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Applying an Evolutionary Algorithm for the Analysis of Mental Disorders in Macro-urban Areas: The Case of Barcelona

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ABSTRACT *Spatial analysis is widely used to study geographic patterns of diseases. To locate groups of close spatial units where the treated prevalence is significantly high or low, the latest contribution is a tool based on a Multi-objective Evolutionary Algorithm, which has not yet been used in macro-urban areas: this study is the first attempt for this purpose. To do so, spatial distribution of the treated prevalence of mental disorders in basic health areas was analysed within the Barcelona metropolitan zone during 2009. The results highlight inequitable zones that need further attention, and geographically weighted regression shows that socio-economic factors influence treated prevalence although there may be additional factors involved.*

Application d'un algorithme évolutionnaire pour l'analyse de troubles mentaux dans des zones macro-urbaines : l'exemple de Barcelone

RÉSUMÉ *on fait grand usage des analyses spatiales pour étudier des tendances géographiques de maladies. Aux fins de la localisation d'unités spatiales rapprochées, lorsque les prévalences examinées sont fortement élevées ou basses, la toute dernière contribution est un outil fondé sur un algorithme évolutif multi-objectifs, que l'on n'a pas encore utilisé dans des domaines macro-urbains ; cette étude est*

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une première tentative dans cet objectif. Pour ceci, on a analysé la répartition spatiale de la prévalence traitée de troubles mentaux dans des secteurs de santé de base dans la région métropolitaine de Barcelone au cours de 2009. Les résultats soulignent la présence de zones inéquitables nécessitant une attention supplémentaire, et une régression à pondération géographique indique que les facteurs socioéconomiques influent sur la prévalence traitée ; en outre, certains autres facteurs pourraient également avoir un rôle à jouer.

Aplicación de un algoritmo evolucionario para el análisis de los trastornos mentales en zonas macrourbanas: el caso de Barcelona

Resumen *el análisis espacial se utiliza ampliamente para estudiar los patrones geográficos de las enfermedades. Para localizar a los grupos de unidades espaciales cercanas donde la prevalencia tratada es significativamente alta o baja, el último aporte es una herramienta basada en un Algoritmo evolucionario de objetivo múltiple, que no se había usado en zonas macrourbanas, este estudio es el primer intento que se realiza con este fin. Para hacerlo, se analizó la distribución espacial de la prevalencia tratada de las dolencias mentales en zonas sanitarias básicas de la zona metropolitana de Barcelona durante 2009. Los resultados destacan las zonas poco equitativas que precisan de una mayor atención y la regresión geográficamente ponderada demostró que los factores socioeconómicos ejercen influencia sobre la prevalencia tratada, sin embargo, pueden estar asociados factores adicionales.*

运用进化算法分析密集城市地区的心理疾病: 以巴塞罗那为例

摘要: 空间分析被广泛运用于研究疾病的地理格局。一项基于多目标进化算法的最新工具有助寻找治疗普及率显著偏高或偏低的封闭式空间单元集群, 然而该工具尚未运用于密集城市地区, 本研究是该领域的首例尝试。为此, 2009 年在巴塞罗那城市区对基础保健地区的心理疾病治疗普及率空间分布进行了分析。结果指出需要额外关注的不等同地区, 而地理加权回归显示社会经济因素对治疗普及率构成影响, 但此外也可能涉及其他因素。

Keywords: *Multi-objective Evolutionary Algorithm; treated prevalence; spatial clusters; macro-urban areas*

JEL classification: C61; I14; I18; R58

1. Introduction

Urbanicity can bias the morbidity of a large number of diseases due to such typical features of urban environment as overcrowding, social disparities, urban lifestyle, immigration, etc. (Godfrey & Julien, 2005). These potential biases are emphasized in macro-urban or metropolitan areas because of their micro-spatial structure organized in small districts, neighbourhoods, etc. The presence of spatial clusters with high or low values of incidence, prevalence and/or mortality in this kind of areas could indicate situations of inequity for health planners and decision-makers (Koschinsky, 2013).

Epidemiological studies in metropolitan areas introduce special methodological difficulties. One of these is the lack of international agreement on their spatial definition that could be based on the number of inhabitants, population density or socio-demographic and economic characteristics (OECD, 2012). High metropolitan population, easy mobility and a high degree of accessibility also promote the concentration of health facilities which influence the increase in their demand and use, according to Say (Battistella, 2010) and Roemer's Laws (Delamater et al., 2013). Health planning mainly manages these geographical areas through infra-municipal catchment areas, which are characterized by great accessibility and proximity to users. The main limitation in the study of these small areas is the degree of availability of morbidity data and the difficulty of its interpretation, because it could be infraestimated when compared to less populated areas (Wennberg et al., 2013). Besides, ecological studies in geographical areas, especially small ones, must take ecological fallacy into account in order to avoid drawing conclusions at an individual scale (person) from aggregated data (Ocaña-Riola, 2010).

Spatial clustering methods are the most commonly used to assess spatial patterns of diseases (Auchincloss et al., 2012). Spatial clusters group close spatial units, from a geographical point of view, which show significantly high or low prevalence scores, also called hot or cold spots (Kidner et al., 2004). There are different spatial clustering tools including frequentist methods like Moran's *I*, Getis and Ord's *G* and *Spatial Scan Statistics* (Anselin, 1995; Ord & Getis, 1995; Kulldorff, 1997). In the group of non-frequentist methods, we can highlight the Bayesian ones (Besag et al., 1991). Some examples of these studies in macro-urban areas are: (i) the study of spatial patterns in the tuberculosis incidence in Beijing (13.57 million inhabitants; Liu et al., 2012) and the dengue fever incidence in census zones of Guayaquil (Ecuador) (2.5 million inhabitants) using frequentist Local Indicators of Spatial Association—(Castillo et al., 2011), (ii) the analysis of brucellosis prevalence in Kampala parishes (Uganda) (1.2 million inhabitants) by using frequentist *Spatial Scan Statistics*—(Makita et al., 2011); and (iii) the study of cancer mortality in census tracts of 11 cities including Madrid (3.2 million inhabitants) and Barcelona (1.6 million inhabitants) in Spain using Bayesian methods (Puigpinós-Riera et al., 2011).

Multi-objective Evolutionary Algorithms (MOEAs) are one of the latest methods to emerge in spatial cluster analysis (García-Alonso et al., 2010; Moreira et al., 2014). MOEAs derive from artificial intelligence to approximate efficient Pareto-based solutions for complex multi-objective problems (Coello-Coello et al., 2007). In fact, MOEA can process the identification of spatial clusters as a multi-objective problem searching for: (i) significantly high/low values (maximum/minimum means) of, for example, prevalence and/or incidence scores; (ii) homogenous values (minimum standard deviation, SD); and (iii) proximity (minimum distance between spatial units).

A MOEA specifically designed to solve spatial multi-objective problems was used to find clusters with high spatial autocorrelation scores for the treated prevalence of schizophrenia in Andalusia (Spain; García-Alonso et al., 2010) and to seek both high and low treated prevalence clusters of depression in Catalonia (Spain; Salinas-Pérez et al., 2012). Both studies analysed municipalities as the basic spatial units, which could be an important limitation in macro-urban areas because their high population and density may be hiding relevant situations between districts. In fact, the population of the Barcelona metropolitan area is over 40% of the total population of Catalonia and includes very large municipalities like Barcelona (more than 1.6 million inhabitants and 15,903 inhabitants per km^2). The use of a single treated prevalence value for these huge municipalities can hide significant spatial clusters within them.

The analysis of the spatial distribution of mental disorders and its relationship to socio-economic facts on a macro-urban scale is justified by scientific literature, but there are still not many examples of spatial clustering analysis. Different studies have noted a statistical dependence among psychiatric prevalence and specific characteristics of urban areas like pollution, built-up environments, drug use and social exclusion (Wang, 2004; Allardyce et al., 2005; Curtis et al., 2006; Kirkbride et al., 2007; Perälä et al., 2008; Kelly et al., 2010; Duncan et al., 2013). The opportunity of this type of epidemiological studies is also justified because of the high prevalence and burden of mental diseases in these areas (Kessler & Üstün, 2008).

Based on the above and due to limitations of a previous study done in Catalonia (Salinas-Pérez et al., 2012), this paper aims to analyse the spatial distribution of the treated prevalence of mental disorders in the Barcelona metropolitan area. The city was divided into Basic Health Areas, the smaller spatial unit with reliable data, in order to carry out the analysis at micro-spatial level. The resulting spatial clusters were characterized by using demographic and socio-economic indicators, and the emerging relationships were also identified and described. These relationships have been studied using Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR).

Section 2 provides details about the data set and explains the methodologies used. In Section 3, both hot and cold spots are identified, located and analysed. Section 4 includes an extensive discussion on the results. Section 5 describes the limitations of the study and, lastly, section 6 provides the conclusions and future research lines.

2. Methods

2.1. Scope of the Study

In Spain, the public health system is universal with separate planning and provision and includes both public services and private ones with contract agreements (Salvador-Carulla et al., 2010). In Catalonia, the lowest level of health zoning is the basic health area (BHA), which provides primary health care. Primary care centres treat the mildest outpatient psychiatric cases while more severe ones are transferred to their reference Mental Health Community Centre. Therefore, the mental health catchment areas are structured in many BHAs. The BHAs are the smallest territorial units where reliable mental health information can be found for precise geographical identification and the location of hot and cold spots of treated prevalence of mental disorders.

This research analysed the geographical distribution of mental disorders in BHAs in the Barcelona metropolitan area and surrounding BHA (the whole health region) in 2009. The metropolitan area of Barcelona is a territorial entity in Catalonia (Trullén, 2012), a region or ‘autonomous community’ in north-eastern Spain. This macro-urban area includes the capital of this region (Barcelona) and 35 adjacent municipalities around the city. It has a population of 3,239,337 inhabitants (National Statistics Institute, 2012) in 636 km^2 and is the second most populous urban area in Spain after Madrid (Dijkstra et al., 2011).

Analysing the Barcelona metropolitan area and its adjacent municipalities allows us to avoid the boundary problem that appears when data values of the neighbouring areas outside of the study zone exist but are not known. This analysis evaluates what is happening in the BHA bordering the Barcelona metropolitan area.

The Barcelona health region has 207 BHAs including 142 in the metropolitan area. They are very heterogeneous because they can be structured by different administrative units such as municipalities, census districts and/or census sections. This complexity is due to their political design, their main purpose being to attend similar inhabitant collectives.

2.2. Data and Variables

This research has been carried out using the 2009 database provided by the Catalonian Department of Health: the Minimum Data Set for Outpatient Mental Health Centres (CMBD-SMA), safeguarding the privacy of patients to prevent geographical identification of individual cases. Unfortunately, 13 BHAs did not provide complete information for 2009, so these areas showed an underestimation of their treated prevalence. Although prevalence data from these areas were adjusted considering data from surrounding areas—standard spatial interpolation, this missing information could affect both the analysis and the interpretation of, mainly, cold spots.

The number of psychiatric patients analysed was 105,177. The number of inhabitants in each BHA was obtained from the Continuous Municipal Register (National Statistics Institute, 2010). Patient sex and age provided information to calculate the standard rates of treated prevalence of mental disorders (per 1,000 population) using the direct method (Rezaeian et al., 2007) that took into consideration, as a reference, the population of the metropolitan area of Barcelona.

A standard set of demographic and socio-economic indicators was calculated for hot and cold spots and for the rest of the BHAs. These indicators included dependency and ageing indexes, unemployment, the unmarried, those living alone, single-parents, illiteracy, those with university studies, people who own more than two vehicles, migration and, finally, socio-economic conditions (high, medium and low) related to inhabitant employment status. Most of these indicators have been related to psychiatric morbidity and were included in the European Socio-Demographic Schedule (Beecham et al., 2000; Tibaldi et al., 2005). The indicator assessment was carried out by census-tract level data aggregation (minimum statistic level) from the 2001 population census (National Statistics Institute, 2007). In those cases where census tract and BHA did not fit spatially, a proportional allocation was done.

2.3. Spatial Analysis

2.3.1. Exploratory Analysis. Global Moran *I* and Getis and Ord's *G* (Anselin, 1995) have been used to analyse if both the treated prevalence and the residuals of the regression models are spatially distributed at random or not. The treated prevalence and socio-economic indicators of the BHA identified as hot/cold spots were statistically compared to the other BHAs (not including in hot/cold spots) by using two non-parametric methods for independent samples: the Kruskal–Wallis test and the comparison of medians.

Multi-objective Evolutionary Algorithm. MOEA is a methodology used to solve complex multi-objective problems through optimization, achieving feasible and efficient Pareto-based solutions by using the biological principles of genetics and evolution. Our MOEA design is based on the 'Strength Pareto Evolutionary Algorithm v.2' (SPEA2; Zitzler et al., 2002). This algorithm searches for sets of solutions, obtaining efficient results for complex problems with non-convex, discontinuous, and multi-modal solution spaces, which is like what happens when the spatial distribution of mental health diseases is analysed (Konak et al., 2006). The full technical aspects of this methodology have been described in depth in previous papers (García-Alonso et al., 2010, 2011, 2013).

The MOEA was specifically designed to identify spatial clusters that show significantly (on a statistical basis) high or low values for the variable analysed, in our case: the prevalence of mental disorders. The objectives of the model were:

(1) To maximize (for hot spots) or minimize (for cold spots) the mean ($\overline{P}$) of the treated prevalence of mental disorders in each solution with n BHAs (initially, n = 10).
(2) To minimize the SD ($\mathrm{MinSD_p}$) of the treated prevalence of mental disorders in each solution with n BHAs (initially, n = 10). This objective aspires, on a statistical basis, to identify homogeneous hot or cold spots.
(3) To minimize the minimum distance—assessed by using relative proximity rates—(MinRP) that links all the BHAs in each solution. This objective aims to obtain groups of geographically close spatial units.

For each solution with n BHAs, these objectives were evaluated by the MOEA using a 'fitness function' that mathematically groups the results obtained by applying them—the objectives. The algorithm was modified to include not only the SPEA2 fitness function (Zitzler et al., 2002; Konak et al., 2006) but also other ones like: w, the weighted sum of objectives (Das & Dennis, 1997; Coello-Coello et al., 2007), standard ranking selection (Coello-Coello et al., 2007) and the fuzzy evaluation of weighted objectives (Lee et al., 1995; Wang & Terpenny, 2005).

The MOEA iteratively tries to obtain better and better non-dominated solutions (BHA groups or clusters) by using genetic operators that generate new solutions from existing ones. Concretely, three operators were employed: selection, crossover and mutation. In each generation, the fitness functions assess all the solutions and the operator selection chooses the best ones to preserve them (elitism) and/or to use them to improve the population (set of different solutions). Between two solutions, the crossover operator can be simple (solutions are cut in the same position between two BHA codes) or double (there are two cuts in each solution). Finally, the mutation operator introduces diversity by changing one or more codes at random to avoid local optima (Fonseca & Fleming, 1995). Once this process is finished, the feasibility—inexistence of duplicate codes—of each new solution is checked and, if necessary, is repaired by using mutation.

The heterogeneous size of the spatial units could bias the results of the spatial analysis. To prevent this, the geographical distance between municipality j and municipality i was transformed into a relative proximity rate (rp_{ji}), which was calculated for each pair of spatial units. Several levels of relative proximity were defined in a [1, $\mathrm{rp_{max}}$] range. The first level for a pair of spatial units (rp_{ji} = 1) means that they are neighbourhoods (and have shared borders). The rest of the levels were calculated successively since the first level is established by using a statistically defined radius calculated by a standard statistical sensitivity analysis. The relative proximity rates were limited ($rp_{ji} \leq 10$) to avoid unnecessary computation time.

The initial population, a group of solutions selected at random, had 100 solutions with 10 different BHA codes each. The standard genetic operators were systematically used to improve the fitness function values for each solution. Elitism was taken into consideration after 20 generations. The structure of the MOEA is described in Table 1 (García-Alonso et al., 2010).

When a new population of non-dominated solutions is considered (Ph_1), the process goes to step 2 till the stopping criterion is satisfied. This algorithm stops the process when the values of the fitness functions for all the solutions cannot be significantly improved (mean squared error lower than 2.5% of the corresponding mean fitness value).

Some geographical discrepancies were detected when comparing results of the four fitness functions. For this reason, the QQ-plots method (Beirlant et al., 2004) was used to select the spatial units which were identified most frequently.

3. Regression Models

Demographic and socio-economic indicators were analysed using Ordinary Least Squared (OLS) and Geographical Weighted Regression (GWR). OLS is a standard

Table 1. Structure pseudocode of the MOEA/HS algorithm for the identification of hot/cold spots in a geographical space

1 Create the external NDF[a]	
2 For i = 1 to s[b] do	
3 Initial population design, S	At random Based onregional divisions Calculatedfour times in different computer processors, one per each fitness function
4 For i = 1 to g[c] do	
5 Compute the fitness of each individual in S and NDF	SPEA2 standard Weighted sum of objectives Fuzzy evaluation of weighted objectives
6 Preserve all non-dominated solutions in NDF	
7 If NDF is too big then the truncated operator removes unnecessary solutions	Extreme solutions are preserved in the variables space
8 Empty registers in NDF are filled out using dominated solutions	
9 Binary tournament selection with replacement	Elitism is optional, inthis case is implemented after 20 generations. Two stopping criteria(statistical error) are analysed
10 Crossover (Elitism is optional)	Simple Double
11 Mutation (elitism is optional)	At random Distance-based Fitness-based
12 Repair process	Structural and technicalinfeasibilities by mutation Non-dominated solutions are saved in anexternal file
13 End for	
14 End	

Notes: [a]External non-dominated solution file (NDF); [b]Number of different initial solutions (s); [c]Number of generation (g).

regression method (Greene, 2011), and GWR is a type of regression which considers geographical space. GWR is especially useful when residuals show spatial autocorrelation (Cardozo et al., 2012).

GWR was developed in order to avoid spatial influences (spatial dependence and spatial non-stationarity) in the regression models by including territory as a new component (Brunsdon et al., 1996). GWR provides a local model of the dependent variable by fitting a regression equation for every feature in the data set. Regression coefficients vary according to the location of variables considering their geographical coordinates. For each local regression, the closest values have a higher weight than the furthest. This distance decay is simulated through a fixed Kernel function defined in ArcGIS© (version 9.3), which fixes a geographical distance to fit the regression, and a bandwidth based on the Akaike Information Criterion (AIC) method, which identifies the optimal distance based on the geographical distribution of the features (Fotheringham, 2002).

4. Results

4.1. Spatial Clusters

The spatial distribution of the treated prevalence of mental health diseases in the Barcelona health region and metropolitan area is shown in Figure 1. The treated prevalence mean is 30.24 per 1,000 inhabitants (±1.71; p = 0.05) and the SD is 12.45 which indicates that prevalence values vary widely in different BHAs. These

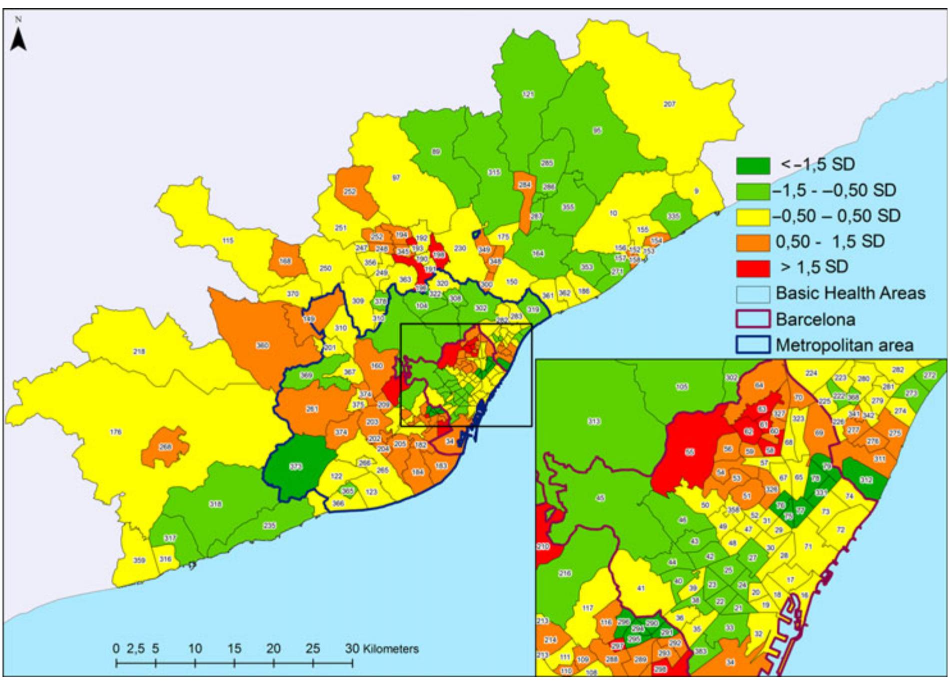

Figure 1. Spatial distribution of the treated prevalence of mental disorders (cases/1,000 inhabitants, 207 spatial units: basic health areas) in the Barcelona metropolitan area. Colour intervals generated by the mean plus/minus a number of times multiplied by the standard deviation (SD).

differences are not randomly distributed in the territory according to the global Moran's I ($I = 0.06$, $z = 8.73$, $\alpha \leq 0.01$), but this indicator disagrees with the Getis and Ord's G ($G = 0.0$, $z = 0.6$, $\alpha \leq 0.10$), which indicates randomness.

The MOEA identified 27 BHAs as hot spots (red) and 29 BHAs as cold spots (blue), shown in Figure 2, and their basic statistics were summarized in Table 2. The prevalence mean of the hot spots was 46.06 patients per 1,000 inhabitants while for the cold spots it was 14.65. The treated prevalence differences between hot/cold BHAs and hot/cold BHAs compared to non-hot/non-cold BHAs are statistically significant according to the Kruskal–Wallis test and median analysis ($p = 0.000$).

The first hot spot (HS1) was located around Sabadell and Mollet del Vallès (four BHAs). The second (HS2) appeared mainly around the Llobregat river in the south of Barcelona city (nine BHAs). Finally, the last one (HS3) was located in northern Barcelona (Nou Barris, Horta-Guinardó and Gràcia districts, 14 BHA).

On the other hand, 29 BHAs were identified as cold spots. These were located in a more scattered way than hot spots. There were two large clusters linked to the city of Barcelona, the first one (CS1) appearing around the Badalona and Mongat municipalities (7 BHAs) and the second (CS2) groups being many BHAs of Sarrià-Sant Gervasi, Les Corts, Eixample and l`Hospitalet de Llobregat districts (16 BHA). Another well-defined cold spot (CS3) is located in the Sant Martí district and the municipality of Sant Adrià del Besòs (six BHAs).

Lastly, the MOEA identified several isolated and dispersed BHAs as hot spots (two BHAs) and cold spots (seven BHAs). These BHAs have not been mapped because they are probably artefacts of the analysis.

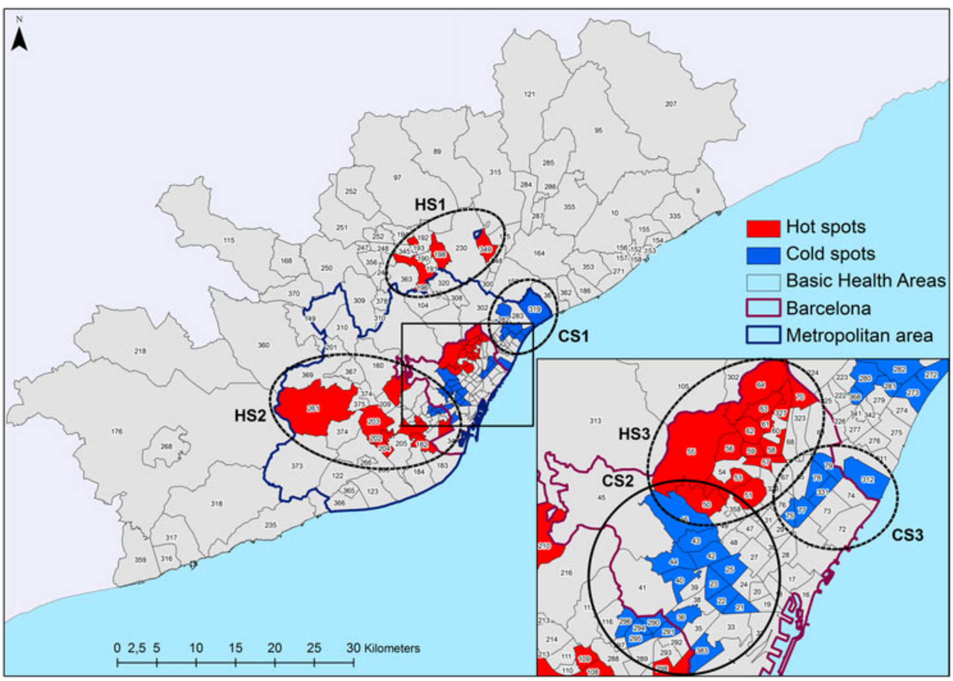

Figure 2. Spatial distribution of hot spots and cold spots of treated prevalence of mental disorders in the Barcelona Metropolitan Area and Health Region.

Table 2. Basic statistics for the study area and for hot/cold spots (patients per 1,000 inhabitants)

	N	Mean	SD	Confidence interval $p = 0.05$
Basic health areas: total	207	30.24	12.45	±1.70
Hot spots	26	46.71	8.70	±3.52
HS1	4	45.54	7.01	±11.16
HS2	9	44.79	11.01	±8.46
HS3	13	48.39	7.63	±4.61
Non-HS	180	27.88	11.05	±1.62
Cold spots	30	14.20	9.52	±3.55
CS1	7	22.72	4.67	±4.32
CS2	17	14.61	8.83	±4.54
CS3	6	3.12	0.55	±0.57
Non-CS	178	32.96	10.73	±1.59

4.2. Socio-economic Characterisation of Hot and Cold Spots

Demographic and socio-economic characteristics of hot/cold spots and for the rest of BHAs are shown in Table 3. The Kruskal–Wallis test indicates significant differences in these indicators between groups (HS1, HS2, HS3, CS1, CS2, CS3 and the rest of BHAs), except in the unemployment ($p = 0.052$) and non-married ($p = 0.155$) rates. On the other hand, the median test has not detected differences between these groups for unemployment ($p = 0.065$), non-marrieds ($p = 0.326$), those with university studies ($p = 0.187$) and high socio-economic condition ($p = 0.067$) rates.

Relationships between psychiatric treated prevalence in hot/cold spots and socio-economic indicators were determined by using OLS. The regression model has been carried out with three groups of populations: the first taking into account all BHAs; the second with all dealing with BHAs without the hot spots; and the third with all BHAs without the cold spots. In the first two analyses, four explanatory variables were identified: the dependency index, rate of university studies, high economic condition rate and population density. In the third one, however, the significant explanatory variables were the high economic condition rate, the single-parent rate and non-marrieds (Table 4).

The residuals of OLS regression are spatially auto-correlated, as shown in the global Moran's I index (Table 4). For this reason, a GWR model was also designed in order to reduce spatial effects and improve the model fit. Results indicate an improvement in the global fit and a reduction of spatial dependence on residuals (Table 4).

Finally, Figures 3 and 4 show the geographical distribution of standard residuals and the regression coefficients obtained in the GWR analysis. The intervals correspond to the mean of the residuals and coefficients plus/minus the SD).

5. Discussion

5.1. The MOEA Approach for Spatial Clustering Analysis

The MOEA designed for spatial clustering analysis identified hot and cold spots of the treated prevalence of mental disorders in the Barcelona metropolitan area. The differences found between global Moran's I and Getis and Ord's G highlighted the

Table 3. Demographic and socio-economic characteristics of hot and cold spots of treated prevalence of mental disorders and the study area

	Population density	Dependence index	Ageing index	Un-employment rate	Non-married rate	Living alone rate	Single-parent rate	Illiteracy rate	University studies rate	≥2 vehicles rate	Migration rate	High socio-economic condition rate	Medium socio-economic condition rate	Low socio-economic condition rate
HS	4,082.10	46.02	127.62	11.68	60.09	7.00	12.03	8.48	8.81	20.70	3.98	6.45	44.28	42.48
HS1	3,783.01	47.72	106.12	11.94	60.26	6.46	11.35	10.46	5.67	29.69	3.08	5.92	48.61	38.14
HS2	2,210.22	40.18	87.92	11.37	59.92	5.57	10.64	9.66	8.38	26.50	3.76	6.97	45.92	40.69
HS3	13,192.10	50.33	176.41	11.84	60.17	8.30	13.36	6.87	10.25	13.03	4.47	6.20	41.36	45.54
CS	3,512.27	50.29	154.86	10.85	62.46	9.22	13.63	7.19	18.69	17.53	5.57	10.42	44.68	38.87
CS1	4,811.10	41.66	95.36	11.43	60.38	5.92	11.00	9.43	10.03	28.04	3.23	8.12	45.19	39.41
CS2	2,747.35	53.08	172.95	10.39	63.28	10.37	14.27	6.66	22.63	16.31	6.59	11.83	45.57	37.10
CS3	23,954.72	47.94	148.16	12.09	61.07	7.69	13.52	7.27	11.05	12.70	3.68	7.03	40.84	45.42
Non-HS/CS	1,148.26	44.17	103.91	10.67	61.87	7.24	11.57	8.49	12.11	27.04	4.75	9.02	45.61	38.52
Total	1,421.62	45.32	113.79	10.82	61.75	7.52	11.95	8.29	12.73	24.78	4.78	8.92	45.31	39.04

Source: Spanish population census (2001).

Table 4. Multi-variable analysis of psychiatric treated prevalence by OLS and GWR

OLS

Independent variables	Coefficients	Standard error	t
Psychiatric-treated prevalence model			
Intercept	47.140***	5.972	7.894
Dependency index	−0.097	0.137	−0.709
University studies rate	0.127	0.205	0.620
High economic condition rate	−1.252***	0.360	−3.476
Population density	−0.0002***	0.0001	−3.313
R^2	0.172	Adjusted R^2	0.156
Residual sum of squares	26,442.203	F	10.492***
AIC	1,601.390	Moran's I of the residuals	0.384 (Z = 29.597 SD)
Non-hot spot BHA model			
Intercept	56.739***	6.140	9.241
Dependency index	−0.387***	0.139	−2.776
University studies rate	0.514**	0.209	2.457
High economic condition rate	−1.555***	0.378	−4.110
Population density	−0.0002***	0.0001	−4.130
R^2	0.214	Adjusted R^2	0.196
Residual sum of squares	17.277.027	F	11.992
Non-cold spot BHA model			
Intercept	102.687***	15,462	6.641
High economic condition rate	−0.955***	0.193	−4.937
Single-parent rate	1.465***	0.453	3.232
Non-married rate	−1.274***	0.315	−4.044
R^2	0.298	Adjusted R^2	0.285
Residual sum of squares	15,399.672	F	13.623

GWR

Independent variables	Coefficients			Standard error		
	Min	Max	Mean	Min	Max	Mean
Psychiatric-treated prevalence model						
Intercept	33.734	62,321	45.504	6.140	17.725	6.726
Dependency index	−0.362	0.167	−0.071	0.140	0.440	0.154
University studies rate	−0.487	0.642	0.036	0.215	0.671	0.235
High economic condition rate	−2.251	–0.583	−1.042	0.388	1.135	0.430
Population density	−0.0003	0.00003	−0.0002	0.0001	0.0002	0.0001
Local R^2	0.128	0.316	0.166	–	–	–
Local standard error	–	–	–	8.022	11.280	10.984
R^2	0.217		Adjusted R^2		0.171	
Residual sum of squares	25,010.809		Bandwidth		21,769.041	
AIC	1,602.158		Moran's I of the residuals		0.090 (Z = 7.324 SD)	

Notes: *$p \leq 0.1$; **$p \leq 0.05$; ***$p \leq 0.01$.

need to use alternative methods, like the MOEA proposed, to identify and locate spatial patterns in the geographical distribution of mental disorders. To the best of our knowledge, this is the first analysis of this type carried out to date in a macro-urban area. These hot/cold spots would have been lost in an analysis carried out at municipality level. Due to the use of very small spatial units, this design allowed checking for deeper differences in large cities and reduced the ecological fallacy (Ocaña-Riola, 2010).

The study of the Barcelona health region, rather than just the Barcelona metropolitan area, avoided the boundary problem. Thus, the MOEA can identify

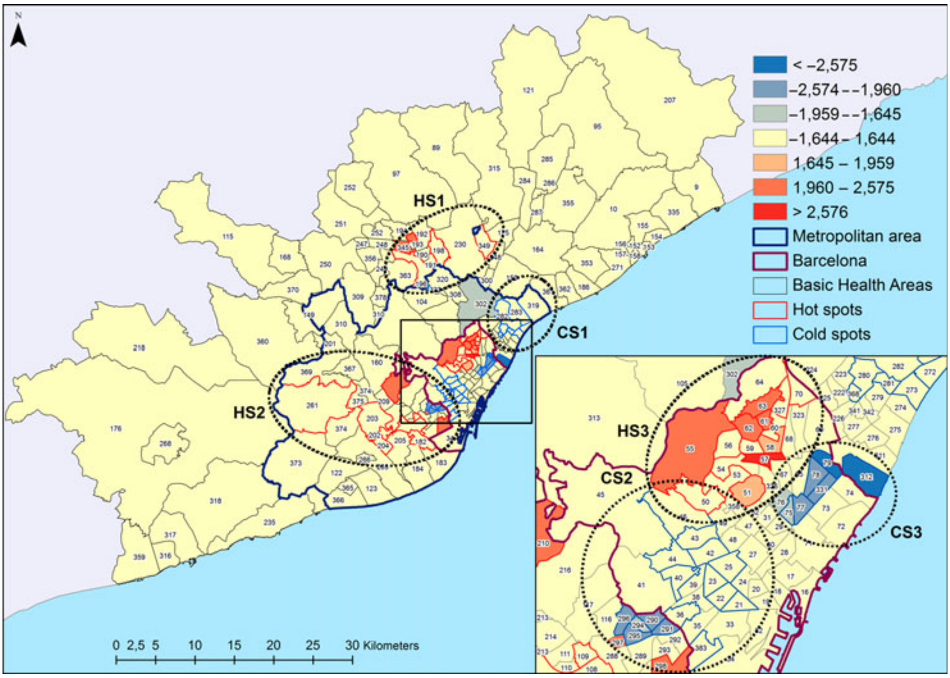

Figure 3. Spatial distribution of standard residuals of Geographical Weighted Regression analysis in the Barcelona Metropolitan Area and Health Region.

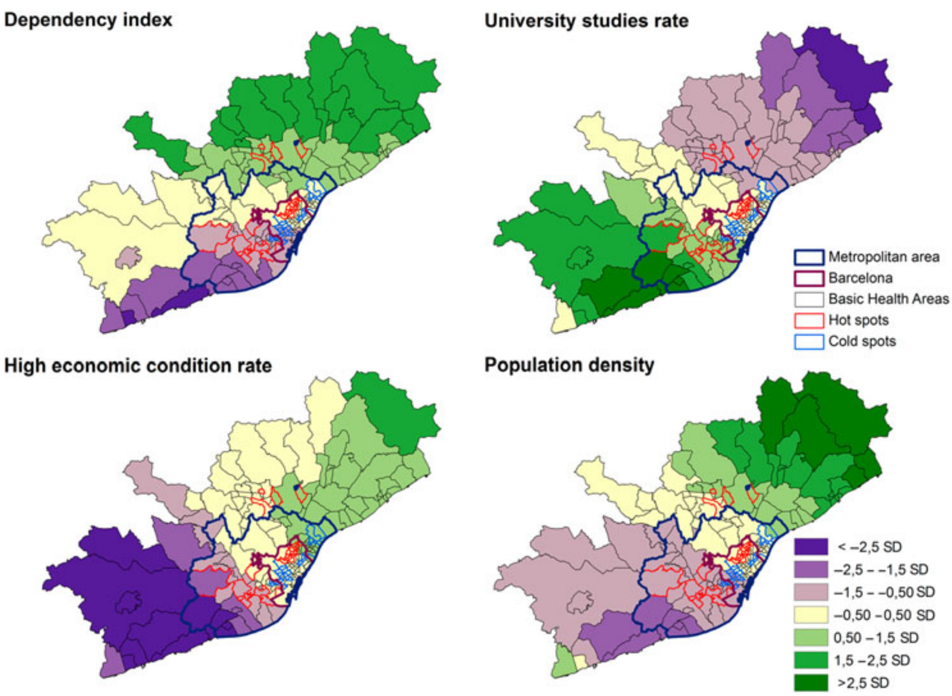

Figure 4. Spatial distribution of local coefficients (elasticities) of Geographical Weighted Regression analysis in the Barcelona Metropolitan Area and Health Region.

spatial clusters in a wider area that includes the borders of the study zone. On the other hand, the interactions between health region values and outside bordering prevalence values were studied on a regional scale in a research report for the Catalonian Department of Health (Salvador-Carulla et al., 2013b).

The selection of spatial units (census tracts, ZIP codes, health areas, municipalities, counties or administrative zoning) depends on the availability of data or on technical and methodological limitations. In general terms, the best choice is the smallest spatial unit available. This study has used the minimal spatial unit where epidemiological data are collected, the BHA. This lets us analyse infra-municipal geographical variations in large cities but not in less populated areas. In these cases, different spatial units (BHAs and municipalities) could be combined in the same analysis in order to manage the maximum amount of reliable information.

The spatial analysis of our study area highlights three main hot spots (HS1, HS2 and HS3) which are surrounded by three cold spots (CS1, CS2 and CS3). The closeness between these two types of spots is very common in geographical studies and may indicate a spatial relationship between them: high prevalence zones surrounded by low prevalence ones (Sridharan et al., 2011; Salinas-Pérez et al., 2012). The MOEA was suitable for identifying cold spots that are located between hot spots (these structures are usually missed or considered as a single cluster by other methodologies). However, it should be noted that CS2 and CS3 include some of the areas with incomplete prevalence data. Both clusters should be interpreted with caution because of the potential bias regarding their size that is caused by incomplete data.

The MOEA has also identified nine isolated BHAs as hot or cold spots, which can be considered spurious results, although they should be analysed in detail. As stated before, the MOEA was designed to evaluate solutions with a fixed number n of BHAs ($n = 10$). This number n was determined by a sensitivity analysis (repeating the analysis varying n) in an attempt to maintain geographical diversity and reduce computational time. For analysing these isolated BHAs, the expert knowledge of mental health managers, planners and clinicians is indispensable (Gibert et al., 2010).

5.2. Spatial Patterns of Mental Disorders in the Barcelona Metropolitan Area

Sometimes persons living in macro-urban areas must cope with high levels of stress produced by: high levels of traffic congestion, noise and pollution, densely populated areas, etc. (Godfrey & Julien, 2005). These characteristics, such as social, genetic and environmental determinants, could be relevant factors in contributing to the prevalence of mental diseases in macro-urban areas (Fryers et al., 2003). For this reason, the analysis of the potential spatial patterns of these illnesses in these zones could be of importance to support mental health decision-making by taking into account local evidence (Lewin et al., 2009; Salvador-Carulla et al., 2013a).

HS1, which is located in an industrial area, has substantial values (Table 3) of population density, dependence and ageing indexes. It also has a medium socio-economic condition rate, characterized by high illiteracy and low university study rates, as other research also states (Sabes-Figuera et al., 2012). HS2 is situated in an industrial area and has substantial values of population density, unemployment and medium and low socio-economic condition rates and is also characterized by high illiteracy and low university study rates. Finally, HS3 is situated in a residential area where there is a high density of specialized health care centres and hospitals. It also has high values of a dependence index and a medium socio-economic condition rate and is noted for the highest population density, ageing index and vehicles rates as well. High prevalence values can be related to low incomes as shown in Fortney et al. (2007). However, this fact could also be attributed to the concentration of high quality health centres (Ngamini Ngui & Vanasse, 2012). In fact, the so called 'Jarvis' Law' states that mental hospital utilization decays as distance increases (Sohler & Clapis, 1972; Smith et al., 2007).

CS1 is mainly located in an innovative district, where mental health determinants might be less frequent than in others, while socio-economic characteristics are below average in most cases. CS2, located in a residential area with large green spaces, has high values in the ageing index, university studies and high socio-economic condition rates. CS3 is in a residential area and the socio-economic factors have higher values than expected, for instance, in high population density, the ageing index or the low socio-economic condition rate. These structural conditions could favour low prevalence scores.

5.3. Relationships between Socio-economic Indicators and Spatial Clusters

The OLS do not indicate significant relationships between variables for hot or cold spots. However, when analysing prevalence, taking into consideration all the BHAs (global model), OLS gives a R^2 and adjusted R^2 values of 0.17 and 0.16, respectively. More than 15% of treated prevalence could be explained by only four variables (Table 4). Two of the independent variables are significant at the 0.01 level. The *F*-statistic and its associated *p*-value show that the global model has great statistical significance.

BHA-treated prevalence is related positively to the university study rate (p = 0.536) and negatively to population density (p = 0.001), the dependence index (p = 0.479) and high economic condition rate (p = 0.001). The OLS regression model is strengthened when hot spot BHAs are not included in the analysis. The university study rate (p = 0.015) is positively related to treated prevalence while population density (p = 0.000), the dependence index (p = 0.006) and a high economic condition rate (p = 0.000) are negatively related to treated prevalence. On the other hand, prevalence in non-cold spot areas (excluding cold spot BHAs in the analysis) is related positively to the single-parent rate (p = 0.001) and negatively to the non-married rate (p = 0.000) and the high socio-economic condition rate (p = 0.000).

The R^2 and adjusted R^2 obtained using GWR (0.22 and 0.17, respectively) improve OLS results. The AIC coefficients show similar scores and the residuals are smaller than those from the OLS model (Table 4). The GWR results highlight that the good economic condition rate is the most influential and negative variable in treated prevalence, followed by the dependence index. Population density has a very weak impact on the GWR model but this variable has a higher predictive capacity in the peripheral BHAs than in central BHAs. R^2 shows that socio-economic variables have a relevant influence on treated prevalence but there are other unexpected factors that have not been considered. These factors probably include aspects related to specialized service allocation as other studies indicate (Salvador-Carulla et al., 2008; Ngamini Ngui & Vanasse, 2012; Rodero-Cosano et al., 2014).

With the GWR method, it has been possible to analyse the spatial variability of local coefficients of independent variables (Figure 4). However, the spatial variation of the coefficients should be interpreted carefully since *t*-values showed non-significant coefficients in some areas at a 0.05 level.

For example, the mean of the elasticities (β coefficients) of the dependency index is –0.071. However, these elasticities are higher in the south than in the north. On the other hand, the β coefficients mean of the university rate is 0.036 and is higher in the north than in the south. Elasticity values of the high economic condition rate and population density have a distribution similar to that observed for the dependency index.

If we focus our attention on the hot spots, HS1 is related negatively to population density, the university study rate and the high economic condition rate, the last being the most important variable followed by the rate of university studies. However, HS2, compared to HS1, is more deeply influenced by the dependence index and the rate of university studies: the first variable has a negative influence while the second relates positively to treated prevalence, although the high economic condition rate is still the most significant variable. The main variables in HS3 are the dependence index and high economic condition rate, with negative relationships; these results are in line with the previous ones.

When analysing the cold spots, the most important variable is the high economic condition rate with its negative influence, followed by the dependence index. Finally, the rate of university studies affects them very little.

These results are in line with previous research. In fact, a recent study (Rodero-Cosano et al., 2014) has related the spatial clusters of depression in Catalonia to urbanicity, high unemployment, a high educational level and poor accessibility to mental health facilities.

6. Conclusions

The MOEA has identified and located spatial clusters with statistically significant high or low values of treated prevalence of mental disorders in the Barcelona metropolitan area. This analysis has led to the location of relevant hot and cold spots that integrate both infra-municipal areas (Basic Health Areas) and municipalities in different combinations. These spatial clusters can provide informed evidence for mental health planning and policy designs.

The MOEA reduces the limitations of classic spatial analysis methods and can be used to identify spatial clusters which otherwise could have been detected as one sole large one or missed altogether. This procedure allows us to understand the socio-economic variables that could influence the prevalence of mental disorders in macro-urban areas.

According to GWR, the low level of study rate and the relatively low level of incomes are some of the socio-economic characteristics that could be the most influential variables in the treated prevalence of mental disorders, coinciding with previous research (Fortney et al., 2007; Sabes-Figuera et al., 2012; Rodero-Cosano et al., 2014).

Futures lines of research are: first, analysis of the treated prevalence of mental disorders in less populated villages; second, the identification of other risk variables related to specialized service allocation for mental health prevalence in macro-urban areas; third, to check if the treated prevalence of mental disorders is differs significantly between rural, urban and macro-urban areas; and, finally, to analyse the treated prevalence of mental disorders in other macro-urban areas in order to identify common risk variables.

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