An Open-Source Approach for Measuring Level of Urbanity

Kasthurisinghe K.[1*], Bandara N.S.[2] A.B.Jayasinghe [3]

[1]Undergraduate, Department of Town & Country Planning, University of Moratuwa, Sri Lanka

[2]Lecturer, Department of Town & Country Planning, University of Moratuwa, Sri Lanka

[3]Senior Lecturer, Department of Town & Country Planning, University of Moratuwa, Sri Lanka

kavindikasthurisinghe7@gmail.com[1], niroshans@uom.lk[2], amilabj@uom.lk[3]

Abstract

In the realm of urban studies, accurately measuring urbanity levels is paramount for effective planning and sustainable development. Traditionally, measuring the urbanity levels requires large amount of data sets and ground verifications both of which are labor-intensive and time-consuming. Recognizing the limitations of such conventional methods, this study attempted to increasingly explore the potential of Open-Source GIS tools and data sources. This study presents an open-source data-oriented approach that leverages web-based data sources for a fast and accurate method of measuring urbanity levels. The proposed approach utilizes open and big data sources as primary data inputs and evaluates the applicability and accuracy of this method. By integrating Point of Interest (POI), OpenStreetMap (OSM) data with Open-Source GIS tools, this research aims to comprehensively assess urbanity levels of selected urban centers across three major corridors in Sri Lanka namely Kandy corridor, Galle corridor, and Negombo corridor. Three key parameters determining the level of urbanity including density, diversity, and land use-mix were derived through literature and employed in the methodology to systematically identify and measure the level of urbanity. Results denote that Kiribathgoda, Panadura, and Wattala cities obtained the highest level of urbanity in Kandy, Galle and Negombo corridors respectively. This provides valuable insights for informed decision-making in sustainable planning endeavors. Importantly, this method offers a scalable solution for assessing urbanity levels in urban centers worldwide. This research presents a transformative framework for measuring urbanity levels, streamlining data collection, and enhancing analytical precision, thereby advancing urban studies and informing more efficient urban development strategies. In conclusion, the developed method of this study holds significant implications for guiding urban planning initiatives and informing policy decisions aimed at achieving sustainable urban development objectives.

Keywords: Urbanity, GIS, Open Data, Sustainable Development

1.Introduction

Urbanity in spatial planning refers to the quality or characteristic of urban areas that are well-designed, vibrant, and conducive to human habitation, shaped by factors like dimensions, population density, diversity, mobility, instability, and transparency of a settlement (Louis Wirth, 1938). In the context of rapid urbanization and digital transformation, studying urbanity has gained new importance, necessitating creative techniques that align with the complexity of contemporary urban landscapes. Traditional methods for measuring urbanity often involve manual data collection and long-lasting spatial data like road and building density, while emerging methods leverage big data sources, such as remote sensing, image interpretation, and big data fusion. Big data fusion, an underexplored research area, integrates various big data types to understand urban phenomena, including urbanity levels. This approach is particularly pertinent given the urgency for timely urban analysis to guide city development decisions. In response, this research proposes a multifaceted approach utilizing multisource big data, including Point of Interest (POI) data, to comprehensively assess urbanity levels by analyzing density, diversity, and accessibility. This methodology promises valuable insights for urban planners and researchers, aiming to enhance urbanity in new city developments. Specifically, the study explores the applicability of open-source and big data methods for measuring urbanity levels in selected urban centers along Sri Lanka's Kandy, Galle, and Negombo corridors.

2. Literature Background

Urbanity can be broadly explained through various socio-economic activities within buildings and open spaces, emphasizing the diverse and lively atmosphere generated from good public spatial qualities. Urbanity, as defined by various scholars, encompasses a range of characteristics and attributes unique to urban living. Wirth (1938) describes urbanity as the gathering of a large, dense, and heterogeneous mass of people, emphasizing density, diversity, mobility, instability, and transparency. Jacobs (1961) and Cook (1980) highlight the socio-economic activities occurring in and through buildings and open spaces, while Gehl (1989) focuses on the emergence of urbanity through these interactions. Montgomery (1998) sees urbanity as the interrelationship between activity, urban image, and urban form, and Marcus (2010) relates it to the socio-economic performance developing within urban form. Buettner (2015) underscores population concentration as a determinant of urbanity, and Walter Siebel points to social formations distinguishing urban areas from rural ones.

Xiaoyang Li and Zhaohua Lu (2021) discuss urbanity arising from specific morphological and configurational attributes, whereas Shuchen Xu, Yu Ye, and Leiqing Xu (2017) emphasize the diverse and lively atmosphere generated by good public spatial qualities. Finally, Romolu Karafta (2014) defines urbanity through the quantity of people fostering social interaction.

Urbanity level identification methods in the literature can be categorized into four groups: criteria-based measures, population proportion methods, indices, and the use of big data. Criteria-based methods involve pre-determined criteria to identify urbanity, such as the coexistence and interactions of activity, form, and image (Montgomery, 1998) or the integration of diversity, density, and accessibility (Ye and Van Nes, 2014; Ye et al., 2016). Jacobs (1961) highlights variety through the combination of residential, commercial, and civic uses, enhancing appeal, safety, and economic viability. The population proportion method, as discussed by Ulrich Niklas et al. (2020) and Elliott et al. (2017), measures urbanity by the rate of urbanization, focusing on the percentage of the population living in urban areas. Indices-based identification considers parameters like population size, density, and city size distribution, incorporating social, economic, and environmental factors (Liu et al., 2011; He et al., 2017). However, these methods often rely on limited, socio-economic datasets and overlook near-real-time data. In contrast, the use of big data is an emerging research area, offering a plural, open, and accessible approach to urbanity measurement. For example, Jihghu Pan, Xiuwei Zhu, and Xin Zhang (2022) integrated various big data types, such as night light satellite data, POI data, and urban activity data, to assess urban vitality in China. This novel multi-source geospatial data fusion approach holds promise for more accurate and timely urbanity level identification in urban planning.

The multisource geospatial big data fusion approach analyses the location-related big data collected from multiple sources. This approach can be considered an integrated approach that mixes and masters different data sources to obtain the most representative data. Big data fusion ensures the aggregation of data either independently or collectively (Ngbede, et al., 2019). Big data fusion is a very effective way to solve problems in urban context, such as traffic congestion, noise pollution, air pollution and so on. Recently, urban research is trying to use multi-source big data fusion methods to understand the complex phenomenon of the urban context (Liu, et al., 2019).

Numerous scholars have emphasized the assessment of urbanity levels from a socio-economic perspective, exploring factors as previously mentioned. However, concerning spatial planning, scholars have proposed measuring urbanity through the integration of three key factors: accessibility, density, and diversity (Ye and Van Nes, 2014; Ye et al., 2016). Additionally, a methodological approach for determining urbanity levels, presented by Yu Ye and Akkelies Van Nes in 2013, underscores the spatial dependence on street network configuration. This approach involves streets with high integration values on various scales, contributing to elevated building density and a substantial degree of land use diversity. Accessibility is measured through space syntax analysis. This provides the most recent update on the components utilized for measuring urbanity levels.

3. Materials and Methods

3.1. Case Study Area

The study area of the research is three transportation corridors in Colombo UP, Sri Lanka. So here for choosing the urban centers which had urban development potential through this corridor. In the Kandy corridor (A01), the primary urban centers under consideration include Kelaniya, Kiribathgoda, and Kadawatha. Kelaniya is envisioned as a new development area, emphasizing industrial and commercial growth. Meanwhile, Kadawatha is slated for mixed-use development within the Kandy corridor. Moving to the Galle corridor (A02), the selected urban centers for investigation are Panadura and Kalutara. In the Negombo corridor, the identified urban centers are Wattala and Ja-Ela.

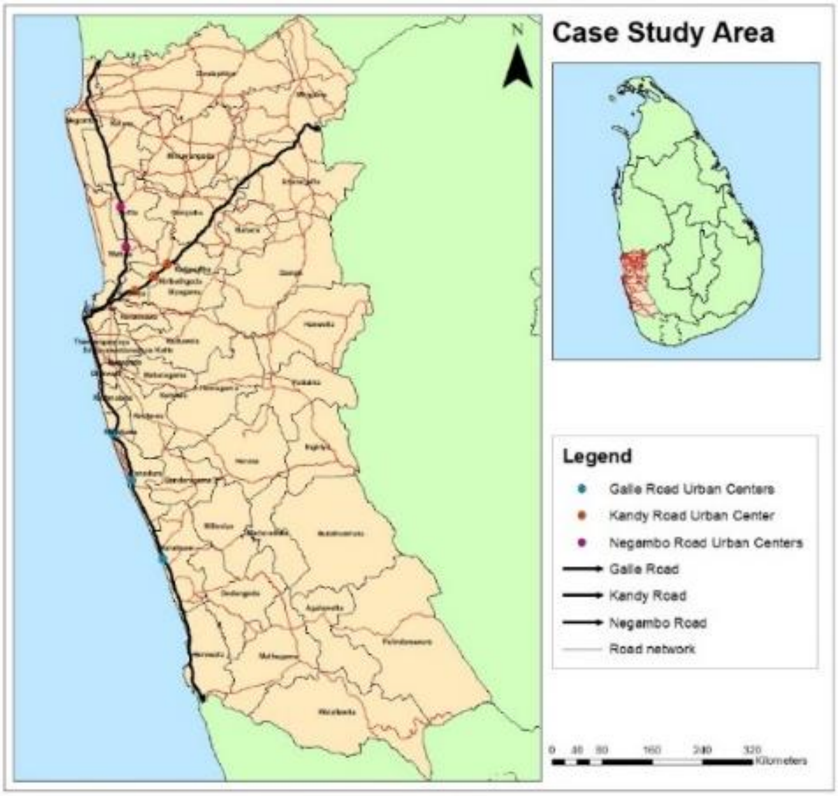


Figure 1 - Case Study Area

These towns are connected because of 'ribbon growth' along these corridors. There is a rapid growth of urbanization along the main corridors. Accordingly, urban population has increased in such areas. The presence of significant urban areas in a region offers an excellent opportunity to utilize the novel method of fusing multisource open geospatial big data for assessing the degree of urbanity.

3.2. Methodological Framework

As shown in Figure, the study followed a three-step methodological framework to conduct the study. The following three steps include: (a) Identifying datasets and data sources; (b) preparing datasets; and (c) Geographic Information System (GIS)-based modelling.

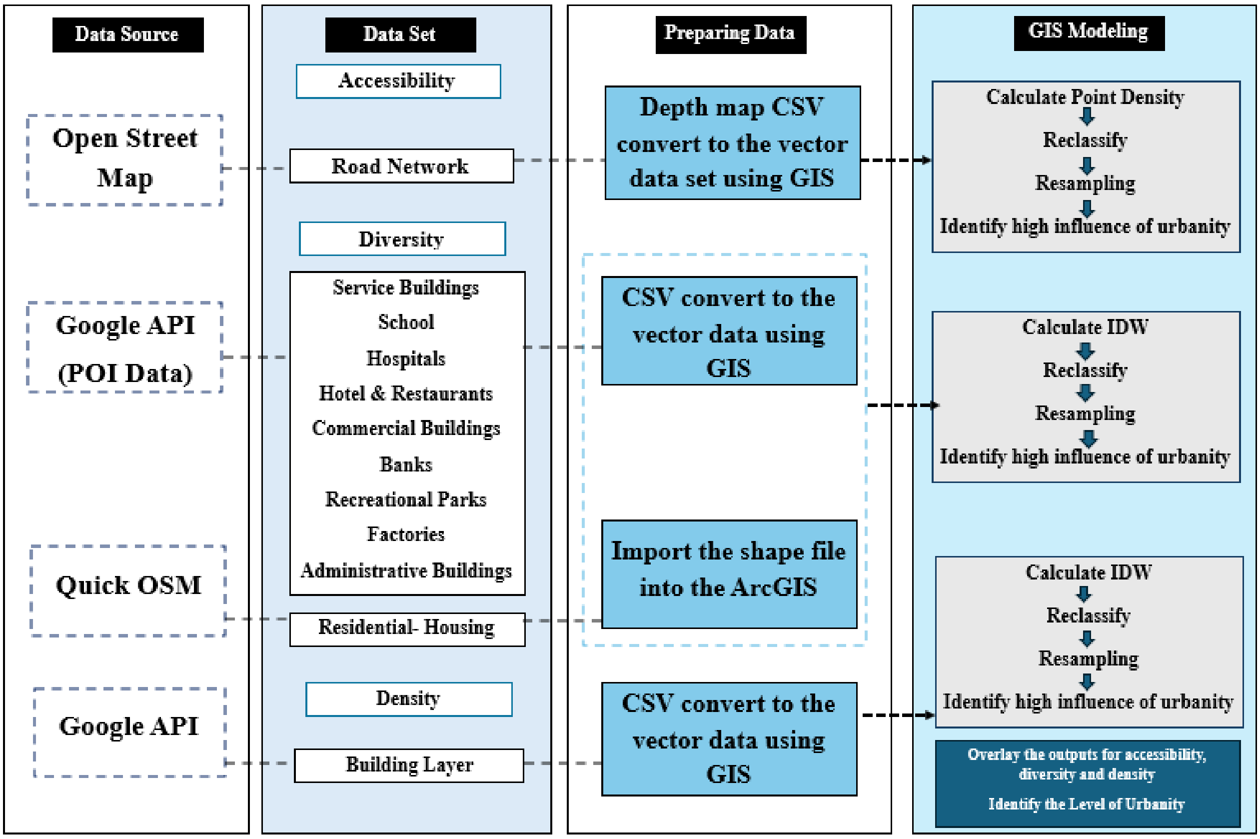


Figure 2 : Methodology Framework

3.2.1. Data Sources and Datasets

The study identified the significance of accessibility, density, and diversity in measuring the urbanity level. The data sets and related sources which were collected to measure the urbanity level are mentioned in Table 1.

As mentioned in following table, road network data were collected from OpenStreetMap (OSM) to measure the urbanity level through accessibility and POI data were collected from Google API to understand the density and diversity of the study area. Furthermore, the methodology was developed to understand the urbanity level interconnected of these three components.

Table 1 - Data and feature extraction

	Data Source	Data used for
Data and feature extraction		Accessibility
	OSM	Road Network
	Google API	Density
		Building layer
		Diversity
		Service Buildings Schools Hospitals Hotels & Restaurants Commercial Buildings Residential Apartments Banks Recreational Parks Factories Administrative Buildings
	QGIS Python plugin – Quick OSM	Residential – Housings

Based on the reviewed literature, the study derived that most of the studies have tried to understand urbanity level based on the attributes that define accessibility, density, and diversity. With that for the accessibility analysis in here used the Open Street Map. The OSM used as the source for obtain road network data. High precision and comprehensive topological linkages are provided by OSM data, which also includes attribute information like road grade and types. The OSM data is available for free to download as the ESRI shapefile format from the OSM website and by using QGIS plugin as well. OSM data are publicly accessible, enabling anybody to use, modify, and distribute this geographic information without restriction (Open Street foundation, 2021).

Furthermore, the density and diversity of the urban context analysis through the POI data. POI data deemed a crucial subset of urban spatial geographic big data (Chen et al., 2016), serves as a precise representation of the intensity of social and economic activities, as well as the composite utilization of functions in spaces. This form of data proves to be more accurate in delineating such activities compared to alternative data types. POI data span a wide range of areas and are notably easy to collect and centralize in large quantities. POIs essentially denote locations where human activities occur and serve as attractions that draw people to visit specific places, including but not limited to restaurants, shops, museums, universities, or parks (Gao, Janowicz, and Couclelis, 2017). In total, the dataset comprises a significant number of POI points, each with associated attributes including name, category, latitude, longitude, and others. This dataset, while rich in information, requires careful curation to enhance its utility and relevance in analyzing urban dynamics. And used the Quick OSM for downloading the data and this plugin was free and quickly can collect the Google API data. Here for the analysis Non – POI data assumed as the residentials which collected from the Quick OSM. And these POIs are validated by field.

3.2.2. Data Preparing

As the first step of the methodology, data was obtained through Google API, OSM and Quick OSM. The methodology is going to be considered as analyzing accessibility, diversity, and density. Therefore, the Google API data was collected as the csv file and converted to Shp format for the purpose of visualization and analysis of the research outputs. And all the other data is already formatted as the Shp format, and it will be easy to analysis and visualize the research outputs.

Basically, the POI data was gathered using python script and the advantage of this POI data is it can be simply identifiable. The POI data extracted the 1500(m or km) radius buffer zone within each urban center.

3.2.3.GIS Modelling

After converting all the data into one format- Shp, GIS modeling was done. The data which represent accessibility, diversity and density were analyzed separately to understand level of urbanity. With this method it is easy to understand the level of urbanity temporally. The analysis was done using QGIS software and for the closeness analysis UCL Depth map software has been used. The basic process of the analysis is,

I. Analyze urbanity level from the data selected to represent accessibility.
II. Analyze urbanity level from the data selected to represent diversity.
III. Analyze urbanity level from the data selected to represent density.
IV. Understand the difference between these three outputs of accessibility, diversity, and density.
V. Combine these three results as a composite map to understand the urbanity level.

The initial step of GIS modeling is to convert all vector data into raster format and calculate the point density and Inverse Distance Weighted (IDW). As mentioned in the methodology chart (figure 02), do the steps for each data set and finally weight them according to the spatial weights. Finally, the output shows the urbanity level according to the given spatial weights.

3.2.4. Incorporating diverse spatial analysis methods into a unified GIS model

In this research, the space syntax method was used to measure the degree of spatial configuration of the street network, space matrix measures the degree of various types of building density on the urban block, and Mixed Used Index (MXI) will measure the degree of land use mix. Through the application of GIS, it is possible to integrate the results of the space syntax, space matrix, and MXI analysis to compare the various spatial variables. The space syntax approach includes a collection of theories and methods designed to assess the street network configuration, considering topological, geometrical, and metric distances (Hillier and Hanson, 1984; Hillier et al., 1993; Hillier, 1996; Hillier, 1999). It describes the spatial configurations of urban and architectural structures and their influences on patterns of behavior. For the space syntax analysis here used the closeness parameters, it shows the generating origin destination trips. The depth map software has been used for the calculation of network centrality parameters of closeness. The impact radius(n), 1000m was set as the parameters to run the tool.

The space matrix is determined by multiplying the plot coverage by the building height. The space matrix technique exhibits several building types and building densities simultaneously, which is an important contribution (Berghauser-Pont and Haupt, 2010). The mix of intensity, compactness, pressure, non-built space, and height can now be quantitatively described, making it feasible to discriminate urban form more effectively than in the past (Berghauser-Pont and Haupt, 2007, p. 63).

The MXI model quantitatively assesses the extent of functional diversity by considering the percentage of dwellings, workplaces, and amenities within urban blocks. The term "Dwellings" encompasses diverse residential living arrangements, including houses and apartments. The term "Working" pertains to locations of employment, such as offices, administrative buildings, factories, services, stations, and laboratories. The category of "Amenities" encompasses various commercial facilities, including shopping malls, schools, hospitals, hotels, restaurants, recreational facilities, cinemas, grocery stores, supermarkets, guest houses, cafes, banks, and pharmacies. The entropy index can be used to represent the land use mix, which helps to identify the different types of land use distribution in a particular area. Entropy can be express as below,

$$\boxed{Entropy(I_H) = (-)\frac{\sum_{i=1}^{n} P_i\ (\ln P_i)}{\ln J}}$$

P_i - Proportion of total land use

J - Total land uses

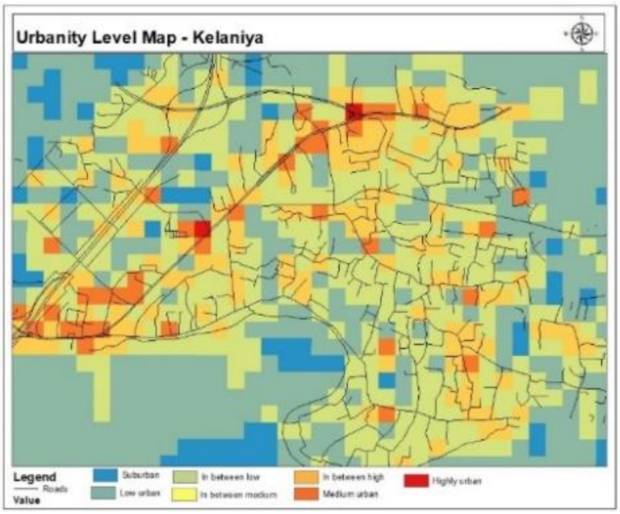
Entropy values vary from 0 to 1. If the value is equal to 0 or near to 0 ($I_H \approx 0$), it represents monofunctional areas. If the value is equal to 1 or near to 1 ($I_H \approx$) 1), it represents mix-used/ mix functional areas.

The outcomes derived from space syntax, space matrix, and MXI analyses can be consolidated using GIS techniques to compare distinct geographical variables. Utilizing GIS software, the vector-based space syntax data, polygon-based space matrix, and MXI data can be transformed into a unified grid. The grid's dimensions cover a segment of the roadway and an adjacent building to facilitate correlation between vector-based and polygon-based data. It is crucial for the raster size of the grid to be appropriately large, preventing the segregation of building block variables from street network integration variables. However, an excessively large grid raster size may compromise the precision of the vector-based analysis. In this study, a cell size of 100 x 100 meters is selected for the raster. Subsequently, the outcomes of the spatial analysis are categorized into three levels: high, medium, and low values, facilitating a straightforward comparison.

4.Results

Following the application of the analytical methods, the results will be systematically presented in a series of maps. These maps will visually illustrate the spatial distribution and patterns identified during the analysis, providing a comprehensive and detailed representation of the findings. This cartographic approach will facilitate a clearer understanding of the data, enabling more effective interpretation and communication of the research outcomes.

Understanding the urbanity level of urban centers along the Kandy Corridor (A01)



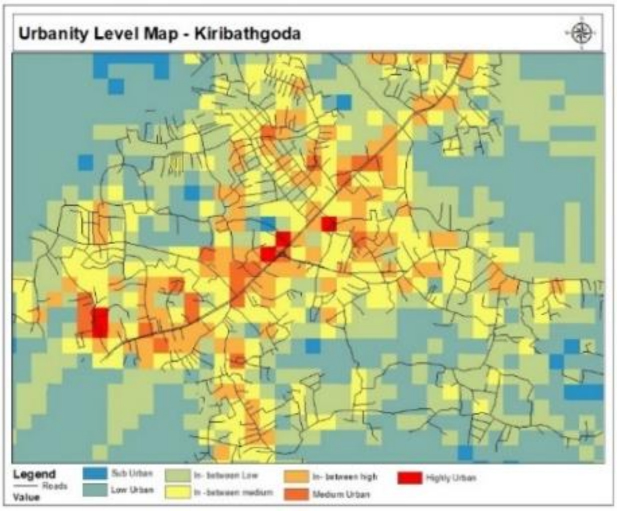


Figure 3 : Urbanity Level Map - Kiribathgoda

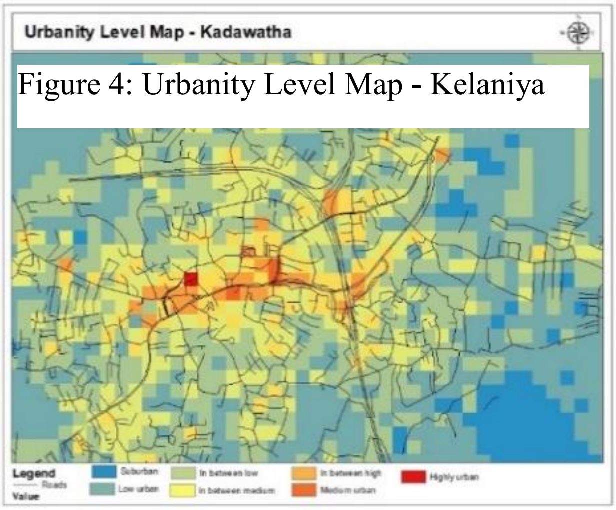


Figure 4: Urbanity Level Map - Kelaniya

Figure 5 : Urbanity Level Map: Kadawatha

As per the space syntax, elevated integration values highlight the significance of the Colombo–Kandy (A1) main road and the entrance to the Colombo–Katunayake Expressway, with most streets and roads in the Kelaniya area exhibiting high or moderate integration values, indicating notable accessibility. The space matrix map shows that medium-rise block buildings, where socio-economic activities and commercial buildings are concentrated, and clusters of low-rise block residential buildings, are prevalent in Kelaniya. High-rise buildings, primarily factories, are situated close to the main road. Aligning these findings with ground conditions, the Kelaniya urbanity level map reveals high urbanity levels around Pattiya Junction and Thorana Junction along the Colombo–Kandy main road, characterized by mixed-function buildings with compact clustering and high building density, including high-rise structures.

According to the space syntax map, elevated integration values underscore the significance of the Colombo–Kandy (A1) main road, with the space syntax chart highlighting a high. Despite this, the overall assessment of the road network indicates a moderate level of accessibility. The space matrix map reveals that medium-rise block buildings, where socio-economic activities and commercial establishments are concentrated, are prevalent. High-rise buildings in Kiribathgoda, due to numerous retail shops with high plot coverage and building heights, surpass those in Kelaniya. Additionally, clusters of low-rise block buildings, primarily residential, are abundant, with a functional mix high value. Comparative analysis between observed data and actual ground reality highlights Kiribathgoda as a focal point of heightened urbanity along the Colombo–Kandy route. This urban complexity is marked by an influx of daily commuters and three key junctions: Market Junction, Clock Tower Junction, and University Junction. Market Junction, featuring the Kiribathgoda Market and main bus stops, serves as a central hub for daily commuters. Clock Tower Junction is characterized by a dense concentration of retail establishments, while University Junction, primarily inhabited by university students, contributes to the dynamic urbanity of Kiribathgoda.

The space syntax analysis reveals that the Bo-tree junction and the junction originating from the Kadawatha expressway exhibit high integration in the Kadawatha area, yet Kadawatha overall displays a lower integration value compared to Kelaniya and Kiribathgoda. The space matrix in Kadawatha is similar to Kelaniya, with medium-rise block buildings where socio-economic activities are concentrated, and a significant presence of commercial structures, while clusters of low-rise block buildings predominantly serve residential purposes. In terms of functional mix, mono-functional establishments surpass bi-functional and mixed-functional ones in Kadawatha, with the highest functional mix value. The Bo-tree junction emerges as a focal point with a notably high urbanity level, serving as a pivotal entry point into the Central Business District (CBD) of Kadawatha and effectively dividing the Colombo–Kandy Road into Ragama and Kandy. Characterized by a concentration of retail establishments and significant daily commuter presence, the Bo-tree junction's elevated urbanity, strategic transportation connectivity, and commercial vibrancy underscore its crucial role in Kadawatha's urban fabric.

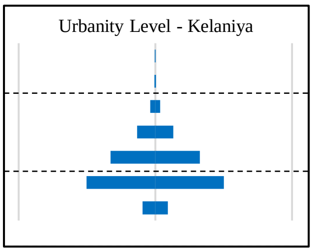


Figure 8: Urbanity Level - Kelaniya

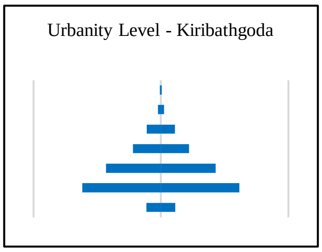


Figure 7 : Urbanity Level - Kiribathgoda

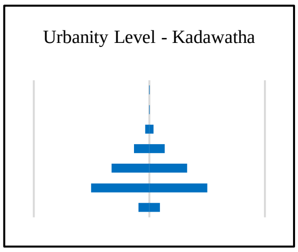


Figure 6 :Urbanity Level - Kadawatha

Table 2 : Match Rate of Kandy Corridor

Urban center	Ci = cells with values from middle urban areas + cells with values from highly urban areas	Cj = cells with middle values from the spatial integration analysis + cells with high values from the spatial integration analysis	Match Rate
Kelaniya	25	180	13.8%
Kiribathgoda	28	195	14.3%
Kadawatha	5	158	3.16%

According to these three urbanity level graphs here can identify the urbanity level in seven levels. Mainly it came under three categories as high, medium and the low levels. In high urban areas can be identified as highly urban, medium urban then in medium level can be identified in three levels in in- between- high, in-between-medium, and in-between-low. When it comes to the low level of urban areas can be identified in low urban and suburban areas. In one-by-one level can identified how it represents the urbanity level of the city. So, according to these three urban centers the Kiribathgoda urban center had the high urbanity level value that because it has the high level of all these weights and specially highlighted the highly urban and medium urban areas. According to the urbanity level analysis these three urban centers have suburban characteristics. As literature mentioned the rate is called match rate, divided by cells with high and middle integrated values obtained from the space syntax analysis. As this index method implies, the higher the match rate, the higher the balance between street network integration, building density, and land use diversity.

According to the match rate index the Kiribathgoda match rate (14.3%) is quite higher than the other two urban centers. So according to these analysis Kiribathgoda is the high urbanity level in Kandy corridor among the three urban centers.

Understanding the urbanity level of urban centers along the Negombo Corridor (A01)

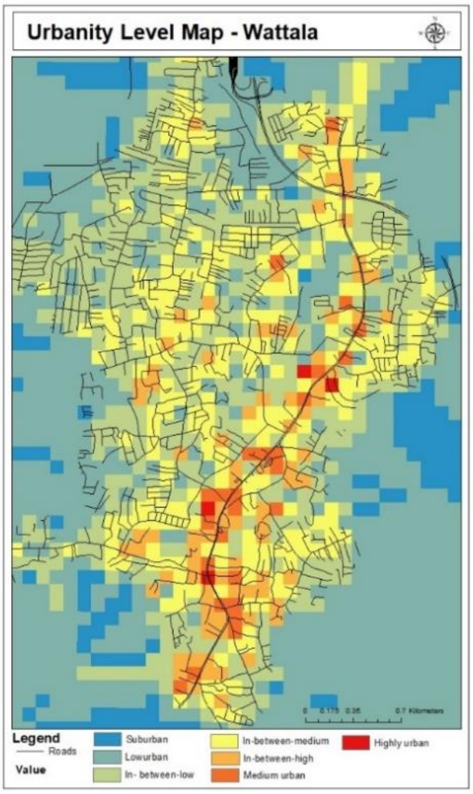
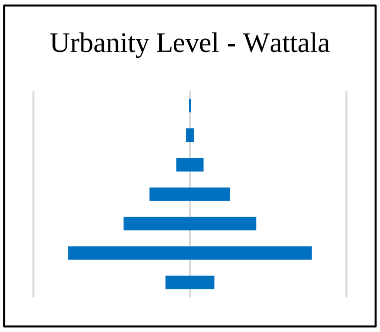


Figure 9 : Urbanity Level Map - Wattala

Figure 10 : Urbanity Level Map: Ja

The space syntax, elevated integration values indicate the significance of the Colombo–Negombo (A3) main road, with most streets and roads in Wattala exhibiting high or moderate integration values, suggesting notable accessibility. The space matrix, medium-rise block buildings, where commercial activities are concentrated, predominate, with a moderate value. Clusters of low-rise block residential buildings are located away from the main road, and the functional mix has a high value. According to the urbanity level map, Wattala exhibits a high level of urbanization due to extensive retail establishments and a considerable influx of daily commuters. Elevated urbanity levels are seen in areas with large retail outlets and two key junctions hosting primary bus stops, particularly the junction where two major roads converge, enhancing Wattala's urban character. As a pivotal urban center along the Colombo-Negombo corridor (A3), Wattala serves as a focal point with concentrated commercial and transportation activities. The inner-city area features pockets of medium-sized urban developments, while medium-level urban areas are interspersed further from the main road.

High integration values highlighted by the space syntax underscore the importance of the Colombo–Negombo (A3) main road in Ja-Ela, where most streets exhibit either high or moderate integration, indicating substantial accessibility, particularly evident in inner-city areas alongside the main road. The space syntax specifically shows a significantly high value, comparatively higher than Wattala's values. The space matrix reveals Ja-Ela's predominantly residential landscape with high and medium-rise block buildings, while high-rise structures show minimal presence. The urbanity level map identifies a specific junction in Ja-Ela marked by notably high urbanity, notably at the convergence point of the Ja-Ela railway station and bus stand. This junction serves as a vital transportation and commercial hub, housing banks and diverse retail outlets, enhancing the area's urban vibrancy.



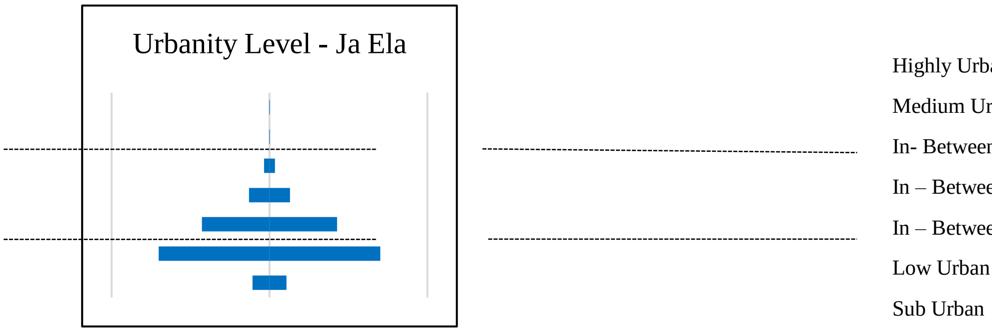


Figure 11 : Urbanity Level Wattala

Figure12: Urbanity Level Ja Ela

Table 3 : Match Rate of Negombo Corridor

Urban center	Ci = cells with values from middle urban areas + cells with values from highly urban areas	Cj = cells with middle values from the spatial integration analysis + cells with high values from the spatial integration analysis	Match Rate
Wattala	65	134	48.5%
Ja - Ela	53	151	35.09%

According to these two urban centers the Wattala urban center had the high urbanity level value because it has the high level of all these weights and specially highlighted the highly urban and medium urban areas. It means according to the Ja- Ela urbanity level graph the Wattala graph clearly see the more highly and medium urban areas compared to the Ja- Ela urban center.

Wattala match rate is quite high (48.5%) The reason for this is clear: because Wattala features high-density development, the cells with high or middle values of spatial integration overlap with cells which have a high degree of building density, thus expressing a high match rate.

Understanding the urbanity level of urban centers along the Galle Corridor (A01)

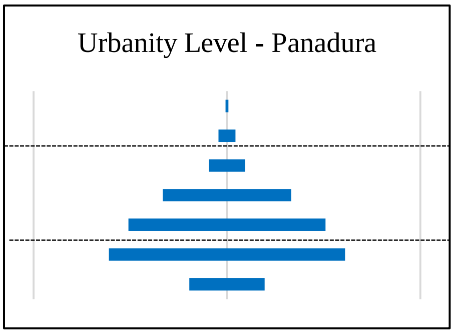
Figure 13 : Urbanity LFigure 14: Urbanity Level Map –

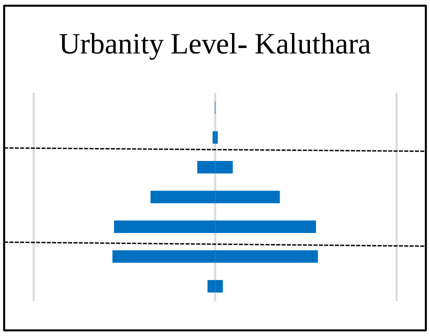
Panadura Kaluthara

As per the space syntax value, elevated integration values highlight the significance of the Colombo–Galle (A2) main road in Panadura, where most streets and roads show high or moderate integration, indicating significant accessibility. The concentration of origin destinations along the Colombo-Galle Main Road, Old Main Road, and Panadura–Rathnapura Main Road underscores the area's high accessibility. The space matrix reveals a predominance of low-rise block buildings, with residential areas further from the Galle Road, while diversity is higher near the Colombo–Galle main road. Functional mix mirrors this distribution, with most bi-functional and mixed-functional establishments concentrated along the main road. The urbanity level map of Panadura illustrates a linear "Ribbon" type commercial development along the Galle Road, with residential areas extending into the hinterlands due to direct access to Colombo and the main Galle Road. Key junctions such as Panadura Junction with its bus station and recreational park, Panadura Hospital Junction, and Arpico Junction with schools and tuition classes, stand out as high-urban areas. The area attracts a daily commuter population of 85,000 to 100,000, making it a major hub in the Kalutara District.

As per the space syntax map, elevated integration values emphasize the significance of the Colombo–Galle (A2) main road in Kalutara, where most streets and roads exhibit high or moderate integration, indicating substantial accessibility. Surprisingly, the highest space syntax values are found on inner roads rather than the Colombo–Galle main road, reflecting the area's overall high accessibility. Observing the space matrix reveals a predominance of low-rise block buildings, with residential areas situated away from the Galle Road, while diversity is higher closer to the main road. Functional mix patterns also mirror this distribution, with bi-functional and mixed-functional establishments concentrated along the Colombo–Galle main road. Despite these dynamics, Kalutara registers a lower status in terms of urbanity, indicating a suburban character. The area around the Kalutara bus stand stands out as a highly urbanized zone amidst its suburban surroundings.

According to the urbanity level analysis of the two urban centers, Panadura emerges with a higher urbanity level due to its elevated weights across various criteria, particularly emphasizing highly urban and medium urban areas. In contrast to Kalutara, the graph depicting Panadura's urbanity level illustrates a greater concentration of highly and medium urban zones.





Highly Urban
Medium Urban
In- Between – High
In – Between – Medium
In – Between – Low
Low Urban
Sub Urban

Figure 15: Urbanity Level Pandura

Figure 16 : Urbanity Level Kaluthara

Table 4 : Match Rate of Galle Corridor

The match rate in Panadura is notably high at 45.55%. This can be attributed to the high-density development characteristic of the area. Cells exhibiting middle to high values of spatial integration coincide with regions characterized by significant building density, resulting in a pronounced match rate.

Discussion and Conclusion

The application of this methodology has demonstrated a high degree of accuracy in determining the urbanity levels of various urban centers. This success is attributed to the alignment of highlighted areas on the map with the ground realities, thereby validating the reliability of the results obtained. Furthermore, the study successfully classified the identified urban centers into distinct urbanity levels, as high, medium, and lower. Through an in-depth discussion of seven urban centers situated along main corridors mentioned above this research provided valuable insights into the urban landscape of Sri Lanka. The analysis not only identified the urbanity level of each center but also shed light on their unique characteristics and developmental trajectories. Importantly, the findings underscore the effectiveness and accuracy of data fusion techniques in identifying urbanity levels across different urban centers.

This study aimed to address the challenge of identifying urbanity levels in urban areas without relying on ground-level observation and data collection. By employing a big data fusion approach, the research sought to effectively and accurately determine urbanity levels in urban centers across Sri Lanka. The methodology combined multiple data sets, including OSM data, POI data, and Quick OSM data, to integrate three distinct spatial parameters: spatial integration values, density values, and land use mix values. Preliminary findings

Urban center	Ci = cells with values from middle urban areas + cells with values from highly urban areas	Cj = cells with middle values from the spatial integration analysis + cells with high values from the spatial integration analysis	Match Rate
Panadura	82	180	45.55%
Kalutara	11	77	14.28%

suggest that these techniques are useful in visualizing and quantifying various spatial properties of the built environment, such as street network integration, building density, and functional mix. This approach marks a departure from traditional qualitative analyses by providing a framework for comparing and interpreting multiple spatial parameters to explain the quantitative aspects of spatial evolution.

The identification of urbanity levels appears to be influenced by both spatial integration and the match rate between spatial variables. Areas with higher values derived from spatial integration analyses and a high match rate between spatial variables consistently demonstrate heightened urbanity levels. The study's outcomes effectively pinpoint urban centers with elevated urbanity levels, aligning with real-world observations. These findings have significant implications for guiding urban planning initiatives and informing policy decisions aimed at achieving sustainable urban development objectives. By delineating areas with high urbanity levels, the research provides valuable insights that can facilitate the monitoring of urbanization trends and support future planning interventions. Also, Urban planners, policymakers, architects, and environmentalists can use this methodology to understand which areas are experiencing rapid urbanization and prioritize resource allocation and information development accordingly. By gaining an understanding of urban growth patterns, these professionals can identify areas with high urbanity levels that may require densification or redevelopment to accommodate growing populations and economic activities while also preserving green spaces.

References

Aral, H. E., Uysal Bilge, F., & Doğu Demirbaş, G. U. (2022). Urbanity in the Open Spaces in Developing Nodes along Main Arteries: Söğütözü Node on Dumlupınar Road in Ankara.

Berghauser-Pont, M. and Haupt, P. (2010), Spacematrix: Space, Density and Urban Form, Amsterdam: NAICanuto, R., & Amorim, L. (2012). Establishing parameters for urbanity. In Eighth International Space Syntax Symposium; Greene, M., Reyes, J., Castro, A., Eds.

Canuto, R., & Amorim, L. (2012). Establishing parameters for urbanity. In *Eighth International Space Syntax Symposium; Greene, M., Reyes, J., Castro, A., Eds*.

Elias, S., & Beirão, J. N. (2022, May). Evaluating Urbanity by Measuring Urban Morphology Attributes. In *International Symposium on Formal Methods in Architecture* (pp. 219-248). Singapore: Springer Nature Singapore.

Fu, R., Zhang, X., Yang, D., Cai, T., & Zhang, Y. (2021). The relationship between urban vibrancy and built environment: An empirical study from an emerging city in an Arid Region. *International journal of environmental research and public health*, *18*(2), 525.

Huang, B., Zhou, Y., Li, Z., Song, Y., Cai, J., & Tu, W. (2020). Evaluating and characterizing urban vibrancy using spatial big data: Shanghai as a case study. *Environment and Planning B: Urban Analytics and City Science*, *47*(9), 1543-1559.

Liu, J., Xu, S., Ma, H., Wang, S., & Li, F. (2023). The Rationality of Urban Financial Network Layout Based on Poi Data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *48*, 353-359.

Li, X., & Lu, Z. (2021). Quantitative measurement on urbanization development level in urban Agglomerations: A case of JJJ urban agglomeration. *Ecological Indicators*, *133*, 108375.

Li, S., Wu, C., Lin, Y., Li, Z., & Du, Q. (2020). Urban morphology promotes urban vibrancy from the spatiotemporal and synergetic perspectives: A case study using multisource data in Shenzhen, China. *Sustainability*, *12*(12), 4829.

Montgomery, J. (1998). Making a city: Urbanity, vitality and urban design. *Journal of urban design*, *3*(1), 93-116.

Niu, B., Ge, D., Yan, R., Ma, Y., Sun, D., Lu, M., & Lu, Y. (2021). The evolution of the interactive relationship between urbanization and land-use transition: A case study of the Yangtze River Delta. *Land*, *10*(8), 804.

Niklas, U., von Behren, S., Soylu, T., Kopp, J., Chlond, B., & Vortisch, P. (2020). Spatial factor—Using a random Forest classification model to measure an internationally comparable urbanity index. *Urban Science*, *4*(3), 36.

Oliveira, V., & Medeiros, V. (2016). Morpho: Combining morphological measures. *Environment and Planning B: Planning and Design*, *43*(5), 805-825.

Priyashani, N., Kankanamge, N., & Yigitcanlar, T. (2023). Multisource Open Geospatial Big Data Fusion: Application of the Method to Demarcate Urban Agglomeration Footprints. *Land*, *12*(2), 407.

Priyashani, N., Kankanamge, N., & Yigitcanlar, T. (2023). Multisource Open Geospatial Big Data Fusion: Application of the Method to Demarcate Urban Agglomeration Footprints. *Land*, *12*(2), 407.

Rajšp, A., Hericko, M., & Fister Jr, I. (2021). Preprocessing of roads in OpenStreetMap based geographic data on a property graph. In *Central European Conference on Information and Intelligent Systems* (pp. 193-199). Faculty of Organization and Informatics Varazdin.

Van Nes, A., Pont, M. B., & Mashhoodi, B. (2012). Combination of Space syntax with spacematrix and the mixed use index: The Rotterdam South test case. In *Space Syntax Symposium 8, Santiago, Chile* (pp. 1-29). SSS 8.

Wang, Z., Zheng, J., Han, C., Lu, B., Yu, D., Yang, J., & Han, L. (2024). Exploring the Potential of OpenStreetMap Data in Regional Economic Development Evaluation Modeling. *Remote Sensing*, *16*(2), 239.

Wu, Z., Wei, X., He, X., & Gao, W. (2023). Identifying Urban Built-Up Areas Based on Spatial Coupling between Nighttime Light Data and POI: A Case Study of Changchun. *Buildings*, *14*(1), 19.

Xu, S., Ye, Y., & Xu, L. (2017). Complex power: An analytical approach to measuring the degree of urbanity of urban building complexes. *International Journal of High-Rise Buildings*, *6*(2), 165-175.

Ye, Y., & Van Nes, A. (2013). Measuring urban maturation processes in Dutch and Chinese new towns: Combining Street network configuration with building density and degree of land use diversification through GIS. *The Journal of Space Syntax*, *4*(1), 18-37.

Yue, Y., Zhuang, Y., Yeh, A. G., Xie, J. Y., Ma, C. L., & Li, Q. Q. (2017). Measurements of POI-based mixed use and their relationships with neighbourhood vibrancy. *International Journal of Geographical Information Science*, *31*(4), 658-675.

Ye, Y., & Van Nes, A. (2012). Making Spatial Diagnosis in Combining Space Syntax, Spacematrix and MXI with GIS of new and old towns. In *EAAE/ISUF International Conference 2012*.