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Article

GIS-Based Assessment of Public Transport Accessibility and Spatial Inequalities in Chennai

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Abstract: The Global South is affected by increasing urbanization and vehicular density, creating significant challenges in urban mobility and public transport accessibility. Chennai, one of the major metropolitan cities of India, serves more than 3.2 million (32.24 lakh) passengers daily and is under increasing pressure to provide equitable and sustainable public transport services to its residents. This study proposes a framework to assess public transport accessibility and spatial inequality using a Geographic Information System (GIS).

Public transport data were obtained from the General Transit Feed Specification (GTFS), road network data were obtained from OpenStreetMap (OSM), and demographic data were obtained from the Census of India. The study further assesses public transport accessibility through ward-level spatial analysis. The distance from bus stops to residential areas was determined using 400 m and 800 m walking-distance buffers.

The findings suggest a significant improvement in accessibility, as indicated by ward-level bus stop coverage, which increased from 78.12% within a 400 m walking distance to 96.09% within an 800 m walking distance. However, some peripheral wards still show significantly lower accessibility, indicating spatial inequalities in public transport provision. The proposed GIS framework provides a low-cost, scalable decision-support tool for route rationalization, accessibility assessment, and evidence-based planning to support more sustainable and equitable urban mobility.

Keywords: Public Transport Accessibility, Geographic Information System (GIS), Bus Stop Accessibility, Walking Buffer Analysis, OpenStreetMap (OSM), General Transit Feed Specification (GTFS), Spatial Inequality, Chennai Metropolitan Area.

1. INTRODUCTION

Contemporary urban growth has never been greater and is changing mobility patterns worldwide. Owing to current global development trends, the world is becoming increasingly urban. In fact, it is expected that by 2050, nearly 68% of the global population will be living in urban areas. This rapid urban growth places tremendous pressure on existing transportation networks.

Furthermore, travel demand often outstrips the development of transport infrastructure in the Global South. In these cities, frequent traffic congestion causes more than just inconvenience. Traffic congestion results in annual economic losses of billions of dollars while increasing greenhouse gas emissions and noise pollution.

According to researchers, mobility plays a vital role in a country's economic development, and efficient public transport is essential for sustainable growth. In urban areas, efficient public transport systems reduce travel time, improve workforce productivity, and enhance the quality of life. The Smart City approach was introduced to address these challenges by integrating urban development with Smart Mobility (SM). By using modern Information and

Communication Technologies (ICT), Smart Mobility transforms conventional transportation into connected and sustainable systems that improve accessibility while reducing environmental impacts.

In the past, transportation planning relied heavily on labour-intensive travel surveys and household travel diaries. These methods are often static, expensive, and provide representations of travel behaviour that are subject to sampling bias. The emergence of Geographic Information Systems (GIS) and big data has transformed transportation planning by providing spatial context for route optimization and infrastructure planning.The use of structured datasets, such as GTFS for public transport information and OpenStreetMap (OSM) for road networks, enables planners to conduct rigorous quantitative assessments of accessibility. For cities in the Global South, implementing proprietary sensor-based systems is often expensive, whereas open-source data integration provides a cost-effective alternative.

Chennai is one of the largest metropolitan cities in India and serves more than 3.2 million (32.24 lakh) passengers daily through one of the country's largest urban public transport networks operated by the Metropolitan Transport Corporation (MTC). The city, with a multimodal transport system comprising 3,407 buses, Metro Rail, and Suburban Rail, faces various operational challenges. Studies reveal that government departments have never updated the digital maps of exact routes but have marked them only as stage stoppings. Research by groups such as the Citizen Consumer and Civic Action Group (CAG) shows that commuters often face glitches in official transit tracking apps due to GPS errors and outdated data, along with an ‘accountability gap’ in fleets.

Although past studies have evaluated public transport accessibility, most limit it to the city level. Few if any consider ward-level accessibility disparity. Furthermore, there has yet to be a comparative assessment for Chennai using more than one walking distance threshold. To overcome these limitations, this paper presents a GIS-based framework to assess the ward-level accessibility in the Chennai Metropolitan Area. The study integrates bus stop locations from GTFS with ward boundaries, OpenStreetMap, and Census information on one GIS platform. The walking-distance buffer analysis applied 400 m and 800 m service areas, to determine the extent of each ward covered by existing bus stops.

The study showed that the average coverage of bus stops at the ward level improved from 78.12 percent within a 400 m walking distance to 96.09 percent within an 800 m walking distance. Even though almost all the wards met 800 m accessibility with high coverage, some peripheral wards continued to show lower coverage in comparison with others.

This research contributes a GIS-based method that is practical, scalable, and cost-effective. The suggested framework can help transportation planners and policymakers identify as-yet-underserved areas, improve the deployment of resources, and promote transport justice within a climate-resilient and just multimodal system.

2. RELATED WORK

A. GIS-Based Public Transport Accessibility Assessment

Accessibility is a measure of how easy it is to get to destinations or to engage in activities that are spatially distributed. Urban transport planning plays a vital role in modern cities because it determines mobility, economic opportunities, and social fairness. Historically, travel demand assessments were based on costly, manual, static household diaries and travel surveys, which were subject to sampling bias. Nevertheless, the smart city framework emphasizes Smart Mobility (SM), using ICT to convert traditional vehicle technology into appropriately sustainable technology in a smart network. The use of Geographic Information Systems (GIS) to assess accessibility through spatial analysis has been widely adopted in both research and practice, as this allows planners to identify service gaps and facilitates evidence-based decision-making. With increasing use, Big Data is not only being combined with network analysis and demographic data but also being used to assess transport equity more comprehensively.

B. GTFS and OpenStreetMap for Accessibility Analysis

Since 2005, the GTFS, which stands for General Transit Feed Specification, has transformed accessibility analysis by providing standard, machine-readable information for use across networks regarding route details, stop locations, service frequencies, etc. Researchers use GTFS to evaluate the accessibility of transit services using real-world operational features. GTFS's integration with OpenStreetMap (OSM), a collaborative open-data effort providing routable road and pedestrian networks, enables better representation of pedestrian connectivity to transit stops. This combination offers a very low-cost framework, which is critical for Global South cities, where proprietary monitoring systems (AVL-APC) can cost $2.5 million for a mid-sized fleet. Utilizing open-source datasets promotes replicability and scalability, enabling the adaptation of methodologies across various urban regions with minimal implementation effort.

C. Walking-Distance Buffer Analysis and Spatial Inequality

Maximum walking distance is one of the most accepted indicators for studying transit access. Past studies have typically adopted 400 m and 800 m thresholds to correspond to comfortable and longer walking catchments respectively. A 400 m buffer represents a comfortable walk of about 5 minutes, while an 800 m buffer corresponds to a distance considered significantly farther. Unlike Euclidean buffers derived from a map, network-based assessment using OSM provides a better estimate of distance actually covered by pedestrians. Studies frequently highlight that the distribution of transit services is uneven, leading to a core–periphery accessibility gradient, whereby places in the centre have high service density while places in the periphery have low density of services. To achieve "Transport Justice," identification of these disparities is critical to eliminatee "transportation deserts"—regions where demand exceeds supply, caused by population growth or distribution.

TABLE 1: COMPARISON OF PREVIOUS STUDIES AND THE PROPOSED RESEARCH

Reference	**Study Area**	**Data Used**	**Method**	**Limitation**
Williams et al. (2015)	Nairobi	GTFS/Open Data	GIS-based Accessibility Mapping	Did not evaluate transport equity at the local administrative level.
Martens (2017)	Conceptual Framework	Transport Planning Data	Transport Justice Framework	Conceptual study without GIS-based spatial analysis.
Recent GTFS Studies	Multiple Cities	GTFS + OSM	GIS Accessibility Assessment	Limited application in cities of the Global South and limited ward-level analysis.
Proposed Study	Chennai, India	GTFS + OSM + Census Data + Ward Boundaries	GIS-Based Buffer Analysis (400 m & 800 m)	Addresses ward-level accessibility assessment and spatial inequalities.

D. Research Gap

Despite advancements in GIS-based evaluation, several critical limitations remain in the existing literature:

- Scale and Resolution: The majority of research focuses on corridor or city-level accessibility. There is little empirical work examining spatial inequality at the ward level, the unit of allocation for local resources.
- Comparative Buffer Analysis: Though the standard indicators 400 m and 800 m buffers have measured walking friction, a comparative analysis using both thresholds together to delineate this friction has not yet been conducted for major Indian cities like Chennai.
- Economic Barriers in the Global South: In resource-poor settings, the high cost of proprietary monitoring systems hinders assessments at the ward level, making the use of passively generated open data (GTFS/OSM) in a validated, low-cost framework especially valuable.
- The Accountability Gap: In many cases, planned schedules do not match real-world operations, so assumptions built into standard models may not hold. Chennai's Citizen Consumer and Civic Action Group (CAG) has found that official transit apps fail because of GPS inaccuracies and outdated information, thus creating a significant accountability gap. Most accessibility models do not account for these operational realities when identifying underserved regions.

E. *The Proposed Study*

To overcome these limitations, the present study develops a three-layer GIS-based model to evaluate bus stop accessibility at the ward level across the CMA. This study conducts a spatial analysis on a single platform, integrating heterogeneous datasets such as GTFS for transit supply, OpenStreetMap (OSM) for routable pedestrian networks, and Census data for demographic demand. Using 400 m and 800 m network-based buffers, accessibility is quantitatively assessed to detect spatial inequities and possible "public transport deserts." The Accessibility Atlas will help planning authorities such as CUMTA and MTC to adopt evidence-based route rationalization as a decision-support tool to promote transport justice.

3. STUDY AREA AND DATA SOURCES

A. *Study Area: Chennai Metropolitan Area (CMA)*

Chennai, the Tamil Nadu state capital, is one of the largest cities in India and South India's major economic, industrial, educational, and cultural centre. The area under the CMA (Chennai Metropolitan Area) is 1189 km². The population of this city is above 8 million. As a consequence of urbanization, population growth, and increasing demand for travel, the traffic of the city has come under considerable strain, leading to congestion and increased dependence on public and private transport.

The Metropolitan Transport Corporation (MTC) operates the public transport system of Chennai. The MTC bus system has been effective; its services are used by 3.2 million (32.24 lakh) people daily at present. The MTC runs about 3,407 buses that are integrated with the Chennai Metro Rail and Suburban Rail systems to provide multimodal connectivity in the city. The connective network is voluminous, but while public transport may be widely available in the main urban areas—which have benefited from extensive development—it may not be as accessible in the swiftly growing outlying areas.

The Chennai Metropolitan Area, which is also the administrative unit of the study, is divided into 201 wards, a suitable spatial unit for ward-level accessibility assessment. Bus stop density and public transport accessibility are often higher in the central wards. However, various peripheral wards show comparatively lower service coverage as a result of urban sprawl and uneven transport infrastructure development. These differences in accessibility indicate the importance of systematic accessibility assessment to ensure equity in public transport planning. Chennai was chosen as the study area due to its characteristic features as a rapidly growing metropolitan city with diverse land use, varied population density, and an extensive public transport system. Due to these qualities, the city serves as an ideal case study for assessing public transport accessibility at the ward level using GIS-based approaches. The results of the study are useful to transportation planners and policymakers in identifying underserved areas and improving service coverage.

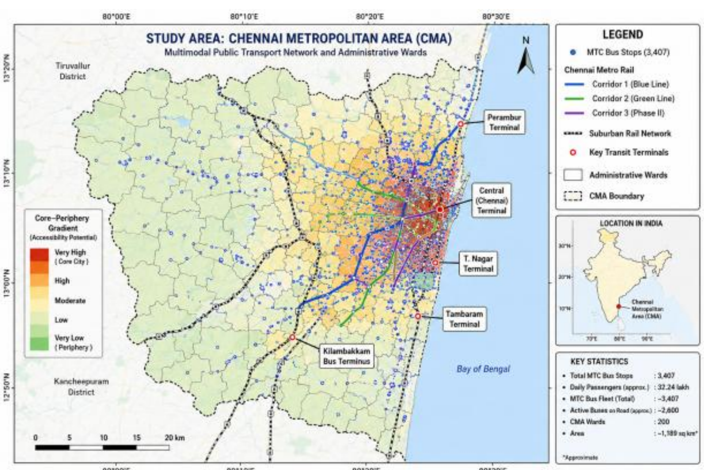

Fig 1. Study area map of the Chennai Metropolitan Area (CMA)

Figure 1. Study area map of the Chennai Metropolitan Area (CMA) showing administrative ward boundaries, MTC bus stops, Chennai Metro Rail corridors, Suburban Rail networks, and major transit terminals. The figure illustrates the core–periphery accessibility gradient that forms the basis of the subsequent accessibility analysis.

B. Data Sources and Preprocessing

Using GIS techniques, this study evaluates the accessibility of public transport in the Chennai Metropolitan Area at the ward level, integrating multiple spatial datasets. The evaluation takes into account the locations of bus stops, administrative ward boundaries, road network data, and demographic data to analyze the spread of public transport services. All datasets were imported into the QGIS environment, where they were processed and standardized for spatial analysis.

C. Bus Stop Data (GTFS)

The bus stop locations were sourced from the GTFS dataset provided by the Metropolitan Transport Corporation (MTC), Chennai. The relevant information relating to all bus stops in the study area was obtained from stops.txt. This point-feature dataset served as the primary dataset used in the creation of accessibility buffers and assessment of bus stop coverage.

D. Administrative Boundary Data

The Greater Chennai Corporation (GCC) supplied polygons for the ward boundaries of the Chennai Metropolitan Area. The analysis covered 201 administrative wards. These served as the spatial units for the study to calculate ward-level accessibility and compare variations in public transport coverage.

E. Road Network Data

Road network information was obtained from OpenStreetMap (OSM). It served as a reference layer for preparing the map and visualizing the transport network of the study area.

F. Demographic Data

Data from the Census of India was collected at the ward level to provide further information on the population distribution across Chennai, which was used to interpret the spatial accessibility results and analyze the differences in public transport service coverage among wards.

G. Data Preprocessing

All datasets were reviewed for completeness and consistency prior to running the spatial analysis. Duplicate records, invalid geometries, and attribute inconsistencies were detected and corrected. All data were projected to WGS 84 / UTM Zone 44N (EPSG:32644), ensuring consistent spatial representation across the datasets. This projected coordinate system utilizes meters as the measurement unit and was employed to create accurate 400 m and 800 m walking-distance buffers and calculate ward-level coverage areas.

TABLE 2. DATA SOURCES USED IN THE STUDY

Dataset	Source	Purpose
Ward Boundaries	Greater Chennai Corporation (GCC)	Ward-level spatial analysis
Bus Stop Locations	Metropolitan Transport Corporation (MTC) GTFS	Public transport accessibility assessment
Road Network	OpenStreetMap (OSM)	Spatial reference and map preparation
Population Data	Census of India	Demographic analysis and ward information

4. METHODOLOGY

A. Overall Research Framework

This research uses a Geographic Information System (GIS)-based framework to examine public transport accessibility at the ward level in the Chennai Metropolitan Area. The methodology comprises five steps: (i) data collection, (ii) data preprocessing, (iii) buffer creation, (iv) accessibility assessment at the ward level, and (v) analysis.

The bus stop locations from GTFS were overlaid with administrative ward boundaries and OSM data using QGIS. To assess accessibility, service areas of 400 m and 800 m walking distances were generated around bus stops. The coverage areas obtained were intersected with ward polygons to obtain accessibility percentages for each ward. Finally, descriptive statistical analysis was carried out to compare both walking-distance thresholds.

Fig 2. Overall Research Methodology

B. Data Preparation

The requisite spatial datasets, such as GTFS bus stop locations, ward boundary polygons, road network data from OpenStreetMap (OSM), and Census data, were imported into QGIS. Before analysis, all datasets were checked for completeness, duplicates, and invalid geometries. All datasets were converted to the WGS 84 / UTM Zone 44N (EPSG:32644) projected coordinate reference system for spatial analysis. This projection is in meters and is suitable for calculating walking-distance buffers and area-based accessibility measures in Chennai.

C. Bus Stop Buffer Generation

The accessibility of bus stops was evaluated using the commonly used walking-distance thresholds for accessibility studies in public transport: 400 m and 800 m. The Buffer tool in QGIS was applied to all bus stops to create service areas representing maximum walking distance to reach bus stops. To ensure that intersecting accessibility zones are not counted multiple times, the individual buffers were merged using the Dissolve operation. This produced a single, continuous accessibility layer for the 400 m and 800 m service areas, representing the spatial coverage of the existing bus stop network across the Chennai Metropolitan Area.

D. Ward-Level Accessibility Assessment

To determine accessibility at the ward level, the dissolved buffer layers were overlaid on the administrative ward boundaries using the Intersection tool in QGIS. The overlapping segments of the polygons represent the bus stop service area covered by each ward. The area of the intersected polygons was calculated using the Field Calculator. The total area of each ward was obtained from the ward boundary data.

$$\text{Coverage}(\%) = \left(\frac{\text{Area Covered by Buffer}}{\text{Total Ward Area}}\right) \times 100 \qquad (1)$$

where:

Area Covered by Buffer represents the area of a ward falling within the 400 m or 800 m service area,

Total Ward Area represents the total geographic area of the ward.

The accessibility percentages calculated were added as new attribute fields (coverage_400 for 400 m and coverage_800 for 800 m), which were used to prepare thematic maps showing ward-level accessibility patterns.

E. Statistical Analysis

A statistical analysis was performed to summarize the spatial accessibility results for both walking-distance thresholds. The accessibility percentages of all 201 wards were presented through the statistical indicators of minimum, maximum, mean, median, standard deviation, and IQR.

The statistical comparison of the 400 m and 800 m service areas allowed us to evaluate the extent to which increasing walking distance improves accessibility. Through this quantitative evidence, spatial variations in public transport coverage were identified, allowing for the identification of wards with comparatively lower accessibility.

F. GIS Workflow

The entire GIS workflow applied in this research is summarized below.

- ✧ Data collection from GTFS bus stops, ward boundaries, road networks, and census data.
- ✧ Cleaning and verifying data, and transforming the coordinate system to EPSG 32644.
- ✧ Creation of 400 m and 800 m bus stop buffers.
- ✧ Merging intersecting buffer areas.
- ✧ Intersection of dissolved buffers with ward polygons.
- ✧ Covered area and total ward area calculation.
- ✧ Computation of ward-level accessibility percentages.
- ✧ Preparation of thematic maps and descriptive statistical analysis.

TABLE 3. GIS OPERATIONS USED IN THE STUDY

GIS Operation	**Purpose**
Buffer	Generate 400 m and 800 m walking-distance service areas around bus stops
Dissolve	Merge overlapping buffer polygons into continuous service areas
Intersection	Identify buffer-covered areas within each administrative ward
Field Calculator	Calculate covered area, ward area, and accessibility percentage
Statistics	Compute descriptive statistics for accessibility assessment

5. RESULTS AND DISCUSSION

A. Ward-wise Bus Stop Distribution

The analysis of the bus stop distribution across the Chennai Metropolitan Area is shown in Figure 3. The map shows that the distribution of bus stops is uneven across the wards. The density of bus stops is generally higher in the central and intermediate wards. In contrast, several peripheral wards show lower densities of bus stops. This spatial configuration implies that a greater density of public transport infrastructural development exists in the older urban areas, and less in the outer wards.

The uneven distribution of bus stops has created significant accessibility inequalities across wards. It is expected that residents living in wards with higher bus stop density would have shorter distances to public transport. On the contrary, those in wards with lower bus stop densities may have less accessible bus services, resulting in spatial inequalities in accessibility to public transport.

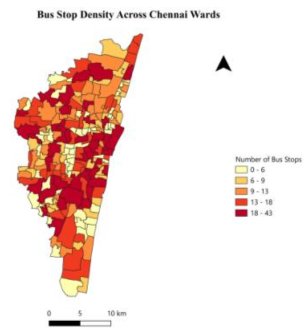

Fig 3. Ward-wise Bus Stop Distribution in Chennai.

B. Ward-wise 400 m Bus Stop Coverage

Figure 4 illustrates the ward-wise bus stop coverage within a 400 m walking distance. According to the statistical analysis, the mean of the 400 m coverage is 78.12%, the minimum is 15.52%, the maximum is 100%, the median is 87.18%, and the standard deviation is 21.87. The results show that many wards have good walking-distances to bus stops within the 400 m threshold.

Nonetheless, the coverage map for 400 m also shows considerable variation among the wards. Although many wards have nearly total coverage, some wards have comparatively low coverage values. In these wards, residents may have to walk further to access bus services. This variation shows that the 400 m walking threshold is not uniformly accessible across the wards of Chennai.

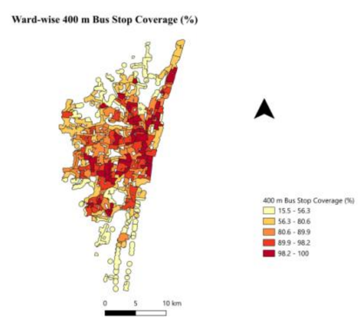

Fig 4. Ward-wise 400 m Bus Stop Coverage (%).

Table 4. Statistical Summary of Ward-wise Bus Stop Coverage within a 400 m Walking Distance

Table 4 (400 m Coverage Statistics)

Statistic	**Value**
Mean Coverage	78.12%
Median Coverage	87.18%
Minimum	15.52%
Maximum	100%
Standard Deviation	21.87

C. Ward-wise 800 m Bus Stop Coverage

The ward-wise bus stop coverage within 800 m is shown in Figure 5. The study results reveals that the mean value of coverage for 800 m increased to 96.09 per cent, with a minimum of 32.56 per cent, a maximum of 100 per cent, a median of 100 per cent, and a standard deviation of 10.46. The outcome shows a substantial increase in accessibility when the walking-distance threshold is increased from 400 m to 800 m.

According to the 800 m coverage map, most wards achieve very high coverage levels, and several wards approach or achieve full coverage. Based on these results, bus stop accessibility becomes more equally distributed at 800 m across the metropolitan area. Some wards, however, still show low coverage values, implying that improvements in bus stop provision or route planning are still required.

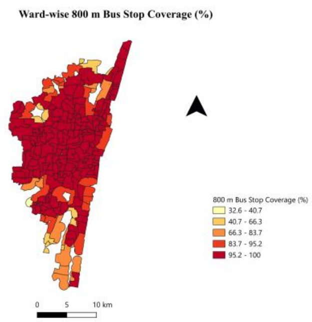

Fig 5. Ward-wise 800 m Bus Stop Coverage (%).

Table 5. Statistical Summary of Ward-wise Bus Stop Coverage within an 800 m Walking Distance

Table 5 (800 m Coverage Statistics)

Statistic	Value
Mean Coverage (%)	96.09
Median Coverage (%)	100.00
Minimum Coverage (%)	32.56
Maximum Coverage (%)	100.00
Standard Deviation	10.46

D. Comparison of 400 m and 800 m Accessibility

Figure 6 compares the average bus stop coverage with walking-distance buffers of 400 m and 800 m. The average coverage for all wards is 78.12% at 400 meters, and it rises to 96.09% at 800 meters—an improvement of 17.97 percentage points. This represents an overall increase in average accessibility of 23%, relative to the 400 m coverage. This shows that extending the walking-distance threshold significantly expands the effective service area of the existing bus stop network.

The comparison suggests that, if the acceptable walking distance is increased, the spatial coverage of bus stop accessibility across the wards of Chennai will increase. The higher 800 m coverage indicates that, when a wider walking-distance parameter is adopted, most wards are served by bus stops. Nonetheless, the lower coverage at the 400 m level indicates that access is still unequal within shorter walking distances. This should be taken into account in future planning for public transport.

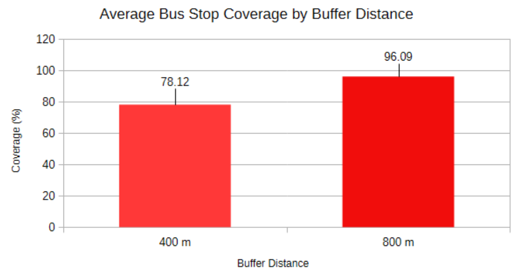

Figure 6. Comparison of Average Bus Stop Coverage for 400 m and 800 m Buffers.

TABLE 6. COMPARISON OF AVERAGE WARD-WISE BUS STOP COVERAGE FOR 400 M AND 800 M WALKING-DISTANCE BUFFERS.

TABLE 6 (COMPARISON)

Buffer Distance	**Average Coverage (%)**
400 m	78.12
800 m	96.09

E. Discussion

The study shows that in Chennai, public transport access exhibits a clear spatial gradient. Central and better-connected wards tend to have higher bus stop densities and accessibility. Peripheral wards, on the other hand, tend to have lower bus-stop densities and correspondingly lower coverage. This pattern confirms spatial inequality in the provision of public transport in the region.

Consistent with other GIS-based accessibility studies, transit accessibility tends to decline toward the urban periphery, notably due to lower service density and larger residential catchments. The present analysis shows that Chennai follows a similar spatial pattern. Ward-level accessibility analysis helps in identifying underserved areas.

The contrasting outcomes between the 400-metre and 800-metre evaluations indicate that the choice of a walking-distance threshold greatly affects accessibility assessment. The 400 m standard is a stricter measure of convenient access to stops, while the 800 m standard reflects broader service access. Planning authorities should use both thresholds to identify underserved wards, as well as prioritize future bus stop additions or route enhancements.

The analysis using geographical information system (GIS) techniques confirms that, while the bus network provides adequate coverage at a threshold distance of 800 m in Chennai, access within the 400 m walking distance is considerably less even. These findings may be used to plan interventions that improve public transport accessibility and reduce spatial inequalities across the metropolitan area.

6. CONCLUSION AND FUTURE WORK

This study proposes a GIS-based framework to assess the accessibility of public transport in the Chennai Metropolitan Area using ward-level spatial analysis. The research evaluated the differences in spatial accessibility through analysis of bus stop distribution, 400 m walking-distance coverage, and 800 m walking-distance coverage. The analysis shows how GIS can effectively be used to measure public transport service coverage and support evidence-based planning.

The ward-level analysis of accessibility showed that the average coverage of bus stops within a 400 m walking distance is 78.12%, and that this average coverage increases to 96.09% with the 800 m walking-distance buffer. The findings reveal that increasing the walking threshold has a significant impact on overall accessibility. Nonetheless, certain peripheral wards still show comparatively lower accessibility than the urban central areas, indicating the existence of spatial inequalities in public transport service delivery.

Transportation authorities can use the decision-support information provided by the thematic maps and statistics produced in this study. By implementing the proposed GIS-based methodology, planners can identify underserved wards, prioritise investment in infrastructure, and enhance spatial equity in service provision. The study shows that open-source GIS techniques can be an efficient and effective method for conducting accessibility assessments in fast-growing metropolitan cities.

Future research can build on this by leveraging real-time General Transit Feed Specification (GTFS) data, bus frequency data, and live vehicle location data to assess spatial and temporal accessibility. Incorporating population density, land-use attributes, and socio-economic indicators would allow for a more comprehensive assessment of transport equity and accessibility demand.

The proposed framework can be further enhanced by developing a Transit Gap Index (TGI) that assesses accessibility, service supply, and population demand to more precisely identify deprived wards. In addition, machine learning and spatial optimization techniques may be incorporated to recommend new bus stop locations and route improvements. The framework and methodology developed in this study could be adapted for other metropolitan regions to support sustainable, equitable, and data-informed public transport planning.

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