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Multiscale evaluation of an urban deprivation index: Implications for quality of life and healthcare accessibility planning

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A B S T R A C T

Deprivation indices are widely used to identify areas characterized by above average social and/or material disadvantages. Especially spatial approaches have become increasingly popular since they enable decision makers to identify priority areas and to allocate their resources accordingly. An array of methods and spatial reporting units have been used to analyze and report deprivation in previous studies. However, a comparative analysis and assessment of the implications of the choice of the reporting unit for quality of life and health care accessibility planning is still missing. Based on a set of ten socioeconomic and health-related indicators, we constructed a weighted deprivation index for the urban area of Quito, Ecuador, using four different reporting units, including census blocks, census tracts, and two units based on the automatic zoning procedure (AZP). Spatial statistics and metrics are used to compare the resulting units, and a participatory expert-based approach is applied to evaluate their suitability for decision making processes. Besides structural differences regarding their size and shape, no strongly marked statistical or qualitative differences were found in the four analyzed spatial representations of deprivation. The four representations revealed similar spatial patterns of deprivation, with higher levels of deprivation in the peripheries of the city, especially in the southern and north-western parts. The study also suggests that census blocks, due to their fine spatial resolution, were considered most useful for quality of life and health care accessibility planning by local stakeholders.

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1. Introduction

Deprivation indices are practical measures that can be used to identify areas characterized by socioeconomic marginalization and limited access to services, including inadequate access to clean water, household overcrowding, unemployment, lack of formal education, etc. (Cabrera Barona, Murphy, Kienberger, & Blaschke, 2015; Havard et al., 2008; Townsend, 1987). Evidence has also shown that people living in areas with a higher quality of life have a lower risk of developing health problems (Pampalon & Raymond, 2000; Stjärne, Ponce de Leon, & Hallqvist, 2004). Therefore, area-based deprivation indices, generally constructed from census data, have proven to be closely related to the health status of the population (Boyle, Gatrell, & Duke-Williams, 2001; Carstairs, 1995; Lalloué et al., 2013). The spatial analyses of socioeconomic disadvantages under a multidimensional perspective can hence further support policies and decision making aimed at reducing poverty, enhancing quality of life as well as the health status of the population (Alkire & Santos, 2013; Mideros, 2012; Schuurman, Bell, Dunn, & Oliver, 2007).

A wide range of studies have proposed and utilized different methods and techniques to construct deprivation indices, including principal component and multi-criteria analysis as well as participatory approaches (Bell, Schuurman, & Hayes, 2007; Bell, Schuurman, Oliver, & Hayes, 2007; Cabrera Barona et al., 2015; Folwell, 1995; Lalloué et al., 2013; Pampalon, Hamel, Gamache, & Raymond, 2009; Pasetto, Sampaolo, & Pirastu, 2010). However, less attention has been paid to addressing the influence of the choice of the reporting units or spatial representations of deprivation (Schuurman et al., 2007). However, the choice of the scale and the reporting unit can have both conceptual and practical implications that users should be aware of when taking decisions based on such indices (Hagenlocher, Kienberger, Lang, & Blaschke, 2014).

Oftentimes, neighborhoods have been used to evaluate the local

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place effects on health, and most of the previous deprivation studies have used administrative or census areas as the unit of analysis (Haynes, Daras, Reading, & Jones, 2007). However, since *a-priori* defined units do not capture the real spatial distribution/variability of deprivation, one could also aim to present the information in zones which are as internally homogeneous as possible in terms of deprivation.

One of the challenges when working with such aggregated data is the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984). The MAUP influences not only the results, but also how these results are interpreted (Marceau, 1999). It has two components: (1) the scale effect, and (2) the zoning effect. The scale effect occurs when the same data is grouped at different spatial resolutions (Openshaw & Taylor, 1979; Arbia & Petrarca, 2013), such as census blocks, districts or regions, etc. (Schuurman et al., 2007). The latter is a result of the fact that a set of spatial units, at the same scale, can be grouped in different ways (Openshaw, 1984; Schuurman et al., 2007) and this effect is not the result of the variation in the size of the units (Schuurman et al., 2007). The scale effect is also related to the population size, whereas the zoning effect is related to the construction of new zones' boundaries at a given scale (Haynes et al., 2007).

These two effects generate different results after a statistical analysis, and hence can have an important influence on decision-making (Schuurman et al., 2007). For this reason, the evaluation of whether the chosen reporting units or spatial representations of deprivation have any meaning for information users (e.g. decision makers, practitioners, etc.) becomes an important issue to consider (Haynes et al., 2007).

Despite the strong evidence of MAUP effects in different spatial representations of deprivation, there has not been much focus on the evaluation of their implications in deprivation literatures. We argue that understanding the MAUP effects in different regionalizations of deprivation is relevant for several practical issues, including the identification of ecological fallacies, the choice of the optimal scale of analysis, and the correct interpretation of the phenomenon of deprivation.

Against the background of the above described challenges, this study aims to analyze the effects of four different spatial representations of deprivation, including census blocks, census tracts and two Automated Zoning Procedure (AZP)-based zones. The overall goal of this work is hence to analyze whether important multiscale differences exist between different spatial representations of deprivation. To achieve this the following research questions are addressed: (1) do important statistical and structural differences exist between different spatial representations (reporting units) of deprivation?, and (2) do the different spatial representations of deprivation generate important differences regarding their interpretation by local experts?

To answer these questions, a mixed-methods approach is applied, consisting of a quantitative and a qualitative (participatory, expert-based approach) analysis of the four different representations of deprivation.

2. Methods

The study was carried out in Quito, the capital city of Ecuador (Fig. 1). Quito is located approximately 2800 m above sea level in the northern Ecuadorean Andes. The administrative urban area of the city comprises 34 urban Parishes and is home to more than 1.5 million inhabitants (INEC, 2010). Socioeconomic marginalization is still prevalent in some areas of Quito (Cabrera Barona et al., 2015). Even though significant improvements have been made in Ecuador in the field of healthcare compared to the past decades (Rasch & Bywater, 2014), socioeconomic disparities continue to exacerbate health inequalities, especially in marginalized communities (Parkes et al., 2009).

Fig. 2 shows the overall workflow of our study from the conceptualization of deprivation to its spatially explicit assessment based on a set of normalized, weighted indicators while using different reporting units. As indicated above, we selected two groups of units to represent deprivation in Quito: administrative units (census blocks and census tracts) and units based on zone design. The latter includes zones generated by applying the Automated Zoning Procedure (AZP) (Openshaw, 1977; Cockings & Martin, 2005), an approach that can be used to maximize the internal homogeneity of information within zones and the heterogeneity between them. The objective of using AZP-based zones is to have areas designed taking into consideration specific real phenomena, creating zones with different structural characteristics as compared to pre-defined artificial administrative areas. The AZP was considered useful for this study since the spatial datasets available are aggregated at census block and census tract level. Alternative regionalization methods that we could have used, such as the geon approach (Lang, Kienberger, Tiede, Hagenlocher, & Pernkopf, 2014) are based on the integration and analysis of gridded datasets.

2.1. Index construction at census block and census tract level

A deprivation index was constructed using a set of ten socioeconomic and health-related indicators (Table 1). They were chosen following a rights-based perspective that considers basic living conditions for human wellbeing (Cabrera Barona et al., 2015; Mideros, 2012; Ramírez, 2012) and their affinity to material and social deprivation as documented in previous deprivation studies (Cabrera Barona et al., 2015; Lalloué et al., 2013; Pampalon & Raymond, 2000; Pasetto et al., 2010; Stjärne et al., 2004). Four indicators represent population characteristics in the study area: i.e. (1) *percentage of the population that is disabled for more than a year*, (2) *percentage of the population that does not have any level of formal education or instruction*, (3) *percentage of the population that has no public social insurance (incl. health insurance)*, and (4) *percentage of the population that works without payment (unpaid jobs)*. Five additional indicators representing household conditions were also included in the analysis: (5) *percentage of households with four or more persons per dormitory (overcrowding)*, (6) *percentage of households without access to drinking water from the public system*, (7) *percentage of households without access to the sewerage system*, (8) *percentage of households without access to the public electricity grid*, and (9) *percentage of households without garbage collection service*. Finally, (10) the *distance to the nearest primary healthcare service (in meters)* was used as an indicator for access to healthcare. Data for these indicators were extracted from the 2010 Ecuadorian Population and Housing Census (INEC, 2010) at the census block level. Since the raw data were expressed in absolute numbers, the datasets were transformed into percentages. After normalizing the indicators using min–max normalization, multicollinearities in the data were evaluated based on variance inflation factors (VIF) (OECD, 2008). All VIF values obtained were smaller than five, indicating that all indicators could be used for the construction of the deprivation index. Indicator weights were calculated by means of principal component analysis (PCA) following guidelines published by the OECD (2008). The significance of the Bartlett's test of sphericity was lower than 0.05, which enabled us to run the PCA. The final weights were re-scaled to sum up to one (Table 1).

In addition to collecting data at census block level, we also extracted data for the above mentioned indicators at the census tract level. A census tract area is formed by the union of census blocks. For both levels, i.e. census blocks and census tracts, the

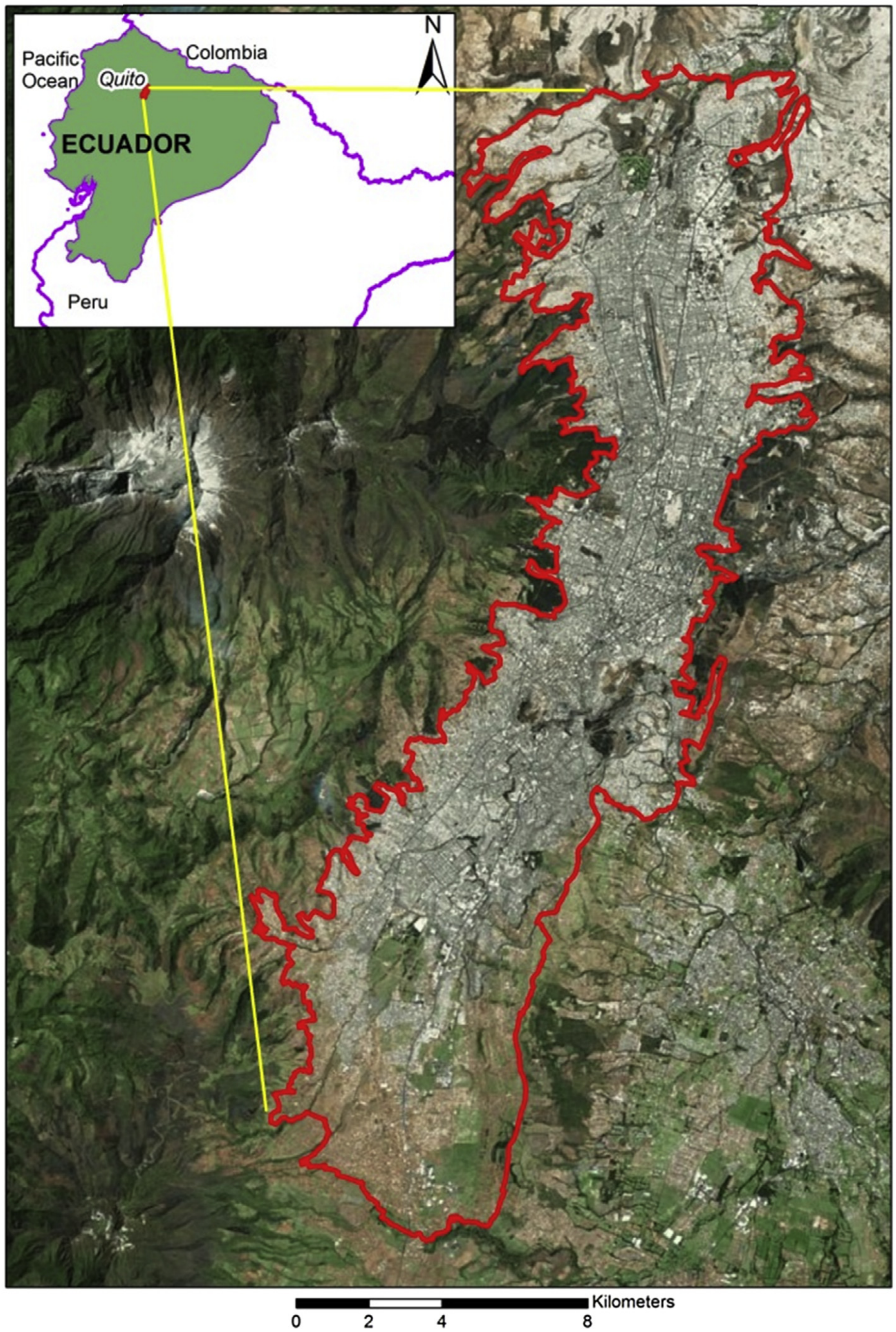

Fig. 1. Study area.

deprivation index (*DI*) was calculated by means of weighted additive aggregation:

$$DI = \sum w_i I_j$$

The resulting *DI* scores were normalized again using linear min–max normalization to obtain comparable index scores for the two different spatial representations.

2.2. Automatic zoning procedure (AZP)

Since the AZP offers an algorithm to deal with the MAUP (Flowerdew, Manley, & Sabel, 2008; Martin, 2003; Openshaw, 1977, 1984), it was used to create two further spatial representations (or zoning systems) of deprivation for the study area. This was achieved by integrating two different inputs: (1) normalized deprivation scores at the census level, and (2) landscape structural and texture variables.

As shown in Fig. 2, for the first AZP-based representation, zones were designed based on the normalized scores of the deprivation index and its underlying indicators. The homogeneity attributes of each census block were defined using the deprivation index (*DI*) as the threshold variable and the ten indicators as the homogeneity features. The study area consists of 4036 census blocks. This set of polygons was considered as the basic zoning system for the

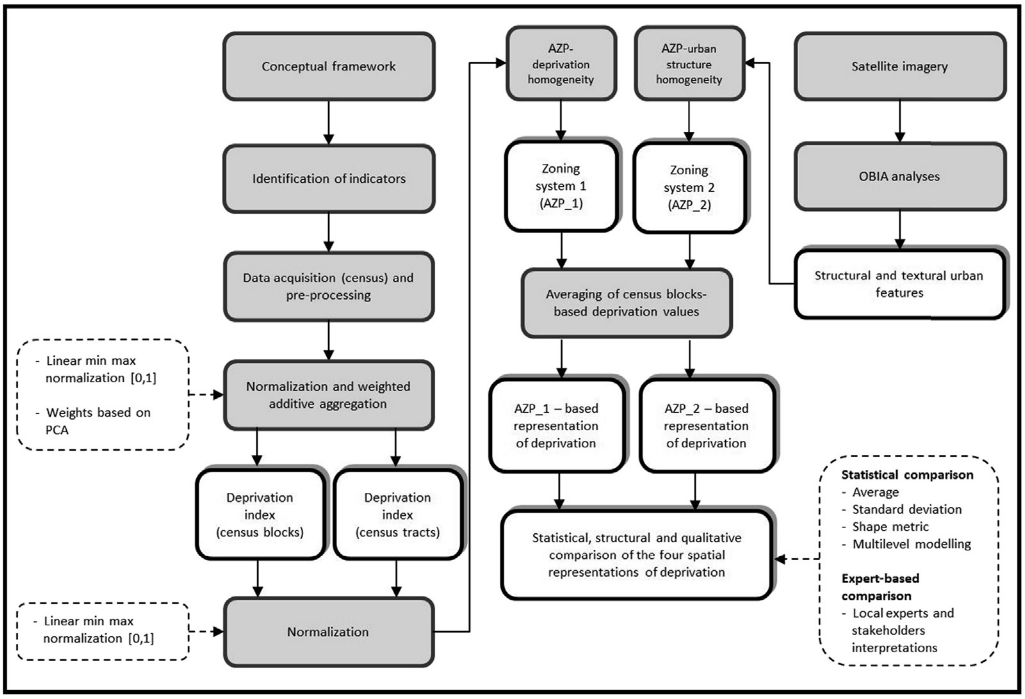

Fig. 2. Overall workflow. Gray boxes represent general processes, white boxes with dashed borders specific methods and white boxes represent results.

Table 1
Deprivation indicators and weights based on PCA.

Indicators (normalized) $\boldsymbol{I_j}$	Weights $\boldsymbol{w_i}$
% of the population that is disabled for more than a year	0.155
% of the population that does not have any level of formal education or instruction	0.097
% of the population that has no public social insurance	0.133
% of the population that works without payment	0.020
% of households with 4 or more persons per dormitory	0.106
% of households with no access to the public drinking water	0.089
% of households without access to the sewerage system	0.127
% of households without access to the public electricity grid	0.101
% of households with no garbage collection service	0.115
Distance (meters) to the nearest healthcare service	0.057

subsequent AZP-based analysis. In AZP analyses the choice of values for the threshold is subjective (Cockings & Martin, 2005). Therefore, several tests were conducted to achieve new zones reasonably consistent with areas that are likely to ensure internal homogeneity in terms of deprivation values. Following this approach, we obtained 46 polygons for this zoning system, and called it AZP_1. Deprivation values of census blocks were aggregated into the zones of AZP_1 to obtain the AZP_1 deprivation representation.

Assuming that people who live in similar physical housing conditions have similar social and demographic characteristics (Duque, Patino, Ruiz, & Pardo-Pascual, 2015; Jain, 2008; Taubenböck et al., 2009), remote sensing data was used to derive structural and textural features as an input for the second AZP-based representation (see Fig. 2). These were used as threshold variables and homogeneity features when creating new zones using once again census blocks as the basic zoning system. Object-based image analysis (OBIA; Blaschke, 2010) was used to establish a database of structural and textural features based on high-resolution optical satellite imagery (Rapid Eye, 5 m spatial resolution) acquired in 2010. Further, the normalized difference vegetation index (NDVI) was used to mask non-urban land cover, such as water bodies and green areas. Structural and textural variables were extracted using the FETEX 2.0 tool (Ruiz, Recio, Fernández-Sarría, & Hermosilla, 2011). The object-based multi-resolution segmentation algorithm (Baatz & Schäpe, 2000) divides an image into regions with similar properties and hence supports the detection of different building structures and shapes linked to the presence of urban areas (Blaschke, 2010). The first derivative near the origin (FDO) (Ruiz et al., 2011) was used as the threshold variable of the AZP_2. Ten different structural variables and six textural features (Balaguer, Ruiz, Hermosilla, & Recio, 2010; Duque et al., 2015; Haralick, Shanmugam, & Dinstein, 1973; Ruiz et al., 2011) were considered as the homogeneity features for this AZP. Following this approach, we obtained 41 polygons for this new zoning system, called AZP_2. AZP_2 is divided into zones that quantitatively differentiate the heterogeneity of urban structures in the study area, or in other words, areas that are internally homogenous in terms of their urban structure. Ultimately, deprivation scores of census blocks were aggregated into the resulting zones of the AZP_2 to obtain the final AZP_2 representation of deprivation.

2.3. Comparison of deprivation representations

The four different spatial representations of deprivation used in this study (i.e., census blocks, census tracts, AZP_1, and AZP_2) were compared by applying both quantitative and qualitative approaches.

To compare the four representations quantitatively, three different measures were used: (1) descriptive statistics (average, standard deviation), (2) a measure of shape, and (3) statistical measures of multilevel modeling. These measures were chosen taking into consideration previous experiences in MAUP and AZP analyses (Haynes et al., 2007; Schuurman et al., 2007). Descriptive statistics have been widely applied in multiscale evaluations of deprivation indices to address MAUP (Schuurman et al., 2007). These kinds of statistics can be applied to understand how geographic scales affect both mean values and the range of values of an index (Prouse, Ramos, Grant, & Radice, 2014).

Since two of the four spatial representations used in this study are based on the AZP, it becomes important to analyze whether structural differences exist between these AZP-based representations and the pre-defined administrative areas which often have very different boundaries. The shape is a metric that can be used to evaluate the zoning design and zone structure (Haynes et al., 2007). To calculate the shape metric, we used the average measure of the perimeter squared over the area of each zone (Cockings & Martin, 2005; Flowerdew et al. 2008; Haynes et al., 2007) for each of the four representations of deprivation. Lower values of this metric denote more compact shapes (Haynes et al., 2007).

Correlation and regression analyses are also often used to evaluate MAUP effects (Openshaw, 1984; Pietrzak, 2014). Our study, however, makes use of a more sophisticated regression analysis called multilevel modeling. Multilevel modeling allows to analyze hierarchical structures (Nezlek, 2008) by identifying variances at the level of areas and at the level of individual data contained in these areas (Haynes et al., 2007; Nezlek, 2007). To calculate the measures of multilevel modeling, two variables at level 1 (individual level) and one variable at level 2 (area level) were used. These variables were applied in four multilevel models, with one model for each representation of deprivation: census blocks, census tracts, AZP_1 and AZP_2.

In this context, the self-perceived quality of life (SPQoL) and the self-perceived health condition (SPHC) were used as level 1 variables. The two variables were extracted from a household survey that was carried out between July and October 2014 in the city of Quito. A two-stage sampling strategy was applied. In the first stage, the study area was divided in 269 hexagons of which 18 were randomly selected. The number of hexagons was determined considering the interviewers' capacity in terms of time and financial resources. In the second stage, pseudo-random interviews were carried out applying a door-to-door interview petition and interviewing people that were able or wanted to answer our questions. Following this approach, 489 valid responses regarding the SPQoL and the SPHC were obtained. The survey used a 1–5 Likert scale to assess the SPQoL and the SPHC, whereby in the case of the SPQoL a value of 5 indicates that the interviewed person was very satisfied with his/her quality of life, and in the case of the SPHC a value of 5 indicates having excellent health. The level 2 variable (i.e., the area-level measure in the multilevel model) was the deprivation index (*DI*) score. Since four spatial representations of deprivation were considered in the analysis, four multilevel models were calculated. Having individual level measures nested in area-based measures originates in hierarchical structures (Nezlek, 2008), and, in this study, having individual information of the SPHC and the SPQoL nested in area-based spatial representations of deprivation, is a multilevel-based problem (Duncan, Jones, & Moon, 1993). The general model of level 1 is (Nezlek, 2007):

$$Y_{ij} = \beta_{0j} + r_{ij}$$

Where Y_{ij} represents the value of one dependent variable (here: the SPQoL) of the *i* th individual in an area, β_{0j} is the individual-level intercept and r_{ij} represents the error at the individual level. We can add to the Y_{ij} equation one or more independent variables. Therefore the individual-level equation can be expressed as (Park & Kim, 2014; Russell, 1996):

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$$

Where X_{ij} represents the value of one independent variable of the *i* th individual in an area *j*, and β_{1j} is the individual-level slope of the lineal equation. Here, the independent variable X_{ij} at the individual level is the SPHC.

To construct the level 2 equation, the slope of the level 1 model is used as a dependent variable in the level 2 model (Nezlek, 2007; Park & Kim, 2014):

$$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + \mu_{0j}$$

Where γ_{01} is the slope of the area-level variable Z_j (here: the deprivation index) and μ_{0j} is an error term (random term) at the area-level. Since four different spatial representations of deprivation are used in this study, four Z_j independent variables were included in the analysis. For each one of these four independent variables, a multilevel model was performed.

The β_{1j} coefficient can be expressed as:

$$\beta_{1j} = \gamma_{10} + \mu_{1j}$$

where γ_{10} represents the overall individual-level slope controlled by the area-level variable and μ_{1j} is another area-level random term. The following measures were used to compare the different deprivation reporting units trough the multilevel modeling equations: the Akaike information Criterion (AIC), the between-area (level 2) variance partition coefficient (VPC), and the within-area between-individual (level 1) intra-class correlation coefficient (ICC) (Merlo, 2003; Park & Lake, 2005; Steele, 2008).

To qualitatively compare the four different spatial representations of deprivation regarding their usefulness for quality of life and health care accessibility planning, an online survey was conducted in July 2015 amongst local experts and stakeholders. The following questions were asked: (1) Does this map represent socioeconomic deprivation patterns in Quito?, (2) Could this map be useful for planning in order to improve the quality of life of the population?, and (3) Could this map be useful for planning in order to improve healthcare services accessibility? The options to answering these questions were: (a) strongly agree, (b) agree, (c) neutral, (d) disagree, and (e) strongly disagree. Further, the respondents were asked to provide supplementary information regarding their professional background. The respondents of the survey work in the areas of geographic and spatial sciences, health, and social and economic sciences. Because a focus group of experts is a small group of the population, we employed a snowball sampling method (Goodman, 1961) to obtain a large enough sample considering logistical limitations when asking local experts (Kounadi & Leitner, 2015). The online questionnaire was distributed via E-mail and social networks, and the approached respondents could redistribute the questionnaire to other experts. Following this approach, we received responses from 58 participants.

3. Results

3.1. Spatial representations of deprivations

Fig. 3 shows the four different spatial representations of deprivation used in this study: (a) census blocks, (b) census tracts, (c)

AZP_1, and (d) AZP_2. In all cases, we can see higher levels of deprivation in the peripheries of the city, especially those located in the south and north-west of the city. However, when having a more detailed look at the spatial patterns important differences in deprivation values between the different reporting units are discernible.

Fig. 4 shows a subset of the four different spatial representations. Fig. 4a and b shows the census-based reporting units and Fig. 4c and d the AZP-based reporting units. The larger scale map is the census blocks-based spatial representation. We have to consider that AZP_1 and AZP_2 have the same scale as the census blocks but they are generalized representations (averages) of deprivation. Moving from a generalized level (Fig. 4d and c) to a more detailed level, reporting units such as census tracts (Fig. 4b) or census blocks (Fig. 4a) support a more detailed identification of small neighborhoods with lower deprivation values. As Schuurman et al. (2007) argue, it is clear that higher resolution data, such as smaller and more numerous spatial units, can assist in identifying specific populations requiring services such as healthcare services in a context of socioeconomic deprivation.

3.2. Statistical comparison of the four different spatial representations

Table 2 shows that the four different spatial representations yield similar mean deprivation scores. In general, deprivation is relatively low across the study area, with averages not exceeding 0.2 (on a scale from zero to one). In stark contrast, the shape values of the four different spatial representations are very different, for example census blocks and census tracts reveal more compact

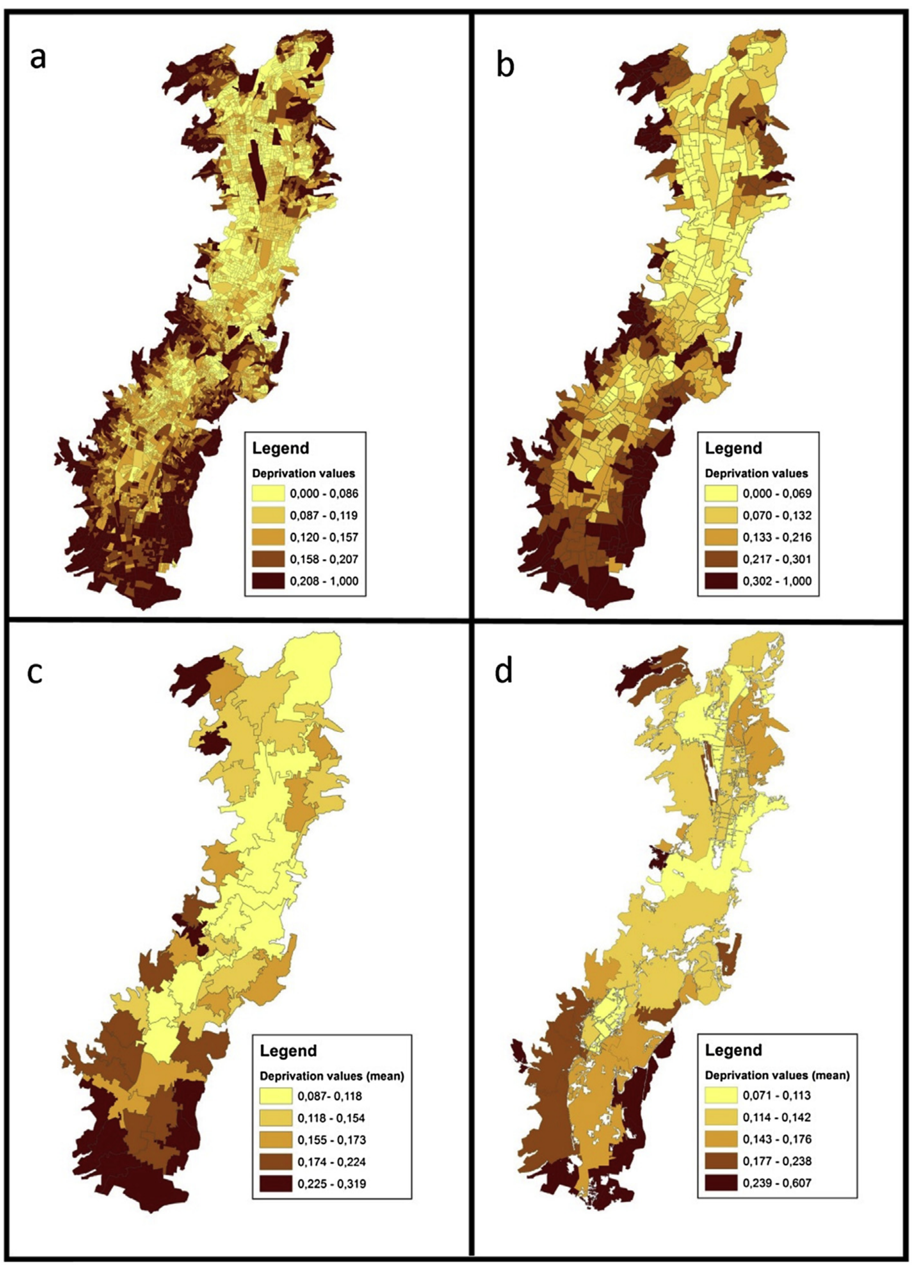

Fig. 3. The four representations, with reporting units based on: (a) census blocks, (b) census tracts, (c) AZP_1, (d) AZP_2. Deprivation values are divided in 5 classes. The classification scheme is based on quantiles.

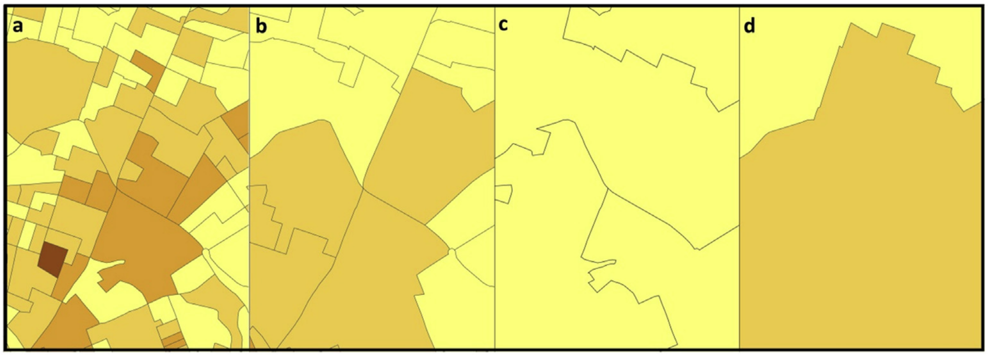

Fig. 4. Visualization of scale and zoning effects for the four representations of deprivation: (a) census blocks, (b) census tracts, (c) AZP_1, (d) AZP_2. The colors range correspond to the legends in Fig. 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

shapes as compared to the AZP-based representations. This difference makes sense as census-based areas are zones delineated following a human perspective (i.e., as a function of population and administrative areas), whereas the AZP-based areas are data-driven zones that are delineated based on variables such as the urban structure of the city or the different indicators of deprivation. AZP_2 reveals the most irregular shapes, which can be explained by the fact that the zones are based on urban structure (such us texture) and land use/land cover composition.

Multilevel modeling revealed further differences between the census-based and the AZP-based representations (see Table 3). It is particularly remarkable how the best models' performances (lower Akaike information Criterion-AIC values) belong to the AZP-based models. In addition, the variance partition coefficients (VPC) for the AZP-based models show that more variance of the dependent variable (here: the self-perceived quality of life - SPQoL) could be ascribed to differences between the zones in the study area in terms of deprivation. By contrast, for the census-based models, the intra-class correlation coefficients (ICC) show that more variance of the SPQoL could be ascribed to differences of the SPHC within and between the deprivation zones of the study area. The results in Table 3 can be interpreted as follows: for instance, in the case of the AZP_2, 32% of the variance of the SPQoL can be ascribed to differences of self-perceived health condition (SPHC) within and between different deprivation zones. Further, 68% of the variance of the SPQoL can be ascribed to differences in deprivation levels between zones.

Summarizing the results of the multilevel modeling shown in Table 3, one can say that the AZP-based deprivation representations better explain the variance of self-perceived quality of life (SPQoL) between zones, which is also reflected by better model performances as indicated by the AIC values. However, the AIC values of the census-based models are not fundamentally different compared to the AIC values of the AZP-based models. Further, the census-based models better explain the variance of self-perceived quality of life (SPQoL) considering differences of the self-perceived health conditions (SPHC).

Table 2
Descriptive statistics and shape metric for the four deprivation reporting units.

Reporting units	Deprivation descriptive statistics		Shape	
	Average[a]	Standard deviation	Average	Standard deviation
Census blocks	0.16	0.09	27.17	11.83
Census tracts	0.20	0.15	34.43	13.27
AZP_1	0.16	NA	89.49	39.06
AZP_2	0.16	NA	422.72	325.60

[a] For AZP-based zones, average is corrected considering the number of census blocks in each zone.

Table 3
Multilevel modeling statistics for the four deprivation reporting units.

Reporting units	AIC	ICC	VPC
Census blocks	1253.64	0.44	0.56
Census tracts	1222.67	0.33	0.67
AZP_1	1208.03	0.33	0.67
AZP_2	1190.91	0.32	0.68

3.3. Expert-based evaluation of the four different spatial representations

The results of the expert-based evaluation also revealed differences between the four spatial representations of deprivation (see Table 4). In the case of the first question, “Does this map represent socioeconomic deprivation patterns in the city of Quito?” between 20 and 23.2% of the participants strongly agreed that the four representations correctly represent deprivation in the study area, indicating that the respondents feel that the kind of spatial representation does not matter when visualizing deprivation in the study area. This similarity changes in the case of agreeing or disagreeing with the statement that the different reporting units correctly represent deprivation: agreement decreases from census-based representations to AZP-based representations (from 66.1% and 52% to 47.9% and 47.7%).

In the case of the question “Could this map be useful for planning in order to improve quality of life of the general population?” the results are similar to the first question: 20%–26.8% of the respondents strongly believe that the different spatial representations can be useful for quality of life planning. In the case of census blocks-based representation, more than 60% of respondents agreed, 7.1% were neutral, and only 5.4% disagreed. This representation is the one that has more people agreeing (and less people disagreeing) regarding its usefulness for quality of life planning.

For the third question “Could this map be useful for planning in order to improve healthcare services accessibility?” we also identified a similar pattern as in the second question: census blocks are generally considered as better representations of deprivation. Moreover, we can generally say that census blocks (i.e., the smallest reporting unit used in this study) were considered the most suitable representation of deprivation by the respondents, as well as the best tool to support quality of life and healthcare accessibility planning.

Table 4
Summary of responses related to consistency of deprivation representation of study area, usefulness for quality of life (QoL) planning and usefulness for healthcare accessibility planning for all the four representations of deprivation.

Reporting units	Deprivation representation (%)	Usefulness for QoL planning (%)	Usefulness for healthcare accessibility Planning (%)
Census blocks	N = 56 Strongly agree: 23.2 Agree: 66.1 Neutral: 8.9 Disagree: 1.8 Strongly disagree: 0.0	N = 56 Strongly agree: 26.8 Agree: 60.7 Neutral: 7.1 Disagree: 5.4 Strongly disagree: 0.0	N = 57 Strongly agree: 31.6 Agree: 49.1 Neutral: 14.0 Disagree: 3.5 Strongly disagree: 1.8
Census tracts	N = 50 Strongly agree: 20.0 Agree: 52.0 Neutral: 20.0 Disagree: 8.0 Strongly disagree: 0.0	N = 50 Strongly agree: 20.0 Agree: 52.0 Neutral: 20.0 Disagree: 8.0 Strongly disagree: 0.0	N = 50 Strongly agree: 24.0 Agree: 48.0 Neutral: 22.0 Disagree: 6.0 Strongly disagree: 0.0
AZP_1	N = 48 Strongly agree: 22.9 Agree: 47.9 Neutral: 14.6 Disagree: 14.6 Strongly disagree: 0.0	N = 48 Strongly agree: 25.0 Agree: 35.4 Neutral: 20.8 Disagree: 18.8 Strongly disagree: 0.0	N = 48 Strongly agree: 25.0 Agree: 31.3 Neutral: 27.1 Disagree: 16.7 Strongly disagree: 0.0
AZP_2	N = 44 Strongly agree: 22.7 Agree: 47.7 Neutral: 18.2 Disagree: 11.4 Strongly disagree: 0.0	N = 43 Strongly agree: 20.9 Agree: 44.2 Neutral: 18.6 Disagree: 14.0 Strongly disagree: 2.3	N = 44 Strongly agree: 25.0 Agree: 38.6 Neutral: 22.7 Disagree: 9.1 Strongly disagree: 4.5

N represents the number of respondents for each specific question.

4. Discussion

The MAUP can be challenging when the variables of a statistical analysis have different aggregation levels. However, when reporting units of different representation systems do not have the same shape, averaging is not very sensitive to these differences (Briant, Combes, & Lafourcade, 2010). This is also confirmed by the findings of our study.

Individual-level factors such as individual health are often influenced by area-level factors (Cockings & Martin, 2005) and this two-level relationship can also be extended to quality of life concepts (Diener, Inglehart, & Tay, 2013). At the same time, healthcare needs are linked to quality of life conditions (Chow, 2012). Individuals with a good self-perceived health status living in areas with low levels of deprivation may have a high self-perceived quality of life.

This study considers different scales and reporting units (or spatial representations) in the context of a spatial deprivation analysis in Quito, Ecuador, and evaluates their implications for planning purposes. Scale effects were evaluated by analyzing the results of the spatial representation of deprivation at the census block level in relation to its representation at the census tract level and the two AZP-based representations. The deprivation index (*DI*) calculated at the census tract level has a smaller scale than the other three spatial representations used in this study. The scale of the AZP-based representations is equal to the scale of the census blocks, since these representations are aggregations of census blocks areas. Results from our analysis suggest that spatial representations of deprivation at the census block level could better support the identification of the variance of health-related data within and between different deprivation zones. Additionally, when evaluating the usefulness of the different spatial representation for QoL and healthcare planning, census blocks received the highest acceptance by the local stakeholders and decision makers. Our findings hence suggest that using census blocks as a reporting units in spatial deprivation analysis can be considered an appropriate choice to analyze QoL and health-related data. These findings are also supported by other studies. For example, Schuurman et al. (2007) argue that the MAUP effect is best ameliorated by using large scales, such as the census blocks scales. Openshaw (1984) and Cockings and Martin (2005) also showed that increasing the zone size influences correlations in aggregated data. Furthermore, deprivation indices constructed using the smallest census areas possible have been proven to capture inequalities in health and to be a good support for health planning (Cabrera Barona et al., 2015; Havard et al., 2008; Pampalon et al., 2009). Summarizing the above statements, it can be said that deprivation indices represented in large scales minimize scale effects, and are good supporters for QoL and healthcare analyses and planning.

However, despite the clear benefits of using census blocks as reporting units of deprivation, other zoning systems can be used as reporting units, such as the AZP-based spatial representations of deprivation generated in this study. The two AZP-based spatial representations showed practically the same deprivation mean as the spatial representation of deprivation based on census blocks, and practically the same ICC and VPC as the spatial representation based on census tracts. This clearly shows that the data variability between the two working scales of this study (census blocks and census tracts) did not markedly change. Therefore, no extreme scale implications are found, which supports the idea that the MAUP is less pervasive when data variability is preserved from one scale to another (Briant et al., 2010). As shown in the results section, the shape measure strongly varied between the census-based and AZP-based representations of deprivation. However, this variation does not seem to affect the statistical characteristics of deprivation and QoL and health-related relationships calculated in this study. This is in line with Briant et al. (2010), who found that newly designed zones developed from census areas do not alter socioeconomic data relationships and estimations. The AZP-based reporting units of this study are zones that are internally homogeneous in terms of deprivation and urban structure. Nonetheless it is important to note that the underlying initial "building blocks" for these zone-designed reporting units are census blocks. All area-based analyses in new zoning systems are likely to be heavily dependent on the initial "building blocks" used to construct these zones, as well as on the aggregation of these "building blocks" (Openshaw, 1984; Cockings & Martin, 2005).

5. Conclusion

Using both quantitative and qualitative approaches, no strongly marked differences were found between the four analyzed spatial representations of deprivation: only structural differences (i.e. regarding their shape) were found between the census-based and AZP-based representations. The spatial representation of deprivation based on census blocks is the most detailed reporting unit in this study. The local experts and stakeholders considered this unit as the most useful for quality of life and healthcare accessibility planning, although some of the experts also indicated that they preferred other spatial representations. Some decision makers in Ecuador take actions based on low resolution information, such as information based on parishes or provinces. Based on our findings, we conclude that considering higher resolution census areas can assist in pin-pointing more precisely areas characterized by high levels of deprivation. One of the challenges associated with place-specific measures of deprivation is data availability, especially since this also impacts the transferability to, or comparability of results between, different study areas (Bell, Schuurman, Oliver, et al., 2007). However, the indicators considered in our study are indicators where data is commonly provided by population and housing censuses. Additionally, the methodology described in this study can be transferred to other regions to further evaluate MAUP implications in the context of deprivation studies.

In general terms, our findings suggest that, in the context of our study, census blocks can be considered as the best option to spatially represent area-based measures of deprivation, while further studies are needed to validate these findings. Additionally, it is important to draw attention to the fact that aggregation processes in spatial representations of deprivation undoubtedly have MAUP implications, and that both developers of deprivation indices as well as their users need to be aware of the potential impact that these implications can have on deprivation, quality of life, and healthcare analyses.

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