TeMA

Journal of
Land Use, Mobility and Environment

Cities need to modify and/or adapt their urban form, the distribution and location of services and learn how to handle the increasing complexity to face the most pressing challenges of this century. The scientific community is working in order to minimise negative effects on the environment, social and economic issues and people's health. The three issues of the 14th volume will collect articles concerning the topics addressed in 2020 and also the effects on the urban areas related to the spread Covid-19 pandemic.

TeMA is the Journal of Land Use, Mobility and Environment and offers papers with a unified approach to planning, mobility and environmental sustainability. With ANVUR resolution of April 2020, TeMA journal and the articles published from 2016 are included in the A category of scientific journals. From 2015, the articles published on TeMA are included in the Core Collection of Web of Science. It is included in Sparc Europe Seal of Open Access Journals, and the Directory of Open Access Journals.

THE CITY CHALLENGES AND EXTERNAL AGENTS.
METHODS, TOOLS AND BEST PRACTICES

Vol.14 n.2 August 2021

print ISSN 1970-9889 e-ISSN 1970-9870
University of Naples Federico II

TeMA

Journal of
Land Use, Mobility and Environment

THE CITY CHALLENGES AND EXTERNAL AGENTS. METHODS, TOOLS AND BEST PRACTICES

2 (2021)

Published by
Laboratory of Land Use Mobility and Environment
DICEA - Department of Civil, Architectural and Environmental Engineering
University of Naples "Federico II"

TeMA is realized by CAB - Center for Libraries at "Federico II" University of Naples using Open Journal System

Editor-in-chief: Rocco Papa
print ISSN 1970-9889 | online ISSN 1970-9870
Licence: Cancelleria del Tribunale di Napoli, n° 6 of 29/01/2008

Editorial correspondence
Laboratory of Land Use Mobility and Environment
DICEA - Department of Civil, Architectural and Environmental Engineering
University of Naples "Federico II"
Piazzale Tecchio, 80
80125 Naples
web: www.tema.unina.it
e-mail: redazione.tema@unina.it

The cover image is a train passes a rail road crossing that is surrounded by flooding caused by rain and melting snow in Nidderau near Frankfurt, Germany, Wednesday, Feb. 3, 2021. (AP Photo/Michael Probst)

TeMA. Journal of Land Use, Mobility and Environment offers researches, applications and contributions with a unified approach to planning and mobility and publishes original inter-disciplinary papers on the interaction of transport, land use and environment. Domains include: engineering, planning, modeling, behavior, economics, geography, regional science, sociology, architecture and design, network science and complex systems.

With ANVUR resolution of April 2020, TeMA Journal and the articles published from 2016 are included in A category of scientific journals. From 2015, the articles published on TeMA are included in the Core Collection of Web of Science. TeMA Journal has also received the *Sparc Europe Seal* for Open Access Journals released by *Scholarly Publishing and Academic Resources Coalition* (SPARC Europe) and the *Directory of Open Access Journals* (DOAJ). TeMA is published under a Creative Commons Attribution 4.0 License and is blind peer reviewed at least by two referees selected among high-profile scientists. TeMA has been published since 2007 and is indexed in the main bibliographical databases and it is present in the catalogues of hundreds of academic and research libraries worldwide.

TeMA Journal of Land Use, Mobility and Environment

THE CITY CHALLENGES AND EXTERNAL AGENTS. METHODS, TOOLS AND BEST PRACTICES

2 (2021)

Contents

Covid-19 vs City-21

EVERGREEN

REVIEW NOTES

TeMA
Journal of
Land Use, Mobility and Environment

TeMA 2 (2021) 189-209
print ISSN 1970-9889, e-ISSN 1970-9870
DOI: 10.6092/1970-9870/8003
Received 18th April 2021, Accepted 1th Agust 2021, Available online 31st Agust 2021

Quantifying the urban built environment: a neighbourhood-scale analysis

Felix Ndidi Nkeki [a]*, Monday Ohi Asikhia [b]

[a] Department of Geography and Regional Planning
University of Benin, Benin City, Edo State, Nigeria
e-mail: nkekifndidi@gmail.com
ORCID: https://orcid.org/0000-0001-7817-9192
* Corresponding author

[b] Department of Geography and Regional Planning
University of Benin, Benin City, Edo State, Nigeria
e-mail: asikhia@hotmail.com
ORCID: https://orcid.org/0000-0002-9196-7561

Abstract
The quantification of the built environment has been approached from two major perspectives-regional-scale and neighbourhood-scale. Few studies have attempted to quantify the built environment from the neighbourhood-scale and none of these studies attempted to examine the interactions that exist between the respective built environment indicators and the spatial variation of such interaction which may help under the emerging travel-related prototypical neighbourhoods. Two types of datasets were used in the study and these are neighbourhood-based field surveys and data extracted from a satellite image. These were used to compute indicators which were in turn used to measure the built environment of Benin metropolitan region. The interaction between the indicators revealed that the quantification of the built environment categorised the region into 3 distinct prototypical neighbourhoods-pedestrian-oriented zones, transit-oriented zone, and car-oriented zone.

Keywords
Built environment; Travel behaviour; Land-use; Entropy; Neighbourhood-scale.

How to cite item in APA format
Nkeki, N. F., & Asikhia, M, O. (2021). Quantifying the urban built environment: A neighbourhood-scale analysis. *Tema. Journal of Land Use, Mobility and Environment*, *14 (2)*, 189-209. http://dx.doi.org/10.6092/1970-9870/8003

1. Introduction

The built environment (BE) describes the anthropogenic related spatial and physical entities of an urban landscape characterised by the land-use patterns, neighbourhood design and urban morphology. The BE has been argued in the literature (Schwanen & Mokhtarian, 2005) to be a fundamental factor in the study of travel behaviour (TB). The drive to understanding this link has continued to provoke attention from diverse disciplines because the findings in most of the existing literature show a pronounced level of inconsistency (Yang et al., 2019). For example, a handful of literature has revealed that increased urban area density, proximity to certain linear infrastructure and land-use diversity are the three main components of the BE that influence TB since they are associated with smaller shares for the private car and a larger proportion of travel by public mode and cycling/walking (Limtanakool et al., 2006; Schwanen et al., 2004; Frank & Pivo, 1994; Newman & Kenworthy, 1989; Dargay & Hanly, 2004). Other studies have reported that cities with compact density are associated with a longer travel length (Norland & Thomas, 2007). Yet, other studies have suggested that the relationship between the BE and TB is mostly equivocal because there are no direct effects (Kockelman, 1997; Limanond & Niemeier, 2004; Miller & Ibrahim, 1998; Pickrell, 1999; Badoe & Miller, 2000).

The major reason for the mixed findings may be tied to the selected variables, methods and scale of measuring the BE indicators. The majority of the existing literature tends to quantify the BE from a larger grain/macro-scale perspective (Yang & Zhou, 2020; Tsai, 2005; Nari & Zhang, 2018). Fewer studies have quantified the BE using a neighbourhood or finer/micro-scale analysis (Lee & Moudon, 2006; Guzman et al., 2020) and they paid no attention to the neighbourhood types that may emerge from the integration of the BE indicators and how such spatial units are defined from travel-based modal split perspective. Also, the complexity of the BE requires the consideration of several other dimensions (beyond density, diversity and design) holistically to offer an all-inclusive and robust measure that includes all aspects of the BE of the city under study. The identified gaps were addressed by this study thereby presenting a significant contribution to global literature on urban studies.

This study is necessary because each neighbourhood may likely present distinct characteristics that may impact travel activities differently. The BE has been measured at two major scales-local-neighbourhood and metropolitan-wide (Comendador et al., 2014). In contemporary literature, several interrelated spatial indicators have been used to quantify the BE. Prominent among these are density, diversity and design (Cervero & Kockelman, 1997; Lee & Moudon, 2006). Quantifying BE within the scale of the neighbourhood may reveal heterogeneous urban landscape patterns within the metropolitan region. It is expected that the result would promote understanding and aid further analysis regarding the interactions of the BE indicators within each neighbourhood. The major objectives of this study are to quantify the BE of the Benin metropolitan region (BMR), a large African-sized urban area (a case study from a developing region) using several spatial indicators disaggregated to the neighbourhood-level which is the scale of analysis. Also, the interactions of these indicators within the neighbourhoods were analysed. It is expected that each spatial unit would show not only the associated but also the strongest BE component that characterises such neighbourhood. This may help to understand how each spatial unit would possibly influence TB. Such findings will guide the decisions of urban planners and transport analyst on the appropriate land-use policies and transport planning strategies that may drive urban sustainability.

2. Literature Review

2.1 Measures of the built environment

The quantification and spatial characterisation of the urban BE of any metropolitan region are far from been significantly achieved and has presented a challenging scenario regarding fully understanding and achieving a consensus on the BE-TB interaction. This absence of consensus may be linked to both the methodological and theoretical setbacks reflected in efforts to correctly explain BE interactions with other urban activities and its quantification within a specific spatial extent (Gehrke and Clifton, 2016). A plethora of other empirical studies mostly emanating from the US utilizes either sprawl or land-use mix to quantify the BE of cities (Yang & Zhou, 2020; Ewing et al., 2016; Gehrke & Clifton, 2017; Burchell et al., 1998; Cervero & Wu, 1998; Christian et al., 2011; Mavoa et al., 2018).

Some other studies have taken it further by identifying and integrating a series of BE indicators to define the urban physical landscape. Prominent among these are the 3Ds concept consisting of density, diversity and design of urban areas (Cervero & Kockelman, 1997) which investigated the influence of the BE on travel demand. The BE of the San Francisco Bay Area was measured along three chief dimensions-density, diversity and design. Other studies have further extended these indicators by incorporating two additional D indices and routes and these are destination accessibility, distance to transit and travel route (Lee & Moudon, 2006; Ewing et al., 2014; Ewing & Cervero, 2001).

The 5 Ds indices consisting of density, diversity, design, destination accessibility, distance to transit (Ewing & Cervero, 2010; Choi, 2018) and travel route characteristics identified so far in literature tend to capture a substantial number of dimensions that define the BE. However. it is clear in the literature that the route characteristics identified by Lee & Moudon (2006) are captured in the design dimension earlier presented by Cervero & Kockelman (1997). Lee & Moudon (2006) described route index from ratio, length and area perspective-the ratio of a more and less direct route to access the closest urban activities such as schools and shopping stores; the total length of sidewalk with a spatial unit; and lesser grain size of the household block. To achieve a composite and robust measure of BE especially concerning TB understanding, there is a need to include major indicators that may affect all aspects of travel modes such as transit, car and walking/cycling. Some scholars have achieved a high level of indicators selection for quantifying the BE characteristics and its relation to land-use and TB studies but then some of these may have selection bias (Lee & Moudon, 2006) since the selected indicators only included variables that may influence walking mode leaving out other equally significant modes. Nkeki & Asikhia (2019) included urban sprawl indicators to account for the BE effect on car mode choice.

Quantifying the BE using the 5Ds indices (density, design, diversity, distance to transit or some centrality, destination accessibility (Ewing et al., 2014; Choi, 2018) and sprawl (S) as included in Nkeki & Asikhia, (2019) would, without doubt, present a robust, well represented and consolidated measure of any BE. Also, it would help to build a useful framework in global literature that may bring some level of order and consistencies in land-use-TB related studies (Ewing et al., 2014).

2.2 Scales of measuring built environment

Literature has shown that the scale of modelling the effects of the BE on TB continue to play an integral and intriguing role in the consistency of the results (Yang et al., 2019; Handy et al., 2005). By implication, BE needs to be defined at such a scale since travel-land-use interactions take place at such a geographic unit. However, two major scales of modelling BE have been identified in the literature, they include regional or metropolitan-wide level and local or neighbourhood level of analysis. The formal is often based on aggregate methodology by examining features at the macro/holistic level through averaging out all outcomes or measuring large geographic framework such as region, metropolitan area, states, political area, urban city, by sprawl indicator (Yang & Zhou, 2020; Tsai, 2005; Nari & Zhang, 2018). This geographic scale has been seriously criticised for its tendency of introducing bias and may cause ecological fallacy, hence impacting significantly on the results (Ewing et al., 2017). The latter, on the other hand, is based on the disaggregate methodology which analyses data at the micro-level or finer grain spatial unit. It defines the built environment closer to the household location by breaking down outcomes into a smaller geographic framework such as neighbourhood, street block, etc (Lee & Moudon, 2006; Guzman et al., 2020).

2.3 Indicators of the built environment and their implications to travel pattern

The 5Ds and S indicators of quantifying the BE as identified in the existing literature exhibit significant influence on TB. Each may have some level of an implication that may help to characterise the spatial units of interest based on the interaction of these dimensions.

The density dimension had been defined with various variables that ranged from population distribution to urban footprint distribution. Population density as a variable to define the density dimension of the BE is primarily and commonly adopted as the measure of density (Choi, 2018; Ewing et al., 2017; Yang & Zhou, 2020), this is because the data is mostly and readily accessible and very easy to compute. Others adopted residential and employment densities which measures the activity intensity within a spatial unit (Yu & Peng, 2020; Ewing et al., 2014). Yet, others included infrastructural density which measures the intensity of urban infrastructures such as road, rail and paved surfaces (Yu & Peng, 2020; Nari & Zhang, 2018), in these studies, density was used to represent the intensity of people residing interactively within an area. Another measure of density dimension is the urban patch index (Nkeki & Asikhia, 2019; Wang et al., 2020). This is a robust method though not as popular as the population intensity method due to its computational complexity and data scarcity. It measures the intensity and fragmentation of the general urban landscape which consist of population residence, employment spaces and overall activities and infrastructure such as roads, rail, pavement, etc. Also, it shows that true density can influence travel in all directions. However, as shown in literature density exhibit a significant influence on TB (James et al., 2014; Cervero & Kockelman, 1997). For example, higher density encourages walking and other non-motorised travel modes by implication, more compact geographic landscape may lower the automobile usage (Cervero & Kockelman, 1997; Nari & Zhang, 2018; Cho & Rodriguez, 2014; Levinson & Wynn, 1963) and also, shortens the travel distance (Hu & Huapu, 2007).

The diversity dimension simply describes the level of land-use mix in an urban space. The land-use mix is an important variable in urban studies since it promotes understanding of the land-use pattern and its relationship with other interacting activities. It is also used to calculate the magnitude of balance among the land-uses with a defined spatial unit. The diversity dimension has been used for over 2 decades to quantify the BE for TB related studies (Ewing et al., 2014; Nkeki & Asikhia, 2019; Gehrke & Clifton, 2016). In land-use-transport planning, diversity has been shown in previous studies to significantly impact TB. For example, higher land-use mixed areas tend to encourage walking due to the short distance that connects activity locations while lower mixed areas tend to promote longer travel distance and hence encourages motorised travel modes (Guzman et al., 2020; Ewing et al., 2014; Gehrke & Clifton, 2016).

Design dimension typically describes the general patterns of infrastructure that result in a specific spatial arrangement. Design dimension is among the first 3D variables, which is often measured by urban overland linear transport infrastructure, such as road, rail and pedestrian network pattern (Ewing & Cervero, 2010); block size, the density of 4-way intersections, sidewalk density and number of parking space (Nkeki & Asikhia, 2019; Choi, 2018). Design variables have been found to significantly affect travel. For example, literature (Yu & Peng, 2020) has shown that road density may produce more ride-sourcing demand; Ewing et al. (2014) revealed that 4-way road intersections increase walking trips (though there is a mixed reaction in literature as some believe that it may trigger the search of other modes for intermediate-distance travel); yet another study found that smaller block sizes and longer sidewalks along the main streets significantly influences walking (Lee & Moudon, 2006). However, it is believed that a certain urban design pattern promotes certain TB. For example, the presence of sidewalk in a neighbourhood may encourage walking and discourages automobile trips; the high the density of street intersection, the higher the likelihood to walk because higher urban density and activity concentration may emerge; a grid pattern of road network may force block kind of neighbourhood design which encourages people to walk; corridor road design encourages transit dependence (Asikhia & Nkeki, 2013).

The destination accessibility dimension measures the ease of accessing the commuters residence or source/neighbourhood from a certain activity-based location such as the central business district (CBD), shopping centre, etc. In most cases, a neighbourhood's level of accessibility is measured by its distance from the CBD. This is because the shorter the distance of a neighbourhood to a major activity centre, the shorter would the commuters travel, it is expected that this would promote walking and for a neighbourhood with an average distance to an activity centre with a grid design, car usage may be encouraged while in a corridor road design, the probability for transit usage may increase (Asikhia & Nkeki, 2013; Schwanen et al., 2001). The longer the distance of a neighbourhood from an activity centre, the more the likelihood of automobile dependence. The destination accessibility dimension has been quantified with several variables such as regional or local trip attraction activities, the distance between residence and job location.

Distance to transit has been quantified by some variables such as the average of the shortest route between commuters residences or work location and the nearest bus stop/rail station (Ewing et al., 2014; Choi, 2018); transit route density of a neighbourhood (Nkeki & Asikhia, 2019). The closer a neighbourhood is to a transit route or the higher the transit route density, the higher the probability of transit performing more than other modes. This dimension tends to strongly encourage automobile usage and discourages walking, biking and other pedestrian modes. It has been shown to manifest a positive relationship with TB (Yu & Peng, 2020).

Sprawl dimension is often neglected in choosing BE indicators that influence TB. Very few studies have used sprawl to quantify BE (Tsai, 2005; Nkeki & Asikhia, 2019). It may be mistaken for a kind of low-density development. Cities may grow either by increasing density or sprawling (Nkeki, 2016). Whatever the case, sprawl and density influence TB differently. For example, higher density promotes pedestrian modes while a higher level of sprawl encourages automobile usage.

2.4 Summary

The review of existing literature demonstrates that very few or no study has holistically measured the BE using several other dimensions that look beyond density, diversity and design or distance and destination accessibility. Most of the literature either utilized the initially proposed 3Ds or some of the 3Ds and included the later additional 2Ds. It is the view of this study that to conduct a robust quantification of the BE for TB study, all dimensions/indicators should be exhausted. Also, the review shows that no study has attempted to examine the interactions between the BE indicators and how such interactions varies spatially. This study intends to present an all-inclusive and robust quantification of the BE for TB study.

3. Methodology

3.1 Study region

The study area is the BMR which is roughly 506 km^2 in the urbanized area and has over 1.1 million inhabitants. From the census estimate, the region is composed of 248,620 households and an average of 6-7 persons per household (NPC, 2006). It is located between latitudes 6° 16′ to 6° 33′ N and longitudes 5° 31′ to 5° 45′ E (Fig. 1a & b). There are 55 major neighbourhoods characterised by high to low urban density from the CBD. Density reduces with increasing distance from the CBD. Unlike the cities of most advanced countries where building floors reach an average of 10, the region is dominated by single floor buildings making density essentially horizontal. The CBD is a prominent region known for essentially commercial activities and it falls within the King square/core neighbourhood (see map 'b' in Fig.1)

Also, the massive unauthorized land-use conversion occurring in the CBD is unprecedented. However, in this area, commercial activities predominate and rapidly engulfing and replacing other land-uses.

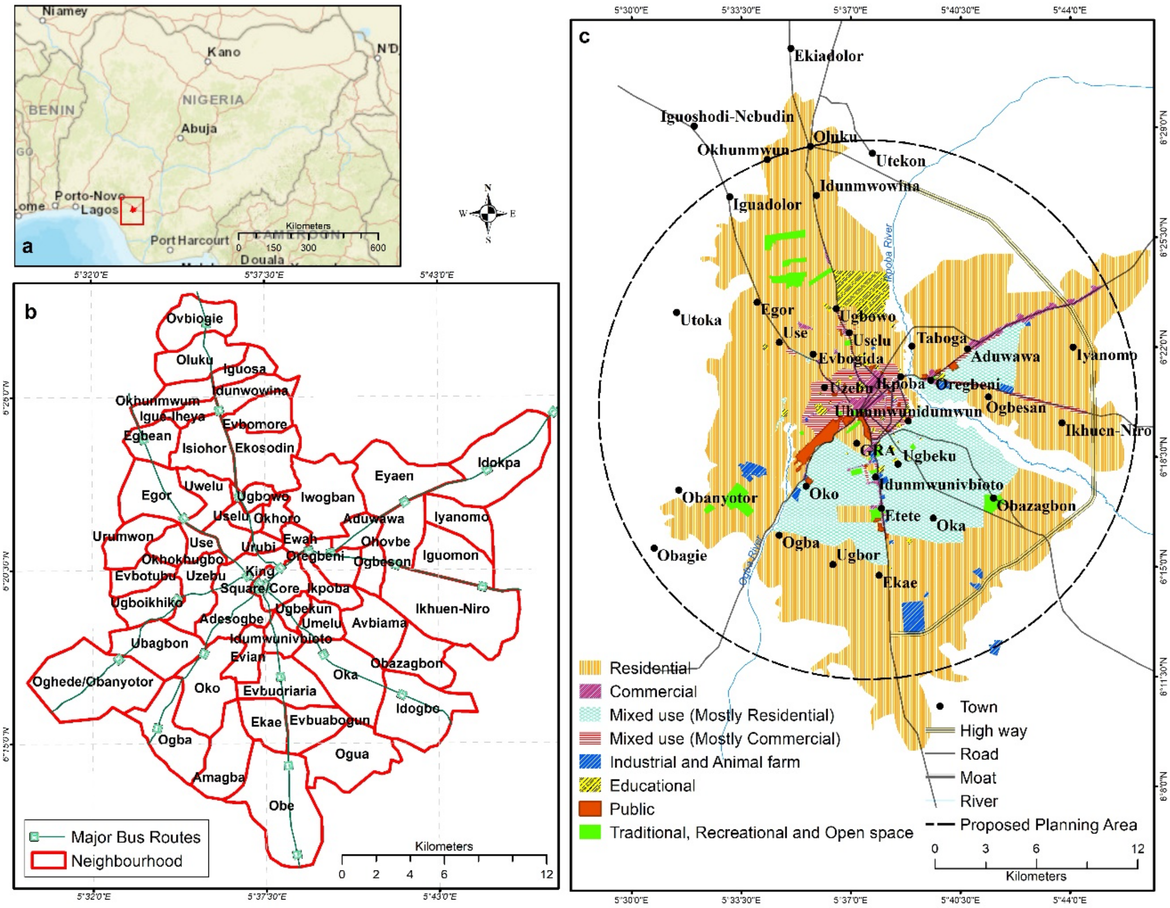

Fig.1 Location of the study area map 'a' is the location of Benin in Nigeria; map 'b' is Benin metropolitan region and the neighbourhoods; map 'c' is land-use of Benin

For example, within the King-Square/Ring-Road axis, tending towards the New-Benin market axis (northeastern part of the region), commercial land-use continuously spread over roughly 1.7 km^2. At the New-Benin market area, commercial land-use formed a cluster covering over 1.2 km^2. Such activities are also found along trunk roads (Fig.1c). Predominantly, residential land-use tends to concentrically envelop the core region and spread towards the outer part of the metropolis, particularly along the trunk roads.

3.2 Data

Two major sources of data were utilized in this study and these datasets were categorized into primary data and secondary data. The first part of the primary datasets was obtained from a comprehensive neighbourhood-based field survey. This involved the identification, recording and capturing of data with a GPS device. The datasets that were extracted from this field survey were implemented to derive such indicators as the availability of sidewalks in the neighbourhood and the number of regular bus routes within the neighbourhood. The second part of the primary data collection comprises the counting of housing (residence) and job (employment, commercial and administrative land-uses). This was done with a 200m x 200m quadrat which covers 40,000 m^2 of urban space. The mean centre points of each of the identified 55 neighbourhood polygons were determined with ArcGIS spatial statistical module. With the mean centre tool, a 200m x 200m quadrat was delineated for each polygon and with the help of the worldview satellite data, the locations on the ground were identified before fieldwork. The number of houses and job locations were captured for the 55 locations from the field. This data was used for diversity analysis.

The secondary datasets were extracted from the high-resolution (2m spatial resolution) worldview image (provided by Digital Globe Foundation) of the entire region. These datasets were used to calculate the urban density and local sprawl indicators.

3.3 Satellite data processing and classification

The satellite data was classified to assess the built-up area of the region. Computing urban density and local sprawl indicators, urban patches were mined from the worldview imagery using GIS and remote sensing procedures. These procedures combined presented a robust empirical methodology prescribed in this study for measuring the BE. This spatial data was used for urban density and local sprawl indexes computation. The overall proposed procedure for the analysis is shown in Fig.2. The image was entered into ENVI version 5.1 for seamless mosaicking since the imagery was acquired in tiles (mosaicking is a photogrammetric algorithm that helps to combine several raster scenes into one while maintaining a uniform spectral characteristic). The single raster scene was re-projected and transformed. The projected coordinate system, with Universal Transverse Mercator (UTM)–Minna UTM zone 31°N was adopted.

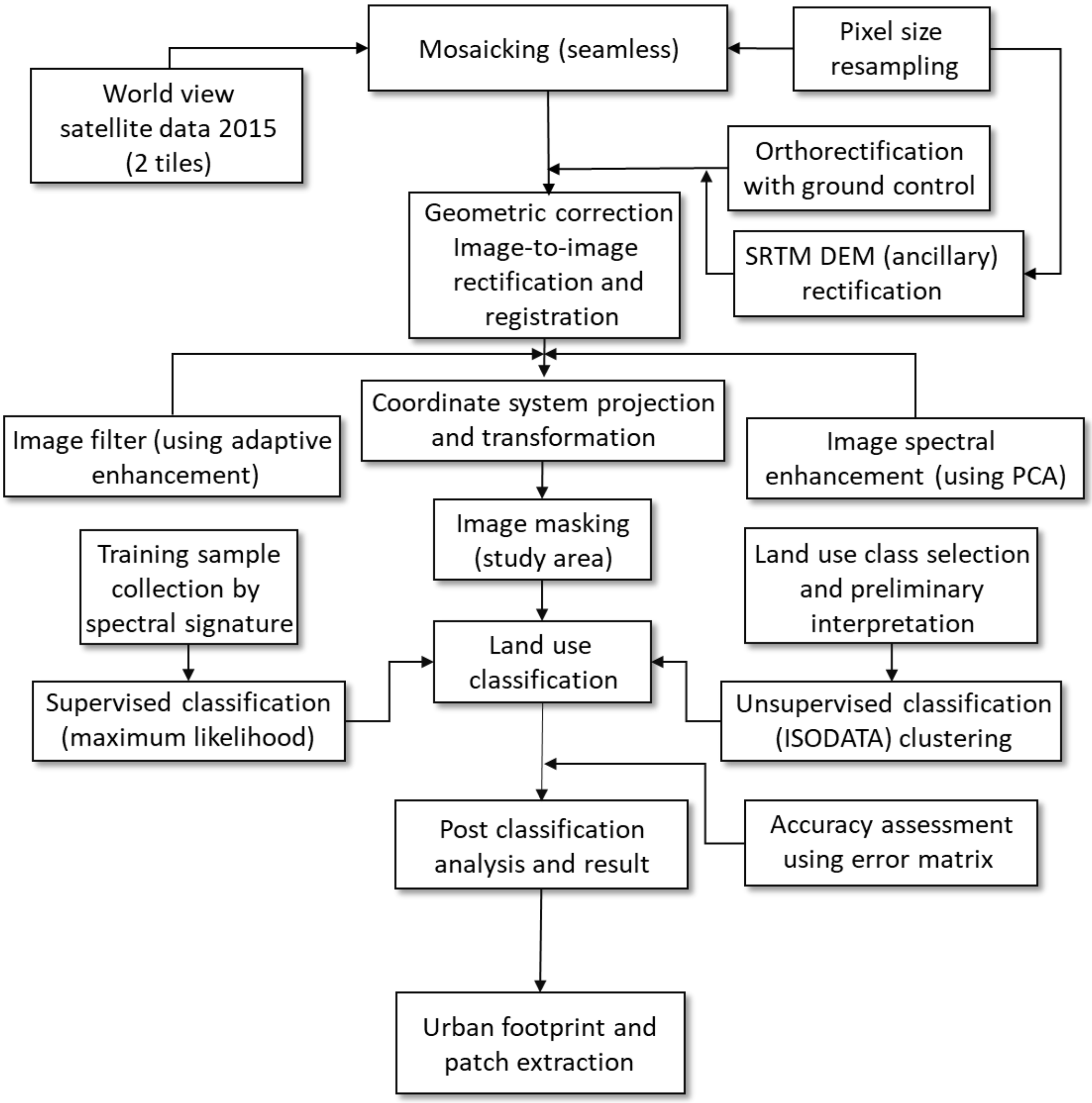

Fig.2 A methodological flow chart for the land-use classification and urban patch extraction

From ENVI the transformed image was exported to imagine raster (.img) for further correction concerning spectral and geometric distortion. The image was subjected to orthorectification processes in ERDAS IMAGINE photogrammetric software 2014 version. In carrying out orthorectification processes, 45 well-distributed ground control points within the study region and ancillary (SRTM DEM) data were employed. To further improve the image (SRTM data) spectral quality, it was resampled independently in ERDAS IMAGINE using the resample pixel size algorithm in the software. The bilinear interpolation resampling method was used. The bilinear interpolation method was preferred because it is the most appropriate resampling technique for continuous value data like elevation and slope. The DEM image was resampled from 30 x 30 m to 2 x 2 m. The reason for this is to avoid pixel conflict during image–to image rectification process. The rectified and enhanced world view data in IMAGINE raster format was clipped to the study region using the mask algorithm in ERDAS IMAGINE.

There are two types of image classification in GIS operation–unsupervised and supervised classification. Both procedures were applied to the image scene to get possible maximum accuracy in characterisation. The unsupervised classification with ISODATA (Iterative Self–Organising Data Analysis) clustering approach was applied, this allowed preliminary land-use class selection and interpretation. It automatically aggregated the multispectral data into several classes based on intrinsic similarity within the pixel of the image. This spectral detail assisted in the class selection and naming through on-screen visual assessment, which involves the careful grouping of pixels and delineating areas with a large quantity of a particular class. The proposed classes for the study region include urban or built-up area, vegetation area and water body. Other land-uses were not included because extracting the built-up area is the focus of the analysis. There were 5 initial classes. The pixel cluster that defined the urban area; those that defined the water body and those that defined vegetation were broken into riparian vegetation along the river; dense vegetation cluster and light vegetation clusters agricultural areas. Since the focus is the urban footprint, the riparian, dense and agricultural vegetation related classes were classified as vegetation. Generally, the unsupervised classification returned 121,705,593 pixels for built-up area; water body has 996,714 and vegetation has 333,596,613 pixels.

		Ground truth (Pixels)		
Class	**Built–up area**	**Waterbody**	**Vegetation**	**Total**
Unclassified	0	0	0	0
Built–up area	129,524	461	10,496	140,481
Waterbody	310	18,846	1,042	20,198
Vegetation	325	68	782,870	783,263
Total	130,159	19,375	794,408	943,942
		Ground truth (Percent)		
Class	**Built–up area**	**Waterbody**	**Vegetation**	**Total**
Unclassified	0.00	0.00	0.00	0.00
Built–up area	99.51	2.38	1.32	14.88
Waterbody	0.24	97.27	0.13	2.14
Vegetation	0.25	0.35	98.55	82.98
Total	100.00	100.00	100.00	100.00
Class	**Commission (Percent)**	**Omission (Percent)**	**Commission (Pixels)**	**Omission (Pixels)**
Built–up area	7.80	0.49	10,957/140,481	635/130,159
Waterbody	6.69	2.73	1,352/20,198	529/19,375
Vegetation	0.05	1.45	393/783,263	11,538/794,408
Class	**Prod. Acc. (Percent)**	**User Acc. (Percent)**	**Prod Acc. (Pixels)**	**User Acc. (Pixels)**
Built–up area	99.51	92.20	129,524/130,159	129,524/140,481
Waterbody	97.27	93.31	18,846/19,375	18,846/20,198
Vegetation	98.55	99.95	782,870/79,4408	782,870/783,263
Overall Accuracy = (931,240/943,942) 98.65%; Kappa Coefficient = 0.9521				

Tab.1 Confusion matrix for supervised image classification

The supervised classification was conducted by collecting training samples using the region of interest tool (ROI) of ENVI and these sample polygons were saved as a spectral signature file for further usage. This was achieved using the spectral information from the unsupervised classification method and additional details were extracted from various statistical computations during training sample creation. Land-use supervised classification was performed using the maximum likelihood algorithm with equal a priori probability weighting (which guarantee all classes having the same a priori probability).

Classification accuracy assessment for the image was carried out with about 100 randomly distributed ground truth points within the limit of the study region. The generated points are based on stratified random sampling type and stratification is proportionate (i.e. 40, 40 and 20 points for urban, vegetation and waterbody respectively) across all classes. These points were used to compute the confusion matrix for the classified data, based on the Kappa coefficient (Tab.2). The overall accuracy of the classification is 98.65% with a Kappa Coefficient of 0.95. The observed high level of classification accuracy was expected because three classes of land-use types were selected which correspondingly are the major classes distinctively captured by the very high-resolution imageries. Also, the various image spectral enhancements implemented made the classification less complex by grouping similar pixels. The classified land-use data were exported and entered into ArcGIS 10.4.1 software from where such data was manipulated using the raster calculator in the ArcGIS toolbox. The raster calculator was used to extract the built-up area from the classified raster. This was carried out by reclassifying the built-up area as 1 and others as 0 using the reclassify tool in ArcGIS. The raster calculator was then instructed to extract 1 (built-up area) as a separate layer. This facilitated statistical estimation and disaggregation of the classes and patches. The extracted urban patches were used as data for calculating the urban density and sprawl.

3.4 Indicators

Urban patch density

Density was quantified using a spatial metrics-urban patch density index (PD). The value of PD is simply the number of urban patches in a neighbourhood divided by the total landscape area (neighbourhood) in m^2. This was calculated using Eq.1 in Tab.2 presented by (McGarigal & Ene, 2014).

Indicators	**Formula/measurement**		**Description**
Density dimension			
Urban density	$PD = \frac{N}{A}\,(1{,}000{,}000)$	(1)	Density of built-up patch in a neighbourhood calculated by urban patch density index (PD).
	Diversity dimension		
Land-use mix	$(EI) = (-1) \times \frac{\left[\left(\frac{b1}{a}\right)\times In\left(\frac{b1}{a}\right)+\left(\frac{b2}{a}\right)\times In\left(\frac{b2}{a}\right)\right]}{In(n)}$	(2)	The proportion of jobs to housing location within neighbourhood-calculated by a spatial entropy index. The value of the index varies between 0 and 1.
	Design dimension		
Street intersection density	$SI\ Density = \frac{NoN}{A}\,(1{,}000{,}000)$	(3)	The density of street intersection within neighbourhood-computed by street intersection density index (SI Density).
The presence of sidewalks in the neighbourhood	Binary		Availability of sidewalk in the neighbourhood-measured with binary 1=yes; 0=no.
Destination accessibility dimension			
Distance to CBD	Average length		The average distance of the neighbourhood to CBD in Km.
Transit route density/accessibility dimension			
Transit accessibility	Count		Number of regular bus routes within the neighbourhood
Sprawl dimension			
Local sprawl	$H_n = -\sum P_i log_e(P_i)$	(4)	The index gives a value that varies from 0 to $In(n)$.

Tab.2 Definition of indicators for measuring built environment

In the formula *N* = overall sum of patches in the neighbourhood excluding any background patches; *A* = area coverage of the neighbourhood under consideration in m^2. To enable the interpretation of patch density per km^2, the PD value for each neighbourhood was multiplied by 1,000,000. FRAGSTATS spatial metric was used to conduct the calculation (Nkeki, 2016; Ramachandra et al., 2012). In the interpretation, increasing value of PD means disaggregation of the urban landscape (low density), while decreasing value of PD implies increasing density and more compacted landscape.

Land-use mix

Spatial entropy statistic was used to calculate the land-use mix utilizing data from the 200m x 200m quadrat this consist of the number of housing and job location for the 55 neighbourhoods in the study area. The major reason for modelling these land-use types is to create a spatial dataset for quantifying the built environment. The entropy index is fast becoming known and accepted as the most common method of quantifying land-use mix and diversity in global literature. For example, several studies have used it to quantify the degree of homogeneity or diversity of many land-uses, such as job and residential land-uses (Strauss & Miranda-Moreno, 2013; Silva, 2014; Kockelman, 1997). The entropy index as modified for the land-use mix by (Zahabi et al., 2012) is presented in Tab. 2. In the formulation (Eq.2 in Tab.2), EI = land-use mix entropy index; a = total number of land-uses of the two land-use categories; $b1$ = the job/commercial land-use category; $b2$ = the housing/residential land-use category; n = the total number of land-uses in the mix (in this case 2). The field calculator module in ArcGIS 10.7.1 was employed for the computation of this spatial entropy index based on the Eq. 2 specification. The resulting value of the index varies between 0 and 1, where 0 depicts a homogenous land-use scenario (i.e. a single land-use) while 1 corresponds with a perfect mix scenario (i.e. all land-use categories are equally present).

Street intersection density

Street Intersection (SI) density index was used here as one of the indicators for defining the design dimension of the built environment. SI Density was measured in this study by computing a neighbourhood based four-way street intersection points density. These points were extracted from the worldview satellite data and used to calculate the density of intersections per square kilometre of the respective neighbourhoods. The formulation developed to compute the SI Density index is presented in Eq.3 in Tab.2. In this specification, *NoN* = number of nodes (street intersection points in the neighbourhood); *A* = area of the neighbourhood in m^2 (to convert to km^2 the value of SI Density was multiplied by 1,000,000). By this, the SI Density index would be interpreted as the number of nodes per km^2. By implication, neighbourhoods with a higher intersection density may promote more pedestrian travel (Reiff, 2003). The density of the intersection points would aid the characterisation of the neighbourhoods based on the level of grid design they are structured. A neighbourhood characterised by grid design tends to promote short distance travel and may also discourage transit mode of travel. The SI Density index was calculated in ArcGIS. Another design dimension is the presence of a sidewalk in the neighbourhood (Tab.2).

Local sprawl

Quantifying sprawl has been a long-time issue in global literature. The specification of robust indicators has played down the problem of measuring sprawl. The entropy statistic in its diverse modification has become a steady resource for quantifying urban sprawl (Bhatta et al., 2010; Sarvestani et al., 2011). However, the Shannon entropy index was computed to quantify and detect the local sprawl pattern by estimating the degree of concentration or dispersion of urban patches in the neighbourhoods. Shannon's entropy statistic for measuring sprawl was calculated here with the formulation by Bhatta et al. (2010) in Eq. 4 in Tab. 2. The parameters are defined as H_n = Shannon's entropy index; P_i = proportion of urban patches i in each neighbourhood; n = Overall number of neighbourhoods in the study area. The index gives a value that varies from 0 to $In(n)$. A value near 0 implies the compactness of patches while a value near $In(n)$ indicates the dispersion of patches. Dispersion is interpreted as the occurrence of sprawl.

Distance to CBD

Distance to CBD was defined as destination accessibility dimension using the average distance of the neighbourhood centroid to the CBD through a regular bus route or a major road in such a neighbourhood.

Transit accessibility

Transit accessibility was used to define the transit route density dimension and it measured the field data on the number of regular bus routes within the neighbourhood.

3.5 Reclassification and rasterization of the indicators

The 7 indicators which were used to quantify the BE of the Benin region were further analysed to understand the interactions and how such indicators collectively play out to define not only the BE but also the travel-related prototypical neighbourhood. The essence of this is to advance knowledge on the travel outcome of the emerging BE. To achieve this, the indicators were rasterized (with a pixel size of 100x100) and using the raster calculator and reclassify tool in ArcGIS the indicators were systematically re-coded and classify into a common 3 components measurement scale where 1 represent car-oriented neighbourhood, 2 represent transit-oriented neighbourhood, and 3 represent pedestrian-orientated development. The reclassification was done in such a way that the BE characteristics that trigger certain TB were classified accordingly.

Neighbourhoods with high PD index values (ranging from 2,084.45-5,276.20) were classified as 1 (low density since the patches are less compacted); the neighbourhoods with PD index values ranging from 1091.16-2,084.44 were classified as 2; while the neighbourhoods with PD index values ranging from 17.71-1,091.15 were classified as 3. This approach was used to classify land-use index, SI density index, local sprawl index and distance to CBD index. Availability of sidewalk index has 2 categories 0 and 1. The neighbourhoods where sidewalks are present were classified 3, while others were classified 2. Neighbourhoods with transit accessibility index ranging from 2-7 were classified as 2 (high transit accessibility neighbourhoods); neighbourhoods with 1 index value were classified as 1 (low transit accessibility); while neighbourhoods with 0 index value were classified as 3. The weighted overlay operation was performed on the reclassified indicator raster images with equal-weighted influence to produce an output raster. The weighted overlay analysis assigns the most unique code (i.e. the classification code of 1,2 or 3) to a neighbourhood and this is derived from the most significant class of all the indicators for such neighbourhood.

4. Results and Discussion

This section presents the various methods for extracting and measuring BE indicators to be used in defining the study region for TB study. To accomplish this, numerous land-use indexes were implemented, they include urban patch density index (density), local sprawl entropy index, land-use mix entropy index (diversity), street intersection density (design). Other BE variables that were presented in this section are the average distance of the neighbourhood to CBD (distance accessibility) and the number of regular bus routes in the neighbourhood (transit accessibility).

4.1 Quantifying urban density

To generate data for the PD index, an image classification was conducted using GIS and remote sensing techniques which were discussed in detail in the methodology section. Over 1 million urban built-up patches were extracted from the land-use section of the image classification. These patches were entered into ArcMap and using the patch analyst algorithm in the spatial metrics tool the PD index was computed. The result of the PD index is presented in Fig.3a. The PD index result (Fig.3a) is interpreted as the number of patches per km^2. On the one hand, the lesser the value of the PD index, the denser the urban built-up area. It simply means that the associated urbanised portion is more compacted. On the other hand, the higher the value of the PD index, the sparser the built-up area. By implication, a PD index of one (1) means that there is 100 per cent built-up or that the patch is one whole block within such neighbourhood.

The result was displayed in a choropleth map using a natural breaks Jenks classification with 5-classes. As expected, the general pattern of PD (as revealed in Fig. 3a.) is that density reduces with increasing distance from the CBD. It shows that 14 neighbourhoods clustering contiguously in the core region (covering roughly 71 km^2) have a low PD index between 17-402 patches per km^2.

This means that the built-up patches are more aggregated. Hence, density is higher in these neighbourhoods. Among these neighbourhoods, Ugbekun has the highest density with the lowest PD index value of 17.71. However, the pattern of density spread was interrupted in Ewah, Ikpoba and Avbiama neighbourhoods. These neighbourhoods are where the Ikpoba River passes through which created a natural obstacle and slows down development.

At the outskirt, 5 neighbourhoods manifest the highest PD index (3,219-5,276 patches per km^2). By implication, they have the lowest urban concentration. These neighbourhoods are sparsely built-up and the closest to the King square/core region is over 10 km away.

4.2 Measuring land-use mix

Land-use mix was analysed with spatial entropy statistic which was modified to disaggregate the result of the entropy index values into neighbourhoods utilizing data from the 200m x 200m quadrat this consist of the number of housing and job location for the 55 neighbourhoods in the study area. The result of the analysis (Fig. 3b) shows that 7 neighbourhoods returned high entropy index values greater than 0.71 indicating strong heterogeneousness of land-use. These neighbourhoods are Umelu (with an index value of 1.00); Iwogban (0.99); Aduwawa (0.99); Ugbekun (0.97); Evbuoriaria (0.97); Ogbeson (0.89); Ewah (0.78). There is only 1 neighbourhood (Umelu) characterised by an entropy index equal to 1.00. It means that this neighbourhood's land-use components are heterogeneous and are in a perfect mix. Figure 3b shows that King-Square and 31 other neighbourhoods (such as Oghede/Obanyotor, Ugboikhiko, Urumwon, Egor, Idunwowina, Eyaen, Iyanomo, Evbuabogun, Ogua, etc.) returned entropy values less than 0.48, indicating that such neighbourhoods are characterised by homogenous land-use composition. This means that one land-use type is dominant in these neighbourhoods. The dominant land-use types for each neighbourhood is shown in Fig. 4. However, the general pattern of the region's land-use distribution is a complex mixture of residential and commercial land-uses which formed a cluster around the King-Square which in turn is defined by homogenous land-use characteristics.

In the peripheral area, neighbourhoods with a single dominant land-use type formed patches around the heterogeneous land-use composition. One weakness of the entropy index is that it does not show the dominating land-use type in areas of the homogenous composition. To identify the dominant land-use type in each neighbourhood, the percentage values of the land-use types were plotted against the corresponding neighbourhoods (Fig.4). Fig.4 shows that King-Square is the only significant homogenous commercial land-use-based neighbourhood.

This is because it returned an entropy index value of 0.24 of which 85 per cent of the buildings are commercially based. This is not unexpected since it has become the commercial hub of the region over the years. Furthermore, 32 neighbourhoods that returned entropy index values less than 0.50 which is the mean of the index are homogenous residential. By implication, these neighbourhoods are classified as residential areas (see Fig.4).

For planning and further explanation, the neighbourhood–based land-use diversity result was reclassified into groups based on entropy values. The first group are neighbourhoods that returned entropy values of 0.22–0.30, these were named *pure residential areas* and *pure commercial areas*.

The second group are neighbourhoods that returned entropy values of 0.31-0.39, these were named *largely residential*. Thirdly, neighbourhoods that returned entropy values of 0.40-0.47 were named *weakly mixed land-use*. Fourthly, neighbourhoods that returned entropy value of 0.48-0.71 were named *robust mixed land-use* and finally, those that returned entropy value of 0.72-1.00 were named *complete mixed land-use*.

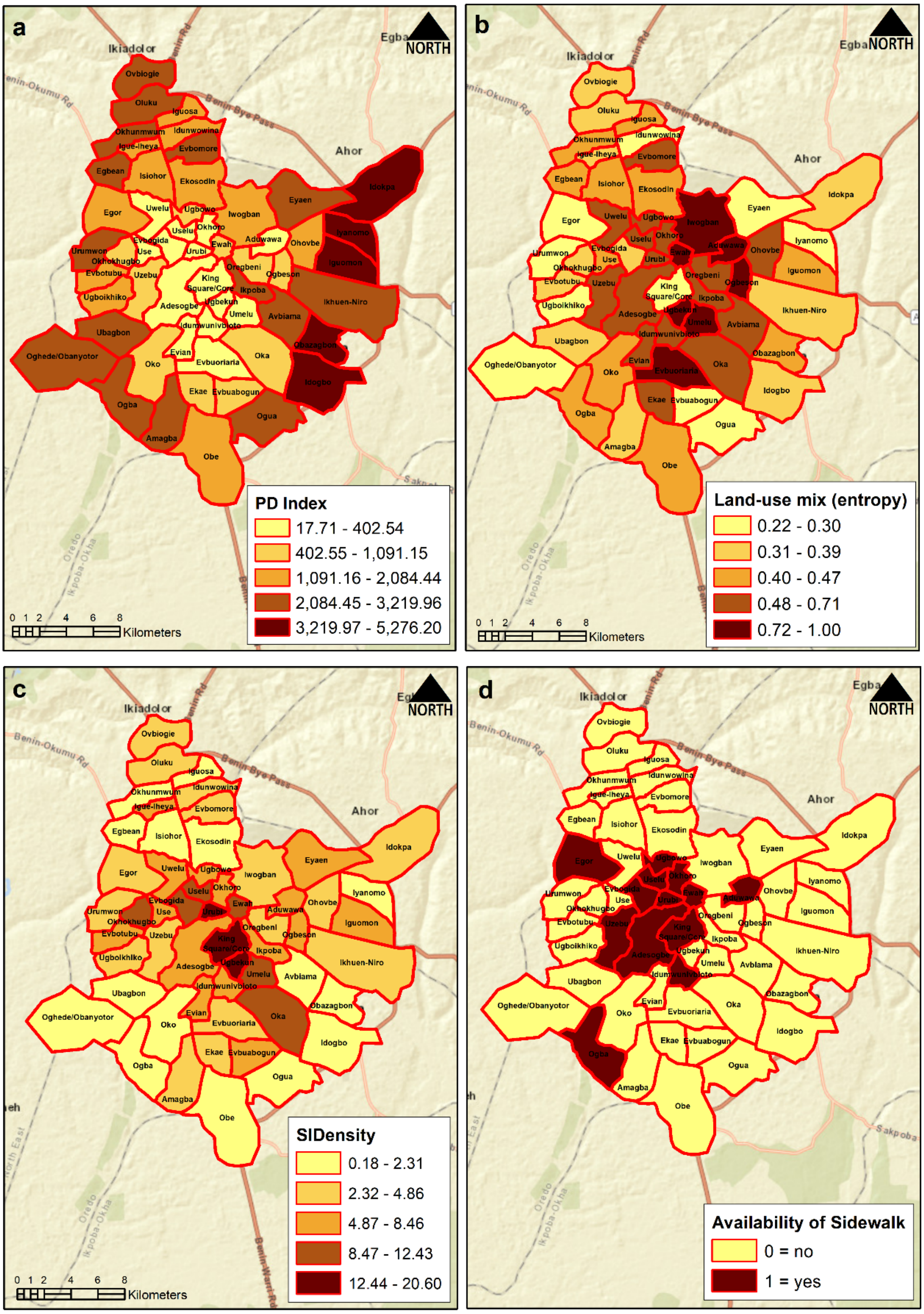

Fig.3 (a) is a patch density index (PD); (b) is a land-use mix entropy index; (c) is street intersection index (SI density), and (d) is the availability of sidewalk

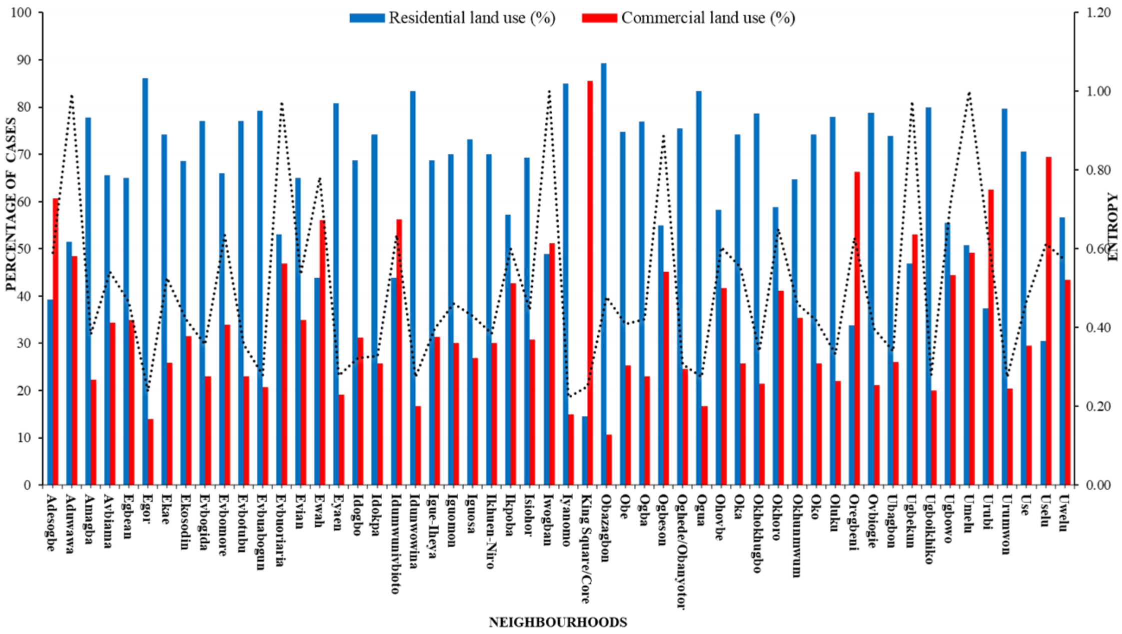

Fig.4 Neighbourhood-level comparison of land-use types concerning entropy index

4.3 Measuring SI Density index

Design dimension was generated from two platforms-the first is a GPS-based field survey for capturing neighbourhoods with sidewalks, parking spaces and the second is the use of GIS techniques to compute a Street Intersection (SI) Density index. This section is specifically designed to focus on generating spatial data which was used to quantify the BE of the study region. Generally, 2,024 4-way street intersections were found in the region and this was used for the computation of indicators. The result of the SI Density index is presented in Fig.3c. The result shows that Ugbekun has the highest SI Density index value of 20.6, indicating that the neighbourhood is characterised by roughly 20 street intersections per km2. This is followed closely by the King-Square and Urubi with roughly 15 street intersections each per km2. However, neighbourhoods with a higher density of street intersections tend to cluster in the centroid of the region. The majority of the neighbourhoods at the edge of the city have a low SI Density index of between 0 and 5.29 intersections per km2. A Higher SI Density index means a higher level of grid design and this structure may encourage short distance travel and may discourage transit mode of travel.

4.4 Availability of sidewalk

Another indicator of the design dimension is the availability of sidewalks within the neighbourhood. The presence of a sidewalk in a neighbourhood is an urban design issue that encourages people to walk more often to their place of work. Fig.3d revealed a binary measure of the status of sidewalk availability within neighbourhoods of the region where 0 represent no sidewalk and 1 represent yes (i.e. the presence of sidewalk). Fig.3d shows that among the 55 neighbourhoods, 13 have sidewalks and the majority of these neighbourhoods formed a cluster at the central or core axis of the study region. However, 3 neighbourhoods seem to be detached from the cluster because they are closer to the edge of the city. These neighbourhoods are Egor, Ogba and Aduwawa.

4.5 Distance to CBD

The average distance of each neighbourhood to the CBD was used to define the destination accessibility dimension. Distance to CBD was measured using the average distance of the neighbourhood to the CBD through a regular bus route or a major road in such a neighbourhood. The respective distances were entered into ArcGIS to generate a choropleth map of the region depicting the distance relationship of the adjacent neighbourhoods with CBD located in the King-Square neighbourhood (Fig.5a).

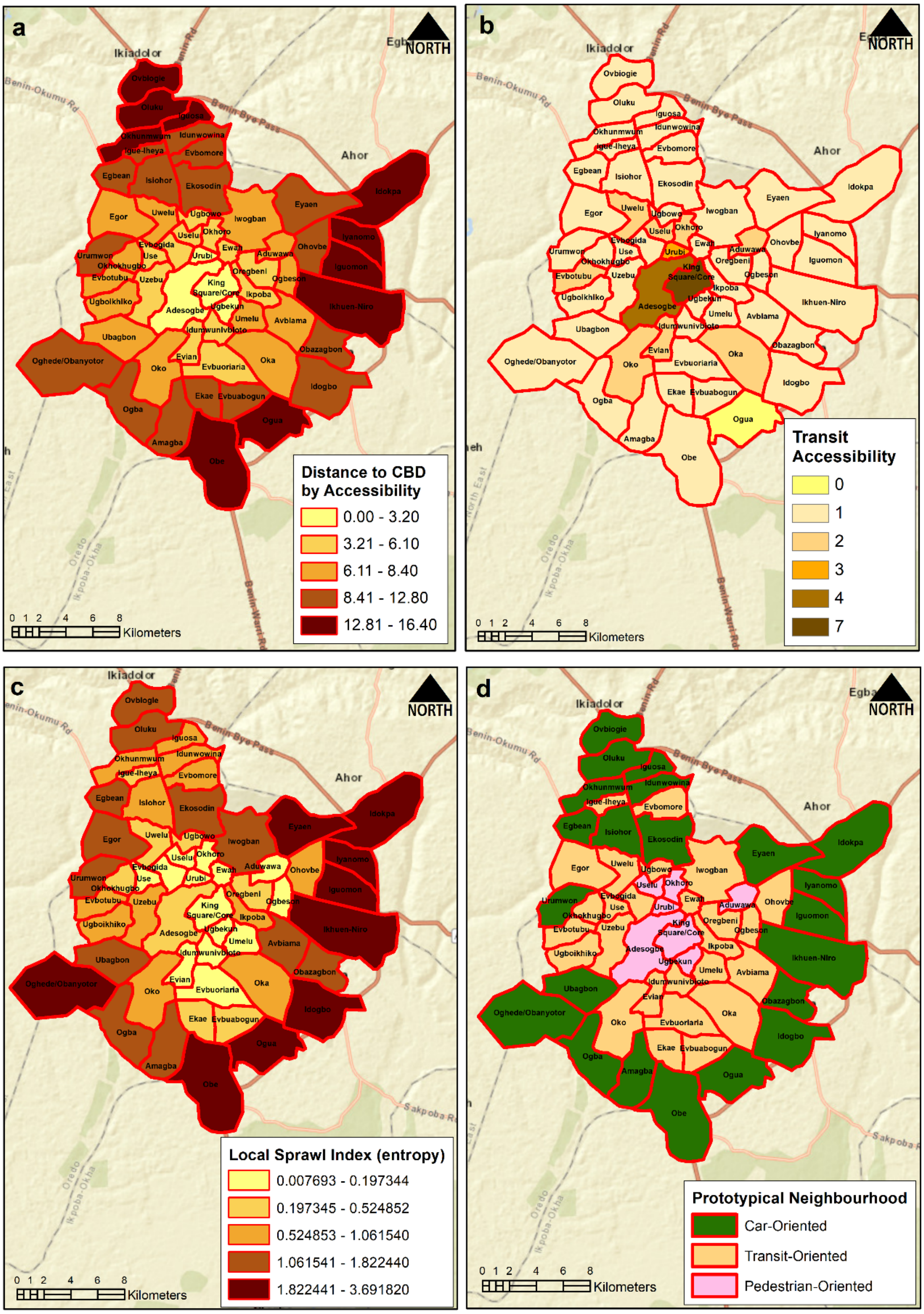

Fig.5 (a) is distance accessibility index; (b) is transit accessibility index; (c) is the local sprawl entropy index, and (d) is the type of neighbourhood in the Benin region

The general pattern is as expected–accessibility decreases with increasing distance from the CBD (the colour ramp in Fig.5a presents a clear visual explanation). Accessibility is lower in the peripheral areas, specifically the northwest, northeast and southeast parts of the region. This is because urban expansion is more rapid in these areas due to the influence of the high priority roads.

The overall average distance in the region is 8.94 km and the maximum distance to the CBD is 16.4 km, the minimum distance to the CBD is 1.7 km. Ovbiogie has the maximum distance from the CBD while Adesogbe has the minimum distance. This means that Adesogbe is the most accessible neighbourhood (by bus route) from the CBD and Ovbiogie is the least accessible neighbourhood (by bus route) from the CBD. 9 neighbourhoods returned the highest friction of distance from the CBD of over 13.1 km. These are depicted by the darkest shade in Fig.5a. For further computation, any neighbourhood whose distance from the CBD is higher than the regional average is interpreted as a neighbourhood with low accessibility while those with a distance lower than the regional average is interpreted as a neighbourhood with high accessibility. Low accessibility neighbourhoods may promote automobile usage. A custom filter result in Fig.5a revealed that 26 of the 55 neighbourhoods are low accessibility areas. This is because their distance values are above the regional average of 8.94 km. Some of these neighbourhoods are Ovbiogie, Idokpa, Oluku, Iyanomo, Okhunmwum, Ikhuen-Niro, Iguosa, Obe, Ogua, etc.

4.6 Transit accessibility

Transit route density/accessibility dimension was measured with the number of regular bus routes within the neighbourhoods. King-Square has 7 regular bus routes indicating that accessibility is higher in this neighbourhood. This is followed by Adesogbe (with 4 bus routes) and Urubi (with 3 bus routes). Other neighbourhoods are either 2, 1 or 0 number of regular bus routes (Fig. 5b). King-Square, Adesogbe and Urubi are characterised by not less than 3 regular bus routes, indicating higher accessibility correspondingly are part of the highest accessible neighbourhoods from the CBD (Fig.5a). Ogua has the least level of accessibility. This is because there is no regular bus route in the neighbourhood and it has a friction of distance of over 13 km.

4.7 Local sprawl

Spatial Shannon's entropy index for urban sprawl was used to empirically measure sprawl dimension in the study area and this was calculated at the neighbourhood level. The overall result of the computation is presented in Fig. 5c which is a choropleth map of the 5-class Jenks classification. The data used for the computation is the urban patch extracted from the classified World view image of the study region.

The entropy index value for the sprawl measurement ranges from 0 to $\log_e(n)$. Since the index was computed neighbourhood-wise and there are 55 neighbourhoods, then $n = 55$. $\text{Log}_e(55)$ therefore is 4.007. In this study, entropy values near 4.007 are interpreted as the occurrence of urban sprawl. Those near to 0 is interpreted as compactness (no sprawl). The result of the analysis shows that urban sprawl is stronger at the periphery specifically at the southwest, southeast and northeast part of the region. 9 neighbourhoods returned entropy values greater than 1.82. These are: Idokpa (3.69); Ikhuen-Niro (3.13); Oghede/Obanyotor (2.77); Idogbo (2.67); Obe (2.25); Eyaen (2.22); Iguomo (2.15); Iyanomo (2.15); and Ogua (2.12). Other neighbourhoods that returned entropy values greater than 1 (but less than 2) are: Iwogban (1.82); Obazagbon (1.81); Ogba (1.63); Ubagbon (1.60); Oluku (1.58); Avbiama (1.53); Ovbiogie (1.52); Amagba (1.50); Egor (1.46); Ekosodin (1.28); Egbean (1.25); Urumwon (1.22); Okhunmwum (1.06); and Evbomore (1.01). Among these, 5 neighbourhoods are located in the northwest while 2 are located in the northeast.

These 23 neighbourhoods whose entropy index values are greater than 1 and nearer to 4.00 ($\log_e(55)$) reveals the occurrence of sprawl. Though, Idokpa and Ikhuen-Niro manifest stronger urban sprawl occurrence. Ugbekun returned the lowest entropy index values (0.007693) indicating that it is more compact than any other neighbourhood since it is closer to zero (0). This confirms the previous result regarding PD that Ugbekun has the highest urban density in the region. However, the sprawl index values were saved for further analysis as data for measuring the BE.

4.8 Defining travel-related prototypical neighbourhood

Fig.5d depicts the result of the overlay analysis for defining the travel-related prototypical neighbourhoods. It shows that the quantifying of the BE of the region using 7 indicators, categorized BMR into 3 distinct prototypical neighbourhoods. 7 neighbourhoods in the inner cluster around the CBD formed the pedestrian-oriented zone and 26 neighbourhoods that concentrically formed a cluster around the pedestrian zone were categorized into the transit-oriented zone while 22 neighbourhoods likewise that formed a cluster around the transit-oriented zone were categorized into the car-oriented zone. The car-oriented zone is formed at the edge of the city and the neighbourhoods of this zone are characterised essentially by low density, a high degree of sprawl, low transit accessibility, high distance accessibility, and low street intersection density. These BE characteristics promote high dependency on car use (Cho & Rodriguez, 2014; Nkeki & Asikhia, 2019) and it is clear in literature such a level of dependency on combustible modes of travel poses a significant threat to human well-being (Fenu, 2012). The inner zone is characterised by high urban density, high land-use mix, low sprawl magnitude, high transit and distance accessibility, and availability of sidewalks in most of its neighbourhoods. This inner zone classified as pedestrian-oriented manifest the BE characteristics that encourage people to walk (Kim & Brownstone, 2013). This is because trip length is significantly reduced and potential destinations are brought closer together within walkable distance. The zone in between the car-oriented and pedestrian neighbourhood clusters is the transit-oriented zone. This zone is characterised by the BE indicators that promote transit mode of commuting and these are medium urban density, high land-use mix, medium street intersection density, medium distance and transit accessibility and medium-low degree off sprawl. The transit-oriented zone is a zone of intermediate level of BE indicators, especially those that favour transit performance.

5. Conclusion

In this study, the various indicators of the 6 dimensions of the BE in land-use-TB studies were modelled. These were used to quantify the BE of the Benin metropolitan region from the neighbourhood-scale perspective. This was achieved by implementing spatial metrics for measuring urban density, spatial entropy for quantifying sprawl and land-use mix, the index for quantifying urban design and other measurements of accessibility. The result shows that the urban density of the study region reduces with increasing distance from the core region. It was also discovered that 13 neighbourhoods, aggregately covering about 71 km^2 which formed a cluster in the core region have the highest urban density. These neighbourhoods formed the pedestrian-oriented zone and part of the transit-oriented zone which is a prototypical neighbourhood design for transit and pedestrian mode of travel.

The result of urban sprawl indicates that the region manifests urban sprawl characteristic which is stronger at the edge of the city specifically in the northeast, southwest and southeast part of the region. Fundamentally, the region is experiencing a dispersed and haphazard urban growth specifically taking place on the edge of the city and mostly along the corridor roads. Entropy statistics for land-use mix revealed that the general pattern of the region concerning land-use diversity is a complex mixture of residential and commercial land-uses. This is largely influenced by the location of the King-Square because the mixed cluster is formed contiguously around the King-Square neighbourhood which is itself a homogenous land-use neighbourhood. In the peripheral area, neighbourhoods with a single dominant land-use type formed patches around the heterogeneous land-use composition. King-Square is the only homogenous commercial land-use neighbourhood in the region. However, based on entropy statistic results, 5 land-use categories (from the residential and commercial land-uses) were identified and these were named *pure residential* and *pure commercial*, *largely residential*, *weakly mixed land-use* and *robust mixed land-use*.

The quantification of the SI Density index for urban design of BMR yielded a substantial result that seems to delineate the region into a cluster of neighbourhoods with high-density street intersections and a cluster of neighbourhoods with a low-density street intersection. The former is located around the CBD and the latter is formed in the periphery, contiguously around the CBD. Expectantly, the general pattern of accessibility in the region is a decrease in accessibility with increasing distance from the CBD. The result of the indicators has a common characteristic. They were able to distinctively separate the core axis from the peripheral axis and a zone of transition was also formed between the core and periphery from the interaction of the indicators. This indicates that there is indeed a core-periphery relationship in the region.

5.1 Policy and planning implication

An important policy consideration from the global perspective is to encourage concentrated density and promote mixed land-use developments. This is well articulated in literature and is fast becoming a sustainable method of solving the problem of long commuting distance and time, reduce vehicular traffic congestion, and cut down fossil fuel usage. This policy tends to discourage sprawl and any other urban structure that may promote over-dependent on cars for personal travel. Most large cities have started to leverage functional transit systems such as light rail transit and bus rapid transit that can convey a large number of people to multiple destinations. BMR is yet to key into the policy plan. This characterises most cities in Africa. However, the result obtained in this work can inform policymakers and urban planners on the existing urban structure and neighbourhood characterisation for a comprehensive master plan and future transport demand optimisation and regulations. Since the methodology adopted here was able to quantify each neighbourhood and define their BE structure based on their relationship with TB. The 3 prototypical neighbourhoods that emerged from the result of the analysis is a sign of a robust method of quantifying the BE which seems to reveal the influence of tradition planning apparatus.

Future planning and public policies for sustainable development must begin from the grassroots, such as neighbourhoods or communities. It is evident that from such a spatial entity, a development-oriented policy can be formulated specifically for different local areas. This is because peculiarity exists in different urban spaces, attempting to change these inherent local urban trails that have formed over a long time may be counter-productive. Hence, sustainable development can be achieved by implementing policies that would integrate properly into the urban fabric of concern. This understanding is key for a successful implementation of existing robust ideologies emerging from global scholars on travel and land-use. For example, there is a growing wishful concern for urban areas to be compact, activity-driven, accessible, mixed-use, transit-rich and pedestrian favourable, but this is yet to be achieved not only in the policies guiding Africa cities but also in large European cities (La Rocca, 2010). Several policy guidelines that show concern for the environment and urban liveability have been put forward. They include the integration of cycling into the transport policy (Fenu, 2012; Masoumi et al., 2020); mass transit mobility using light rail transit (LRT) and bus rapid transit (BRT) for corridor areas (Zacharias, 2020); and increased walking for good health and fitness purposes.

For these policies to be effectively implemented, urban governance must first be tailored towards understanding the complexity of the urban space and various interactions within. The approach put forward in this study would be of essential help to the policy and urban planners of BMR since it has identified local areas of need and the potential differential transport policy interventions that may be associated with neighbourhoods. For example, the delineated transit-oriented neighbourhoods can be improved by re-designing the corridor roads to allow for BRT deployment. Policies that promote walking and cycling must be advocated in pedestrian-oriented neighbourhoods. Every road in this neighbourhood cluster (undermining the surfacing type) must be designed to be pedestrian-friendly by constructing sidewalks and cycling lanes along the roads. These public infrastructures would encourage a change in the travel behaviour of the commuters. There is an urgent need to reduce the number of car-oriented neighbourhoods in the region. This can be achieved by manipulating the neighbourhood BE to reduce sprawl development through edge city growth restrictions or promoting self-contained suburban development. Alternatively, make these neighbourhoods transit-friendly by increasing transit accessibility.

References

Asikhia, M. O., & Nkeki, F. N. (2013). Polycentric employment growth and the commuting behaviour in Benin Metropolitan Region, Nigeria. *Journal of Geography and Geology, 5* (2), 1-17. https://doi.org/10.5539/jgg.v5n2p1

Badoe, D. A., & Miller, E. J. (2000). Transportation-land use interaction: Empirical findings in North America, and their implications for modeling. *Transportation Research D, 5* (4), 235-263. https://doi.org/10.1016/S1361-9209%2899%2900036-X

Bhatta, B., Saraswati, S., & Bandyopadhyay, D. (2010). Urban sprawl measurement from remote sensing data. *Applied Geography, 30*, 731-740. https://doi.org/10.1016/j.apgeog.2010.02.002

Burchell, R. W., Shad, N. A., Listokin, D., Philip, H., Downs, A., Seskin, S., . . . Gall, M. (1998). The Costs of Sprawl-Revisited. *TCRP Report 39.* Washington, DC: National Academy Press.

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research D, 2* (3), 199-219. https://doi.org/10.1016/S1361-9209(97)00009-6

Cervero, R., & Wu, K. L. (1998). Sub-centring and commuting evidence from the San Francisco Bay Area, 1980-90. *Urban Studies, 35* (7), 1059-1076. https://doi.org/10.1080/0042098984484

Cho, G., & Rodriguez, D. (2014). Location or design? Associations between neighbourhood location, built environment and walking. *Urban Studies, 52* (8), 1434-1453. https://doi.org/10.1177/0042098014537691

Choi, K. (2018). The influence of the built environment on household vehicle travel by the urban typology in Calgary, Canada. *Cities, 75*, 101-110. https://doi.org/10.1016/j.cities.2018.01.006

Christian, H. E., Bull, F. C., Middleton, N. J., Knuiman, M. W., Divitini, M. L., Hooper, P., . . . Giles-Corti, B. (2011). How important is the land use mix measure in understanding walking behaviour? Results from the RESIDE study. *International Journal of Behavioral Nutrition and Physical Activity, 8* (55), 1-12. https://doi.org/10.1186/1479-5868-8-55

Comendador, J., López-Lambasb, M. E., & Monzónb, A. (2014). Urban built environment analysis: Evidence from a mobility survey in Madrid. *Procedia - Social and Behavioral Sciences, 160*, 362 – 371. https://doi.org/10.1016/j.sbspro.2014.12.148

Dargay, J., & Hanly, M. (2004). Land use and mobility. *World Conference on Transport Research.* Istanbul.

Ewing, R., & Cervero, R. (2001). Travel and the built environment: A synthesis. *Transportation Research Record 1780*, 87-114. https://doi.org/10.3141/1780-10

Ewing, R., & Cervero, R. (2010). Travel and the built environment: A meta-analysis. *Journal of the American Planning Association, 76* (3), 265-294. https://doi.org/10.1080/01944361003766766

Ewing, R., Hamidi, S., Grace, J. B., & Wei, Y. D. (2016). Does urban sprawl hold down upward mobility? *Landscape and Urban Planning, 148*, 80-88. https://doi.org/10.1016/j.landurbplan.2015.11.012

Ewing, R., Hamidi, S., Tian, G., Proffitt, D., Tonin, S., & Fregolent, L. (2017). Testing Newman and Kenworthy's theory of density and automobile dependence. *Journal of Planning Education and Research, 38* (2), 167-182. https://doi.org/10.1177/0739456X16688767

Ewing, R., Tian, G., Goates, J. P., Zhang, M., Greenwald, M. J., Joyce, A., Kircher, J., & Greene, W. (2014). Varying influences of the built environment on household travel in 15 diverse regions of the United States. *Urban Studies, 52* (13), 2330-2348. https://doi.org/10.1177/0042098014560991

Fenu, N. (2021). Bicycle and urban design. A lesson from Covid-19. *Tema. Journal of Land Use, Mobility and Environment*, *14* (1), 69-92. https://doi.org/10.6092/1970-9870/7716

Frank, L. D., & Pivo, G. (1994). Impacts of mixed use and density on utilization of three modes of travel: single-occupant vehicle, transit, and walking. *Transportation research record*, 1466, 44-52.

Gehrke, S. R., & Clifton, K. J. (2016). Toward a spatial-temporal measure of land-use mix. *The Journal of Transport and Land Use, 9* (1), 171-186. https://doi.org/10.5198/jtlu.2015.725

Gehrke, S. R., & Clifton, K. J. (2017). An activity-related land use mix construct and its connection to pedestrian travel. *Environment and Planning B: Urban Analytics and City Science, 46* (1), 9-26. https://doi.org/10.1177/2399808317690157

Guzman, L. A., Pena, J., & Carrasco, J. A. (2020). Assessing the role of the built environment and sociodemographic characteristics on walking travel distances in Bogotá. *Journal of Transport Geography, 88*, 1-11. https://doi.org/10.1016/j.jtrangeo.2020.102844

Handy, S., Cao, X., & Mokhtarian, P. (2005). Correlation or causality between the built environmentand travel behavior? Evidence from Northern California. *Transportation Research Part D, 10*, 427-444. https://doi.org/10.1016/j.trd.2005.05.002

Hu, P., & Huapu, L. (2007). Study on the impacts of urban density on the travel demand using GIS spatial analysis. *Journal of Transportation Systems Engineering and Information Technology, 7* (4), 90-95. https://doi.org/10.1016/S1570-6672(07)60033-6

James, P., Berrigan, D., Hart, J. E., Hipp, A. J., Hoehner, C. M., Kerr, J., Major, J. M., Oka, M. & Laden, F. (2014). Effects of buffer size and shape on associations between the built environment and energy balance. *Health & Place, 27*, 162-170. https://doi.org/10.1016/j.healthplace.2014.02.003

Kim, J., & Brownstone, D. (2013). The impact of residential density on vehicle usage and fuel consumption: Evidence from national samples. *Energy Economics, 40*, 196-206. https://doi.org/10.1016/j.eneco.2013.06.012

Kockelman, K. (1997). Travel behaviour as a function of accessibility, land use mixing, and land use balance: Evidence from the San Francisco Bay area. *Transportation Research Record, 1607*, 116-125. https://doi.org/10.3141/1607-16

La Rocca, R. A. (2010). La mobilità negli strumenti di governo delle trasformazioni urbane. *TeMA-Journal of Land Use, Mobility and Environment, 3*(1). https://doi.org/10.6092/1970-9870/131

Lee, C., & Moudon, A. V. (2006). The 3Ds + R: Quantifying land use and urban form correlates of walking. *Transportation Research Part D, 11*, 204-215. https://doi.org/10.1016/j.trd.2006.02.003

Levinson, H., & Wynn, H. F. (1963). Effects of density on urban transportation requirements. *Highway Research Record, 2*, 38-64.

Limanond, T., & Niemeier, D. A. (2004). Effect of land use on decisions of shopping tour generation: A case study of three traditional neighborhoods in WA. *Transportation, 31*, 153–181. https://doi.org/10.1023/B:PORT.0000016578.21486.af

Limtanakool, N., Dijst, M., & Schwanen, T. (2006). The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium-and longer-distance trips. *Journal of Transport Geography, 14*, 327-341. https://doi.org/10.1016/j.jtrangeo.2005.06.004

Masoumi, H. E., Asim, M., Anwer, I., & Aslam, S.A.B. (2020). Logistic models explaining the determinants of biking for commute and non-commute trips in Lahore, Pakistan. *TeMA. Journal of Land Use, Mobility and Environment, 13*(3), 291-308. https://doi.org/10.6092/1970-9870/6983

Mavoa, S., Eagleson, S., Badland, H. M., Gunn, L., Boulange, C., Stewart, J., & Giles-Corti, B. (2018). Identifying appropriate land-use mix measures for use in a national walkability index. *The Journal of Transport and Land Use, 11*(1), 681-700. https://doi.org/10.5198/jtlu.2018.1132

McGarigal, K., & Ene, E. (2014). *Fragstats: spatial pattern analysis program for categorical maps.* Retrieved from: www.umass.edu/landeco/research/fragstats/fragstats.html

Miller, E. J., & Ibrahim, A. (1998). Urban form and vehicular travel: Some empirical findings. *Transportation Research Record, 1617*, 18-27. https://doi.org/10.3141/1617-03

Nari, A., & Zhang, L. (2018). A multi-dimensional multi-level approach to measuring the spatial structure of U.S. metropolitan areas. *The Journal of Transport and Land Use, 11*(1), 49-65. https://doi.org/10.5198/jtlu.2018.893

Newman, P. W., & Kenworthy, J. R. (1989). Gasoline consumption and cities: A comparison of US cities in a global survey. *Journal of American Planning Association, 55*, 24-36. https://doi.org/10.1080/01944368908975398

Nkeki, F. N. (2016). Spatio-temporal analysis of land use transition and urban growth characterization in Benin metropolitan region, Nigeria. *Remote Sensing Applications: Society and Environment, 4*, 119-137. https://doi.org/10.1016/j.rsase.2016.08.002

Nkeki, F. N., & Asikhia, M. O. (2019). Geographically weighted logistic regression approach to explore the spatial variability in travel behaviour and built environment interactions: Accounting simultaneously for demographic and socioeconomic characteristics. *Applied Geography, 108*, 47-63. https://doi.org/10.1016/j.apgeog.2019.05.008

Norland, R. B., & Thomas, J. V. (2007). Multivariate analysis of trip-chaining behavior. *Environment and Planning B: Planning and Design, 34*, 953-970. https://doi.org/10.1068/b32120

NPC. (2006). *Population and housing census of the federal republic of Nigeria.* Nigeria: National Population Commission.

Pickrell, D. (1999). Transportation and land use. In J. Gomez-Ibanez, W. Tye, & C. Winston (Eds.), *Essays in Transportation Economics and Policy.* Washington, DC: Brookings Institution Press.

Ramachandra, T. V., Aithal, B. H., & Sanna, D. D. (2012). Insights to urban dynamics through landscape spatial pattern analysis. *International Journal of Applied Earth Observation and Geoinformation, 18*, 329-343. https://doi.org/10.1016/j.jag.2012.03.005

Reiff, B. (2003). *Statistical analysis of urban design variables and their use in travel demand models.* Oregon, USA: Oregon Department of Transportation.

Sarvestani, S., Ibrahim, A. L., & Kanaroglou, P. (2011). Three decades of urban growth in the city of Shiraz, Iran: A remote sensing and geographic information systems application. *Cities, 28*, 320-329. https://doi.org/10.1016/j.cities.2011.03.002

Schwanen, T., & Mokhtarian, P. (2005). What if you live in the wrong neighborhood? The impact of residential neighborhood type dissonance on distance traveled. *Transportation Research D, 10*, 127-151. https://doi.org/10.1016/j.trd.2004.11.002

Schwanen, T., Dieleman, F. M., & Dijst, M. (2001). Travel behavior in Dutch monocentric and polycentric urban systems. *Journal of Transport Geography, 9*(3), 173-186. https://doi.org/10.1016/S0966-6923(01)00009-6

Schwanen, T., Dieleman, F. M., & Dijst, M. (2004). The impacts of metropolitan structure on commute behaviour in the Netherlands: a multilevel approach. *Growth and Change, 35*, 304-333. https://doi.org/10.1111/j.1468-2257.2004.00251.x

Silva, J. A. (2014). Spatial self-selection in land use travel behaviour interactions: Accounting simultaneously for attitudes and socioeconomic characteristics. *The Journal of Transport and Land use, 7* (2), 63-84. https://doi.org/10.5198/jtlu.v7i2.696

Strauss, J., & Miranda-Moreno, L. F. (2013). Spatial modeling of bicycle activity at signalised intersections. *The Journal of Transport and Land use, 6*(2), 47-58. https://doi.org/10.5198/jtlu.v6i2.296

Tsai, Y. (2005). Quantifying Urban Form: Compactness versus 'Sprawl'. *Urban Studies, 42* (1), 141-161. https://doi.org/10.1080/0042098042000309748

Wang, L., Chen, R., Sun, W., Yang, X., & Li, X. (2020). Impact of High-Density Urban Built Environment on Chronic Obstructive Pulmonary Disease: A Case Study of Jing'an District, Shanghai. *International Journal of Environmental Research and Public Health, 17* (1), 252-267. https://doi.org/10.3390/ijerph17010252

Yang, J., & Zhou, P. (2020). The obesity epidemic and the metropolitan-scale built environment: Examining the health effects of polycentric development. *Urban Studies, 57*, 39-55. https://doi.org/10.1177/0042098019844177

Yang, L., Hu, L., & Wang, Z. (2019). The built environment and trip chaining behaviour revisited: The joint effects of the modifiable areal unit problem and tour purpose. *Urban Studies, 56* (4), 795-817. https://doi.org/10.1177/0042098017749188

Yu, H., & Peng, Z. (2020). The impacts of built environment on ridesourcing demand: A neighbourhood level analysis in Austin, Texas. *Urban Studies, 57* (1), 152-175. https://doi.org/10.1177/0042098019828180

Zacharias, J. (2020). The contribution of a tramway to pedestrian vitality. *Tema. Journal of Land Use, Mobility and Environment, 13*(3), 445-457. https://doi.org/10.6092/1970-9870/7197

Zahabi, S. A., Miranda-Moreno, L. F., Patterson, Z., & Barla, P. (2012). Evaluating the effects of land use and strategies for parking and transit supply on mode choice. *The Journal of Transport and Land use, 5* (2), 103-119. https://doi.org/10.5198/jtlu.v5i2.260

Image Sources

Fig.1: Authors;

Fig.2: Authors;

Fig.3: Authors;

Fig.4: Authors;

Fig.5: Authors.

Author's profiles

Felix Ndidi Nkeki

He is a Doctor of Transport Geography, a PhD he obtained from the Department of Geography and Regional Planning, University of Benin, Nigeria. His PhD research is focused on the built environment and travel behaviour using advanced modelling techniques. His other areas of research interest are transportation and regional development, urban transport and land-use planning, applied GIS and remote sensing, spatial statistics and modelling.

Monday Ohi Asikhia

He is a Professor in the Department of Geography and Regional Planning, Faculty of Social Sciences, University of Benin. His research interests are in the areas of urban and regional planning with a special interest in public facilities planning.