Article

Noise Disturbances and Calls for Police Service in València (Spain): a Logistic Model with Spatial and Temporal Effects

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Abstract: The purpose of this paper is to explore the presence of spatial and temporal effects on the calls for noise disturbance service reported to the Local Police of València (Spain) in the time period from 2014 to 2015, and investigate how some socio-demographic and environmental variables affect the noise phenomenon. The analysis is performed at the level of València's boroughs. It has been carried out using a logistic model after dichotomization of the noise incidents variable. The spatial effects consider first and second order neighbours. The temporal effects are included in the model by means of one and two weeks temporal lags. Our model confirms the presence of strong spatio-temporal effects. We also find significant associations between noise incidence and specific age groups, socio-economic status, land uses and recreational activities, among other variables. The results suggest that there is a problem of "social" noise in València that is not exclusively a consequence of coexistence between local residents. External factors such as the increasing number of people on the streets during weekend nights or during summer months increase severely the chances of expecting a noise incident.

Keywords: noise disturbances; residents complaints; logistic regression; spatio-temporal effects; socio-demographic and environmental effects; GIS

1. Introduction

In Europe, one of the challenges that modern urban cities face is environmental noise. The first noise abatement actions essentially consisted in legislation fixing maximum sound levels and technological progresses: vehicles, aeroplanes and machines had to comply with noise limits at the time of manufacture [1]. However, this policy could not solve completely the noise problem since the growth of road, rail and air traffic were partly offsetting the technological improvements. This situation led to the enactment of the Directive 2002/49/EC of the European Parliament and of the Council whose aims were (1) "to define a common approach intended to avoid, prevent or reduce on a prioritised basis the harmful effects, including annoyance, due to exposure to environmental noise" and (2) to provide "a basis for developing Community measures to reduce noise emitted by the major sources, in particular road and rail vehicles and infrastructure, aircraft, outdoor and industrial equipment and mobile machinery". In the case of València (Spain), the aforementioned Directive was transposed first into a regional law (*Ley 7/2002, de 3 de diciembre, de la Generalitat Valenciana, de Protección contra la Contaminación Acústica*) and then into a national legislation (*Ley 37/2003, de 17 de noviembre, del Ruido*).

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Nevertheless, none of the instruments referred above targeted "social" noise (neighbourhood noise) since it was thought to be dealt locally. This was the case of the City Council of València which decided to issue an ordinance to solve the noise problem (*Ordenanza Municipal de Protección Contra la Contaminación Acústica* from June, 26, 2008). This ordinance established, among other questions, the regulation of ZAS zones, that is, areas in which the levels of noise exceed the limits allowed by the law. When an area is declared a ZAS zone (which literally means acoustically saturated zone in Spanish, *Zona Acústicamente Saturada*) the City Council can implement special measures in order to reduce environmental noise. These measures can be referred to the number of licensed premises (especially in the case of bars, pubs and nightclubs), the closing hours, the development of activities that may provoke noise, the limitation of the vehicle traffic or whatever measures considered appropriate.

Even though this ordinance was enacted in 2008, the problem of the noise has not been resolved yet. Evidence of this can be found in the fact that the Local Police of València records approximately 11000 calls for service related to noise disturbances every year.

As a result of the collaboration between the Local Police of València and the University of València in a larger project, a prior study of the calls for service for noise disturbances in València (Spain) was conducted [2]. The study covered a two-year period (2014-15) and the available data contained the following variables: time, date and geographic location of the calls for service. A descriptive analysis showed that the calls were concentrated in specific boroughs and at specific times: mainly between 10pm to 4am during the weekends, with a peak in June. This pattern suggested that people's recreational activities (and thus, "social" noise) could be the main cause of noise disturbances in València.

The current study aims to add to the knowledge of the "social" noise problem in two ways: (1) exploring the presence of spatial and temporal effects on the calls for service for noise disturbances reported to the Local Police of València (Spain) in the period 2014-15 and (2) investigating the effect of socio-economic, demographic and environmental characteristics of each borough.

Regarding the choice of the method, a logistic model enables the estimation of the likelihood of the report of a call for service, but also permits to confirm that there exists a spatio-temporal effect on the calls that are also affected by the variables.

Different authors have used logistic models in the analysis of crime data. Some studies show the application of logistic regression models to predict the probability of burglary activities with respect to the event density epicenter, using a regular grid for localizing events [3]. Other authors have investigated the potential of applying predictive analysis in an urban context through a logistic model and a neural network, using a raster grid [4]. Finally, logistic model have also been used to interpret the patterns observed in the attacks of the insurgents in Baghdad. To test the hypothesis of heterogeneity, repeat victimization and denial policing the authors used a regular grid that decomposed the city of Baghdad into $3,456$ cells [5]. Unlike these three studies, our approach identifies the incidents over an irregular grid: the one formed by the boroughs of València. We chose this approach since all socio-economic and demographic variables for this administrative unit are available in the Statistics Yearbooks published by [6].

2. Materials and Methods

2.1. Binomial logistic model

The occurrence of a noise incident can be described by a Bernoulli random variable, Y, such that $Y = 1$ if an incident has occurred and $Y = 0$ otherwise ($Y \sim B(1, p)$). The effect of a set of variables, $\{X_1, X_2, \ldots, X_k\}$, on Y can be modelled in this context by means of a *binomial logistic model*, in which the logarithm of the odds in favour of the noise occurrence depends linearly on the variables. Namely,

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$$\text{logit}(P(Y=1)) = \log\frac{P(Y=1)}{P(Y=0)} = \beta_0 + \sum_{i=1}^{k}\beta_i x_i, \tag{1}$$

where the variables can be numerical or categorical. If X_i is categorical with J categories, the model includes it through $J-1$ dichotomous variables, $X_{ik}, k = 1, 2, \ldots, J-1$, so that $X_{ik} = 1$ if $X_i = k$ and 0 otherwise. The missing category, which is taken as a reference and whose choice is arbitrary, is included in the model when $X_{ik} = 0, \forall k$. This decomposition of X_i avoids redundancy in the parameters.

Having fitted the model, $P(Y=1)$ is estimated by means of π_1,

$$\pi_1 = \frac{\exp(\beta_0 + \sum_{i=1}^{k}\beta_i x_i)}{1 - \exp(\beta_0 + \sum_{i=1}^{k}\beta_i x_i)} \tag{2}$$

a expression easily derived from (1).

2.2. Model parameters interpretation

The β coefficients in the model are directly related to the odds in favour of the occurrence of a call, which is simply called the odds ratio of the event of interest. In effect, if X_i is a numerical variable, let's keep the rest of the variables constant and substitute in (1) the values x_i and $x_i + 1$, respectively. Taking antilogarithms and dividing both expressions, we will obtain,

$$\exp(\beta_i) = \frac{\frac{\pi_1(x_i+1)}{1-\pi_1(x_i+1)}}{\frac{\pi_1(x_i)}{1-\pi_1(x_i)}},$$

that is, $\exp(\beta_i)$ is the change in the odds ratio when the variable increases one unit, the rest of the variables remaining constant.

If X_i is a categorical variable with only two categories, represented by 0 and 1, from the quotient of the antilogarithms of (1) for both values of X_i, it follows that $\exp(\beta_i)$ is the odds ratio of X_i when the rest of the variables do not change.

Finally, if X_i is a polytomous variable decomposed in dichotomous variables as above explained, $\exp(\beta_{ik})$ is the odds ratio for the category k and the reference category, as long as the rest of the variables do not change.

An exhaustive presentation of logistic models can be found in [7].

2.3. Neighbourhood structure

A model that studies the spatial effect on the noise phenomenon, requires the definition of a suitable neighbourhood structure for the spatial unit being used. Such a structure depends on the criteria used to define the concept of neighbour. If we define as *neighbours* those boroughs sharing a border, a criterion that seems the most appropriate for an irregular lattice like the one we are considering, the neighbourhood matrix W is defined by,

$$w_{ij} = \begin{cases} 0, & i = j = 1, \ldots, n; \\ 1/n_i, & \text{if } j \in V(i), \text{ with } n_i = \#V(i); \\ 0, & \text{if } j \notin V(i), \end{cases}$$

where i and j represent two of the n boroughs and $V(i)$ the set of neighbours of i. With this structure, no borough is its own neighbour, and the values in each row sum to unity because the weights w_{ij} are standardised. For other neighbourhood structures see [8].

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2.4. Data

The 092 call center of the Local Police of València (PLV) receives complaints of incidents that occur in the city. During the years 2014 and 2015, around 480,000 incidents were recorded. For each of them time, date, type of incident and location by geographic coordinates are known.

The aim of this work, as we have already pointed out in the Introduction, is the analysis of the incidents related to *noise* by using a logistic model that allows to assess the presence of spatio-temporal effects and the influence of some variables on the phenomenon of noise. Therefore, the database is filtered to obtain only the information related to noise incidents.

A second filter is applied in order to exclude the incidents occurred in the boroughs belonging to districts 17 to 19 of the city of València, which are displayed in Figure 1 (left). These are three peripheral and sparsely populated districts which are located to the North, West and South of the city, staying away from the urban core. Few calls from these districts are recorded, about 3.5% of the total of the two years analysed. Hence, applying this second filter, a total of 22,419 calls are due to noise problems in districts 1 to 16, 11,577 in 2014 and 10,842 in 2015.

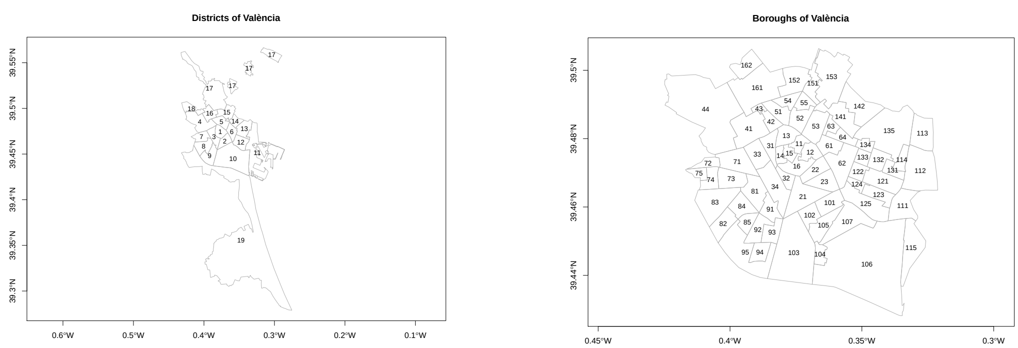

Figure 1. Districts (left) and boroughs (right) of València

Figure 1 (right) shows the 70 borough of València in which districts 1 to 16 are divided and their identification numbers. A complete list of the names of all boroughs can be found in Table A1 in the Appendix.

2.5. Data transformation and variables

The original database contains 22,419 calls related to noise incidents. Exact time of the event, day, and geographical location are recorded for each call. We divided the period of the day as follows: day (from 5am to 21pm) and night (from 22pm to 4am). In order to meet our objectives, this database is disaggregated on the basis of three dimensions: the period of the day on which the call can occur (day/night), the date (from 1 to 730 in order to cover the two years of study) and the borough where the call is located (70), which in turn gives rise to 102,200 ($2 \cdot 730 \cdot 70$) records. Thus, our dataset contains 102,200 records each of which incorporates the information shown in Table 1 for the corresponding combination of a period of the day, a date (from 2014 or 2015) and a borough.

We can distinguish in Table 1 three subsets of variables: those related to temporal effects (1 to 3), those that inform us about incidents that occurred in previous weeks in the borough and its neighbours (4 to 9) and those describing the characteristics and environment of the borough, which include the district within which the borough is placed (10), demography (11 to 15), services that may represent noise sources (16), a socio-economic index (17), traffic-related information (18), age of the buildings (19), land uses (20

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variable	meaning
(1) weekday	day of the week
(2) month	month of the year
(3) period	period of the day
(4) noise_1	number of noise calls 1 week before in the borough
(5) noise_2	number of noise calls 2 weeks before in the borough
(6) noise_{11}	number of noise calls 1 week before in the 1 lag borough neighbourhood
(7) noise_{12}	number of noise calls 1 week before in the 2 lag borough neighbourhood
(8) noise_{21}	number of noise calls 2 week before in the 1 lag borough neighbourhood
(9) noise_{22}	number of noise calls 2 week before in the 2 lag borough neighbourhood
(10) district	district to which the borough belongs to
(11) inhab	number of inhabitants in the borough
(12) inhab14	percentage of inhabitants in the borough aged under 15
(13) inhab1529	percentage of inhabitants in the borough aged between 15 and 29
(14) inhab65	percentage of inhabitants in the borough aged 65 or over
(15) mphouse	average number of members per household
(16) barrest	number of bars and restaurants per 100 inhabitants in the borough
(17) svi	socio-economic vulnerability index
(18) mainroad	number of km of non-pedestrian main road located in the borough
(19) buildage	average age of the buildings located in the borough
(20) educuse	percentage of land in the borough dedicated to educational use (undergraduate and university level)
(21) greenuse	percentage of land in the borough dedicated to green areas
(22) botellon	binary variable indicating if the practice of “botellón” is usual in the borough
(23) noise	number of noise calls in the borough

Table 1. Enumerated list of variables used in the analysis and their meaning

to 21) and presence of “botellón” frequent locations within borough boundaries (22). All the variables corresponding to borough characteristics (11 to 22) vary yearly (for 2014 or 2015).

The district to which each borough belongs to is used as a categorical variable in order to capture a part of the spatial heterogeneity of the noise phenomenon in València that may be missed by the variables 11 to 22 (which are all obtained at the borough level). The choice of the district instead of the borough itself is due to avoid model overfitting issues.

The socio-economic vulnerability index is a continuous variable that takes values in the interval [1,5] and the lower its value, the more vulnerable the borough. It is a synthetic index made up from 10 variables which considers, among others, the academic level of the residents, the value of vehicles and dwellings registered/located in the borough and an approximation of average income at the district level. Details can be found in [9].

“Botellón” is a popular phenomenon among Spanish teenagers and young adults that consists in gathering in public spaces to socialize and drink alcohol [10,11]. The binary variable related to “botellón” was constructed and validated following several media and police sources, being highly correlated in space with the presence of pubs and nightclubs across the city.

Finally, variable number 23 in Table 1 is the number of noise calls that take place in the borough, which is converted into a binary variable to become the response of the logistic model. Hence, in view of the variables indicated in Table 1, the logistic model chosen for this research follows the next mathematical expression,

$$\begin{aligned}\text{logit}(\text{noisebin}) &= \beta_0 + \beta_1\text{weekday} + \beta_2\text{month} + \beta_3\text{period} + \beta_4\text{noisebin}_1 + \beta_5\text{noisebin}_2 \\ &\quad + \beta_6\text{noisebin}_{11} + \beta_7\text{noisebin}_{12} + \beta_8\text{noisebin}_{21} + \beta_9\text{noisebin}_{22} + \beta_{10}\text{district} \\ &\quad + \sum_{k=11}^{22} \beta_k\text{variable}_k. \end{aligned} \tag{3}$$

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The response variable, *noisebin*, and the rest of variables related to noise in (3), $noisebin_t$, and $noisebin_{ts}$ with $t = 1, 2$ and $s = 1, 2$, are categorical binary variables derived from the original noise variables defined in Table 1. These variables take the value 0 if the corresponding *noise* variable is 0, and 1 otherwise. The subscripts t and s stand for the temporal and spatial lag, respectively.

3. Results

This section presents the outcomes and interpretations that derive from the use of the statistical model represented by Equation 3, on the basis of the following three hypotheses regarding the occurrence of noise disturbance events,

1. the presence of spatial and temporal (*weekday*, *month* and *period*) effects,
2. the effect that incidents happened one or two weeks earlier in the borough neighbourhoods, $noise_{ts}$, and in the borough itself, $noise_t$, have on what occurs now in the borough, and
3. the effect that a set of variables linked to the borough has on the occurrence of noise incidents.

The model has been fitted using the *glm* function of the stats package of statistical software R [12]. Table 2 analyzes the significance of changes in model deviance as variables are being added. The column *Deviance* shows the deviance reduction when adding each variable to the model. The significance of this reduction is contrasted by means of a χ^2-test with the degrees of freedom associated with the variable (column *Df*). Despite having been included in the final model, $noisebin_{12}$ does not reduce model deviance significantly.

	Df	Deviance	Resid Df	Resid Dev	p-value
NULL			100239	88454.79	
weekday	6	1692.29	100233	86762.50	0.00
month	11	918.26	100222	85844.23	0.00
period	1	1409.47	100221	84434.76	0.00
noisebin_1	1	319.50	100220	84115.26	0.00
noisebin_2	1	361.51	100219	83753.75	0.00
noisebin_{11}	1	255.37	100218	83498.38	0.00
noisebin_{12}	1	1.85	100217	83496.53	0.17
noisebin_{21}	1	393.44	100216	83103.09	0.00
noisebin_{22}	1	18.69	100215	83084.39	0.00
district	15	296.35	100188	77919.11	0.00
log(inhab)	1	2320.00	100214	80764.40	0.00
inhab14	1	180.97	100213	80583.42	0.00
inhab1529	1	381.78	100212	80201.65	0.00
inhab65	1	29.17	100211	80172.47	0.00
mphouse	1	1111.22	100210	79061.26	0.00
barrest	1	365.69	100209	78695.57	0.00
svi	1	167.76	100208	78527.81	0.00
mainroad	1	43.18	100207	78484.63	0.00
buildage	1	60.84	100206	78423.79	0.00
educuse	1	10.04	100205	78413.74	0.00
greenuse	1	109.99	100204	78303.75	0.00
botellon	1	88.30	100203	78215.46	0.00

Table 2. Model deviance analysis

Table 3 shows the result of the fit, with the odds ratio associated to each coefficient, $\exp(\beta)$, and its 95% confidence interval (CI). *Sunday*, *June* and *District 1* appear in blank in the table because they are the categories taken as reference for the variables *weekday*, *month* and *district*, respectively.

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variable	β	SE	p-value	exp(β)	95% CI exp(β) Lower	Upper
Monday	-0.89	0.04	0.00	0.41	0.38	0.44
Tuesday	-0.83	0.04	0.00	0.43	0.40	0.46
Wednesday	-0.76	0.03	0.00	0.47	0.43	0.50
Thursday	-0.70	0.03	0.00	0.50	0.46	0.53
Friday	-0.45	0.03	0.00	0.64	0.60	0.68
Saturday	-0.08	0.03	0.01	0.92	0.87	0.98
Sunday						
January	-1.00	0.05	0.00	0.37	0.33	0.40
February	-0.83	0.05	0.00	0.43	0.40	0.47
March	-0.55	0.04	0.00	0.58	0.53	0.62
April	-0.65	0.04	0.00	0.52	0.48	0.57
May	-0.44	0.04	0.00	0.65	0.59	0.70
June						
July	-0.28	0.04	0.00	0.75	0.70	0.81
August	-0.48	0.04	0.00	0.62	0.57	0.67
September	-0.35	0.04	0.00	0.70	0.65	0.76
October	-0.49	0.04	0.00	0.61	0.56	0.66
November	-0.74	0.04	0.00	0.47	0.43	0.52
December	-0.78	0.04	0.00	0.46	0.42	0.50
night	0.63	0.02	0.00	1.88	1.81	1.96
noisebin_1	0.13	0.02	0.00	1.14	1.08	1.19
noisebin_2	0.20	0.02	0.00	1.22	1.17	1.28
noisebin_{11}	0.07	0.02	0.00	1.08	1.03	1.12
noisebin_{12}	-0.03	0.03	0.40	0.97	0.90	1.04
noisebin_{21}	0.18	0.02	0.00	1.20	1.14	1.25
noisebin_{22}	0.10	0.04	0.00	1.11	1.03	1.19
log(inhab)	0.93	0.03	0.00	2.52	2.39	2.65
inhab14	0.13	0.01	0.00	1.14	1.11	1.17
inhab1529	0.12	0.01	0.00	1.13	1.10	1.16
inhab65	0.04	0.01	0.00	1.04	1.03	1.05
mphouse	-2.04	0.16	0.00	0.13	0.09	0.17
barrest	0.18	0.02	0.00	1.20	1.15	1.24
svi	-0.38	0.03	0.00	0.68	0.64	0.73
mainroad	0.02	0.01	0.06	1.02	1.00	1.03
buildage	-0.00	0.00	0.00	1.00	0.99	1.00
educuse	0.01	0.00	0.00	1.01	1.00	1.01
greenuse	-0.02	0.00	0.00	0.98	0.98	0.99
botellon	0.29	0.03	0.00	1.33	1.25	1.42
District 1						
District 2	-0.76	0.07	0.00	0.47	0.40	0.53
District 3	-1.02	0.07	0.00	0.36	0.31	0.42
District 4	-1.05	0.10	0.00	0.35	0.28	0.42
District 5	-1.07	0.10	0.00	0.34	0.28	0.41
District 6	-0.81	0.10	0.00	0.44	0.35	0.54
District 7	-1.23	0.11	0.00	0.29	0.23	0.35
District 8	-1.22	0.11	0.00	0.30	0.23	0.36
District 9	-1.38	0.11	0.00	0.25	0.20	0.30
District 10	-1.10	0.10	0.00	0.33	0.27	0.40
District 11	-1.29	0.11	0.00	0.28	0.22	0.34
District 12	-1.04	0.10	0.00	0.35	0.28	0.43
District 13	-1.13	0.11	0.00	0.32	0.25	0.39
District 14	-1.47	0.12	0.00	0.23	0.18	0.29
District 15	-1.37	0.13	0.00	0.25	0.19	0.32
District 16	-1.23	0.12	0.00	0.29	0.22	0.36

Table 3. Results of the logistic model

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First, note in Table 3 that the coefficients of the levels associated to weekdays, months and districts are all negative. This is because the reference categories are those with the highest number of incidents [2]. A negative coefficient means that odds favourable to the existence of calls due to noise incidents are lower in those days, months or districts than those in the reference category. With regard to the variable representing the two periods considered for each day, the odds of the night are 88% higher than those of the day, as $\exp(\beta_{\text{night}}) = 1.88$.

The statistical significance of these findings allows to validate the first of the hypotheses that we had established: there are spatial and temporal effects that drive noise disturbance events in València. Furthermore, in order to better appreciate the influence of space and time in the occurrence of noise incidents, the model can be used to map noise call probabilities at the borough level. Figure 2 shows two very disparate scenarios in relation to the noise phenomenon: the probabilities estimated for Monday nights in the month of January and those estimated for Sunday nights in June (considering the year 2015). According to these two maps, the existence of both spatial and temporal effects seems clear. Indeed, most of the boroughs presenting the highest probabilities are located in the city center of València (District 1) or in two of its neighbouring districts (Districts 2 and 3). The temporal effects are even more evident: only the probability of Borough 112 exceeds 0.3 for Monday nights of January, whereas a total of 20 boroughs get an estimation over 0.5 for Sunday nights within the month of June.

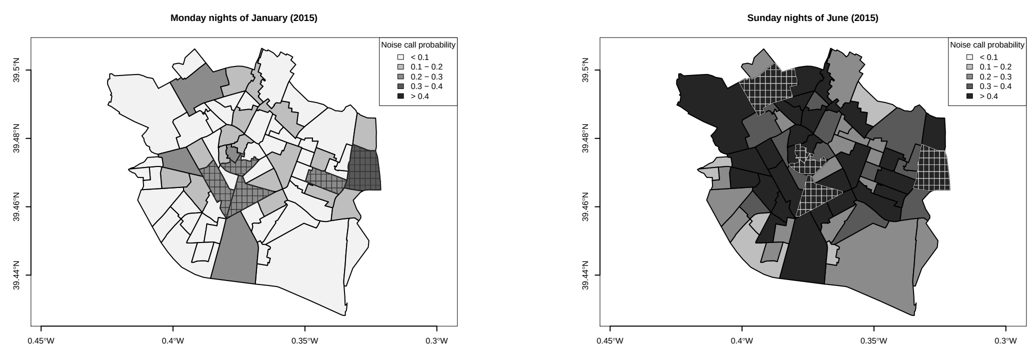

Figure 2. Probability of a noise call estimated for Monday nights of January (left) and Sunday nights of June (right) in the boroughs of València (year 2015). The five boroughs with the highest probabilities under each of the two scenarios are highlighted with a striped pattern

The sign and significance of the coefficients of the variables that represent the occurrence of noise incidents in previous weeks in the borough and its neighbourhood indicate the existence of a positive spatio-temporal effect. That is, the occurrence of previous incidents makes more likely that they occur again. The effects of the temporal lag of order 2 considering the borough and its first-order neighbourhoods, $noisebin_2$ and $noisebin_{21}$, are the most pronounced, with increments of 22% and 20% in the corresponding odds ratios. On the other hand, the variable $noisebin_{12}$ is the only one from this group lacking of statistical significance, which is not surprising in view of Table 2.

It is important to note that the inclusion of lagged variables representing the history of the phenomenon of interest in the close space and time is vital to produce variability in model predictions. Indeed, in the absence of lagged variables, the sequence of probabilities predicted for the whole set of boroughs under any scenario would always keep the same order relationships. As an illustration, the boroughs highlighted in each of the maps shown in Figure 2 are the five presenting the highest probabilities for the occurrence of a noise call event. Although both subsets share three boroughs (16, 21 and 112), the use of the lagged variables is what generates variations in the other two members.

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Most of the variables linked to the demographic composition of the neighbourhood, log(*inhab*), *inhab14*, *inhab1529* and *inhab65*, show significant effects and a behaviour consistent with what could be expected, positive coefficients. Regarding the interpretation of their odds ratios, one needs to account for the magnitude of each variable (a caution that was not required when considering the variables discussed in the former paragraphs because all of them were categorical). For instance, the variable log(*inhabitants*) presents a very high odds ratio of 2.52. Hence, a unit increase in log(*inhabitants*), which implies an unrealistic population growth factor of $e \approx 2.7183$, will lead to a 152% increase in the odds ratio. A more probable increase in the population of, say, the 10%, produces an odds ratio of only 1.09.

Other characteristics of the boroughs also produce significant and reasonable parameter estimations. The variables *barrest*, *educuse* and *botellon* display a positive association with odds ratio. In particular, the contribution of "botellón" to the noise problem is remarkable.

On the other side, the socio-economic vulnerability index and the percentage of land that is used for green areas present a negative coefficient that indicates a reduction in the odds ratio of noise calls. The variable *mainroad* receives a positive but non-significant estimation.

Finally, the variables *mphouse* and *buildage* display a more controversial result. The demographic variable *mphouse* shows a significant and negative association with odds ratios, even though it is positively correlated with *inhab14* and *inhab1529* (Figure 3). Data exploration helps to check that some of the highest values of *mphouse* take place at peripheral and calm boroughs of the city, which may be confounding the interpretation of this variable. Regarding *buildage*, one may expect a positive association with the noise phenomenon, as older buildings should be, on average, less acoustically isolated. Moreover, old buildings are more concentrated around the city center of the city, which appears to be the zone that is most affected by the noise phenomenon. Therefore, we find difficult to explain the effect detected for this variable.

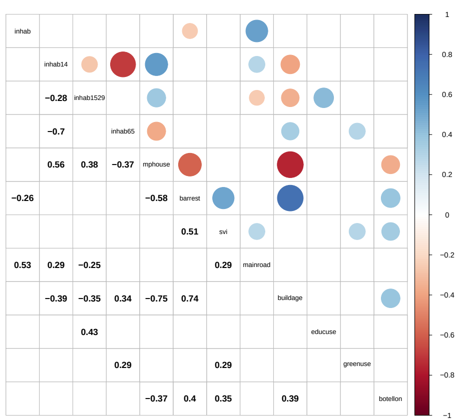

Figure 3. Correlation matrix for the variables representing borough characteristics. Only the correlation coefficients that are significant at the 0.05 level are shown. Figure generated with the corrplot R package [13]

4. Discussion

The results confirm the main hypotheses set out in the research: the existence of spatio-temporal effects on noise calls and the influence that certain variables representing some characteristics of the boroughs of València have on the phenomenon. We now discuss several aspects related to both dimensions of the problem in more detail.

Regarding spatio-temporal effects, the model applied shows that what happened in a borough or its neighbours in the previous two weeks positively influences the existence of new calls. We already highlighted that this fact is key to allow variability in model predictions, keeping the model updated according to recent calls. Furthermore, it is clear that late-night calls are more likely, and that noise-related

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calls are more likely to occur as the week goes by, with the weekend as the highest point. The months of May to September, with June leading the way, are also more likely to register noise-related disturbances than the rest of the year. What the model seems to be pointing out, albeit indirectly, is that the problems of noise in a borough are not exclusively problems of coexistence, and therefore generated by its residents, but that there is an external factor due to the greater presence of people on the streets on weekend nights, which increases during the summer months. València is a city located on the shores of the Mediterranean, approximately 39° North latitude, with a mild climate. The noise problem is greater in those areas of the city with greatest number of leisure venues where people from different parts of the city gather. This conclusion is reinforced by our model as the covariate describing the density of bars and restaurants presents a significant positive effect.

Concerning the factors that may generate noise annoyances among the residents of an urban area, vehicle traffic is largely known as one of the most important [14–16]. The only traffic-related variable included in our model did not receive a significant estimation. At this point, it is of need to remark that most of the research on the noise phenomenon relies on physical measures as the equivalent continuous sound level (Leq), measured in decibels (dB). There should be an association between "real" noise levels at a borough over a certain period of time and the number of calls that people make [17], but it is obvious that both approaches to the noise problem could lead to different conclusions. Particularly, it is not clear, at all, that the boroughs of València that suffer from heavy traffic are generating many police calls on this issue. Taking this into consideration, we discuss some other interesting findings regarding borough characteristics and noise disturbance calls.

Our model also confirms the existence of socio-demographic effects on the calls for service for noise disturbances. It stands to reason that an increase in the number of inhabitants can affect the number of calls for service. With respect to the variables representing some population age groups, it is plausible that youngest and oldest cohorts are particularly implicated in noise calls: the first, as likely noise generators, the second, as likely callers because they are usually more sensitive to noise.

Socio-economic status, measured through a socio-economic vulnerability index, shows a negative association with noise disturbances. This result is consistent some previous research works that have found higher levels of noise exposure at disadvantaged areas [18], but it differs from other research outcomes also developed in the context of a Spanish city [16].

Land uses are usually employed for modelling noise levels [19]. We considered educational and green land uses. The first shows a positive relationship with the odds of a noise call, which seems reasonable as children and young adults (university students) tend to meet in the surroundings of the buildings where they share their studies. Green areas display a negative association with noise events, which is in agreement with research suggesting that green spaces are capable of mitigating noise levels [20].

In conclusion, we have proved that the noise problem in València is correlated with multiple social and environmental variables and the spatio-temporal nature of the phenomenon. In this regard, based on the density pattern of noise calls shown in [2], we can assure that they follow a non-random spatial distribution. The existence of clusters is obvious, as well as certain rejection dynamics. All this suggests future lines of work in the field of spatio-temporal point processes. A log-Gaussian Cox model such as the one described in [21] or a multi-scale area-interaction model [22] may be used to model the point pattern of the noise phenomenon.

Author Contributions: L.S. and F.M. conceived and designed the study, L.M-G. collected the data, A.I., Á.B-R. and F.M. conducted statistical analyses. The original manuscript was draft by L.S., A.I., L.M-G. and F.M. The final version of the manuscript was prepared by Á.B-R. and F.M. All authors have read and approved the final version of the manuscript.

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Conflicts of Interest: The authors declare that they have no conflict of interest.

Appendix

borough	2014	2015	borough	2014	2015
11 LA SEU	203	92	85 FAVARA	47	111
12 LA XEREA	123	62	91 LA RAIOSA	134	82
13 EL CARME	286	199	92 L'HORT DE SENABRE	149	151
14 EL PILAR	219	297	93 LA CREU COBERTA	76	44
15 EL MERCAT	461	380	94 SANT MARCEL·LÍ	79	102
16 SANT FRANCESC	370	374	95 CAMÍ REAL	48	62
21 RUSSAFA	600	608	101 MONT-OLIVET	197	98
22 EL PLA DEL REMEI	104	136	102 EN CORTS	171	137
23 LA GRAN VIA	149	107	103 MALILLA	202	290
31 EL BOTÀNIC	124	143	104 LA FONTETA S. LLUÍS	21	24
32 LA ROQUETA	118	83	105 NA ROVELLA	132	172
33 LA PETXINA	228	155	106 LA PUNTA	46	85
34 ARRANCAPINS	327	293	107 CIUTAT DE LES ARTS I DE LES CIÈNCIES	117	121
41 CAMPANAR	145	159	111 EL GRAU	211	237
42 LES TENDETES	66	98	112 EL CABANYAL-EL CANYAMELAR	614	659
43 EL CALVARI	75	34	113 LA MALVA-ROSA	194	145
44 SANT PAU	130	121	114 BETERÓ	78	41
51 MARXALENES	120	233	115 NATZARET	71	75
52 MORVEDRE	203	177	121 AIORA	294	292
53 TRINITAT	129	121	122 ALBORS	106	99
54 TORMOS	113	86	123 LA CREU DEL GRAU	123	114
55 SANT ANTONI	90	103	124 CAMÍ FONDO	47	48
61 EXPOSICIÓ	62	36	125 PENYA-ROJA	252	272
62 MESTALLA	320	344	131 L'ILLA PERDUDA	98	88
63 JAUME ROIG	101	88	132 CIUTAT JARDÍ	287	260
64 CIUTAT UNIVERSITÀRIA	47	71	133 L'AMISTAT	135	114
71 NOU MOLES	299	251	134 LA BEGA BAIXA	100	58
72 SOTERNES	44	18	135 LA CARRASCA	41	13
73 TRES FORQUES	205	160	141 BENIMACLET	315	286
74 LA FONTSANTA	63	90	142 CAMÍ DE VERA	43	7
75 LA LLUM	29	21	151 ORRIOLS	234	195
81 PATRAIX	205	186	152 TORREFIEL	311	247
82 SANT ISIDRE	88	68	153 SANT LLORENÇ	67	30
83 VARA DE QUART	65	152	161 BENICALAP	486	393
84 SAFRANAR	65	114	162 CIUTAT FALLERA	75	30

Table A1. Yearly noise incidents per borough

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