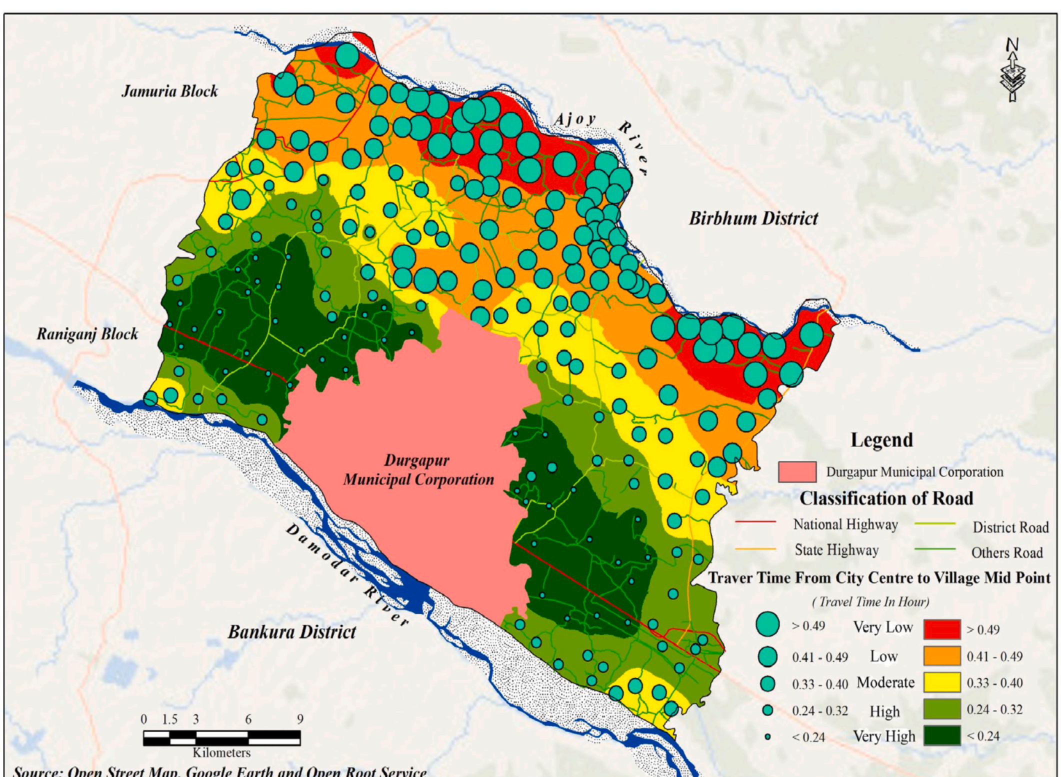


Fig. 5. Shortest distance and travel time estimation.

high-accessible zone in terms of travel time, was found to be less than 0.32 h but more than 0.24 h. The connectivity and the presence of higher importance roads and their accessibility with length and number are crucial factors in reducing travel time. Furthermore, the study found that the travel time from the very high-accessible zone to the city's outermost area had increased. In contrast, the low travel time zone was found also to be adjacent to the city center, where interlinking road connectivity was limited. The study highlights Shorter distances between destinations increase accessibility and reduce travel time where interlinking roads were available, leading to a more livable and sustainable urban environment. That's why urbanization process or growth of built-up area took place across the study area where it found.

4.7. Built-up expansion intensity index (BEII)

The output value of BEII has been classified into five categories to interpret properly for the time-period 2001–2011 and 2011–2021 i.e., very low expansion intensity index (less than0.50), low expansion intensity index (0.50–1.00), moderate intensity index (1.01–1.50), high expansion intensity index (1.51–2.00), and very high expansion intensity index (greater than2.00) respectively (Fig. 6a and 6b). The mean BEII has been found to be during 2011–2021, 0.28% per year whereas in the time-period of 2001–2011 it has been observed to be 0.54% in respect of total study area. The BEII was comparatively high during 2001–2011 than the very recent year. In the direction of ENE, the mean BEII has been observed 0.24% and 0.03% per year during 2001–2011 and 2011–2021. In the direction of ESE and NNE, the mean value has been observed to be 0.72% and 0.11% per year in first time period whereas during 2011–2021, it has been observed to be 0.23% and 0.05% per year. In the direction of NNW, SSE and WNW the mean built-up expansion intensity index has been observed to be 0.96%, 0.66% and 0.64% per year whereas afterwards it has been found to be 0.21%, 0.72% and 1.11% per year during 2011–2021 respectively in the periphery region of DMC (Table 5). From the result of BEII, it has been observed that the maximum area in all the direction faces low to very low expansion intensity rate in both time frames. In the years 2001 to 2011, expansion rates in the WNW and NNW directions of the study area's western side after the distance of 8500 m from the boundary of Durgapur municipal corporation and in the SSE and ESE directions of the study area's eastern side from very close of the municipal corporate boundary to 8000 m. the expansion rates have been found to be high to very high. During 2011–2021, the high to very high expansion rate has been observed in the direction of WNW of western side up to boundary of study area from the DMC and ESE and SSE direction of eastern side up to 9000 m from very close of boundary line of DMC. From the above result it has been found that the expansion rate was high in 2001–2011 compared to 2011–2021. In first time frame the expansion was found in the surroundings regions of NH60 and afterwards this has been shifted towards the NH-2.

4.8. Built-up density

Built-up Density is an important metric for determining the amount of built-up in a particular region. The built-up density was measured using the above equation and on the basis of distance from the city center, direction from the city center, and village wise to demonstrate the density precisely (Fig. 7a, 7b and 7c). The built-up density has been classified into five categories for interpreting. This ranges from less than 0.05 km^2 (very low density), 0.5 to 0.15 km^2 (low density), 0.15 to 0.25 km^2 (moderate density), 0.25 to 0.35 km^2 (high density) and greater than 0.35 (very high density). At the direction of ENE, the average density has been observed 0.020 sq. /km in 2001 and the highest density has been observed at the distance of 16500 m from city center which was 0.14 km^2 whereas in this direction 19.58% and 2.86% of total periphery area have been experienced by very low and low density. In 2011, the average density has been increased by 0.044 km^2 and the highest density has been observed at the distance of 19000 m from the city center in the direction of ENE. Maximum area in this direction faces low to very low density about in 21.46% of total area in the periphery region of DMC and afterwards in 2021, the average density has been increased and the area of moderate and low-density region have found to be increased compared to others classes. In the direction of ESE, the average built-up density has been found to increase from 0.13 km^2, 0.21 km^2 and 0.23 km^2 in 2001, 2011 and 2021 while the highest density has been located at the distance of 17500 m (0.64 km^2) in 2001, 9000 m (0.89 km^2) in 2011 and also 9000 m which was 0.93 km^2 in 2021 respectively. In this direction, the very high-density region has been increased whereas the very low-density region has been decreased continuously within this time frame. In the direction of NNE, the average density has been observed to be 0.04 km^2 in 2001, 0.05 km^2 in 2011 and 0.06 km^2 in 2021 while the highest density has been observed to be 0.78 km^2 during 2001, 2011 and 2021 at the distance of 18000 m from the city center. In the direction of NNW, the average density has been observed to be increased continuously which were 0.13 km^2 in 2001, 0.22 km^2 in 2011 and 0.24 km^2 in 2021 while the highest density has been observed to be 0.74 km^2 at the distance of 14500 m and 0.92 km^2 in at the same distance. The average density has been found to be increased from 0.29 km^2 in 2001 to 0.36 km^2 in 2011 and 0.43 km^2 in 2021 respectively while the

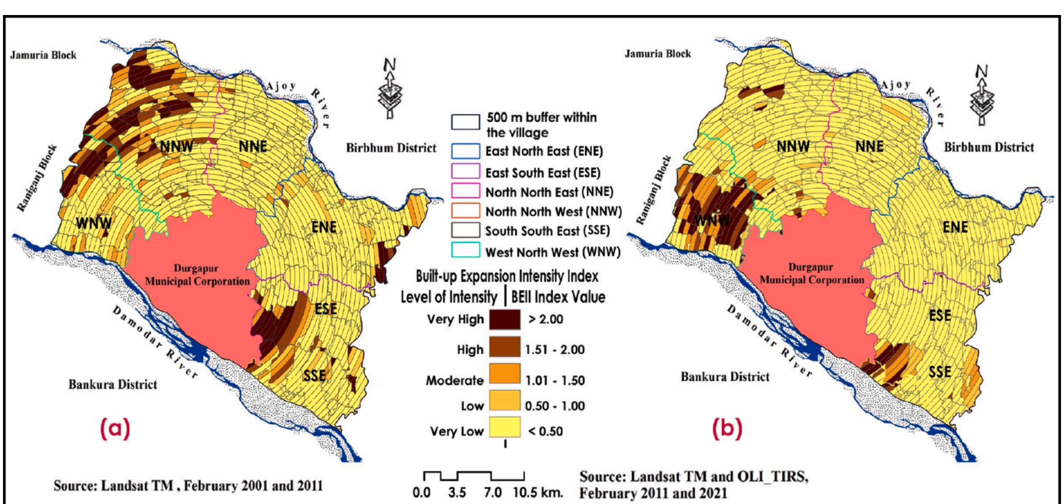


Fig. 6. Built-up Expansion Intensity Index [BEII] in the *peri*-urban and rural neighborhood of DMC during **[a]** 2001 – 2011 and **[b]** 2011 – 2021.

Table 5
Built-up Expansion Intensity Index (BEII).

Built-up Expansion Intensity Index [BEII]	ENE		ESE		NNE		NNW		SSE		WNW	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2001 – 2011	0.24	0.63	0.72	1.43	0.11	0.33	0.96	1.51	0.66	2.06	0.64	1.09
2011–2021	0.03	0.11	0.23	0.56	0.05	0.21	0.21	0.62	0.72	1.23	1.11	1.40

Source: Computed by the authors.

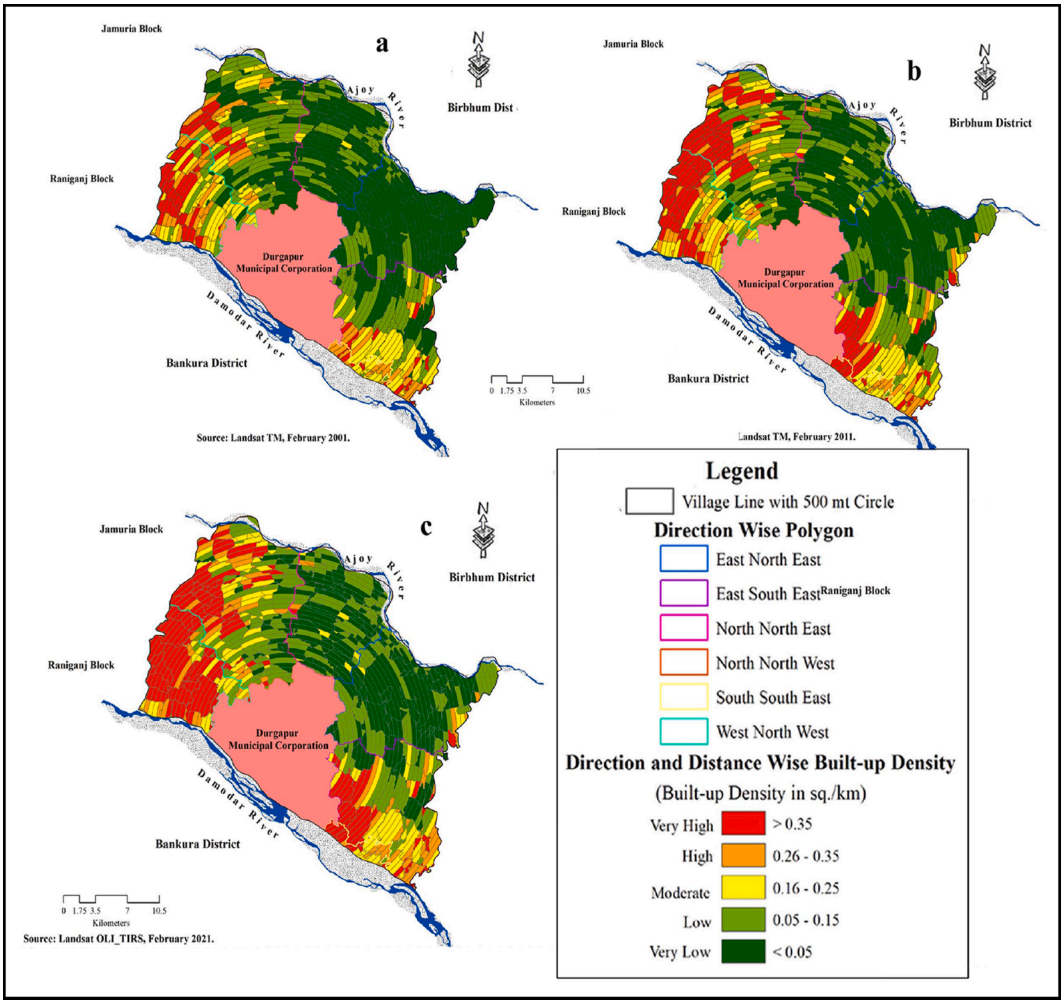


Fig. 7. Built-up Density in the *peri*-urban and rural neighborhood of DMC during **[a]** 2001, **[b]** 2011 and **[c]** 2021.

highest density has been observed at the distance of 17500 m in 2001 and 2011 and 13000 m respectively in direction of SSE. In 2001, 2011 and 2021, the average density has been observed to be 0.29 km^2, 0.36 km^2 and 0.47 km^2 in the direction of WNW while the highest density has been observed to be 0.91 km^2 at the distance of 9500 m in 2001 and 2011 and 0.96 km^2 at the distance of 15500 m in the outskirt of Durgapur municipal corporation. The area of very high-density region has been found to be continuously increased which were 4.21%, 5.97% and 9.77% of total peripheral area whereas the area of very low region has been found to be decreased continuously within this time frame.

4.9. Relationship analysis between Built-up density and road density

The GWR model has been developed considering the built-up density and kernel density of the road network (Fig. 8a-8i) in Arc-GIS platform. The built-up density from the last three decades i.e., 2001, 2011, and 2021, has been used based on census data (Census of India) in this study to assess whether there is a strong or weak association. According to the model's output, the local R^2 and adjusted R^2 values in 2001 these were found to 0.78 and 0.71 and recorded to be 0.81 and 0.74 in 2011; however, it seems that they are 0.83 and 0.77 in 2021. An increasing R-squared value over time can be a sign that the association between the two variables is getting stronger. Because of this, the road density in relation to their importance is one of the more encouraging factors for the spread of built-up areas over the research region. A clearer picture of the development of road arteries through time can be seen in the rising r-square values, which also enhanced opportunities for built-up extension in the *peri*-urban area and connected the rural neighborhood. Generally speaking, we are aware that increased connectivity between locations through the use of road arteries facilitates economic growth.

The standard residual for built-up density were mapped individually for the mentioned year. The highest standard residual value which is more than 2.5 indicate the observed built-up density is greater than the predicted frequency has been observed minimum area in 2001 at direction of WNW, NNW, SSE and ESE respectively. In 2011, the highest standard residual value has been observed at the direction of NNW, ENE

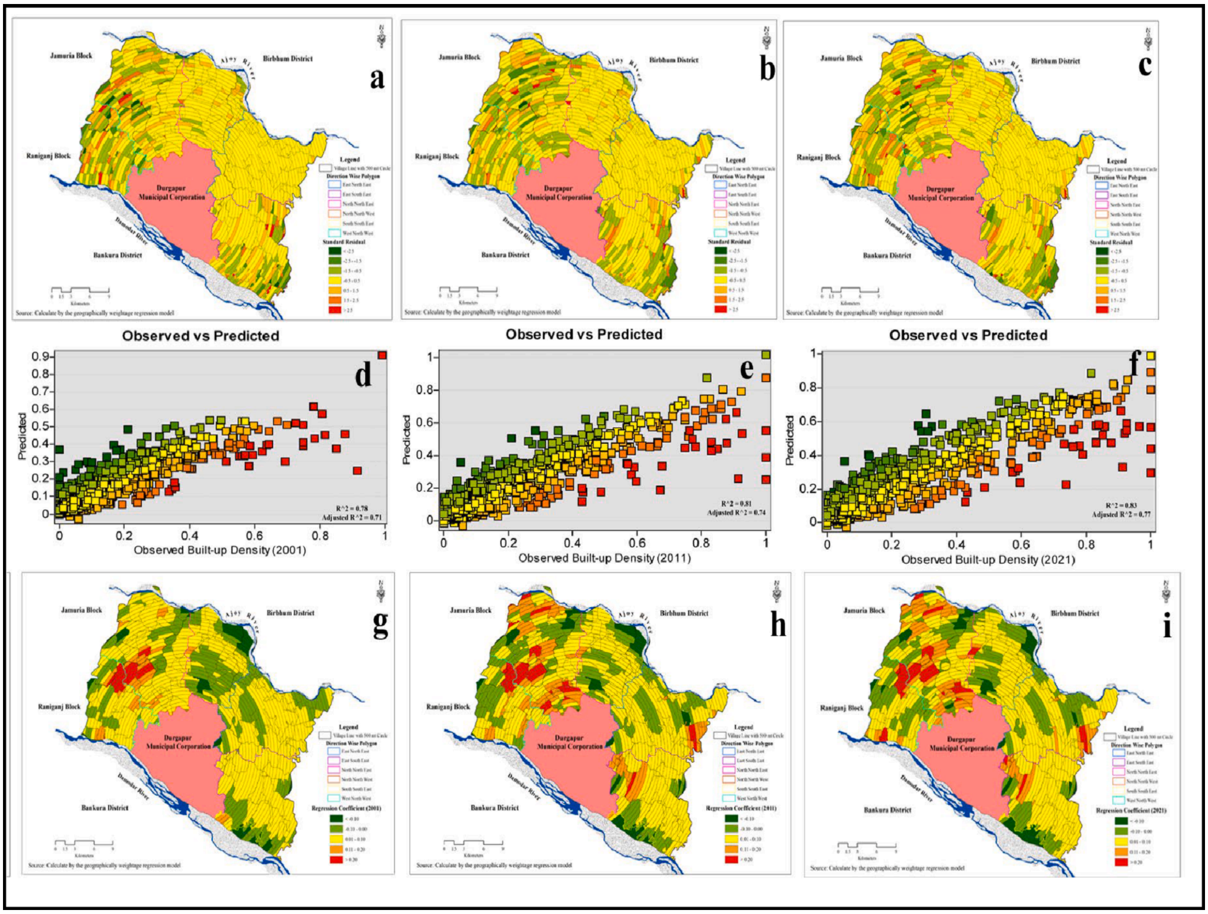


Fig. 8. Standard residual mapping in the *peri*-urban and rural neighborhood of DMC during **[a]** 2001, **[b]** 2011 and **[c]** 2021, Predicted and Observed built-up density in the *peri*-urban and rural neighborhood of DMC during **[d]** 2001, **[e]** 2011 and **[f]** 2021, Regression coefficient mapping of GWR in the *peri*-urban and rural neighborhood of DMC during **[g]** 2001, **[h]** 2011 and **[i]** 2021.

and ESE while in 2021, about the same characteristics has been observed. The lowest standard residual value which is −2.5 indicates the observed built-up density is less than the expected frequency (Brunsdon et al., 1999). In 2001, it has been observed in the direction of WNW, NNW and ESE. In 2011, it has been found in WNW and NNW direction while the about the same standard residual character has been observed. The scatter plot of observed frequency and expected frequency is more linear in 2011 and 2021. In 2011, the regression coefficient area has been increased which has been observed at the direction of WNW, NNW, ENE and NNE. In 2021, the coefficient of kernel density has been again increased and it has been observed at the all the direction in this outskirt of Durgapur Municipal Corporation without SSE direction. Both the positive and the negative coefficient values increase during the intervening period whereas the increased rate of coefficient value is high. The higher coefficient value of kernel density indicates that the when the road density increased the mean of built-up density also tends to increased (Xu and Ouyang, 2017). Thus, it can be observed from the foregoing explanation that the goodness of fit of the GWR model increases progressively and that there is a strong correlation between road density and built-up density. Near the road, the built-up area has a stronger tendency to expand in the periphery region of Durgapur Municipal Corporation (Song et al., 2020).

In 2001, the maximum built-up area has been spread over towards the NNE while in 2011 and 2021 the% of built-up area has been remarkably increased towards the upward direction. In Ondal and Pandabeswar blocks and along the NH-2 have the highest% growth have been observed due to presence of railway station, important district road, NH-60 etc. Built-up density also increased from 2001 to 2021 due to built-up growth in outskirt of Durgapur Municipal Corporation (Gupta and Chatterjee, 2015; Buchori et al., 2020; Banzhaf et al., 2009; Shaw and Das, 2018). The maximum area of DMC's *peri*-urban region has very low BEII score during 2001 to 2021. In the first time period, the region along the NH-2 and near the NH60 has been experienced high and very built-up expansion intensity whereas in the second time-period, the highest BEII has been shifted towards the northern direction surroundings of NH-60 and along the boundary line of DMC at the eastern direction and afterwards in third time period, the highest expansion intensity has been again along the WNW and smallest area of SSE as well as ESE direction. Along the NH-60 and NH-2 the maximum BEII value has been observed during 2011 to 2021. The result of regression revels that the built-up density and kernel density both are very much interrelated because of any region's economic development is triggered by strong infrastructure and transportation links (Nong et al., 2018).

5. Conclusion

This study has identified the characteristics of the built-up area, road network, and their relationship in the study region. The Connectivity Index, Shimbel Index, Average Shortest Path Length, Shortest Distance and Travel Time Estimation, as well as road density assessed using kernel density by weightage approach in accordance with road importance, have all been used to measure accessibility. On the other hand, built-up expansion intensity index and built-up density have been examined to demonstrate the characteristics of built-up areas. The association between the road network and built-up area was then observed using a Geographically Weighted Regression (GWR) model that used kernel density and built-up density.

Due to the presence of numerous linking roads, the centre of the study area was where the average shortest path length and shimbel index value were determined to be highest. The intersections of roads where one or more connecting roads come together from various directions have been determined to have the highest values of the connectivity index. Due to the well-developed road network, the shortest distance and travel time estimation were found to be highest along the NH-2, while the highest values of kernel density were found to be along the NH-2 and some of the NH-60. Based on an analysis of built-up density from 2001 to 2021, it was discovered that between 2001 and 2011, the NH-2 experienced the highest built-up growth, which then spread to other roads in the north. Built-up density was also high during this initial time period and later spread and along with the built-up growth. The road network has been identified as one of the critical determinants for the growth of built-up areas by the Geographically Weighted Regression model, it has been analysed.To ensure a smooth transition, the ADDA or local governments should prepare and put into action a plan. The findings of this study could help regional planners assess the current state of active transportation options and pinpoint areas that need more attention to make them more accessible when allocating new urban facilities or reallocating those that are already there to lessen the negative effects that individual motorized transportation has on urban mobility.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors thank the United States Geological Survey (USGS) for making available Landsat 5, and Landsat 8 satellite images which were downloaded from the Earth Explorer for this study. The authors also sincerely wish to thank the learned reviewers for their valuable comment which have greatly enhanced the paper.

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