Journal of Urban Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/cjut20

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To cite this article: Pablo Martí, Leticia Serrano-Estrada, Almudena Nolasco-Cirugeda & Jesús López Baeza (2022) Revisiting the Spatial Definition of Neighborhood Boundaries: Functional Clusters versus Administrative Neighborhoods, Journal of Urban Technology, 29:3, 73-94, DOI: 10.1080/10630732.2021.1930837

To link to this article: https://doi.org/10.1080/10630732.2021.1930837

JOURNAL OF URBAN TECHNOLOGY
2022, VOL. 29, NO. 3, 73–94
https://doi.org/10.1080/10630732.2021.1930837

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Revisiting the Spatial Definition of Neighborhood Boundaries: Functional Clusters versus Administrative Neighborhoods

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ABSTRACT

This study revisits the debate surrounding the definition of neighborhood boundaries by addressing the disconnect between the city's Administrative Neighborhoods and its functional organization. A method is proposed for dividing the city into more meaningful units through the spatial distribution of urban activities by retrieving data from *Google Places*. The dataset was pre-processed and spatially divided into Functional Clusters. A comparison between functional and administrative subdivisions of the city was undertaken, from which three overall conclusions could be drawn. First, a function-based city partition allows economically active urban areas to become the neighborhood's center, thereby creating a polynuclear neighborhood structure that would potentially encourage greater cross-movement of people throughout the city. Second, the specialization of activities becomes more evident in Functional Clusters than in Administrative Neighborhoods. Third, access to up-to-date data makes possible a timely diagnosis of the quantity and diversity of urban activities—i.e., economic activities, services, and facilities—through *Google Places* data. The value of this contribution is to inform urban decision-making and policies in order to better balance the provision of a neighborhood's economic activity.

KEYWORDS

Neighborhood boundaries; functional clusters; urban economic activities; *Google Places*; social networks

Introduction

Economic activity growth in cities has brought new challenges to the design of urban intervention strategies (Kärrholm, 2012). As suggested by Zukin (1993), the transformation of city "landscapes of production" into "landscapes of consumption" has affected urban planning and the design of city spaces (Kärrholm, 2012; Mubi Brighenti and Kärrholm, 2018). Moreover, the morpho-spatial reconfiguration of cities is greatly influenced by the concentration of economic activities (Kärrholm, 2012; Saraiva and Pinho, 2016). Indeed, the link between the physical aspects of the urban form and the clustering of city functions contributes to create a specific type of urban life (Crooks et al., 2015; Kropf, 1996).

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This article has been corrected with minor changes. These changes do not impact the academic content of the article.

Urban activity together with other factors (i.e., social preferences and urban morphology) have a significant impact on the perceived character of neighborhoods (Cranshaw et al., 2012; Kropf, 1996). In fact, "the availability and easy access to the range of goods and services that provide for residents" necessities and amenities give neighborhoods a sense of place and identity (Mehta and Mahato, 2018:2). Indeed, at cognitive and perceptual levels, neighborhood units are largely defined by the association of spatial features to socioeconomic and behavioral aspects (Kropf, 1996; Lynch, 1960). On this basis, many authors have highlighted the importance of considering the types of functions and establishments when partitioning the city (Brown, 1991, 1993; Cranshaw et al., 2012; Rösler and Liebig, 2013; Saraiva and Pinho, 2016) given that a concentration of specific economic urban environments may contribute to the fragmentation of the urban landscape (Graham and Marvin, 2002).

Traditionally, the catchment area of specific services—typically defined by administrative partitions—has been a key criterion for the definition of neighborhood boundaries (Devine, 1975; Perry, 1929). Frequently, these administrative partitions do not correspond to the current functional organization of the city. Lack of awareness of this disconnect challenges the effective provision of economic activities, services, and facilities, affecting social indicators such as equity and accessibility planning (Abdullahi et al., 2018; Omar, 2019; Serag El Din et al., 2013), which may thereby result in poor decision-making while defining urban intervention and regeneration strategies. The identification of neighborhood units regarded as functional urban areas has been approached from a variety of perspectives in the Urban Studies and Planning literature (Chen et al., 2017). Research dedicated to this issue contributes towards a better understanding of the character of the urban landscape and makes some headway in defining accurate public policies and enhancing the development of more effective urban intervention proposals (Gu, 2010; Kropf, 1996; Saraiva and Pinho, 2016). Grounded in the abovementioned theoretical reasoning, this research addresses the knowledge gap identified by Ellen and Turner (1997:855) regarding the need for a method to define more "meaningful neighborhood boundaries." Therefore, the aim of this study is to propose a method for partitioning the city into meaningful neighborhood units—hereafter referred to as Functional Clusters—that reflect the spatial distribution of economic activities, services, and facilities. The proposed method is applied to an illustrative case study, where the delimitation of the Administrative Neighborhoods is compared to the Functional Clusters. The hypothesis is that Functional Clusters better reflect the character of the urban environment than existing traditional Administrative Neighborhood partitions.

The novelty of this research is twofold. First, the method for obtaining Functional Clusters uses *Google Places* data as a source of information on today's urban activity and elaborates a process that allows different degrees of granularity in the analysis. Second, the comparison between Functional Clusters and Administrative Neighborhoods contributes to the contemporary methodological and theoretical debate on the spatial definition of neighborhood boundaries.

This paper is structured as follows: the literature section covers some of the most relevant research on both the definition of spatial neighborhood boundaries and the assessment of spatial patterns related to urban activity through social media; next, a description of the illustrative case study and the sources is given, followed by an explanation of the method; finally, the results are presented, discussed, and the main conclusions are drawn.

Literature Review

Spatial Neighborhood Boundaries

Jenks and Dempsey (2007) provided a comprehensive outline of the various scholarly definitions of the term "neighborhood," but, in general terms, scholars agree that neighborhoods are "a geographically defined subarea of the city where residents are presumed to share both spatial proximity and some degree of mutual circumstance" (Chaskin et al., 2001:98). Furthermore, these are "subareas of towns and cities whose physical or social characteristics distinguish them from one another" (Rohe, 2009:99). Thus, the term "neighborhood" encompasses spatial and non-spatial features, such as, intangible social elements (Jenks and Dempsey, 2007). Therefore, when both place and human activity are interlinked—as Hallman (1984:102) suggested, "through occupancy and use by its residents"—a geographical area can be considered a neighborhood.

Nonetheless, the delimitation of the city's spatial subdivisions based merely on human activity is a challenging task, which is one of the main reasons for the controversial and longstanding debate on the relevant determinants for defining neighborhood boundaries (Jenks and Dempsey, 2007). Previous work in the field has considered city subdivisions based on census tracts and administrative areas (Steiger et al., 2015), statistically defined clusters (Martin, 1998), and land use classification (García-Palomares et al., 2017). As these numerically-based subdivision criteria may "fail to accurately represent the neighborhood conditions that make a difference in people's lives" (Ellen and Turner, 1997:844), other more citizen-oriented approaches have considered perceptual and cognitive information for identifying neighborhood boundaries (Cranshaw et al., 2012; Nejat, 2018).

This paper adopts Hallman's definition of neighborhoods as functional entities that support residents' needs for services and facilities (Hallman, 1984; Jenks and Dempsey, 2007), taking into account that the quantity, quality, and diversity of uses and functions in a neighborhood encourage or discourage activities that involve using and staying in urban spaces (Rohe, 2009). These factors affect social and economic dimensions (Ellen and Turner, 1997) and, in turn, the urban livability of the space (Mehta and Mahato, 2018). This approach recognizes that communities can be weakened by the dispersion of people and activities (The Urban Task Force, 2003) or the lack of nearby facilities, institutions, and services, which forces residents to "concentrate activity and connections *beyond* rather than *within* the neighborhood" spatial limits (Chaskin et al., 2001:9; Furstenberg, 1993). Therefore, defining more meaningful boundaries based on the availability and proximity of urban activities could potentially encourage residents to stay *within* the neighborhood, thus supporting the livability of its urban spaces.

Urban Activity Patterns through Location-Based Social Networks

Pioneering research in the identification of geographical urban activity patterns—spatial distribution of economic activities, services, and facilities—was traditionally carried out by using store-by-store and street-by-street data collection and clustering techniques (Guy, 1976; Lee and McCracken, 1982; Saraiva and Pinho, 2016). The conclusions of this approach are similar to those that use different techniques involving more technological processes for data collection and categorization, as well as spatial analysis and clustering (Hossain, 1999; Saraiva, 2013; Sarma, 2006). *In situ* data collection is complemented and/or substituted by online catalogues, or official registers from local governments and other institutions, such as National Statistics Institute, commerce associations, etc. Clustering, among other types of analysis, has been calculated by using specialized software.

Nowadays, the great data collecting potential of crowd-sourced social media is being exploited to analyze a diverse range of topics related to the functional organization of the city (Arribas-Bel and Tranos, 2018), such as the relationship between urban form and function (Crooks, Pfoser et al., 2015; Crooks, Croitoru et al., 2016); the identification of POIs—points of interest—(Van Canneyt et al., 2012; Deng and Newsam, 2017; García-Palomares et al., 2015; Van Weerdenburg et al., 2019) and their accessibility in terms of density and diversity (Shen and Karimi, 2016); the characterization of livelihoods according to the collective behaviors of residents (Cranshaw et al., 2012); and the delimitation of functional areas to understand social and spatio-temporal aspects of the city (Chen et al., 2017; Rösler and Liebig, 2013).

In line with these studies, this research sources geolocated data from the social network *Google Places*, which has previously been used to identify economic activity for measuring urban entropy and urban complexity (Bustos Hernándes, 2015; López Baeza et al., 2017; Serrano-Estrada et al., 2016), as well as to research socioeconomic patterns of urban areas (Cenamor et al., 2017).

Illustrative Case Study and Sources

Alicante City, Spain was used as an illustrative case study as it is representative of other mid-sized Mediterranean cities that have encouraged modern commercial, tourist, and leisure formats in the last decades (Nieto, 2015). This provincial capital, at the heart of the Spanish Mediterranean Arc, with 329,988 registered inhabitants (Spanish Statistics Institute, 2018), is considered an important European holiday destination hub (Suau-Sanchez and Burghouwt, 2012). Moreover, like other Mediterranean cities, Alicante has at least two different types of administrative spatial divisions that do not correspond with each other, nor do they reflect the social or functional reality of the city. For instance, this municipality is divided into eight census districts, which are subdivided into 253 census sections (Spanish Statistics Institute, 2018), and into 42 Administrative Neighborhood areas according to the official database of the Urban Guide of the City of Alicante (Ayuntamiento de Alicante, 2018). The latter division reflects the historical growth of the city, observable in the existing patterns of the urban fabric. However, neither division considers today's dynamic socioeconomic perspective suggested by, for example, the distribution and types of urban activities (Noulas et al., 2013) that are crucial for determining the direction of urban interventions (Mankalpa et al., 2015; Temes Cordóvez et al., 2016).

Two main sources were used for this study: The administrative neighborhood spatial delimitation of Alicante municipality and the geo-location data from *Google Places*. The spatial delimitation of Alicante's 42 administrative neighborhoods (Ayuntamiento de Alicante, 2018) was used as the city's baseline division. The spatial extent of all administrative neighborhoods together was considered as the area within which *Google Places* data were collected. The software program Social Media Urban Analyzer

(SMUA) (Martí et al., 2019), which retrieves data via *Google Places* was used for this purpose. The data from *Google Places* were retrieved as a listing of places which include all urban activities and open public spaces registered in the platform within the search area up to the date of retrieval—January 23, 2018. The raw dataset included, in total, 57,578 geo-referenced places.

Each listed place has associated metadata. From the large quantity of data variables available through the *Google Places* API, this research selects and retrieves only the following: the spatial coordinates—latitude and longitude—the name of the place; the ID —place unique identifier number—and the place type, which are tags or descriptors. These place types in *Google Places* datasets are relevant for this study since they provide detailed information as to what kind of urban activity occurs in each place retrieved.

Identifying and Delimiting Functional Clusters Using *Google Places* Data

The method adopted consisted of three phases. First, data pre-processing was necessary to refine the places in the *Google Places* dataset. Second, the place types were categorized into the hierarchical APA benchmark categories (American Planning Association, 2018a). Finally, identification, spatial delimitation, and analysis of Functional Clusters were carried out.

Pre-Processing of Google Places *Retrieved Data*

The pre-processing of the raw dataset involved the following stages (See Figure 1):

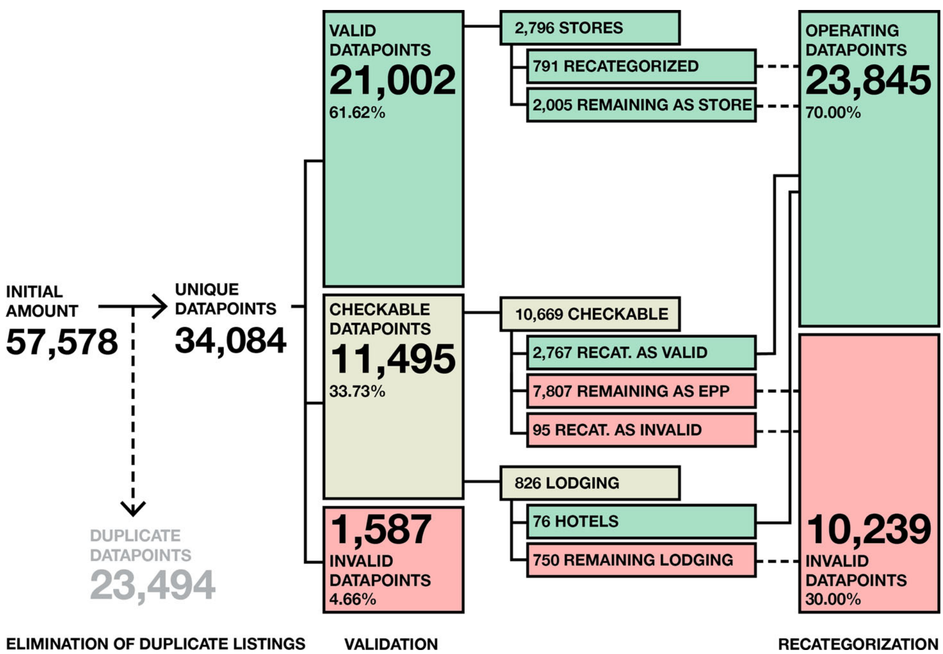

Figure 1. Pre-processing data summary

- elimination of duplicate data
- validation of places related to urban activities—specifically economic activities, services, and facilities
- re-assignment of *Google Places* place types when necessary.

These steps ensured that each datapoint represented a unique register and was correctly assigned to a pre-defined *Google Places* place type (Google Developers, 2018).

Elimination of Duplicate Place Listings. A script was designed to eliminate duplicate place listings by considering three specific data variables: name of the place; place ID; and geographic coordinates.

Google Places assigns a unique ID to each place (Google Developers, 2018), and the criteria adopted for eliminating duplicate listings were twofold. Places are considered duplicate listings if they have the same ID, or if they have a different ID but the same name and the same geographic coordinates. Those places with different IDs, different names, and the same geographic coordinates are considered unique as they may, for example, be different economic activities within the same building.

Validation of Places. Recognizing which datapoints represent economic activities, services, and facilities entailed revising their originally assigned place types. In total, *Google Places* currently supports 128 standard predefined place types. However, the raw retrieved dataset for Alicante included only 103 place types. This is because the diversity of urban activities changes from one city to another.

Another relevant consideration is that place types are automatically assigned by *Google* or manually designated by the individual who is registering a service or facility in the platform. Thus, according to the authors' experience, some places may include more or fewer place types or descriptors than others.

Some of these place types are ambiguous and misleading; for example, the *establishment place* type which, as opposed to *electronics_store*, does not offer enough information on the kind of economic activity that takes place in the space. In view of the above observations, this study adopts the most specific place type assigned to each place.

After eliminating duplicate registers, three types of datapoints were recognizable: valid datapoints, invalid datapoints, and checkable datapoints. The valid datapoints are those places which represent mostly urban activities, i.e., economic activities, services, and facilities. These include a significant number of datapoints assigned to the generic *store place* type which does not provide enough information about the type of activity. The registers tagged with this ambiguous place type have been checked and reassigned, where possible, a more specific place type.

The invalid datapoints are those places that do not represent services or facilities and, therefore, were excluded. Invalid datapoints included in the case study dataset can be grouped as follows:

- geometric regions that do not represent services or facilities: *administrative_area_level_1, 2, 3, 4, and 5; colloquial_area; country; geocode; locality; neighborhood; political;*

postal_ code; postal_code_prefix; postal_code_suffix; postal_town; sublocality; sublocality_level_1, 2, 3, 4, and 5; and subpremise.

- datapoints that represent street names and/or are assigned by *Google Places* to the place types: *intersection; route; street_address; and street_number*.
- datapoints that represent places with no economic activity. These are mostly the place types: *parks; plazas; natural_features; landmarks;* and *campground*.

The checkable datapoints that require reviewing before being considered valid or invalid datapoints can be divided into two groups:

(1) Datapoints assigned to the *lodging place* type include different types of lodgings (apartments, residential buildings, hotels, etc.) that, in some cases, may be considered as an economic activity, for example, hotels. Residential only buildings are not considered as an economic activity.
(2) Datapoints assigned to several broad and generic place types, namely, *Establishment, Point_of_Interest,* and *Premise* (EPP), that may or may not contain economic activities and would be better assigned to a more specific place type that reflects their type of activity.

Re-Assigning Place Types to Google Places Checkable Datapoints. This step was useful for the grouping and homogenization of data into refined place types. This procedure consisted of first, assigning datapoints from the categories EPP and *store* to a specific pre-defined *Google Places* place type; and second, separating and assigning the *hotel place* type to hotels that were originally tagged as lodging and not as hotel.

From all the EPP datapoints retrieved (10,669), only six were originally assigned to both *premise* and *park place* types. As for the rest, it was necessary to resort to the place name variable to identify the type of activity of each datapoint and reassign a place type. All the words included in the EPP datapoint place names were sorted by frequency, using a simple Python script,[1] and the 1,500 most frequented terms were closely analyzed to see if they could be associated with a pre-defined *Google Places* place type. For instance, place names containing the words "*restaurant*," "*meson*," and "*casa de comidas*" were assigned to the *Google Places*' *food place* type. Terms related to street names were considered invalid EPP datapoints. Finally, 76 places were eliminated as they did not represent an economic activity.

The *store place* type was too generic and thus, the same process was adopted for reassigning place types. Datapoints originally assigned as lodging were reassigned a place type according to their kind of accommodation. Only those datapoints reassigned to the hotel category have been considered as economic activities:

- *Residential*: residential buildings and condos—*urbanización, edificio residencial*
- *Hotel*: tourist accommodation, such as hotels and hostels
- *Apartment*: places defined as rental apartments—short-term accommodation
- *Lodging*: places that could not be included in the previously mentioned place types. Some of these places have been registered in *Google Places* with the name of a person or a random name that does not provide further information about the type of accommodation (e.g., *La Casita, La Lonja, and Maralic*).

Additionally, new place types were created for those places whose names provided enough information about the type of economic activity, but no suitable predefined *Google Places* place type was found. These new place types are: *association; cleaning_service; design_studio; events_venue; industry; leisure; logistics; lottery; professional_service; theater;* and, *electronics_repair*. Over 25.94 percent of EPP datapoints were assigned a place type using the described criteria and 76 (9.20 percent) datapoints in the lodging category were assigned to the *hotel place* type.

Refined Google Places *Dataset*

After data pre-processing, there were 23,845 operating datapoints remaining in the refined *Google Places* dataset (See Figure 1) which represent 70 percent of the unique dataset datapoints. These included: 21,002 originally valid datapoints; 2,767 EPP datapoints with an assigned *Google Places* place type; and 76 *hotel* datapoints. As for the number of refined place types, considering both *Google Places* and newly created place types, 107 place types were obtained in total.

Recategorizing Operating Datapoints: from Google Places *Categories to APA Land Based Classification Standards Benchmark Categories*

In order to permit an analysis of the types of economic activities, services, and facilities with different degrees of granularity, a grouping of the *Google Places* place types is proposed following previous research from Martí et al. (2019). To this end, the Land Based Classification Standards categories have been adopted (American Planning Association, 2018a) as benchmark categories. Specifically, this classification is the one that addresses the "functional dimension," one of the five available LBCS dimensions, which refers to "the economic function or type of establishment using the land" (American Planning Association, 2018b). This hierarchical classification provides an overall fine-grain land use class taxonomy of nine Level 1 categories, 47 Level 2 categories, and 159 Level 3 categories (Deng and Newsam, 2017). All refined *Google Places* place types were assigned to APA Level 1 (See Figure 2) and Level 2 (See Table 1) category codes, respectively.

From the 47 APA Level 2 categories originally available, the case study's *Google Places* and newly proposed place types could only be assigned to 28 APA Level 2 categories. The remaining 19 Level 2 categories have not been used. Specifically, no place types were assigned to the following APA Level 2 subcategories:

- 1100 Private household
- 1200 Housing services for the elderly
- 3200 Wood, paper, and printing products
- 3300 Chemicals, and metals, machinery, and electronics manufacturing
- 4300 Utilities and utility services
- 5500 Natural and other recreational parks
- 7200 Machinery related
- 7400 Heavy construction
- 8100 Oil and natural gas
- 8200 Metals—iron, copper, etc.

Table 1. Number of *Google Places* and newly proposed place types included in APA Level 2 subcategories according to the case study's operating datapoints

	APA Level 2 sub-categories	Google Places *place* types and newly proposed *place* types	Number of *place* types per APA Level 2 sub-category	
			Place types	Newly proposed
1	1300 Hotels, motels, or other accommodation services	hotel	1	
2	2100 Retail sales or service	store; florist; health; grocery_or_supermarket; clothing_store; car_repair; gas_station; pharmacy; locksmith; car_dealer; furniture_store; bicycle_store; home_goods_store; book_store; car_wash; electronics_store; shopping_mall; hardware_store; shoe_store; liquor_store; convenience_store; art_gallery; supermarket; department_store	24	
3	2200 Finance and Insurance	atm; finance; insurance_agency; bank	4	
4	2300 Real estate, and rental and leasing	real_estate_agency; car_rental	2	
5	2400 Business, professional, scientific, and technical services	lawyer; professional_service; travel_agency; copy_store; veterinary_care; accounting; moving_company; design_studio; electronics_repair; consulting; cleaning_service	7	4
6	2500 Food services	food; bar; café; restaurant; meal_delivery; night_club; meal_takeaway	7	
7	2600 Personal services	parlor; laundry; hair_care; beauty_salon	4	
8	2700 Pet and animal sales or service (except veterinary)	pet_store	1	
9	3100 Food, textiles, and related products	bakery	1	
10	3400 Miscellaneous manufacturing	industry; jewelry_store	1	1
11	3500 Wholesale trade establishment	movie_rental	1	
12	3600 Warehouse and storage services	storage	1	
13	4100 Transportation services	parking; bus_station; light_rail_station; post_office; airport; taxi_stand; transit_station; train_station; logistics	8	1
14	4200 Communications and information	library	1	
15	5100 Performing arts or supporting establishment	stadium; movie theater; theater; events_venue	2	2
16	5200 Museums and other special purpose recreational institutions	museum; natural_feature; zoo	3	
17	5300 Amusement, sports, or recreation establishment	casino; gym; spa; amusement_park; bowling_alley; leisure; lottery	5	2
18	5400 Camps, camping, and related establishments	rv_park	1	
19	6100 Educational services	school; university	2	
20	6200 Public administration	courthouse; local_government_office; city_hall	3	
21	6300 Other government functions	embassy	1	
22	6400 Public Safety	fire_station; police	2	
23	6500 Health and human services	doctor; physiotherapist; hospital; dentist	4	
24	6600 Religious institutions	hindu_temple; place_of_worship; mosque; church	4	
25	6700 Death care services	funeral_home; cemetery	2	
26	6800 Associations, nonprofit organizations, etc.	association		1
27	7100 Building, developing, and general contracting	general_contractor	1	
28	7300 Special trade contractor	electrician; roofing_contractor; plumber; painter	4	

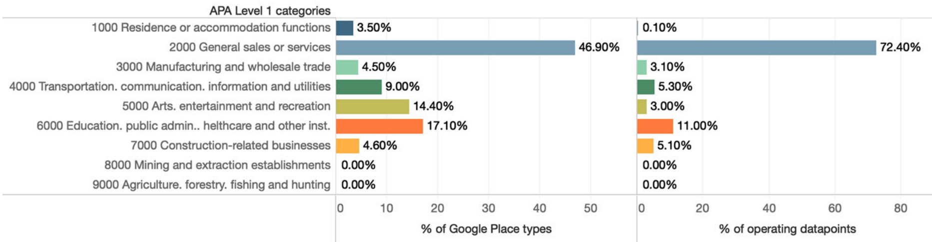

Figure 2. *Google Places* operating datapoints and their respective place types assigned to APA Level 1 categories

- 8300 Coal
- 8400 Non-metallic mining
- 8500 Quarrying and stone cutting establishment
- 9100 Crop production
- 9200 Support functions for agriculture
- 9300 Animal production including slaughter
- 9400 Forestry and logging
- 9500 Fishing, hunting and trapping, game preserves
- 9900 Unclassifiable function.

As can be observed, the majority of these subcategories correspond to the APA Level 1 categories (8000 Mining and extraction establishments, and 9000 Agriculture, forestry, fishing, and hunting) (See Figure 2).

The refined place types classification provides fine grain information as to specific uses in an urban area. For instance, *hair_care* and *beauty_salon* are considered, in the refined dataset, as two different place types. As previously stated, the APA category classification provides a hierarchical approach, grouping economic activities of the same type. In this case, the *hair_care* and *beauty_salon Google Places* place types are grouped into the APA 2000 *General Sales and Services* Level 1 (main category), 2600 *Personal Services* Level 2 (subcategory).

Therefore, in this research, the refined *Google Places* place types are used to infer the diversity of economic activities, services, and facilities within each urban unit, whereas the APA categorization is useful to recognize the functional character of clusters separately and in relation to the rest of the clusters.

Delimitation of Functional Clusters

The operating datapoints are visualized by means of cartography and grouped into 42 Functional Clusters (FC 0 to FC 41) by using Quantum GIS open-software. The spatial delimitation of these 42 clusters is compared to the existing 42 Administrative Neighborhoods (AN 1 to AN 42). This process comprised two phases: the cluster calculation, and the cluster borders definition.

A spatial cluster calculation by proximity of the refined datapoints was performed using a *k*-Means clustering algorithm, a popular clustering method in literature, adopted across different domains (Fortunato, 2010; Khan and Ahmad, 2004), and useful to partition topological nodes into groups. This algorithm presents quick convergence to an acceptable result and, after a certain number of iterations, the position of the centroids remains stable (Fortunato, 2010). The only problems raised in the literature are the need for (a) experimenting with different numbers of clusters, and (b) close visual exploration of the resulting clusters for further validation (Béjar et al., 2016). To overcome these limitations several trial runs were conducted to test clustering results yielded by different K-values (See Figure 3, left). The experiments were performed considering K-values from k=5 to k=50. It was observed that low K-values (i.e., k=5 and k=6) resulted in rather different clustering results. However, higher K-values (i.e., k=40 to k=51) yielded very similar clustering partitions (See Figure 3, right). Therefore, in this specific case study, k=42 is selected as the K-value because the resulting clusters provide consistency—as results started to converge around k=40, and it coincides with the number of Administrative Neighborhoods, thus allowing a straightforward comparison.

Once the clusters were iteratively calculated by the *k*-Means algorithm and all datapoints were spatially linked to the centroid of the closest cluster using the Euclidean distance, each of the 42 clusters and their corresponding datapoints were given a code number and a color to aid visual representation.

The Euclidean distance was considered instead of Manhattan or Network distances for several reasons. First, no meaningful differences were identified when compared to the cluster subdivision using Manhattan distance, and second, the Euclidean distance is quicker for computer calculations. Furthermore, the differences between Manhattan and Network distances are not significant in the specific case of Alicante and are unlikely to be in other Spanish Mediterranean cities whose urban fabric is mainly based on a regular orthogonal grid (See Figure 4a and b).

The 42 clusters of datapoints obtained lack border lines. Therefore, a Voronoi diagram was constructed for partitioning of the area into 23,845 coded Voronoi polygonal regions

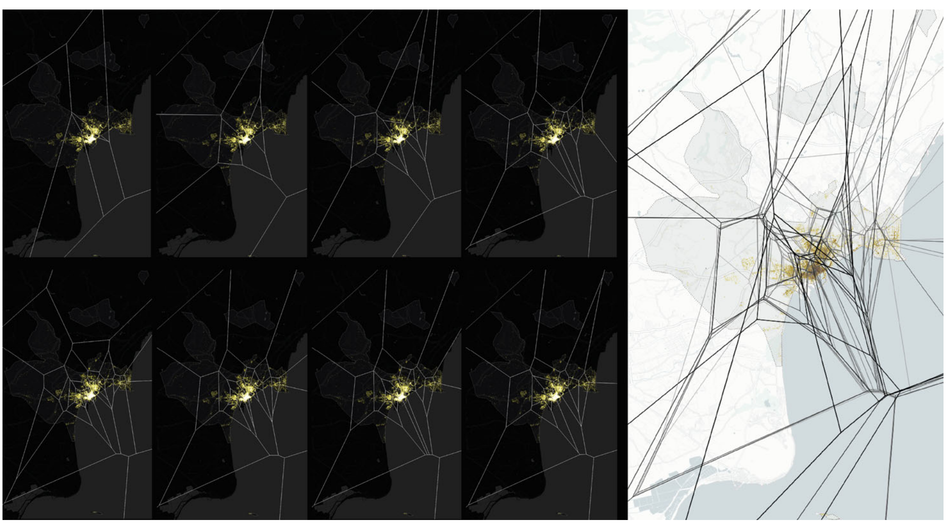

Figure 3. Left: Voronoi experiments in increasing number of K-values from 5 to 42. Right: Superimposed representation of Voronoi experiments with high K-values ranging from 40 to 51

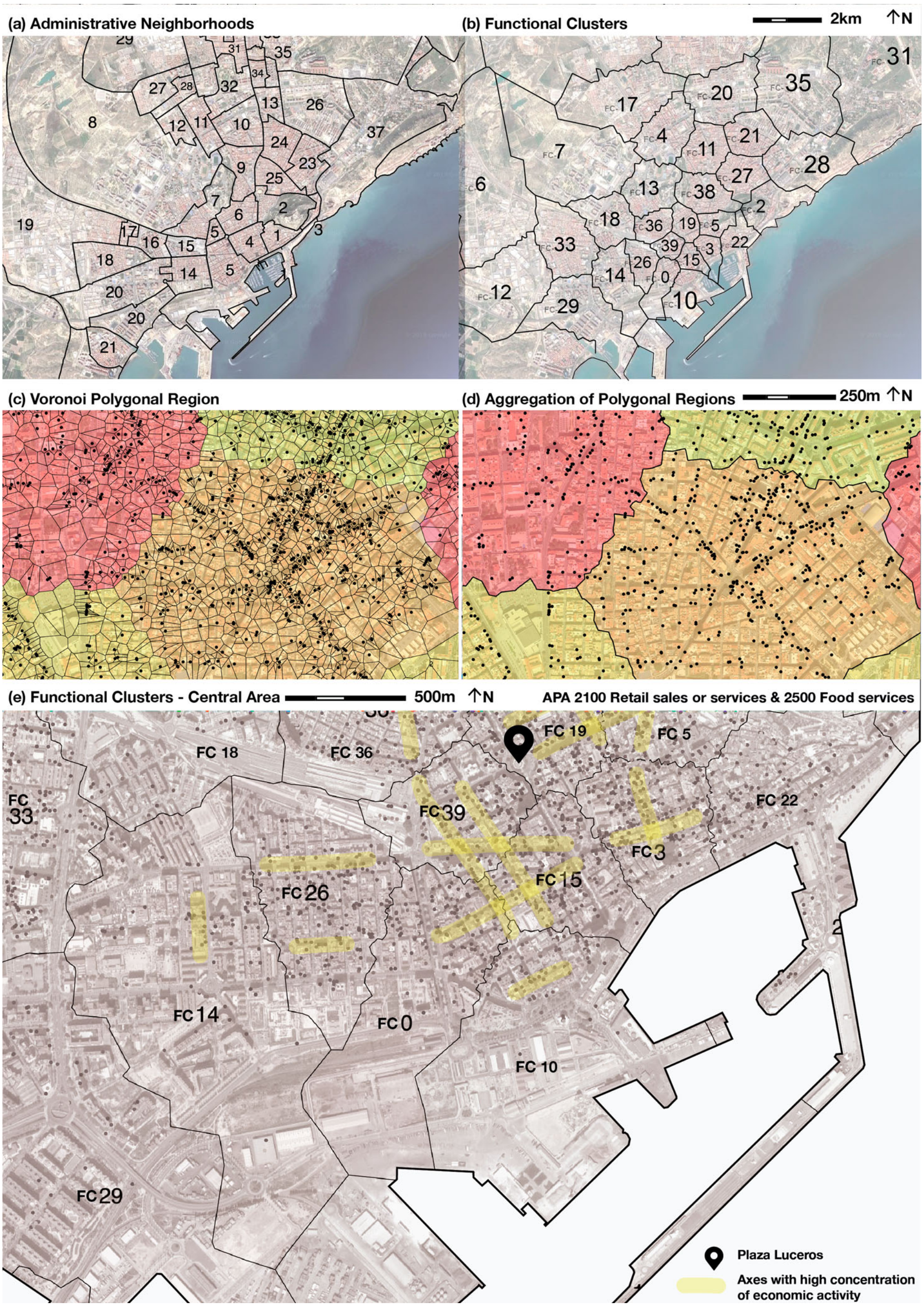

Figure 4. (a) Alicante's identified 42 Functional Clusters (b) Alicante's existing 42 Administrative Neighborhoods; (c) Voronoi polygonal regions and (d) definition of Functional Clusters by grouping these polygons; (e) Alicante's central area exemplifying how economically active segments of axes fall within Functional Cluster areas

whose center is each datapoint (See Figure 4c). The aggregation of the coded Voronoi polygonal regions forms shapes that ultimately define the cluster borderlines (See Figure 4d). Each spatial partition represents a grouped unit of economic activities, services, and facilities, and thereby a Functional Cluster.

Administrative Neighborhoods vs. Delimited Functional Clusters

The Functional Clusters obtained were analyzed and compared to Administrative Neighborhoods taking into account two different aspects: their physical characteristics (shape and size), and, their functional features, in terms of the diversity and specialization of economic activities, services, and facilities. For this purpose, the two data categorizations dealt with in the previous sections were considered: the refined *Google Places* categories and the benchmark APA categories.

Physical Characteristics

The resulting tessellation of Functional Clusters differs significantly to that of the city's recognized Administrative Neighborhoods. In fact, the size and shape of the polygon delimitations are more homogeneous than those of the Administrative Neighborhoods. Moreover, these polygons progressively increase in size as they get further away from the city center because both the amount and the proximity of economic activities, services, and facilities decreases in the less compact urban areas of the periphery.

Unlike what is observed in the Administrative Neighborhoods, where most active street segments and intersections tend to be located along the neighborhood boundary assigning each side of the street to different neighborhoods, in the Functional Cluster, tessellation all of these active axes and nodes become the cluster's core, thus creating a polynuclear structure of city neighborhoods (See Figure 4e). Moreover, when one of these active axes, due to its length, traverses two or more Functional Clusters, it is observed that, in all cases, both sides of the street belong to the same Functional Cluster. In general terms, a similar situation can be found in relation to intersections and squares.

Exceptionally, for the city of Alicante, only one economically active intersection was found to be located at the junction of two clusters. This is the case of the area occupied by Plaza Luceros (See Figure 4e), a circle recognized as the most socially relevant open public space of the city (Martí et al., 2017) in which the southwest area belongs to the FC 39 while the rest of the square is connected to FC 19. Therefore, the space has two functionally—and perceptibly—different sides, each one strongly linked to nearby clusters of economic activities, services, and facilities. This fact suggests that there could be different significance between the city scale and the cluster scale. Therefore, including perceptual parameters of public spaces in the study of Functional Clusters could be an interesting approach for future research.

Overall, the Functional Cluster tessellation obtained redefines axes according to their actual function as an inter-neighborhood conduit of social life, rather than a neighborhood boundary. Sometimes, the concentration of economic activities, services, and facilities becomes a livable intersection, or sometimes it runs along an axis. In the first case, the aggregation of activities at the Functional Cluster's center becomes the active neighborhood nucleus, especially where these activities and services are located on ground floors, as shown in Figure 4e), where the refined *Google Places* economic activities categorized as APA 2100 and APA 2500 can be seen.

Functional Features

The analysis indicated that the spatial distribution of activity types is more homogeneous in the 42 Functional Clusters than in the Administrative Neighborhoods.

In general terms, the economic activities of the case study fall within two predominant Level 1 APA categories: category 2000 (*general sales or services*) and category 6000 (*education, public administration, health care and other institutions*). In all 42 Functional Clusters both categories were ranked first and second respectively, based on their frequency of economic activities.

A greater degree of granularity was obtained in the analysis as two approaches were adopted to analyze and compare the functional features of both the Administrative Neighborhoods and the Functional Clusters. On the one hand, the functional diversity and the quantity of economic activities, services, and facilities of each cluster with respect to the rest of the clusters were analyzed using the refined dataset; and, on the other hand, the functional specialization of each cluster was identified by using APA second-level categories. In both cases, the total number of economic activities, services, and facilities per category was adopted as the main criteria.

In terms of the functional diversity, Figure 5 shows the number of *Google Places* place types in both Functional Clusters and Administrative Neighborhoods. By comparing the functional diversity of economic activities, services, and facilities between the Functional Clusters and the Administrative Neighborhoods, it became apparent that the types of activities were more evenly distributed in the former tessellation than in that of the latter (See Figure 5). Clusters FC 40 and FC 5 are the two most relevant Functional Clusters in terms of functional diversity with the presence of 25 different place types. While FC 5 is in a central location of the city, FC 40 is located in a residential tourist area that is very well connected to other neighborhoods, and even municipalities, through main structural axes. This cluster is characterized by the presence of large residential blocks, isolated high-rise buildings, and single-family housing units, with mostly private and semi-public open spaces. The economic activity, services, and facilities in cluster FC 40 run along the intersection of two axes, and are concentrated mainly in the ground floor of buildings. This intersection happens to fall right at the geometric center of the Functional Cluster.

As for the quantity of economic activity, services, and facilities per category and per cluster, Figure 5 shows that two out of the three most relevant clusters—FC 3 and FC 15—are located in the city center. The cluster ranked third is cluster FC 40 which, as mentioned before, is also the most diverse. The findings suggest that the diversity and quantity of urban activities reflects the functional character of the urban area in which they are located. The city center has more quantity but a slightly less diverse economic offer, being mostly stores, restaurants, bars, clothing stores, whereas residential areas that are further away from the city center have more varied economic activity, services, and facilities to satisfy the demand of local residents.

As for the clusters' functional specialization, the presence of the APA second-level categories in each cluster can be observed in Figure 5. The diagram permits a twofold

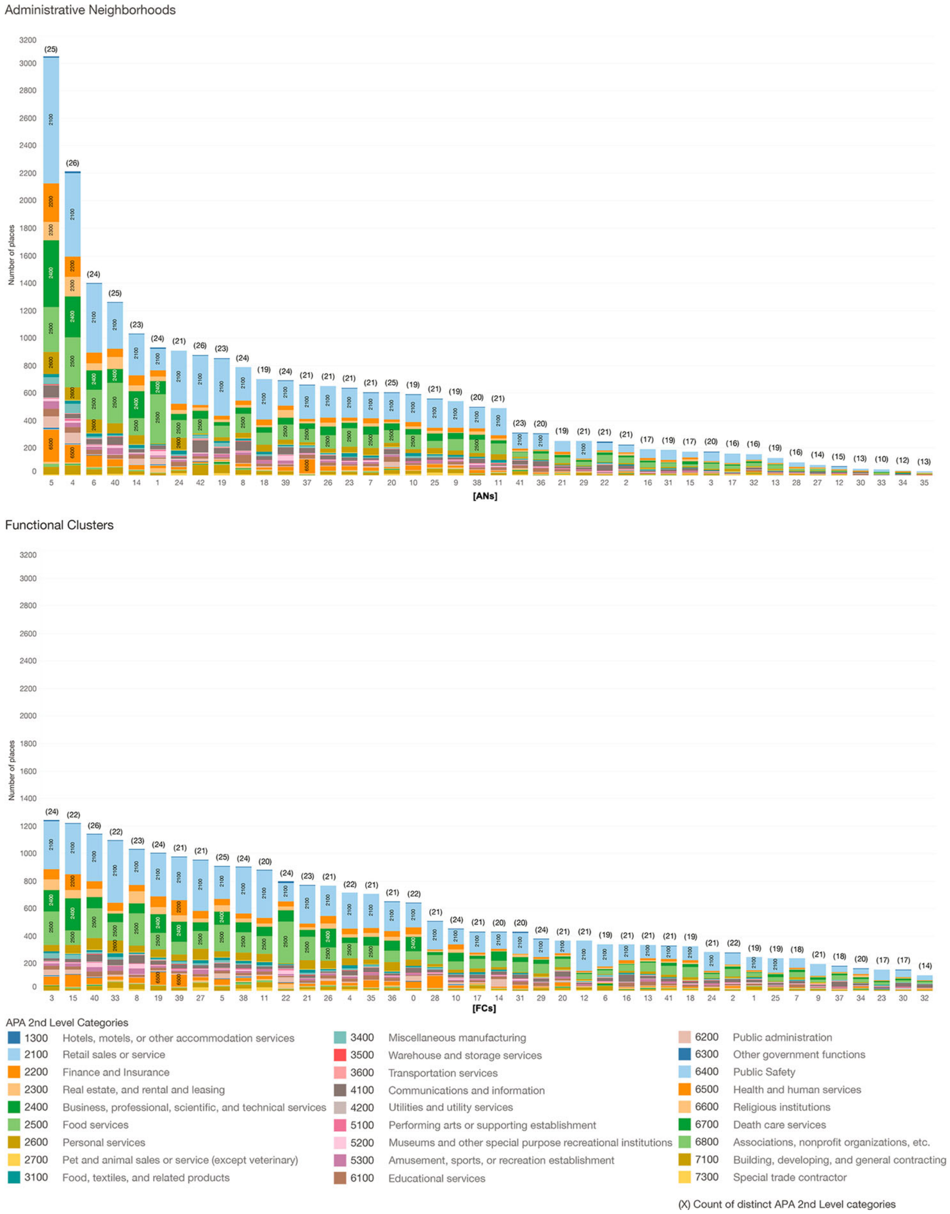

Figure 5. Comparison between the diversity and quantity of APA second level categories and number of *Google Places* place types within Administrative Neighborhoods (upper) and Functional Clusters (lower). In parenthesis, the total number of place types (diversity) per neighborhood and cluster, respectively

reading: first, the total number of places per type found in each cluster and, second, the distribution of each type of economic activity across all clusters and neighborhoods. Both the Administrative Neighborhoods and the Functional Clusters are compared. In the former, there is a high concentration of activities (mainly in neighborhoods AN 5 and AN 4) while in the latter, the spatial distribution of urban activity across all clusters is more homogeneous.

Furthermore, almost all Functional Clusters have a noticeable presence of two APA second-level categories: 2100 Retail sales or services and 2500 Food Services. Thus, the functional specialization becomes more evident with the proposed city subdivision into Functional Clusters. Specifically, worth highlighting is cluster FC 22, located at the heart of the historic city center where not only does the predominant urban activity correspond to businesses within the APA second-level category 2500 Food Services, but it is also where most of these types of activities occur when compared to other Functional Clusters. Moreover, clusters FC 8 and FC 40, two of the five top ranking clusters in terms of the amount of economic activity, services, and facilities present, are the most relevant of all Functional Clusters in the transportation category. This may be a potential indicator of their strong connectivity to other more central neighborhoods, while being functionally independent.

Discussion and Conclusion

This research confirms that there is a significant degree of disconnect between Alicante's traditional Administrative Neighborhood partitions and the city's functional organization. In order to assess the disconnect, a method was proposed to divide the city into Functional Clusters. These polygons represent more meaningful units in terms of urban activity and better reflect the current functional character of the urban environment.

Urban areas with clustered economic activities belonging to different administrative entities is one of the key issues currently being faced by many cities. For instance, today's Sternschanze, an entertainment and nightlife district in the city of Hamburg was, until 2008, part of three different districts (Hamburg-Mitte, Eimsbüttel, and Altona). Indeed, this area, which has a clustered spatial organization of highly specialized economic activities, has been recognized as an entity due to the administrative challenges and lack of consensus between the policies adopted by the three districts. One of the main challenges of this process has been to delineate the district's limits (Bürgerschaft der Freie und Hansestadt Hamburg, 2006), which could have benefited from the method proposed in this study.

In terms of the source of information selected, the geo-located fine grain listing of urban activities from *Google Places* has proven to be rather useful for the recognition of different clusters of urban economic activities, services, and facilities. Moreover, since this crowd-sourced information is constantly updated, changes over time can be monitored. These updates are valuable for keeping track of possible changes in urban activity and are useful for informing the implementation of policies and the design of urban intervention strategies based on the functional organization of the city. However, using *Google Places* datasets is not without its challenges. A thorough pre-processing of data is required before to using the dataset since this social network was designed for an entirely different purpose. For instance, duplication of places found in the raw dataset is frequent due to the ease with which users can freely create and/or edit place registrations. Another challenge of using *Google Places* datasets is that data are classified into too many similar categories that complicate detailed analysis. Re-categorizing data into the APA functional categories has helped to overcome this challenge and has allowed a different granularity level in the analysis.

Indeed, the Functional Clusters derived from the present distribution of economic activities in Alicante do not correspond to the city's current administrative spatial delimitation. In this case study, although economic activities and services on both sides of an axis give its urban environment a unique character, currently they belong to two different Administrative Neighborhoods. However, with the proposed Functional Clusters, economically active axis segments take the place of main centers of activity. Hence, the boundaries of existing administrative divisions that may have been understood as "edges" behave more like "seams" (Jacobs, 1961), and become the heart of the new Functional Clusters, thereby creating a polynuclear structure of neighborhoods with greater cross-movement of people.

Furthermore, the Functional Clusters obtained presented a more homogeneous distribution and degree of specialization in terms of the quantity and diversity of urban activities, when compared to the Administrative Neighborhoods (See Figure 5). More specifically, in terms of quantity of urban activities, the two ANs with the most and least registered places have 3,047 and 30 places, respectively, whereas the FCs showed a proportionally much smaller difference, with 1,244 and 114 places, respectively. This also means that, in terms of diversity, the cluster with the least place types—FC 32—has almost four times more diversity than the neighborhood with the least place types—AN 35. Still more evidence is the fact that there are only 9 FCs (as opposed to the 17 ANs) with fewer than 20 different place types.

This was not predictable since the spatial clustering was performed exclusively by taking into account the proximity between datapoints and not the types of urban activities. A possible explanation of this diversity in the case study responds to the functional characteristics of the case study selected: a predominantly mixed-use Mediterranean city.

In any case, this study concurs with previous research and provides additional evidence on the extent to which a city subdivision based on its current functional distribution leads to a better understanding of the type of urban life that is being created (Cranshaw et al., 2012; Crooks et al., 2015; Kropf, 1996; Noulas et al., 2013; Zhang et al., 2013). Therefore, defining Functional Clusters and acknowledging the quantity, distribution, and diversity of economic activity, services, and facilities within them, can be of great value in informing planning processes and shaping the direction of urban regeneration policies (Cranshaw et al., 2012; Noulas et al., 2013; Zhang et al., 2013). For instance, knowing the degree of functional specialization is useful when designing land-use strategies that guarantee the availability and diversity of urban activities in a neighborhood, thus encouraging residents to stay and support the livability of its urban spaces.

The main contribution of this paper to the state of the art is threefold:

- the use of *Google Places* data to define up-to-date functional divisions of the city
- the pre-processing and re-categorization of *Google Places* listings of economic activity into benchmark categories that allow an assessment at different degrees of granularity
- the capacity to identify a degree of specialization and complexity of urban activity (in terms of quantity and diversity) for each Functional Cluster.

The novelty of the proposed methodological framework lies in two aspects. First, it uses a social network that specifically includes information about places and urban activities "on offer." Therefore, a detailed listing of the available economic activities, services, and facilities in a given urban area can be obtained. Previous studies whose focus was to delineate urban functional areas using social media data have used more socially driven social networks that do not deal with the available urban activities in a place, but rather the demand for activities, that is, where people add a register on the particular social network (i.e., visit, tweet or check-in). For instance, the work of Cranshaw et al. (2012) that uses data retrieved from *Foursquare* and *Twitter*; and that of Chen et al. (2017:49) which collects datasets from *Tencent*, one of the "largest online social media platforms in China."

Second, the grouping of the original *Google Places* place types into the hierarchical APA categorization provides a degree of granularity that allows the assessment of the functional dimension at different scales. A more general Level 1 categorization could be used for regional scale analysis; the Level 2 is, as demonstrated in this study, useful for city scale assessment; and the Level 3 or its equivalent, *Google Places* place types, can be considered for conducting street, and even urban block-scale analysis. The first and third cases have not been fully explored, and as such are potential future directions for research.

To sum up, this paper broadens the debate on how to understand the neighborhood unit, based on today's urban functional reality. The study suggests that existing administrative boundaries are becoming increasingly obsolete and the use of social network data cannot be neglected in the present debate on neighborhood units.

Note

1. Script understood as a sequence of instructions carried out by another program.

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Acknowledgments

This work was supported by the Conselleria de Educación, Investigación, Cultura y Deporte, Generalitat Valenciana (Spain). Project: Valencian Community cities analyzed through Location-Based Social Networks and Web Services Data. Ref. no. AICO/2017/018.

Funding

This research was funded by Conselleria de Innovación, Universidades, Ciencia y Sociedad Digital, Generalitat Valenciana, Spain -(GV/2021/177).

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