The Relationships between Depression Spatial Clusters and Mental Health Planning in Catalonia (Spain)

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Abstract. This study aims to analyse potential risk factors which could influence the occurrence of hot spots of depression. They cannot only be explained through municipal socio-demographic characteristics and which is why causes at catchment area level should also be studied. Indicators at both spatial levels were analysed by a multi-level regression model. The analysis included various socio-demographic, geographical and service allocation indicators. According to scientific literature, unemployment and rurality were identified as risk factors for depression and, therefore, for hot spots. On the other hand, low educational levels and poor accessibility showed little relationship here while other studies indicated otherwise. Preliminary results described diverse risk factors at two levels which were related to a high likelihood of hot spots, although more in-depth analysis will be needed.

Keywords: Spatial cluster, risk factor, multilevel analysis, catchment areas, mental health.

1 Background

Spatial data can be analysed through a large and growing number of spatial statistical methods for detecting spatial patterns in their geographical distribution [1]. Spatial clustering analysis usually has two stages [2]: first, to identify spatial clustering by an exploratory spatial data analysis; second, to relate clusters to other factors in order to find their original causes by some multivariate method.

Epidemiological research uses these analyses intensively to study spatial patterns in diseases [3,4]. In this area, Multi-objective Evolutive Algorithms were used (MOEA), especially designed for solving multi-objective spatial problems [5] in order to identify hot spots and cold spots of treated prevalence of depression at municipality level in Catalonia (Spain) [6]. This research aimed to locate these significant spatial clusters, describing them together with some characteristics of mental health catchment areas;

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it did not seek, however, to link them to socioeconomic risk factors of depression or other factors potentially related to variations in medical practice.

Scientific literature has related depression to different socio-economic indicators. For instance, unemployment [7] and rurality [8] are considered to be among its major risk factors. In addition to these, other socio-economic indicators such as poverty, belonging to minorities, gender and low incomes have been related to such prevalence and hospital admissions for depression [9].

Thus, socio-economic variables are key but there may be other factors involved. In a previous article, mental health catchment areas were described through several indicators related to specialised service allocation such as their accessibility, availability and adequacy. This last concept is the smallest geographical healthcare area where different studies have found the existence of variations in health care delivery that could be useful for health planning [10,11]. In mental health, the smallest specialized care area is usually the catchment area served by Mental Health Community Centres.

Thus, socio-economic and demographic characteristics of the population and indicators in health service allocation, at two geographical scales or levels (municipality and mental health catchment area), may be related to spatial clusters of very high or low depression cases. Hierarchical linear models are specially designed to analyse data at different levels, in this case geographic scales. These models often use health fields [12,13,14,15,16,17,18], covering many of the multilevel models described in the theory.

The main objective of this article is to analyse potential risk factors which may influence the occurrence of hot spots or spatial units where treated prevalence scores for depression in Catalonia are significantly high. Depression clusters have been identified and described in a previous paper by a MOEA. The relationships are studied by two multilevel models which use several socio-economic and service provision indicators at municipal scale and in catchment areas.

2 Methods: Multilevel Logistic Regression Models

In general, univariate multilevel models [19,20] assume that there is a hierarchical data set, with one single outcome or response variable (Y) that is measured at its lowest level, and explanatory variables at the rest of existing levels. If the outcome is a dichotomous or binary variable representing the presence or absence of a characteristic, our interest is in predicting the probability (percentage) of subjects that present the characteristic ; then the common approach is to use generalized linear models [21,22], in particular the logistic regression model. In this case, Raudenbush & Bryk [23] or Goldstein [19] describe the multilevel extension of generalized linear models that give explanatory variables (x_{ij}) for the different levels. The probability of the desired outcome $P(Y = 1|x_{ij}) = \pi_{ij}$ is predicted using the logit function $\mathrm{Logit}(\pi_{ij}|x_{ij}) = \log[\pi_{ij}/(1 - \pi_{ij})]$ in two steps: firstly, modelling the linear regression equation at the lowest level with the explanatory variables of the logit function of π_{ij} and, later, using the inverse of the logit function; thus we can predict the probability π_{ij} by explanatory variables at different levels.

The OR obtained by the model represents the odds that an outcome will occur given a particular value x^{*}_{ij}, compared to the odds of the outcome occurring with another value x_{ij}. Special interpretation is obtained when an explanatory variable is binary, representing whether there has or has not been exposure to a factor to evaluate the association between the exposure to the factor and its outcome. OR represent the ratio between the odds for the presence and absence of the exposure factor, obtained by e^{β} where β is the specific coefficient of the explanatory binary variable.

HS was modelled to allow the differentiation of relationships. The dependent variable is whether there is (1) or is not (0) a HS (binary). The independent variables for catchment areas and municipality levels are explained above.

With this amount of variables at both levels, and since our hypothesis is not based on a strong theory, we have used an exploratory procedure to select the most parsimonious model. The strategy to construct the linear model for the logit component has been from the bottom up, starting with a single model and proceeding to add parameters which are tested using the Wald test for significance after they have been added. Due to that, sometimes there was recoding of some initially numerical variables into categorical variables using the percentiles, or reducing categories in initially categorical variables.

We have started by building [20] the intercept-only model, then the best model was fitted with fixed lower-level explanatory variables, and finally the higher-level explanatory variables were added. All models were built nested, using full maximum likelihood via adaptive Gaussian quadrature [24].

3 The Study Case

3.1 Scope of the Study

Catalonia is a Spanish region located in the Northeast of the Iberian Peninsula with 7.5 million inhabitants. The Catalonian Public Health System is universal, as in the rest of the country, and the provision of care includes both public and private organisations under contract agreements with the health administration. Regarding mental health care, Mental Health Community Centres for adults are assigned to large city districts or whole municipalities forming catchment areas or small mental health areas [25]. Catalonia is divided into 74 catchment areas, which include a total of 946 municipalities. Catchment area levels were reduced to 60 because several areas in populated cities corresponded to infra-municipal level and so they were grouped into 7 units which coincide with municipal levels.

3.2 The Dependent Variable: Depression Hot Spot in Catalonia

Depression clusters were identified by a MOEA, located and described in a previous article [6]. The multivariate spatial problem was to find groups of close municipalities (spatial unit of analysis) with significantly high prevalence through the maximization of the treated prevalence of depression, minimizing the standard deviation of prevalence and minimizing the distance between spatial units. The MOEA's solutions were evaluated by means of four fitness functions selecting the most frequent municipalities. Thus, this type of problem does not have a unique solution. Finally, the results were mapped in a Geographic Information System (GIS).

The MOEA found six hot spots formed by 39 municipalities which were included within 13 catchment areas. The first is situated in the Seu d'Urgel region located in Lleida, which is mainly a rural area whose activity focus is on agriculture. The second is Baix Berguedà near the Seu d'Urgel region which lies in transition to the plains of the Catalan Central Depression. This region has always been sparsely populated and here agriculture, cattle ranching and forestry have proven generally complementary to one another and compatible with tourism. The third is in the Catalonia central area in Barcelona including the North Anoia region with its important paper-making industry, along with the neighbouring municipalities of La Segarra, a grain-growing region. The fourth is located in Barcelona province within the Vallès Oriental region, which is an urban area whose main economic activity focuses on the industrial and services sectors. The fifth, as in the case mentioned above, is a rural zone with a major wine sector. Finally the last hot spot is located in Borges Blanques, mainly a rural area.

Municipality hot-spots have an average of 8.16 cases per 1,000 inhabitants: the median is 7.85 and its standard deviation is 6.49. The highest value is 35.80 while the lowest is 1.74 per 1,000. The main statistical values are shown in table 1.

Table 1. Basic statistics of the dependent variable

Su	Nº mun.	Catchment areas	Mean	Median	Standard deviation
HS1	3	Bages	9.9	8.3	3.4
HS2	8	Bages, Berga and Osona	12.0	9.0	10.1
HS3	7	Anoia and La Segarra	11.6	9.6	6.6
HS4	11	Vallès Oriental and Osona	4.6	3.3	3.2
HS5	9	Alt Penedès, Garraf, Gavà, Martorell and Sant Feliu	5.2	5.4	2.0
HS6	1	Borges Blanques	13.9	13.9	

Thus, the hot spot municipality is a binary variable that divides municipalities into two classes depending on whether they have not been detected as hot spots (category 0) or they have been (category 1), located and described above. Therefore, the dependent variable corresponded to level 1 in our multi-level analysis.

3.3 Independent Variables

Level 1: Municipalities.

Scientific literature has related depression to different socio-economic indicators, such as unemployment, poverty, rurality etc. Consequently it is also important to analyse the relationship between the spatial cluster with high values of depression-treated prevalence and socio-economic indicators. Based on studies on the spatial distribution of mental-illness prevalence, the indicators selected are: population density, unemployment, income and university studies.

Depression-treated prevalence (PRE) is a variable which was calculated using the gender, age, municipality of residence and main diagnosis through the direct method [26] that took into consideration the population of Catalonia and is measured in cases per 1,000 inhabitants.

The population density (DENS) is a binary variable related to rurality [27]. The municipalities were separated into two groups: those whose population density is lower than 45 inhabitants per square kilometer (0) indicating municipalities with very low density and, therefore, highly rural; and those whose population is greater or equal to 45 inhabitants per square kilometer (1) which indicates moderately rural municipalities.

The unemployment rate (UNE) measures the prevalence of unemployment and its percentage is calculated by dividing the number of unemployed individuals by the active population currently between 16-64 years of age [28].

Income (INC) is a continuous variable that allows the economic poverty level to be evaluated by measuring the income per inhabitant [29].

University studies (UNI) is a proxy indicator of the educational level of municipality populations and was calculated using the number of inhabitants who had finished their degrees [28]. Municipalities were classified in three categories: values below 7.39 (0), values between 7.39 and 9.86 (1) and values above 9.86 (2).

The main statistics of these variables can be studied in Table 2.

Table 2. Municipal level variables initially considered independent in the analysis

							Percentiles				
	Type	**N**	**Mean**	**SD.**	**Mín**	**Máx**	**25h**	**33.3h**	**50h**	**66.7h**	**75h**
PRE	Num.	946	2.57	2.9	0	35.8	0	1.1	1.99	2.97	3.61
DEN	Num.	946	437.47	1562.9	0.93	18871.88	13.01	20.42	44.99	110.28	182.74
UNE	Num.	946	7.15	3.18	0	21.14	4.81	5.6	6.93	8.46	9.46
INC	Num.	943	17840.53	4192.9	7403	40109	15076	16157	17717	19030.33	19845
UNI	Num.	946	9.21	3.76	0.85	36	6.67	7.39	8.48	9.86	10.8

Level 2: Mental Health Catchment Areas.

Catchment areas in Catalonia have been previously described in four domains: urbanicity, service availability, accessibility to care and adequacy or appropriateness. These domains have been used in previous studies on the spatial distribution of mental-disorder prevalence. If hot/cold spots are spatially associated with specific catchment areas, it could be relevant to analyse if they are mainly rural or urban, if their accessibility is high or not, and so on.

The percentage of hot spots (PHS) is a numerical variable that indicates the percentage of hot spot municipalities in the catchment area.

Urbanicity (URB) was determined following a classification of the OECD [30], so that the variable was classified as being predominantly urban (0), significantly rural (1) and predominantly rural (2). The level ‘predominantly urban’ means 85% of the inhabitants reside in municipalities whose density is greater than 150 inhabitants/km^2, ‘significantly rural’ when this percentage is between 50% and 84%, and ‘predominantly rural’ when it is lower than 50%.

The accessibility (ACE) to the MHCC of each catchment area was assessed using a standard Geographical Information System (GIS) and was obtained from an article which studied accessibility to health services in Catalonia [31]. Accessibility was measured in minutes taken by car to the corresponding MHCC from the least accessible zone of the catchment area in intervals of fifty minutes, consequently selected intervals are: 0-15 min (0), 15-30 min (1), 30-45 min (3), 45-60 min (4), and >60 min (5).

MHCC availability (AVA) was measured by the rate of outpatient MHCC per 100,000 inhabitants. It indicates the relationship between the number of MHCC and the inhabitants in the catchment area. This indicator does not consider the differences in staff allocated to each MHCC. Therefore, the variable was classified as adequate when the values were within the range 1-2.5 (0) and inadequate when the values were outside this range, that is, <1 or >2.5 (1).

Lastly, the adequacy (ADE) of the provision of mental health services in the catchment areas was assessed by a group of PSICOST experts using information from the Mental Health Atlas of Catalonia [25]. This assessment includes all types of services such as hospitalization units, day hospitals, day centres, etc. Experts rated 7 levels of provision in every catchment area in (very high, high, medium high, medium, medium low, low and very low). This rating was represented in semaphore scale and agreed with official results from the Department of Health of Catalonia. Level 1 indicates that all types of services have been allocated to the catchment area and that most of them are located within it, while level 7 indicates that some types of services have not been allocated to it. For this research the variables are classified into two values: 0 when adequacy is very high or high and 1 when adequacy is medium, low or very low.

The main statistics of these variables can be studied in Table 3.

Table 3. Catchment area level variables initially considered in the analysis

Numerical Variables	N Municipalities	Mean	Sd.	Min	Max	Median 50th percentile
NUM (Number of municipalities in the catchment area)	946	15.77	17.33	1.00	73.00	10.00
PHS	39	3.34	7.83	0.00	29.41	0.00

4 Results

Taking into account the above explanation, we can obtain the model coefficients whose reduction allows us to assess the most fitting model. Based on the results of Model 1, we can see that there are differences in prevalence between areas of mental health, as well as between municipalities, although population differences at this level are more pronounced.

According to the results of the model (table 4), rurality, accessibility and adequacy are the three most important risk factors at catchment area level, and the unemployment rate shows a protective factor.

Table 4. Final estimation of fixed effects (full maximum likelihood via adaptive Gaussian quadrature)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value	Odds ratio	Confidence interval
For INTERCEPT, β_0							
INT, γ_{00}	-2.991	1.035	-2.890	58	0.005	0.050	(0.006,0.399)
URB, γ_{01}	-1.690	0.611	-2.766	58	0.008	0.184	(0.054,0.627)
For PRE slope, β_1							
INT, γ_{10}	0.288	0.111	2.584	878	0.010	1.333	(1.072,1.659)
ACC, γ_{11}	0.111	0.047	2.333	878	0.020	1.117	(1.018,1.226)
For DENS slope, β_2							
INT, γ_{20}	3.013	0.905	3.328	878	<0.001	20.352	(3.442,120.335)
ADE, γ_{21}	-2.651	1.208	-2.194	878	0.028	0.071	(0.007,0.756)
For UNE slope, β_3							
INT, γ_{30}	-0.577	0.144	-4.015	878	<0.001	0.562	(0.424,0.745)
PHS, γ_{31}	0.014	0.003	4.986	878	<0.001	1.014	(1.009,1.020)
ADE, γ_{32}	0.063	0.034	1.857	878	0.064	1.065	(0.996,1.138)
For UNI3 slope, β_4							
INT, γ_{40}	-0.646	0.291	-2.222	878	0.027	0.524	(0.296,0.927)

In short, the intercept in the model is the expected log-odds of HS for a municipality with zero value for all the predictor variables. In this case, this expected log-odds corresponds to a probability of 1/[1+exp(2.991)]=0.047, that is approximately 39/946.

In level 1, university studies directly reduce the probability of being a hot spot. This factor decreases the probability of being a hot spot when taking values 0, 1, 2. In this case, using as reference the municipalities whose percentage is under7.39 of university, the probability of being a hot spot must be divided by 2 (OR=$e^{-0.646} = 0.524$) for municipalities with a percentage between 7.39 and 9.86, and divided by 4 (OR=$e^{-0.646*2} = 0.275$) for municipalities with a percentage over 9.86. The employment-rate factor may seem to act as a protective factor for a municipality hot spot, since the probability would have to divide it by 2 (OR=$e^{-0,577} = 0.561$). However, this factor affects the variable percentage of hot spots and adequacy in level 2. This causes the probability of being a hot spot to increase for each unit increase in the percentage of the hot spot factor (OR=$e^{0.014} = 1.014$) and increase in catchment areas with poorer adequacy (OR=$e^{0.063} = 1.065$).

In principle, density values above 45 produce an increase in probability, multiplying it by 20 (OR=$e^{3.013} = 20.35$). However, probability is roughly divided by 14 (OR=$e^{-2.651} = 0.071$) in municipalities with density values higher than 45 and medium or low adequacy values. Finally, the prevalence factor increases the probability per each unit increase of prevalence (OR=$e^{0.288} = 1.333$), and influences the accessibility variable increasing the probability of its being a hot spot.

In level 2, urbanicity affects in such a way that the more rural the municipality is (0 to 2), the less probability it has of being a hot spot. Regarding a predominantly urban municipality, the probability is reduced to almost one fifth (OR=$e^{-1.69} = 0.184$) in the case of being significantly rural, and reduced almost 30 times (OR =$e^{-1.69*2} = 0.034$) in the case of being predominantly rural. Moreover, for the same value of prevalence, the municipality may experience an increase in the probability of being a hot spot for each 15 minute increase of time regarding accessibility (OR=$e^{0.111} = 1.117$).

5 Discussion

As mentioned in the introduction, scientific literature has related depression to different socio-economic indicators, among these highlighting unemployment [7] and rurality [8] as the most important risk factors. In fact, urban counties in the USA had higher hospitalization rates for depression than rural counties [9]. The results obtained are coherent with respect to this relationship.

Unemployment was the second most important socio-demographic risk factor for depression in Spain [32] in accordance with the literature [33]. High depression admissions in hospitals are related to a high unemployment rate [9]. In our research the employment rate factor may seem to act as factor which reduces the risk that a municipality is hot spot, although this factor affects the percentage of hot spot variables and adequacy at level 2, which coincides with the above study.

Focusing on the educational level, according to the scientific literature it was found to be related to the prevalence of depression and anxiety [34]. Patients who are better educated make significantly more medical visits due to depression than other patients [35]. However, hospital admission of patients with depression is not related to the educational level [9]. Nevertheless, the results show that a high level education reduces the risk of depression prevalence.

Finally, poor accessibility has appeared as a risk factor increasing depression prevalence in our research. However, other authors have supported that high accessibility has previously been associated with patients with depression making more mental health visits [35]. Therefore, this variable needs further study.

6 Conclusion

The spatial data analysis of depression, as well as schizophrenia, was included in the mental health atlas of Catalonia which is the first mental health report in Spain about integral mental health care. Spatial analysis has allowed the identification of geographical areas where the distribution of depression is not random and may be due to well-known but also unknown risk factors. This research endeavours to be an initial approach to the identification of these factors at two geographical levels, although deeper analysis must be carried out. These results may help planners and decision-makers in their search for efficiency, quality and equality in mental health care.

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