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Cómo citar este artículo: SACRAMENTO GUTIERRES, F. R.; TORRENTE, A. O. & TORRENT-MORENO, M. y *Responsive Geographical Information Systems For Spatio-Temporal Analysis Of Mobile Networks In Barcelona* [en línea] Fecha de consulta: dd-mm-aa. En: ACE: Architecture, City and Environment, 14 (40): 163-192, 2019. DOI: http://dx.doi.org/10.5821/ace.14.40.5349 ISSN: 1886-4805.

ACE Architecture, City, and Environment
Arquitectura, Ciudad y Entorno

Journal of the Centre of Land Policy and Valuations | Polytechnic University of Catalonia and of The Thematic Network Architecture, City and Environment

RESPONSIVE GEOGRAPHICAL INFORMATION SYSTEMS FOR SPATIO-TEMPORAL ANALYSIS OF MOBILE NETWORKS IN BARCELONA

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Initial submission: 05-10-2017
Definitive remission: 06-12-2018
Initial acceptance: 26-01-2018
Definitive acceptance: 14-01-2019

Keywords: WebGIS; Responsive visualization; Open data; Smart Cities

Structured Abstract

Objective
This paper proposes a methodology for using mobile telephone network coverage data from the Mobile Coverage (GenCat) platform for detecting spatial and temporal patterns in multiple scales and at different geographical granularity levels (administrative and Urban Atlas classes). The paper outlines a Responsive Geographical Information Systems ("Responsive Mobile Coverage (RMC)") of a large number of point data of mobile networks integrating summarization techniques and dynamic visual models.

Methodology
For that purpose, an integrated framework of Exploratory Data Analysis (EDA) and GIS Cloud Computing is described and implemented using open source tools such as Jupyter (Python), ArcGIS Online and the ESRI Web AppBuilder for ArcGIS. The methodology was tested with data of Barcelona in August 2015.

Conclusions
The RMC framework presents capabilities to integrate additional information from the Catalonian Big Data landscape, and therefore, improve the access to Open data for public sector, private companies, citizens and scientists. The developed methods have potential for the definition and analysis of the distribution of aggregation indicators in cities, monitoring the precision of mobile networks in different administrative and urban contexts, and enabling citizens to make sense of such data for improving their scientific knowledge, daily life and fostering collective decision making.

Originality
The paper demonstrates that RMC can be a very useful tool for responsive visualization and improving different decision-making processes in Barcelona. We suggest an approach to data

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science, where the complete workflow takes place inside a Big Data paradigm, to produce reproducible results, using the best practices in scientific research.

1. Introduction

In recent years the increase in scale in traditional data sources due to global changes in Big Data Technologies, plus the explosion in the availability of sensor and mobile data resulted in massive volumes of data (Valls, 2019; Li *et al.,* 2016; Lee and Kang, 2015; Chen *et al.,* 2014). In the case of wireless communications implies the application of an efficient network planning of cellular mobile communication. Thus, the telecommunication network industry develop actions related to network site identification and planning, signal strength measurements with coverage estimation for the expansion of system.

Most of these data is locked into the digital vaults of corporations, where they configure the basis of their business intelligence strategy, and are therefore proprietary. However, from the study of the city standpoint, there are three valuable data sources worth mentioning which provide unprecedented amounts of machine-readable data for urban research and city planning: Open data, User-generated content and Internet of Things (IoT). In fact, the availability of Open Data Portal which gives access to open data, such as mobile coverage, enabling citizens to make sense of such data for improving their scientific knowledge, daily life and fostering collective decision making (Marras *et al.,* 2018). Currently, some cities willing to share their datasets in collaborative projects, such as the Mobile Coverage (GenCat) which consists in an initiative of the Government of Catalonia to create a map to provide information on the state of mobile telephone network coverage in Catalonia (Generalitat de Catalunya, 2018). The Mobile Coverage (GenCat) map allows to:

- provide users with a heatmap on which they can check the quality of mobile coverage in Catalonia of the four main operators (Movistar, Vodafone, Orange and Yoigo) and filter data according to the technology used (2G, 3G or 4G).
- identify the areas in Catalonia that need to improve their mobile coverage.
- help improve the efficiency of basic services for general public.
- create the Catalan Government's first crowdsourcing project.

The Mobile Coverage (GenCat) platform uses an android app to records citizens data through their mobile devices on the level of coverage per operator (2G, 3G and 4G) and the device's location, which are then used to draw up a map, available on both mobile phones and the website. This Mobile Map Viewer includes limited pre-defined use cases, which can only address the most common needs of citizens, but do not allow for interactive visualizations combining different data sources and visual models. In this sense, the use of an open source environment with Big Data capabilities can enable citizens to interactively explore the spatial-temporal patterns of this mobile coverage data. Thus, with Big Data Driven approaches is possible to perform an effective Exploratory Data Analysis (EDA) and also implement a Responsive geographical information systems (GIS) integrating summarization techniques and dynamic visual model to better explore the spatial and temporal data in multiple scales and at different geographical granularity levels (administrative and Urban Atlas classes for the Functional Urban Area (FUA) of Barcelona). There exists a quantity of literature in which space-time integration and quantitative methods for spatio-temporal data analysis have been facilitated and discussed (Kaewnoi *et al.,* 2016; Pucci *et al.,* 2015; Dijst, 2013; Long and Nelson, 2013; Goodchild, 2013; Richardson, 2013; Tranos *et al.,* 2013).

In short, very few existing studies present systematic spatio-temporal analytical frameworks and workflows for integrating emerging Big Data with Responsive GIS to guide urban knowledge discovery in practice (Ghahramani *et al.,* 2017, 2018; Marques *et al.,* 2017; Zhang and Thomas, 2016; Riera, 2013). Responsive geographical information systems (GIS) address the needs of the decision-maker working in a spatially oriented environment where data is regularly updated, where the data is often voluminous, incomplete, and noisy, and where timely and geographical decisions must be made. Such environments stretch the capabilities of traditional GIS.

Nowadays, there is the challenge of implement summarization capabilities and responsive visualizations of mobile point clouds, and on the cognitive side, there is the challenge of displaying a visualization that can be easily assimilated by the user. A summarization method will generalize the raw information, and generate a new dataset that is by definition smaller, and therefore easily consumed both by the visualization technology, and by the user. The challenge here is to choose a summarization technique that can preserve, as much as possible, the important traits of the original information. Therefore, with such data it would be of great significance to explore and understand how cities function in short-term temporal scales compared with traditional long-term strategic planning in the new era of Big Data (Batty, 2013).

The objective of this article is to develop a methodology for the spatial analysis and exploration of mobile phone data in a space-time context toward hotspot detection and mobile (statistical)-based indicators under a cloud computing framework. Our research questions are:

(1) How can we define and calculate meaningful spatial temporal indicators using point clouds of the Mobile Coverage (GenCat)?
(2) How can we measure and visualize the spatial differences of these indicators within different geographic granularity levels in Barcelona?
(3) How do these spatial-temporal indicators vary between districts, neighborhoods and urban classes of Barcelona?

In this paper, we propose an integrated framework (“Responsive Mobile Coverage (RMC)”) that enables citizens to explore and visualize the spatial-temporal patterns of Mobile Coverage (GenCat) and arrange them into an interactive dashboard. Our solution offers a Responsive Data Visualization of mobile (statistical) indicators within different geographical granularity levels. A back-end aggregator built upon state-of-the-art technologies provides unified access to heterogeneous data. On top of it, a front-end interface allows users to explore responsive visualizations.

This article is structured as follows: Section 2 describes the conceptual framework; the available data and research material; the methods for the Exploratory Data Analysis (EDA) of Mobile Coverage data; the exploratory spatial data analysis (Cluster and Outlier Detection and Hot and Cold Spots); Data aggregation and Responsive visualization system and its capabilities. Then Section 3 shows the results of EDA, Cluster and Outlier Detection, Hot and Cold Spots and the analysis and responsive visualization of the aggregation indicators. Section 4 depicts discussions and future directions. Finally, section 5 presents the main conclusions of the paper.

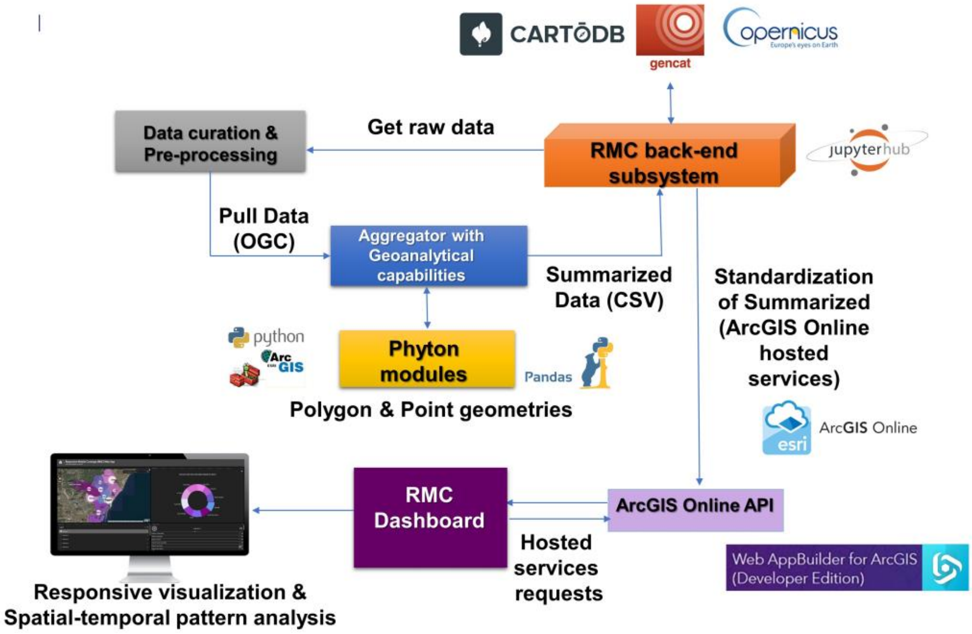
2. Material and Methods

2.1 Conceptual Framework

Recently, new technologies based on Cloud Computing have emerged to process and analyze a large volume of point cloud data. We present the framework "Responsive Mobile Coverage (RMC)" with an Exploratory Data Analysis (EDA) component and its analysis results. To prioritize different areas, detecting and summarize hotspots and mobile (statistical)-based in a fast and accurate way were implement a second component, Responsive GIS.

The framework RMC is composed of a back-end subsystem acting as data aggregator and manipulator, accompanied by a web-based frontend subsystem. The back-end corresponds to a web based platform, developed with Jupyter Nootbooks, to perform EDA based on to data curation, pre-processing, analysis of the data sets and to summarize their main characteristics, often with visual methods. The front-end enables citizens to leverage the data provided by the back-end, developed with the ArcGIS Online Cloud Computing platform, to visualize multiple responsive perspectives of the summarized information. Figure 1 depicts the architecture of the Cloud Computing framework.

Figure 1. **System architecture of the "Responsive Mobile Coverage (RMC)"**



Source: Eurecat (2019).

The data volume generated by mobile phones in Barcelona city and the need to analyze the information near the real-time are the challenges facing researchers. Three sets of data were obtained for analysis purposes: administrative data for Barcelona, mobile phone data in a specific format from Mobile Coverage (GenCat) application, and Urban Atlas. The data sets are described in Section 2.2. The purpose of this use case was to investigate suitability of mobile data to find spatial-temporal indicators and hotspots according different granularity levels using

Cloud Computing technologies. The first part of the analysis focused on EDA methods of mobile telephone data to explore visual models of the raw data, perform aggregations and hot spot analysis at different granularity levels. The final part of the approach explores the summarized spatial-temporal indicators, derived from EDA, with responsive visualization techniques.

2.2 Available data and research material

The information about the administrative levels (OGC shapefile provided by the CartoBCN, under CC BY 3.0.), the mobile data coverage (provided by the Open Data from the Generalitat de Catalunya, namely the CSV records collected by the Mobile Coverage (GenCat) application) and urban atlas (OGC shapefile provided by the Copernicus layers (Pan-European-Copernicus Land Monitoring Service) were processed and integrated in a GIS database according the Open Geospatial Consortium (OGC) standards considering the Coordinate Reference System (CRS) "ETRS89 / UTM zone 31N (EPSG:25831)". Therefore, for the development of the Exploratory Data Analysis (EDA) the OGC shapefiles were imported to Jupyter Notebook and converted to (geo)dataframes (using the python libraries "Pandas" and "Geopandas"). For the development of the "Responsive Mobile Coverage (RMC)" Web App, the shapefiles were imported to the ESRI Cloud system "ArcGIS Online" and stored as weblayers (ArcGIS Online hosted features and services).

A long-term data sharing and preservation plan was implemented to store and make publicly accessible the raw data, processed data and the RMC Web App. These files were integrated in the EDA platform and in the ESRI Cloud System as web services through the ArcGIS Online account of Eurecat - Technology Centre of Catalonia.

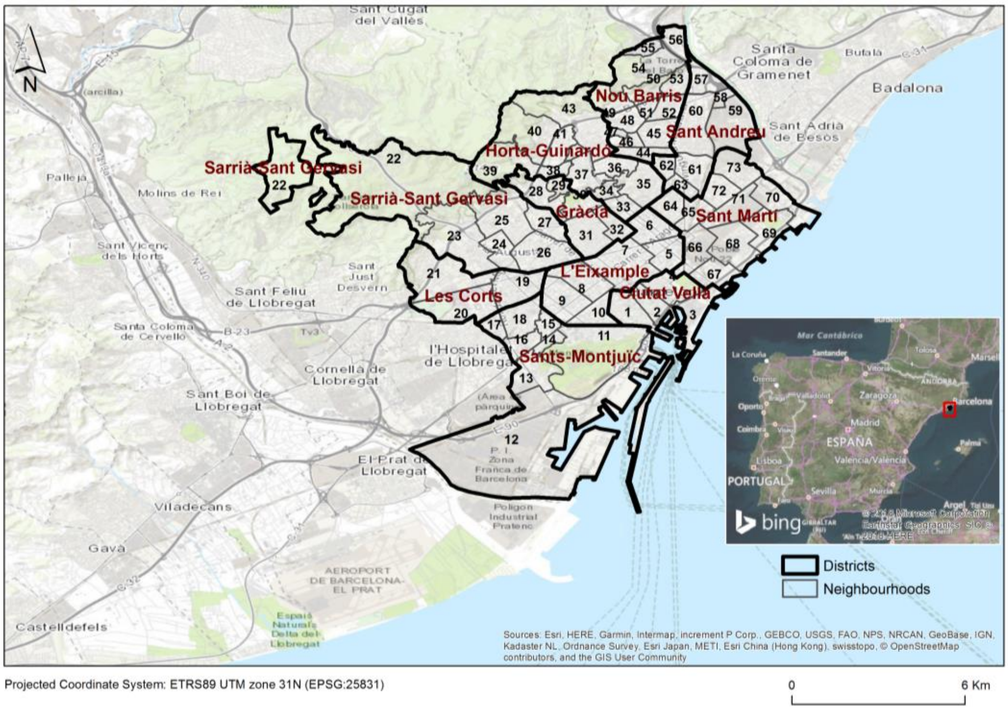
2.2.1 Administrative boundaries

The city of Barcelona is divided into 10 districts, each of them administered by a "regidor" (councilor), with powers in local issues such as urbanism, making these boundaries both administrative and political.

The current division was approved in 1984 and obeys to historic matters, being some of the districts former towns around the city of Barcelona (Demographia, 2017) incorporated in the 19th and 20th centuries. Since 2009, the districts are further divided into a total of 73 neighborhoods (Figure 2 and Table 1), whose delimitation obeys to different characters granted by their historic background, complementing without substituting the existing district division.

Since the neighborhoods and district boundaries obey to real differences in the character of the different units, they present the opportunity to study the distribution of the mobile data coverage phenomena with a high degree of confidence that are not biased by the modifiable areal unit problem (MAUP) (Openshaw, 1984; Gehlke and Biehl, 1934), which occurs when point observations are aggregated into arbitrarily defined units. In this sense, should be mentioned that he modifiable areal unit problem (MAUP) is a source of statistical bias that can significantly impact the results of statistical hypothesis tests. MAUP affects results when point-based measures of spatial phenomena are aggregated into districts, for example, population density or illness rates. The resulting summary values (e.g., totals, rates, proportions, densities) are influenced by both the shape and scale of the aggregation unit.

Figure 2. **Location map of Districts and Neighbourhoods of Barcelona**



Source: BingMaps, ESRI and CartoDB.

Table 1. **Districts and neighbourhoods of Barcelona**

Districts	Neighbourhoods
Ciutat Vella	El Raval (1), El Barri Gòtic (2), La Barceloneta (3), Sant Pere, Santa Caterina i la Ribera (4)
L'Eixample	Fort Pienc (5), Sagrada Família (6), Dreta de l'Eixample (7), L'Antiga Esquerra de l'Eixample (8), La Nova Esquerra de l'Eixample (9), Sant Antoni (10)
Sants-Montjuïc	El Poble-sec (11), La Marina del Prat Vermell (12), La Marina de Port (13), La Font de la Guatlla (14), Hostafrancs (15), La Bordeta (16), Sants-Badal (17), Sants (18)
Les Corts	Les Corts (19), La Maternitat i Sant Ramon (20), Pedralbes (21)
Sarrià-Sant Gervasi	Vallvidrera, el Tibidabo i les Planes (22), Sarrià (23), les Tres Torres (24), Sant Gervasi – la Bonanova (25), Sant Gervasi – Galvany (26), El Putget i Farró (27)
Gràcia	Vallcarca i els Penitents (28), El Coll (29), La Salut (30), Vila de Gràcia (31), Camp d'en Grassot i Gràcia Nova (32)
Horta-Guinardó	El Baix Guinardó (33), Can Baró (34), El Guinardó (35), La Font d'en Fargues (36), El Carmel (37), La Teixonera (38), Sant Genís dels Agudells (39), Montbau (40), Vall d'Hebron (41), La Clota (42), Horta (43)
Nou Barris	Vilapicina i la Torre Llobeta (44), Porta (45), El Turó de la Peira (46), Can Peguera (47), La Guineueta (48), Canyelles (49), Roquetes (50), Verdum (51), La Prosperitat (52), La Trinitat Nova (53), Torre Baró (54), Ciutat Meridiana (55), Vallbona (56)
Sant Andreu	Trinitat Vella (57), Baró de Viver (58), Bon Pastor (59), Sant Andreu de Palomar (60), La Sagrera (61), El Congrés i els Indians (62), Navas (63)
Sant Martí	El Camp de l'Arpa del Clot (64), El Clot (65), El Parc i la Llacuna del Poblenou (66), La Vila Olímpica del Poblenou (67), El Poblenou (68), Diagonal Mar i el Front Marítim del Poblenou (69), El Besòs i el Maresme (70), Provençals del Poblenou (71), Sant Martí de Provençals (72), La Verneda i la Pau (73)

Source: Wikipedia

2.2.2 Mobile phone data

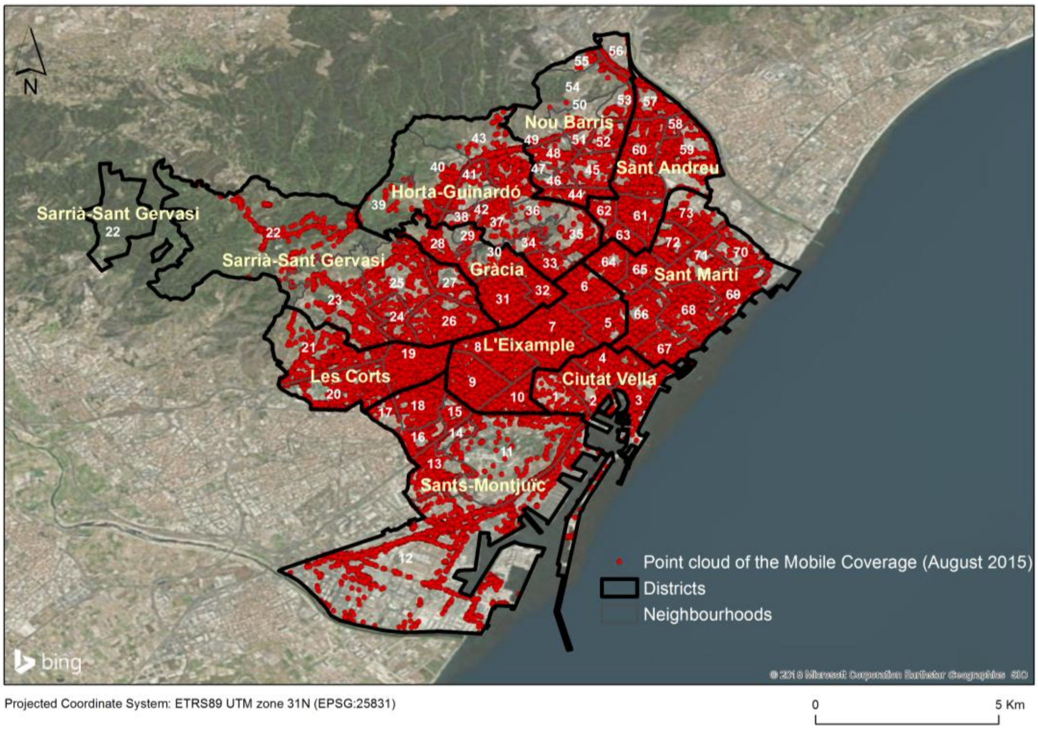
Mobile Coverage is an initiative of the Government of Catalonia to create a map to provide information on the state of mobile telephone network coverage in Catalonia. The map is drawn up with the help of users of mobile devices who have the app installed. These anonymous users record data on their position and the level of coverage the operator in that zone is providing, which is sent to a server.

The data is processed in such a way that it is impossible to identify the owner of the mobile device, their phone number or which device has supplied the information. The amalgamation of all the data from the different mobile devices that have the Mobile Coverage app installed will form a map which will be available on devices that use iOS and Android systems as well as on the Internet. On the map, users can consult:

- Their own measurements.
- All the measurements taken by participants in the initiative.

Users can also check the quality of coverage in particular areas of Catalonia according to their chosen operator (Movistar, Vodafone, Orange or Yoigo) and filter the data according to the technology used (2G, 3G or 4G). In this paper, was considered data of Mobile Coverage for August 2015 (total of 47364 records for the period 01/08/2015 until 31/08/2018) (Figures 3). The data only comprises precision (dBm), intensity of the signal information (minimum, average and maximum); timestamp, provider, network type (2G, 3G and 4G), latitude and longitude. The data does not contain information relating to voice call information or text messages (SMS).

Figure 3. **Distribution of Point clouds of the Mobile Coverage (GenCat) for August 2015**



Source: BingMaps and Generalitat de Catalunya (GenCat).

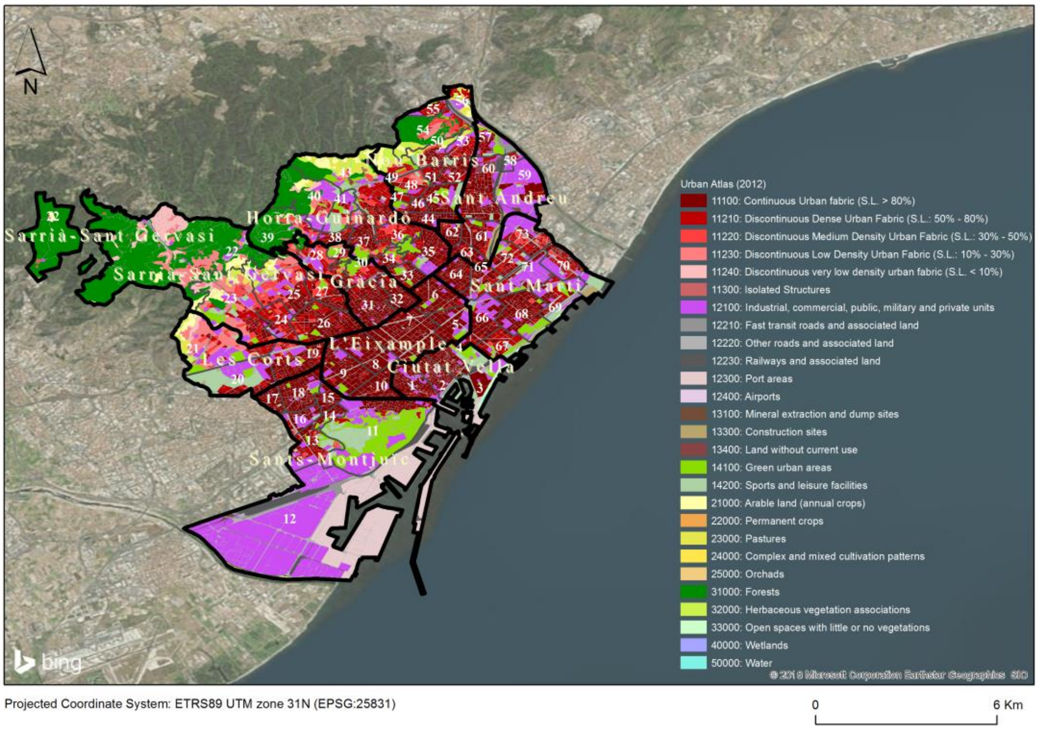
2.2.3 Urban Atlas

The Urban Atlas provides pan-European comparable land use and land cover data for Functional Urban Areas (FUA), which consists of a city plus its commuting zone. This is defined in the EU-OECD functional urban area definition (EU-OECD FUA) (OECD, 2013).

The Urban Atlas is a joint initiative of the European Commission Directorate-General for Regional and Urban Policy and the Directorate-General for Enterprise and Industry in the frame of the EU Copernicus programme with the support of the European Space Agency (ESA) and the European Environment Agency (EEA) (Copernicus Programme, 2018). The data set “Urban Atlas 2012” for the FUA “Barcelona City” includes a nomenclature with 17 urban classes with MMU 0.25 ha and 10 Rural Classes with MMU 1ha (Figure 4).

Regarding the periodicity of the official information, and to analyze the spatial temporal patterns of mobile coverage data (2015) within the urban classes (2012), we assumed that between the period 2012- 2015 the urban classes of the FUA of Barcelona are not as subject to significant transformations because they are not very dynamic processes.

Figure 4. **Urban classes included in the Functional Urban Areas (FUA) of Barcelona**



Source: BingMaps and Urban Atlas - Copernicus Land Monitoring Service.

2.3 Exploratory Data Analysis (EDA) of Mobile Coverage data

We have implemented some interactive exploratory spatial data analysis algorithms in Jupyter Notebook (Python 3) to better understand the characteristics of our dataset. In this procedure, we pre-processed the aforementioned data by combining, grouping, and rearranging our data to prepare input data for application of summarization techniques (data aggregation) and for integration in the responsive visualization tool. On the exploratory data analysis phase, we extracted visual models of spatio-temporal patterns of the precision and intensity of signal by mobile networks, network type (2G, 3G and 4G) and by the different granularity levels. Also the spatial nature of georeferenced mobile data should be considered in the exploratory analysis, namely the Cluster and Outlier Detection and Hot and Cold Spots. This kind of analysis aims to describe distributions, spatial autocorrelation, spatial data association (Hot and Cold spots), discovering trends, and identifying spatial outliers.

2.3.1 Exploratory spatial data analysis

Understanding the behavior of interacting systems is a long standing issue, including rapidly growing interest in dynamics of spatial-temporal events. Individual distribution often takes place in different patterns, i.e., gradients or clusters. These patterns are the geographic result of the interaction of different variables. We have implemented an interactive exploratory spatial data analysis algorithm (with ArcPy module of ArcGIS) to better understand the characteristics of our dataset. To identify important patterns and trends, and act upon the findings, data summarization through visualization should be implemented and some insight can be derived. In spatial analysis, for understanding the degree to which object is similar to other nearby objects, the correlation among different spatial objects needs to be defined. In this case, Moran's Index and other Local Indicators of Spatial Association (LISA) can be utilized to measure spatial correlations. Spatial autocorrelation describes the tendency of two objects nearer to each other along the time axis. It states that pairs of objects that are close to each other are more likely to be similar than pairs further apart. Consequently, the absence of autocorrelation implies the independence of data.

- *Cluster and Outlier Detection (Global Moran's I and Local Moran's I)*

The global spatial autocorrelation measures the clustering of values of a variable inside a geographical area, as the existence of zones of higher of lower values, such as the measurements of precision of mobile networks, that would be expected by chance alone (the null hypotheses is that values reveals a random distribution in space).

In spatial statistics, the global Moran's I (Moran, 1950) is commonly used as a measure of spatial autocorrelation, and describes the distribution of values in space in either dispersed (negative values) or clustered (positive values) usually in the range of -1 to 1, but normally transformed into z-scores. It is defined as follows:

$$I = \frac{N}{W}\,\frac{\sum i\ \sum j\, wij(xi-\bar{x})\ (xj-\bar{x})}{\sum i\,(xi-\bar{x})^2}$$

where:
N is the total number of features
i, j are the indices of the features
x is the studied variable
w is the spatial weights matrix, with zeroes in the diagonal
W is the sum of all elements of *w*

The results are extremely dependent on the choice of the spatial weights matrix (w), which can be binary and contain only ones and zeroes (contiguity, k-nearest neighbors) or the result of a distance decay function (where weights are assigned according to a defined measure of distance). Nevertheless, the global Moran's I assumes homogeneity and only describes the overall dispersion or clustering of the area of study in a single statistic. Then it is possible to find local clusters using local spatial autocorrelation.

According to Anselin (1995), the Local Indicators of Spatial Association (LISA) allows assess the clustering of each individual spatial unit (i), through the calculation of a local Moran's I for each of them, exploiting the fact that Moran's I is the sum of individual cross products:

$$Ii = \frac{(xi - \bar{x})}{Si^2} \sum_{j=1, j \neq i}^{n} wij\,(xj - \bar{x})$$

where the denominator expands to:

$$Si^2 = \frac{\sum_{j=1, j \neq i}^{n} (xj - \bar{x})^2}{N - 1}$$

The sign of the computed local Moran's I indicates if the value of the feature is related to its neighboring features, with positive local I values, and consequently belongs to a cluster of high or low values. On the other hand, if it is an outlier with unrelated values compared to its neighbors, we are in presence of negative local I values.

In this sense, the global Moran's I provides a single result for whole area of study. In contrast, the interpretation of the local I of a feature depends on three combined factors:

- The sign of the standardized value of interest.
- The sign of the standardized spatially lagged variable.
- The statistical significance of the result.

To assess whether the values of the variable of interest are higher or lower than the mean, the variable is standardized, with positive values indicating a relatively high value and negative values indicating a comparatively low value, in relation to the mean of the distribution.

The same process is applied to the spatially lagged variable, with high (positive) standardized values corresponding to high values of the neighboring features, on the other hand, low (negative) standardized values corresponding to low values in the neighboring features.

- High-High (HH) - Local spatial cluster of high values: high value features surrounded by other high value features in their neighborhood.
- Low-Low (LL) - Local spatial cluster of low values: low value features surrounded by other low value features in their neighborhood.
- High-Low (HL) - Local high spatial outlier: high value features surrounded by low value features in their neighborhood.
- Low-High (LH) - Local low spatial outlier: low value features surrounded by high value features in their neighborhood.

The statistical significance can be determined analytically from the z-scores (considering a normal distribution), or as in the case of the present paper, computing permutation-based pseudo p-values. Features with pseudo p-values above a threshold (in this case the standard 0.05 was chosen) were considered statistically non-significant and not included in any category.

The results of Observed General G statistic of spatial association, Expected General G statistic of spatial association, z-score, and p-value can be also inspected using a High-Low Clustering report.

- *Hot and Cold Spots (Local Getis-Ord's G*)*

Local G statistics of local spatial autocorrelation were introduced and developed by Getis and Ord (Getis and Ord, 1992; Ord and Getis, 1995) from the perspective of point pattern analysis. Their approach to quantifying spatial autocorrelation allowed a more general definition of spatial weights, respect the work of Moran (1950) and Geary (1954).

In the same way to local Moran's I statistics, local Getis-Ord G statistics can detect spatial clusters of high values (hot spots) and low values (cold spots). However, they cannot be used to identify local spatial outliers (features with values very different than values in their neighborhood). Thus, G-statistics are more useful when negative spatial correlation is in the area of study is not very frequent. When applied point patterns, G-statistics for a point feature were defined as the ratio between the number of observations within a distance of a point divided by total point count. When generalized to areal units, they focus on associations among (nonnegative) attributes of a feature and the attributes of features in its neighborhood (defined by the spatial weights matrix).

There are two versions of the G-statistic, which just vary in whether just the neighboring features are taken into account (Getis-Ord G) or the value of the feature is also included (Getis-Ord G *) when comparing the value of the feature to its spatial context. So, the G statistic for feature *i* is defined as the ratio of the weighted average of the values in the neighboring locations of *i*, to the sum of all values in the area of interest, excluding the value of feature *i*.

$$Gi = \frac{\sum_{j \neq i} wij\, xj}{\sum_{j \neq i} xj}$$

Likewise, the G* statistic for feature *i* is also defined as the same ratio, but including the value of feature *i* in both the numerator and denominator (which is constant across the calculations for all features).

$$Gi* = \frac{\sum_{j} wij\, xj}{\sum_{j} xj}$$

In both situations the neighborhood is defined by the spatial weights matrix *w*, which for spatial features is a sparse matrix which comprises mainly zeroes. The differences between both matrices are in the diagonal, which in the case of the G statistic is composed only of zeroes. After the calculation of the Getis-Ord G-statistics, its interpretation for any given feature depends on the combination of two factors:
- The sign of the statistic.
- The statistical significance of the result.

Therefore, positive values of the statistic indicates a hot spot (high-high cluster) of features with high values, while a negative value indicates a cold spot (low-low cluster) of features with low values. This interpretation is the same as in the Moran's I statistics, without the consideration of spatial outliers (HL or LH). As in the case of the local Moran's I, statistical inference can be determined analytically from the z-scores of the results (assuming a normal distribution), but because of its skewed distribution, it was based on pseudo p-values computed using conditional permutation. Features with pseudo p-values above a threshold (the standard value of 0.05) were deemed statistically non-significant and not considered in any category. Statistical significance was further categorized with the values under the thresholds of 0.05 (statistically significant), 0.01 (highly statistically significant) and 0.001 (very highly statistically significant).

In this sense, the Hot Spot Analysis script calculates the Getis-Ord G * statistic for each feature in the dataset. Statistically significant spatial clusters of high values (hot spots) and low values (cold spots) were identified in the studied area. The script identifies statistically significant geospatial hot and cold spots regardless of whether or not the False Discovery Rate (FDR) correction is applied. Features in the +/-3 bins reflect statistical significance with a 99 percent confidence level; features in the +/-2 bins reflect a 95 percent confidence level; features in the +/-1 bins reflect a 90 percent confidence level; and the clustering for features in bin 0 is not statistically significant. The higher (or lower) the z-score, indicates the intensity of the clustering. A high z-score and small p-value for a feature indicates a spatial clustering of high values of the variable "Precision". A low negative z-score and small p-value indicates a spatial clustering of low values of the variable "Precision". A z-score near zero indicates the absence of spatial clustering.

2.3.2 Data aggregation

We then computed the spatial-temporal information of precision and intensity of signal and Hot and Cold Spots, per districts, neighborhoods and urban classes of Barcelona. In order to study the spatial-temporal pattern of these variables by different granularity levels, we use thirteen aggregation indicators:

- Indicator 1 - Precision of the best of all mobile networks by district.
- Indicator 2 - Precision of the best of all mobile networks by Neighborhood.
- Indicator 3 - Measurements of the Orange network by granularity levels.
- Indicator 4 - Number of monthly occurrences per type of Network coverage (2G, 3G and 4G) per district.
- Indicator 5 - Number of monthly occurrences per type of Network coverage (2G, 3G and 4G) per Neighborhood.
- Indicator 6 - Number of monthly occurrences per type of Network coverage (2G, 3G and 4G) per Urban Atlas classes.
- Indicator 7 - Number of Cold Spot (99% Confidence) per Neighborhood.
- Indicator 8 - Number of Cold Spot (95% Confidence) per Neighborhood.
- Indicator 9 - Number of Cold Spot (90% Confidence) per Neighborhood.
- Indicator 10 - Number of Not Significant Spot per Neighborhood.
- Indicator 11 - Number of Hot Spot (90% Confidence) per Neighborhood.
- Indicator 12 - Number of Hot Spot (95% Confidence) per Neighborhood.
- Indicator 13 - Number of Hot Spot (99% Confidence) per Neighborhood.

2.4 Responsive visualization

The visualization runs in a responsive mode, showing the spatial temporal indicators between districts, neighborhoods and urban classes of Barcelona. The “Responsive Mobile Coverage (RMC)” Web App allows the user to interact with it by not only selecting different modes of display, but also visualizing data of any selected municipality.

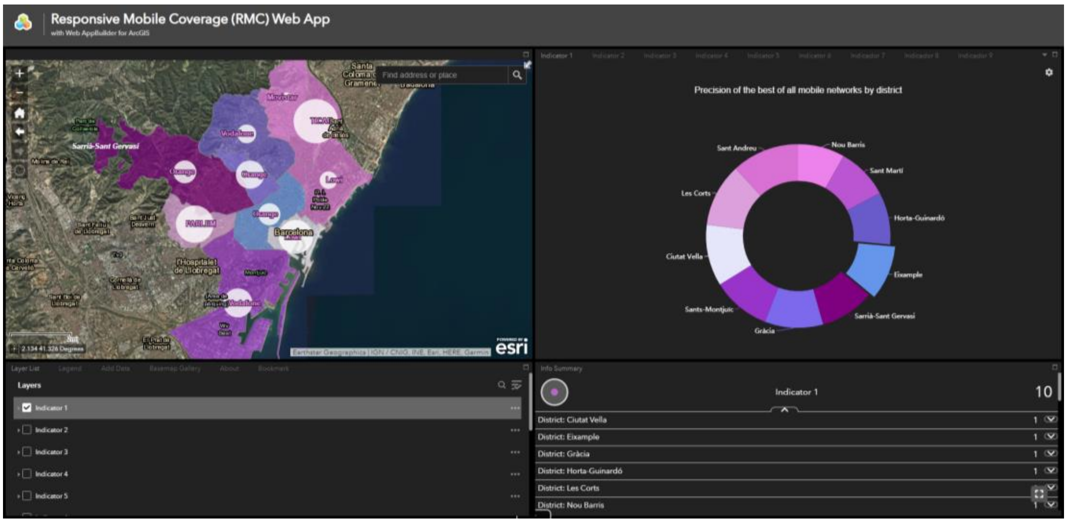
The visualization gives an overview of the dynamic of the indicators, which helps describe indicators of mobile coverage precision and signal quality at different granularity levels. It can also be useful for telecom operators for better informed planning and management, as well as for urban planners and researchers for exploratory behavioral analysis of the mobile coverage in Barcelona.

The RMC tool was developed with the ArcGIS Online Cloud Computing platform (Figure 5), namely with the Web AppBuilder for ArcGIS (Developer Edition). Therefore, the thirteen aggregation indicators can be exploited in the RMC through the following geospatial functionalities:

- *Layer List widget* - provides a list of operational layers and their symbols, and allows end users to turn individual layers on and off. Each layer in the list has a check box that allows end users to control its visibility.
- *Legend widget* - displays labels and symbols for the indicators layers in the RMC map (e.g. indicator 4).
- *Add Data widget* - enables end users to add data to the map by searching for layers in ArcGIS Online or Portal for ArcGIS content, entering URLs, or uploading local files. In this way, end users can temporarily add layers to and remove layers from the RMC map. This aspect will be discussed in the section 4.
- *Basemap Gallery widget* - presents a gallery of basemaps and allows end users to select one from the gallery as the basemap for session app.
- *About widget* - displays information’s about the “Responsive Mobile Coverage (RMC)” Web App.
- *Bookmark widget* - stores a collection of map view extents (that is, spatial bookmarks) displayed in the RMC app. It also allows end users to create and add spatial bookmarks.
- *Info Summary widget* - provide a count of features in the current map extent for each indicator specified. Each indicator in the widget panel can be expanded to show a list of features in the current extent, and some of them are grouped by a specified field (e.g. indicator 2).
- *Chart widget* - displays quantitative attributes of indicators as a graphical representation of data. It allows end users to observe possible patterns and trends out of indicators.

The Responsive Mobile Coverage (RMC) Web App is available at http://arcg.is/1C5znr.

Figure 5. **Responsive Mobile Coverage (RMC) Web App**



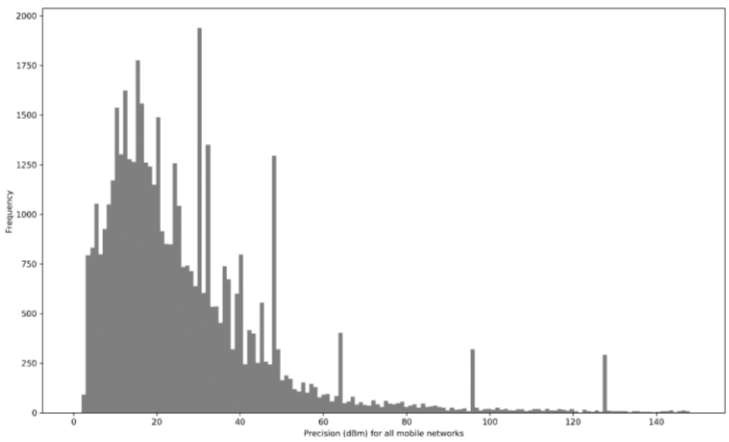
Source: ESRI and Eurecat (2019).

3. Results

3.1 Exploratory data analysis for finding patterns and trends in Mobile Coverage Data

In this section we present the results of the Exploratory data analysis (EDA) for the mobile coverage data set for August 2015, to detect the more relevant spatiotemporal patterns and trends of the variable "Precision". We can observe that the precision values vary from 0 to 149 dBm, where the majority of the values are concentrated in the range between 0 and 50 (Figure 6).

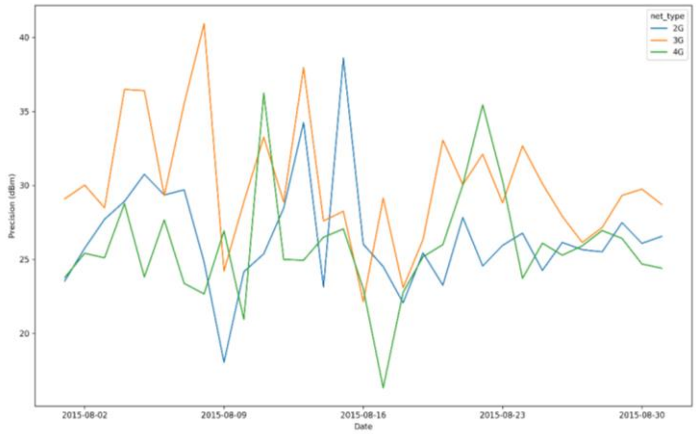
Figure 6. **Distribution of precision (dBm) for all mobile networks**



Source: Eurecat (2019).

Concerning the precision pattern by type of network (2G, 3G and 4G) we point out the presence of higher and more constant values for the 3G network during the month. The 2G and 4G exhibits a more irregular pattern with a relevant decrease of precision of 2G network at August 9 and a slightly increase of the precision of 2G at the middle of August. We also note a very evident decrease in the 4G in 16 August and also an increase of this network at 23 August (Figure 7).

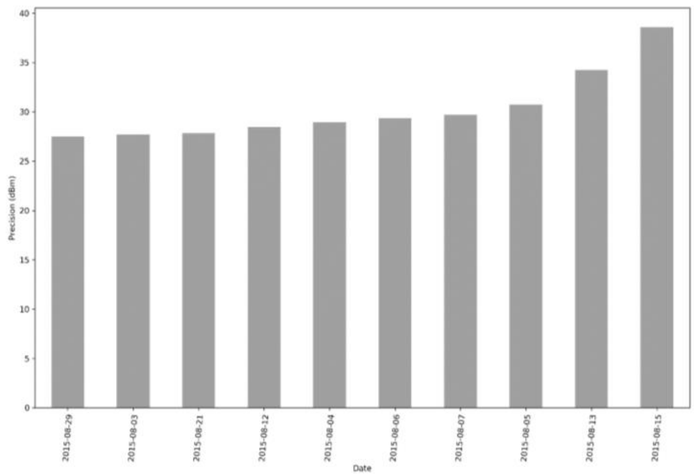
Figure 7. **Precision (dBm) of 2G, 3G and 4G network type during August 2015**



Source: Eurecat (2019).

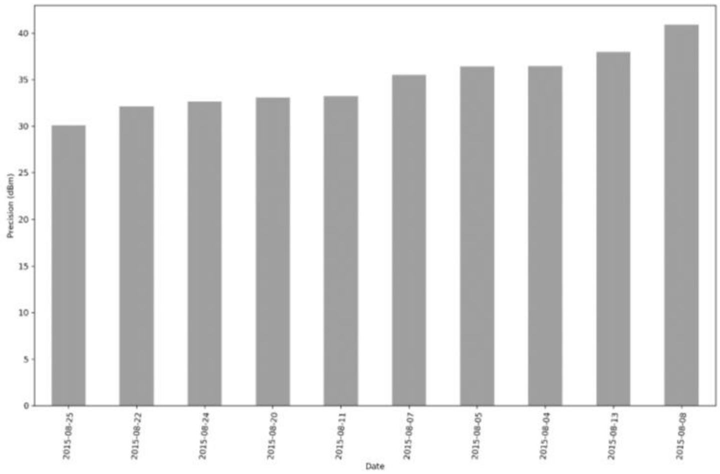
In figures 8, 9 and 10 we can be observed the top ten days with mean maximum precision for 2G, 3G and 4G networks. Therefore, for 2G the maximum value of precision is between 13 and 15 August. In the case of 3G network the maximum value of precision occurred in 8 August. Finally, in 11 August we can observe the maximum value for 4G network.

Figure 8. **Top ten days with mean maximum precision (dBm) for 2G network**



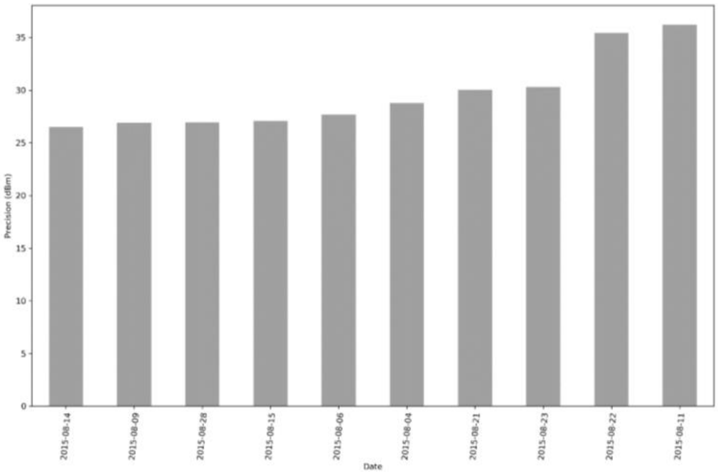
Source: Eurecat (2019).

Figure 9. **Top ten days with mean maximum precision (dBm) for 3G network**



Source: Eurecat (2019).

Figure 10. **Top ten days with mean maximum precision (dBm) for 4G network**

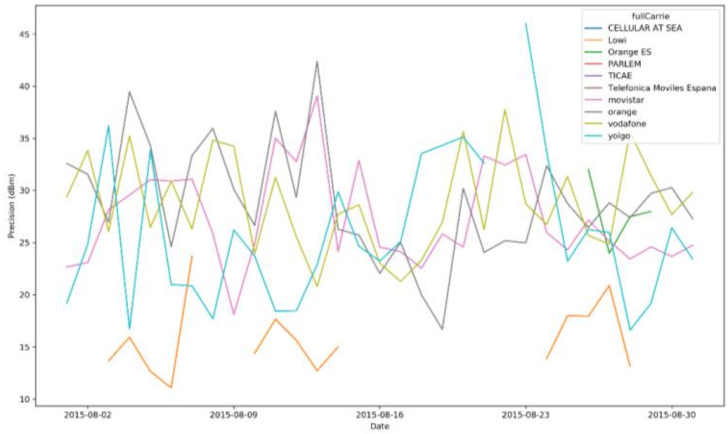


Source: Eurecat (2019).

In terms of precision by mobile provider (carrier) we highlight the higher values for Orange, Movistar and Vodafone (Figure 11). Yoigo presents an irregular pattern throughout the month, with many rises and falls in accuracy values. Orange and Movistar reaches peak levels on 13 August; and Vodafone on 22 August.

Finally, the analysis of the precision levels for all mobile networks by district and neighborhood levels can be found in indicators 1, 2 and 3. Also the number of monthly occurrences per type of network coverage (2G, 3G and 4G) per district, neighborhood and Urban Atlas classes can be explored in indicators 4, 5 and 6 (see section 3.4.).

Figure 11. **Precision (dBm) of mobile network operators**

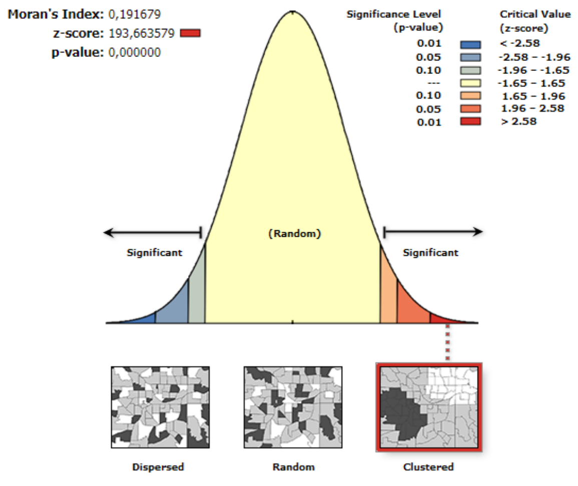


Source: Eurecat (2019).

3.2 Cluster and Outlier Detection (Global Moran's I and Local Moran's I)

Concerning the Spatial Autocorrelation analysis based on the variable "Precision", we obtained a Global Moran's I Index of 0.19 which indicates a distribution of clustered values in space (Figure 12). Given the z-score of 193.66, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

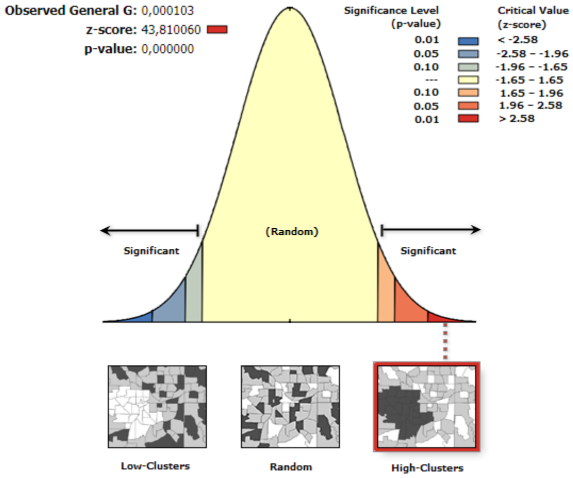
Figure 12. **Spatial Autocorrelation report of the Mobile Coverage data**



Source: Eurecat (2019).

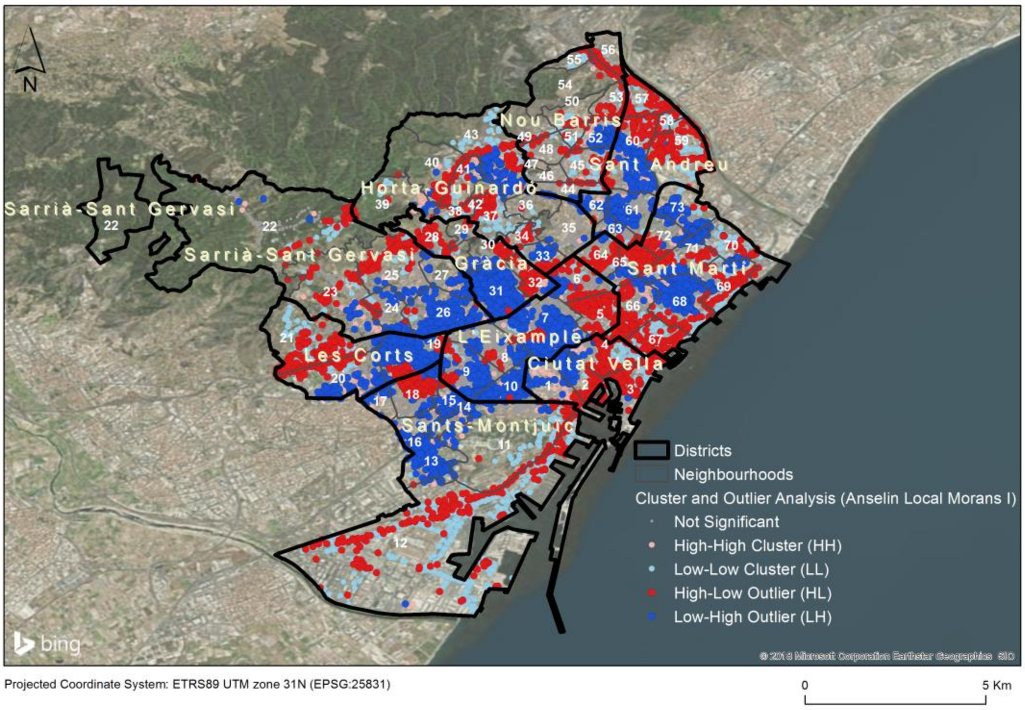
Considering the Local Indicators of Spatial Association (LISA), we obtained an Observed General G of 0.000103. Given the z-score of 43.81, there is a less than 1% likelihook that this high-clustered pattern could be the result of random chance (Figure 13). Therefore, we observed a prevalence of High-Clusters with statistical significance, namely: High-High Cluster (7943), High-Low Outlier (3077), Low-Low Cluster (12092) and Low-High Outlier (5948) (Figure 14).

Figure 13. **High-Low Clustering report of the Mobile Coverage data**



Source: Eurecat (2019)

Figure 14. **Cluster and Outlier Detection (Global Moran's I and Local Moran's I)**



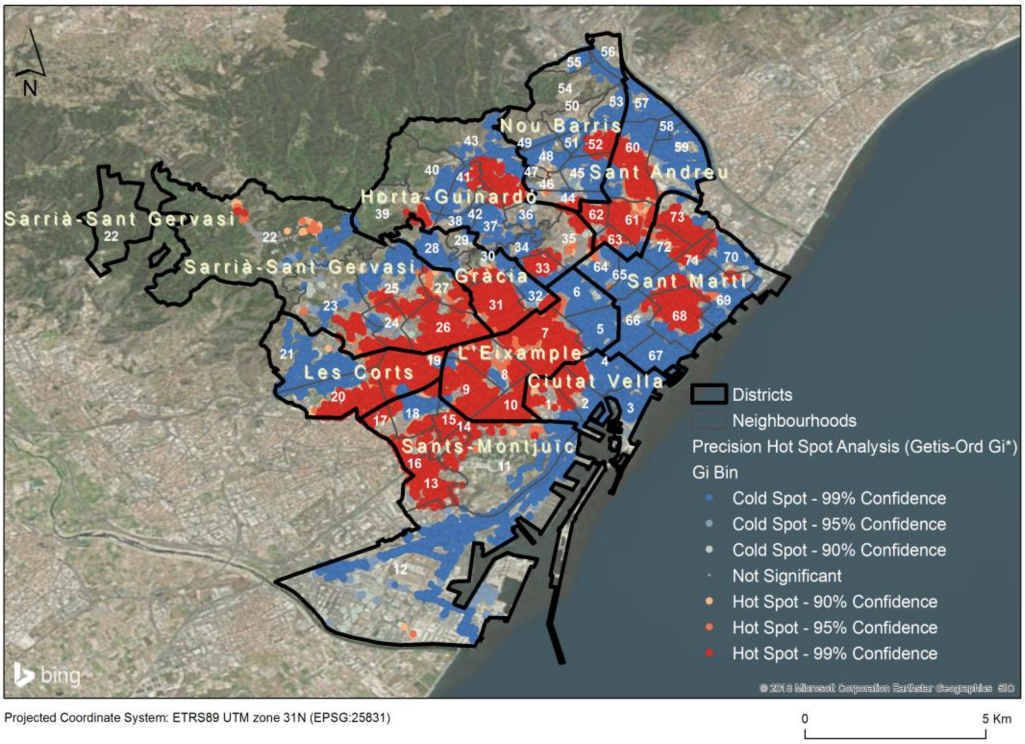
Source: Bingmaps and Eurecat.

Local Moran's spatial clusters of high intensity (red) and low intensity (blue), as well of high (intense red) and low (intense blue) spatial outliers. Statistical significance determined using permutation-based pseudo p-values (999 permutations), with a threshold of p' < 0.05.

3.3 Hot and Cold Spots (Local Getis-Ord's G*)

In the resulting map for the point data retrieved from Mobile Coverage (Figure 15), the Getis-Ord G* statistic was capable of isolating clusters of hot and cold spots. However, in contrast with the Moran's I map (Figure 14), their Getis-Ord G* counterparts provide a clearer measure of statistical significance, visualized with a diverging color scale with darker and more saturated hues corresponding to the higher significance levels.

Figure 15. **Hot and Cold Spots (Local Getis-Ord's G*)**



Source: Bingmaps and Eurecat (2019b).

Local Getis-Ord G* spatial clusters of high intensity (red) and low intensity (blue) with darker and more saturated hues corresponding to the higher statistical significance levels. Statistical significance determined using permutation-based pseudo p-values (999 permutations), with a threshold of $p' < 0.05$.

Thus, the analysis of number of Hotspots and Cold Spots (with different confidence intervals) per neighborhood (see indicators 7-13) can be further explored in section 3.4.

3.4 Analysis and responsive visualization of the aggregation indicators

Indicator 1 - Precision of the best of all mobile networks by district

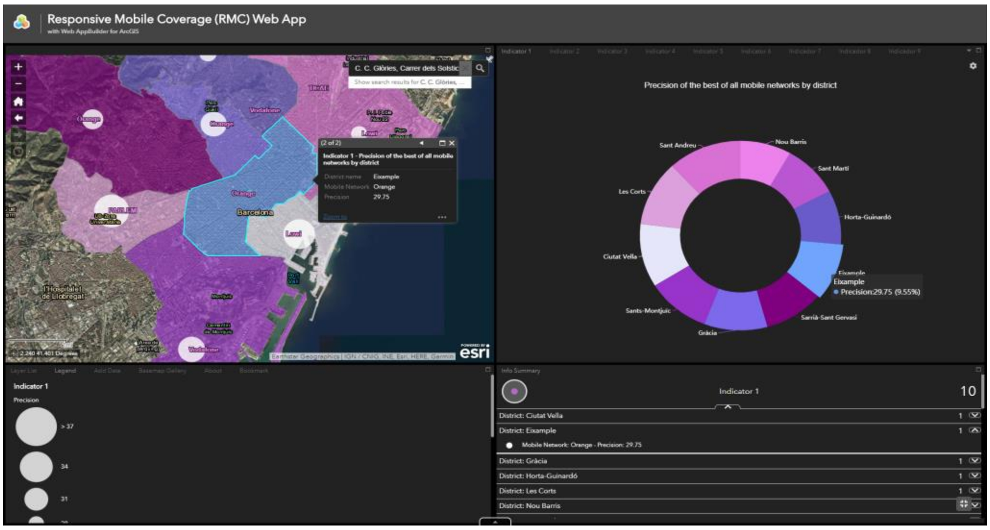
In the analysis of mobile network precision by district, we highlight that in Sant Andreu the 'Ticae' network presents the highest value (37 dBm); followed by the 'Parlem' network in

Les Corts (35 dBm); 'Lowi' in Ciutat Vella (34 dBm) and Sant Martí (28 dBm); 'Vodafone' in Sants-Montjuïc (32 dBm) and Horta-Guinardó (29 dBm); 'Orange' in the districts of Gràcia (32 dBm), Sarrià-Sant Gervasi and L'Eixample (both with 30 dBm); and finally 'Movistar' in Nou Barris with a precison value of 32 dBm.

In the specific case of the precision of the Orange network we can observe that the highest values occurred in the districts of Gràcia (32.2 dBm), Sant Andreu (30.9 dBm) and Sarrià-Sant Gervasi (30.5 dBm); while in districts of Nou Barris (25.3 dBm), Horta-Guinardó (25.9 dBm) and Ciutat Vella (26.5 dBm) the lowest values of accuracy are found.

The values of this indicator can be interactively explored and visualized in the RMC Web App (Figure 16).

Figure 16. **Responsive visualization of indicator 1 in the RMC Web App**



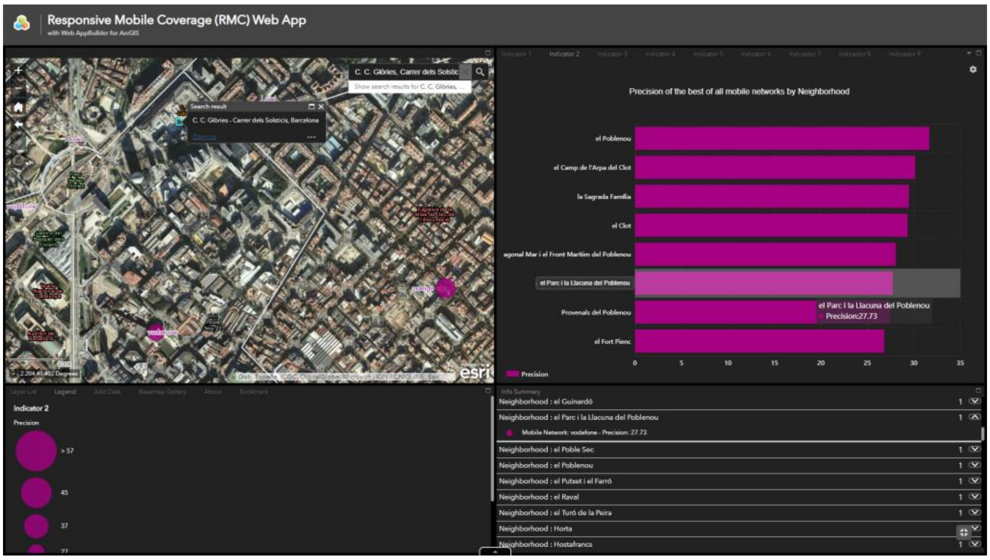
Source: ESRI and Eurecat (2019a).

<u>Indicator 2 - Precision of the best of all mobile networks by Neighborhood</u>

In the analysis of mobile network precision by neighborhoods, we highlight that the Orange network is the most represented at this granularity level (presented in 27 neighborhoods), followed by Lowi (17) and Movistar (9). However, 'Lowi' presents the highest values of precision in the ranking list of neighborhoods: Sants-Badal (17) with 57 dBm and La Barceloneta (3), Sant Pere, Santa Caterina i la Ribera (4) and La Vila Olímpica del Poblenou (67) all with 48 dBm. On the other hand, 'Lowi' also presents lowest values of precision in the neighborhoods of La Trinitat Nova (53) with 22 dBm and Trinitat Vella (57) with 20 dBm.

The values of this indicator can be also interactively explored and visualized in the RMC Web App (Figure 17).

Figure 17. **Responsive visualization of indicator 2 in the RMC Web App**



Source: ESRI and Eurecat (2019a).

Indicator 3 - Measurements of the Orange network by granularity levels

This indicator allowed to verify the highest levels of signal (minimum, medium and maximum) and of precision of the Orange network in the different levels of granularity (district, neighborhood and classes of urban atlas). In La Sagrera (61) the higher value of precision (146 dBm), for a maximum signal of 19 dBm, occurs in the class ‘Railways and associated land’. In the case of Vila de Gràcia (31) the precision of 124 dBm for a minimum, maximum and average signal of 2 dBm occurs in the class of ‘Industrial, commercial, public, military and private units’. Interestingly, for the neighborhoods of Diagonal Mar i el Front Marítim del Poblenou (69) and El Besòs i el Maresme (70) the highest value of precision (105 dBm) occur in the class of ‘Construction sites’. The lowest values of precision occur at the level of ‘Other roads and associated land’ in the neighborhoods of La Font d'en Fargues (36), Canyelles (49), La Prosperitat (52) and Vallbona (56).

The values of this indicator can be interactively explored and visualized in the RMC Web App (Figure 18).

Indicator 4 - Number of monthly occurrences per type of Network coverage (2G, 3G and 4G) per district

In the analysis of number of occurrences of type of network coverage by district, we highlight that in Sant Martí presents the highest values for 2G (4120), 3G (7182) and 4G (7235, the maximum value for all network types); followed by the district of Eixample with 4280 occurrences for 2G type (higher than in Sant Martí), 6783 occurrences for 3G and 6407 occurrences for 4G (both lower than in Sant Martí).

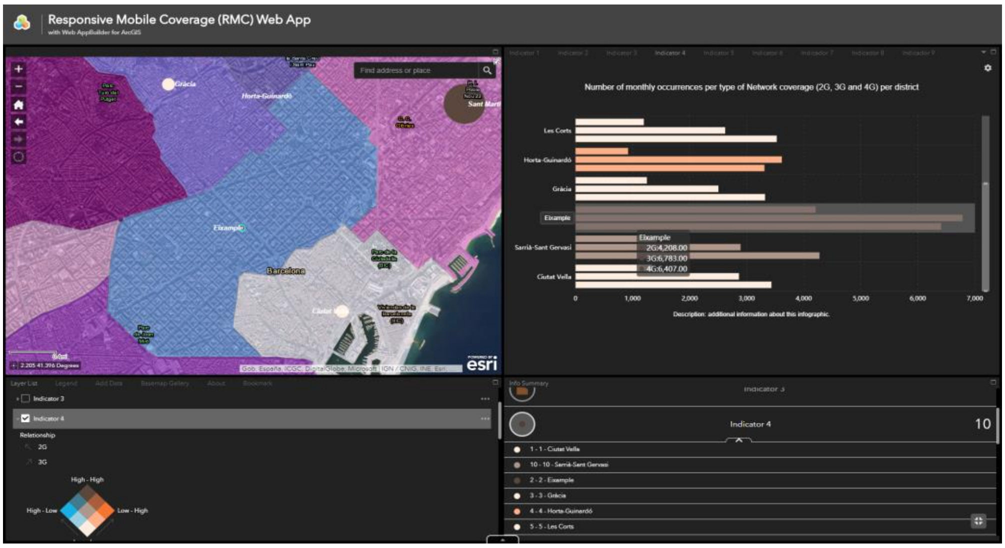
On the other hand, the minimum values for 2G type occurs in the district of Horta-Guinardó (with 921 presences), for 3G type in the district of Nou Barris with 2494 and for 4G type in Sant Andreu with 2670 occurences.

The values of this indicator can be interactively explored and visualized in the RMC Web App (Figure 19).

Figure 18. **Responsive visualization of indicator 3 in the RMC Web App**

Source: ESRI and Eurecat (2019a).

Figure 19. **Responsive visualization of indicator 4 in the RMC Web App**



Source: Eurecat (2019)

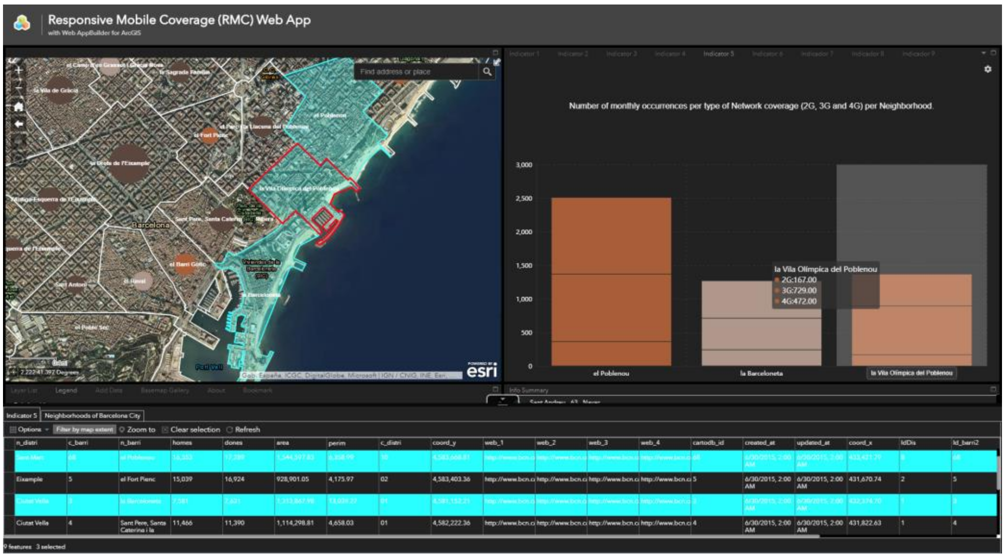
Indicator 5 - Number of monthly occurrences per type of Network coverage (2G, 3G and 4G) per Neighborhood

In the analysis of number of occurrences of type of network coverage by neighborhood, we highlight that in Dreta de l'Eixample (7) the highest values for all network types, namely 2G with 1198, 3G with 1865 and 4G with 2109 occurrences. In terms of 4G the neighborhoods of Les Corts (19) and Vila de Gràcia (31) also presents high values, with 1613 and 1400 occurrences, respectively. Concerning the 3G network, such as the Dreta de l'Eixample (7), the neighborhoods of La Nova Esquerra de l'Eixample (9) and El Parc i la Llacuna del Poblenou (66) presents a very representative value (1269 and 1229). For the 2G network the neighborhoods of Bon Pastor (59) and La Nova Esquerra de l'Eixample (9) presents significant values (908 and 839, respectively), despite being lower than in Dreta de l'Eixample (7).

On the other hand, the minimum values for 3G and 4G occurs in the neighborhood of Ciutat Meridiana (55) (with 47 and 39 occurrences, respectively) and for 2G in the neighborhood of La Clota (42) with 26 occurrences.

The values of this indicator can be interactively explored and visualized in the RMC Web App (Figure 20).

Figure 20. **Responsive visualization of indicator 5 in the RMC Web App**



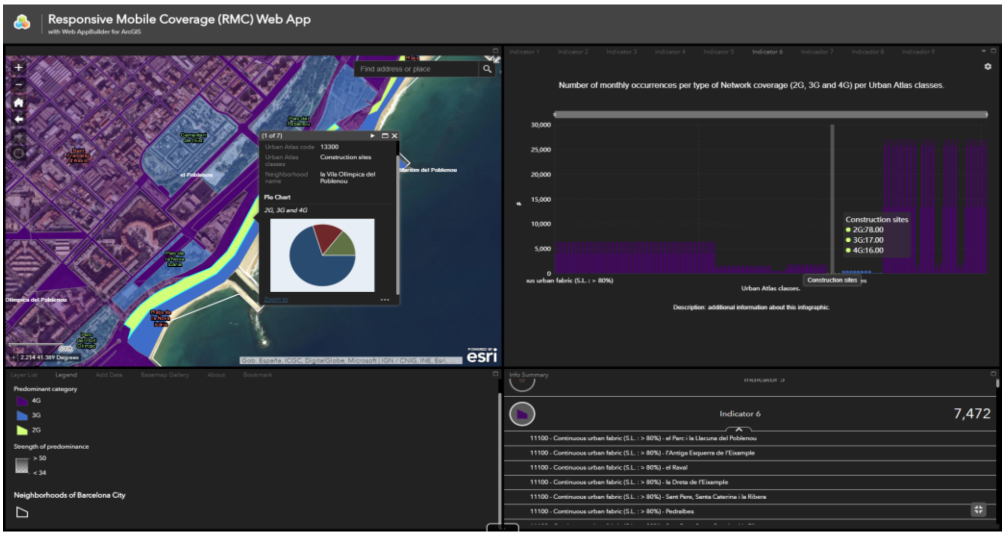
Source: ESRI and Eurecat (2019).

Indicator 6 - Number of monthly occurrences per type of Network coverage (2G, 3G and 4G) per Urban Atlas classes

In the analysis of number of occurrences of type of network coverage by Urban Atlas classes, we highlight that in the class ‘Other roads and associated land (code 12220)’ the highest values for all network types, namely 2G with 13368, 3G with 25754 and 4G with 27014 occurrences. In terms of 4G the classes ‘Continuous urban fabric (S.L.: > 80%) (code 11100)’ and ‘Fast transit roads and associated land (code 12210’ also presents high values, with 6486 and 2154 occurrences, respectively. Concerning the 3G network, such as the class ‘Other roads and associated land (code 12220)’ with 25754, the classes ‘Continuous urban fabric (S.L.: > 80%) (code 11100)’ and ‘Industrial, commercial, public, military and private units (code 12100)’ presents a very representative values (6223 and 1712, respectively). The 2G network presents a similar pattern of 3G, the classes ‘Continuous urban fabric (S.L.: > 80%) (code 11100)’ and ‘Industrial, commercial, public, military and private units (code 12100)’, and also presents a very representative value (3984 and 1078, respectively). On the other hand, the minimum values for 2G occurs in the classes ‘Land without current use (code 13400) with 17 and ‘Isolated structures (code 11300) with null occurrences. For the 3G, the classes ‘Herbaceous vegetation associations (natural grassland, moors...) (code 32000) also presents null value. Finally, in the case of the network 4G type, the minimum value of 1 occurs in the class ‘Isolated structures (code 11300).

The values of this indicator can be interactively explored and visualized in the RMC Web App (Figure 21).

Figure 21. **Responsive visualization of indicator 6 in the RMC Web App**



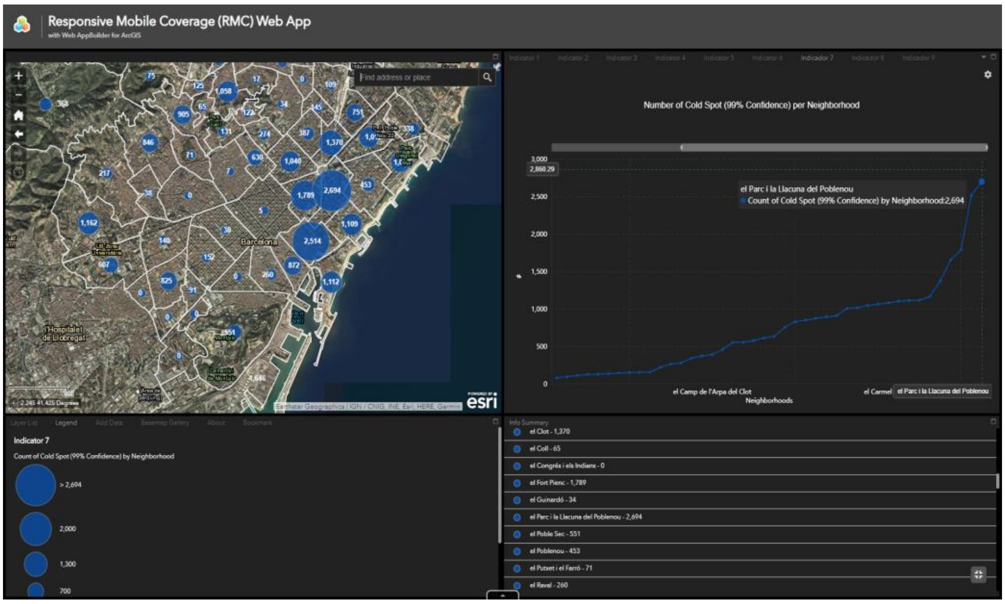
Source: ESRI and Eurecat (2019).

<u>Indicator 7, 8, 9 - Number of Cold Spot (99%, 95%, 90% Confidence) per Neighborhood</u>

The analysis of Coldspots with 99% Confidence level revealed the Neighborhoods of El Parc i la Llacuna del Poblenou (66) with 2694, Sant Pere, Santa Caterina i la Ribera (4) with 2514, Fort Pienc (5) with 1789, La Marina del Prat Vermell (12) (1646) and El Clot (65) with 1370 are the most representative neighborhoods of Cold Spot (99% Confidence) (indicator 7). On the other hand, the neighborhoods of Sant Antoni (10), La Marina de Port (13), La Font de la Guatlla (14), La Bordeta (16), Sants-Badal (17), Sant Gervasi – Galvany (26), El Congrés i els Indians (62) do not have any coldspot hotspot ocurrence.

The values of the indicator 7 (but also the indicators 8 and 9) can be interactively explored and visualized in the RMC Web App (Figure 22).

Figure 22. **Responsive visualization of indicator 7 in the RMC Web App**



Source: ESRI and Eurecat (2019).

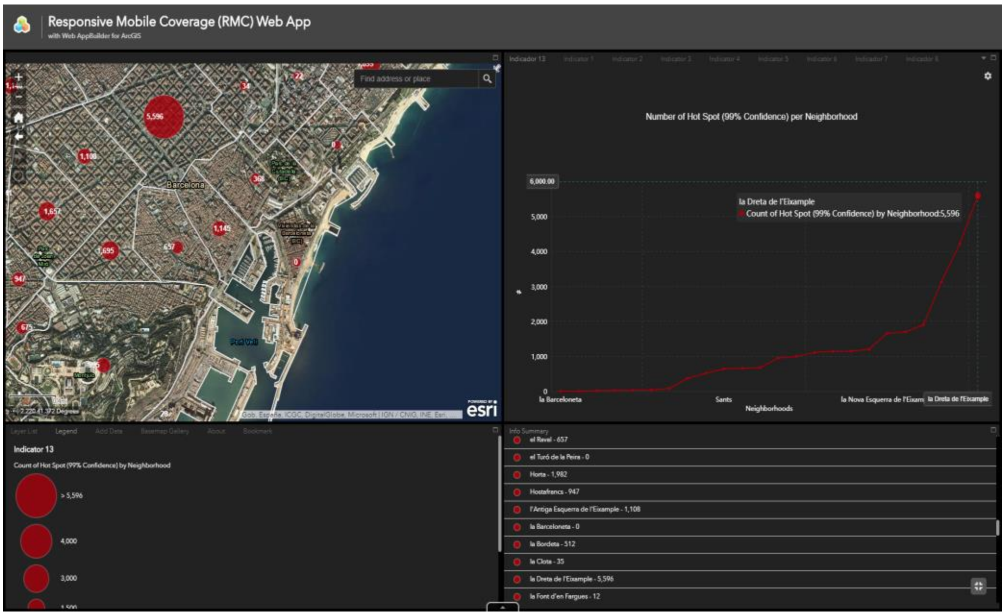
In the analysis of the distribution of hotspots at the level of the neighborhood of Barcelona we must emphasize that the Dreta de l'Eixample (7) (5596), Les Corts (19) (4217), Vila de Gràcia (31) (3136), Horta (43) (1982) and La Verneda i la Pau (73) (1935) have a higher number of hotspot occurrences. On the other hand, the neighborhoods of La Barceloneta (3), El Coll (29), La Teixonera (38), Montbau (40), El Turó de la Peira (46), Can Peguera (47), La Guineueta (48), Canyelles (49), Roquetes (50), Verdum (51), La Trinitat Nova (53), Torre Baró (54), Ciutat Meridiana (55), Vallbona (56), Trinitat Vella (57), Baró de Viver (58), El Camp de l'Arpa del Clot (64), El Clot (65) and La Vila Olímpica del Poblenou (67) do not have any hotspot ocurrence.

<u>Indicator 11, 12, 13 - Number of Hot Spot (90%, 95%, 99% Confidence) per Neighborhood</u>

The values of the indicator 11 (but also the indicators 12 and 13) can be interactively explored and visualized in the RMC Web App (Figure 23). (31) (3136), Horta (43) (1982) and La Verneda i la Pau (73) (1935) have a higher number of hotspot occurrences. On the other hand, the neighborhoods of La Barceloneta (3), El Coll (29), La Teixonera (38), Montbau (40), El Turó de la Peira (46), Can Peguera (47), La Guineueta (48), Canyelles (49), Roquetes (50), Verdum (51), La Trinitat Nova (53), Torre Baró (54), Ciutat Meridiana (55), Vallbona (56), Trinitat Vella (57), Baró de Viver (58), El Camp de l'Arpa del Clot (64), El Clot (65) and La Vila Olímpica del Poblenou (67) do not have any hotspot ocurrence.

The values of the indicator 11 (but also the indicators 12 and 13) can be interactively explored and visualized in the RMC Web App (Figure 23).

Figure 23. **Responsive visualization of indicator 13 in the RMC Web App**



Source: ESRI and Eurecat.

4. Discussion and future developments

The use of classical GIS applications which are mostly too expensive, need a significant knowledge of geography and cartography concepts, spatial analysis and geoprocessing methods, and manipulation and programming techniques of Big data datasets to deliver interactive maps, responsive visual models and provide complex spatial analysis functionalities to the end users. It is crucial to adopt an adequate workflow to handle this abundance of data and transform it into knowledge, otherwise we will be data-rich but information-poor.

So by means of the present “RMC” web app solution, expert and non-expert users from anywhere do not need to install expensive GIS software in their machine to get spatial information, interactive maps and responsive visual models. This interface allows to request a service, which includes geospatial data and different responsive tools for spatial analyses. Besides, by the relative richness of the interface contents, it can replace the desktop GIS software, and users can have access to spatial-temporal mobile phone Open data and city information of Barcelona (by administrative and Urban Atlas classes for the Functional Urban Area (FUA), and be more informed, which increase the ability to participate in territorial development and decision making.

In this sense, to understand the precision of mobile phone in a dynamic spatial interaction structure, were introduced summarization techniques, which also supports interactive analysis of spatial information and thematic attributes, such as their relations with administrative and Urban Atlas classes of Barcelona. It demonstrated that RMC is a very effective technology for integration multi-source spatial data and to support investigation and exploration information of Open Data Portal from the Generalitat de Catalunya. Thus, the RMC features can turn out useful to citizens and scientists, for their scientific investigation related to spatio-temporal analytics of aggregated indicators, in particular hotspots and cold spots of mobile data networks.

In addition, the technological solutions presented in this study could be used as an efficient method to running GIS services and applications in the Cloud. The ArcGIS Online Cloud is an ideal environment for developing and deploying applications built on Web AppBuilder for ArcGIS and provides virtually unlimited computing power for intensive GIS analyses, spatial data processing and data sharing. Using ArcGIS Online and the Web AppBuilder for ArcGIS ArcGIS users can use, manage, and distribute GIS services over the Web to support desktop, mobile and web mapping applications.

Furthermore, the developed Responsive Geographical Information System revealed be an ideal tool to facilitate the integration and analysis of other Open Data, and encourage public participation in city urban planning of Barcelona. Finally, it would be very useful to apply the RMC framework to other small and medium Spanish cities.

5. Conclusions

The RMC provides a low cost and an efficient way to deliver Open Data, interactive maps and responsive visual models to the citizens and scientists. The developed methods have potential for measuring the distribution of aggregation indicators in cities, monitoring the precision of mobile networks in different urban contexts, and enabling citizens to make sense of such data for improving their scientific knowledge, daily life and fostering collective decision making.

The RMC framework also presents capabilities to integrate additional information from the Catalonian Big Data landscape, and therefore, improve the access to Open data for public sector, private companies, citizens and scientists. It considers aspects of data organization, harmonization, sharing as well as semantic and technical interoperability to produce seamless geospatial information and improve the data access for a wide community of different user groups.

The study demonstrates that RMC can be a very useful tool for responsive visualization and improving different decision-making processes in Barcelona. We suggest an approach to data science, where the complete workflow takes place inside a Big Data paradigm, to produce reproducible results, using the best practices in scientific research.

Acknowledgements

This research was carried out within the framework of the research project “Responsive and Augmented Geovisualization of Large Point Clouds (ReViz)”, funded by Eurecat. Ref: PDC 2016.

Author's contributions: The work has been developed and written by both co-authors in a joint and integrated manner.

Conflict of Interest: The authors declare no conflict of interests.

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