RESEARCH PAPER

UNRAVELING THE SPATIAL DYNAMICS: EXPLORING THE URBAN FORM CHARACTERISTICS AND COVID-19 CASES IN YOGYAKARTA CITY, INDONESIA

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ABSTRACT. The urban area is a spatial system that significantly impacts residents' health risks. Despite the fact that urban areas house only 55% of the global population, they account for 95% of COVID-19 cases, highlighting the urgent need to understand the role of the urban environment in disease spread. This research explores the critical impact of urban form characteristics on public health risks, focusing primarily on the dynamics of COVID-19 transmission. The aim of the study study is to elucidate the spatial association between urban form elements such as connectivity, density, and heterogeneity and the incidence of COVID-19 cases, with a specific focus on Yogyakarta. Using global (OLS) and local (GWR) spatial regression models, we analyzed the relationship between these elements and COVID-19 prevalence at the neighborhood level rigorously. Our findings reveal a pronounced spatial correlation, particularly highlighting the significance of connectivity and heterogeneity. These factors explain over 95% of the variance in case numbers, while density shows no substantial link. This study's originality lies in its hypothesis-driven examination of urban form impact on COVID-19 transmission, providing new insights into the spatial determinants of health risks in urban settings. Practical implications of our research are profound, providing evidence-based guidance for urban planning and disaster preparedness strategies to mitigate future health crises better. The study contributes valuable insights into designing healthier and more sustainable urban environments by providing a nuanced understanding of how the urban form influences the spread of disease.

KEYWORDS: urban form, COVID-19 case, neighborhood unit, spatial relationship

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INTRODUCTION

Recent findings published by UN-Habitat highlight that urban areas are at the forefront of the COVID-19 pandemic (UN-Habitat 2021). Urban areas have accounted for 95% of reported cases worldwide since the onset of the pandemic, and the United Nations (UN) recommends that cities implement effective strategies for urban management to address this situation. The COVID-19 situation in many urban areas exhibits diverse dynamics, including in the Special Region of Yogyakarta. The local government has reported escalating issues throughout the months during the situation, with the Sleman and Bantul districts exhibiting the highest distribution of confirmed cases compared to the Yogyakarta City area. The city's case ratio is surpassing the provincial average, with an average of 4.86 cases per 100 people, and the highest incidence rate at 0.07%, signifying seven active cases for every 100 residents in each neighborhood unit. Data from the Yogyakarta City Health Service highlights a notable escalation in case rates during mid-2021, particularly in June and July. This increase is predominantly seen in areas with very high population densities, reaching up to 100 people per hectare. The discrepancy can be attributed to the higher-risk population in these two communities, which are concentrated in urban areas, while the city of Yogyakarta itself serves as the central hub and epicenter of urban activity, spreading its influence throughout the surrounding regional area (Subkhi & Mardiansjah, 2019).

Regarding research substance, spatial morphology should consider the physical aspect of urban form as a crucial contextual element. The concept of spatial configuration plays a critical role in shaping urban forms and their characteristics of interaction (Whitehand et al., 1996; Seungkoo Jo, 1998; Clifton et al., 2008; Cortes, 2005; Berghauser Pont, 2018;). This issue is significant because urban forms reflect the impact and historical patterns of human activities and external factors, which shape the image and character of living spaces in tangible and measurable dimensions (Wheeler, 1971; Hillier & Iida, 2005; Batty, 2008). Various perspectives highlight the significant influence of urban forms on mobility patterns and human activities (Marshall et al., 2018). Another study highlights the detrimental impact of socio-economic inequalities on pandemic resilience, emphasizing the urgent need to address these inequalities through the pursuit of Sustainable Development Goals (Bhattacharjee & Sattar, 2021). By bridging these gaps, cities can increase their resilience and improve living standards for all residents.

Additionally, the research examines into the intricate socio-geographical dynamics of COVID-19, illustrating how natural and socio-economic factors interact to shape the pandemic spread and societal norms (Kolosov et al., 2021). The analysis of urban concepts suggests that human interactions within an area are closely linked to the spatial configuration of that area. Furthermore, existing literature indicates that outbreaks of infectious diseases like COVID-19 tend to spread according to specific pathways (Hamidi et al., 2020; Kim et al., 2020; Liu, 2020). The spread of these diseases is intricately linked to the physical environment where the outbreak occurs (Fathi et al., 2020; Gross et al., 2020). Urban forms, therefore, encompass physical features and spatial configurations that can act as catalysts for disease spread (Sharifi & Khavarian-Garmsir, 2020).

In the context of COVID-19, urban areas play a crucial role in the spread of the disease and the level of outbreak risk. This is influenced by factors such as infrastructure, design, land use patterns, and population size (Hamidi et al., 2020; Silalahi et al., 2020). Furthermore, the literature underscores the transformative potential of deliberate urban design in equipping global neighborhoods to effectively confront pandemics (Ghishan et al., 2023). By prioritizing health-conscious and navigable living environments while simultaneously mitigating disease transmission risks, cities can bolster community resilience worldwide. The significance of population density and proximity to pandemic epicenters as key determinants suggests that sustainable development goals (SDGs) could markedly enhance pandemic preparedness and urban health outcomes (da Silva et al., 2021). Therefore, it is important to consider the environmental aspects of urban areas and the typologies of spaces and their interactions (Brizuela et al., 2019; Yao et al., 2021). However, the discussion regarding the association between urban space characteristics and disease outbreaks still raises numerous questions, particularly regarding the risk factors involved (Aritenang, 2022; Wahid & Setyono, 2022). Consequently, the relationship between urban forms and infectious diseases has reached a definite consensus, requiring a more cases study research with a comprehensive multi-factorial approach to urban spatial elements.

This study hypothesizes that the spatial characteristics of urban form, including connectivity, density, and heterogeneity, influence the distribution and spread of COVID-19 cases in urban areas. To address existing gaps in the literature, we investigate these relationships through a mixed-method approach using GIS spatial statistics and Space Syntax analysis in the context of Yogyakarta, Indonesia. This research question focuses on exploring the correlation between urban form elements and COVID-19 cases, identifying spatial patterns, and understanding the impact of urban spatial configurations on disease transmission risk. By utilizing a specific case study and integrating quantitative analysis with spatial data exploration techniques, our study aims to provide unique insights into the spatial dynamics of COVID-19 transmission in Indonesian urban contexts, contributing valuable knowledge for urban planning and public health interventions.

MATERIALS AND METHODS

Study Area

This study focuses on quantitative measurements to examine the relationship between health dimensions, specifically the level of COVID-19 cases, and various elements of urban form, including spatial connectivity and accessibility, density aspects, and heterogeneity of spatial functions. The study was conducted in Yogyakarta City, which consists of 14 sub-districts (Kemantren) and 45 neighborhoods (Kelurahan) as the spatial units for analysis. These units represent the smallest spatial scale for data processing and analysis. Fig. 1 provides a visual representation of the unit of observation and a description of the research location.

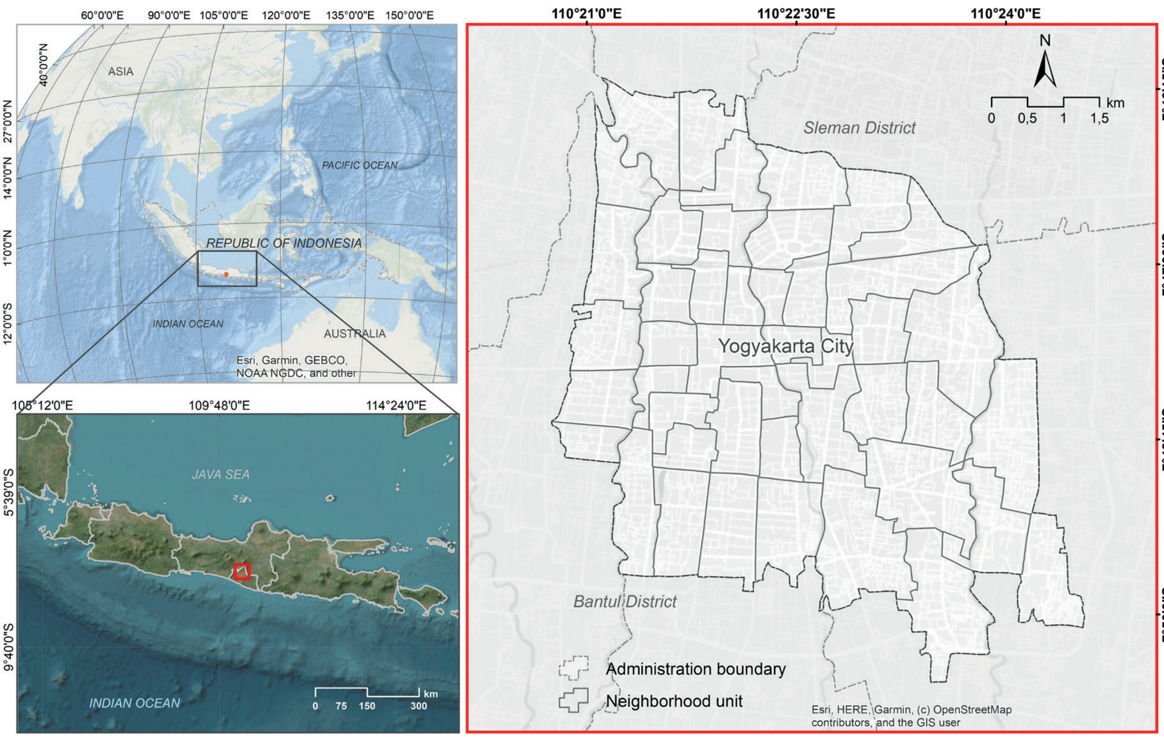

Fig. 1. The study focuses on Yogyakarta city and provides a description of the analysis units at the neighborhood scale

The observation period spans one and a half years, from March 2020 to August 2021. All data were aggregated on a monthly cumulative basis for each neighborhood unit. The measured parameters of urban form are categorized into three elements: spatial connectivity, spatial density, and heterogeneity of spatial functions. Each of these elements is calculated using methods from relevant literature. Geospatial data (shapefiles of street networks, building footprints, and building functions) were collected from the municipal spatial planning authority, ensuring the reliability of the input data.

Methodology and Data Analysis

Urban form refers to the physical characteristics and spatial layout of urban areas (Batty, 2008; Berghauser Pont, 2018). It encompasses the arrangement, design, and configuration of various elements within the built environment, such as land use, streets, buildings, public spaces, and other physical infrastructure. In this research context, we use three parameters as critical components of spatial configuration: connectivity and accessibility, density, and spatial heterogeneity.

Spatial connectivity and accessibility are assessed using the space syntax approach (Hillier, 1988; Hillier et al., 2007;

Table 1. Description of urban morphological aspect and each parameter methods

Aspect	Methods/ analysis	Parameters	Variable notation	Data source
COVID-19 Cases	Spatial Autocorrelation (Global Moran's I)	Spatial pattern of case prevalence	Y	Local public health authorities (*Dinkes Kota Yogyakarta*)
Connectivity-Accessibility	Space Syntax (integration)	Global spatial integration	X_1	Topographic maps: *Rupa Bumi Indonesia* (BIG)
		Local spatial integration	X_2	
	Space Syntax (choice/ centrality)	Global betweenness centralities	X_3	
		Local betweenness centralities	X_4	
Urban Density	Spatial (weighted) density	Built up area density	X_5	Open Street Map (OSM)
		Settlement density	X_6	
		Population density	X_7	Population and civil registration authorities (*Disdukcapil Kota Yogyakarta*)
Heterogeneity	Spatial (Shannon's) entropy	Public facilities dispersion	X_8	Open Street Map (OSM);
		Land use mix concentration	X_9	Department of land and spatial planning (*DPTR Kota Yogyakarta*)

* The data are grouped according to the variables in a spatial relationship model, i.e., the aspect of case occurrence and urban form characteristics.

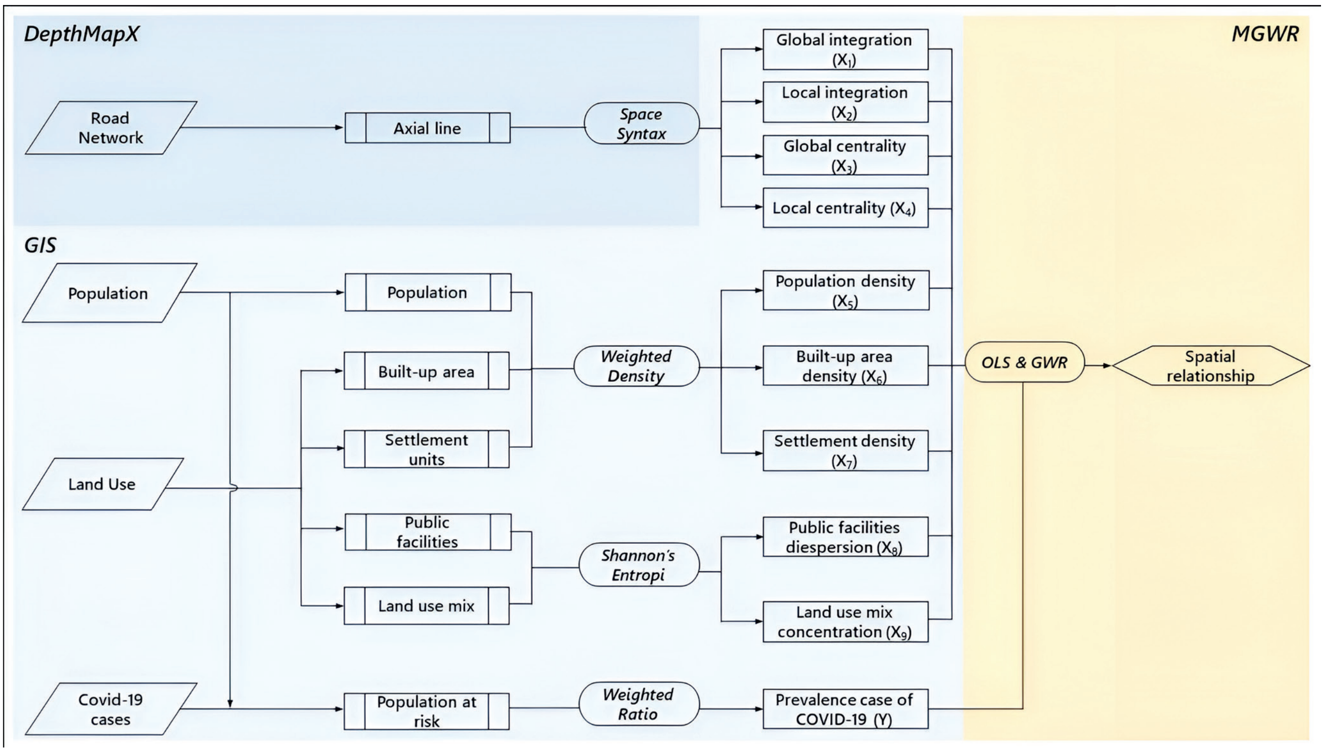

Fig. 2. The stages of data processing and analysis

Varoudis et al., 2013), which analyzes spatial arrangements from building scales to urban areas (Berghauser Pont, 2018). By examining the topology of road networks, space syntax models potential movements, interactions, and patterns of people (Van Nes & Yamu, 2018). In this study, the road network coverage is adjusted to the observation area boundary, with a 500-meter buffer radius from the outer boundary to minimize edge effects of the road network geometry (Gil, 2016). Parameters used in space syntax analysis include mean depth, integration, and betweenness centrality, which are crucial for estimating spatial accessibility within each observation area. Density aspect incorporates population size, built-up area, and settlement density. Density calculation in this study uses a statistically weighted measure, modifying the conventional approach to improve accuracy (Ottensmann, 2018). The aspect of spatial heterogeneity is assessed by quantitatively characterizing landscape pattern differences using the entropy matrix calculations, which have been demonstrated to be relevant in describing urban landscapes (Wang & Zhao, 2018). Variables used in the entropy calculation include the distribution of public facilities and spaces, as well as the land use mix within each observation unit (Jackson, 2003; Lu et al., 2020).

To explore the relationship between urban form elements and COVID-19 cases, a spatial statistical analysis using modeling techniques was conducted. The conceptualization of the models consists of a global relationship model utilizing Ordinary Least Squares (OLS) regression (Páez & Scott, 2004; Mollalo et al., 2020) and a local relationship model employing Geographically Weighted Regression (Brunsdon et al., 1996; Nakaya et al., 2005; Oshan et al., 2019). Both models utilize spatial statistical techniques to investigate the relationship between variables in a location-based context. These models differ from traditional regression in that they consider the geographic attributes of each measured variable in their calculations (Berliner, 2015).

The OLS model is used to examine the relationship between a dependent variable and a set of explanatory variables in a global context, where the spatial variability of each variable is generally equated (Getis & Ord, 2010). The OLS model is represented by the following Eq. 1:

$$y_i = \beta_0 + \sum_{i=i\ldots 3} \beta ixi + \varepsilon \quad (1)$$

where in area *i*, y_i is the dependent variable, which represents the degree of incidence; $\beta 0$ is the intercept; xi is the selected explanatory variable; β is the regression coefficient; and ε is the random error or residual generated by the model.

On the other hand, the Geographically Weighted Regression (GWR) model examines the local relationship between the dependent variable and the explanatory variable, incorporating location weights in the form of a bandwidth or kernel (Brunsdon et al., 1996). In this study, the GWR technique is adjusted to the Poisson distribution, due to the discrete nature of the dependent variable that represents disease cases (Nakaya et al., 2005). The Poisson distribution includes an offset value that is determined by the population size at risk to increase the model's sensitivity in capturing local effects on various factors that influence the dependent variable, in this case, the prevalence of COVID-19 cases. The Eq. 2 for the GWR model is as follows:

$$y_i = poisson\left[N_i exp\left(\beta_0\left(u_i, v_i\right) + \Sigma_k \beta_k\left(u_i, v_i\right) x_{k,i}\right)\right] \quad (2)$$

where β_0 (u_i, v_i) is the intercept coefficient at location *i*; β_k (u_i, v_i) is the coefficient of the explanatory variable $X_{k,i}$ for location *i*; *N* is the offset value at location *i*; and (u_i, v_i) is the coordinate matrix at location *i*.

The data analysis process begins by converting each parameter into geospatial format. Each parameter is then processed based on its respective variable category, which is defined as a dependent variable (response) or independent variable (explanatory). In this study, the response variable refers to the number of COVID-19 cases, whereas the explanatory variables derive from the calculation of parameters associated with urban form elements.

Once all the data has been formatted in the same way, each data point can be processed according to the criteria and categories of variables to be analyzed. The analysis process involves several applications and methods, including space syntax using DepthmapX, Geographic Information System (GIS), and Multiscale Geographic Weighted Regression (MGWR). The spatial relationship analysis is conducted by integrating all the data into a modeling application to obtain statistical test results. The data flow in this study is illustrated in Fig. 2 and involves grouping variables according to the unit of analysis for both the dependent and independent variables. The case prevalence variable is aggregated periodically based on observation time, while the urban form is analyzed at the neighborhood unit level. This ensures that the output of each parameter can be analyzed on a uniform scale.

RESULTS

Spatial Pattern of Covid-19 Cases

The prevalence of COVID-19 cases in the study area provides an understanding of the extent to which the disease has affected the population over a specific time period. This prevalence is represented by cumulative proportions, which offer a measure of the likelihood that individuals will be affected by the disease at any given time. Analysis results reveal variations in prevalence among different neighborhood units. Throughout the entire observation period, the average prevalence across all observation areas was 5.19 cases. The Notoprajan area has the lowest prevalence, averaging only 3.10 cases, whereas the Kotabaru area has the highest prevalence, with an average of 7.24 cases. Other areas with high prevalence include Semaki, Mantrijeron, Rejowinangun, Purwokinanti, Terban, Purbayan, Muja Muju, Prenggan, and Bausasran, with prevalence values ranging from 6.18 to 6.77 per respective population. These areas exhibit an above-average case prevalence, indicating a higher risk of COVID-19 transmission compared to other observation areas. The prevalence of COVID-19 in each neighborhood unit across the study area is presented in Table 2.

Furthermore, the spatial analysis conducted on these parameters provides a detailed description of the pattern and distribution of values, offering explicit insights. The analysis of prevalence values in each neighborhood unit reveals a spatial clustering pattern. This is supported by the results of the spatial autocorrelation test that indicates a significant relationship among the prevalence values. The prevalence values in the study area exhibit an expected index value of -0.023, with a variance of 0.009. The Global Moran's I index yields a value of 0.329, with a *p-value* of 0.000 and a *z-score* of 3.822. In a statistical context, the index value interpretation suggests that the spatial patterns observed are unlikely to occur randomly across the observation units. The significant Moran's index value indicates that the prevalence rate of COVID-19 cases in both high and low classes demonstrates a spatial distribution that corresponds to

Table 2. The results of the prevalence case in each neighborhood unit

Neighborhood	Population	Case	Prevalence		Neighborhood	Population	Case	Prevalence
Baciro	12347	683	5.53		Pandeyan	12213	566	4.63
Bausasran	7505	464	6.18		Panembahan	9062	545	6.01
Bener	4958	260	5.24		Patangpuluhan	7721	354	4.58
Brontokusuman	10853	495	4.56		Patehan	5901	329	5.58
Bumijo	10313	506	4.91		Prawirodirjan	9358	492	5.26
Cokrodiningratan	8870	356	4.01		Prenggan	11501	717	6.23
Demangan	8708	472	5.42		Pringgokusuman	12284	506	4.12
Gedongkiwo	14044	680	4.84		Purbayan	10286	657	6.39
Giwangan	8028	378	4.71		Purwokinanti	6186	398	6.43
Gowongan	7947	300	3.78		Rejowinangun	12807	844	6.59
Gunungketur	4536	270	5.95		Semaki	5185	351	6.77
Kadipaten	6816	387	5.68		Sorosutan	15623	667	4.27
Karangwaru	9712	458	4.72		Sosromenduran	7417	294	3.96
Keparakan	9822	407	4.14		Suryatmajan	4616	230	4.98
Klitren	9672	531	5.49		Suryodiningratan	11270	572	5.08
Kotabaru	2929	212	7.24		Tahunan	9194	478	5.20
Kricak	13336	557	4.18		Tegalpanggung	9204	550	5.98
Mantrijeron	10148	669	6.59		Tegalrejo	9250	423	4.57
Muja Muju	10946	692	6.32		Terban	9269	595	6.42
Ngampilan	10224	418	4.09		Warungboto	9253	467	5.05
Ngupasan	5603	323	5.76		Wirobrajan	9346	438	4.69
Notoprajan	8215	255	3.10		Wirogunan	11285	474	4.20
Pakuncen	10941	449	4.10					

*Prevalence values are calculated for every 100 people in each neighborhood; the highlighted columns show values above the average in each class

their respective class values. This implies the presence of spatial autocorrelation, where areas with similar prevalence values tend to cluster together. A summary of the statistical test (Global Moran's I) for this parameter is depicted in Fig. 3.

The Connectivity and Accessibility Aspect

The analysis of connectivity and accessibility of the observation units is based on the concept of space syntax, which examines the connectedness of the road networks and their spatial configuration. This aspect is considered crucial for understanding the potential movement by identifying more frequently accessed routes. The results include the integration (INT) and centrality (CH) indexes of the road networks, assessed at local and global radii (see Table 3). The local radius measures spatial integration within an 800-meter range, while the global radius represents patterns on a larger spatial scale, taking into account movement from outside the study area.

The integration analysis results indicate that there are varying levels of inter-spatial accessibility across all observation areas. Figs. 4 (a) and (b) illustrate the pattern of the integration index, which indicates inter-spatial accessibility throughout the observation areas. Higher integration values indicate greater spatial accessibility, reflecting the potential for movement within the urban system. The concentration is observed in the Warungboto, Rejowinangun, Gunungketur, Semaki, and Giwangan areas, indicating the potential for movement within the local and global radius. The highest level is concentrated in the middle-to-southeast area (represented by the area with red lines). Meanwhile, the lowest index reveals that the distribution pattern spreads to the northwest, or the area of the city bordered with other districts (represented by the area with blue lines).

The results of the centrality analysis show that areas such as Gunungketur and Semaki display a relatively high centrality pattern, indicating their significance in terms of through-movement at the local radius. Similarly, global centrality is concentrated in the areas traversed by primary and secondary collector paths, as shown by the red lines in Figs. 4 (c) and (d). This centrality suggests a consolidated road network in these regions, where effective connections can be established between any pair of spatial elements within each unit. Overall, the analysis of betweenness centrality provides insights into the potential for efficient movement and the effectiveness of road networks in the study area, both at the local and global coverage.

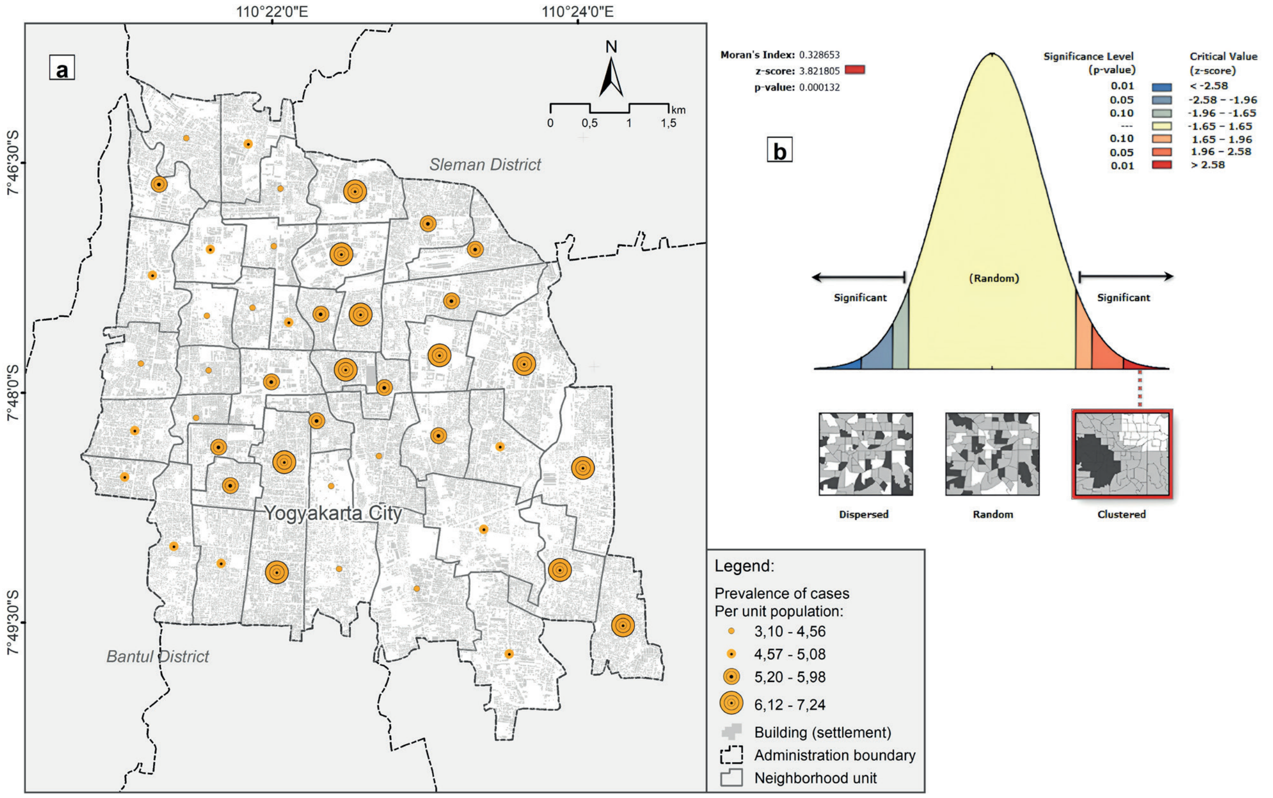

Fig. 3. (a) The illustration shows the prevalence of cases in each neighborhood unit; (b) The results of the spatial statistical test showed a clustered pattern in the observation area

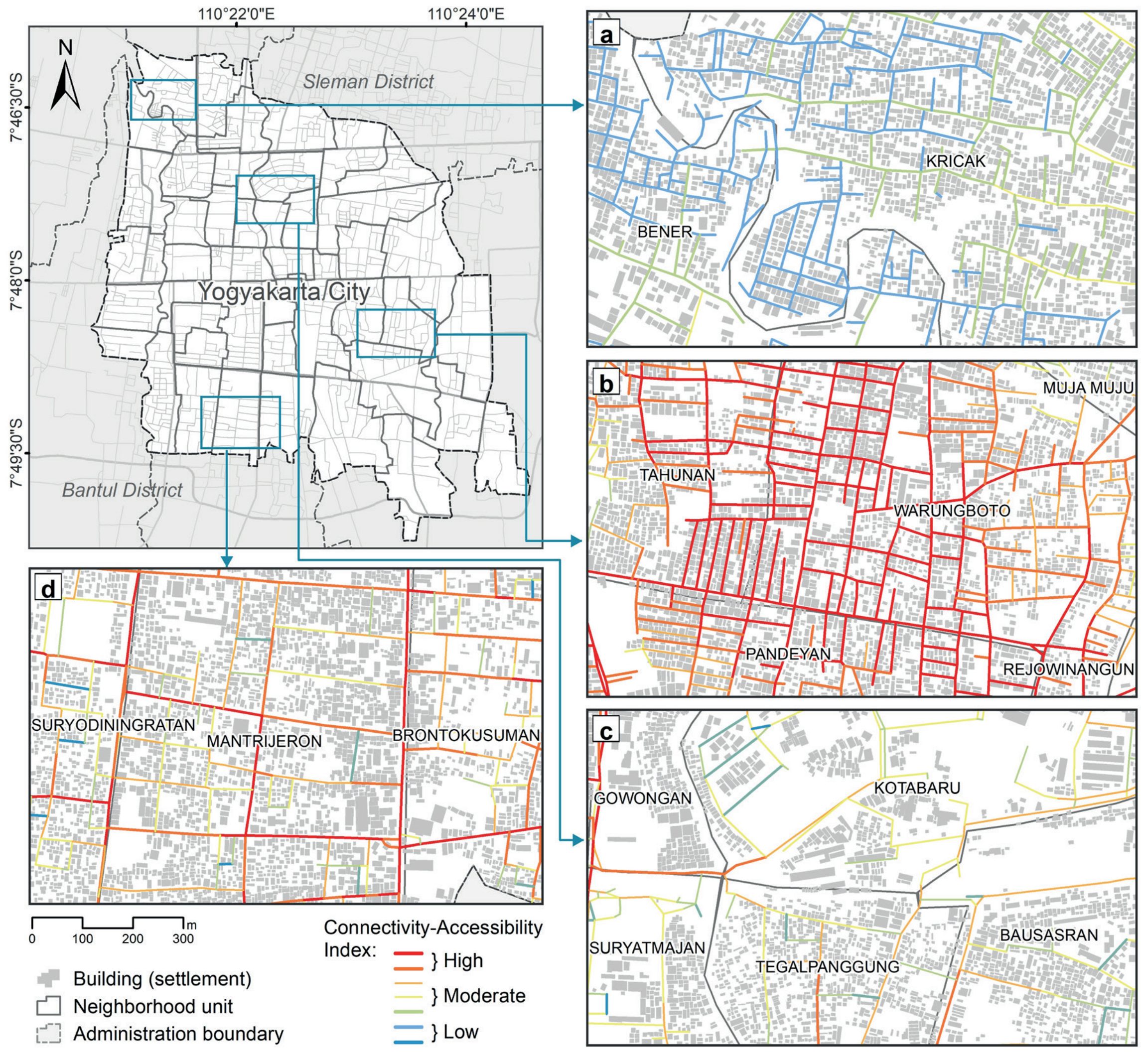

Fig. 4. The results of the connectivity-accessibility analysis using the space syntax are as follows: (a) low-level global integration; (b) high-level local integration; (c) moderate global centrality; and (d) high-level local centrality

Table 3. Average index of integration and centrality of road networks in each neighborhood unit

Neighborhood	INT (local)	INT (global)	CH (local)	CH (global)		Neighborhood	INT (local)	INT (global)	CH (local)	CH (global)
Baciro	2.593	4.708	0.896	0.176		Pandeyan	2.962	5.035	0.873	0.379
Bausasran	2.189	4.666	0.696	0.187		Panembahan	1.917	4.825	0.550	0.405
Bener	1.422	3.188	0.652	0.070		Patangpuluhan	1.594	5.287	0.201	0.405
Brontokusuman	2.071	4.474	0.733	0.110		Patehan	1.390	4.108	0.489	0.039
Bumijo	2.311	4.435	0.846	0.283		Prawirodirjan	2.467	5.543	0.647	1.013
Cokrodiningratan	2.257	3.961	0.795	0.375		Prenggan	2.825	4.514	1.275	0.176
Demangan	1.715	4.106	0.485	0.047		Pringgokusuman	2.772	4.955	1.068	0.261
Gedongkiwo	1.691	4.482	0.529	0.233		Purbayan	1.870	3.677	0.986	0.142
Giwangan	2.189	4.178	0.854	0.129		Purwokinanti	2.423	5.404	0.709	0.518
Gowongan	2.474	4.905	0.707	0.897		Rejowinangun	2.932	5.058	1.040	0.335
Gunungketur	3.031	5.760	0.990	1.276		Semaki	3.194	5.423	1.121	0.772
Kadipaten	1.736	4.751	0.605	0.102		Sorosutan	2.322	4.603	0.750	0.149
Karangwaru	1.696	3.326	0.594	0.112		Sosromenduran	2.525	5.054	0.722	0.119
Keparakan	2.258	5.071	0.715	0.554		Suryatmajan	2.665	5.201	0.841	0.568
Klitren	1.832	4.043	0.606	0.174		Suryodiningratan	2.296	4.531	0.709	0.199
Kotabaru	1.482	3.764	0.397	0.028		Tahunan	2.914	4.871	1.087	0.139
Kricak	1.837	3.357	0.891	0.072		Tegalpanggung	1.683	4.348	0.693	0.193
Mantrijeron	2.472	4.778	0.762	0.310		Tegalrejo	2.334	4.488	0.789	0.200
Muja Muju	2.197	4.952	0.609	0.291		Terban	1.766	3.950	0.532	0.179
Ngampilan	2.179	4.822	0.707	0.197		Warungboto	3.457	5.123	1.412	0.281
Ngupasan	2.127	5.317	0.390	0.180		Wirobrajan	2.059	5.079	0.440	0.168
Notoprajan	1.647	5.424	0.405	0.749		Wirogunan	2.568	5.299	0.794	0.503
Pakuncen	2.466	4.802	0.887	0.357						

The average index is used to determine the values of integration and centrality for each neighborhood unit. The results are presented in Table 3. Certain areas exhibit high values for all parameters, as exemplified by Gunungketur and Semaki, with values of 5.76 and 5.42 respectively. Other areas, such as Preggan and Warungboto, have values of 1.28 and 1.41 respectively, which demonstrate high centrality within the local radius. These areas should be considered as they indicate significant potential for spatial accessibility. Overall, the average index provides valuable insights into the levels of integration and centrality in each neighborhood unit, highlighting areas with high connectivity and accessibility.

The Urban Density Aspect

The aspect of urban spatial density encompasses three variables: built-up area density, settlement density, and population density. Built-up area density indicates the intensity of space utilization by non-residential structures, expressed as the ratio of non-residential built-up areas to the total area of a neighborhood. Similarly, settlement density reflects the ratio of land area occupied by residential buildings in the neighborhood. Population density, on the other hand, measures the number of residents per unit area in each neighborhood.

The spatial analysis of urban spatial density is presented in Fig. 5. Built-up area density is derived from the land use blocks within each observation unit, excluding non-residential areas, parks, and riverbanks (Fig. 5a). The results reveal Bumijo, Cokrodiningratan, and Gowongan as examples of high-level built-up area density ratios exceeding 90%. On the other hand, Pakuncen exhibits the lowest density ratio at 70.9%. Despite being the lowest, this value still indicates a relatively high occupancy of built-up land, representing disproportionate land use. Across the entire study area, Yogyakarta falls under the category of cities with very high levels of built-up area density, with an average ratio exceeding 87%. This implies that space utilization and intensity are primarily dominated by built-up areas, leaving less than one-fifth of the total area as open space.

Settlement density captures the level of dwelling intensity within each neighborhood, quantified by the number of buildings (Figs. 5b and 5d). The data for dwelling units is obtained from building footprint records, encompassing various types of residential structures such as houses, flats, apartments, dormitories, and boarding houses, as well as accommodation facilities like inns, hotels, motels, and villas. The results demonstrate that Tegalpanggung and Ngupasan exhibit the highest settlement density, with an average value of 38 units per hectare. This finding aligns with the actual conditions on the field, where Tegalpanggung is characterized by slum areas, particularly along the western side of the Kali Code riverbank. In Ngupasan, the spatial proximity between residential buildings is notably close, resulting in the highest settlement density within the study area.

The analysis of population density reveals that the Yogyakarta city experiences a generally high level of density. Approximately 60% of all neighborhood units are in the very high-density category, for example, Tegalpanggung area (Fig. 5c). Meanwhile, only one neighborhood unit is categorized as moderate density is observed solely in Kotabaru. This result is consistent with the actual conditions on the field, where the number of residents in that particular area is relatively lower compared to other neighborhoods, reflecting the city's population dynamics and distribution.

The analysis of urban spatial heterogeneity yields an index that serves as a measure of concentration for public facilities and land use mix in the entire study area, as depicted in Fig. 6(a). The entropy index calculations generate relative values, providing a spatially quantitative measure of the concentration of these variables. The results show a variety of values for the entropy index of public facilities across each neighborhood area, indicating variations in the distribution of urban space function. On the other hand, the analysis of land use mix reveals a low level of diversity or heterogeneity in all observation areas, suggesting a concentration of specific service functions in certain areas.

The relationship between the entropy index for facilities and the land use mix demonstrates a positive correlation. The graph in Fig. 6(b) illustrates a linear trend between these two variables, with an R^2 value of 0.3107. Although this correlation value may not be considered high, it suggests that the distribution and variability of public facilities tend to align with the pattern of land use mix. In other words, the location of urban service facilities generally corresponds to the heterogeneity of spatial functions within the observation area.

Spatial Relationship Testing

Global Model Estimation using OLS:

The OLS method was used to estimate the global relationship between the response variable and a set of explanatory variables. The OLS results provide predictions on a global scale and include statistical information such as coefficient estimates for the explanatory variables and residual values for each observed variable. The model's performance was evaluated through diagnostic tests to assess its adequacy. Estimated variable coefficients and test results are presented in Table 4.

The AICc (Akaike's Information Criterion-Corrected)

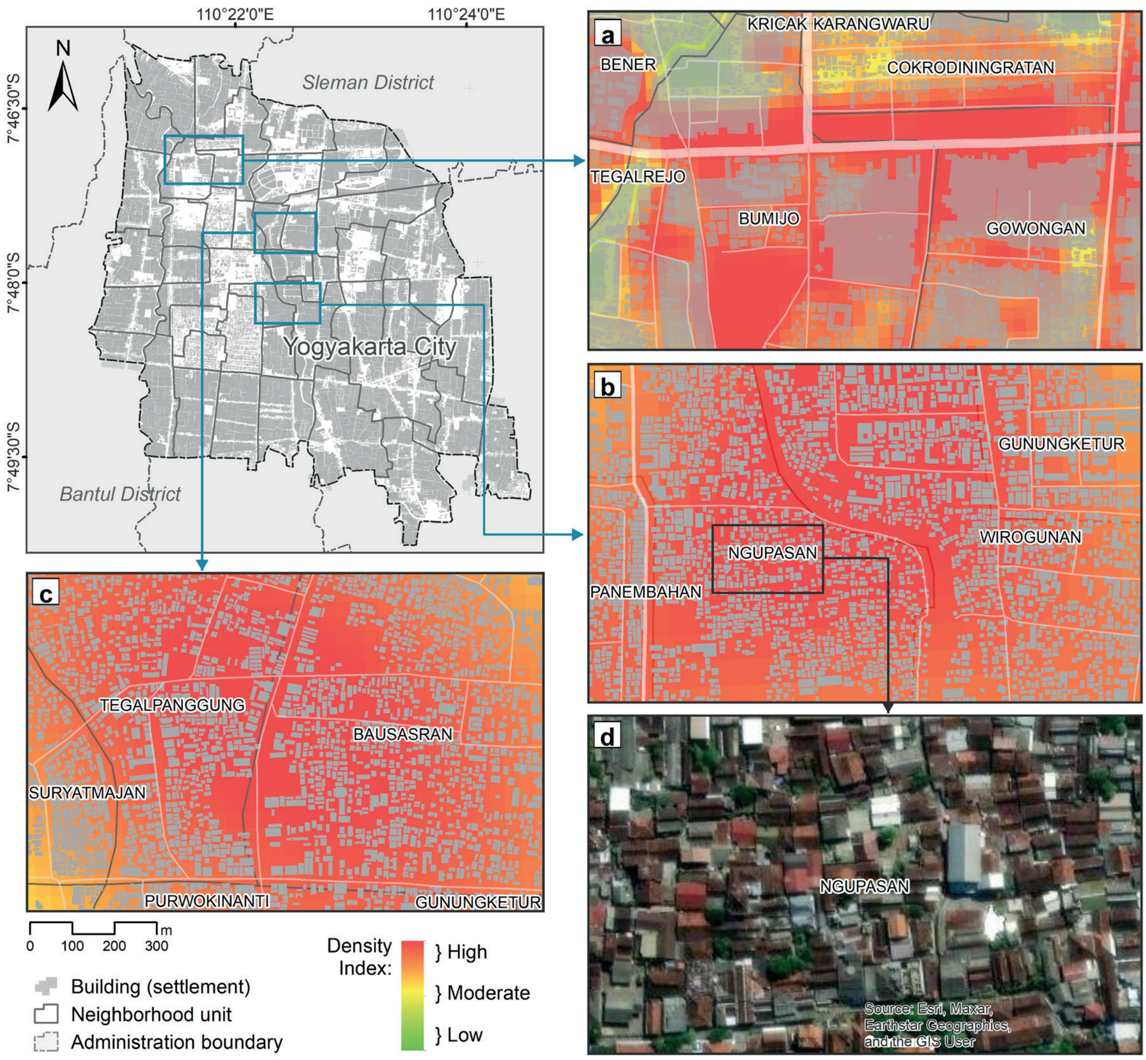

Fig. 5. Urban spatial density of every neighborhood unit includes: (a) high-level built-up density with a ratio of >90% per-unit area, (b) high-level settlement density with >30 units per hectare, (c) high-level population density with >400 people per hectare, and (d) visualization of settlements from high-resolution satellite imagery

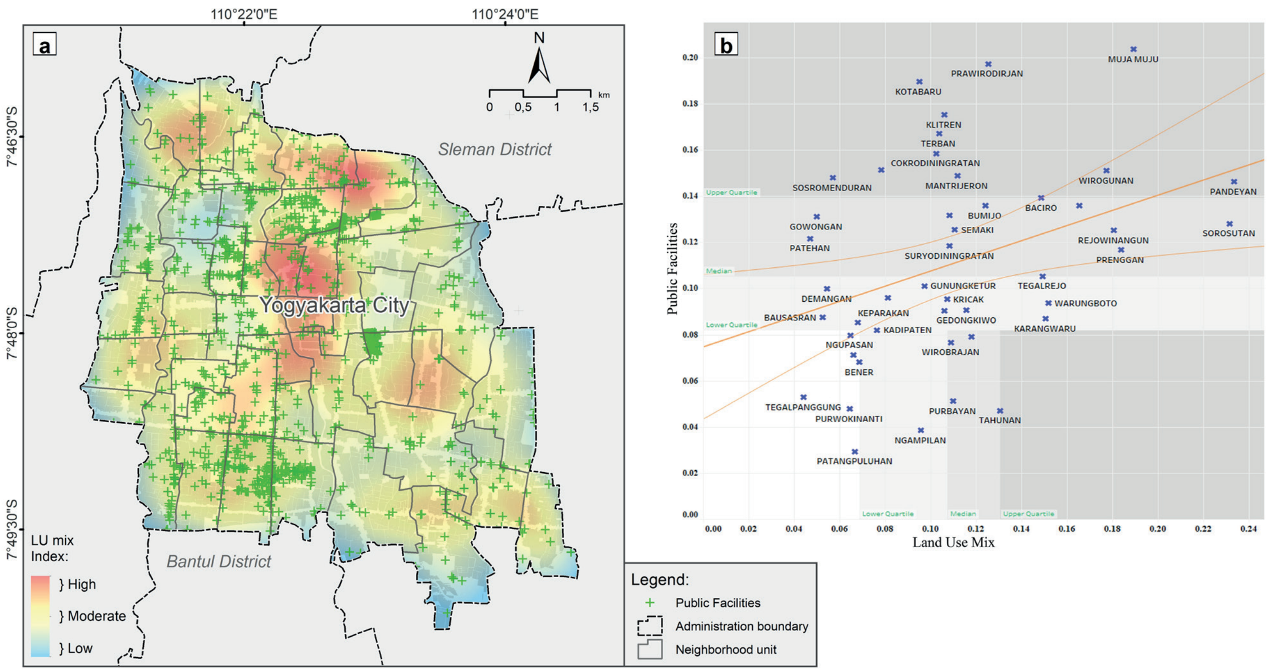

Fig. 6. The results of urban spatial heterogeneity show: (a) the spatial distribution of public facilities and land use mix, and (b) the statistical distribution of the entropy index

Table 4. Statistical summary of explanatory variables and diagnosis of the OLS model

Variables			Coefficient	Std_Error	t_Stat	Prob*	Robust SE	Robust_t	Robust Prob*
		Intercept	4.649763	0.978861	4.750178	0.000004	1.153647	4.030492	0.000074
Connectivity-Accessibility	Local integration	X_1	0.608993	0.187566	3.246816	0.001287	0.187514	3.247712	0.001283
	Global integration	X_2	-0.541646	0.346655	-1.562494	0.119044	0.338523	-1.600028	0.110463
	Local centrality	X_3	-0.856153	0.273999	-3.124663	0.001933	0.305744	-2.800229	0.005377
	Global centrality	X_4	1.699179	0.553574	3.069471	0.002314	0.451213	3.765798	0.000204
Spatial Density	Built-up area	X_5	-0.00198	0.00031	-6.391879	0.000004	0.000262	-7.549206	0.000004
	Settlement	X_6	-0.52968	1.006174	-0.52643	0.598916	1.199278	-0.441666	0.659003
	Population	X_7	-0.00749	0.010702	-0.699898	0.484428	0.011664	-0.642171	0.521161
Heterogeneity	Public facilities	X_8	6.822397	1.439608	4.739065	0.000004	1.283156	5.316889	0.000004
	Land use mixed	X_9	-7.40221	1.220654	-6.064137	0.000001	1.462142	-5.062578	0.000001
Diagnostic results		AIC	AICc	R^2	AdjR^2	F-Stat	F-Prob	Wald	Sigma^2
		968.6817	969.403	0.2173	0.1982	11.3522	0.0001	151.6488	0.7359

*statistical significance is indicated by the value ($p < 0.01$)

test yielded a value of 968.682, indicating relatively good model performance. The R^2 value of 0.217 (coefficient of determination) suggests that only a portion of the response variable can be explained by the explanatory variables. The F-Stat and Wald's test results indicate the overall significance of the model, while the Sigma^2 value represents the OLS estimate of the variance error in the explanatory variable. Although the coefficient of determination is not particularly high, the results indicate a significant relationship between the tested variables and the prevalence of COVID-19 cases in the study area. In other words, there is a general correlation between between urban form characteristics characteristics and the prevalence of COVID-19 cases.

Furthermore, most of the explanatory variables examined, particularly those related to accessibility and spatial connectivity (X_1, X_3, and X_4), showed statistical significance in the global model. However, in terms of density, only variable (X_5) was found to be significant. Additionally, the spatial heterogeneity aspect indicated that all the variables were significantly associated with the case prevalence rate.

Local Model Estimation using GWR:

To examine the relationship between the explanatory variables and the response variable, experiments were conducted using the GWR method with Poisson distribution configuration. The Poisson configuration was chosen because it best fits the nature of the response variable, considering that the case prevalence is discretely distributed. This means that the probability distribution of case prevalence varies across space and time within each observation unit. Table 5 summarizes the statistics from the GWR model's implementation.

The GWR model describes that certain explanatory variables have varying levels of significance. This indicates that not all variables can consistently explain the prevalence of COVID-19 cases across all observation units. According to the summary statistics in Table 5, the global centrality variable (x_3), which represents spatial accessibility, is significant, as well as the heterogeneity aspect, including public facilities (x_8) and land use mix (x_9). However, the density aspect does not show a significant correlation with the spatial distribution of COVID-19 cases. These findings differ slightly from the results of the global OLS model, where all three aspects of urban spatial form were found to be significant. In other words, the GWR model identifies specific variables from different aspects of urban form that are potentially related to the prevalence of cases in the study area.

Table 6 presents the statistical significance of each explanatory variable at the 95% confidence level for each observation unit. The significance of variables in the GWR model takes into account the unique locational attributes that reflect spatial variability. This highlights the importance of considering the location factor in understanding the spatial relationship of a phenomenon. It also indicates that certain characteristics and relationships may not be generalized across all spatial locations. Furthermore, Fig. 7 illustrates the spatial relationships of those variables within each observation area of the neighborhood units in the model.

DISCUSSION

The findings of this study highlight the intricate relationship between urban morphology and the prevalence of COVID-19 across diverse observation units. They reveal the varying impact of urban form elements on the spread of the disease. This research supports the hypothesis that the presence of urban form elements and their relationships with the surrounding spatial and social context significantly affect COVID-19 case numbers.

Table 5. Statistical summary of explanatory variables in GWR estimation along with model diagnostic test results

	Variables									
	Intercept	Connectivity-accessibility				Spatial density			Heterogeneity	
		X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
Coefficient	-4.46	-0.059	-0.098	0.504	-0.181	0	0.103	0.003	1.491	-4.11
StdError	0.41	0.084	0.145	0.13	0.239	0	0.431	0.004	0.589	0.503
t_Stat	-10.87	-0.701	-0.675	3.882	-0.758	-1.206	0.239	-0.604	2.532	-8.17
p-value	0	0.483	0.5	0	0.449	0.228	0.811	0.546	0.011	0
Mean	-3.89	-0.151	0.062	0.334	-0.572	0	0.096	0.12	2.618	-5.978
Std.Dev	2.484	0.634	0.72	1.011	1.076	0.001	3.071	0.024	2.94	2.452
Min	-9.922	-2.472	-1.683	-1.543	-3.138	-0.003	-7.615	-0.069	-2.675	-12.316
Median	-4.286	-0.052	0.062	0.099	-0.549	0	0.315	-0.003	1.906	-5.499
Max	2.305	0.903	2.952	4.345	2.62	0.005	6.534	0.037	13.387	-1.475

Coordinate System	WGS 1984 UTM 49S (Lat, Long)
Diagnostic	Generated value
AIC	93.629
AICc	99.596
BIC	217.989
Optimum Badwidth (confidence 95%)	210
Degree of freedom (n - traces)	346.396
Deviance (goodness-of-fit)	30.421
Percent deviance explained	0.856
Adj. percent deviance explained	0.842
Adj. alpha (confidence 95%)	0.016
Adj. critical t value (confidence 95%)	2.424

Table 6. The significance of each variable (p-value) at the 95% confidence level is determined for each unit of observation

Neighborhood unit	*pX1*	*pX2*	*pX3*	*pX4*	*pX5*	*pX6*	*pX7*	*pX8*	*pX9*	Σ (significant)
Baciro	0.11254	0.43963	0.60634	0.03030	0.00002	0.46821	0.45756	0.74648	0.02607	3
Bausasran	0.31872	0.10461	0.97873	0.21707	0.05190	0.00909	0.00258	0.87477	0.00121	3
Bener	0.01628	0.02314	0.00004	0.00719	0.50403	0.43127	0.29016	0.04803	0.01136	6
Brontokusuman	0.34020	0.43211	0.21995	0.71698	0.26093	0.39812	0.39284	0.72752	0.00239	1
Bumijo	0.40294	0.45987	0.00038	0.18605	0.80357	0.12210	0.44313	0.08217	0.02387	2
Cokrodiningratan	0.27134	0.44551	0.00369	0.07721	0.63443	0.15639	0.40043	0.00516	0.06680	2
Demangan	0.17687	0.67195	0.00765	0.00617	0.00041	0.65011	0.29474	0.00237	0.03113	5
Gedongkiwo	0.05895	0.13442	0.99824	0.84214	0.03457	0.41390	0.41813	0.89379	0.00001	2
Giwangan	0.00777	0.11598	0.60430	0.05689	0.37387	0.16093	0.00421	0.02226	0.00021	4
Gowongan	0.42941	0.41833	0.00046	0.57911	0.62285	0.03206	0.15621	0.04642	0.01955	4
Gunungketur	0.70332	0.32613	0.87576	0.87513	0.10590	0.38609	0.24403	0.85640	0.00131	1
Kadipaten	0.32685	0.20892	0.19935	0.07530	0.15759	0.67374	0.36471	0.94196	0.00019	1
Karangwaru	0.31717	0.18098	0.00000	0.05667	0.22265	0.50602	0.75956	0.00208	0.07978	2
Keparakan	0.48595	0.62817	0.87448	0.82227	0.67010	0.55465	0.74009	0.81728	0.01858	1
Klitren	0.54091	0.72188	0.00158	0.01443	0.04377	0.34145	0.03140	0.00000	0.00481	6
Kotabaru	0.27375	0.30498	0.82777	0.96549	0.57319	0.00084	0.05207	0.00376	0.00039	3
Kricak	0.04122	0.02997	0.00002	0.01839	0.21669	0.63882	0.36099	0.03509	0.01488	6
Mantrijeron	0.36333	0.38400	0.99531	0.65975	0.27088	0.53834	0.19422	0.49678	0.00022	1
Muja Muju	0.41491	0.68873	0.96622	0.94362	0.04200	0.63868	0.70892	0.92128	0.03611	2
Ngampilan	0.79744	0.68861	0.04119	0.15372	0.43381	0.43255	0.28664	0.85977	0.01389	2
Ngupasan	0.37785	0.83887	0.16080	0.15255	0.41131	0.80786	0.72535	0.99263	0.05877	0
Notoprajan	0.37464	0.25883	0.15278	0.08240	0.23717	0.72088	0.37133	0.98580	0.00023	1
Pakuncen	0.51733	0.62773	0.06548	0.10328	0.68319	0.45253	0.48142	0.90499	0.19386	0
Pandeyan	0.35957	0.65999	0.98130	0.95926	0.46253	0.52589	0.42644	0.98981	0.07514	0
Panembahan	0.37950	0.56678	0.76980	0.06836	0.15035	0.69686	0.56361	0.95407	0.01495	1
Patangpuluhan	0.06714	0.05711	0.20733	0.18620	0.06739	0.36267	0.65335	0.86096	0.00003	1
Patehan	0.21595	0.10644	0.31797	0.09803	0.10067	0.59054	0.33403	0.99361	0.00007	1
Prawirodirjan	0.59360	0.52260	0.12496	0.84214	0.25341	0.44810	0.29894	0.98750	0.01516	1
Prenggan	0.25321	0.25229	0.37095	0.95801	0.61492	0.24773	0.19418	0.97026	0.09598	0
Pringgokusuman	0.30222	0.19018	0.03182	0.25180	0.84583	0.03577	0.14803	0.73214	0.07747	2
Purbayan	0.19750	0.16576	0.14723	0.95035	0.36185	0.10783	0.05278	0.91953	0.03702	1
Purwokinanti	0.50154	0.25321	0.42811	0.75152	0.32633	0.30508	0.37022	0.91442	0.03309	1
Rejowinangun	0.74407	0.60466	0.93871	0.91490	0.45710	0.57434	0.78480	0.98312	0.29303	0
Semaki	0.29887	0.55062	0.77764	0.18296	0.05123	0.69133	0.27787	0.82720	0.00054	1
Sorosutan	0.17211	0.50324	0.99656	0.20984	0.03945	0.39462	0.27789	0.99677	0.00679	2
Sosromenduran	0.26933	0.08601	0.01621	0.93395	0.69907	0.05421	0.02022	0.95100	0.01186	3
Suryatmajan	0.15895	0.02847	0.04714	0.56535	0.65708	0.00086	0.00840	0.78999	0.00670	5

Suryodiningratan	0.10799	0.21898	0.86277	0.98084	0.04445	0.52090	0.17996	0.66298	0.00002	2
Tahunan	0.60887	0.79059	0.76885	0.99324	0.09239	0.57384	0.27240	0.89086	0.00062	1
Tegalpanggung	0.22179	0.03786	0.28402	0.44341	0.44051	0.00375	0.00850	0.63464	0.00566	4
Tegalrejo	0.18526	0.40098	0.01263	0.07980	0.85887	0.12600	0.50275	0.03047	0.15961	2
Terban	0.46613	0.63422	0.56805	0.70384	0.69844	0.04186	0.03053	0.00002	0.05533	3
Warungboto	0.74419	0.82117	0.79805	0.99422	0.25571	0.53018	0.56895	0.96984	0.11884	0
Wirobrajan	0.21027	0.16935	0.15024	0.13002	0.16865	0.59731	0.51015	0.97606	0.00049	1
Wirogunan	0.72732	0.49266	0.82737	0.99805	0.31798	0.46680	0.68795	0.97549	0.02036	1
Σ (significant)	3	4	13	5	7	7	7	11	34	91

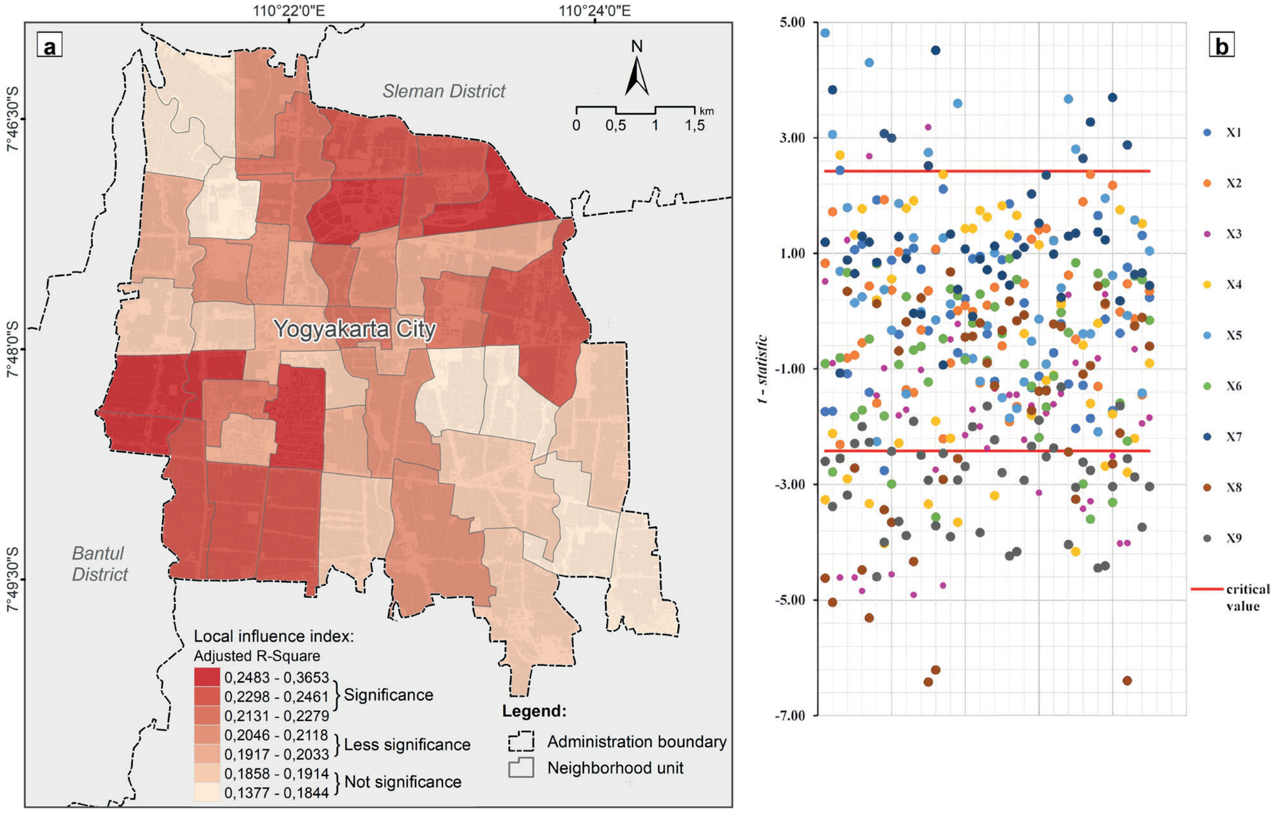

Fig. 7. The distribution of spatial relationships based on the GWR model is generated according to each neighborhood unit, including: (a) illustration of the local influence index adjusted by (R^2), and (b) distribution of significance level described by the tstatistic

This research reveals a significant link between urban connectivity, accessibility, and the spread of COVID-19. We found that areas with higher connectivity and accessibility tend to become hotspots for the virus spread, highlighting the crucial role of urban design in facilitating or mitigating disease transmission (Hamidi et al., 2020; Kwok et al., 2021). This pattern is particularly noticeable in our research location's central areas, which are adjacent to multiple districts. The urban configuration is characterized by a network of intersecting roads and a defined adjacent boundary, fosters extensive connectivity across the city. Such a layout significantly increases the opportunities for human interaction, elevating the virus transmission risk. These observations emphasize the importance of considering each location's unique characteristics and contexts when examining how urban form influences disease prevalence. This discussion is supported by the recent literature (Yechezkel et al., 2021), which indicates that urban connectivity can markedly affect the spread of infectious diseases by facilitating increased human movement and interaction.

Contrary to expectations, our study revealed that spatial density does not correlate strongly with COVID-19 case prevalence. This suggests that the mere concentration of buildings or population cannot predict outbreak severity, challenging prevalent notions within urban planning and public health domains. It indicates that other dimensions of urban form, such as the quality of public spaces or the nature of human activities within dense areas, may play more critical roles in disease spread dynamics (Wong & Li, 2020).

Furthermore, the heterogeneity of spatial functions within urban areas has shown significant associations with COVID-19 prevalence, highlighting the dual impacts of spatial arrangements. The concentration of public facilities correlates positively with COVID-19 cases. This suggests that areas with abundant public utilities may facilitate higher human interaction levels, increasing transmission risk (Yao et al., 2021). Otherwise, a diverse land use mix is inversely related to case numbers, possibly due to the dispersion of activities reducing crowding and direct contact between individuals. These findings point to the complexity of urban environments, where different configurations of space and function can either mitigate or exacerbate health risks.

Our research critically examines the current COVID-19 mitigation and preparedness policiesthat appear to overlook the valuable insights offered by urban science. Despite the deployment of numerous policies spanning science, technology, and innovation aiming to curb the virus's spread and strengthening socio-economic and community health resilience, there is an evident gap in incorporating urban scientific knowledge (Djalante et al., 2020; Putera et al., 2022). The case of Yogyakarta underscores the urgency of integrating urban science and spatial knowledge into virus mitigation strategies and preparedness planning. It enables the development of customized strategies considering the unique urban form and morphological characteristics of different city areas, such as informal settlements and kampungs (Wirastri et al., 2023).

Moreover, the disparity in urban forms across various city areas underscores the necessity for a nuanced approach to policy development, utilizing data on urban form elements to assess virus risk levels and determine the requisite medical support. This result ensures that all urban areas are adequately equipped to respond effectively to potential outbreaks, irrespective of their socio-economic status or regional characteristics. Our findings further highlight the complexity of urban environments in shaping the prevalence of COVID-19. The heterogeneity of spatial functions within urban areas reveals a dual impact on transmission rates, with the concentration of public facilities correlating positively with case numbers. At the same time, a diverse land use mix shows an inverse relationship, underscoring the importance of considering different spatial arrangements and their potential to mitigate or exacerbate health risks.

Additionally, understanding the spatial distribution of cases within a city is crucial for targeted interventions and resource allocation. Analyzing the relationship between urban forms and COVID-19 prevalence on finer spatial scale, such as at the neighborhood level, could provide more insights into local transmission dynamics. This detailed analysis could also identify specific urban form elements thar are most strongly associated with increased risk, enabling policymakers to prioritize interventions in areas where disease spread is most likely to occur.

However, the research limitations primarily stem from focusing on a specific urban area in Yogyakarta, which may limit the generalizability of findings to other urban contexts. Other factors influencing disease transmission dynamics, such as socio-economic conditions and cultural practices, still need to be further explored. Additionally, the study's cross-sectional design restricts the ability to determine causal relationships between urban form characteristics and COVID-19 prevalence. Despite these limitations, the research provides valuable insights into the spatial dynamics of disease transmission in cities. By integrating urban science and spatial knowledge into pandemic mitigation strategies and preparedness planning, cities can develop tailored approaches for unique urban form characteristics, ensuring equitable and effective responses to potential outbreaks.

CONCLUSIONS

In conclusion, our study provides compelling evidence supporting the hypothesis that urban form elements, particularly connectivity and accessibility, density, and spatial heterogeneity, play a crucial but underexplored role in shaping the spread of COVID-19. Our analysis of Yogyakarta City revealed clear associations between these urban morphological factors and the incidence of COVID-19 cases, reinforcing the importance of considering urban science and spatial knowledge when formulating effective pandemic mitigation and preparedness policies. By challenging the prevailing policy paradigm that often overlooks the intricate relationship between urban morphology and disease prevalence, our findings underscore the necessity of integrating urban science insights into public health strategies. This integration allows cities to better anticipate and mitigate the risks associated with future outbreaks. This research advocates for a multidisciplinary approach that combines urban planning and public health perspectives, emphasizing the need for detailed observation of urban form elements in order to develop resilient and healthy urban environments. The study thus contributes to the growing body of evidence that calls for a reassessment of how urban form considerations are integrated into disease mitigation and preparedness planning, aiming to enhance urban resilience in the face of ongoing and future health challenges.

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