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Intra-urban Disparities in the Quality of Life in the City of Porto: A Spatial Analysis Contribution

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Intra-urban disparities in the quality of life in the city of Porto: a spatial analysis contribution

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Abstract

Geographical Information Systems (GIS) are an essential tool to integrate and manage large amounts of data (statistical and graphical) and to visualise the modelling efforts of the contemporary city. The further use of spatial analysis methods, in particular the exploratory analysis of data and spatial econometric models, is a promising way forward to analyse urban reality.

In this analysis, we used a conceptual model and a geographical database developed for the city of Porto (Portugal) under a previous research on the topic of intra-urban disparities in the local quality of life.

The aim of this paper is to contribute to the interdisciplinary debate on the relevance and use of this type of techniques, which enable us to describe spatial distributions, identifying patterns of spatial association, concentration areas or hot spots, in order to look into distributive features such as concentration, persistence and transitions that might provide interesting interpretations of complex territorial structures, such as the cities.

Keywords: urban disparities; spatial analysis; quality of life
JEL codes: R58, O21

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Introduction

In the past few years urban analysis has benefited from a series of technological developments, among which Geographic Information Systems (GIS) clearly stands out. These constitute an essential tool for integrating and managing large volumes of data (both statistical and geographical) and have powerful visual display capabilities very useful to present the results of efforts to model the contemporary city.

The breakthroughs associated with the use of spatial analysis methods – particularly statistical and spatial econometrics – available in most GIS, on the other hand, have been much less perceptible, since they keep being sparsely used by researchers in this area. With this paper we intend to contribute towards the interdisciplinary debate on the relevance and utility of such techniques, in particular, to investigate distributional characteristics such as concentration, persistence and transitions which can be interesting reading keys of complex territorial structures such as cities are.

Given the current centrality regarding the concept of life quality in cities - while an integrating framework for the various policies and agents' actions – we chose to apply these spatial analysis techniques to study the spatial patterns of variables which influence the conditions of life and well-being of communities and individuals in urban areas.

The empirical study is based on a conceptual model of intra-urban disparities in the local life quality developed for the case of the city of Porto (Portugal) and a database, both established under an earlier investigation. The analysis now carried out aims to highlight the extent to which the use of techniques that describe the spatial distributions, easily identifying atypical locations or spatial outliers and, on the other hand, discovering patterns of spatial association, concentration areas or hot spots may open new analytical perspectives regarding the urban reality. Since these can suggest spatial gradients or other forms of spatial heterogeneity, they can subsequently be complemented by other approaches, namely spatial econometric modeling techniques which are able to explicitly incorporate the mechanisms that support the spatial patterns.

With the support of statistical indicators of spatial autocorrelation and maps covering the patterns of intra-urban differentiation, we discuss the current unbalances in the quality of life of Porto's population, highlighting the more unfavorable situations and their meaning in the city development.

1. Evaluating quality of life in cities

In order to plan and intervene more effectively at urban level, by improving the well-being of populations and reducing socio-economic inequalities, there is a need for new decision-making mechanisms. The building of responses to today's challenges, in terms of public policies, are in fact closely linked to the available information on the life conditions and actual experiences of individuals in their daily lives, to better define target domains, establish priorities and deploy resources.

Research on the quality of life has already evolved over a number of decades and claimed several achievements in terms of theoretical debate and the definition of the actual concept, and in terms of the methodological approaches used to evaluate it. One of the more commonly used approaches to measure the empirical results is based on the construction of objective social indicators selected so as to include the various tangible and intangible determinants of the well-being of the individual and of the communities. Based on the analysis of how these indicators have evolved, we can assess the direction and intensity of changes that have taken place.

The subjective approach in place since the 1970s forming the overall matrix of a vast number of studies have, in turn, enabled a better understanding of how individuals feel about their daily lives, not only with regard to the social, economic and environmental context in which they live, but also to their values, preferences and desires. Studies on happiness and personal satisfaction have enabled an increased access to well-being measures based on the perception of individuals, which are increasingly felt as being necessary and complementary to the objective indicators.

1.1 Research based on objective indicators

Many of the studies on quality of life use as their main source of information institutional statistics available for the geographical area to which the analysis relates, which can vary from a micro scale (block) to a much larger scale (regions, countries, etc.).

In these cases, the concern typically behind the research relates to characterisation – and, sometimes, monitoring – of the conditions and objective life opportunities involved in the area of study. In general, studies carried out for this purpose require a large amount of data from various official sources. If the work scale is highly disaggregated, greater efforts must be put into the primary collection of information, meaning that the results generally obtained include large databases and indicator systems.

There are two unavoidable challenges in this type of research. The first one relates to the definition of the conceptual model, in other words, the identification of the specific domains of quality of life and their breakdown in dimensions, which should be taken into account by the empirical analysis. The second challenge relates to the selection of indicators to be used.

As regards the domains, the fact is that there is no single universal list of domains as absolute reference; therefore, they have to be chosen according to the evaluation aims and to the cultural, spatial and temporal context to which the evaluation relates.

From a practical point of view, several criteria have been used to facilitate the operation of the domain and sub-domains to be favoured in each specific case. One of the ways is to use pre-established lists widely legitimised by international political bodies or that build on theoretical models produced in the context of academic research. Another option is to choose based on the opinion of technical experts.

Either way, having defined the domains – and the dimensions considered significant for each of them -, the next step concerns the selection of indicators, which is eminently a technically subjective and demanding process. As Madureira Pinto (2010, p. 190) stated: “The selection/construction of indicators is a scientific research operation which, despite its tempting simplicity often shown, fully justifies the great care taken in terms of concept, technique and methodology in its implementation”.

Trewin and Hall (2010) prepared a practical guide to support the development of indicators on social progress, where, in choosing the indicators, they show how useful it is to start by identifying those which appear to be the best from a conceptual point of view, something which could be described as the “ideal” indicators and that may or may not actually exist.

Situations in which these “ideal” indicators are not available are precisely where the biggest challenges lie, as we need to find the best proxies. The first essential exercise is to evaluate on a case-by-case basis the existing gap between the best available indicator and the ideal indicator. If the gap is considerable, one of the possible ways is to use not a proxy but various indicators which, taken together, can account for the reality being assessed.

To minimise the margin for subjectivity associated to the choice of indicators, a common practice is to establish a set of basic selection criteria beforehand, which are usually defined according to the specific aims of each project.

1.2 Measuring spatial disparities

Most of the assessments of quality of urban life, regardless of the type of indicators used, provide a reading of reality based on averages, leaving out those that sometimes represent very marked contrasts in terms of the living conditions and well-being of populations. In this sense, there has been a growing and broader awareness of the importance of developing methodologies and analyses that take account of spatial inequalities.

Although this theme is not new, as far as the context of urban geography is concerned[3], it is still current and relevant in view of the ongoing social, economic and environmental changes that tend to accentuate the differences between social groups, and between places within the cities – giving rise to serious phenomena of spatial fragmentation – and in view of the need to promote policies to address these challenges. Indeed, to improve the quality of urban life and fight against inequalities, answers must be found that need to be designed and put into practice at the local scale, within the community itself. This is the reason why identifying and understanding the patterns of intra-urban disparities of the quality of life is an essential requirement to support the design of strategies and setting of priorities for intervention at the block level or other neighbouring units. To be better aware of the existing differences in living conditions and well-being is a key input for the emergence of a new generation of less standardised, and conversely, innovative, integrated polices designed according to specific combinations of problems, potential, resources and players.

The analysis of variations in the quality of life in cities, however, raises major challenges, among which a huge effort involving the collection of data and compatibility of multiple sources. Despite the shortcomings in official statistics for disaggregated geographical scales[4], many institutions holding relevant databases for the

[3] The seminal work of M. Pacione on inequalities in large urban centres is an unavoidable reference, identifying the more unfavourable situation in terms of quality of life (Pacione, 1995; 2003).

[4] The small number of variables collected at the intra-urban scale as part of the European project "Urban Audit IV" is a perfect example of this situation. Population censuses are still the richest source of information when we consider the more disaggregated spatial units.

characterisation of local conditions are now making them available (often through their own websites). While this facilitated access to sectoral databases – often containing geographical references such as street and door number, or which are even associated to digital mapping – opens new possibilities to intra-urban possibilities, the same applies to the dissemination of new technologies, among which the geographical information systems (GIS). These systems allow the integration, aggregation and analysis of the different types of data available for a given territory, promoting new ways of testing new methods to analyse the spatial variations of the quality of life.

2. Intra-urban disparities in the quality of life in the city of Porto

This analysis uses a conceptual model and indicators established as part of a prior research carried out by one of the authors, Martins (2011), which defined a territorial typology describing the different realities within the urban centre concerning the living conditions and well-being of the resident. In this approach, the various neighbourhoods were aggregated into homogenous groups, based on a cluster analysis, according to their "status" in each of the quality of life domains considered.

The analysis now carried out aims to highlight the extent to which the use of techniques that describe the spatial distributions, easily identifying atypical locations or spatial outliers and, on the other hand, discovering patterns of spatial association, concentration areas or hot spots may open new analytical perspectives regarding the urban reality.

2.1 Analysis model and baseline data

The conceptual perspective adopted – based on the idea that quality of life has to do with the many conditions in which peoples' daily lives take place, but also with their opportunities to make choices – assumes that quality of life is the result of a complex, cumulative process in which many interactions take place between the various domains which all work together towards human well-being.

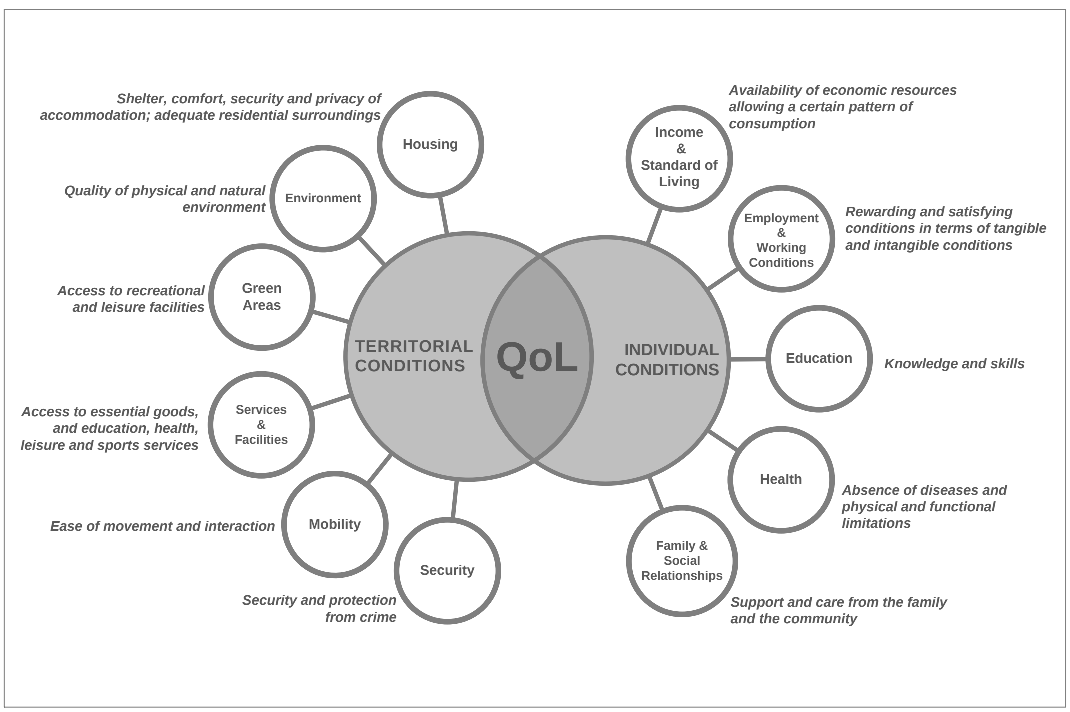
The building of the model started out with a review of the conceptual schemes previously proposed, in different contexts and with different purposes. As such, the systematisation and compared analysis made by the European Foundation for the Improvement of Living and Working Conditions (Eurofound), integrated in the

"Monitoring Quality of Life in Europe" report (Fahey, Nolan and Whelan, 2003) was a very useful benchmark. A review of a vast number of documents on projects to evaluate the quality of life at local level extended the list of domains and provided a better notion of the choices by reference to similar aims to measure variations of the quality of life at intra-urban scale.

It was on this basis that several other selection criteria were adopted. On the one hand, we assumed that it would not be possible to provide a very comprehensive model, but rather choose domains to form its "solid core" that raised no doubt as to their direct influence on the quality of life, and where it would be feasible to establish measures to put the exercise into practice. On the other hand, and since the purpose was for the results to provide support to local management and planning, we clearly assumed that areas related to common good would be of interest, that could be established as priority action areas of public policies.

The analytical model developed is structured into two main sections: territorial conditions, associated to neighbourhood living conditions, and individual conditions. The thematic areas were chosen for each of the two sections in order to characterise them, and a key indicator was also chosen to characterise each of these.

Figure 1 – Conceptual model of intra-urban disparities in the local life quality

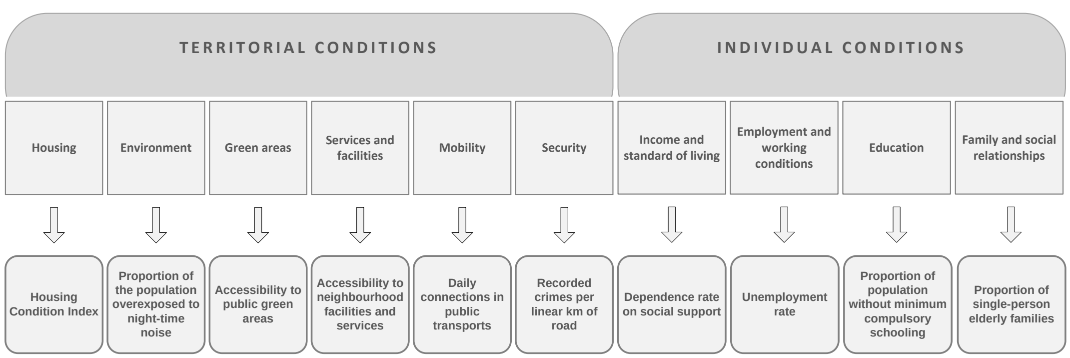


The statistical section was the geographical unit of reference used to collect the key indicators. There are 413 statistical sections in the city of Porto, defined by the National Statistics Office, which correspond to the units formed from the statistic sub-sections (which largely overlap with the city blocks) and contain about 300 accommodations.[5]

With regard to the indicators used – all objective measures – the study used the census data provided by the National Statistics Office, but a major effort was also made to generate new data. This task was necessary in situations for which indicators were not available, but where it appeared to be possible to calculate them using the baseline elements, regardless of their nature (digital thematic maps, data lists associated to postal addresses, matrices of numerical variables, etc.), performing a set of operations and analyses using GIS tools. With the exception of housing conditions, all key indicators on the territorial conditions were obtained in this way.

Despite the effort put into the study, it was not possible to collect good data, at neighbourhood scale, for the health domain, therefore the analysis presented below only uses the other ten indicators.

Figure 2 – Thematic areas and key indicators



[5] Martins (2011) offers a detail and informed presentation of the options made in terms of the analysis model, and in particular of the indicators chosen and the geographical units of reference used.

2.2. Spatial statistical analysis

The first step was to use spatial autocorrelation indicators and methodologies in order to identify patterns and measure levels of spatial association between the various statistical units, and in particular to detect and map clusters and spatial outliers.

The Moran's I Index was used for each of the statistical indicators. This index is defined as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n} (X_i - \bar{X})^2}$$

and $S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}$

where X_i represents the value of the indicator in the statistical section i, $\bar{X}$ the average of the values of indicator X and W_{ij} a general element of the contiguity matrix or spatial weights matrix, which defines the structure of the spatial relationships between the different statistical sections. Matrix W was defined based on contiguity-based spatial weights, thus two sections are considered as neighbouring units if they share a common boundary (we used the "queen contiguity" criterion, thus considering that two sections are neighbouring units if they share any point, so including both common boundaries and common corners).[6] Therefore,

W_{ij} = 1, if the statistical sections i and j share a common boundary,

W_{ij} = 0, otherwise

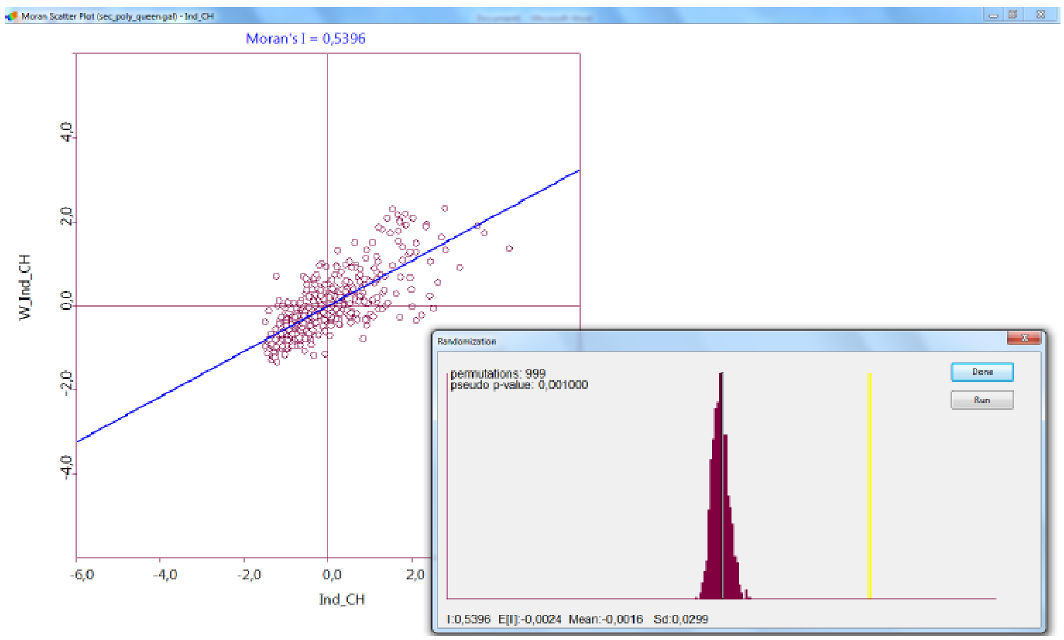
and W_{ii} = 0.

The diagram shown below corresponds to the Moran scatter plot and concerns the "housing conditions" indicator, with the variable of interest (standardized values of the indicator) on the x-axis and the spatial lag on the y-axis, where the value of the Moran's I Index corresponds to the slope of the straight line drawn in blue. Although this index is similar to Pearson's correlation coefficient, but taking into account the spatial dimension, its values do not fall strictly between -1 and +1, although they are usually in that range. The reading of the value obtained is done in a similar manner: a positive value of this coefficient indicates a positive spatial correlation between the statistical unit indicator and the value of that indicator in the neighbouring units, and the

[6] On the definition of matrix W, in particular, on the range of criteria that can be used to define neighbourhood and on the relevance of the matrix, see Getis and Aldstadt (2004), Getis (2009) and Harris *et al* .(2011).

correlation will be stronger the higher the value obtained. The statistical significance of the indicator was based on a random permutation procedure to obtain empirical significance levels (pseudo p-values).

Figure 3 – Moran scatter plot (housing conditions)



As we can see in the next table, the Moran's I Indices for the 10 indicators are all positive and statistically significant (pseudo p-values of about 0.001), indicating a strong spatial correlation for all the variables.

Table 1 - Moran's I Indices

Territorial Conditions	Housing Conditions	CH	0.5396
	Population overexposed to night-time noise	R55	0.3406
	Accessibility to public green areas	EV	0.8581
	Accessibility to neighbourhood facilities and services	ESP	0.7564
	Connections in public transports	LT	0.5252
	Recorded crimes	CRIM	0.4820
Individual Conditions	Dependence rate on social support	PS	0.4329
	Unemployment	TD	0.3625
	Population without minimum compulsory schooling	SEO	0.5101
	Single-person elderly families	ID1	0.2571

The use of the local Moran's I Index provides us with a more detailed analysis of the statistical units under study. This is one of the so-called LISA statistics (Local Indicators of Spatial Association), which, for every observation, give an indication of the extent of significant spatial clustering of similar values around that observation.[7]

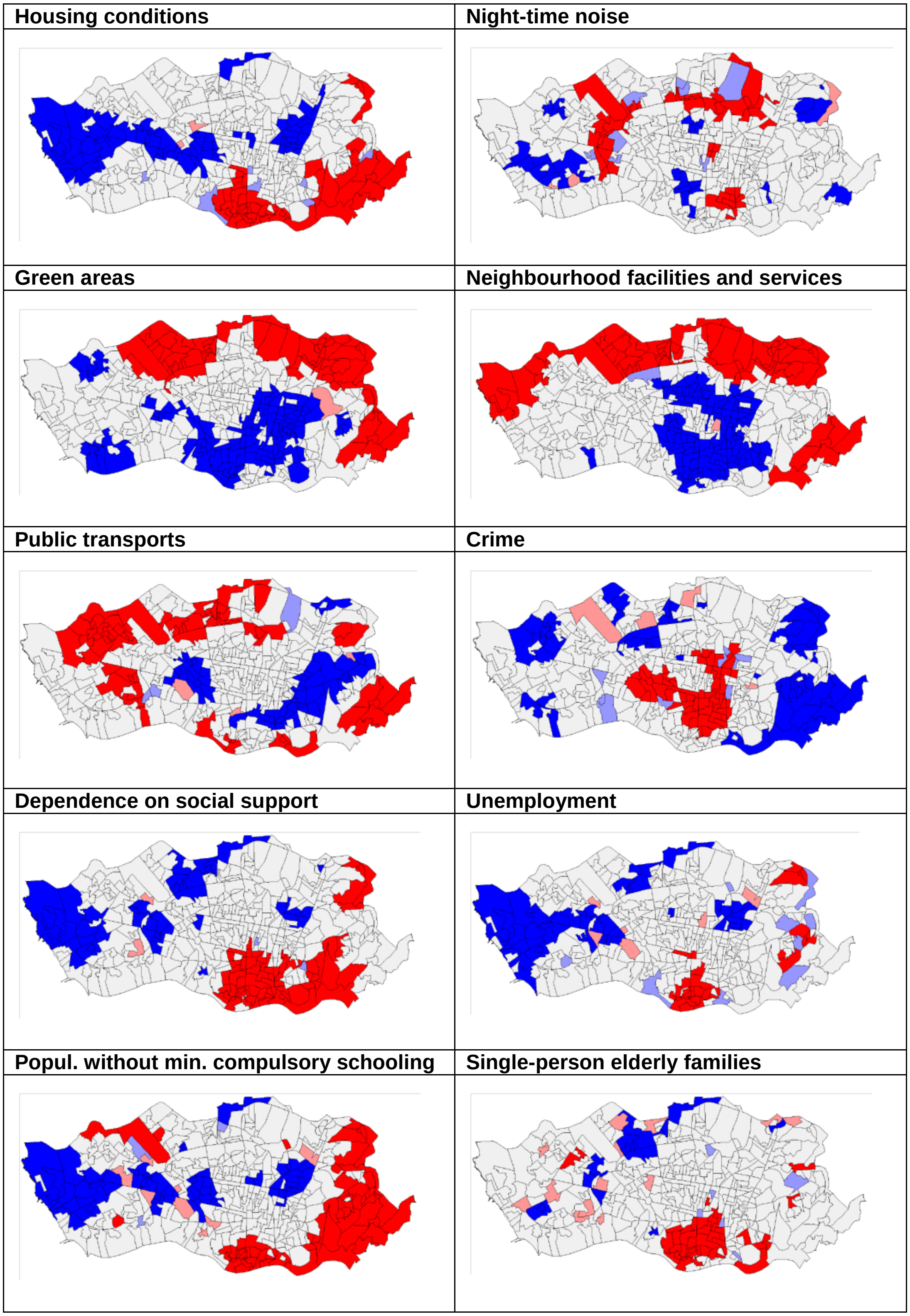
Based on this local Moran's I Index we obtain the so-called cluster map. This map identifies the units for which the local Moran statistics was considered statistically significant (pseudo p-values<0.05 based, as before, on a random permutation procedure). Locations are colour coded by type of spatial autocorrelation: red for high-high (HH: high value at a location and high value in the spatial lag that reflects the weighted average of the neighbouring values), blue for low-low (LL), pink for high-low (HL) and light blue for low-high (LH). Grey corresponds to the cases in which the local Moran index was not considered to be statistically significant.

The first two cases, which correspond to cases of positive spatial autocorrelation, are normally referred to in the literature as spatial clusters, and the other two cases, of negative spatial autocorrelation, correspond to the so-called spatial outliers.

The next page shows these cluster maps for the 10 indicators, showing the spatial differentiation of the city in the various domains of quality of life included in the conceptual matrix defined in this study.

[7] For a detailed explanation of the LISA statistics, see Anselin (1995).

Figure 4 – Clusters Maps



The results show that in any of the analytical dimensions we can detect extensive areas corresponding to homogenous conditions – either more favourable or less favourable. The indicators which nonetheless appear to be associated to a lower spatial concentration are, in the case of territorial conditions, the exposure to noise and, in the case of individual conditions, the isolation of the elderly.

While there is no single pattern of intra-urban inequalities, we do see a city with better living conditions in its western part, contrasting with the reality seen in its eastern periphery and central area. This is the geography shown by the indicators more related with the socio-economic level of the population: housing conditions, dependence on social support, unemployment and education level.

Since the evaluation of inequalities should not be limited to the variables related with the economic status, but also with the territorial distribution of opportunities that characterise well-being, we used, as mentioned before, indicators intended to measure the physical accessibility to amenities such as green areas, main facilities and neighbourhood commerce. As regards the dimensions more related with the provision of infrastructures and services in the territory, the most striking aspect of their spatial distribution relates to the greater concentration of favourable conditions in the central area of the city, which appears as the best furnished territory.

Even for the eastern part of Porto, lacking in many aspects and accumulating a concentration of negative conditions in almost all domains, we can identify one indicator throughout the territory where conditions are homogeneous and clearly favourable, which is the criminality rate.

By analysing the territorial contrasts in the urban centre of Porto from a univariate perspective, we can say that no sub-space shows a concentration of unfavourable conditions in all domains (and the reverse is also true), which means that they all show potential and added-value that can be worked on by urban policies. As mentioned in a recent EU document on urban development in Europe, “Deprived urban neighbourhoods can create a new image for themselves. They very often suffer from a bad image in their cities and regions – an image that does not accurately reflect the true situation in the area and worse than the perception held by the local community of their area” (Piskorz and Goulet, 2009, p. 26). The development of a long-term perspective, based on a solid knowledge of the problems and opportunities and shared by the various actors, will be the starting point of a transformation, one in which all can be involved.

The identification and easy visualisation of these contrasts is, therefore, an important input towards the definition of intervention policies in the city, which may find here a useful tool for a more informed debate on the priorities of public action and to harness efforts in the domains of quality of life and in the more unequal territories.

As the maps show, there are but a few cases of spatial outliers, and no situations of market discontinuities within the urban space. The next table also provides the same reading, summarising, for each indicator, the distribution of the 413 units by type of spatial autocorrelation. A large majority of statistical units (on average about 70%) show no significant spatial autocorrelation. Those that are statistically significant are almost all related to spatial clusters, and the cases of outliers are virtually residual.

Table 2 - Local Moran statistics by type of spatial autocorrelation

	CH	R55	EV	ESP	LT	CRIM	PS	TD	SEO	ID1	Total
n.s.	67,1%	77,7%	55,7%	53,0%	68,5%	68,5%	69,7%	75,5%	65,1%	80,4%	68,1%
HH	12,6%	11,4%	16,0%	18,2%	16,9%	13,3%	16,5%	7,3%	16,0%	9,9%	13,8%
LL	18,2%	8,2%	28,1%	28,3%	13,1%	15,0%	12,8%	13,6%	16,2%	5,3%	15,9%
LH	1,7%	1,9%	0,0%	0,2%	0,7%	2,2%	0,5%	2,2%	0,7%	1,5%	1,2%
HL	0,5%	0,7%	0,2%	0,2%	0,7%	1,0%	0,5%	1,5%	1,9%	2,9%	1,0%
	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%	100,0%

n.s = not significant. For the description of the variables see Table 1.

3. Modelling crime

The previous section made use of spatial statistical methods to describe and visualise the spatial distribution of several indicators of quality of life, allowing us to detect some localisation patterns and to map not only the vulnerabilities of the various territories, but also certain resources and local opportunities.

Following this type of exploratory analysis, a common approach is to use spatial modelling technique in an attempt to explicitly incorporate the mechanisms supporting the various spatial patterns. In this analysis, we carried out a practical exercise based on crime data.

Spatial analysis tools have been increasingly used to analyse and model crime-related variables. Anselin *et al*. (2000) presented a brief review of the literature on the various theoretical and empirical developments of research on crime and place, and in particular on methodological issues in spatial statistical analyses of crime data. At a more applied level, we refer, for instance, to the work of Craglia *et al*. (2001), who focused on the more crime-intensive areas in large metropolitan areas of England and Wales, Martin (2002), who used regression models and spatial analysis techniques to examine residential burglary in Detroit and Zhang and Peterson (2007), presenting a spatial analysis of neighbourhood crime in Nebraska.

All these studies show the importance of considering the spatial effects (spatial dependence and spatial heterogeneity) in modelling crime. Spatial autocorrelation occurs when the dependent variable and/or the error term in a specific location is correlated with observations of the dependent variable and/or error term in neighbouring locations. To address these "neighbour effects" we need to define the spatial weights matrix.

One of the chances of considering these spatial effects in the model is through the so-called spatial lag model, which includes, besides the usual explanatory variables, the spatially lagged dependent variable (which consists of a weighted average of the neighbouring values), formally expressed as follows:

$$\mathbf{Y} = \rho\, \mathbf{WY} + \mathbf{XB} + \mathbf{u}$$

where $\mathbf{Y}$ is a vector (n×1) of observations of the dependent variable, $\mathbf{W}$ is the (n×n) spatial weights matrix, ρ is the spatial autoregressive coefficient, $\mathbf{X}$ is the matrix (n×k) of observations of explanatory variables, $\mathbf{B}$ is a vector (k×1) of unknown regression coefficients, and $\mathbf{u}$ is a vector (n×1) of error terms.

A second model usually considered for spatial autocorrelation is the spatial error model, in which the spatial dependence is expressed through a spatial process for the error terms (either an autoregressive or a moving average form). The model is expressed as follows

$$\mathbf{Y} = \mathbf{XB} + \mathbf{u}$$

where $\mathbf{u} = \lambda\mathbf{Wu} + \boldsymbol{\varepsilon}$, in the autoregressive form, or where $\mathbf{u} = \lambda\mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\varepsilon}$, in the moving average form ($\boldsymbol{\varepsilon}$ is a homoscedastic and uncorrelated error term, $\mathbf{Wu}$ and $\mathbf{W}\boldsymbol{\varepsilon}$ are spatially lagged error terms and λ the autoregressive coefficient).

We can also consider a third type of model that combines the two preceding models into one, that is, a mixed spatial lag model with spatial error.

Note that to estimate the model by OLS without taking into account the spatial dependence leads to a biased and inconsistent estimators in the case of the spatial lag model (since the spatial lag variable incorporates the values of the dependent variable of neighbours, and of the neighbours' neighbours, leading to the simultaneous estimate of the dependent variable, in addition to being correlated with the disturbance term); statistical inference can also not be done in the usual way. In the case of the spatial error model, although the consequences are less severe, the OLS method is not the best suited either. The most appropriate methods are based on the maximum likelihood principle or on the application of instrumental variables.

As regards the explanatory variables of crime, the literature indicates (see references above) those relating to the population structure (for e.g., the elderly, single-person families, education level), income levels, unemployment, and to the provision of services and facilities. In the case of the city of Porto, and using the indicators on the various domains analysed in the quality of life model, the best specification to explain crime (defined as recorded crimes per linear km of road) was obtained by using as explanatory variables the housing conditions indicator and access to neighbourhood facilities and services. The remaining possible explanatory variables, in particular those relating to the unemployment rate and the proportion of single-person elderly families, were not statistically relevant.

In a first stage, the model was calculated through the OLS model, yielding the following results in the diagnostic for spatial dependence:

Moran's I (error)	:	0,370395	(p-value: 0,00000)
Lagrange Multiplier (spatial lag model)	:	159,1523041	(p-value: 0,00000)
Robust LM (spatial lag model)	:	4,1566369	(p-value: 0,04147)
Lagrange Multiplier (spatial error model)	:	158,9758927	(p-value: 0,00000)
Robust LM (spatial error model)	:	3,9802255	(p-value: 0,04604)

The Moran's I statistic with the estimation residuals is clearly significant, suggesting a possible problem of spatial autocorrelation. This statistic is, however, very sensitive to errors in model specification and not only to the possible spatial autocorrelation, in addition to not giving any indication on the type of model best suited to spatial autocorrelation. To this end, the more appropriate ones are the Lagrange Multiplier test for spatial error autocorrelation. The first two tests refer to the spatial lag model and the other two to the spatial error model. In either version the test indicates no rejection of the null hypothesis that spatial autocorrelation exists, therefore, following the strategy presented by Anselin (2005), we will consider the version of the model to which the lowest p-value of the robust version of the test corresponds.[8]

The spatial lag model was estimated by spatial two-stage least squares, which is a consistent estimation method for this model. This method uses the spatially lagged independent variables (**WX**) as instruments to estimate the coefficient for the spatially lagged dependent variable (**WY**). The White consistent standard errors for the estimators of the regression coefficients were also taken into consideration.[9]

Dependent variable: CRIM

Variable	Coefficient	z- Statistic	p-value
Constant	14.497	2.343	0.0191
CH	-1.815	-3.626	0.0003
ESP	-0.011	-2.348	0.0189
W_CRIM	0.596	3.334	0.0009

Pseudo R-squared = 0.472 N = 413

All explanatory variables are statistically significant, for a level of significance of about 2% for the ESP variable, and less than 0.1% in the other two cases.

[8] The robust versions of the tests (in the sense that they do not require the assumption of normality in the errors) should only be used if the standard versions indicate no rejection of the null hypothesis, as is the case. For more details on the tests and the strategy referred to, see Anselin (2005).

[9] The models (and spatial statistics presented before) were estimated using the programmes GeoDa and GeoDaSpace (see Anselin, 2005 and Chasco, 2013); on the estimation methods, see also Anselin (1988 and 1999) and Kelejian and Prucha (1988).

The estimate of the coefficient associated with the spatially lagged dependent variable is of about 0.6, thus indicating a strong contagious effect of the neighbourhood on the different statistical units. The signs of the estimates of the coefficients of the other two explanatory variables are, as expected, negative; in the case of housing conditions, an increase in the value of the indicator, reflecting worse housing conditions, would reduce the crime rate (usually associated with richer areas of the city and, consequently, with better housing conditions). Similarly, the crime rate will tend to be higher in areas where there are more facilities and neighbourhood services; the greater the concentration, the less the value of the indicator, hence the negative sign of the estimate of the coefficient.

The Anselin-Kelejian (1997) test was used as it enables the testing of the remaining spatial autocorrelation in the residuals of the 2SLS estimation, with the value obtained for this statistics of 0.0771, with a p-value of 0.78128, which seems to clearly show that the spatial dependence detected was in fact accounted for with this model. Nevertheless, the specification of a mixed spatial lag and spatial error model was also tested, but the coefficient λ was not statistically significant, the other results remaining very similar. Therefore the spatial lag model shown seems to be the best suited to reflect the crime behaviour, incorporating within it the particularly important spatial effect.

Conclusions

Based on a conceptual model and a database on the intra-urban disparities in the quality of life in the city of Porto, we carried out a spatial statistical analysis of data. Building on Moran's I statistics, global and local, and on the related cluster maps, we were able to analyse and visualise the spatial differences of the city as regards the various domains of quality of life included in the conceptual matrix defined in this study.

The results indicate that extensive areas corresponding to homogeneous conditions – either more favourable or less favourable – can be detected in any and all analytical dimensions. Although no single pattern of intra-urban inequalities was identified, we were able to detect areas of the city showing better living conditions, in contrast with others in which the situation is less favourable.

By analysing the territorial contrasts in the urban centre of Porto from a univariate perspective, we can say that no sub-space shows a concentration of unfavourable conditions in all domains (and the reverse is also true), which means that they all show potential and added-value that can be worked on by urban policies.

This analysis was complemented by a study on crime through spatial econometric models, which showed the relevance and importance of using these models. Disregarding these spatial effects, besides ignoring their quantification and statistical significance would induce serious limitations on the results obtained by the econometric models estimated in the traditional way.

The identification and easy visualisation of the existing contrasts in the different domains is, therefore, an important input towards the definition of intervention policies in the city, which may find here a useful tool for a more informed debate on the priorities of public action and to harness efforts in the domains of quality of life and in the more unequal territories.

References

Anselin, L. (1988), Spatial Econometrics: Methods and Models, Kluwer Academic Press, Dordrecht.

Anselin, L. (1995), Local Indicators of Spatial Association – LISA, *Geographical Analysis*, 27 (2), pp. 93-115.

Anselin, L. (1999), Spatial Econometrics, Bruton Center, School of Social Sciences, University of Texas.

Anselin, L. (2005), Exploring Spatial Data with GeoDa: A Workbook, Spatial Analysis Laboratory, University of Illinois.

Anselin, L., Cohen, J., Cook, D., Gorr, W. and Tita, G. (2000), Spatial analysis of crime, Criminal Justice 2000, National Institute of Justice/NCJRS, pp. 212-62.

Anselin, L. and Kelejian, H. (1997), Testing for spatial error autocorrelation in the presence of endogenous regressors, *International Regional Science Review*, 20**,** pp. 153-182.

Chasco, C. (2013), GeoDaSpace: A resource for teaching spatial regression models, Rect@ Series Monografías 4, pp. 119-144

Craglia, M., Haining, R. and Signoretta, P. (2001), Modelling High-intensity Crime Areas in English Cities, *Urban Studies*, 38 (11), pp. 1921–1941.

Fahey, T., Nolan, B. and Whelan, C. T. (2003), Monitoring quality of life in Europe, Dublin, European Foundation for the Improvement of Living and Working Conditions.

Getis, A. (2009), Spatial Weights Matrices, *Geographical Analysis*, 41, pp. 404-410.

Getis, A. and Aldstadt, J. (2004), Constructing the Spatial Weights Matrix Using a Local Statistics, *Geographical Analysis*, 36 (2), pp. 90-104.

Harris, R., Moffat, J. and Kravtsova, V. (2011), In Search of 'W', *Spatial Economic Analysis*, 6(3), pp. 249-270.

Kelejian, H. H. and Prucha, I.R. (1988), HAC estimation in a spatial framework, *Journal of Econometrics*, 140**,** pp. 131-154.

Madureira Pinto, J. (2010), Reflexões sobre indicadores sociais, *in* Teixeira, A. A. C., Silva, S. T. and Teixeira, P., O que sabemos sobre a pobreza em Portugal?, Porto, Vida Económica, pp. 189-207.

Martin, D. (2002), Spatial Patterns in Residential Burglary - Assessing the Effect of Neighborhood Social, *Capital Journal of Contemporary Criminal Justice*, 18 (2), pp. 132-146.

Martins, I. (2011), Os territórios da qualidade de vida no Porto - Uma avaliação das disparidades intra-urbanas, Ph.D. Thesis, Faculdade de Letras da Universidade do Porto.

Pacione, M. (1995), The geography of multiple deprivation in Scotland, *Applied Geography*, 15 (2), pp. 115-133.

Pacione, M. (2003), Urban environmental quality and human wellbeing – A social geographical perspective, *Landscape and Urban Planning*, 65, pp. 19-30.

Piskorz, W. and Goulet, R. (2009), Promoting Sustainable Urban Development in Europe.Achievements and Opportunities, Brussels, European Commission.

Trewin, D. and Hall, J. (2010), Developing Societal Progress Indicators: A Practical Guide, Paris, Organisation for Economic Co-operation and Development.

Zhang, H. and Peterson, M. (2007), A Spatial Analysis of Neighbourhood Crime in Omaha, Nebraska Using Alternative Measures of Crime Rates, Internet Journal of Criminology.