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Radiofrequency electromagnetic fields and some cancers of unknown etiology: An ecological study☆

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ABSTRACT

Simultaneously with the increase of Radiofrequency Electromagnetic Fields (RF-EMF) in recent decades, there has been increasing concern about their potential relation with the etiology of several tumors. At this time, the techniques of spatial data analysis jointly with the study of the personal exposure to these fields offer a new approach to the problem.

This paper presents the results of a preliminary epidemiological study, combining Epidemiology, Statistics and Geographical Information Systems (GIS), in which we analyzed the correlation between exposure to RF-EMF in the city of Albacete (166,000 inhabitants, southeast Spain) and the incidence of several cancers with unspecific causes (lymphomas, and brain tumors).

We used statistical tools to analyze the spatial point patterns and aggregate data with the aim to study the spatial randomness and to determine the zones with the highest incidence from 95 tumors studied (65 lymphomas, 12 gliomas and 18 meningiomas). We also perform a correlation (Spearman) study between the personal exposure to RF-EMF in 14 frequency bands, recorded by an EME Spy 140 (Satimo) exposimeter in the city's administrative regions, and the incidence of the tumors registered from January 2012 to May 2015.

The studied cancer cases have a random spatial distribution inside the city. On the other hand, and by means of an ecological study, we verified that the exposure to RF-EMF registered in the city of Albacete shows little correlation with the incidence of the studied tumors (gliomas (ρ=0.15), meningiomas (ρ=0.19) and lymphomas (ρ=-0.03). The proposed methodology inaugurates an unexplored analysis path in this field.

1.- INTRODUCTION

Personal exposure to Radiofrequency Electromagnetic Fields (RF-EMF) has undergone an intense increase due to the development of the information society and communication technologies in the last three decades (Frei et al., 2009a).

Simultaneously with the increase of emissions there has been increasing concern by population in relation to the potential harmful effects on health, which has motivated the execution of multiple epidemiological studies (Röösli, 2014, Bhatt et al., 2016; Cardis et al., 2010; Lecoutere et al., 2016). Among the feared effects, we highlight the possible relation of the RF-EMF with several cancers with unspecific causes (brain tumors: meningiomas, gliomas and lymphomas). In the case of brain tumors (gliomas and meningiomas), although different factors such as some viruses, radiations (Spycher et al., 2015), traumas have been considered as possibly involved in their development, their etiology is unknown (Ohgaki, 2009). The causes of the majority of lymphomas are also unknown, although it is known that several of the risk factors are having a weak immune system, present an infection by the human immunodeficiency virus (HIV) or by the Epstein-Barr virus (Chiu and Hou, 2015; Morton et al., 2006), etc. Environment factors cannot be discarded in any of these tumors ('t Mannetje et al., 2016), which together with genetic factors, have a repercussion in the etiology of human cancers (Baba and Câtoi, 2007). Therefore, more research is needed on the effects of electromagnetic radiation (Balmori, 2015).

In this context, it is interesting to continue research in potential environmental risk patterns. For this purpose, it is necessary to consider time and spatial components in a systematic and controlled way. In this point, the spatial epidemiology combines Epidemiology, Statistics and Geographical Information Systems (GIS) (Beale et al., 2008), which can provide a new analysis path.

To these tools, we added personal characterization of the exposure to RF-EMF through the use of personal exposimeters due to their utility in the execution of the epidemiological studies (Neubauer et al., 2007). The exposimeters which have been used in the majority of the previous studies were the EME Spy models 90, 120, 121, 140, 200 (http://www.satimo.fr), and to a lesser degree, the ESM 140 (www.maschek.de) and the ExpoM models (http://www.fieldsatwork.ch).

Personal exposimeters have the main advantages of their small size, their user-friendly handling, their sensitivity and the large amount of data which they can obtain. Since 2010 with the aim to homogenize the different studies, a protocol was provided which provides the guidelines, among other things to prevent artefacts and biases (Röösli et al., 2010). These are the methodological and technical difficulties of the data analysis which can condition the results of the research which must be taken into account for the correct interpretation of the results (Bolte 2016b).

Hence in recent years, numerous studies have been carried out, carrying the exposimeter next to the body (Bolte and Eikelboom, 2012; Frei et al., 2009a; Joseph et al., 2008; Thuroczy et al., 2008; Urbinello et al., 2014a, 2014b; Viel et al., 2009), fastened to a bicycle (Gonzalez-Rubio et al., 2016), attached to a car (Bolte et al., 2016a) or installed in a drone (Joseph et al., 2016). Studies have also been carried out by transporting multiple exposimeters (Nájera López et al., 2015). Recently, Thielens et al. (2016) have developed a personal exposimeter distributed (PDE) with antennas which are integrated in clothing. Nonetheless due to the limitations of these studies, in reference to shielding, location, etc., models have been developed in order to estimate the exposure based on specific measurements (Aerts et al., 2013a, 2013b; Beekhuizen et al., 2013, 2014; Bürgi et al., 2010; Bürgi et al., 2008; Frei et al., 2009b; Martens et al., 2016).

The studies with personal exposimeters primarily have the following objectives: first, to characterize the personal exposure of the population, and second, to measure the exposure levels in different micro-environments, such as public transportation, outdoor urban areas, other zones inside the houses, etc. (Röösli et al., 2010). The micro-environmental studies using an exposimeter generate easily repeatable measurements, which permits the study of the time evolution of the exposure to RF-EMF (Sagar et al., 2016). Likewise, the studies of small areas are part of the spatial epidemiology, which is concerned with the analysis of the geographical patterns of disease in relation to the environmental, demographic and socio-economic factors, among others (Elliott and Savitz, 2008).

It is interesting to use the spatial data analysis tools (spatial point patterns, geostatistical data and lattice data) implemented with the R software and GIS, since they provide new approaches to evaluate the health risks associated with the RF-EMF (spatial randomness study and the search for the zones with the highest incidence), such as for example, the exposure map of a complete city (Gonzalez-Rubio et al., 2016).

When the experimental studies are not feasible, observational studies (cohort and case and control studies) are usually designed. Observational studies attempt to simulate, as far as possible, all the variables and results that would have been obtained in a controlled experiment.

However, on occasions it is very difficult to acquire personal exposure measurements required for these observational studies (especially in environmental epidemiology). In the case of using personal exposimeters, exposure cannot be determined for long periods of time. For this reason, in these situations, ecological studies are practically the only epidemiology studies possible, with all their limitations. This type of study is focused on the comparison of groups, instead of individuals (Morgenstern, 1982, 1995).

Ecological studies have been frequently used in diverse research areas (Brotherton et al., 2011; Collin et al., 2008; Davis et al., 2017; Kennedy et al., 1996; Wilson et al., 1993) and have been planned in this study as a new approach to the problem of assessment of the exposure to RF-EMF and their potential effects on human health. These ecological studies may be less subject to the effects of random error in the measurement of exposure than other observational studies (Nagata, 2000).

The main objective of this paper was to determine, by means of an ecological study, if the personal exposure to RF-EMF from 14 frequency bands show any type of spatial correlation to specific tumors of unspecific causes (gliomas, meningiomas and lymphomas).

2.- MATERIAL AND METHODS

The type of study carried out to achieve the objectives of this paper was an ecological epidemiology, in which geographically delimited populations were analyzed. Of the different existing types, the one selected for this work was an ecological study with multiple groups (Morgenstern, 1995), which analyzed the association between average exposure levels and the frequency of the disease in different areas (micro-environments).

Firstly, spatial randomness was studied in the distribution of tumors in the city of Albacete and the search for zones with higher incidence, through the analysis of the spatial point patterns and an aggregate data study, comparing both methodologies. Secondly, the correlation was studied between the personal exposure and the incidence of tumors analyzed by means of the Spearman correlation test.

2.1. Characterization of the Personal Exposure.

In the determination of the personal exposure, an EME Spy 140 (Satimo) exposimeter was used. The exposimeter has a mass of 400 g and dimensions of 168.5 x 79 x 46.2 mm. The EME Spy 140 model carried out measurements for the exposure to the electromagnetic fields in 14 frequency bands (FM, TV3, TETRA, TV4&5, GSM Tx, GSM Rx, DCS Tx, DCS Rx, DECT, UMTS

Tx, UMTS Rx, WiFi 2G, WiMAX y WiFI 5G), ranging from 88 MHz up to 6 GHz. This exposimeter has a detection threshold of 0.005 V/m.

For the estimate of the personal exposure in the city of Albacete (Spain), measurements were made by conveying the exposimeter in a bicycle, due to its capacity to reach all the zones and perform the measurements in all the streets as described by Gonzalez-Rubio (2016). In the front section of a bicycle, we fastened a plastic basket (fully isolated from the metal parts) and we then installed an exposimeter, to minimize the body shielding. The bicycle's speed was as low as possible.

The micro-environments selected in this study for the characterization of the personal exposure to RF-EMF were the 110 census sections (administrative regions) of the city of Albacete. They make it possible to accurately determine the resident population in each of them. In Spain, these districts encompass a population, which generally does not surpass 2,500 inhabitants and every inhabitant can only belong to one of them (Figure 1).

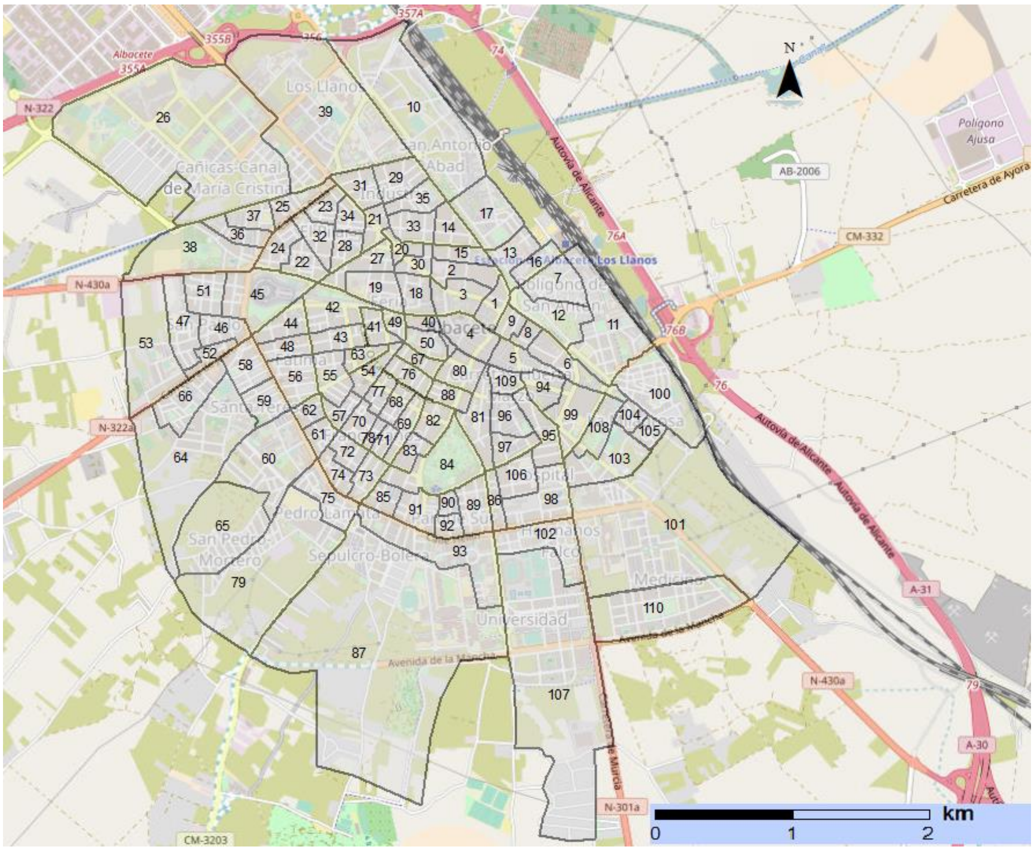

Figure 1. The 110 administrative regions of Albacete

The measurements were performed between 28th of January 2015 and 29th of April the same year. The timetable to make the measurements was between 20:30 and 23:30 at night, avoiding Fridays and Saturdays. Inside each section, we travelled almost all the streets, carrying out a measurement every 4 seconds. A total of 12,019 measurements per frequency were taken, which amounted to a total of 168,266 data, where the figure of 1,540 was the average number of measurement records per administrative region. The total value of the exposure to the recorded radiofrequency was taken into account, comprised by the sum of the 14 frequency bands measured.

2.2 Data Sources.

Resident population data in each of the 110 administrative districts was obtained from the Spain's National Statistics Institute (INE). Based on this data, we prepared a map (in shapefile format) of the city of Albacete with the population data of each micro-environment. On the other hand, the Oncology Service of the University Hospital of Albacete (the only hospital specializing in oncology) facilitated the addresses ensuring anonymity for all cancer cases of gliomas, meningiomas and lymphomas from the 1st of January 2012 until the 1st of June 2015, with prior authorization from the Ethical Committee of Clinical Research and the Research Commission. Finally, the Statistics Service of the Town Council of Albacete provided a representative random sample of 390 anonymous addresses (the Albacete population of 166,383 inhabitants, 95% confidence level and 5% error) for the population of the city of Albacete (control group).

2.3 Analysis software.

For data analysis, besides the own software implemented in the EME Spy 140 exposimeters (EME Spy Analysisv3.20), we used ArcGis 10.2.2 (developed by Environmental Systems Research Institute, ESRI) and R Software 3.2.1. ArcGis was used to process the shapefile format maps; R software was used to carry out the statistical calculations (data normality study, randomness study and correlation analysis) and to work with the shp format maps created with ArcGis. The main R packets used in this project were: splancs, spatstat, sp, maptools, rgdal, RColorBrewer, lattice, nortest, Rcmdr y spdep (Bivand et al., 2013).

2.4. Methodology. Spatial Randomness Study of the Tumors and the Search for a Correlation between the RF-EMF and the Incidence.

Each event (cases and controls) was georeferenced by means of the X and Y coordinates, using the UTM coordinates, datum ETSR 89 (Figure 2), for the spatial randomness study, by means of point patterns (Diggle, 2013) and the use of aggregate data. Both analyses were achieved with the assistance of R software.

In point pattern analysis, it is necessary to solve the problem of population density effect on disease incidence values. Which means, there will be more cases of cancer in those zones where there is a higher population, hence the simple observation of the spatial distribution would be useless. This problem is solved through the comparison of the spatial distribution of the cases with the locations of a set of controls taken at random from population (control pattern). The spatial randomness study of tumors was performed according to the described methodology, for the spatial variation of the relative risk, by Bivand et al. (2013). A Montecarlo Test (Kelsall and Diggle, 1995) was complied, which is based on the null hypothesis that the cases (tumors) and controls have the same spatial distribution, which means that cases have a random spatial distribution. If we randomly simulate (multiple times) the labelling of cases and controls for all the events of the study area, the new series of cases and controls would have the same spatial distribution as the original. If this fails to happen, then the relabeling of the cases and controls will produce different patterns, discarding the random distribution of the tumors.

In reference to the analysis by means of aggregate data, based on the number of cases of the disease and the resident population in each census section, the incidence is calculated in each section for every 100,000 inhabitants in the study period. This distribution was used to prepare the spatial correlation analysis for each type of tumor according to the locations of the entities (census sections) and the attribute values (incidence of tumors) by means of the Moran's I test tool (Bivand et al., 2013).

Subsequently using both tools, the city zones with the highest incidence of tumors were searched.

Finally, a correlation (Spearman) study was done between two sets of values associated to each administrative region: the first is the average value of the exposure to RF-EMF and the second is the incidence of the different tumors.

3.-RESULTS

3.1. Tumors: lymphomas, gliomas and meningiomas

From the 95 cases available for the three types of tumors with unspecific causes studied, 65 were lymphomas, 12 gliomas and 18 meningiomas (30 brain tumors). The incidence in Albacete, in that period, were similar to the data available for Spain in the studied tumors as shown in Table 1. In Figure 2, the cases of disease and the random control sample have been georeferenced.

Table 1: Incidence of tumor types in Albacete and in Spain (between the 1st of January 2012 and the 31st of may 2015: 41 months) (na: not available for this period. * Spanish Society of Medical Oncology)

Incidence: cases per every 100,000 inhabitants (annual)	Meningioma	Glioma	Total Brain	Lymphoma
Albacete (urban city centre)	3.2	2.1	**5.3**	**11.4**
Spain*	na	na	**5.1**	**12.1**

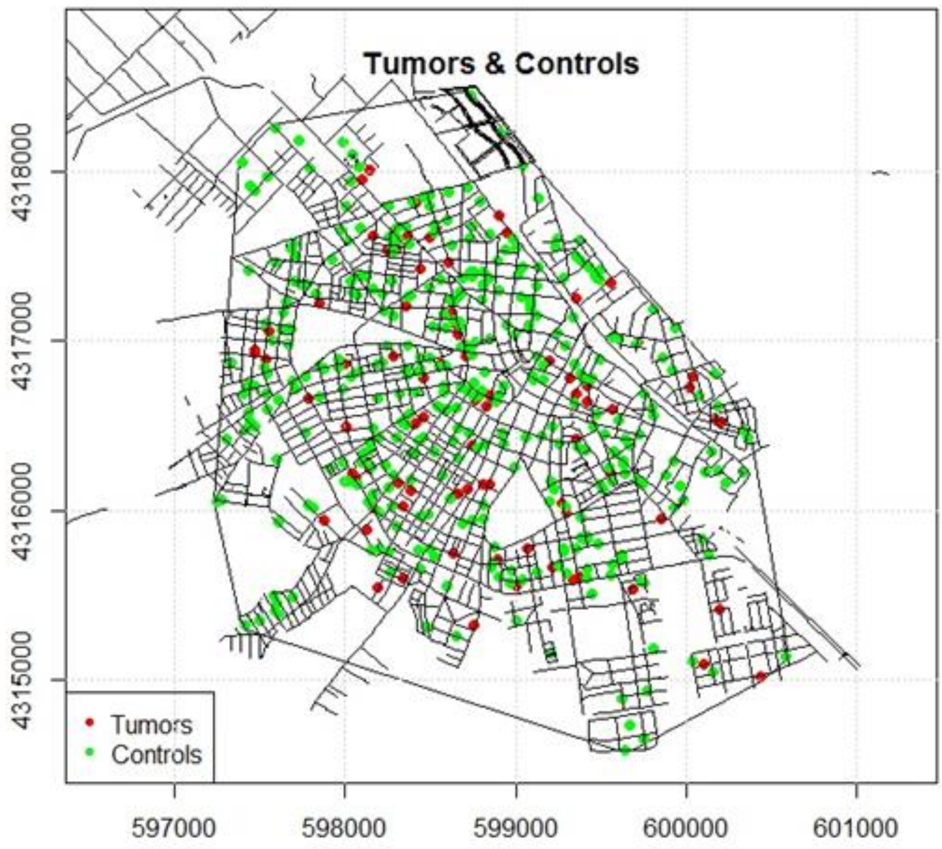

Figure 2. Tumors and controls (UTM coordinates)

3.2.- Randomness and Incidence Study

Spatial Point Patterns

First, the randomness study of the different tumor types was performed. Based on the map of Figure 2, the density of the population controls and the tumors were determined. The analysis permits the verification of the null hypothesis which would establish that the tumors follow the pattern of the control points (which would mean that the distribution of the cases is random). Subsequently, regions were searched where the risk of tumor was significantly higher and lower than the average risk of the entire study area. The distribution of each tumor type is shown in Figure 3.

Table 2 compiles the p-values of the spatial point patterns study in the different types of tumors, in an isolated way and in their different groups. They are all above 0.05 hence the null hypothesis cannot be discarded and consequently, the cases (tumors) and the population controls follow the same pattern in the city as a whole. This means, the distribution is random, both the tumors studied in an individual way (meningioma, glioma and lymphoma) as well as the grouped tumors (brain tumors and total tumors).

Table 2: Spatial randomness analysis of the tumors by means of the spatial point patterns.

Null hypothesis: The spatial distribution of the tumors is random	Meningioma	Glioma	Total Brain	Lymphoma	Total tumors
p-value	0.31	0.75	0.54	0.39	0.42

Figure 3 also shows the zones with a significantly greater or lower risk ("sensitive" zones) as well as the average risk of the entire study area for the three causes: meningiomas, gliomas and lymphomas jointly with the control sample. These zones are indicated by means of dark color plots (greater incidence) and light color plots (lower incidence) displaying the different areas depending on the tumor type studied.

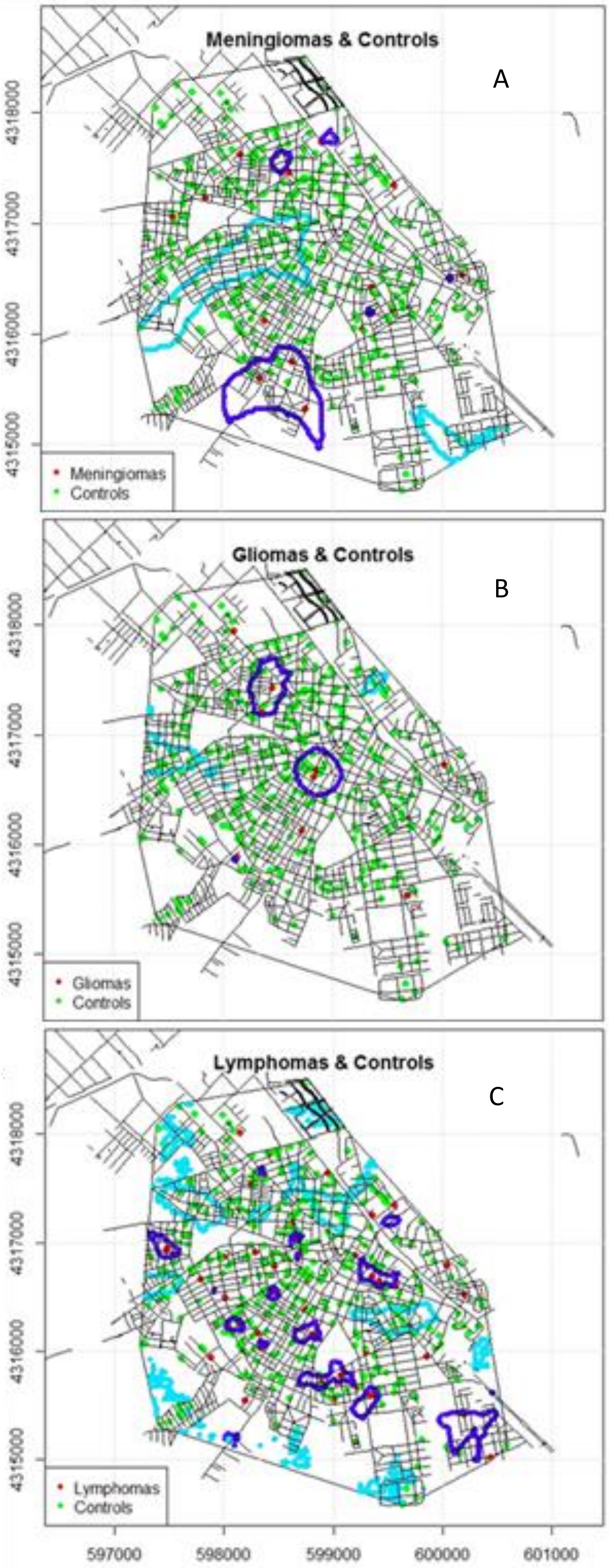

Figure 3. Distribution of cases and controls as well as "sensitive" zones for Meningiomas (A), Gliomas (B) and Lymphomas (C). The dark blue and the light blue lines identify the regions inside which the total tumor risks are significantly higher and lower respectively (UTM coordinates).

Figure 4 compiles the data of the brain tumors (A) and the total tumors (B), as well as the highest risk zones.

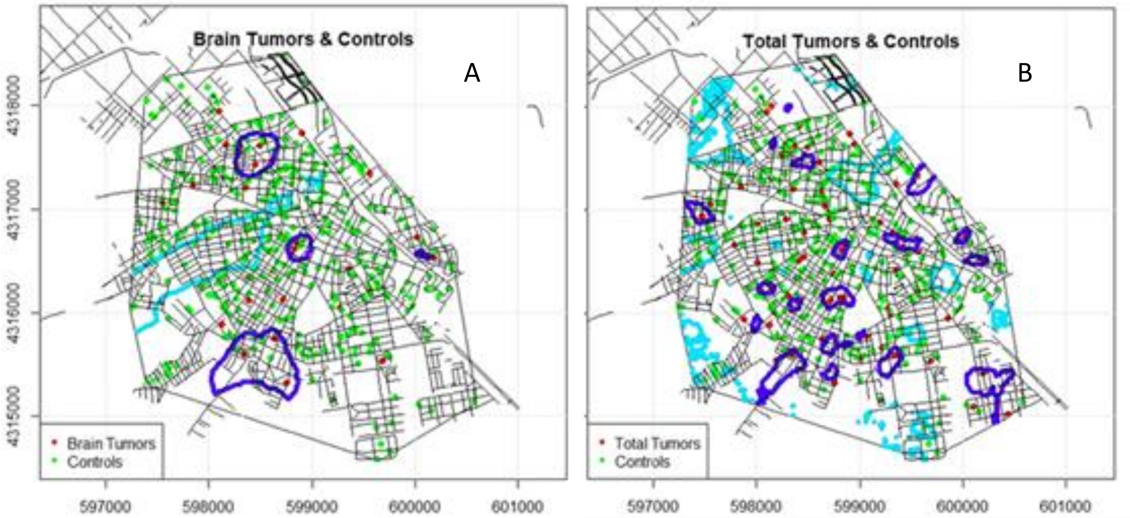

Figure 4. Distribution of cases and controls as well as "sensitive" zones for brain tumors (A) and total tumors (B). The dark blue and the light blue lines identify the regions inside which the total tumor risks are significantly higher and lower respectively (UTM coordinates).

Aggregate Data

Table 3 compiles the results of the spatial randomness study through the analysis of the aggregate data (Moran's I test) for the incidence of the different tumor types, in an isolated way and in their different groups.

Table 3: Spatial randomness of the tumors through the aggregate data analysis (Moran's I test).

	Moran I	p-value
Meningioma	-0.02	0.60
Glioma	0.03	0.06
Total Brain	-0.01	0.82
Lymphoma	-0.05	0.10
Total tumors	-0.04	0.19

The obtained results do not permit discarding the null hypothesis which would establish the randomness in the distribution of the tumors incidence. In the case of the gliomas, we can observe that the p-value is in the randomness limit with a value of 0.06, which could be due to the rare available cases.

The same as in the case of the spatial point patterns, the zones were searched inside the city with an above average risk Figures 5 and 6.

Comparison between spatial point patterns and aggregate data

Both the spatial point patterns study and the aggregate data analysis clearly show the spatial randomness of the studied tumors (meningiomas, gliomas and lymphomas) in the city of Albacete. Likewise, comparing the Figures 3 and 4 with the Figures 5 and 6, we can observe that for both the different tumors and their groups, that the zones with the highest incidence inside the city are similar independently of the type of analysis used.

Figure 5: Incidence of Meningiomas (A), Gliomas (B) and Lymphomas (C): Cases per every 100,000 inhabitants.

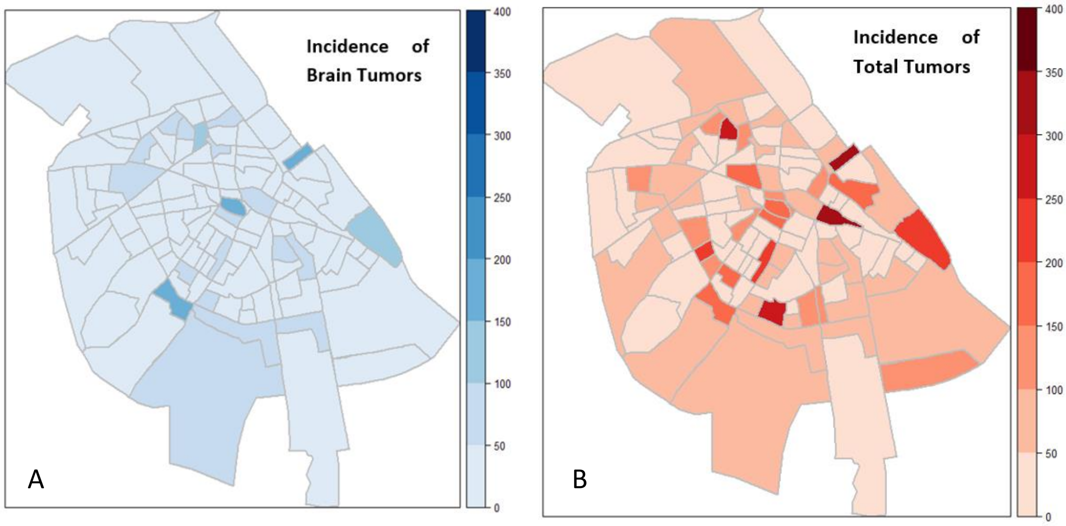

Figure 6: Incidence of brain tumors (A) and total tumors (B): Cases per every 100,000 inhabitants.

3.3.- Personal Exposure to RF-EMF and Correlation Study

Figure 7 and Table 4 show the average values of total exposure (14 frequency bands) to RF-EMF of each census section of the city. None of the administrative regions exceeded the legal limit established for the urban zone and fixed at 6.14 V/m, according to the Art 8/2001 of June 28th for facilities management of Radiofrequency (Castilla-La Mancha).

Qualitatively comparing this figure with the Figures 3, 4, 5 and 6, we observe that the sections with greater exposure to RF-EMF do not coincide in any case with the areas with the highest incidence of tumors.

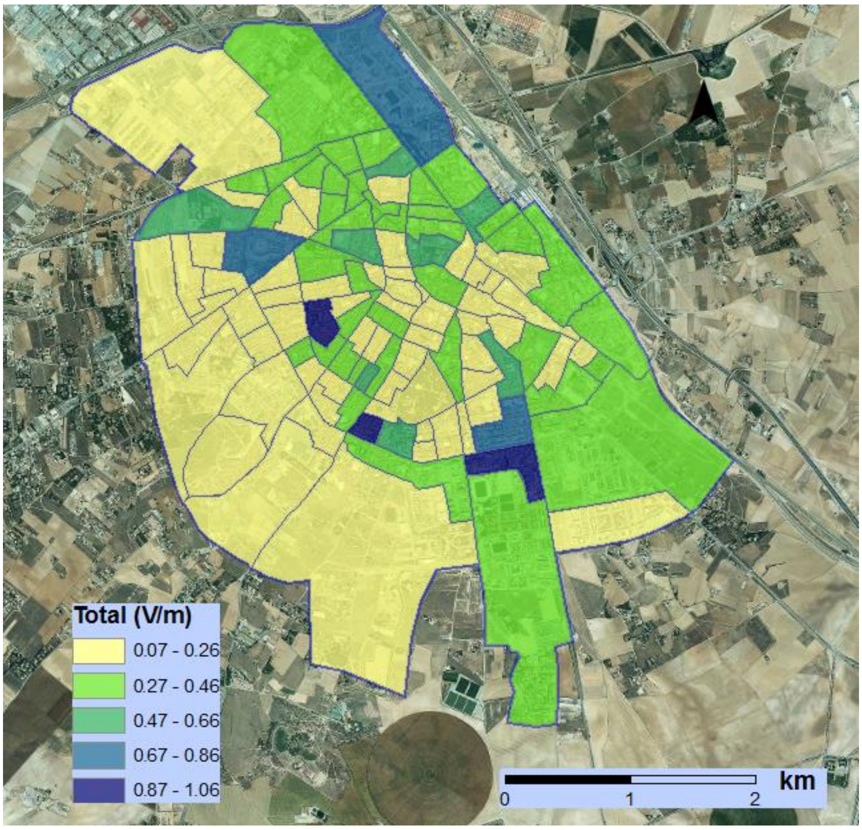

Figure 7: Average exposure values to RF-EMF per administrative region in Albacete.

Table 4. Average total exposure to RF-EMF (V/m) per administrative region.

District 1		District 2		District 3		District 4		District 5		District 6		District 7	
Section	E (V/m)	Section	E (V/m)	Section	E (V/m)	Section	E (V/m)	Section	E (V/m)	Section	E (V/m)	Section	E (V/m)
1	0,17	18	0,17	40	0,26	53	0,14	67	0,23	80	0,14	94	0,15
2	0,36	19	0,58	41	0,45	54	0,28	68	0,21	81	0,35	95	0,56
3	0,53	20	0,32	42	0,33	55	0,87	69	0,41	82	0,08	96	0,09
4	0,39	21	0,42	43	0,10	56	0,25	70	0,27	83	0,20	97	0,17
5	0,18	22	0,21	44	0,23	57	0,40	71	0,50	84	0,18	98	0,72
6	0,10	23	0,27	45	0,82	58	**0,07**	72	0,22	85	**1,03**	99	0,43
7	0,32	24	0,32	46	0,09	59	0,11	73	0,39	86	0,23	100	0,45
8	0,11	25	0,33	47	0,11	60	0,12	74	0,22	87	0,18	101	0,35
9	0,20	26	0,15	48	0,15	61	0,22	75	**0,07**	88	0,13	102	0,90
10	0,66	27	0,36	49	0,12	62	0,44	76	0,44	89	**0,07**	103	0,38
11	0,40	28	0,43	50	0,24	63	0,10	77	0,25	90	0,24	104	0,13
12	0,17	29	0,45	51	0,12	64	0,11	78	0,37	91	0,63	105	0,45
13	0,49	30	0,29	52	0,20	65	0,08	79	**0,07**	92	0,21	106	0,15
14	0,33	31	0,31			66	0,18			93	0,44	107	0,31
15	0,34	32	0,10									108	0,26
16	0,29	33	0,23									109	0,08
17	0,41	34	0,43									110	0,12
		35	0,46										
		36	0,12										
		37	0,36										
		38	0,47										
		39	0,32										

Finally, Table 5 compiles the result of the Spearman correlation study between the incidence of tumors per every 100,000 inhabitants and the average exposure value to RF-EMF in the different census sections. In all cases, it showed little correlation between the studied tumors and the recorded exposure data.

Table 5: Spearman correlation test between exposure to EF-EMF and incidence of tumors in each section.

	ρ of Spearman	p-value
MENINGIOMA	0.19	0.04
GLIOMA	0.15	0.13
TOTAL BRAIN	0.28	0,003
LYMPHOMA	-0.03	0.72
TOTAL TUMORS	0.13	0.19

4.-DISCUSSION

4.1 Measurements

Sources of biases and uncertainties using personal exposimeters have been extensively discussed (Bolte, 2016). In this context, we would like to highlight the following difficulties:

Average values: In this study, we worked with the average values of RF-EMF measured in each administrative region, following the criteria of the majority of studies conducted up to date in order to improve the comparison of data. However, given that the data distribution is not normal, other solutions are possible (medians and percentiles) (Bhatt et al., 2016a; Najera et al., 2016).

Low frequency: This study includes frequencies ranging from 88 MHz to 5.85 MHZ. Low frequencies have not been evaluated. Outdoor average extremely low frequency magnetic fields (ELF-MF) in public areas in urban environments range between 0.05 and 0.2 µT; stronger values (of the order of a few µT) may occur directly beneath high-voltage power lines, at the walls of transformer buildings, and at the boundary fences of substations (Gajšek et al., 2016). When many measurements are averaged, as usually happens when exposimeter data are analyzed, this will tend to average-out this possible exposure.

Exposure inside houses and buildings and Z-dependence: In future studies, the authors intend to perform measurements inside houses or to use some type of specific software tool in order to obtain the exposure level inside the houses and buildings of each district. In addition, measurements could be performed at different heights (z-dependence) (Waldmann-Selsam et al., 2016); experiences with drones could help to discriminate measurements at heights (Joseph et al., 2016).

Electromagnetic environmental noise: It is a challenge in this type of studies to verify that the measured values are not imputable to unavoidable environmental noise. However, the high sensitivity of the exposimeter and the calibration process every 2 years guarantee the reliability of the measurements. The EME Spy 1140 calibration relies on an antenna calibration. Manufacturer realizes in an anechoic chamber and in a Transverse Electromagnetic (TEM) cell the equipment calibration.

4.2 Study Characteristics

The main drawback of these types of ecological studies (Ávila, 2007) is that it is difficult to analyze the possible correlation between exposure and disease, in order to interpret that the current exposure reflects the exposure level of the past. However, it is known that in the case of environmental studies using an exposimeter, they generate highly repeatable measurements in the time period (Sagar et al., 2016; Urbinello et al., 2014a). Hence in a city like Albacete in which there has not been a major variation of emission sources, question that if it happens globally, it would not be a bad approach to suppose that the current exposure is similar to the exposure level in recent years, coinciding with the latency period of tumors.

The population's migration or movement during the study period could be another inconvenience, since the affected population could have emigrated prior to the detection of the disease, or several persons could have immigrated to the studied population, thus creating a selection bias (Polissar, 1980). To minimize this problem, a short time period was chosen in the selection of the tumors, close to the measurement samples, in which it is more difficult for significant migratory phenomenon to occur. In fact, several measurements overlapped with the recording of several cases (from January to May 2015). Accordingly, this also prevented analyzing recent exposures with old tumor data.

The ecological studies are often subject to confusion due to the absence of the measurement for several covariables (atmospheric pollution, diet, habits, among others). However due to the design of the aggregate data map in which the resident population is exactly known, it would be possible to study and include new covariables in future studies (Gonzalez-Rubio et al., 2016).

Also, when making individual inferences based on the group studies, we detected what is known as an "ecological fallacy" (error which is committed when it is determined that the results obtained from an ecological study would be the same as those which would be obtained in a study with individual observations) which has caused errors in the analysis of the different epidemiological studies (Susser, 1994) and which is necessary to consider when analyzing the obtained results.

With the aim to minimize the problems described in the exposure characterization studies through the use of personal exposimeters (Bolte, 2016b), we opted for an exposimeter which did not generate anisotropy problems, which possessed high sensitivity, and the measurements were made with the exposimeter separated from the body to thus minimize the potential problems of body shielding. Likewise, as indicated above, the measurements were performed every 4 seconds, with the aim to collect the highest number of records.

Another limitation of the micro-environment studies is that they do not necessarily reflect the population's exposure, because the stay time in different micro-environments can differ among the study's populations (Röösli et al., 2010). For this reason, a timetable was selected for the data collection between 20:30 and 23:30 at night, avoiding Fridays and Saturdays, since we aimed to possess measurements in a timetable and on days in which the majority of people were in their homes. However, in future studies, it would be advisable to carry out measurements at other hours in order to be able to compare the results. In addition, thus it was intended since the available cases of tumors were geopositioned by the patient's house, to characterize the exposure to which this individual was subjected when he/she was in his/her own house, in spite the fact that all the measures were made in all the streets at ground level.

The definition of the induction period of the tumors varied in the bibliography. Several authors consider the induction period as the time which ranges from the start of the exposure up to the onset of the disease (Armenian and Lilienfeld, 1983). Other authors describe the induction as the minimum exposure period required to trigger the disease and the latency period as the period that has elapsed after the minimum required exposure has been completed up to the appearance of the disease (Checkoway et al., 1990). In any case, this would first require a time period and an exposure intensity sufficient to trigger an effect and secondly, a time period in order for the remaining contributing factors to act. One limitation of this study would be the difficulty to detect, in the case that they exist, the long induction periods, since the long-term exposure is unknown, which could be the object of future studies.

4.3 Spatial Data Analysis and Correlation Search

The point patterns analysis is more accurate in the spatial randomness study and in the search of the zones with the highest incidence since there is no problem with border regions. However, the aggregate data study permits the accurate preparation of a correlation study between the average intensity and the incidence of the different tumor types. The combination of these two techniques, for which no precedents have been found in the bibliography, would corroborate the results of this paper, thus being able to compare them by using two different methodologies. Nonetheless, the study's main difficulty is the rare number of cases due to the reduced incidence of the disease; therefore in future studies it is intended to apply other alternative methods of analysis, for example, Application of the Double Kernel Density Approach (Davarashvili et al., 2016). The obtained results would question the studies which, if any type of correlation were found, would be exclusively based in the location of the emission sources (Atzmon et al., 2012; Dode et al., 2011; Elliott et al., 2008; Shahbazi-Gahrouei et al., 2014; Stewart et al., 2012). However, since this deals with the first epidemiological study which analyzes the incidence of the RF-EMF on specific tumors (gliomas, meningiomas and lymphomas) in a city, it is not possible to compare the results with other research papers.

5.- CONCLUSION

The studied tumors have a random spatial distribution inside the city of Albacete and the accumulation of cases in the zones with highest incidence is due to random chance.

Likewise, we have found little correlation between personal exposure to RF-EMF and the incidence of cancers with an unspecific cause which were analyzed in the entire city (gliomas, meningiomas y lymphomas).

The use of spatial data analysis techniques in these types of studies could be a useful and powerful tool which permits the reproduction of these results in other locations.

Ecological studies would be interesting, in the aforementioned circumstances. We intend to provide a follow up to this work, incorporating new measurements at different times, new cases of cancer detected, as well as other methods of analysis.

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