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Urban street network and data science based spatial connectivity evaluation of African cities: implications for sustainable urban development

Bewketu Mamaru Mengistie · WenZhong Shi · Man Sing Wong · Rui Zhu

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Abstract The aim of the study was to evaluate spatial connectivity and socioeconomic status of African cities using street network datasets and geospatial methods. The drivable street network was collected from OpenStreetMap, and spatial connectivity has developed at the cityscape level and central business districts (CBD). At the cityscape level, almost all studied cities have minimum spatial connectivity as illustrated by metrics like betweenness centrality, average node average and intersection density metrics where maximum values were 0.11, 6.28 and 359 nodes/km2 respectively. The spatial connectivity of CBD was higher compared cityscape level, which indicated the availability unbalanced growth of drivable street network in the sample cities. Moreover, the study has also founded relationship between spatial connectivity and socioeconomic status of cities which in turn have implications to the sustainability of urban areas.

Keywords OpenStreetMap · Drivable streets · Spatial connectivity · Sustainable Development · African cities

Introduction

Cities are composed of complex network systems including streets, social network, and other service networks (Batty et al., 2012). For instance, social networks refer the intangible interconnectedness between individuals, specialized groups, or communities where nodes are people and edges indicate the level of interpersonal relationships (Shen & Karimi, 2016). Street network on the other hand, refer spatial infrastructures over which human mobility and transportation of goods and services are accomplished. Generally, urban street network encompasses drivable, walkable and cycling network (Marshall et al., 2018; Strano et al., 2013). These networks are composed of arrays of nodes and edges where node represent stops including: origin, intersection, and destination; whereas edges are road segments which interconnect several nodes (Barthélemy, 2011; D'Acci & Batty, 2019). Urban street network can be a planner or non-planner graphs; the first represents 2-dimensions with edges intersecting only at nodes, whereas the latter contains differently graded expressways, overpasses, bridges and tunnels in the graph (Barthélemy, 2011; Strano et al., 2013). Though both graphs are used for developing street networks for better representation

B. M. Mengistie (✉) · W. Shi · M. S. Wong · R. Zhu
Department of Land Surveying and Geoinformatics, Smart Cities Research Institute, The Hong Kong Polytechnic University, Hung Hom, Hong Kong SAR, China
e-mail: bewmam16@gmail.com

B. M. Mengistie
Department of Urban Land Administration, Kotebe Metropolitan University, Addis Ababa, Ethiopia

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of spatial properties i.e., length, width and shape; the prior is usually used in transportation studies (Barthélemy, 2011; Marshall et al., 2018). Street network are useful to understand urban space and human interactions (Masucci et al., 2009). Specifically, user generated big OSM data are a pragmatic way to uncover the status of spatial infrastructures development and support urban planning and management endeavors. Some areas of use in urban science include: modelling traffic and trip (Pun et al., 2019), analyzing city patterns (Boeing, 2019a), and inferring urban designs and histories (D'Acci & Batty, 2019; Fusco et al., 2015; He et al., 2019). User-friendly data mining, processing and analytical framework are highly demanded to generate empirical planning metrics for sustainable urban growth.

Spatial networks are used in several aspects of urban planning and design arenas. The complex spatial structure of systems and specific functional purposes of streets i.e., drivable, walkable, or biking; pin the interest of urban analytics, geographers, and physicists. In urban planning and design, street networks are used for the analysis of urban morphology, transportation patterns, economic agglomerations, infrastructural development, social equity and urban livability and sustainability (Crucitti et al., 2006; Payre, 2010; Sudhira et al., 2004; Wagner, 2008; Zhong et al., 2014). Specifically, network metrics such as centrality measures, data mining, and machine learning algorithms are used to analyze the city's functional centres; land uses patterns, complexity and size of urban areas, and street networks (Toole et al., 2012; Zhong et al., 2014).

Spatial connectivity of cities has impacts on urban socioeconomic growth and resilience (Yu & Gayah, 2020). For instance, the topology of streets are useful to compute morpho aesthetic and network-variety of cities (Acci, 2019) and the concentration of major nodes are applied to evaluate accessibility (Cheng et al., 2013) where a high concentration urban areas enjoy better economic advantages and vice versa (Barrington-leigh & Millard-ball, 2020). Degree distribution and connectivity characteristics like centrality, betweenness are used to quantify traffic flows and economic efficiency of cities (Zhang et al., 2017). Moreover, urban street network have impacts on urban morphology, land use/cover change, energy uses and air pollution and environmental degradation (Barrington-leigh & Millard-ball, 2020; Van de Voorde et al., 2011). Available studies on urban connectivity and accessibility were focused on car-centric streets that is merely main roads and limited to highly developed urban agglomerates of Asia, Europe, and USA where developing urban centers in rapidly urbanizing areas were rarely investigated.

The current study has evaluated the spatial connectivity of rapidly urbanizing cities of Africa to answer the research question of "how is the status of spatial connectivity of African cities both at urban scale and functional neighborhoods i.e., residential, and commercial areas?". This study used urban data science tools and OpenStreetMap (OSM) to evaluate the spatial connectivity.

Urban street network metrics

Several theoretically reached street network measures are available in urban science, design, and planning. For instance, descriptive network metrics like count of nodes, intersection nodes, streets per node average, total street length, and street segment counts are widely used to examine the complexity of the spatial network of cities (Boeing, 2017a, 2017b; Pflieger & Rozenblat, 2010). Moreover, urban street network metrics like average degree of the neighborhood to each node, degree of centrality, clustering coefficient (weighted and average), page rank (maximum and minimum node and page rank), circularity, and centrality (betweenness and closeness) are developed to evaluate the connectivity and centrality status of a city or specific area in the urban space (Barthélemy, 2011; Boeing, 2017a, 2017b; Pflieger & Rozenblat, 2010; Zhang et al., 2017).

Street network measures are mathematically computed based on graphic and spatial elements. For instance, the average degree connectivity, also called the average nearest neighbor degree of nodes, is computed using a weighted degree of nodes (s_i), the weight of edge which links i and j (w_{ij}) and neighbors of node i; $N(i)$ (Vespignani et al., 2004).

$$\mathrm{K}^{\mathrm{w}}_{\mathrm{nn,i}} = \frac{1}{si} \cdot \sum_{j \in N(i)} wijkj \tag{1}$$

The normalized weight of connected edges is derived

$$\frac{wij}{si} \tag{2}$$

and ud to determine the local weighted average of connectivity of nodes where $K^{w}_{nn,\ i}$ is above $K_{nn,\ i}$ when high weighted edges are connected to defined neighbors. The degree of centrality is calculated using counts of nodes (n) involved in the street network and interconnectedness counts to neighboring nodes. Where nodes connected to many adjacent nodes have higher centrality values than less connected ones. Nodes with maximum centrality value have highest impact on spatial connectivity and vice versa. The degree of centrality of a node (k) in a network is calculated using (Abbasi et al., 2012; Vespignani et al., 2004).

$$\sum_{i=1}^{n} \alpha(i,k) \tag{3}$$

where $\boldsymbol{n}$ is the number of nodes in the network and $\alpha(i,k)$= 1 if node i and k are connected or 0; otherwise, moreover clustering coefficient, weighted clustering coefficient, PageRank are used to quantify directed or undirected street network (D'Acci & Batty, 2019; Khonji et al., 2013; Vespignani et al., 2004).

The global properties of networks and descriptive metrics including nodes, edges, degree of each node, weighted degree, clustering, and closeness centrality are used to drive accessibility and interconnectedness between locations and estimate the intensity of travel or trip volumes in urban areas. Street connectivity measures are crucial for analyzing how much areas are cohesive and how fast the spread of information, goods, and people in a city or between cities (Abbasi et al., 2012; Michael Batty, 2013; Gündoğdu et al., 2019; Jiang & Liu, 2009; Pun et al., 2019; Sudhira et al., 2004; Wagner, 2008; Zhang & Kukadia, 2005). Moreover, metrics like betweenness centrality and PageRank, are useful to investigate hubs or central business districts in cities and analyze accessibility in both directed and undirected street networks (Abbasi et al., 2012; Boeing, 2019a; Zhong et al., 2014). A summary of spatial connectivity measures is provided in Table 1.

Table 1 Street network metrics and definition *Sources*: (Barrington-leigh & Millard-ball, 2020; Boeing, 2017a, 2017b; Frank et al., 2010; Pflieger & Rozenblat, 2010)

Street network metrics	Definition
Nodes (n)	Count of nodes in the street network
Count of edges (e)	Count of edges in the street network
Average node average (k-avg)	Mean number of inbound and outbound edges
Intersection nodes (I)	Count of nodes which connects edges
Street per node average (sna)	Number of streets from each node in the network (intersection and dead ends)
Total street length (km) (tsl)	Sum of edge lengths in an undirected network
Street length average (sla)	Mean of edges length in an undirected network
Circularity average (ca)	The ratio of total edges length to the sum of great circle distances between nodes
Average neighbor degree (and)	Mean degree of nodes about each node
Degree of centrality (dc)	The ratio of nodes is each node connected to
Clustering coefficient (cca)	The extent to which a node's neighborhood forms a complete graph
PageRank Maximum (prmax)	Ranking of nodes based on the structure of incoming edges
Street Density	The ratio of total street length to urban area
Intersection nodes density	The ratio of total counts of intersection nodes to urban area
Betweenness centrality (bc)	Frequency of nodes used as a bridge between two or more points
Closeness centrality (cc)	Average farness or inverse distance of a node to other nodes in the network
Average block sizes (abs)	Mean parcels sizes in the urban fabrics

Methodology

Data and study areas

This study has used geospatial datasets including spatial and non-spatial data from open data repositories. High resolution streets, population of cities and Gross Domestic Product value were used (GDP). Urban street network data was collected from OSM database bypassing python-based data analytics codes (Boeing, 2017a, 2017b) and raster population data of cities were freely gathered from the NASA socioeconomic data and application center (SADAC). Moreover, nation level GDP data were collected from World Bank database.

To extract urban street network data of sample cities the study has followed four steps. In the first stage required study settings such as a high-speed computer, anaconda3x and spatial tools used for processing, analysis, and visualization were arranged. At second stage, pre-processing namely selection, simplification and error removal were applied on the desired datasets. Selection of location briefly sample cities and subdistricts and street types was applied using data selection queries. Accordingly, the spatial extent of desired cities was acquired using official city names and based on predefined bounding box from latitude and longitude. In addition, only *'drive'* network of eleven cities were extracted while cycling and walkable streets were excluded from this study to minimize the data into workable unit. After selection of desired data, this study applied simplification and error reduction processes which aims at increasing the quality of the street network datasets. For instance, unnecessary nodes like non-intersection nodes arbitrarily distributed on the curved roads were removed except the pragmatic junction and self-loop nodes using OSM data processing modules (Boeing, 2017a, 2017b; Pflieger & Rozenblat, 2010). In the third stage, spatial connectivity of drivable streets was computed using useful spatial packages/tools namely NetworkX, geopandas, matplotlib and OSMx (Cheng et al., 2013; Strano et al., 2013; Zhang et al., 2017). Street network measures computed in this study are shown Table 1.

This study evaluated the spatial connectivity of major urban agglomerates of Africa. Rapidly growing cities were purposively selected from the northern, western, eastern, central, and southern subregions of Africa. Briefly, the northern subregion of Africa is one of the highly urbanized portions in which most well-developed cities of Africa are located along the Mediterranean Sea coastlines and Nile River Basin. Due to social and political upheavals the has faced several urban problems like lack of affordable housing, unemployment, and vulnerability to climate change impacts. Compared to other subregions cities in this area has lower slum housing proportions and urban areas have played a pivotal role in the economy by tapping tourism revenues (Obeng-Odoom, 2016). Western and Eastern subregions are the least urbanized areas the content. Fast urbanization increases in urban density and interconnectedness are the major spatial features in this subregion while deficits in logistics and transportation, and massive informal settlements negatively affect the sustainable growth of cities. Similarly, central Africa is less urbanized, even not reach a region-wide larger urban population than rural until 2030. The most urbanized part is the southern Africa and have reached the urban majority since 2011. Generally, urban sprawls, slums, informal settlement, poverty, inequality and lack of urban infrastructure including roads and access to utility services are the roadblocks of African cities to achieve sustainable urban development (Obeng-Odoom, 2016; Peter Griffiths, 2018; Lall et al., 2017).

Spatial connectivity analysis

Beyond the limited car-centric commercial roads, this study was based on high-resolution street network datasets. Urban data science tools: python3x, ArcGIS Pro. and OSM network analyst (OSMNX). Descriptive network measures like count of nodes, intersection nodes, total street length and average length of street are computed using OSMNX modules. In addition, this study has adapted urban drivable street network to evaluate African cities spatial connectivity. Urban street network metrics comprising PageRank, closeness, betweenness, intersection node density etc. were computed at cityscape level. In addition, sample commercial and residential districts were investigated across selected cities to understand the availability of disparities between these main urban functional areas. The relationship between spatial connectivity indicators and socioeconomic attributes like walkability, GDP, and population density of studied cities were analyzed.

Eleven big cities comprising Abidjan, Accra, Addis Ababa, Brazzaville, Cairo, Casablanca, Khartoum, Luanda, Lagos, Nairobi, and Johannesburg were purposively selected as sample of the study (Figs. 1, 2).

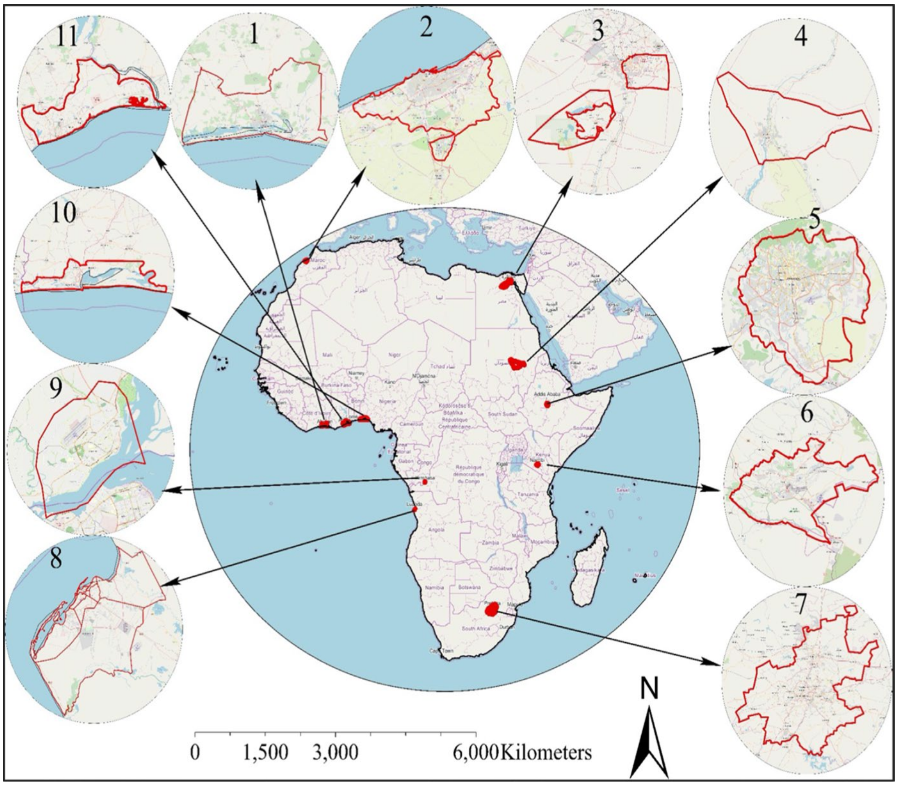

Fig. 1 Map of sample cities. List of cities from 1 to 11 are Abidjan, Casablanca, Cairo, Khartoum, Addis Ababa, Nairobi, Johannesburg, Luanda, Brazzaville, Lagos, and Accra respectively

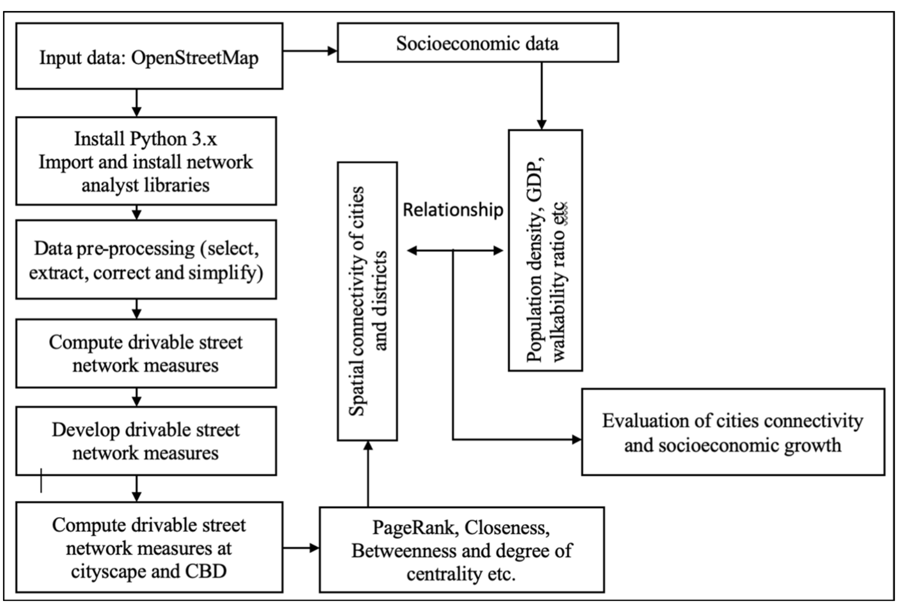

Fig. 2 Flow of the methodology approach

Results

Drivable street network measures

Urban drivable street network measures were computed in 11 cities of Africa. The drivable street network of cities was depicted in Fig. 3. Node counts of sample has ranging between 14,540 and 214,974 where Luanda city has minimum nodes (14,540), whereas Johnsburg of Gauteng Metropolitan Municipality is founded as the most complex drivable street network. This indicates the total number of accessible areas or locations in cities that are directly connected is maximum in most urbanized parts of South Africa .

A metropolitan area which has a higher possibility of travel between places as nuanced by the increased number of edges and nodes in the drivable street networks. Moreover, based on the intersection nodes, which infers the spatial connectivity in the network, Gauteng has maximum intersections with 184,440 nodes followed by Cairo (113,040), Khartoum (103,564) and Casablanca (78,894). The intersection nodes density is also computed to zealously depicts the spatial connectivity. Accordingly, Casablanca, Brazzaville and Addis Ababa have a higher density of intersection nodes per unit of an urbanized area with respective values of 359,229 and 93 nodes per kilometre square. This means the city of Casablanca is the most spatially connected metropolitan drivable street network, followed by Brazzaville and Addis Ababa. In contrast, the capital of Khartoum has minimal intersection nodes per unit of the urbanized area.

The degree of centrality prescribes the potential importance of nodes and edges in the street network's topological structure. The larger the number of neighbours, the higher the vertex rank and degree of centrality. Based on this, if a node in the network has much direct connection to adjoining nodes, it is more central. It positively influences the overall connectivity in the network regardless of the location of nodes. The drivable street network metrics of cities indicate that the aggregated averaged degree of centrality is homogeneous and low in values, with relatively higher values in Luanda, Abidjan, and Nairobi. As a result, the rapidly growing cities in Africa follow monocentric urban morphology, which upheaval transportation connectivity issues and causes traffic congestion in cities. The clustering coefficient average derived from the ratio of neighbour links and the maximum number of links that could exist in the network are also used to quantify how the network nodes are concentrated. Based on these metrics, the studied

Fig. 3 Driveable street network of Luanda, Johannesburg, Brazzaville and Casablanca (**a**–**d**). Urban drivable street network of studied cities were provided in Table 2

cities also have almost homogenous clustering coefficients and PageRank, which ranges from the most relatively clustered Gauteng driving network, 0.0682 (maximum), to 0.01399 Khartoum (minimum). These values affirm that cities are growing in less clustered patterns weighted with a low degree of centrality or connectivity and coarser street densities (Table 3).

The driving street network metrics of African cities are dynamic across locations. Basic network statistics and extended network measures computed in distances series of buffer distances of 0.8, 2 and 4 km are used from most functional locations of cities (i.e., central business districts) to understand local connectivity patterns and morphology. For instance, city-level (overall) measurement of the average neighbor degree in most studied cities registered maximum values and gradually declined with increases in distance from CBD areas. Cairo has a higher average neighbor in central areas than the city's general site, indicating the decrease of compactness from the CBD to outer neighborhoods. In contrast, Johannesburg has a higher average neighbor degree at 4 km buffer areas than others may suggest the polycentricity or existence of other CBD areas.

Similarly, the average clustering coefficient and PageRank of the drivable street network have high values in Johannesburg, Casablanca, Lagos, and Cairo, explaining the availability of high-density drivable networks beyond the walkable distance from the CBD. Spatial centrality measures such as closeness and betweenness centrality are depicted as almost homogeneous patterns across selected cluster distances with higher values in walkable distance and declines with increases in distance from CBD (Fig. 4).

Socioeconomic attributes and spatial measures of street networks

Cities are spatial units in which the agglomeration of economies and high population densities are placed. The development of urban areas has been assessed using different indicators. Infrastructural development and improvement in socioeconomic attributes such as social amenities and GDP are associated with urbanization. Such development in socioeconomic conditions and the availability of job opportunities in cities have contributed to the spatial expansion of urban areas (urbanization) and the growth of physical infrastructures such as roads. Fast urbanization and GDP growth have been observed in Africa for the last 20 years. From five subregions of the continent, the Eastern and Western African countries are passing through rapid urbanization. Specifically, Angola, Ethiopia, Nigeria, and Kenya have registered 4.78%, 4.42%, 4.39%, and 4.13% annual urban population growth for the last two decades. Likewise, economic growth has also been rising, with an average yearly growth rate of 14.2%, 11.9%, 10.69%, and 9.59% in Angola, Ethiopia, Ghana, and Kenya.

In terms of walkability ratio (i.e., indicator of status of walking road infrastructure compared with residents) Johannesburg, Cairo, and Casablanca whereas Khartoum, Addis Ababa and Abidjan are least walkable capitals. In addition, mean annual climatic variables including temperature, precipitation and visibility (i.e., distance viewed in nicked eye) are illustrated (Tables 3, 4, Fig. 5).

The spatial expansion of urban drivable street networks and the global properties of these infrastructures is highly related to cities' socioeconomic attributes. That is, cities that have more complex drivable networks support socioeconomic activities. Highly populated areas are also associated with the availability and accessibility of agglomeration economies (i.e., demand and supply). Hence, the global network properties are computed to understand correspondences between cities' physical properties, like the complexity of the drivable street network and socioeconomic status. The number of nodes, edges, and total street length of cities has a strong positive correlation with socioeconomic metrics' growth. Similarly, the number of driving network nodes and edges in cities has a maximum correlation coefficient of R^2 (0.9827) and correlation (0.991). Furthermore, intersection node density and street density also strongly correlate, as population density and intersection density have high correspondences (Fig. 6).

Cities' socioeconomic attributes, such as walkability ratio, block sizes, and GDP, positively correlated with drivable centrality metrics (betweenness and closeness). This suggests changes in urban drivable street network connectivity have positive implications for the city's growth or that improving the spatial connectivity and morphology of critical urban infrastructures (roads) contributes to urban sustainability.

Table 2 Drivable street network metrics

	Abidjan	Accra	Addis Ababa	Brazzaville	Cairo	Casablanca	Johannesburg	Khartoum	Lagos	Luanda	Nairobi
n	38,649	92,280	56,801	71,430	127,120	83,781	214,974	105,270	57,840	14,540	31,658
e	109,116	250,685	153,054	211,013	310,425	229,479	576,361	330,767	141,406	38,593	77,363
k-avg	5.64	5.43	5.38	5.91	4.88	5.48	5.36	6.28	4.89	5.31	4.88
I	33,459	78,332	49,185	60,389	113,040	78,894	184,440	103,564	42,042	12,558	23,903
sna	2.91	2.78	2.86	2.99	2.9	3.06	2.88	3.21	2.48	2.89	2.57
tsl in km	6436.94	15,739.52	6598.04	26,634.62	14,897.5	21,132.04	51,370.32	13,465.51	42,166.7	1860.43	4855.59
asl	114.51	122.86	81.24	249.13	80.73	164.65	164.76	79.68	585.26	88.89	119.42
ca	1.05	1.05	1.05	1.13	1.05	1.07	1.09	1.02	1.22	1.03	1.07
and	3.05	2.94	2.92	3.24	2.61	2.85	2.86	3.22	2.84	2.88	2.78
Awn	0.04	0.033	0.052	0.04	0.086	0.06	0.037	0.052	0.04	0.04	0.04
Dc	0.00015	5.89E−05	9.49E−05	8.27E−05	3.84E−05	6.54E−05	2.49E−05	5.97E−05	8.45E−05	0.00037	0.00015
Cca	0.037	0.037	0.029	0.03	0.03	0.05	0.07	0.014	0.035	0.03	0.03
Ccw	0.00035	0.000324	0.0007769	3.41E−05	8.47E−05	0.0001541	0.00039941	0.000208	7.13E−05	0.00119	0.00033
Pgmax	0.00011	3.72E−05	6.24E−05	6.54E−05	2.96E−05	4.64E−05	1.63E−05	2.63E−05	8.22E−05	0.0003	0.00014
Pgmin	3.88E−06	1.63E−06	2.64E−06	2.10E−06	1.18E−06	1.79E−06	7.00E−07	1.43E−06	2.59E−06	1.03E−05	4.74E−06

Table 3 Drivable street network metrics

Network metrics	Mean	St-dev	Minimum	Median	Maximum
n	81,304	55,369	14,540	71,430	214,974
e	220,751	149,918	38,593	211,013	576,361
k-avg	5.406	0.437	4.884	5.389	6.284
I	70,891	49,277	12,558	60,389	184,440
sna	2.8692	0.2034	2.4897	2.8919	3.2141
tsl	18,651	15,842	1860	14,897	51,370
asl	168.3	147.4	79.7	119.4	585.3
ca	1.0771	0.0548	1.0206	1.0566	1.2166
and	2.9278	0.1825	2.6129	2.8787	3.2375
awn	0.04822	0.01476	0.03350	0.04286	0.08614
dc	0.000107	0.000095	0.000025	0.000083	0.000365
cca	0.03585	0.01366	0.01399	0.03209	0.06820
ccw	0.000356	0.000345	0.000034	0.000324	0.001187
pgmax	0.000083	0.000080	0.000016	0.000062	0.000296
pgmin	0.000003	0.000003	0.000001	0.000002	0.000010
bc	0.042998	0.026649	0.0063	0.037	0.1139
cc	0.000859	0.000256	0.00039	0.001	0.00135
GDP per Capita ($)	2976.5	1918.035	714	2281	6653.9
wr	1.74	0.223	1.5	1.7	2.2
abs	3.63	1.28	1.7	3.9	5.3
Density (Persons/km^2)	2740	2165	714	5165	6654

Discussion and conclusions

In general this study found minimum and almost homogenous spatial connectivity of street network at cityscape level. Size of drivable street infrastructure in cities were minimum compared to developed metropolitan areas of Europe, North America and China as manifested in the metrics like the total street length, node and intersection node density (Table 2). For instance, the mean and maximum intersection node count and total street length of every towns and cities of North America had about 12,582(km), and 307,848 (km) and 3480 (km) and 79, 046 (km) (Boeing, 2018) are founded higher compared to most of the studied cities (Table 3). Moreover, the low and middle income countries (LMICS) in Latin America, East Asia and Pacific and South Asia has relatively better street connectivity compared to the Sub Sharan Africa (Barrington-leigh & Millard-ball, 2020).

Spatially, this study identified declining pattern of street connectivity (e.g. betweenness and closeness centrality) with increasing distance from central business districts (CBD) in studied cities. Such pattern of spatial connectivity changes were observed in developed countries (e.g. United States) and in others LMICS (Barrington-leigh & Millard-ball, 2020; Boeing, 2019b). Drivable street network metrics have implications on urban sprawl, private car ownership and transit oriented development (Barrington-leigh & Millard-ball, 2020). Between 1990 and 2014 in average African were expanded 5% annually which leads to low population density and sprawl through time (Xu et al., 2019).

Drivable network measures shown the spatial connectivity of urban space using metrics like intersection density, street density, betweenness, and closeness centrality. From studied cities Casablanca was founded highly connected with intersection node

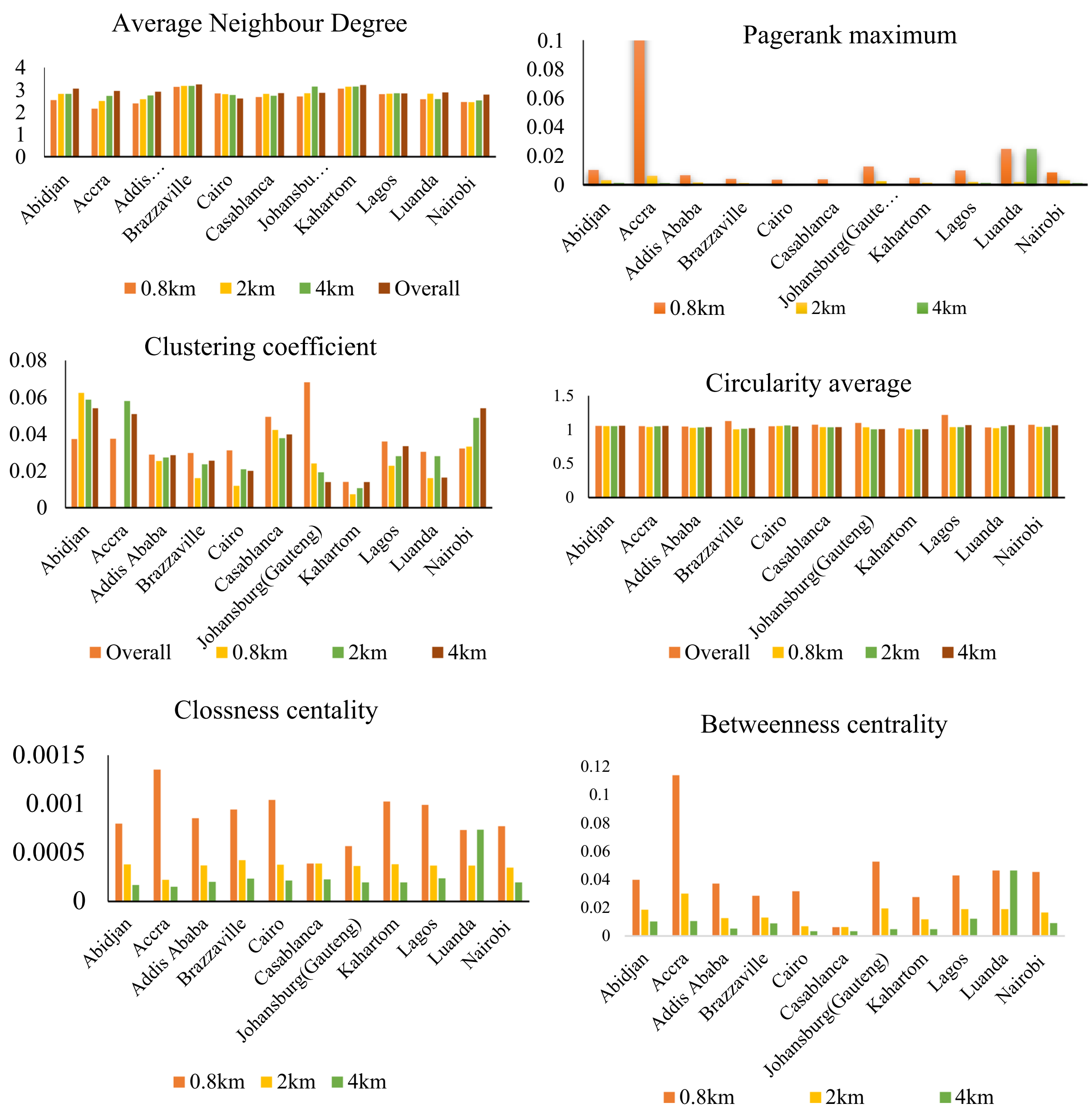

Fig. 4 Driving street network metrics

density (228.8 nodes/km^2) and highest metropolitan population density (15, 273 persons/km^2), whereas Khartoum has minimum intersection, street densities, and urban population (3.4 nodes/km^2 and 66 persons/km^2). Minimum street network connectivity but net increases of private cars in Africa and East Asia cities has contributed to traffic congestion which in turn leads air pollution (Barrington-leigh & Millard-ball, 2020). Street network measures that describe urban form resilience, like the degree of centrality,

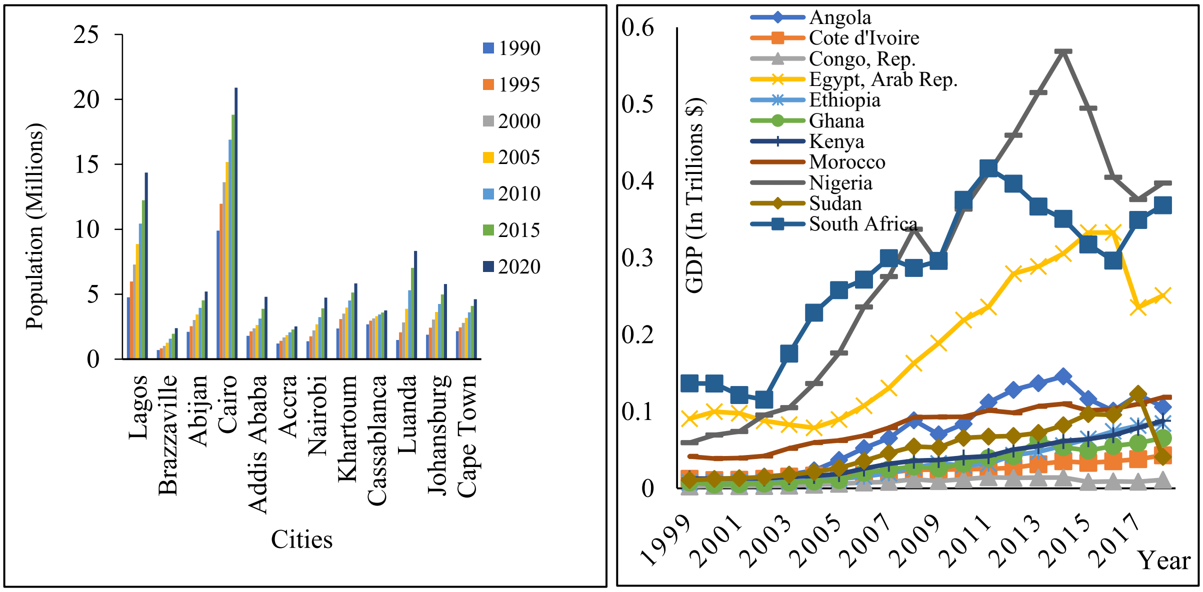

Fig. 5 Population growth and mean GDP

Table 4 Socioeconomic and climatic attributes of cities

Cities	Population (2022)	Density (Person/km2)	Mean annual income ($)	Walkability ratio	Temperature (cc)	Precipitation (mm)	Visibility (km)
Abidjan	5,516,000	1700	5081.4	1.6	29	8.6	9
Accra	2,605,000	1300	5017.3	1.7	18	36.1	22
Addis Ababa	5,228,000	5165	1920	1.6	17	95.3	19
Brazzaville	2,553,000	23,456	15,821.2	1.7	27	54.3	11
Cairo	10,100,166	8011	7032	1.8	15	0.3	9
Casablanca	3,840,000	14,200	11,339.2	1.8	14	20.1	7
Johannesburg	6,065,000	2900	24,319.4	2.2	20	58.9	15
Khartoum	6,160,000	5247	755.2	1.5	26	2.8	13
Lagos	15,946,000	6871	8848.9	1.7	29	51.7	9
Luanda	8,952,000	1372	7036.6	1.7	27	18.8	11
Nairobi	5,119,000	6317	11,382.4	1.7	21	7.8	18

circularity average, clustering coefficient, and PageRank, are homogenous and low in most of the studied cities. Spatial connectivity indicators has relationship with the socioeconomic condition of cities. For instance, closeness and betweenness centrality measures have positive correlation with socioeconomic attributes like walkability ratio, GDP and population density. Future studies would use open and worthful data and urban data science tools such as OSMnx to explore connectivity and accessibility to

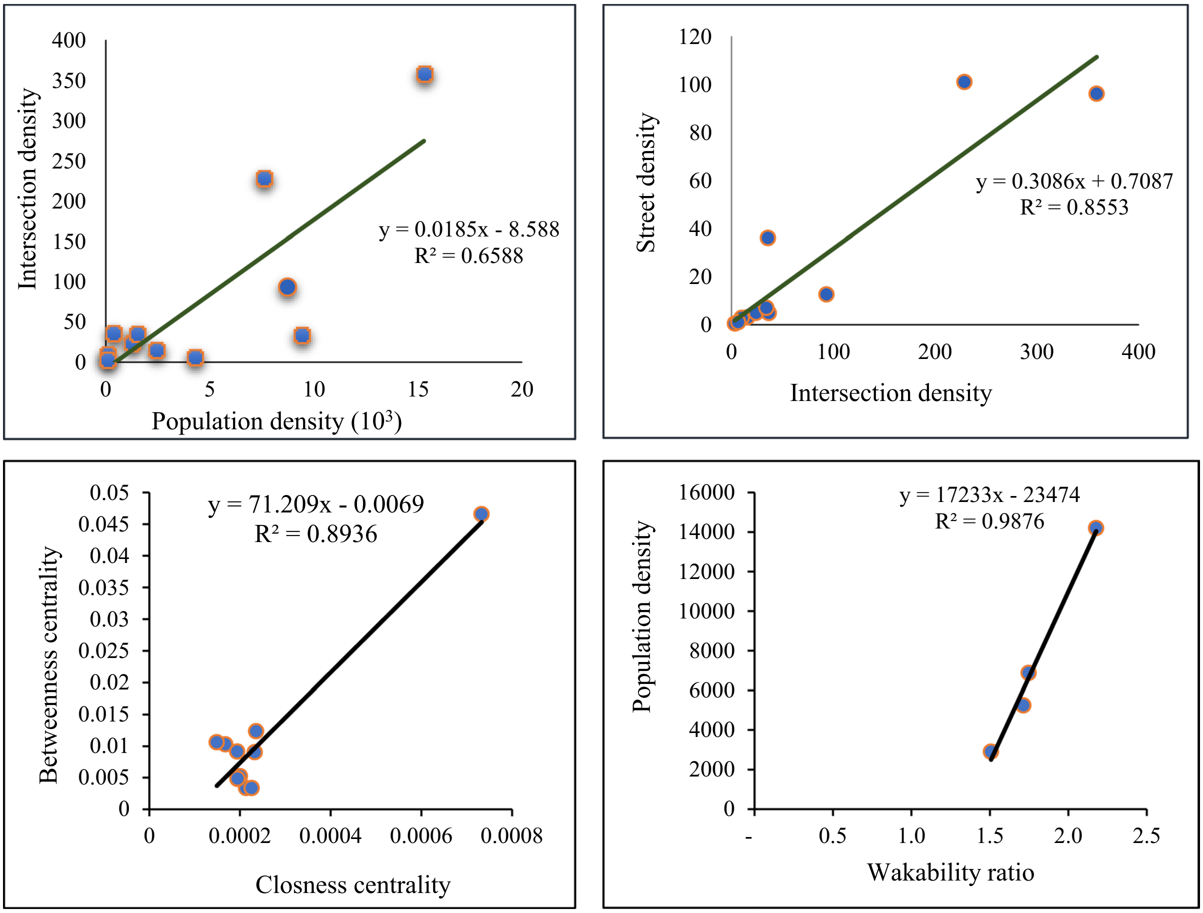

Fig. 6 Drivable street network metrics and socioeconomic attributes

support sustainable development endeavors. Moreover, urban planners and spatial strategists could potentially deploy high-resolution streets to investigate optimal solutions and support the new paradigm shift of deploying activity-based planning and management develop livable, smart, and sustainable cities.

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Declarations

Ethical approval No ethical issues involved in this study.

Consent to participate The submission has been received explicitly from all co-authors, and the authors whose names appear on the submission have contributed sufficiently to the scientific work.

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