Geoportal for electoral geomarketing to detect microzones with potential voters in an urban area

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Geoportal de geomarketing electoral para la detección de microzonas con potenciales votantes en área urbana

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Abstract

This paper presents a methodology for performing electoral geomarketing to identify potential voters from each political party and to understand their characteristics. Such information can be useful for optimizing the resources of a political party when preparing the election campaign. In this paper, a statistical study is conducted to analyze the relationship between electoral data and several socio-demographic, dependence, migratory, economic, and educational variables. A geoportal, called GeoChess (https://upvusig.car.upv.es/geochess/) is used to create all the thematic maps, graphs, and the majority of statistical studies. The geoportal permits visualization of the thematic maps and graphs shown in this work.

Resumen

En este trabajo se presenta una metodología para realizar geomarketing electoral que permita identificar a los potenciales votantes de cada partido político y conocer sus características. Esta información puede resultar útil para optimizar los recursos de un partido político al preparar la campaña electoral. Se realiza un estudio estadístico para analizar la relación entre los datos electorales y diversas variables sociodemográficas, de dependencia, migratorias, económicas y educativas. Se utiliza un geoportal, llamado GeoChess (https://upvusig.car.upv.es/geochess/) para crear todos los mapas temáticos, gráficos y la mayoría de estudios estadísticos. El geoportal permite visualizar los mapas y gráficos temáticos que se muestran en este estudio.

Keywords: Geomarketing; geospatial database; geoportal; potential voters; socio-demographic variables; multivariate analysis

Palabras clave: Geomarketing; base de datos geoespacial; geoportal; votantes potenciales; variables sociodemográficas; analisis multivariable

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1. INTRODUCTION

Marketing has been completely revolutionized since the last quarter of the 20th century. Marketing strategies applied to geolocalized data, known as geomarketing, are used to determine the best marketing strategies according to the exact location of customers, points of sale, and other relevant factors (Banos, Wandosell, & Concepcion Parra, 2016). With current technology as an enabler, society's reliance on more precise spatial data is rapidly increasing (Jurisic, Ravlic, Loncaric, & Pugelnik, 2016). Geomarketing studies are conducted with the help of a geographic information system (GIS), which provides the skill to handle locations and geometries.

Geomarketing normally focuses on expanding businesses and store rationalization; however, utilizing it for the political domain is advantageous (Pavía, Larraz, & Montero, 2008). Thus, rather than using the data of the internal customers of a company, employing the data of voters of a given political party is beneficial for finding its potential voters instead of finding potential customers. This leads to electoral or political geomarketing. Electoral geomarketing can be defined as a set of statistical techniques that allow the data of electoral results to be evaluated, and their relationship with other types of sociological data in a given area is analyzed. Such an analysis achieves better strategic planning for electoral decision making. Electoral geomarketing aids in recognizing critical areas where a given party can obtain the largest number of potential voters. The current paradigm of analyzing the current candidates' information and communication demands require better knowledge acquisition regarding their electoral areas and involves mastering different geographic information technologies applied to observe their voters.

According to the study by Bednar and Gerber, 2011, the direction of voting tends to behave in an identical manner in the same territory on a microscale. Most researchers analyze election results at the first level of administrative divisions. However, data aggregation at the level of administrative districts or cities could give unexpected results (Eskov, 2014). On the microscale, analysts have conventionally maintained that geography is a relevant influence on voting patterns, which is generally known as the district effect. This theory is backed by the argument that by establishing contact with neighbors and friends who live locally, especially with discussions on politics, people tend to consider the local majority point of view. Citizens are inclined to become organized to achieve any objective when they feel united through their confidence or belief in a particular topic. Such confidence is prone to appear in local contexts where people have had many interactions with other people. It is more difficult to trace these links over long distances, where frequent interactions are not possible. The spatial regression analysis performed by Gimpel et al., 2006, also revealed that contributions to parties and campaigns are strongly affected by the local context.

In this paper, we obtained the votes acquired by each political party in the local elections conducted in 2015 in Valencia (Spain), as well as the different categories of the population residing in the 593 census districts in that city. With this information, we searched for census districts where such a population existed, but where the political party did not obtain the expected votes. Consequently, we considered that there are potential voters in these census districts. This knowledge (to know where the potential voters of a political party are located) can be useful in the plan for the subsequent elections as promotion can be adapted to the population segments with high percentages of homes in the desired voting market rather than trusting in a massive homogeneous promotion. Consequently, the likelihood of the desired segment responding is higher and the party's use of resources is optimized.

To relate the socio-demographic variables in each census district and the direction of voting, in this work, we used multivariate statistical analysis methods that were programmed in a geoportal, which we called GeoChess (https://upvusig.car.upv.es/geochess/). This geoportal displays thematic maps, charts, and dispersion diagrams, and calculates the correlation between the votes for the political parties that existed in 2015 and the considered economical and socio-demographic variables. It also performs cluster analysis and selects census areas using the database attributes. The GeoChess analysis tools are limited and many more statistical analyses can be performed with a standard GIS or statistical software. We created GeoChess to help non-GIS users to understand the analyses performed by this work and the manner in which cartography and statistics can help to make decisions because it allows users to easily understand how variables are distributed by studying the zonal thematic maps.

This paper is presented as follows: Section 2 comments the data employed to obtain the results of this paper and the data repository used in the statistical analysis that GeoChess ran; Section 3 describes the methodology used to perform political geomarketing; Section 4 offers a practical case analyzed by GeoChess after selecting a political party and locating the zones where, in statistical terms, more potential voters existed for this party; finally, we discuss the obtained results, and the final conclusions are provided.

2. DATA

The first step in the electoral geomarketing was to identify the delimitations of census districts in Spain, which can be obtained from the Spanish National Statistics Institute (INE, 2015). All the data contemplated in the present research were georeferenced by census districts, i.e., each piece of data was confined to a polygon that corresponds to a census district in the city. In this paper, we will consider the 593 census districts in the city of Valencia (Spain).

We used two data sets in this work, which readers can download from GeoChess Data, https://doi.org/10.17632/YZ24BNJHPS.3 . The employed data were public and free. The first set contained the absolute values of the variables; i.e., the number of people of each category (older adult population, secondary education, etc.) in each census district. This data set can be used in the thematic maps in GeoChess. However, certain census districts are bigger than others, in terms of area, and for the statistical analysis in this paper, we used the second data set, where the values of people in each variable were provided as a percentage, in relation to the total census district population. The percentage of votes to a political party was calculated using the number of valid votes. The use of relative data can prevent the number of people living in a census district from directly influencing the final grouping; however, it can also mask variance heterogeneities and omit the effective size. The electoral data was obtained from the Spanish Home Office for the year 2015 (Spanish Home Office, 2015).

3. METHODOLOGY

Given the volume of socio-demographic and economic variables, and the number of political parties, the GeoChess. Geoportals are increasingly used to provide cartography and the tools required for each application to non-GIS users (Ganning, Coffin, McCall, & Carson, 2014; Panchaud, Enescu, & Hurni, 2017; Resch & Zimmer, 2013). The GeoChess geoportal is a customer-server application. The operation of such applications is complex. Figure 1 illustrates a diagram of the GeoChess framework. The customer component is the web browser that shows the data, while the server component consists of a database and a script that acts as an intermediary between the database and the customer. The programming performed by the customer, like all web pages, is written in HTML, CSS, and JavaScript languages. To draw maps and graphs, and to calculate statistics, the website uses JavaScript libraries like OpenLayers, GeoExt, HighCharts, and Stats.

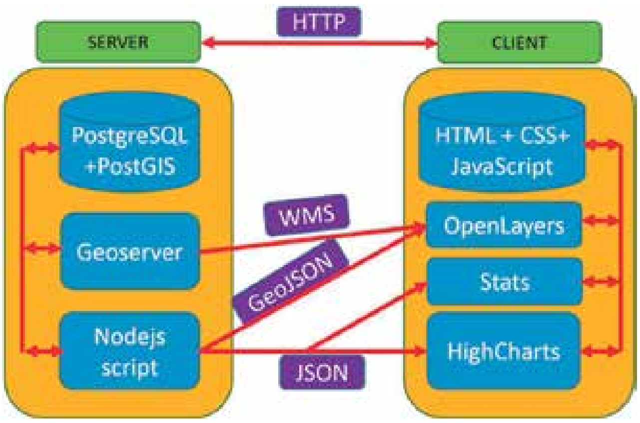


Figure 1: GeoChess architecture

In the server area, the employed database is in PostgreSQL with the PostGIS extension, which adds the skill of handling geometries and performing spatial analyses to PostgreSQL. The script that acts as a bridge for communication between the database and website —the customer— is run in the Node.js® environment, which uses JavaScript as the programming language. This script receives requests from the customer, performs SQL queries to the database, and returns the data to the customer who requested them. The data are sent as JavaScript Object Notation (JSON) or GeoJSON, depending on whether alphanumerical or geographic data were required. The website uses OpenLayers to draw maps. This library requests for geographical data from an application known as a map server. The map server we used was GeoServer. Geoserver is an open-source server solution designed for interoperability, data discovery, dissemination of spatial data using open standards (Jankovic, Govedarica, Navratil, & Fogliaroni, 2018). GeoServer publishes thematic maps via the standard web map service, and these maps are properly symbolized depending on the theme variable. The symbolization of thematic maps was performed according to another standard known as Style Layer Definition.

Figure 2 shows the GeoChess geoportal interface, which is divided into three panels that perform different functions. Panel 1 is a classic layer tree on which it is possible to activate or deactivate thematic maps of the census districts, according to different variables. Panel 2 illustrates the maps. Finally, Panel 3 is like an accordion, and allows the different analysis tools implemented in GeoChess to be shown, which are: the details of the data sample from the selected census districts, a study of the correlations between variables individually, a cluster analysis, and a form to select census districts according to the values of the variables.

3.1. Exploratory data analysis

The first step to run an analysis was to view all the values that the variables demonstrated graphically, to visually analyze the spatial distribution of each variable. GeoChess offers the possibility of seeing a thematic map of each variable by selecting the variable to be shown in Panel 1 (Figure 2). The thematic maps aid in visual recognition of the patterns of the spatial autocorrelation in geographical data sets and the resulting regionalization of data values (Cromley, 1996). The selection of class intervals is a major problem when preparing a thematic map (Mackay, 1955). The class intervals in the GeoChess maps were chosen using the Jenks natural breaks algorithm, which searched for groups of intervals where the variance in each group was minimal, and the variance between groups was maximum (G.F Jenks, 1977; George F Jenks & Caspall, 1971). This algorithm is a standard method for dividing a data set into a certain number of homogenous classes and is commonly used in geographic information system applications (North, 2009).

There are five classes for all the maps in GeoChess. A few classes transmitted less information in the variable value of the layer, but permitted considerably different color ramp values to be used for each class, which facilitated map reading because the element colors were very different (Bertin, 1967). People generally interpret darker colors as representing a more variable value (Brewer, 2005). The GeoChess color ramps followed this criterion. The classical choropleth maps can cause discrepancies between the actual result and the one perceived on the map. These discrepancies can be measured (Ourednik, 2017).

For a simple initial exploratory analysis, GeoChess has a detailed information tool, that shows a summary and comparison of the values of the variables in all the census areas by numerical results and graphs. As a previous step to the multivariate spatial analysis, GeoChess allows the calculation of correlations among the data. This can be performed using the *Correlation* section in Panel 3 (Figure 2). Here, the simplest relations between the vote and its socio-economic conditioning factors are analyzed, and the main factors that explain the electoral behavior in an urban setting are forecasted. These correlations are illustrated graphically by a scatterplot, and by calculating Pearson's and Spearman's correlation coefficients. Each dot in the scatterplot represents the percentage values of two variables in a census district. Therefore, a scatterplot is a tool to analyze the ecological correlation (Robinson, 2009) in contrast to a correlation between two variables that describe individuals. We were careful in not assuming that this type of correlation also applied to individuals because the correlations in the census districts could differ from those at the individual level. Assuming both are equal is an example of ecological fallacy (Vogt & Johnson, 2011).

3.2. Cluster analysis

The cluster analysis has become a common tool for marketing researchers (Punj & Stewart, 1983). It was used in results of this paper to classify the census areas of the city of Valencia, according to the existence of potential voters of a given political party. Therefore, apart from the votes obtained by the political party in the last elections, other variables were taken into account. The

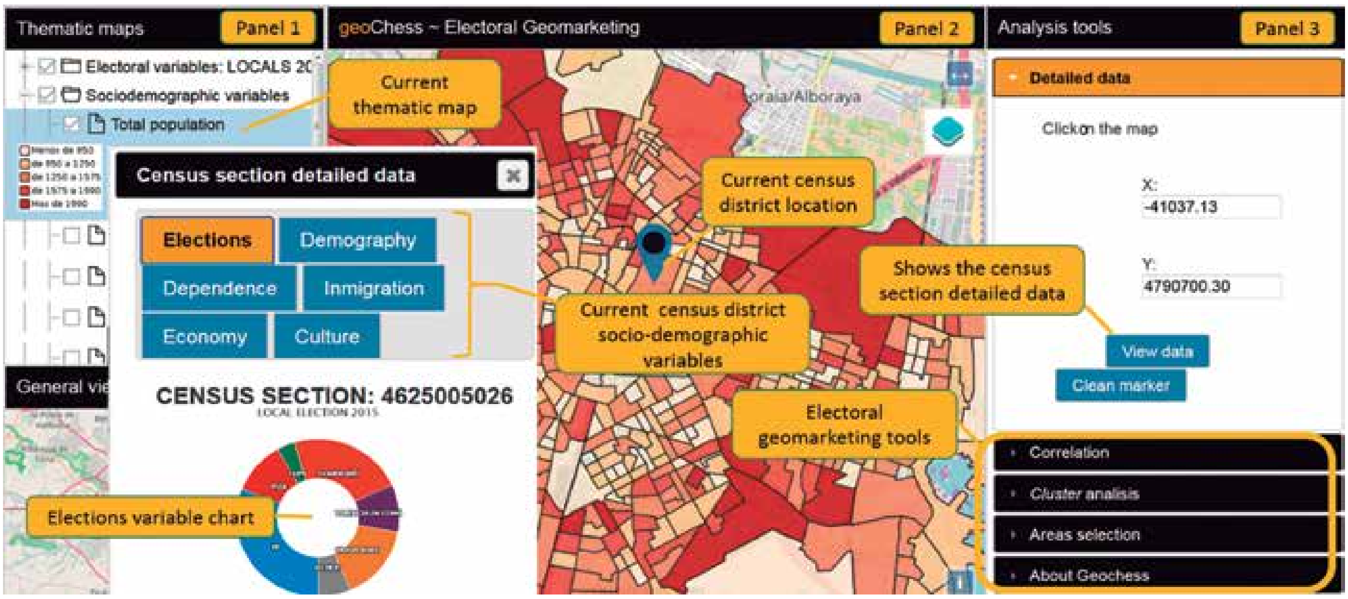
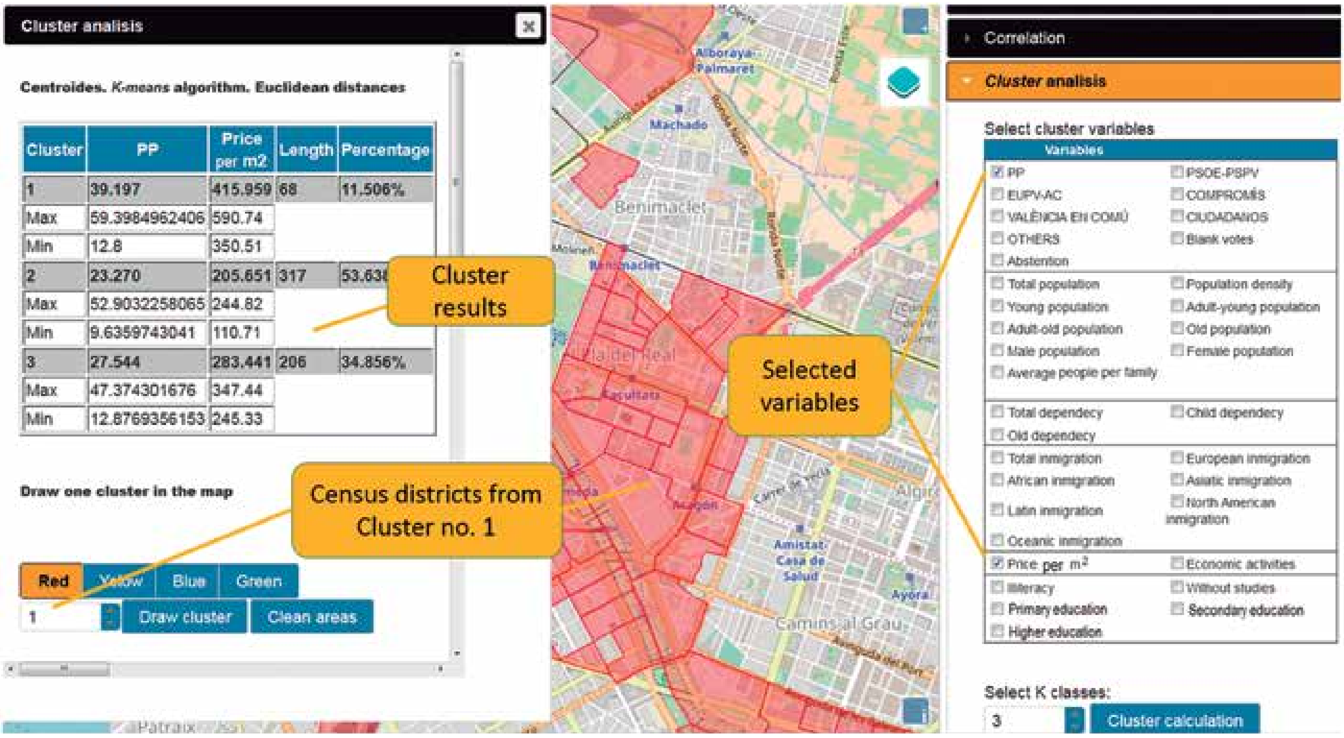


Figure 2: GeoChess interface and tools



Cluster	PP	Price per m2	Length	Percentage
1	39.197	415.959	68	11.506%
Max	59.3984962406	590.74		
Min	12.8	350.51		
2	23.270	205.651	317	53.63[illegible]
Max	52.9032258065	244.82		
Min	9.6359743041	110.71		
3	27.544	283.441	206	34.856%
Max	47.374301676	347.44		
Min	12.8769356153	245.33		

Figure 3: Cluster analysis procedure in GeoChess and representation of the census districts included in Cluster number 1.

K-means method is a standard and straight-forward unsupervised locational clustering approach (Kanungo, Mount, Netanyahu, Piatko, & Silverman, 2002). However, a drawback of this method (Howard & Harris, 1966) is that it starts with an initial solution with a number of groups fixed in advance (Zhou, Xu & Kimmons, 2015). The K-means algorithm was used with the squared Euclidean distance metric in GeoChess. GeoChess also contains a form to select the variables that we wish to include in the cluster analysis and to choose the number of classes (Figure 3).

To analyze the variables selected in the cluster analysis, a box and whiskers chart is useful for each studied cluster and variable. The box and whiskers charts are used to compare the distribution of the data in each category and to analyze the existence of atypical values. It is also useful to have a dispersion diagram that shows the data separation by clusters. GeoChess allows box and whiskers charts of scatterplots to be obtained.

Finally, another useful tool for electoral geomarketing studies is the possibility of selecting census districts according to their inhabitants' socio-demographic characteristics. For instance, if the intention was to emphasize the subject of pensions to obtain votes, then locating the census areas with the maximum older adult citizens would be considerably useful. Consequently, GeoChess permits such selections. Figure 4 shows the census districts with over 30% of older adult population.

4. A PRACTICAL APPLICATION FOR THE CIUDADANOS (CS) POLITICAL PARTY

In this section, the spatial distribution of the votes granted to the *Ciudadanos (Cs)* political party, in the local elections held in May 2015, in the city of Valencia (Spain), was analyzed using GeoChess. However, GeoChess users can select the political party that they want to be analyzed from among those with municipal representation in the cited elections.

4.1. Exploratory analysis of the variables related with votes to the Ciudadanos (Cs) political party

The first step consisted of conducting a preliminary visual study using thematic maps and graphs with information about census districts. Figure 5 is a thematic map that uses the variable that indicates the percentage of votes to the *Cs* political party for the classification, in relation to the number of valid votes in each census area. The census districts in the city of Valencia were explored using the *Detailed Data Tool* in GeoChess to determine the locations where the *Cs* political party had obtained a high percentage of votes.

Table 1 lists the variables that present higher Pearson's correlation indices with the *% Votes contributed to the Cs political party*. A strong linear relation was observed

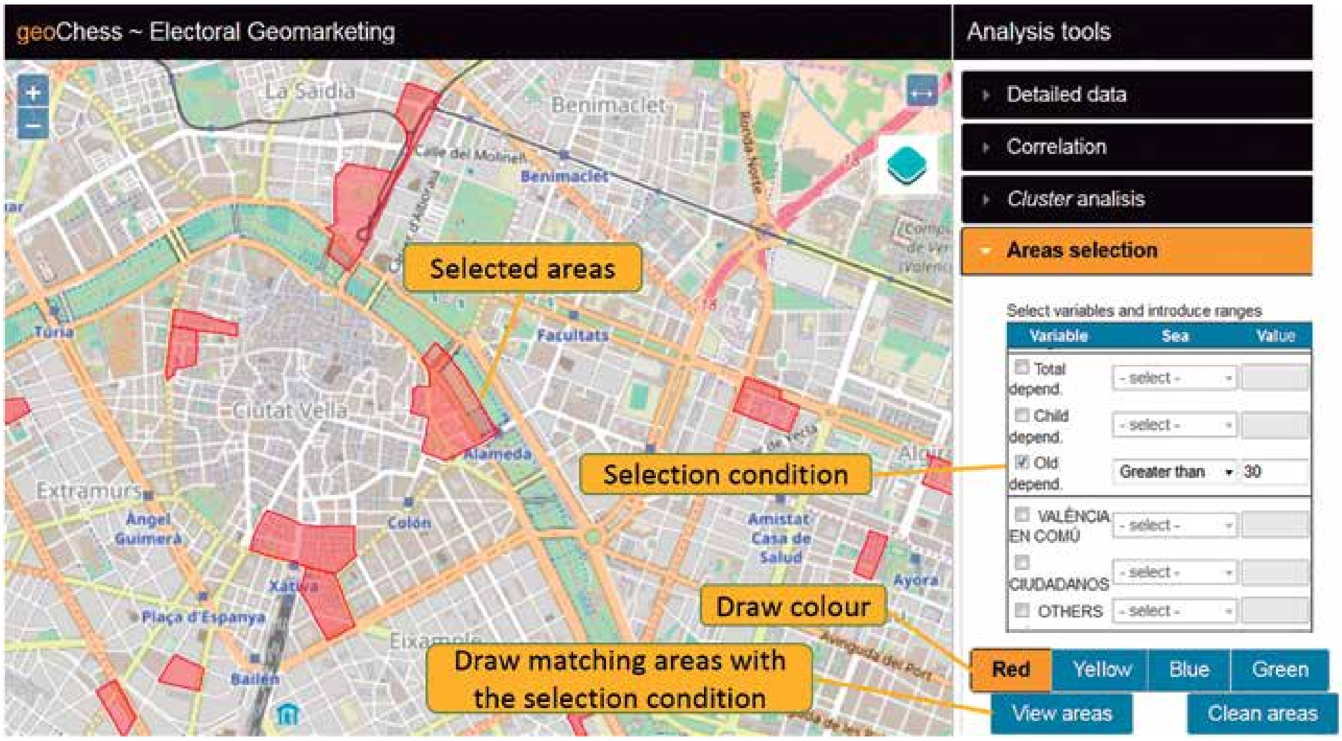


Figure 4: Selection of the areas where the percentage of older adult population exceeds 30% of the total population.

Table 1: Some variables with higher correlation indices with the variable: percentage of votes to the Cs political party. Younger population, Total immigration and Secondary and Higher education variables are considered in percentages in relation to the total population of each census area.

VARIABLE	PEARSON CORRELATION COEFFICIENT
% Younger population	0.4174
% Total immigration	-0.4612
Average price per m2	0.8620
% number of commerces	0.4988
% Secondary Education	-0.5285
% Higher Education	0.7329

between such variable and the *average price per square meter*, with correlation coefficient above 0.8. There are more voters of *Cs* in the census areas having a higher percentage of people with higher education (a positive correlation); consequently, the percentage of people with secondary education was lower (a negative correlation).

4.2 Cluster analysis with percentage of votes to the Cs political party

We consider the % Votes to the *Cs* political party to

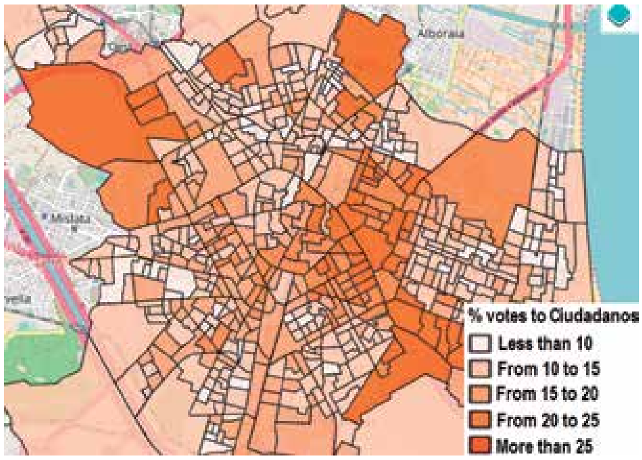
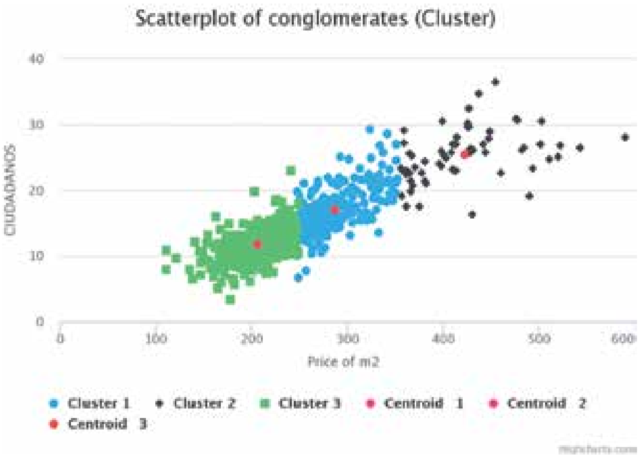
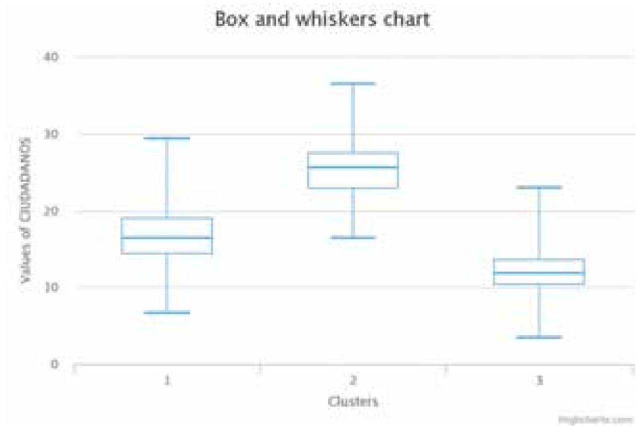


Figure 5: Thematic map using the percentage of votes obtained by the political party Cs

perform the cluster analysis together with % *Younger population*, % *Total immigration, Average price per square meter,* and % *Higher Education,* in order to classify census areas into different categories. We estimated that it would be reasonable to use three classes for distinguishing between the census districts with a high potential (*or hot spots*), or with a medium and low potential. Table 2 lists the centroids together with the maximum and minimum obtained in all three categories. Here, we can observe that the first and second categories include the lowest and highest means of the *% of votes to Cs*, respectively. Similar phenomena occurred with the mean of the variables *average price per square meter* and % *Higher*



(a) Scatterplot showing the distribution of the three classes according to the variables average price per square meter and % Votes to Cs



(b) Box plot of the % Votes to Cs, separately obtained by the three classes obtained in the cluster analysis

Figure 6: Cluster analysis results of three classes using the four independent variables used in table 2 along with the variable % Votes to Cs.

Education. The percentage of the younger population presents a greater similarity among categories. Moreover, the percentage of the total number of immigrants displays an inverse behavior to that of percentage of votes to *Cs*.

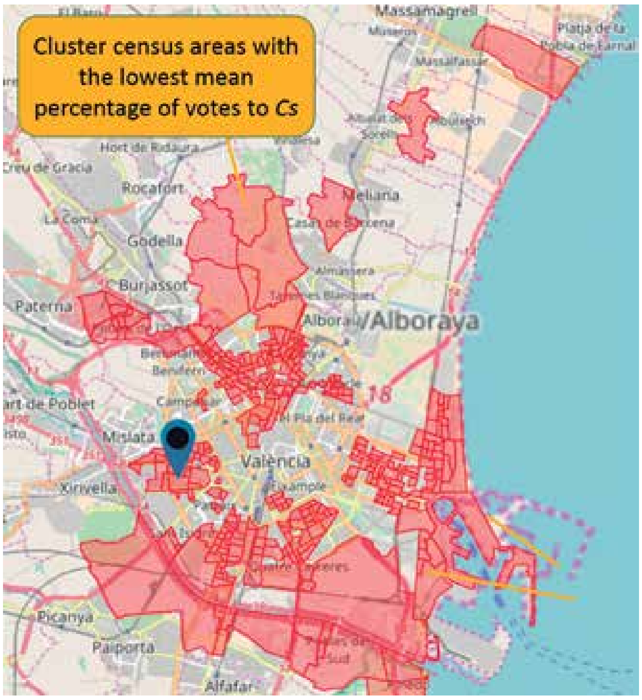
GeoChess allows a dispersion diagram to be viewed where clusters are distinguished by colors, as illustrated in Figure 6(a). Here, we can observe the separation between categories according to the variable *% Votes to Cs* and *average price per square meter*. This geoportal also allows us to obtain the box and whiskers charts, offered in Figure 6(b), with which the separation of the classes obtained in the cluster analysis can be observed.

Figure 7(a) features the census areas from Cluster 1 of table 2 marked in red, whose mean is the lowest in the percentage of votes to Cs. In blue, Figure 7(b) shows the census areas that belong to the cluster 2 with the highest mean in this percentage of votes. Cluster 1 includes 54.7% of the census areas, while only 10.19% belong to the cluster 2 with the highest mean, as we can observe in Table 2.

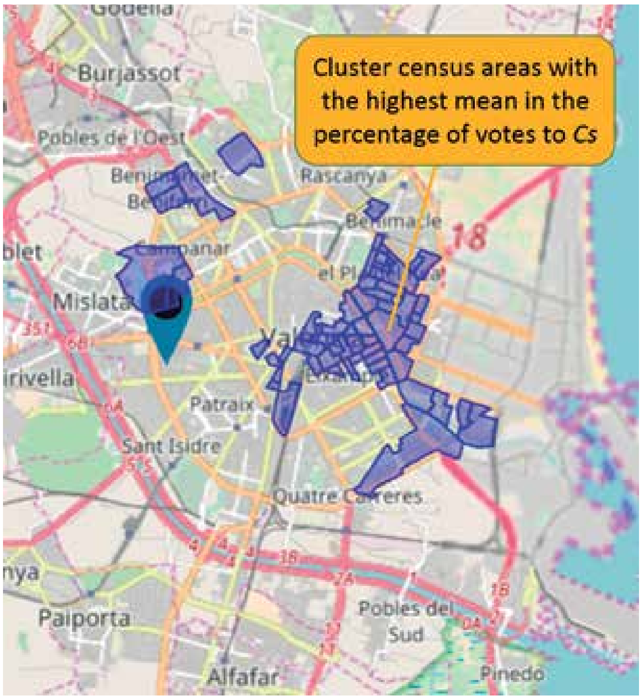
We can see in Figure 7(b) the census districts with more votes to *Cs*, where the average property price per

Table 2: Centroids, maximum and minimum of variables in each cluster using the k-means method and the squared Euclidean distance metric, and using the variables percentage of votes to the Cs party along with % Younger population, % Total immigration, Average price per square meter, and % Higher Education.

CLUSTER	% CS	% YOUNGER POPULATION	% TOTAL IMMIGRATION	PRICE PER M2	% HIGHER EDUCATION	PERCENTAJE OF CENSUS DISTRICTS
1 Centroid	11.820	13.846	18.894	206.309	17.161	54.669%
Max	22.926	22.5629	44.3680	248.9	64.4809	
Min	3.3708	8.58283	5.43175	110.71	0	
2 Centroid	25.406	16.828	9.833	422.617	56.220	10.187%
Max	36.455	29.5029	20.2697	590.74	81.2030	
Min	16.379	9.71659	4	356.03	19.6203	
3 Centroid	16.996	14.387	14.078	286.259	36.896	35.144%
Max	29.323	28.4299	30.9446	352.48	66.0714	
Min	6.6581	7.3908	5.5076	244.19	8.0	



(a) Map with the census areas of the cluster with the lowest mean percentage of votes to Cs



(b) Map with the census areas of the cluster with the highest mean in the percentage of votes to Cs

Figure 7: Results of the cluster analysis with three categories

square meter is high, and there is a high percentage of the younger population along with a high percentage of the population with higher education. We infer that it is not necessary to intensify the electoral campaign in these areas, but to merely maintain it in similar terms to those of the last local elections.

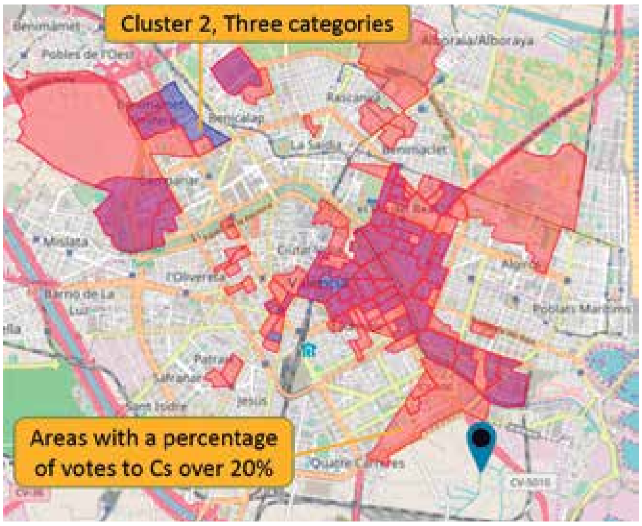
4.3. Locating the areas with more potential voters for the Ciudadanos political party

The GeoChess *Area Selection Tool* allowed us to mark the census areas whose *percentage of votes to Cs* was observed to be in a given interval to be chosen. Consequently, the maximum and minimum values of the percentage of votes considered by users can be included, and the results can be compared with the census sections that belong to a given cluster. To make such a comparison, calculating the clusters by eliminating the variable *% Votes to Cs* from the variables employed to calculate it might be useful. Figure 8 compares the areas where the *Cs* political party obtained a percentage of the votes that exceeded 20% in the local elections of 2015 (in red) with the areas that belong to the cluster with higher values in the variable *average price per square meter*. The objective was to find more optimum areas, i.e., the areas that were classified in the cluster with higher values for the variable *average price per square meter* using variables considered in table 2 where, consecutively, the *Cs* political party's electoral result was lower than expected.

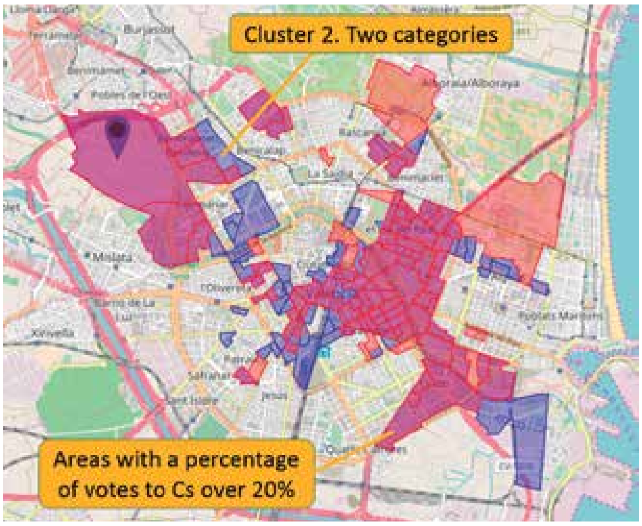
Figure 8(a) shows the cluster analysis results using three classes and Figure 8(b) illustrates the result while considering only two classes. The areas shown in Figure 8 contain more potential voters for the *Cs* political party, where potential characteristics were joined but did not display such a high percentage of voters as expected. Therefore, this is where resources need to be reinforced.

5. CONCLUSIONS

This paper presented a step-by-step geomarketing methodology that could be used to identify the locations of potential voters, for which a tool called GeoChess was designed. Although GeoChess could be applied to any urban system, the results of this paper were obtained to analyze the votes acquired by political parties in the 2015 local elections held in the city of Valencia, Spain. The socio-demographic data of this city were related to the data on local voting and compared with the census areas, or microzones. The objective was to demonstrate the possibility of selecting geographic areas where potential voters fulfilled certain characteristics, and the areas where they did not exist. This helps political parties in identifying the areas to reinforce their electoral campaigns, and the locations where they should be avoided.



(a) Cluster analysis with three categories



(b) Cluster analysis with two categories

Figure 8: Comparing Cluster 2 (blue) to the areas with a percentage of votes over 20% (red). (a) Cluster analysis with three categories. (b) Cluster analysis with two categories.

GeoChess was used to identify those areas in a given territory that are more likely to change the vote, and where potential voters of a given political party may exist. With this information, the areas where this party should center its efforts could be analyzed to obtain the best electoral return with the least resources. The results of this paper showed a way to follow this methodology for the *Cs* political party, which introduced their candidates in the 2015 local elections in Valencia, Spain.

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