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A space-time study for mapping quality of life in Andalusia during the crisis

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1. Introduction

As the Third European Quality of Life Survey pointed out, "the financial and economic crisis has led to deterioration in living and working conditions, with significant negative impacts on the everyday lives of some citizens" across Member States (Eurofound 2012). From a regional perspective, the crisis brought to an end a long period during which regional disparities in Gross Domestic Product (GDP) per head and unemployment in the European Union (EU) were shrinking, and has increased the population at risk of poverty or social exclusion (Eurostat 2011). How has the economic crisis affected the quality of life of the people living in a territory? And, how has the crisis affected the spatial distribution of quality of life? To answer these questions it is key, first, to choose which variable or variables could be used to measure quality of life or well-being and, second, to perform a spatio-temporal analysis of quality of life.

Regarding the first question, how we measure societal progress is important because it impacts on how political decisions are made and how society defines progress (Palumbo 2013). Recent decades have witnessed a growing demand for new methods to measure citizens' well-being, progress and quality of life, given that the GDP per capita and the growth in GDP by themselves appear to be unsatisfactory to describe and compare the well-being and progress of societies since they do not account for social cost (Mazundar 1996; Nussbaum 2000; Sen 1987; Stiglitz et al. 2009; Van den Bergh 2007, 2009).[1] In the context of the EU, European institutions have been developing new policies and strategies to maintain and improve quality of life. Specifically, the "GDP and Beyond" Communication of the European Commission has called for the development of indicators that complement GDP to support policy decisions by more comprehensive information (Commission of the European Communities 2009a; European Commission 2010b).

Regarding the second question, the spatio-temporal analysis of quality of life lends greater strength to the results. The importance of space to social science and many socioeconomic theories has been widely noted (Goodchild 2008; Goodchild and Janelle 2010). The successive reports on economic and social cohesion of the European Commission underline the increasing significance of the spatial dimension of regional and local policies as a means to improve quality of life and reduce economic and social disparities between territories (Commission of the European Communities 2009b; Servillo et al. 2011). Theoretical work on regional economic development has indicated a renewed and growing awareness of its spatial representation (Duque et al. 2007; Duque et al. 2015; Rey and Ye 2010). Matthews (2008) reinforces this view, documenting how in sociological studies the neighbourhood context is an important determinant of human well-being. Tobler's (1970) first law of geography states that "near things" are more related than "distant things". Besides space, things near in time should also be more related than distant things.

[1] See Van den Bergh (2009) for a summary of the vast literature that has identified the imperfections of GDP as a measure of social well-being.

This article explores the spatio-temporal structure of quality of life across the 770 municipalities of Andalusia (a region of southern Spain) prior to the economic crisis in 2007 to the more recent year of 2011. That is, we measure and compare the quality of life within the region, analyse its spatial distribution and study how this distribution has changed from 2007 to 2011. Measuring and monitoring quality of life may be particularly relevant in this period of rapid social and economic change and growing social inequalities. In contrast to most papers published previously (see, for instance, Ferrara and Nisticò 2013; Madonia et al. 2013; Perrons 2012; Sánchez-Domínguez and Ruiz-Martos 2014; Somarriba and Pena 2009; Somarriba et al. 2015), which present composite indices to measure quality of life at the NUTS 2 or NUTS 1 level, we study quality of life at the local level using municipal data and, once the quality of life composite index is estimated, we analyse the spatio-temporal distribution of quality of life using spatial econometric techniques.

To this end, we first develop a composite index of quality of life (the Quality of Life index in Andalusia, QLA) inspired by the capabilities approach (Sen 1980, 1987, 2005; Nussbaum 2000, 2011) and the recent trends in well-being (Boulanger et al. 2009; Eurofound 2012; Eurostat 2008; Gough et al. 2006; Michalos et al. 2011; OECD 2013; Stiglitz et al. 2009). To build the composite index, we use the Distance P2 (DP2) method; a statistical-multivariate method that solves the methodological difficulties related to the aggregation of different dimensional indicators (see Somarriba and Pena 2009; Zarzosa Espina and Somarriba Arechavala 2013). The DP2 allows a multidimensional analysis of municipal disparity, thus permitting us to establish a municipality quality of life ranking for Andalusia and to determine which factors are more correlated with the quality of life.

Secondly, once the quality of life index is obtained for each municipality, we analyse how quality of life is geographically distributed in Andalusia. We perform an exploratory spatial data analysis (ESDA) with spatial autocorrelation tests which allows us to confirm or reject the presence of tendencies or spatial structures in the quality of life index distribution in Andalusia (Anselin 1999b; Haining et al. 2000a, 2000b; Wise et al. 1999). Given that we have found a structure of spatial dependence in QLA, a portion of this dependence might be the result of the influence of the quality of life of neighbouring municipalities. To examine this, we therefore estimate the composite Spatial Quality of Life index in Andalusia (SQLA) analogously to QLA. In order to compare the results of the quality of life indices (QLA and SQLA) with income, the most traditional measure of well-being, we also perform the ESDA with SQLA and income. We then study the presence of local spatial clusters and analyse the changes observed in the spatial distribution of quality of life (QLA and SQLA) and income from 2007 to 2011 by building a bivariate local indicators of spatial association (LISA) cluster map. Lastly, focusing on QLA and SQLA, we estimate three kinds of space-time models that explain the effect of quality of life in Andalusia, both in space and time between 2007 and 2011.

Spatial and temporal perspectives are crucial to address regional development, wealth redistribution, and economic crisis (Duque et al. 2015). Hence, this methodological approach will also be useful to analyse how the economic crisis has affected the spatial distribution of quality of life in Andalusia. The departure point of our analysis is 2007 because this was the most recent year of economic growth in Andalusia. 2011 was selected as our final year of review as it was the year for which the latest full dataset across all indicators was available. The territorial unit of analysis is the municipality. This is the smallest unit of territorial analysis for which data are available. It is worth noting that the highest level of territorial breakdown for which Eurostat provides information is NUTS-3, which is province in the case of Spain. Andalusia is NUTS-2. The region is composed of eight provinces, which are in turn composed of 770 municipalities.

Several reasons justify choosing Andalusia as a reference for our study. Firstly, the impact of the economic crisis has been more devastating in some Member States in southern Europe, including Spain. Within Spain, Andalusia is a less developed region of the EU because its GDP per capita is less than 75% of the average GDP of the EU; hence it is one of the regions benefiting from the EU Regional Policy. Secondly, Andalusia is the third most populated region (NUTS 2) of the EU (8.4 million inhabitants in late 2013) and is one of the European regions with a larger area (almost 87,600 km^2), surpassing a high number of countries in the UE. Finally, from a methodological point of view, proper data for analysing quality of life are available in this region, and the large number of municipalities which make up the region (770) makes the sample size very interesting.

The rest of the paper is structured as follows. In section 2, we discuss the concept and measurement of quality of life. In section 3, we discuss the methodology used to develop a composite index of quality of life and analyse its spatial distribution and changes in 2007 and 2011. In section 4, we describe the relevant indicators to analyse quality of life in Andalusia. In section 5, we present the empirical results. Finally, we discuss the results and provide the main conclusions in section 6.

2. An approach to the quality of life measurement

Associating the notion of well-being to a one-dimensional variable, such as GDP, which measures the aggregate value of the market production of goods and services over a given period of time, seems debatable (Mazundar 1996; Stiglitz et al. 2009; Van den Bergh 2007, 2009). GDP per capita does not consider the consequences of economic development on the lives of people, such as the cost of urbanisation, congestion, or pollution, among others. (Hobijn and Franses 2001; Madonia et al. 2013; Neumayer 2003). Nor does it take into account income distribution (Sen 1979, 1980) or significant assets, such as educational opportunities, employment opportunities, and political freedoms (Nussbaum 2000). Neither GDP nor income takes into account the subjective aspects influencing well-being (Diener 2002; Easterlin 2001; Frey and Stutzer 2002; Oswald 1997). These aspects highlight the need to develop measures that complement GDP to evaluate the social and environmental costs and benefits of services, products, and policy options (Palumbo 2013, 51). For instance, after eight years of crisis, Spain showed a positive rate of growth in 2014. However, is it possible to talk about societal progress in Spain since it was among the group of Member States with the highest levels of unemployment, income inequality, poverty, and early leavers from education of the EU in 2014?

2.1. International initiatives

Over the past decade there have been growing demands from both academic and political sectors, as well as the general public, to develop better approaches to measure economic and social progress and to monitor well-being in a more comprehensive way. This is a key question because the conception used to measure progress and social performance influences the design of public policies and the choice of development strategies (Palumbo 2013). Within this framework, several international initiatives have been undertaken to improve the mapping of quality of life. In what follows, we briefly examine the most relevant.

The Human Development Index (HDI), which has been calculated annually by the United Nations Development Program since 1990 (see UNDP 2013), is a multidimensional index that summarises information from four indicators of income, education, and health. The HDI is based on the capabilities concept, which maintains that income and resources do not provide a sufficient or satisfactory indicator of well-being because they measure means rather than ends (Nussbaum 2000, 2011; Sen 1980, 1990). The capabilities approach conceives a person's life as a combination of various "doings and beings" (functionings), and assesses well-being in terms of a person's freedom to choose among the various combinations of these functionings (capabilities). Given the practical difficulty of analysing capabilities, it is considered that the well-being of a person is a summary of the person's achieved functionings (see Basu 1987; Brandolini and D'Alessio 1998; Kuklys 2005; Robeyns 2006; Sen 1987). As people in different places and times have different values and experiences, the list of the most relevant functionings depends on the circumstances and the purpose of the exercise (Sen 2005).

The Canadian Index of Wellbeing is a composite index developed by the Canadian Research Advisory Group (CRAG) based on a selection of 64 indicators from eight domains: living standards, healthy populations, community vitality, democratic engagement, leisure and culture, time use, education, and the environment (see Michalos et al. 2011). CRAG assumes that "overall well-being" is roughly synonymous with "overall quality of life", "while the quantity of our lives is notoriously limited to one per person, its quality is as varied as the perspectives or domains from which it is viewed" (Michalos et al. 2011, iv).

The Commission on the Measurement of Economic Performance and Social Progress (CMEPSP), led by Stiglitz, Sen and Fitoussi, published a report to identify the limits of GDP as an indicator of economic performance and social progress (Stiglitz et al. 2009). Rather than proposing an index to replace GDP, the Commission considers three conceptual approaches to measure quality of life or overall well-being (Stiglitz et al. 2009, 42): the capabilities approach, which is in close connection with moral philosophy; subjective well-being, which is in close connection with psychology (Diener 2002; Easterlin 2001; Kahneman et al. 1999); and the notion of fair allocations, the standard approach in economics (Boadway and Bruce 1984). The CMEPSP identifies eight dimensions of well-being that should be considered simultaneously (Stiglitz et al 2009, 14): material living standards, health, education, personal activities (including work), political voice and governance, social connections and relationships, environment, and insecurity (of an economic as well as a physical nature).

Following the recommendations of the CMEPSP, the OECD developed the Better Life Initiative project in which they establish 11 dimensions as being essential to well-being, with 2-4 indicators per dimension that include measures of subjective well-being (see http://www.oecd.org/betterlifeinitiative; OECD 2013).

The European Quality of Life Survey (EQLS) is an established tool for documenting and analysing quality of life in the EU developed by The European Foundation for the Improvement of Living and Working Conditions (Eurofound). The first survey was carried out in 2003 and the third and latest in 2011. The EQLS explores issues pertinent to the lives of European citizens, such as employment, income, education, housing, family, health, the work-life balance, life satisfaction, and perceived quality of society across Member States. Eurofound's approach recognises that quality of life is a broader concept than living conditions and refers to the overall well-being of individuals in a society (Eurofound 2012, 7).

Under the roadmap on "GDP and beyond: measuring progress in a changing world", the EU has undertaken several initiatives to identify indicators that complement GDP in policymaking, including social and environmental achievements (such as improved social cohesion, accessibility and affordability of basic goods and services, education, public health, and air quality) and losses (e.g. increasing poverty, more crime, and depleting natural resources) (Commission of the European Communities 2009a, 3). Some of the most important of these initiatives include:

a) The EU Sustainable Development Indicators (EU SDI) initiative, which aims to monitor the European Union Sustainable Development Strategy (Council of the European Union 2006) by supplying information on approximately 100 indicators grouped into 10 themes of the social, economic, environmental, and governance spheres (see Eurostat website).

c) The Europe 2020 Strategy (approved 2010), which aims to coordinate all of the Member States' efforts to collectively exit stronger from the crisis and turn the EU into a smart, sustainable, and inclusive economy (European Commission 2010a, preface). With that aim, the Commission has established eight targets that the Member States should met by 2020 on unemployment, investment in R&D, CO_2 emissions, renewable energy, energy consumption, early school leaving, tertiary education, and poverty.

d) The Quality of Life Indicators project of the European Statistical System Committee (ESSC) that was approved in November 2011. The objective of the set of indicators is to provide an overall sense of how the country is doing in terms of the well-being of its citizens (Eurostat 2008). The set of indicators combines data from several sources for measuring quality of life in the EU in the following dimensions: material living conditions, productive or main activity, health, education, leisure and social interactions, economic and physical safety, governance and basic rights, natural and living environment, and overall experience of life.

2.2. Our proposal

Inspired by the capabilities approach and the recent trends in well-being described above, we present the Quality of Life Index in Andalusia (QLA) to estimate the quality of life of people who live in the municipalities of Andalusia.

The starting point for all the initiatives described in the previous section is that GDP is a very specific measure focusing solely on market values that can misrepresent well-being. Income and resources are important, but cannot by themselves provide a satisfactory estimation of quality of life as they only measure means (instead of ends). Moreover, a central element in improving quality of life is enabling people to achieve their desired goals. The opportunities afforded to people as well as the choices they make are critical, and take place in specific policy and institutional settings, as well as in the context of an economy, community, and society (Eurofound 2012, 10). That is, the relationships among one person and the rest of people and institutions, the economy, and the social context, as well as subjective assessments of well-being, have a significant influence on quality of life. Therefore, quality of life is a multidimensional concept that takes account of the objective circumstances of the person and her subjective evaluation of them. Given that both objective and perceived circumstances are located in society and also in the frames of meaning with which we live, well-being is a dynamic concept (Boulanger et al. 2009; Gough et al. 2006; Muffels and Headey 2013; Stiglitz et al. 2009). Quality of life should be seen as a model in which functioning, personal resources, and external conditions fit together and determine one another (Eurostat 2008).

In analytical terms, we could assume that there is a function g which makes quality of life for the municipality i (QLA_i) depend on a vector of functionings b achieved by the people of the municipality:

$$QLA_i = g(b) \tag{1}$$

Goods and services (including income) undoubtedly contribute to well-being, but we observe that people typically differ in their capacity to transform a given bundle of commodities into valuable functionings (Gough et al. 2006). This can be explained by the existence of conversion factors (physical condition, reading skills, intelligence, public policies, social norms, gender roles, climate, geographical location, etc.) that influence how a person can convert the characteristics of the commodity into a functioning (Robeyns 2005, 99). In addition to goods, the social, economic, family, and political environment determines the creation or expansion of capabilities.

Considering these aspects, the QLA will allow us to assess the degree of relative disadvantage of the Andalusian municipalities, taking the achieved functionings in relevant areas of quality of life (material living conditions, education, health, economic security, leisure and social interactions, etc.) as reference points.

To conclude this section, it should be noted that we have chosen the municipality as the unit of analysis because it is the finest spatial scale for which data are available although we are aware that the capabilities approach focuses on the individual. However, the majority of studies performed in this framework to analyse human development, well-being, quality of life or poverty use secondary data at the country or regional level, the most well known of which is the HDI of the United Nations. The main explanation for this is the lack of self-reported data. To overcome this limitation, and using the capability approach as a reference theory, some researchers have designed (and funded) their own surveys to study well-being (Anand et al. 2009). Other research uses surveys on happiness to analyse the relationship between life satisfaction and capability deprivations or poverty (Suppa 2015), and to analyse the impact of capabilities and choices on well-being (Muffels and Headey 2013).

3. Methods

3.1. Building a composite index of quality of life

The main pros of using composite indices are that they summarise complex and multidimensional realities with a view to supporting decision-makers, are easier to interpret than a battery of many separate indicators, assess the progress of territories over time, facilitate communication with the general public, and promote accountability (Michalos et al. 2011; Nardo et al. 2005; OECD 2008, 13-14). The most troubling issues concerning the development of composite indices are the treatment of measurement units (how to aggregate variables expressed in different units) and the weighting of variables in the composite index (how to aggregate the variables into a single index) (see Booysen 2002; Michalos et al. 2011; Nardo et al. 2005; Permanyer 2011; Ravallion 2010).

We propose the Distance P2 or DP2 composite index developed by Pena Trapero (1977) as a method to solve these problems. The Distance P2 method has some interesting advantages such as the composite index-elaboration method, as we review below. Moreover, DP2 is a quantitative distance index measured in cardinal terms, thus allowing comparisons of quality of life across several spatial and/or time units. From the results, municipalities can be ranked from high to low level of quality of life, and factors which are more correlated to quality of life can be identified. If the same variables and method are used, the results for Andalusian municipalities can be compared with those obtained for other regions or countries. Moreover, DP2 can be used to compare changes in relative positions and even to detect their causes.

Due to the scarcity of data, it is less common to apply the DP2 methodology at the municipal level. Several studies have applied DP2 to build composite indices at a lower level than NUTS-3, among them Castro-Bonaño (2002), Montero et al. (2010), Sánchez-Domínguez and Rodríguez-Ferrero (2003), and Zarzosa (2005).

3.1.1. The Distance P2

Equation (2) shows the type of association between our theoretical proposal for measuring quality of life and the DP2 methodology. In using the Distance P2, we can build a multidimensional index (QLA) by aggregating various functionings or indicators[2] of municipal quality of life as a weighted sum,

[2] One or more indicators can be used to account for each of the functionings; however, for the sake of clarity, we only use "m" to denote functionings or indicators.

$$QLA_i = \sum_{l=1}^{m} a_l b_{il} \quad (2)$$

where i is the municipality; m is the number of functionings; and a_l are the weights assigned to each achieved functioning.

The point of departure of the whole process is a matrix X of order (n, m) where n is the number of municipalities and m is the number of indicators. Each element of the matrix, x_{ij}, represents the state of indicator j in municipality i. Indicators that are negatively related with quality of life are incorporated into the model, thus changing the sign (all their data must be multiplied by -1). Conversely, indicators that are positively related with quality of life remain unchanged. Thus, the increase (decrease) in the values of any indicator indicates an improvement (worsening) in quality of life.

The DP2 composite index in municipality i is defined as follows:

$$DP2_i = \sum_{j=1}^{m} (d_j(i,_*)/SD_j)\left(1 - R^2_{j,j-1,\ldots 1}\right) \quad (3)$$

where $R_1^2=0$,

and where:

- m is the number of indicators;
- $d_j(i,_*)=|x_{ij}-x_{*j}|$ is the difference between the value taken by the j-th indicator in the i-th municipality and the minimum of the indicator in the least desirable theoretical situation taken as a base reference $X_*=\{x_{*1}, x_{*2}, \ldots, x_{*m}\}$;
- SD_j is the standard deviation of indicator j; and
- $R^2_{j,j-1,\ldots 1}$ is the coefficient of determination in the multiple linear regression of x_j over $x_{j-1}, x_{j-2}, \ldots x_1$, already included.

The DP2 composite index solves both the treatment of measurement units and the weighting attached to each observable variable by dividing the distance by SD_j (i.e. d_j/SD_j). Hence, the indicator is simultaneously expressed in abstract units and weighted by the inverse of the standard deviation. In doing so, the distances corresponding to the indicators with a higher dispersion to the mean are less important in determining the composite index.

3.1.2. The base reference

Thus defined, the composite index measures the distance or disparities regarding quality of life between each municipality and a fictitious base reference. In this instance, the base reference (X_*) comprises the results from an imaginary municipality which reflects the worst possible scenario for all the indicators and would therefore be assigned a value of zero in the composite quality of life index (see Sánchez-Domínguez and Rodríguez-Ferrero 2003; Sánchez-Domínguez and Ruiz-Martos 2014; Somarriba et al. 2015; Zarzosa Espina and Somarriba Arechavala 2013). A higher DP2 value therefore indicates a higher level of quality of life as it represents a greater distance from the “least desirable” theoretical situation.

3.1.3. The correcting mechanism

The coefficient of determination, $R^2_{j.j-1,\ldots 1}$, measures the percentage of variance of each indicator explained by the linear regression estimated using the preceding variables ($x_{j-1}, x_{j-2}, \ldots x_1$) in the summation of the calculation formula (equation 3). As a result, the correction factor (1-$R^2_{j.j-}$

$_{1,\dots 1}$) avoids data duplication by eliminating the information contained in the preceding indicators. That is, if ($1-R^2_{j,j-1,\dots 1}$) expresses the part of the variance of indicator x_j not explained by x_{j-1}, x_{j-2}, ... x_1, the part already explained by the preceding indicators is obtained by multiplying each indicator by the corresponding coefficient of determination, $R^2_{j,j-1,\dots 1}$. In other words, the correction factor indicates the proportion of new information attributable to each indicator. Notice that R^2 is an abstract concept unrelated to the measurement units of the indicators.

The result of the DP2 varies when the order of the indicators is changed in the summation. In this process, the first indicator (i = 1) will contribute all its information to the composite index (d_1/SD_1). However, the second indicator (i = 2) will only add that part of its variance which is not correlated with the first indicator: $(d_2/SD_2)(1-R^2_{2.1})$. Similarly, the third indicator will contribute the part of its variance to the DP2 that is not correlated with either the first or the second indicators: $(d_3/SD_3)(1-R^2_{3.2,1})$, and so on. It is therefore necessary to order the indicators based on the information that each of them contributes to the composite index (from highest to lowest). That is, the first indicator to be included is the one that provides the greatest amount of information concerning the objective to be measured, and so on.

We follow the ranking method proposed by Pena Trapero (1977), which is an iterative method based on the Fréchet Distance (FD) where all the coefficients of determination R^2 are set to zero:

$$FD_i = \sum_{j=1}^{m} (d_j(i,_*)/SD_j) = \sum_{j=1}^{m} (|\,x_{ij} - x_{*j}\,| / SD_j) \;; \qquad i = 1, 2, ..., n \tag{4}$$

We then estimate the pairwise correlation coefficients r between each indicator and the Fréchet distance and sort the indicators from highest to lowest according to the absolute values of the pairwise correlation coefficient. Next, we calculate the first DP2 for each municipality and incorporate the indicators in the resulting order. The indicators are then classified by ordering them from highest to lowest in terms of the absolute value of the pairwise correlation coefficient between each component and the DP2. The process continues iteratively until the difference between two adjacent DP2s is zero.

3.1.4. Advantages and disadvantages of DP2 as a method for building composite indices

It is worth noting the main advantages of DP2 as a composite index method. First, it verifies all of the necessary properties for an acceptable aggregation method: existence and determination, monotony, uniqueness quantification, invariance, homogeneity, transitivity, exhaustiveness, additivity, and invariance compared to the base of reference (see Zarzosa Espina and Somarriba Arechavala 2013). That is, if the standard deviation of the indicators are different from zero (which is satisfied in all the indicators selected in this work), the composite indices built using the DP2 method are continuous variables which can take any value between their minimum and maximum value. Therefore, their arithmetic mean and descriptive statistics have the same characteristics and interpretations of any continuous variable. Second, the input order of the indicators governing the relative weight of each variable is determined through an algorithm which reaches convergence when the indicator fulfils a number of desirable properties; that is, it objectively assigns weights to the indicators. Finally, it incorporates an objective way for selecting variables: by using a correcting mechanism, only the new information included is retained from each variable and the duplicity of information is avoided.

Nonetheless, the DP2 method also has some limitations: (1) the investigator defines variables with a positive or negative impact on well-being or quality of life, so that some arbitrariness may be introduced into the model; and (2) it only analyses linear relationships between variables and does not eliminate redundant information between variables of a quadratic or multiplicative nature, for example.

3.2. Analysing the spatial distribution of quality of life

Although the municipality of residence is where we spend most of our time, it is worth noting that people jump spatial scales every day and unconsciously cross administrative lines in their daily activities (working, shopping, etc.) (Matthews 2008). The ESDA analysis, the bivariate LISA cluster map, and the econometric models that we propose have the ability to link movement across space and time, thus allowing us to analyse interrelationships between neighbours within Andalusia for the years 2007 and 2011. We work with the municipality as the unit of analysis because it is the smallest and finest unit of analysis available. However, we are aware that municipalities might represent an aggregation of potentially very heterogeneous individuals, and this aggregation could cause the modifiable areal unit problem (MAUP). The presence of MAUP might affect the magnitude of measures of association, such as spatial autocorrelation coefficients and parameters in econometric models (Anselin 1988; Griffith 1987).

3.2.1. Exploratory spatial data analysis of the distribution of quality of life and income

We perform the spatial autocorrelation analysis from a two-fold perspective (Anselin 1999b; Wise et al. 1999): we first test for the presence of global autocorrelation in quality of life and income and then analyse spatial autocorrelation from a local perspective. Performing an ESDA analysis with quality of life indices and income will allow us to make comparisons between new proposals and traditional quality of life measures.

To detect the existence of spatial dependence from a global perspective, we calculate Moran's I statistic (Anselin 1988; LeSage 2008; Moran 1948). This statistic is calculated as the ratio between the cross product of the deviations from the mean of the variable of interest (y) and their spatial lags, and the square of the deviations:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{k=1}^{n} w_{ik}} \frac{\sum_{i=1}^{n}\sum_{k=1}^{n} w_{ik}(y_i - \bar{y})(y_k - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5}$$

where y_i is the i-th observation of the variable, $\bar{y}$ is its mean, and w_{ik} are the spatial weights corresponding to municipalities i and k.

Moran's I tests the presence of trends or general spatial structures in quality of life distribution over a complete geographic space (Andalusia). To do so, we have used three different conceptualisations of spatial relationships between municipalities (*W*): (1) inverse distance between the centroids of municipalities; (2) inverse distance squared between the centroids of municipalities; and (3) physical contiguity. In the last case, the spatial weight is 1 for two municipalities sharing some common border and 0 otherwise. In all three cases, we have standardised the *W* matrix and the z-score is based on the randomization null hypothesis computation, with 999 permutations. The cut-off distance for inverse and inverse squared distance weights that we used is the Euclidean distance, which ensures that every feature has at least one neighbour (20185.6 metres).

A portion of the structure of the spatial dependence in QLA could be explained by the quality of life of the neighbourhood. That is, the quality of life in a municipality might be explained not only by the values that take the selected indicators (X) in the municipality, but also by the values of these indicators in neighbouring municipalities. In order to analyse this case, we build the SQLA using the Distance P2 method, as has been described in previous sections. The SQLA is a composite index of quality of life which, in addition to each of the indicators x_j, includes the indicators sx_j, where $sx_j = W{*}x_j$. Each of the sx_j indicators represents the weighted average of the neighbouring values of each municipality (Anselin 1999a). Therefore, SQLA reflects the effect of spatial vicinity, that is, it not only reflects the level of quality of life of each municipality, but also includes the quality of life of its neighbours. Global autocorrelation statistics focusing on the general dependency analysis for all units of a geographical space are not able to detect certain local association structures (hot spots) (Anselin 1995; Getis and Ord 1992; Ord and Getis 1995, 2001). Therefore, to identify hot spots or possible centres of statistically significant clustering of municipalities in Andalusia in terms of QLA, SQLA and income, we calculated the LISA statistic with a 99% level of confidence (Anselin 1995). Four categories of spatial autocorrelation are distinguished, two of which suggest local clusters and two that suggest outliers. High values surrounded by high values, and low values surrounded by low values – compared with their average value – are clusters, whereas high values surrounded by low values and low values surrounded by high values are spatial outliers, indicating locations where the pattern changes significantly.

To detect the presence of spatial clusters we have used the Local Indicator of Spatial Association (LISA) (Anselin 1995):

$$I_i = z_i \sum_{k=1}^{n} w_{ik} z_k \tag{6}$$

where $z_i = (y_i - \overline{y}), z_k = (y_k - \overline{y})$, and w_{ik} are the spatial weights.

3.2.2. A bivariate local Moran's statistic

Focusing on the municipalities that belong to clusters or outliers, the bivariate local Moran's statistic (bivariate LISA or BLISA) allows mapping significant locations classified by the association between the QLA (SQLA and income) value at one point in time and the QLA (SQLA and income) value for its neighbours at a different point in time, thus suggesting possible diffusion patterns (Anselin 1995). There is some confusion between the bivariate local Moran Statistic and the space-time Moran's I (López et al. 2011). We use the BLISA approach because it is useful for identifying changes in the location of clusters at two different points in time (Anselin 2005). The bivariate LISA can be defined as in Matkan et al. (2013):

$$I_i^{tt'} = z_i^t \sum_{k=1}^{n} w_{ik} z_k^{t'} \tag{7}$$

where $z_i^t = (y_i^t - \overline{y}_t), z_k^{t'} = (y_k^{t'} - \overline{y}_{t'})$, and w_{ik} are the spatial weights.

3.2.3. Three kinds of space-time models

Focusing on QLA and SQLA, we are now interested in estimating three kinds of space-time models to capture the contemporaneous and non-contemporaneous spatial dependence of quality of life in Andalusia, both in space and in time (two points in time: 2007 and 2011). When we have spatial and temporal data, they can be considered as t time slices of n cross-sectional units, and a range of specifications can be considered (Anselin 2001). A space-time model taxonomy for a spatial autoregressive model when n > t appears in Anselin et al. (2008) and Elhorst (2001). For our purpose, we have specified three space-time models with n = 770 and t = 2 (2007 and 2011) as follows:

1. Pure space recursive model (PSRM)

The PSRM specification is as follows:

$$QLA_{11,i} = \alpha + \gamma W QLA_{07,i} + \varepsilon_i \tag{8}$$

$$SQLA_{11,i} = \alpha + \gamma W SQLA_{07,i} + \varepsilon_i \tag{9}$$

where QLA_{07} ($SQLA_{07}$) and QLA_{11} ($SQLA_{11}$) are the quality of life index values in 2007 and 2011, respectively; W is a nxn spatial weights matrix which reflects the spatial structure of connection between observations; $WQLA_{07,i}$ ($WSQLA_{07,i}$) represents the spatially lagged quality of life in 2007 (i.e. the non-contemporaneous spatial effects or the effect of the quality of life of its neighbours in 2007); γ is the space-time autoregressive parameter and ε_i is a normal random disturbance.

While the Moran scatter plot represents the linear regression between $WQLA_{07,i}$ ($WSQLA_{07,i}$) and $QLA_{11,i}$ ($SQLA_{11,i}$) and reflects the overall pattern of association between the two (Anselin 1996), in a PSRM, dependence pertains only to neighbouring municipalities in the previous period of 2007. This specification becomes quite suitable to study diffusion phenomena (Anselin et al. 2008).

2. Space recursive and simultaneous model (SRSM) and space recursive error model (SREM)

The SRSM specification is as follows:

$$QLA_{11,i} = \alpha + \gamma W QLA_{07,i} + \rho W QLA_{11,i} + \varepsilon_i \tag{10}$$

The SREM specification is as follows:

$$SQLA_{11,i} = \alpha + \gamma W SQLA_{07,i} + u_i \tag{11}$$

$$u_i = ⍰ W u_i + \varepsilon_i$$

where $WQLA_{11,i}$ represents the spatially weighted quality of life in 2011 or the effect of the quality of life of its neighbours in 2011; ρ represents the contemporaneous spatial autocorrelation; and ⍰ is the coefficient in a spatial autoregressive structure for the disturbances u_i.

Although the introduction of a time-lagged spatial dependence term ($WQLA_{07,i}$) has been suggested in the PSRM, spatial dependence has usually been included in a spatial simultaneous autoregressive model (SAR). Chasco and López (2008) presented an application of the SRSM or mixed regressive-spatial autoregressive model in several economic series of Spanish provinces and showed that these series present a contemporaneous and non-contemporaneous spatial dependence with a different time lag.

3. Time-space simultaneous model (TSSM) and time-space error model (TSEM)

The TSSM specification is as follows:

$$QLA_{11,i} = \alpha + \phi QLA_{07,i} + \rho W QLA_{11,i} + \varepsilon_i \tag{12}$$

The TSEM specification is as follows:

$$SQLA_{11,i} = \alpha + \phi SQLA_{07,i} + u_i \tag{13}$$

$$u_i = ⍰ W u_i + \varepsilon_i$$

where ϕ is the time autoregressive parameter. These models include a time lag and a contemporaneous spatial lag.

In order to estimate the parameters of the previous space-time models, asymptotic methods (i.e. maximum likelihood) are preferred (Anselin 2001; Elhorst 2001). However, the PSRM with independent and identically distributed (iid) errors can be estimated by means of ordinary least squares (OLS) (Anselin 2001). We have used the OLS method to estimate the parameters of the PSRM and maximum likelihood (ML) for other models.

4. Data and indicators

The next step is to select indicators that represent the best estimation of the achieved functionings for every municipality in order to measure and compare well-being or quality of life in Andalusia. To develop the composite index of multidimensional quality of life in Andalusia (QLA), we use the official statistics of the Multi-territorial Information System of Andalusia (SIMA) database developed by the Institute of Statistics and Cartography of Andalusia. To develop the indicators, we have essentially taken into account the recommendations and indicators used in the international projects described above. The indicators were also chosen carefully to remove the effect size and meet the following technical criteria (Advisory Committee on Official Statistics 2009; Bell and Morse 2003; Guy and Kibert 1998): relevance, statistically sound, intelligible and easily interpreted, reliability, and allow international comparison. In addition, we follow Ivanovic (1974) regarding the properties that must be met by an indicator in the context of distance methods. According to Ivanovic (1974), an indicator should have a high power of discrimination, that is, its value should vary in all geographical areas studied, because otherwise its contribution to a municipality quality of life measurement would be reduced. To check this property, Ivanovic (1974) proposed the discrimination coefficient (DC):

$$DC_j = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{v>i}^{n} \left| \frac{x_{ij} - x_{vj}}{\overline{X}_j} \right| \tag{14}$$

where n is the number of municipalities; x_{ij} is the value of indicator j in municipality i; x_{vj} reflects the values of indicator j, different from x_{ij} and located after $x_{ij;}$ and $\overline{X_j}$ is the mean of indicator j. This coefficient ranges from 0 to 2 (Zarzosa, 1996). If an indicator takes the same value for all municipalities, DC equals zero, thus indicating that the indicator has zero discriminant power. By contrast, if an indicator only takes a value other than zero for one municipality (and n - 1 is equal to zero in the remaining municipalities), DC is equal to two and the indicator has full discriminant power.

Taking into account these criteria, we build a list of 15 indicators which allow us to take into account several domains of a municipality's quality of life in 2007 and 2011, such as material living conditions, health, education, leisure and social interactions, economic and physical safety, natural and living environment, and political voice. To approximate the advantages of living in a municipality, we use 10 indicators, which are incorporated in the model with their true value. To approximate the drawbacks of living in a municipality, we use five indicators, which are incorporated in the model changing the sign (multiplying by -1). Table 1 shows the title, the relation between the indicator and the QLA index (i.e. how an increase/decrease in the indicator affects QLA), and the definition of the 15 indicators. Table 2 shows the rationale (why the indicator is needed and useful for measuring municipality quality of life), the international projects that use the indicator, and the discrimination coefficients of Ivanovic (1974).

Additionally, to check if the indicators are sufficiently related to ensure inclusion in a composite index, two tests were carried out, showing that the 15 indicators passed the suitability test for 2007 and 2011 (KMO measure of sampling adequacy equal to 0.813 in 2007 and 0.810 in 2011, and *p*-values < 0.001 in Bartlett's test of sphericity in the two years analysed; n = 770).

Insert Table 1 here

Insert Table 2 here

5. Results

5.1. Summary statistics, explanatory factors of quality of life and analysis of disparities in quality of life

Table 3 shows the descriptive statistics of the indicators and QLA_{07} and QLA_{11}. For instance, QLA_{07} is a continuous variable which can take any value between its minimum value (27.24) and its maximum value (68.17). Its average value in the 770 municipalities analysed is 51.10 and its standard deviation is 3.76. QLA_{11} would be interpreted in a similar manner.

Table 4 shows the ranking of the indicators obtained by the iterative calculation of the DP2, the correction factor (1-R^2) of each indicator, and the absolute pairwise correlation coefficients (r) in 2007 and 2011, for both QLA and SQLA. Focusing on QLA and according to the statistical information analysed, the indicators of socio-demographic characteristics (*Dependency* and *Youth*), *Income*, and Broadband Digital Subscriber Line (*DSL)* are the most highly correlated with QLA_{07} and QLA_{11}. Specifically, we found correlations of 0.65 between *Dependency* and QLA_{07} and of 0.62 between *DSL* and QLA_{07}, etc., and correlations of 0.62 between *Income* and QLA_{11} and of 0.54 between *Youth* and QLA_{11}, etc. *Dependency* and *Youth* have a direct impact on the labour market and on public system incomes and expenditures (mainly on public health). Taking into account that the effects of the economic crisis are transmitted more rapidly to economic variables, it is not surprising that *Income* is the most influential variable in 2011. *DSL* as infrastructure that guarantees Internet access also has a high discriminant power in the territory: in 2007, 54 municipalities did not have a DSL supply and 20 municipalities still did not have DSL in 2011. Nevertheless, as these numbers show (Table 3 and DC in Table 2), the situation has improved from 2007 to 2011. By contrast, the indicators *Adult*, *Forest*, and *Unemp* ranked lowest, thus indicating that they are the least correlated with quality of life.

Insert Table 3 here

Insert Table 4 here

Regarding the values of the correction factors (1- R^2), it could be argued that all the indicators analysed provide relevant information for determining quality of life, that is, no indicator is redundant and none is eliminated by the selection criteria implicit in the DP2. In the case that a indicator did not provide different information to QLA from that provided by the previous indicators, its correction factor would be equal to zero (that is, the corresponding coefficient of determination $R^2_{j.j-1,\ \dots\ 1}$ would be equal to one). For example, the *Dependency* indicator, which ranks first in explaining quality of life in 2007, contributes 100% of its information to construct the QLA_{07} (correction factor 1). A correction factor of 0.27 is applied to *Youth* (in third place) because approximately 73% of the information for this indicator was already explained by the two previous indicators (particularly *Dependency*) in the ranking. Continuing with the analysis of 2007, the correction factors of *Forest* and *Unemp* (0.94 and 0.89, respectively) show that although these indicators occupy the last positions, they contributed a very high percentage of new information on quality of life that was not contributed by the 13 previous indicators.

It is interesting to note in Table 3 that the average value of QLA_{11} (47.89) is lower than the average value of QLA_{07} (51.10) and that this difference is statistically significant [t(1538) = 17.46, $p < 0.001$, n = 1,540] with an effect size equal to 0.88 (Cohen's d), thus indicating that the magnitude of the difference is large (Cohen 1988). A comparison of the QLA_{07} and QLA_{11} values confirms that only 46 municipalities that were below the average in 2007 showed a higher QLA in 2011 than in 2007, while all 419 municipalities that were above the average in 2007 showed a lower QLA in 2011 than in 2007. The quality of life of about 13.55% of the population living in 37% of the regional territory was lower than the regional average (51.10) in 2007. In 2011, the quality of life of 17.34% of the population (44% of territory) was lower than regional average (47.89). This indicates that the quality of life in Andalusia worsened from 2007 to 2011 mostly due to the poor behaviour of the demographic variables (*Growth* and *Youth*), *Unemp* and *Income* as a result of the economic crisis (Table 3).

Based on the DP2 additivity property (see Zarzosa Espina and Somarriba Arechavala 2013), it can be inferred that, in 2007, the municipality which reached the highest level of quality of life (QLA_{07} = 68.17) enjoyed a quality of life roughly 2.5 times higher than that of the municipality with the lowest QLA value (27.24). From 2007 to 2011, the differences in quality of life were smaller because the municipality with the highest quality of life in 2011 (QLA_{11} = 60.63) reached a QLA value that was only 2 times greater than the municipality with the lowest quality of life (QLA_{11} = 30.13). The Gini index of QLA also indicates that territorial disparities in quality of life fell from 0.22 in 2007 to 0.20 in 2011.

5.2. Spatial distribution of quality of life and global association

Figure 1 shows the spatial distribution of QLA_{07} and QLA_{11}. In both years analysed, the municipalities located in metropolitan areas and the municipalities in the Costa del Sol area registered the highest values in their respective QLAs. This finding leads us to consider whether some functional relation exists among the QLA values in a given municipality and in nearby municipalities. We therefore calculated Moran's I statistic to examine whether the geographical distribution of QLA in both years is random or, conversely, if it responds to certain agglomeration patterns.

Insert Figure 1 here

Although it is difficult in practice to choose the best *W* matrix (Anselin et al. 2007), following Orford (2004), the results of Moran's statistic (Table 5) reveal that the most significant statistics were produced by the inverse distance (highest z-score). Hence, we have used this measure.

The results (Table 5) suggest a significant and positive spatial autocorrelation across all spatial weights, thus indicating that the quality of life in the municipalities of Andalusia is not distributed randomly in space. Municipalities with high levels of quality of life are surrounded by municipalities with high levels of quality of life and vice versa. These results could be explained by the existence of spatial association in Andalusian municipalities for the different dimensions that affect quality of life. As shown in Table 6, the majority of indicators present a strong autocorrelation structure, especially *Income*, *Unemp* and *Dependency*, thus suggesting that the presence of spatial dependence in a municipality is due to its extension to neighbouring municipalities and favours the concentration of well-being in the area.

Several studies have detected the presence of positive global spatial autocorrelation in economic data, such as income in regions of the United States (Rey and Montouri 1999), GDP in European regions (Dall´erba 2005), and the expenditure of each delegation of Tunisia (Amara and Ayadi 2013). In addition to economic variables, demographic indicators, education and health variables, high-speed networks, voter turnout and environmental variables also present spatial dependence in our work (Table 6).

Since we have found a structure of spatial dependence in QLA, we wonder if much of that spatial dependence could be due to the quality of life of the neighbourhood. To answer that question, we build the SQLA which, in addition to the x_j indicators, includes the sx_j indicators that take into account the spatial relationships between municipalities, and performed the ESDA. The results (Figure 1 and Table 5) confirm this hypothesis because the SQLA composite index of quality of life presents the greatest degree of spatial dependence.

To sum up, given that the underlying spatial distribution of quality of life is not random in Andalusia and the quality of life of each municipality is influenced by the quality of life of its neighbours, social and economic development policies should explicitly incorporate spatial information and be targeted to account for municipal disparities (Amara and Ayadi 2013; Anselin et al. 2007; Dall'erba 2005).

Insert Table 5 here

Insert Table 6 here

5.3. Local association, quality-of-life clusters and income clusters

The next step is to analyse spatial dependence from a local perspective in order to identify clusters of municipalities in terms of quality of life (QLA and SQLA) and income. It is important to recall that the LISA test of local association detects municipalities with particularly high or low QLA (SQLA or income) values compared to the expected average value, and indicates the degree to which a municipality is surrounded by other municipalities with high or low QLA (SQLA or income) values.

Regarding QLA, the results (Figure 2) show that of the 770 municipalities in Andalusia, 133 in 2007 and 120 in 2011 may be located in terms of significant clusters or spatial outliers. Focusing on clusters, high-high type clusters were comprised of 60 municipalities in 2007 and 58 in 2011, which represent 34.2% of the population of Andalusia and 4.16% of the region's total area in 2011. As regards low-low type clusters, these included 64 municipalities in 2007 but 47 municipalities in 2011, which represent 0.61% of the population of Andalusia and 3.18% of the region's total area in 2011.

Five high-high QLA clusters in 2007 and five in 2011 correspond to geographic areas from east to west: two very large municipalities on the Coast of Almeria (only in 2007), the Metropolitan Area of Granada, the Metropolitan Area of Jaen (only in 2011), Costa del Sol (Malaga), the Metropolitan Area of Seville, and the Metropolitan Area of Huelva and West Coast. In these groups, a municipality has a greater level of quality of life not only due to its own endowment in the variables examined, but also due to access to the endowments of neighbouring municipalities. That is, increases in the quality of life of a municipality are linked to increases in the quality of life of neighbouring municipalities. High quality of life is associated with urban areas characterised by a dense population and the good behaviour of demographic indicators (*Growth*, *Youth* and *Dependency*), the highest *Income* per capita, high rates of *Education*, better *DSL* supply, and the lowest level of unemployment. Weak spots are due to the poor behaviour of ecological factors (*Forest* and *Motor*).

Six (four in 2011) low-low type clusters correspond to geographic areas from east to west: Los Filabres and Almanzora Valley (Almeria), the Eastern Mountains of Granada (only 2007), the Sierra Arana of Granada, the Alpujarras of Granada, the Valle del Guadiato (Cordoba), and the Sierra de Aracena (Huelva) – the latter only in 2007. All these clusters exhibited a lower QLA than the average QLA of the region in both years. The municipalities of these clusters share common characteristics that could explain their lower level of quality of life compared to the whole region. These municipalities are primarily located in mountainous rural areas of Andalusia and characterised by a sparse population. They show very low levels in dimensions that positively impact well-being, such as *Income*, *Youth*, *Growth*, and *DSL*, while indicators that negatively impact well-being, such as *Dependency* and *Violent*, show values above the regional average.

Insert Figure 2 here

Comparing QLA and SQLA, it can be said that the clusters are larger in SQLA but the overall patterns are quite similar. The only exceptions regarding SQLA are the high-high cluster of the Metropolitan Area of Jaen detected in both 2007 and 2011, while in QLA it appears only in 2011, and the small high-high cluster of several municipalities of the south-eastern province of Seville in both years, which is not present in QLA.

Regarding income, the results show (Figure 2) the existence of nine clusters in 2007 (eight in 2011) where municipalities with a high level of income are surrounded by municipalities showing similar values for this variable. These high-high clusters correspond to the Metropolitan Areas of the eight largest cities of Andalusia (except Almeria in 2011) in addition to the East Coast of Cadiz. In contrast, there are only three low-low clusters in 2007 and four in 2011, all of which are located in the East area of the region: Filabres and Almanzora Valley (Almeria), the Sierra Arana of Granada, the Alpujarras of Granada and Axarquia (Malaga) – the latter only in 2007. When the resulting income clusters (the traditional measure of well-being) and QLA clusters (a multidimensional measure of quality of life) are compared, it could be said that if public policies promoting development are guided only by the level of average income of municipalities, the existence of municipalities grouped in low-low clusters (for instance in the north and east of the region) would not be detected.

5.4. Bivariate LISA for quality-of-life indices and income

Figure 3 shows the clusters and outliers obtained using a space-time local Moran statistic for QLA, SQLA and income. The resulting bivariate LISA cluster map shows significant locations classified by the association between the QLA (SQLA or income) value at one point in time and the value for its neighbours at a different point in time, thus suggesting possible diffusion patterns. Specifically, Figure 3 shows various forms of spatial correlation between QLA (SQLA or income) levels in 2011 and the average for neighbours' values in 2007. In the three indices analysed, the high-high clusters located in the western part of Andalusia and in the Metropolitan Area of Granada seem to persist over the time period studied. In terms of quality of life (both QLA and SQLA), the persistence of the high-high cluster in the Metropolitan Area of Malaga is significant, as well as the low-low cluster of Valle del Guadiato in the north of Andalusia. The bivariate LISA cluster map for income reveals that the low-low cluster located in the eastern part of Andalusia (Almeria province) tends to expand its surface due to the marked fall in income per capita registered in its municipalities in 2011 as a consequence of the economic crisis. It is interesting to note the appearance of high-low type outliers, that is, municipalities with high QLA and income values in 2011 surrounded by municipalities with low QLA and income values in 2007. These are urban municipalities with a large population and area located in the provinces of Granada and Malaga surrounded by rural municipalities (with less than 10,000 inhabitants and predominantly agricultural). Some of these outliers were already observed in 2011 (Figure 2).

Insert Figure 3 here

5.5. Three kinds of space-time models for QLA and SQLA

Table 7 shows the results of the three kinds of space-time models developed for QLA_{11} and $SQLA_{11}$.

Insert Table 7 here

For QLA_{11}, the results show that a spatial autoregressive model is preferable, that is, a model which incorporates the $WQLA_{11}$ term (such as SRSM and TSSM) because Moran's I error and the Lagrange multiplier error are not significant in the PSRM. The PSRM and SRSM models show the statistically significant presence of non-contemporaneous spatial dependence captured by the $WQLA_{07}$ variable, thus indicating that the average quality of life of a municipality in 2011 depends on the average quality of life of its neighbours in 2007. Nevertheless, the SRSM improves the PSRM because the Akaike information criterion (AIC) is lower and the pseudo-R^2 is higher since the SRSM includes both non-contemporaneous and contemporaneous spatial effects (the latter of which are captured by the WQLA$_{11}$ variable). That is, the average quality of life of a municipality in 2011 also depends on the quality of life of its neighbours in the same year. When the three estimated models are compared, the TSSM is found to be the best because it has the lowest AIC and the highest pseudo-R^2. This third model includes contemporaneous spatial dependence effects, as well as autoregressive time effects (captured by the QLA$_{07}$ time-lagged variable). The results of these three models show that, in addition to time effects, both the spatial diffusion effects of quality of life in 2007 (non-contemporaneous spatial dependence) and the contemporaneous spatial effects of quality of life in 2011 influence quality of life in 2011.

For SQLA$_{11}$, we estimated the PSRM and the SREM, which showed the presence of spatial autocorrelation due to the omission of unobserved variables. Like QLA$_{11}$, the SREM obtained better results than the PSRM in terms of both AIC and the pseudo-R^2. When comparing the three models again, the TSEM yielded the best results. The three models of the SQLA$_{11}$ variable reveal the importance of time effects, non-contemporaneous spatial effects and the spatial effects of the unobservable variables.

To conclude this section, it is worth noting that the selected models, TSSM for QLA$_{11}$ and TSEM for SQLA$_{11}$, share similar effects, such as time effects and non-contemporaneous spatial effects, but the nature of the spatial autoregressive structure of both models is different. In the TSSM, the spatial autoregressive structure is interpreted as substantive spatial dependence, which is caused by the existence of spatial interaction. In the TSEM, however, the spatial autoregressive structure is referred to as nuisance dependence, since it is reflected in the error term, and is caused by the presence of spatial autocorrelation in the errors due to the omission of relevant variables (Anselin 1999a).

6. Discussion and conclusions

The aim of this paper is to explore the spatio-temporal structure or distribution of quality of life in the 770 municipalities of Andalusia from 2007 to 2011. For this purpose, we estimated two composite indices of multidimensional quality of life (QLA and SQLA) in 2007 and 2011 using the Distance P2 method and applied a space-time approach using spatial econometric techniques.

The QLA incorporates information from 15 indicators on material living conditions, health, education, leisure and social interactions, economic and physical safety, natural and living environment, and political voice. The statistical information at the municipal level in Spain is quite scarce, especially with regard to the environment and self-reporting data. These restrictions have conditioned our selection of indicators. However, we have tried to incorporate indicators that could be considered representative of the different dimensions of quality of life proposed in the most relevant international projects and strategies (Commission of the European Communities 2009a; Eurofound 2012; Eurostat 2008; Michalos et al. 2011; OECD 2013; Stiglitz et al 2009; UNDP 2013).

SQLA takes into account the values of selected indicators in a municipality and the values of these indicators in neighbouring municipalities.

The results of QLA and SQLA show that demographic indicators (*Youth* and *Dependency*), *Income*, *DSL,* education, and health have the greatest influence in determining quality of life. As pointed out in other studies, income remains an important variable for quality of life, but non-economic variables are also key determinants of well-being (Ferrara and Nisticò 2013; Madonia et al. 2012; Sánchez-Domínguez and Ruiz-Martos 2014). The plural or multidimensional aspects of quality of life or well-being are a focal point of the capabilities approach (see Nussbaum 2000, 2011; Sen 1980) and for the international projects analysed in a previous section. Our proposal highlights the multidimensional character of quality of life because the results of the QLA and SQLA show that all the indicators chosen provide relevant information for determining quality of life.

From the results of the QLA, it could be said that, on average, quality of life worsened in Andalusia from 2007 to 2011 as a consequence of the economic crisis, but that territorial disparities also decreased in 2011 compared to 2007 as some of the municipalities that were in a worse situation in 2007 improved in 2011, and those above average in 2007 worsened in 2011.

We then analysed the spatio-temporal distribution of QLA, SQLA and income in Andalusia in 2007 and 2011. We performed an ESDA study, a bivariate local Moran´s statistic and three kinds of time-space models. First, the ESDA analysis shows that QLA in Andalusia is not spatially distributed in a random way, but exhibits global spatial autocorrelation because the majority of its indicators present a strong autocorrelation structure, especially *Income*, *Unemp* and *Dependency*. Comparing QLA, income and SQLA, the latter presents the greatest degree of spatial dependence. That is, the presence of spatial dependence in a municipality is due to its extension to neighbouring municipalities and favours the concentration of well-being in the area.

Second, we identified local spatial clusters of municipalities in terms of their quality of life (QLA and SQLA) and income, and analysed their principal characteristics. The high-high clusters are mainly formed by the metropolitan areas of Andalusia, that is, urban municipalities with a population of more than 10,000 inhabitants, where the demographic indicators, *Income*, *DSL*, and education perform well. The low-low clusters are located in mountain areas and are formed by rural municipalities characterised by a sparse population and high rates of *Dependency* and *Violent*. The overall patterns of the QLA and SQLA clusters are quite similar. However, in terms of income clusters, more high-high clusters and less low-low clusters are detected than in terms of QLA. Thus, if public policies promoting development are guided only by the average income level of municipalities, the existence of municipalities grouped in low-low clusters that meet certain characteristics (unemployment, high dependency ratio, high violence, etc.) would not be detected, which could further deepen the social and economic situation of the local residents. Therefore, like other papers (Perrons 2012; Sánchez-Domínguez and Ruiz-Martos 2014; Servillo et al. 2011), this paper suggests that an approach incorporating more components of quality of life, rather than one based solely on measuring income, would be more appropriate for the design and implementation of policies on economic and social development.

Third, the bivariate LISA cluster map for the three indices analysed, which combines the spatial and temporal analysis, confirms the persistence of clusters over the time period analysed in the western part of Andalusia and in the Metropolitan Area of Granada. The bivariate LISA cluster map for income reveals that the low-low cluster located in the eastern part of Andalusia tends to expand its surface as a consequence of the economic crisis.

Finally, the results of the three kinds of space-time models estimated for QLA and SQLA in 2011 confirm the spatial and temporal dependency of quality of life in Andalusia from 2007 to 2011. The results show that a municipality's quality of life is positively related to its quality of life in the previous period and the changes in neighbouring municipalities in both the same time period and in the past. That is, the higher the quality of life of a municipality in 2007, the more likely it is to have a high quality of life in 2011 – history matters. Moreover, increases (decreases) in the quality of life of a municipality in 2011 are linked to increases (decreases) in the quality of life of neighbouring municipalities in both 2011 and 2007 – space matters.

The space-time framework in which we have analysed the quality of life in Andalusia contributes to the current convergence and inequality literature, which lacks systematic comparative space-time studies (Rey and Ye 2010) and focuses mainly on the study of income (Dall´erba 2005; Rey and Montouri 1999; Ye and Rey 2013). The results of this work support the hypothesis that social and economic development policies should explicitly incorporate spatial information, since policies or actions implemented in a municipality may affect the quality of life of citizens residing in nearby or neighbouring municipalities (Amara and Ayadi 2013; Anselin et al. 2007; Dall'erba 2005).

Table 1. Indicators of quality of life

	Indicator	Relation[a]	Definition
1	Income	Positive	Real income per capita as declared in income tax statements, in constant euros December 2011.
2	Property	Positive	Assessed urban and rural rate value per capita as declared on property tax statements, in constant euros December 2011.
3	DSL	Positive	Broadband DSL (Number of Asymmetric Digital Subscriber Line per 100 inhabitants).
4	Growth	Positive	Natural growth (births-deaths per 1,000 inhabitants).
5	Youth	Positive	Youth rate (% population under 20 years/population aged 60 and over).
6	Dependency	Negative	Old-age-dependency ratio (% population aged 65 and over/population from 15 to 64).
7	Unemp	Negative	Unemployment registered at 31 March/population aged 15 to 64 (%).
8	Education	Positive	Percentage of secondary and high school students among the population aged 15 to 24 years.
9	Adult	Positive	Adult education (% of students in the population).
10	Library	Positive	Number of library visits per capita.
11	Voter	Positive	Voter turnout. Ratio between the number of voters who cast their votes and the total eligible voters in the municipal government elections of 2007 and 2011.
12	Death	Negative	Quality of care. Deaths by tumours and disorders of the circulatory and respiratory systems per 1,000 inhabitants (cases 2, 9 and 10, respectively, tenth revision of the World Health Organization ICD).
13	Forest	Positive	Surface timber forest (% of surface timber forest).
14	Motor	Negative	Motorisation rate (number of cars–excluding electric and hybrid cars– per 100 inhabitants).
15	Violent	Negative	Deaths from external causes per 1,000 inhabitants (case 20, tenth revision of World Health Organization ICD).

Note. Adapted from SIMA, Institute of Statistics and Cartography of Andalusia, and the authors.
[a] Relation between the indicator and the quality of life; how the increase/decrease in the indicator affects the quality of life index.

Table 2. Rationale and discrimination coefficients of indicators[a]

	Indicator	Rationale (projects that use the indicator)	DC2007[b]	DC2011[c]
1	Income	Money is an important means to achieving higher living standards and thus greater well-being. Higher economic wealth may also improve access to quality education, healthcare and housing. (OECD)	0.43	0.40

2	Property	Property is a measure of wealth in real assets (e.g. land and dwellings). Such wealth makes up an important part of a person's economic resources, and can protect from economic hardship and vulnerability. (OECD)	0.71	0.60
3	DSL	DSL, as a proxy of availability of high-speed networks, is a key factor for competitiveness and economic security, as it determines the capacity of territories to compete in and benefit from the global knowledge-based economy, technology and market. It facilitates social connections people.	0.83	0.51
4	Growth	Population growth is an indicator of social development.	0.41	0.27
5	Youth	Being young contributes positively to the labour market.	0.56	0.58
6	Dependency	Old-age-dependency represents a risk to the sustainability of the current welfare state. (EU SDS, OECD)	0.44	0.42
7	Unemp	Access to the labour market is a condition for well-being for all people. (EU SDS, OECD)	0.51	0.41
8	Education	It represents educational opportunities. Education is a condition for the full and balanced development of children. (QoL)	0.77	0.92
9	Adult	It is an indicator of education and leisure activities that people enjoy.	1.10	1.05
10	Library	It is an indicator of leisure and culture. (CIW, QoL)	1.20	1.20
11	Voter	Voting is an indicator of good governance. High voter turnout is a measure of public trust in government and of citizens' participation in the political process. (EU SDS, OECD, CIW)	0.15	0.13
12	Death	Death refers to quality in health care and is used by the Spanish National Institute of Statistic as proxy of evitable mortality with proper medical care.	0.51	0.51
13	Forest	Preservation of forest area is a condition for sustainability. It is an indicator of environment (EU SDS)	1.40	1.42
14	Motor	Measure of consumption patterns and sustainable consumption (EU SDS).	0.19	0.18
15	Violent	Personal security is a core element for the well-being of individuals, and largely reflects the risks of people being physically assaulted or falling victim to other types of crime. Crime may lead to loss of life and property, as well as physical pain, post-traumatic stress and anxiety. (EU SDS, OECD)	1.17	1.18

Note. CIW = Canadian Index of Wellbeing; EU SDS = European Union Sustainable Development Strategy; OECD = Project Better Life; QoL = Quality of Life Indicators of the European Statistical System Committee.
[a]n = 770. [b]discrimination coefficient of Ivanovic 2007. [c]discrimination coefficient of Ivanovic 2011.

Table 3. Descriptive statistics of the indicators and Quality of Life Index in Andalusia for 2007 and 2011

	2007[a]			2011[a]		
Indicator	M	SD	Range	M	SD	Range
Income	4,530.08	1,865.62	483.92 - 13,711.17	4,082.45	1,586.50	424.17 - 11,778.59
Property	23,688.50	23,024.71	4,744.75 - 448,682.20	36,411.32	25,642.32	5,205.88 - 335,349.59

DSL	6.76	5.27	0.00 - 40.18	10.92	5.05	0.00 - 37.81
Growth	40.07	163.86	-178.00 - 2,078.00	30.97	129.63	-247.00 - 1,660.00
Youth	93.16	49.29	5.41 - 436.70	88.35	48.58	4.48 - 443.89
Dependency	31.11	12,49	6.93 – 96.88	30.85	11.77	7.20 - 110.53
Unemp	6.62	3.22	0.00 - 21.36	12.91	4.76	0.90 - 30.90
Education	33.73	27.87	0.00 - 165.43	34.01	31.65	0.00 - 220.07
Adult	2.09	3.08	0.00 - 44.52	2.35	3.10	0.00 - 34.94
Library	1.19	1.58	0.00 - 14.28	1.25	1.61	0.00 -14.66
Voter	74.87	9.71	43.64 - 95.33	79.05	8.97	50.37 -100.00
Death	7.36	3.63	0.00 - 31.25	6.73	3.25	0.00 - 25.42
Forest	10.31	15.06	0.00 - 80.66	9.36	14.20	0.00 - 72.70
Motor	59.02	21.17	21.43 - 439.72	61.11	17.67	30.95 - 367.63
Violent	0.40	0.66	0.00 - 7.84	0.42	0.66	0.00 - 8.62
QLA	51.10	3.76	27.24 - 68.17	47.89	3.43	30.13 - 60.63

Note. QLA = Quality of Life Index in Andalusia.
[a]n = 770

Table 4. Correction factors and absolute pairwise correlation between the indicators and quality of life indices in Andalusia for 2007 and 2011 (n = 770)

Position 2007	Indicator	Corrector factor (1-R^2)	Pairwise correlation |r|	Position 2011	Indicator	Corrector factor (1-R^2)	Pairwise correlation |r|
1(2)	Dependency	1(0.18)	0.65(0.68)	1(3)	Income	1(0.36)	0.62(0.65)
2(3)	DSL	0.60(0.34)	0.62(0.67)	2(1)	Youth	0.57(1)	0.54(0.72)
3(1)	Youth	0.27(1)	0.60(0.70)	3(6)	DSL	0.68(0.50)	0.51(0.55)
4(4)	Income	0.33(0.19)	0.59(0.66)	4(2)	Dependency	0.32(0.19)	0.49(0.70)
5(5)	Death	0.69(0.48)	0.54(0.61)	5(5)	Education	0.78(0.59)	0.43(0.56)
6(6)	Education	0.79(0.67)	0.45(0.55)	6(7)	Death	0.71(0.47)	0.42(0.54)
7(9)	Violent	0.95(0.87)	0.38(0.44)	7(10)	Violent	0.96(0.84)	0.41(0.51)
8(8)	Property	0.74(0.56)	0.37(0.45)	8(4)	Voter	0.59(0.46)	0.40(0.57)
9(7)	Growth	0.80(0.60)	0.36(0.51)	9(9)	Motor	0.94(0.82)	0.39(0.52)
10(11)	Library	0.98(0.95)	0.32(0.35)	10(8)	Growth	0.67(0.46)	0.38(0.53)
11(10)	Motor	0.98(0.90)	0.29(0.36)	11(12)	Property	0.83(0.73)	0.35(0.35)
12(12)	Voter	0.67(0.57)	0.21(0.31)	12(11)	Library	0.96(0.88)	0.34(0.41)
13(14)	Adult	0.97(0.88)	0.18(0.04)	13(14)	Adult	0.98(0.91)	0.25(0.10)
14(15)	Forest	0.94(0.82)	0.13(0.01)	14(13)	Unemp	0.74(0.64)	0.14(0.29)
15(13)	Unemp	0.89(0.82)	0.01(0.10)	15(15)	Forest	0.93(0.77)	0.13(0.02)

Note. This table shows the values for Quality of Life Index in Andalusia (QLA); and Spatial Quality of Life Index in Andalusia (SQLA) values given in parentheses.

Table 5. Spatial autocorrelation (Moran's I) of quality of life indices and Income in Andalusia for different conceptualisations of spatial relationships for 2007 and 2011 (n = 770)

	2007			2011		
	Income	QLA	SQLA	Income	QLA	SQLA
Inverse distance	0.553 (31.147)	0.312 (17.658)	0.612 (34.465)	0.565 (31.831)	0.253 (14.329)	0.587 (33.021)

Inverse distance squared	0.610 (28.404)	0.357 (16.667)	0.692 (32.229)	0.622 (28.991)	0.279 (13.059)	0.657 (30.575)
First-order contiguity	0.561 (26.409)	0.334 (15.060)	0.677 (30.386)	0.572 (25.691)	0.263 (11.865)	0.643 (28.807)

Note. QLA = Quality of Life Index in Andalusia; SQLA = Spatial Quality of Life Index in Andalusia.
z-score are given in parentheses. p-values < 0.001 for all the variables.

Table 6. Spatial autocorrelation (Moran's I) of indicators in Andalusia for 2007 and 2011 (n = 770)

Indicator	2007	2011
Dependency	0.531 (29.890)***	0.493 (27.765)***
DSL	0.467 (26.328)***	0.311 (17.525)***
Youth	0.536 (30.225)***	0.536 (30.281)***
Income	0.553 (31.147)***	0.565 (31.831)***
Death	0.236 (13.401)***	0.185 (10.476)***
Education	0.102 (5.840)***	0.095 (5.450)***
Violent	0.064 (3.816)***	0.046 (2.738)**
Property	0.116 (7.413)***	0.229 (13.253)***
Growth	0.183 (10.856)***	0.213 (12.490)***
Library	0.027 (1.648)**	0.049 (2.849)**
Motor	0.095 (6.572)***	0.086 (5.539)***
Voter	0.363 (20.434)***	0.407 (22.885)***
Adult	0.025 (1.581)	0.003 (0.285)
Forest	0.433 (24.399)***	0.472 (26.643)***
Unemp	0.557 (31.364)***	0.535 (30.085)***

Note. z-score in parentheses. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.1.

Table 7. Space-time models for quality of life in Andalusia (n = 770)

Dependent variable: Quality of Life index in Andalusia in 2011 (QLA_{11})				Dependent variable: Spatial Quality of Life index in Andalusia in 2011 ($SQLA_{11}$)		
Variable	PSRM	SRSM	TSSM	PSRM	SREM	TSEM
constant	12.860 (0.000)	10.066 (0.000)	5.155 (0.000)	5.729 (0.002)	3.297 (0.433)	16.117 (0.000)

WQLA_{07}	0.736 (0.000)	0.514 (0.000)	--	--	--	--
WSQLA_{07}	--	--	--	0.896 (0.000)	0.929 (0.000)	--
WQLA_{11}	--	0.280 (0.000)	0.283 (0.000)	--	--	--
We	--	--	--	--	0.776 (0.000)	0.883 (0.000)
QLA_{07}	--	--	0.613 (0.000)	--	--	--
$SQLA_{07}$	--	--	--	--	--	0.759 (0.000)
Adjusted pseudo-R^2	0.240	0.277	0.572	0.625	0.768	0.871
AIC	3591.414	3568.132	3168.713	3890.408	3525.70	3071.5
LM.error	0.060 (0.806)	--	--	378.821 (0.000)	--	--
LM.lag	22.652 (0.000)	--	--	299.632 (0.000)	--	--
RLM.error	136.579 (0.000)	--	--	82.741 (0.000)	--	--
RLM.lag	159.1725 (0.000)	--	--	3.552 (0.059)	--	--
Moran's I error	0.236 (0.406)	--	--	0.456 (0.000)	--	--

Note. Ordinary least squares estimates for PSRM. Maximum likelihood estimates for SRSM and TSSM. PSRM = Pure space recursive model. SRSM = Space recursive and simultaneous model. TSSM = Time-space simultaneous model. SREM = Space recursive error model. TSEM = Time-space error model. AIC = Akaike information criterion. LM = Lagrange multiplier and RLM = robust Lagrange multiplier. *p*-values in parentheses.

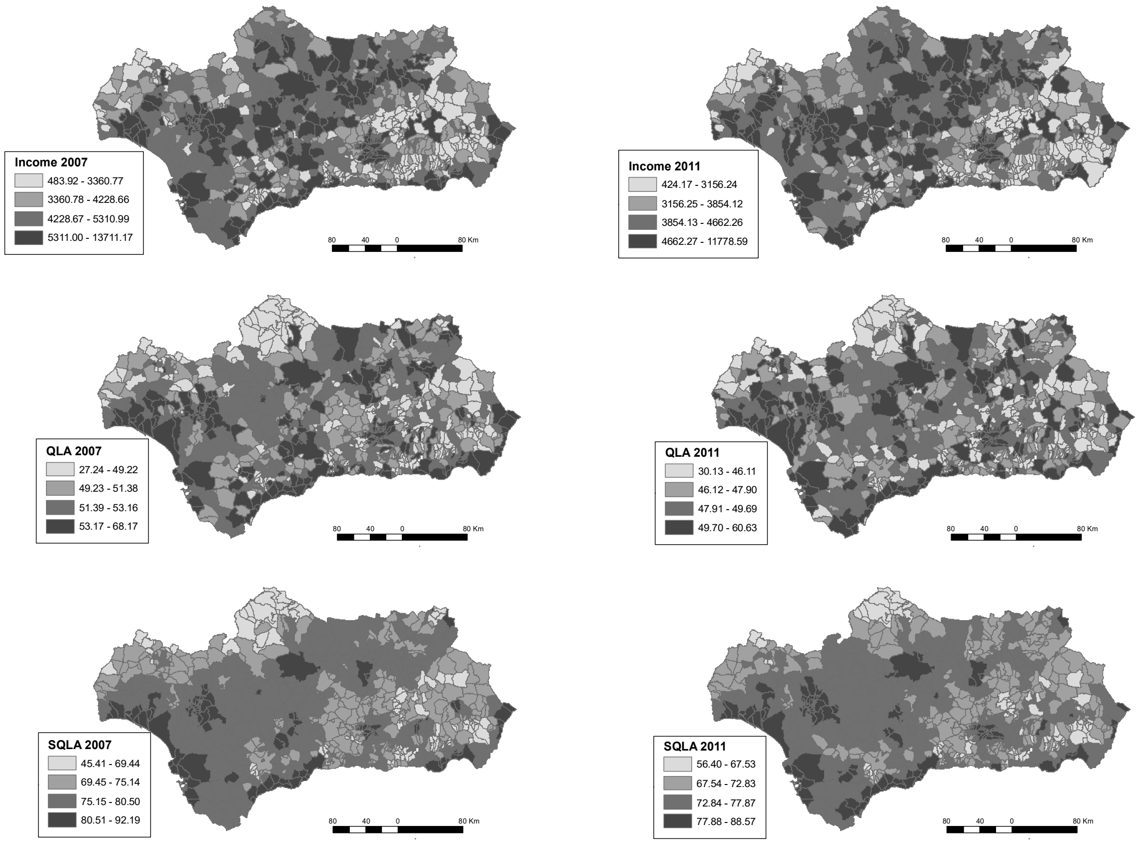

Figure1. Spatial distribution of Income and quality of life indices in Andalusia for 2007 and 2011. QLA = Quality of Life Index in Andalusia. SQLA = Spatial Quality of Life Index in Andalusia. The municipalities are classified into four groups using quartiles.

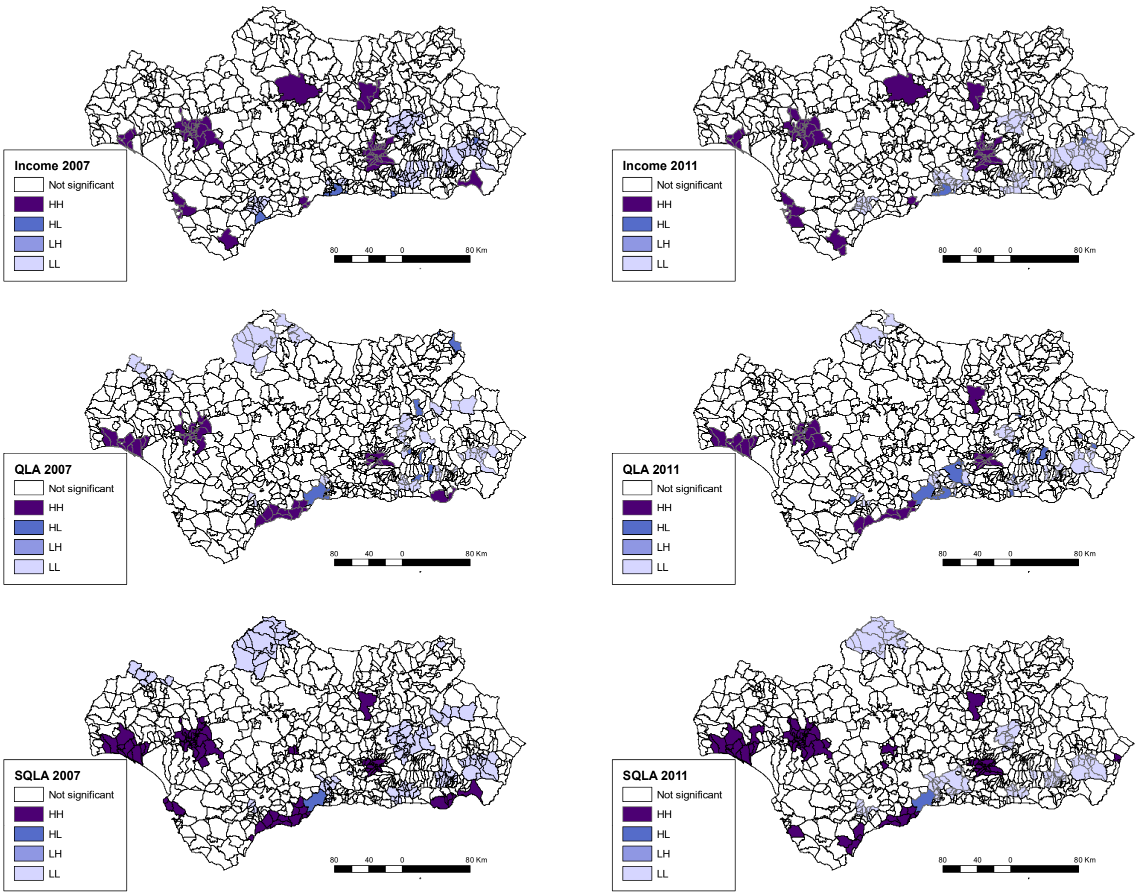

Figure 2. LISA clusters for Income and quality of life indices in Andalusian municipalities for 2007 and 2011. QLA = Quality of Life Index in Andalusia. SQLA = Spatial Quality of Life Index in Andalusia. HH: high-high type clusters, HL: high-low type clusters, LH: low-high type clusers, LL: low-low type clusters. p-value < = 0.01.

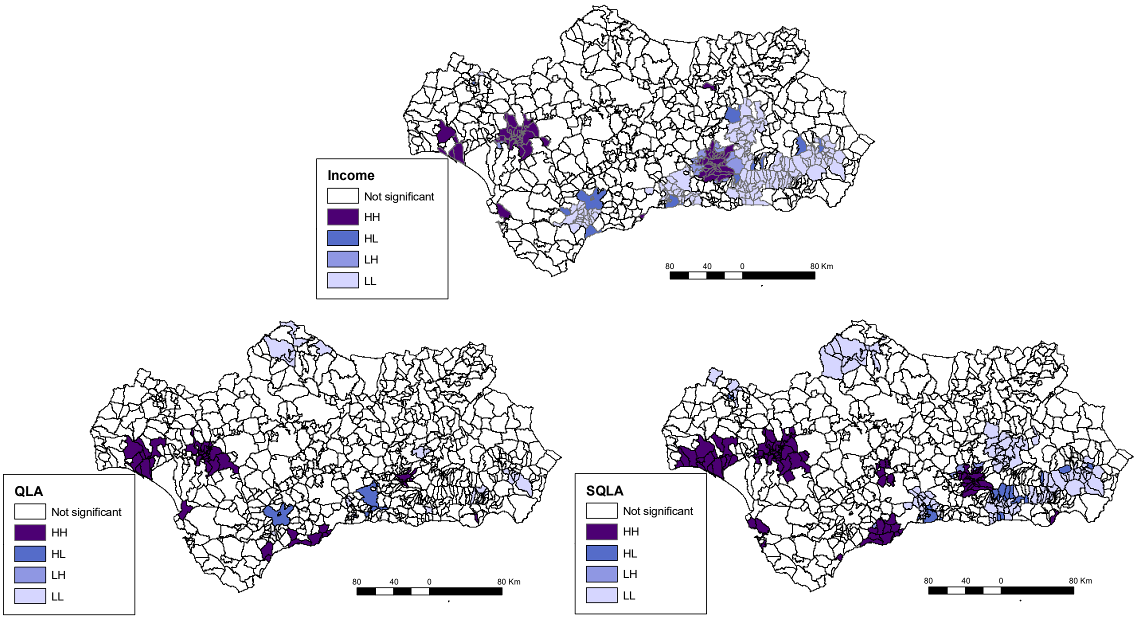

Figure 3. Space-time cluster maps (BLISA) for Income and quality of life indices in Andalusian municipalities for 2007-2011.
QLA = Quality of Life Index in Andalusia. SQLA = Spatial Quality of Life Index in Andalusia. HH: high-high type clusters, the municipalities which formed a cluster with high QLA (SQLA or Income) values in 2011 were also surrounded by municipalities with a high value of QLA (SQLA or Income) in 2007. LL: low-low type clusters, municipalities which formed a low QLA (SQLA or Income) cluster in 2011 were also surrounded by municipalities with low QLA (SQLA or Income) values in 2007. HL: high type cluster in 2011 were surrounded by municipalities with low values in 2007. LH: low type clusters in 2011 were surrounded by municipalities with high values in 2007. p-value < = 0.01.

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