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Understanding the urban structure of the Algerian cities using emerging data: Case study of Algiers

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Abstract
Despite the identification of urban structure and urban centers being crucial for effective policy making (transport policies, urban risk management policies etc) there is a serious lack of studies covering developing countries' urban structure changes, especially north African cities. This is mainly due to the unavailability of the necessary data for urban structure identification. In this contribution we investigate the polycentric development in the Algerian capital, Algiers, using innovative data resources such as LandScan™ High Resolution Global Population Dataset and the POI approach, and spatial statistics. The findings suggest that the structure of Algiers is indeed developing into a polycentric city. The emerging data helped us overcome a serious methodological problem and objectively identify the city structure for better planning.
Keywords: Urban form; Polycentric development; Emerging data; Urban structure.

1. Introduction

Urban structure refers to the distribution mode of populations and activities in urban areas and the way in which they are spatially organized in cities (Amen et al., 2023, Amen & Nia, 2020). According to Chen et al. (2017), it is defined as the spatial arrangement of different land uses in cities or metropolitan areas (...) [and] patterns of urban development. The urban structure also provides information on the trajectories of urban development and expansion. These information are considered crucial for effective and efficient policies (Angel and Blei, 2016; Cai et al., 2017).

It has been shown that the nature of the urban structure has a significant influence on the functioning of human settlements at several levels, affecting the economy and social equity (Meijers and Burger, 2010; Zhang et al., 2017; Garcia-López and Moreno-Monroy, 2018; Li and Liu, 2018; Sun et al, 2019m, Amen, 2021, Aziz Amen, 2022,), transport planning (Lin et al., 2015; Zhao et al., 2017; Kim 2020; Li et al., 2019; Jun 2020), health, epidemiology, and risk management (Requia et al., 2018; White et al., 2018), environmental monitoring (Chen et al., 2021), and many other aspects of human life. That is why researchers from a wide variety of backgrounds have been studying this matter, and the study of the spatial structure of cities has evolved in different academic fields over time and space. Many theories and models have been proposed to describe and explain the different types of urban spatial structures and their evolutions.

At the intra-urban scale, there have been several attempts to model the central space and the distribution of urban activities, including the reference models, which have long been a reference in academic circles, such as the model of Burgess (1925), of Hoyt (1939) and the model of Harris and Ullman (1945)

In their paper on urban spatial structures, Anas et al, (1998) argue that economic activity can be centralized or decentralized at the metropolitan level and concentrated or dispersed at a more local level. Building on this conception, Lee and Gordon (2007) discuss two dimensions of urban spatial structures, the centralization dimension, which reflects the extent to which urban activities are concentrated in the CBD, and the concentration dimension, which measures how they are clustered in centers. Based on these two studies, Meijers and Burger (2010) distinguish two basic dimensional pairs of spatial urban structures: polycentrality/monocentrality and compactness/dispersion (Figure 1). While the first dimension reflects the extent to which population and employment are evenly distributed in the main center and subcenters of an urban agglomeration, the second dimension refers to the extent to which population and employment are dispersed in the non-central locations of an agglomeration. It should be noted that the two dimensions do not necessarily move in the same direction. Indeed, Li (2020) explains that a compact city can be polycentric or monocentric, depending on whether or not there is a concentration of population and employment at the local level.

Urban forms (polycentrism and monocentrism) are among the most researched subjects in urban planning (Peris et al., 2018) (Figure 2). Models and theories, based on mathematical and statistical approaches, try to describe in a precise and exact way the reality of the urban fact mainly from the 1960s of the previous century (Moghadam et al., 2018).

The vast majority of empirical works around urban structures illustrate cases from the USA (Angel and Blei 2016), Europe (e.g. Italy Veneri, 2010, UK Burger et al., 2011; Netherlands Burger and Meijers, 2012; France Aguilera 2005 and Germany Taubenböck et al., 2017), China (Wang et al., 2020; Wei et al., 2020), while works focusing on cities of the South are much rarer.

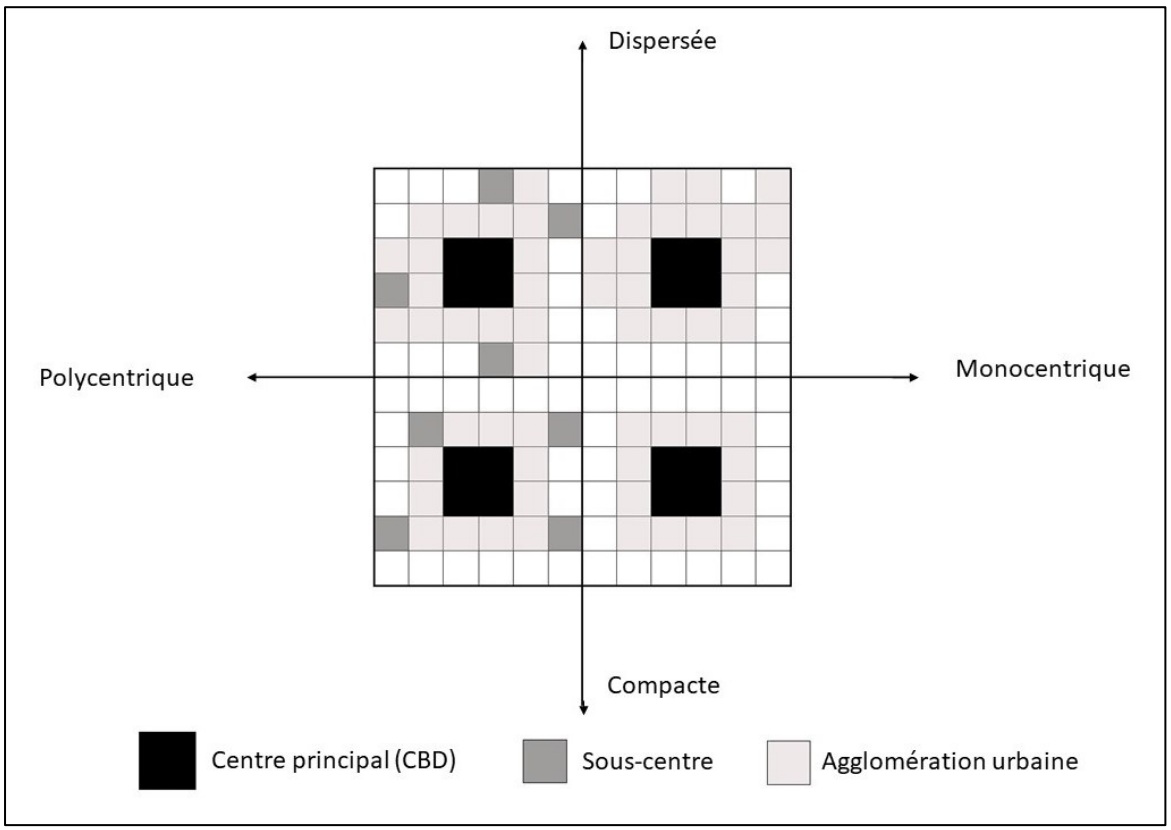

Figure 2 The two dimensions of urban structure (According to Meijers and Burgers 2010).

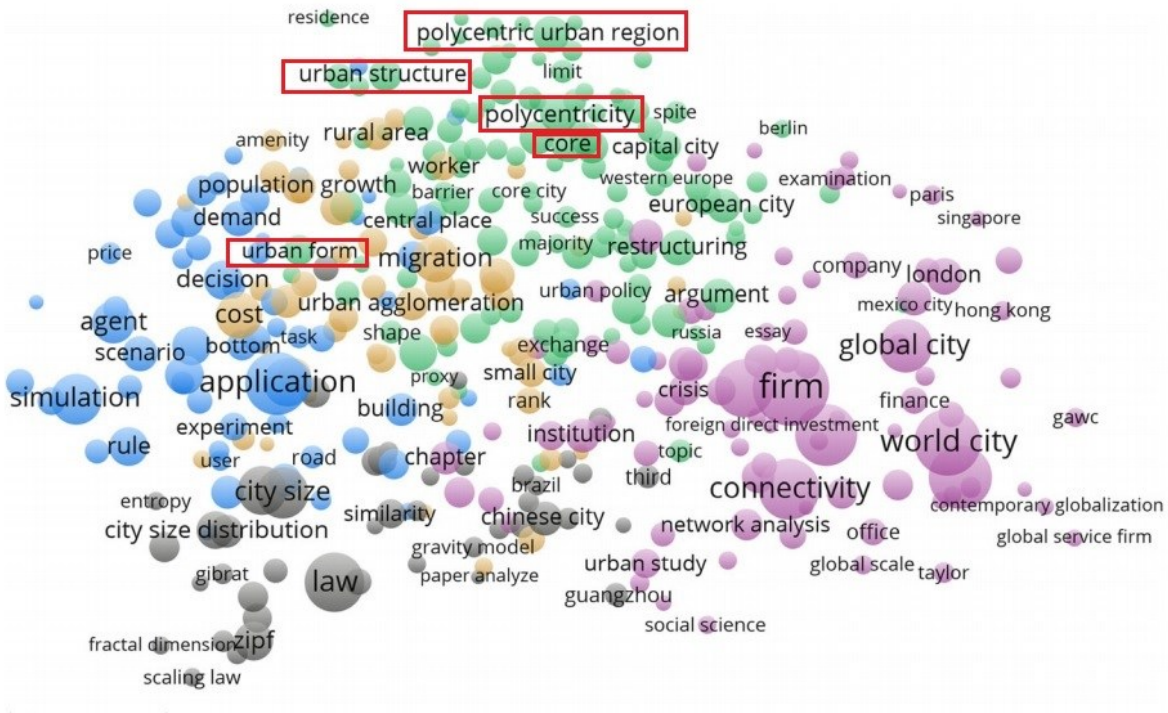

Figure 1 Semantic map of urban systems research vocabulary co-occurrences. (Peris et al., 2018).

Research covering the structural mutations of cities in developing countries is indeed scarce, and when it exists, it is rarely objective. Examples in this category include the work of Fernandez-Maldonado et al (2014) (Lima, Mexico City, and Fortaleza), Agyemang et al (2019) (Kumasi), and Oubraham and Baouni (2020) (the ten most populous urban regions of Algeria).

With a few exceptions, the majority of such works are, to our knowledge, descriptive and follow unsophisticated methods, generally based on observations and historical studies. Most of this research is descriptive and follows an exhaustive logic that is closer to a cartographic inventory than to the identification of any potential polarization or centrality.This is mainly due to the unavailability of the necessary data for urban structure identification.

Regarding the methods of identifying centralities, and investigating the structural nature of urban systems, a wide variety of tools and methods have been developed over time and across the world. In most cases, each researcher investigating the issue develops a special approach of his own (Bartosiewicz and Marcińczak, 2020), depending on the nature of his profile (economist, geographer, urban planner, sociologist ... etc.), the purpose of the research (investigation, economic planning, transport planning or other), the socio-political, economic and geographical context of the area under study, or the data and means available for the investigation.

2. Innovative data sources

The availability and quality of data is indeed a crucial point for any urban structure identification procedure. Conventionally, to define the spatial structure of a given metropolitan area or conurbation, researchers rely on statistical data collected in national censuses or household surveys, regardless of the method used (morphological or functional). Censuses are conducted by national governments, and the data are collected and aggregated according to administrative boundaries. These data sources have the advantage of being highly accurate and representative.

But since the urban reality in many cases exceeds the boundaries of administrative divisions, statistical data aggregated according to administrative boundaries, influence the number and nature of the boundaries of the centralities identified (Cai 2017). In addition, the surveys are conducted periodically, most often every ten years. They therefore have a low update frequency, which could make them obsolete to describe a reality that is rapidly and perpetually changing. The problem is even more serious in countries where the frequency is irregular, such as Algeria, where the last census conducted was in 2008 (14 years). However, Algeria is not unique in this respect; the problem of data availability and quality is at the heart of the challenges facing research and investigation of urban structures in developing countries.

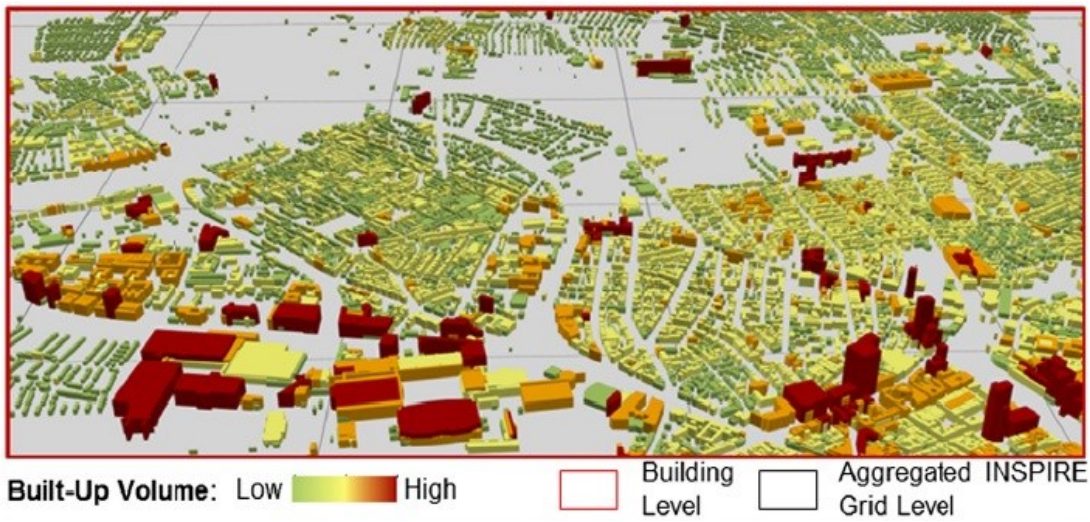

Figure 3. 3D building model of Frankfurt region. (Taubenböck et al., 2017).

Indeed, this is one of the main reasons for the lack of objective studies covering the transformations of urban structures in these countries. To overcome these drawbacks, many researchers have turned to new sources of data, mainly drawn from the arsenal of Big Data and satellite data. A multitude of methods and procedures are being developed around the world to exploit these new resources in the most relevant way possible. Activities on social networks, satellite imagery of all kinds, data from computerized travel maps and many other means are increasingly used to effectively and accurately record the realities of urban spaces. These data not only, identify centers, but also

determine the interactions between them (Zhao et al., 2017). With the development of mobile devices and the popularity of social media (e.g., Twitter, Facebook, Flickr, and Foursuqare, among others), user-generated geodata (including geo-referenced images and geo-referenced records) offer the potential to delineate concentrated places and places and places.

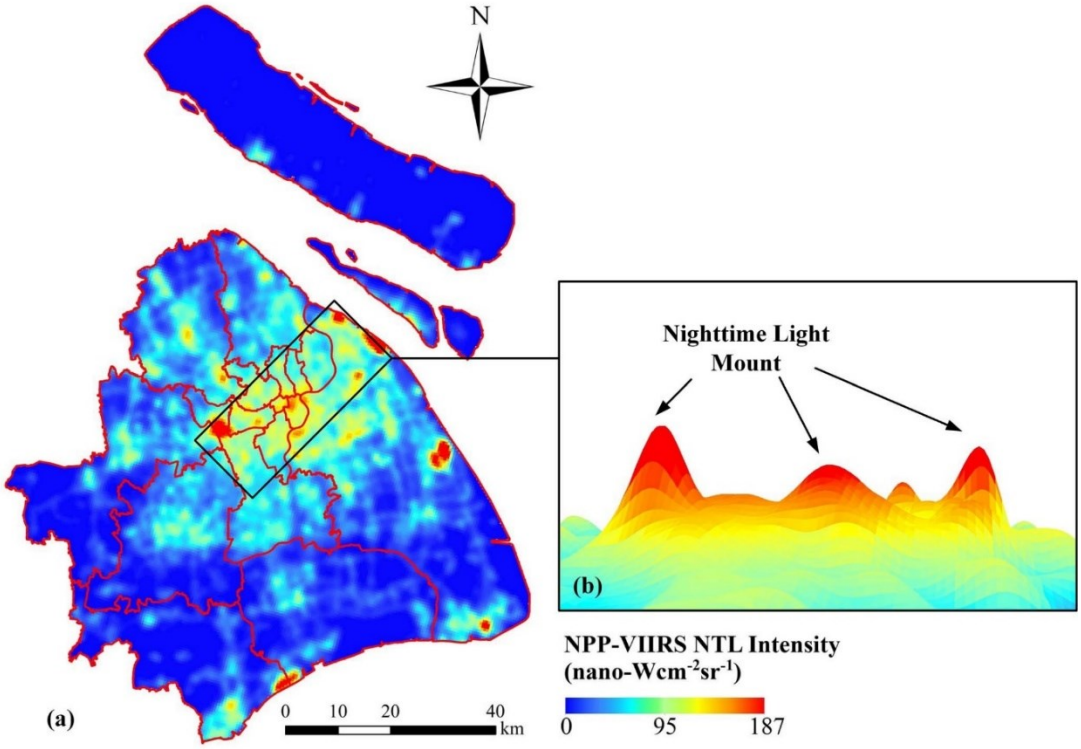

Figure 4. The NTL intensity map of Shanghai. (Chen et al. 2017)

Kim (2019) uses the trajectory data of smart cards of Seoul's public transportation system (transportation smart card data) to identify the spatial structure of the Korean capital. In the paper by Taubenböck et al, (2017) the authors use 3D images constructed using remote sensing methods made by satellites (Figure 3). Several papers that consider urban structure through the population dimension (Liu and Wang 2016; Li and Liu 2018; Li et al., 2019; Li 2020), use data sources such as LandScan™ High Resolution Global Population Dataset, which estimates global population distributions in grids of about 1 km by 1 km. To detect centralities in Berlin, Munich, and Cologne, Sun et al., (2016) used movement data generated from location-based social networks. Chen et al, (2017) exploit the nighttime light intensity (NTL) of the land surface recorded by satellite sensors to identify the urban structure of Shanghai. The researchers use the topographic metaphor of a mountain to identify an urban center or sub-center and the slope of the surface to indicate a gradient of land use intensity and urban functions (Figure 4). In recent years, data mining from social media or bus smart card records or check-ins, and crowdsourcing projects (e.g., Open Street Maps) have provided researchers with an excellent source of geolocated data (Figure 5).

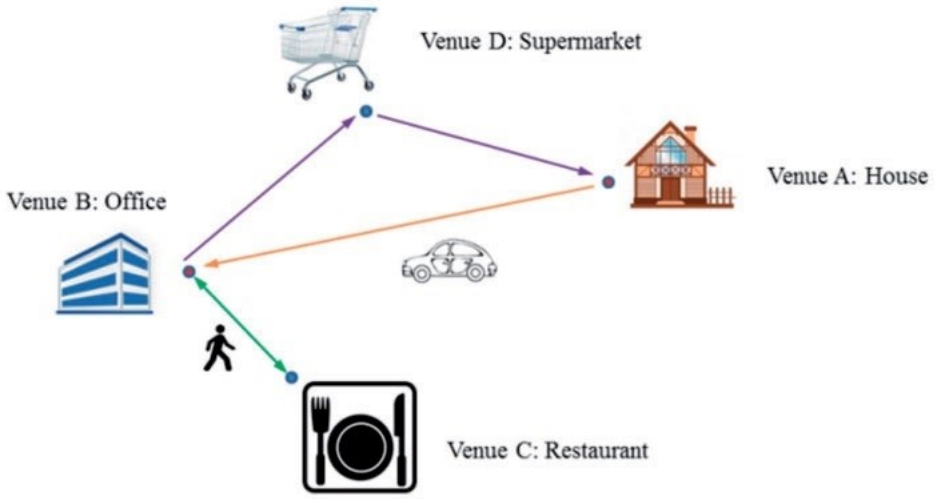

Figure 5. Motion data extracted from location-based social networks. (Sun et al. 2015).

3. Material and Methods

In this contribution we investigate the polycentric development in the Algerian capital, Algiers, using innovative data resources such as LandScan™ High Resolution Global Population Dataset and the POI approach, and spatial statistics. This study is based on a morphological logic and we therefore consider as a center any spatial unit that affects the functioning of the urban system through its capacity to polarize central functions and thus attract flow, or any spatial unit that concentrate individuals (workers, consumers, etc.) to other urban areas, thus emitting flow.

3.1 Population centers or emitting centers:

The LandScan™ High Resolution Global Population database. This is a database developed by the American laboratory "Oak Ridge National Laboratory" that maps the distribution of population on a global scale. The database is developed by combining several data sources at once: demographic and geographic data (slopes, landforms... etc.) available, as well as data from satellite image analysis and remote sensing (land use, road framework...etc.)[1]. LandScan provides fine mesh demographic data at a spatial resolution of about 1 km×1 km (Figure 6), and represents a 24-hour average ambient population distribution. The database is updated annually, and is widely used in the literature (e.g., Dobson et al., 2000; Liu and Wang 2016; Li and Liu 2018; Li et al., 2019; Li 2020; Meng et al., 2021), to study questions deriving from a wide variety of fields, ranging from modeling urban systems and human settlements, to mapping for humanitarian purposes, risk management and disease modeling, to studies of market growth and economic development, not to mention ecology and environmental protection.

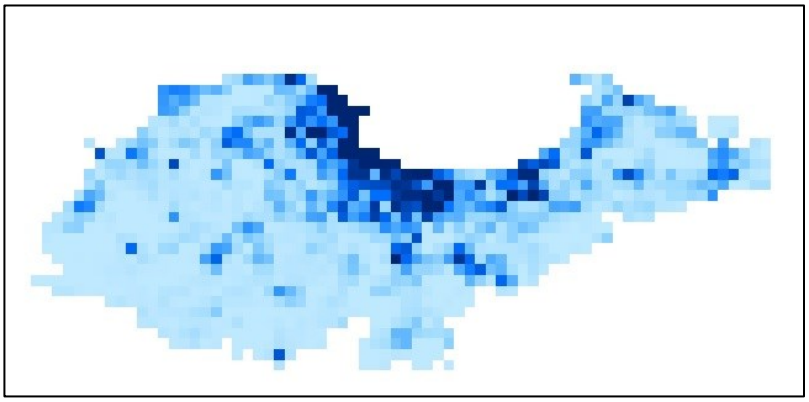

Figure 6. The (1kmx1km) grid of population distribution in Algiers in 2019. (LandScan 2020).

[1] 25 https://landscan.ornl.gov/

3.2 Attractive centers (centers of attraction):

Attractive centers are centers that concentrate both employment and recreation. They are places that attract trips for work, as well as trips for study, shopping, services and relaxation. They are considered trip-polarizing points, a concentration of notable destinations, highly animated places that attract people from all over the city's urban area, sometimes more. To identify these centralities, we use the "Points Of Interest" approach. ISO[2] defines points of interest as physical features, especially functions/amenities closely related to people's lives and daily routines, that can be represented as points and applied to electronic maps. A POI has its specific area of influence and usually contains useful attribute information that can be used to classify urban functions (Wang et al., 2020). The use of POIs overcomes the data problem. Indeed, with the rapid development of Internet-based information collection technologies, a large volume of geographic data, obtained from web maps, is becoming more readily available. POI data are point data on real geographic features, with high accuracy spatial information, in addition to having a wide coverage and fast and frequent updates. These characteristics make the data very advantageous for research, and are widely used for the investigation of urban structures (Li et al., 2018; Deng et al., 2019; Lu et al., 2020), travel and mobility (Yu et al., 2019; Wang and Xu, 2020), urban energy consumption (Wang et al., 2020) and others. Deng et al, (2019), speak of a paradigm shift in urban research methodologies that these sources initiate.

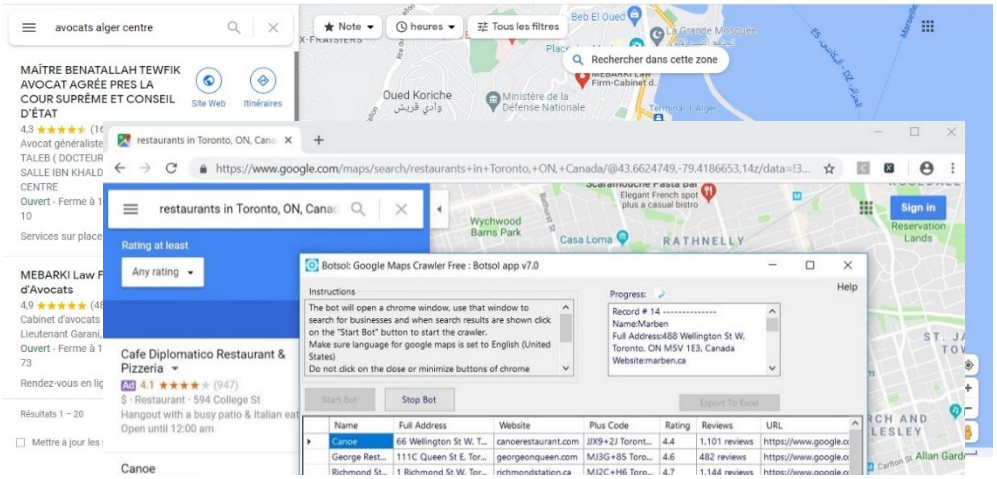

Figure 7 .Example of geographical POIdata, location of lawyers in Algiers Central district (Google Maps)

Figure 8 . Botsol interface displaying the results of an information request (Botsol.com 2022)

To retrieve the data around the POIs we use the important resource that is Google Maps. Indeed, the majority of urban activities, of very varied natures, are reported and listed there, thus, it provides a lot of information on the distribution (geographical coordinates) of the different urban functions (by category) across the territory of Algiers (Figure 7).

Data extraction from the source was done using Google Maps Crawler Botsol, a payware program, which retrieves the names, location, and geographic location (geographic coordinates) of urban functions (Figure 8). It is used in many fields, such as tourism research (Arianto and Budi 2020) or even business research (Gauger et al., 2021).
We classified the various functions into 10 categories: banking and financial services, legal services, business and office buildings, government functions, educational facilities, medical facilities, food and beverage sites, commercial sites, tourist, entertainment and recreation facilities, and transportation facilities and amenities. Proximity activities, such as day care centers, hairdressers and schools, were not considered. These functions can be polarizing, but this is quite rare; their influence does not usually extend beyond the neighborhood level. The extracted data are then transferred to Excel for sorting and processing, in order to be geocoded on ArcGIS Pro.
This approach has the advantage of high representativeness: as diverse as the POI categories are, the data adopted in this research covers the majority of functions that a city can perform. The centers identified in this study are highly

[2] ISO 14825-2004, Intelligent Transport Systems-Geographic Data Files (GDF)-Overall Data

urban functionally intensive and therefore correspond to the definition of a center that we have previously developed.

In order to detect the centers of the Algiers agglomeration, we use Local Moran's I, one of the most commonly used Local Indicators of Spatial Association (LISA). Indeed, these techniques have been widely used in recent studies that address the spatial structure of urban agglomerations (e.g., Vasanen 2012; Fan and Myint, 2014; Li and Liu 2018; Li 2020).

3.3. Local Moran's Index:

The local Moran's I is one of the local statistics proposed by Anselin in his 1995 paper to identify local clusters and local spatial outliers. This is the statistic used in this paper to investigate the location of centers in Algiers. The local Moran's I allows to examine, for each location (spatial unit), the level of similarity with its neighborhood. The areas where the level of local similarity is strong, stand out, allowing to obtain disaggregated studies of the spatial structure of the different phenomena studied. The formula of the local Moran's I is as follows:

$$I_i = \frac{(n-1)\left(x_i - \bar{x}\right)\sum_{j=1}^{n} w_{ij}\left(x_j - \bar{x}\right)}{\sum_{j=1}^{n}\left(x_j - \bar{x}\right)^2}$$

Where i,j are spatial units; n is the number of spatial units studied; xi is the value of the variable in unit i; x is the mean of x; and wij are the elements of the neighborhood spatial interaction matrix.

The Local Moran Index is a tool for analyzing and locating clusters and outliers, it identifies locations of high value concentrations, locations of low value concentrations as well as spatial points with atypical values.

The method discovers spatial units or locations, which are statistically significant at a 95% confidence level of the local Moran's I index, and also classifies them into four categories:

a. Category grids (HH): a situation summarized as High-High: high-density grids surrounded by high-density grids;
b. Category grids Low-Low (LL): Low-Low density grids surrounded by low-density grids;
c. Category grids (HL): High-Low grids (HL): high-density grids surrounded by low-density grids;
d. Category grids (LH): Low-High (LH) grids: low density grids surrounded by high density grids.

There are also zones with insignificant values (these are zones whose values and those of their neighbors are close to the average of the study area).

Clusters of areas (HH) are considered "hotspots", i.e. places with high densities that have a significant influence on spatial functioning. The term "cold-spots" refers to clusters of (LL) zones. The (HL) and (LH) zones are called "spatial outliers", and are places that present values that are spatially atypical (outliers).

The figure below summarizes the protocol of the empirical modeling of the centers and centralities of the city of Algiers.

4. Results and discussions

The findings suggest that the structure of Algiers is indeed developing into a polycentric city. The emerging data helped us overcome a serious methodological problem and objectively identify the city structure for better planning.

4.1 Population centers:

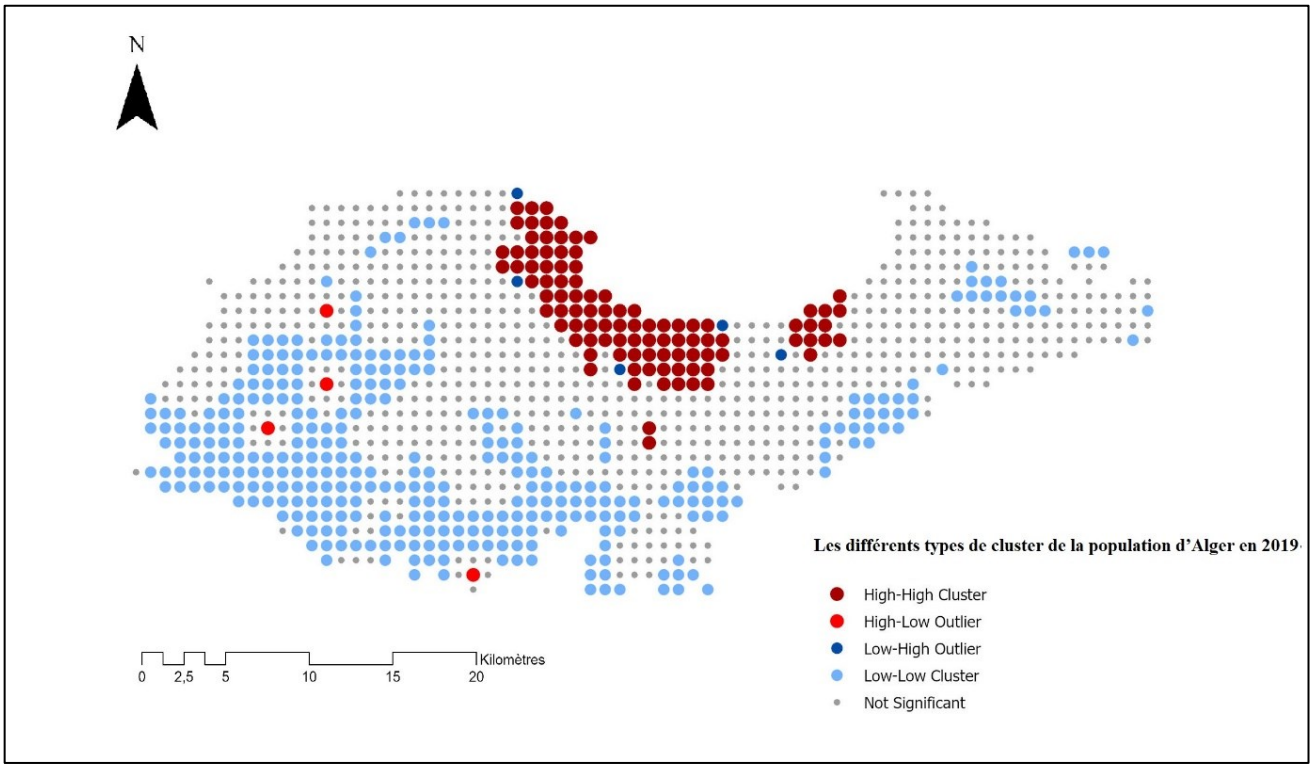

Figure 9. results of cluster and outliers analysis (Author).

The map (Figure 9) represents the results of the cluster and outlier analysis of the population distribution at the level of Algiers metropolitan area performed on ArcGIS Pro, using the population data of the year 2019.
- HH clusters: three clusters of type (HH) emerge (Figure 10). The first cluster corresponds to the historical districts (Medina plus the first colonial districts) of the city. It is the largest cluster and contains a significant concentration of the wilaya's population: more than a third of the inhabitants live in what is equivalent to approximately 7 to 8% of the total surface area of the agglomeration. The second cluster corresponds to the communes of the eastern extension, where almost 4% of the wilaya's population lives. The third cluster is the smallest, and is located in the commune of Baraki. The following table summarizes the primary/basic characteristics of the HH clusters.

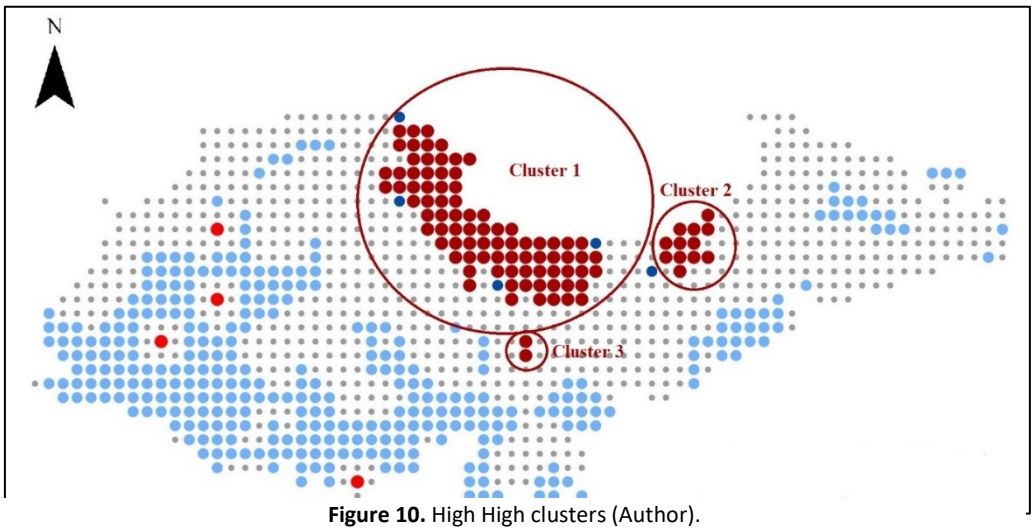

Figure 10. High High clusters (Author).

- HL outliers: As shown in Table 1, four outliers were found in the Algiers agglomeration. The outlier with the highest population concentration is Chéraga, a neighborhood that was originally a colonial village in the heights of Algiers. The new city of Sidi Abdellah, planned to be a technopole, a city capable of responding intelligently to the demographic challenge, corresponds for example to outlier 3. Although they stand out in relation to their

surroundings, these nuclei cannot be considered as centers. They are small in size and contain a minimal population, and thus do not exert any form of influence on their neighborhood. Even if these points cannot be considered urban population centers at this time, they nevertheless provide information on future urban trends in the Algiers agglomeration. Indeed, these nuclei are likely to develop into full-fledged centers.

Table 1. HH population clusters and their characteristics (Author).

HH clusters	Communes	Surface	Percentage of population
Cluster 1	Alger-Centre ; Sidi M'Hamed ; El Madania ; Belouizdad ; Bab El Oued ; Bologhine ; Casbah ; Oued Koriche ; El Biar ; El Harrach ; Bachdjerrah ; Hussein Dey ; Bourouba ; Mohammadia	85 Km²	43%
Cluster 2	Dar El Beïda ; Bab Ezzouar ; Bordj El Kiffan	12 Km²	3.60%
Cluster 3	Baraki	2 Km²	0.56%

HH clusters are therefore the most suitable to be considered as population centers, but the first results must be refined. The local Moran's I is a statistic that makes it possible to identify the particularity of a place in relation to its surroundings; it also makes it possible, through the right choice of neighborhood calculation methods, to estimate the influence it has on its surroundings. This covers two of the three criteria we set as dependent on centrality in the previous chapter. To measure singularity, we filtered the HH clusters resulting from the cluster and outlier analysis performed on ArcGIS Pro. In this way, small clusters concentrating tiny values are eliminated from the selection. Thresholds for population size and area are therefore applied to ensure that the selected centers are significant.
There are a multitude of approaches in the literature for setting thresholds for selecting centers and centralities. Some researchers set the minimum threshold for a population center at 100,000 for population size, and 3 km² for area size (e.g., Liu and Wang 2016; Li and Liu 2018). Li (2020), on the other hand, lowers the threshold to 2 km² in area and 50,000 minimum population, as he examines the evolution of the urban structure over the years, and believes that a lower threshold is more relevant for analyzing the results of earlier years and comparing them to those of later years. In this study, we consider that a sub-center must contain at least two grids (i.e., be a spatial unit of 2 km²), and contain at least 2% of the total population of the agglomeration at a given time. This threshold value is defined to make the selection of centers sensitive to local variations, and makes the results more comparable and objective. Map 2 is a heat-map representation of the population centers located using Moran's local I and filtered according to the thresholds we have chosen. Clusters 1 (which corresponds to the hypercenter) and 2 (located in the east of Algiers) are retained because they meet the minimum threshold criteria set. Cluster 3, which is located in Baraki, was not retained in the final selection because it does not contain the minimum population required. Like the HL points, it is considered a potential future center, and provides information on the future configuration of the Algiers agglomeration. In the end, we find ourselves with two important clusters. The one that corresponds to the hyper-center of Algiers, and the one that corresponds to the eastern extension. According to Oubraham and Baouni (2020), the population center of the hypercenter is composed of two distinct centers that merged with each other over time. Approximately half of the wilaya's population is concentrated in the centers, indicating a low dispersion ratio.

4.2 Activity centers (attraction or polarizing):

Concerning the attractive centers, we extracted the data of the human activities that correspond to the categories of functions retained in the agglomeration of Algiers (Table 2).

Table 2. The different categories of activities studied.

Categories	Detail
Banking and financial services	Banks
	Insurances
Legal Services	Courthouse
	Lawyers
	Notaries

Business and office buildings	Corporate headquarters
Institutions of Government	Ministries
	Embassies
	Executive offices
Educational institutions	Universities
	Training schools and art schools
Medical facilities	Hospitals
Catering sites	Catering services
	Restaurants
Commercial facilities	Commercial facilities
Tourism, entertainment and leisure facilities	Museums and art galleries
	Theaters, opera houses and concert halls
	Cinemas
	Sports facilities
	Hotels
	Picturesque sites and classified sites
	Recreational facilities
	Beaches and waterfronts
Transportation Amenities	

The POI data of the different activities mentioned in the previous table are then extracted, processed and formatted in ArcGIS Pro, in order to be able to locate, thanks to the Moran's local I statistic, the different attractive centers29. As shown in the results, illustrated in Figure 11 and detailed in Table 3 four clusters, representing the points of concentration of the selected activities, stand out. The first cluster is located in central Algiers and Sidi M'hamed and corresponds to the CBD of the capital. It is the most important cluster among the various points identified, and in fact concentrates almost a third of the important activities in the Algiers agglomeration. Several key activities and functions are located there. Clusters 2 and 3, located in the heights of the agglomeration, to the west, contain 17.08% of activities and are mainly centers that have developed from colonial nuclei. Cluster 4, which is the furthest cluster from the CBD, is located to the east of the CBD and concentrates approximately 3% of the total activities studied. In sum, almost half of the activities in Algiers are concentrated in the centers. Indeed, the results indicate that 48.33% of activities are located in centers. This is similar to the results of the population structure, previously studied, and means that the Algiers agglomeration is at an equidistance between dispersion and compactness (i.e., the structure of the population as well as that of the activities is neither compact nor significantly dispersed).

Table 3 The activity clusters of the Algiers agglomeration and their specificities

clusters	Corresponding Communes	Activity concentration (percentage)
Cluster 1	Alger centre et Sidi M'hamed (CBD)	28.42 %
Cluster 2	Hydra et Bir Mourad Raïs	10.52%
Cluster 3	El Biar et Ben Aknoun	6.56%
Cluster 4	Bab Ezzouar et Dar El Beïda	2.83%

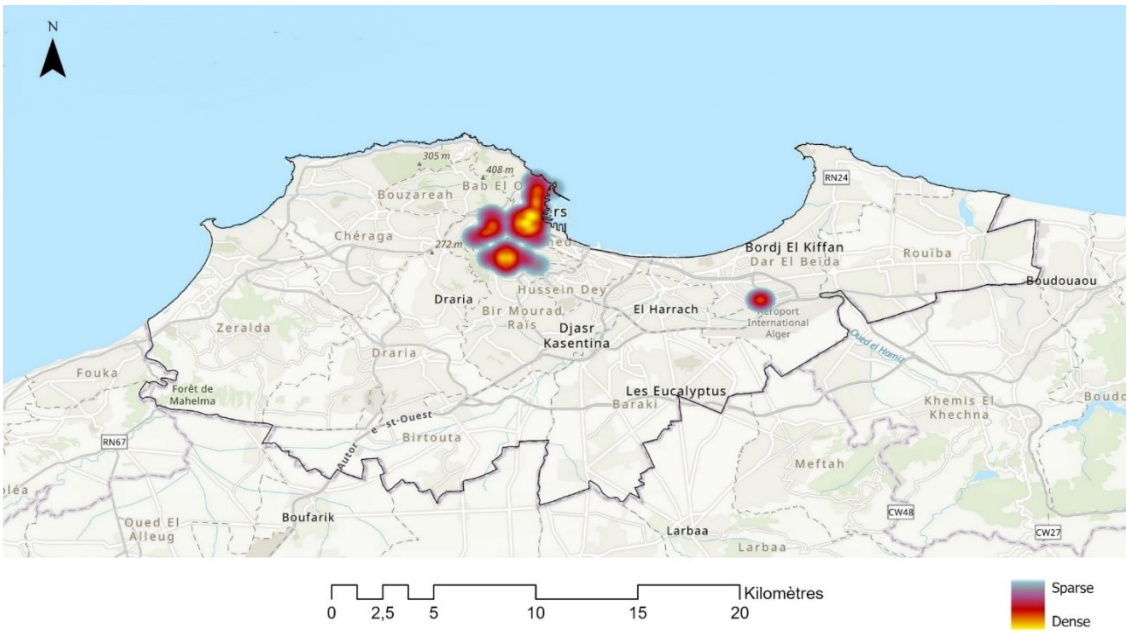

Figure 11. The heat-map of the activity clusters of the agglomeration of Algiers (Author).

4.3 Algiers, a polycentric urban area:

The Algiers conurbation is developing in a clearly polycentric organization. Several centers and centralities, whether transmitting or polarizing, structure its urban area. Indeed, we have identified two major population centers and three centers of attraction. The points that emerged as both transmitting and polarizing centers are those located in

- Algiers center and Sidi M'hamed (CBD), which correspond to the historical centrality of the city of Algiers,
- Bab Ezzouar and Dar El Beïda in the east of the wilaya. These two entities are more than centers, they represent centralities that strongly structure the territory of Algiers.

The CBD remains the most important center, polarizing both population and activities. Even though its population has been decreasing since 1998 (Bakour 2016, p.218), its dominance in the structuring of the urban system remains almost obvious. Indeed, the two central communes (Sidi M'hamed and Algiers center) group together 74% of the command facilities, 69% of the business services facilities and 59% of the private services facilities (e.g., the Algiers stock exchange). This centrality is also, according to Bakour (2016, p.226) an employment hub.

It is followed by the East centrality, which has received particular interest from urban policies. The commune of Bab Ezzouar, for example, records employment densities that are close to those of central Algiers, and is being transformed into a real economic pole (Bakour 2016, p.226), in addition to a higher tertiary sector with national influence that is superimposed on commercial and business centers. On the other hand, the western centers on the heights concentrate both higher tertiary activities as well as high employment densities. Also, these places appear as population centers made up of former colonial villages.

5. Conclusions

The results obtained in this chapter show significantly that the Algerian agglomeration has a polycentric structure. Indeed, the population is structured in two main centers, consisting of the city center and its neighborhood as well as a sub-center in the eastern part. The agglomeration also contains several points that are likely to become real population sub-centers in the future, such as the core of Baraki, Chéraga or the new town of Sidi Abdellah. In addition, the urban space of the capital is organized around three important activity centers. The CBD, or the historical centrality, a sub-center in the East and a center in the West, on the heights of the city. The CBD is the center that contains the largest number of POIs of different categories, followed by the sub-center in the East.

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Conflict of Interests

The authors declare no conflict of interest.

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