ous model. With these two variables, 18% of the municipalities had values above 0,50 for men and 15% for women.

Relative risk with PM_{10} emissions, urbanization rate and percentage of industrial area

The industrial area was separated from urban area (Figure 7 and Appendix Figure A3), which now only includes continuous and discontinuous urban area, and the transport infrastructures. Adjusted R^2values were 0,59 for women and 0,63 for men. Regarding men, higher values were found in both MAs, but for women they were between 0,30 and 0,50 in Lisbon MA. Using these variables, 20% of municipalities had values above 0,50 both for men and women. Also, 3% of the municipalities had values above 0,70 for men.

Relative risk with PM_{10} emissions and percentage of industrial area

With the objective of measuring the possible impact of industry, quarries and aggregate extraction sites on mortality RR values (in particular the hotspot in the south-eastern region in men's RR) the urban area was separated from the industrial area (Figure 8 and Appendix Figure A4). With this model, we were faced with a low percentage of the municipalities with a local R^2 above 0,50; only 8% of municipalities for men and 13% for women, and an adjusted R^2 of 0,48 and 0,46 respectively, the lowest result taking into account all the variables.

Model comparison

We compared the models in terms of standard errors and AICc criterion. Standard errors (Appendix Figures A5-A8) measure the reliability of each coefficient estimate. Confidence is higher when standard errors are small in relation to the actual coefficient values. Moran's *I* values ranged between 0,2107 (the lowest) and 0,6591 (the highest), and while values over 0,5 point to a trend towards clusters, it is possible to say that in general, the model does not tend to clustering (Perrino, 2010; Zhang *et al.*, 2017).

Table 2 presents AICc values for each model. The lowest val-

Table 2. Geographically weighted regression Akaike Information Criterion Corrected values.

	RR & PM_{10}	RR, PM_{10}, & TU	RR, PM_{10}, & PAI	RR, PM_{10}, TU & PAI
Women	-596	-653	-510	-623
Men	-465	-468	-457	-467

RR, relative risk; PM, particle matter; TU, urbanization rate; PAI, percentage of industrial area.

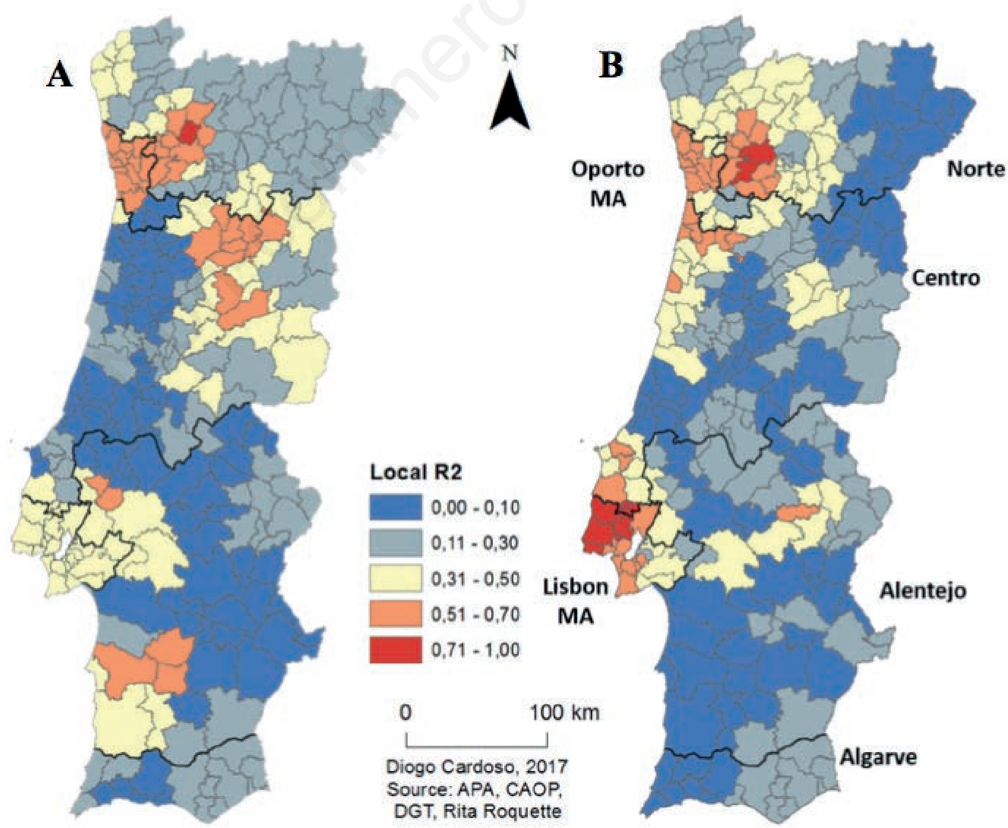

Figure 6. Geographically weighted regression model with particle matter$_{10}$ emissions and urbanization rate values for women (A) and men (B). MA, metropolitan area.

ues correspond to the GWR model, which considers PM_{10} and the urbanization rate. However, the model which considers all variables (PM_{10} Emissions, Urbanization Rate and Percentage of Industrial Area) presented very similar values.

Discussion

The results of this study are in line with the hypotheses initially set. The highest values of correlation are mainly concentrated around the two metropolitan areas of the country, which are the regions with higher PM_{10} emissions, urbanization rate and percentage of industrial area. Nonetheless, those values are higher in the North-western part of mainland Portugal. It was expected that some of the values of lung cancer mortality RR (Figure 3) were not related to those obtained in the GWR models mainly in the southern regions, since smoking is a significant risk factor of lung cancer (about 90% of cases in men and 55% to 80% of cases in women are attributed to cigarette smoking; Levi, 1999). Moreover, even though air pollution is also identified as an important cause of the disease, its impact is expected to be lower. The GWR results between the percentage of industrial area and lung cancer mortality RR represent a lower correlation than the other two variables. A more detailed analysis is necessary in this matter, but this may mean that the impact of the industries is smaller in the emission of PM_{10} with the origin from motor vehicles being higher. As mentioned in the introduction, the use of individual transport is one of the main aggravating factors for the high levels of air pollution in both metropolitan areas (Cristina *et al.*, 2016). The use of urbanization rate is not new in the study of lung cancer mortality, but they tend to have a focus on rural-urban differences and socioeconomic aspects (Riaz *et al.*, 2011; Singh *et al.*, 2012), a different approach from that carried out in this study.

A geographic approach with remote sensing can help to fill in data gaps that hamper current efforts to study air pollution. A study by Hu and Baker (2017) shows that there is a significant positive association between mortality from this type of cancer and $PM_{2.5}$. This result was achieved using data from the MODIS satellite sensor and MISR Annual Global Grid $PM_{2.5}$ data (Hu and Baker, 2017). Nonetheless, the statistically significant association between lung cancer mortality and presence of $PM_{2.5}$ may be indicative of a potential effect of air pollution; the authors suggest that the same association would require a toxicological approach in order to observe the adverse biological mechanism of $PM_{2.5}$ pollution (Hu and Baker, 2017). The model developed in this study yielded satisfactory results and is in line with other similar studies using GWR models (Fu *et al.*, 2015; Ren *et al.*, 2016), or other spatial analyst tools (Bilancia *et al.*, 2009; López-Cima *et al.*, 2011). Even though the study of cancer's spatial epidemiology has had a greater emphasis in the last decade (Roquette *et al.*, 2017), there are only a few studies on the relationship between lung cancer and air pollution in Portugal (Slezakova *et al.*, 2011). This study repre-

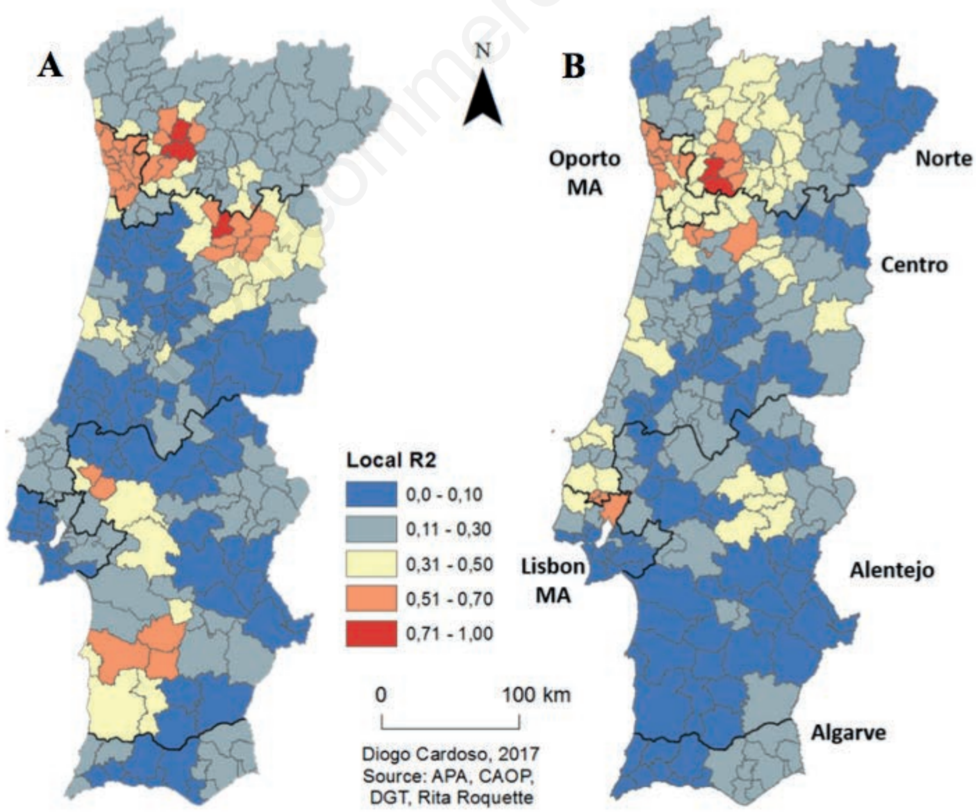

Figure 7. Geographically weighted regression model with particle matter$_{10}$, urbanization rate and percentage of industrial area values for women (A) and men (B).

sents one of the first to use RR mortality data along with spatial regression analysis tools to explore a possible relationship between both factors in mainland Portugal.

One of the advantages of using GWR is that it accounts for spatial autocorrelation in the residuals that are usually found in global modelling. Further, it is possible that a variable that is insignificant at the global level might be important locally (Fotheringham *et al.*, 2008). When relationships are consistent across a study area, an OLS model fits neatly into these relationships; it creates equations that best describe general relationships of data in each area. However, it is not always like that, so often these relationships have different behaviours throughout space. When the exploratory variables exhibit non-stationary relationships (regional variation), the model tends to fail, unless robust models adapted to this problem are applied. The GWR model addresses this issue precisely (Mitchel, 2005).

Identifying causes and effectively addressing them can lead to significant savings in health spending. With the implementation of rigorous legislation on gaseous emissions, health expenditure directly linked to air pollution in Europe has been decreasing. It is estimated that from € 803 billion spent in 2000, it will decrease to € 537 billion in 2020 (Brandt *et al.*, 2013). The convergence of the many studies carried out so far has led to a reconsideration and updating of health standards and guidelines, leading to new long-term research programs in order to analyze the effects of particulate pollution on health (Brandt *et al.*, 2013). However, it is known that these changes always have economic and social impacts, sometimes facing great opposition in certain sectors of society.

Our results sustain the hypothesis that air pollution might be a risk factor for lung cancer. Indeed, it indicates a higher lung cancer mortality RR among municipalities where both urban and industrial areas are also superior. It demonstrated the benefits of GWR, both in respect to model performance and by allowing spatial analysis of the data. Lung Cancer mortality RR was found to be heterogeneously related to human factors at the municipality level in mainland Portugal. Our findings may assist local authorities when assessing risks, and by helping public health entities allocate resources and address the issue according to the specific conditions of each region.

Conclusions

With this research, our objective was not to find the municipalities where people are most likely to die from lung cancer, but rather to assess the impact of the PM_{10} emissions in each municipality and to understand the influence of the urbanization rate and the percentage of industrial area in these values. Furthermore, including two variables that address the land use may be a new method of approaching this subject and generate a more realistic model. As a result, this study contributes to the knowledge of the effects of air pollution on lung cancer and on the use of local spa-

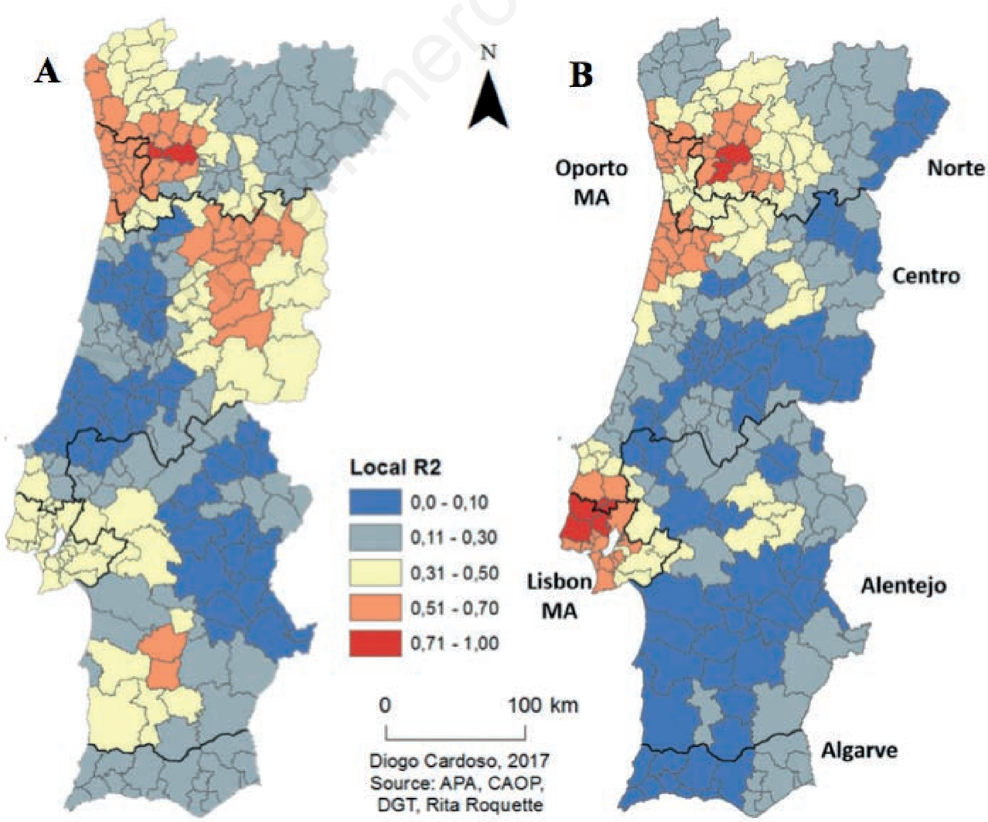

Figure 8. Geographically weighted regression model with particle matter$_{10}$ and percentage of industrial area values for women (A) and men (B). MA, metropolitan area.

tial analyses in epidemiological studies. Such information can be used in urban planning to reduce air pollution.

No evident homogeneous pattern distribution association was found between PM_{10} emissions and lung cancer mortality RR in municipalities across mainland Portugal. There is. The relation between PM_{10}, urban area and industrial areas and lung cancer mortality rates varies spatially, and there are other agents that may influence the lung cancer mortality rate in different areas of mainland Portugal, but we can say that it has a focus on the two metropolitan areas. Several municipalities tend to show values of R^2 always above 0,50 in all models which represents a positive relation. It is pertinent to state that the emission of PM_{10} as the urbanization rate and percentage of industrial area affect the lung cancer mortality RR values in those municipalities. The relation of lung cancer turned out to be higher when the emissions of PM_{10} were joined by the urbanization rate and the percentage of industrial area (R^2 value of 0,63 for men and 0,59 for women). However, when assessing the industrial areas alone, it was noted that their impact is lower in the overall results (R^2 equal to 0,48 for men and 0,46 for women).

Spatial variation in the relations between lung cancer RR and air pollution means that in some places PM_{10} and urbanization rate have a greater effect on mortality than in other places. In the municipalities where the values are high, local authorities should step in to minimize the effects of air pollution and carry out better planning in order to benefit the public health of the local populations. We note that the problem is complex, and that further investigation is needed for a full understanding of this issue.

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