Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

CHARACTERIZATION OF HEALTHY URBAN ENVIRONMENT FOCUSED ON FOOD AND PHYSICAL ACTIVITY: A GIS-BASED METHOD

CARACTERIZACIÓN DEL ENTORNO URBANO SALUDABLE CENTRADO EN ACTIVIDAD FÍSICA Y ALIMENTACIÓN: UN MÉTODO BASADO EN SIG

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ABSTRACT

Healthier urban environments may influence the distribution of cardiovascular risk factors therefore the aim of the present study was to design and implement a multivariate method based on a Geographic Information System (GIS) to characterize and evaluate the environmental correlates of obesity: the food and the physical activity urban environments. The study was conducted in a socio-demographically average urban area of Madrid (Spain), comprised of 12 contiguous census sections (≈16.000 residents). Data were gathered through on-field audits of all food stores and street segments in the study area. We designed a synthetic index integrating continuous measures of both food and physical activity environments, generated by kernel density analyses. The synthetic index ranges from 0 (least healthy) to 100 (most healthy). We found a heterogeneous distribution with 75% and 50% of the area scoring less than 36.8 and 25.5, respectively. The study area was categorized by Jenks intervals defined as high, medium-high, medium-low and low. Thus, 4.2% of the population lived in a healthy area while 41.0% in an unhealthier one. Most of the population (52.8%) was located in an area with a median score, 29.1% medium-high and 26.6% medium-low. Synthetic index provides a feasible way to integrate different measures of barriers and promoters of healthy behaviours in urban environments. This synthetic index may be a relevant tool to inform future urban health interventions.

Key words: obesogenic environment; Geographic Information Systems; food environment; physical activity environment;

RESUMEN

Los entornos urbanos saludables pueden influir en la distribución de los factores de riesgo cardiovascular, por tanto, el objetivo del estudio fue diseñar e implementar un método multivariable basado en Sistemas de Información Geográfica (SIG) para caracterizar y evaluar los entornos relacionados con la obesidad: el entorno alimentario y el entorno de actividad física. El estudio se realizó en una zona sociodemográficamente mediana de Madrid (España), compuesta por 12 secciones censales contiguas (≈16.000 residentes). Los datos fueron recogidos a través de herramientas de auditoria midiendo in situ todas las tiendas de alimentación y todos los segmentos de calle. Se diseñó un índice sintético que integra las medidas de ambos entornos generadas por análisis de densidad de Kernel. El índice sintético oscila entre 0 (menos saludable) y 100 (más saludable). Se encontró una distribución heterogénea con el 75% y el 50% de la superficie con una puntuación menor de 36,8 y 25,5 respectivamente. El área de estudio se clasificó por intervalos "natural Jenks" definidos como alto, medio-alto, medio-bajo y bajo. De esta manera se obtuvo que un 4,2% de la población vive en un área definida como saludable, mientras que un 41,0% lo hacía en una poco saludable. La mayor parte de la población (52,8%) se encuentra en una zona con una puntuación media, 29,1% medio-alto y el 26,6% de medio-bajo. Este índice sintético proporciona una manera factible de integrar diferentes medidas de limitadores/promotores urbanos

Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

de conductas saludables considerándolo una herramienta importante para informar a futuras intervenciones urbanas de salud.

Palabras clave: entorno obesogénico; Sistemas de Información Geográfica; entorno alimentario, entorno actividad física.

1. INTRODUCTION

The obesity epidemic is one of the main public health concerns in the present century (WHO, 2015). The prevalence of overweight (Body Mass Index >= 25 kg/m2) and obesity (Body Mass Index >= 30 kg/m2) in European countries ranges from 45% to 67%. Spain has some of the highest levels of overweight (60.9) and obesity (23.7%) in Europe (WHO, 2015).

The limited success of current individual-level based strategies shows the need for new approaches based on population-level determinants of obesity. These approaches focus on affecting the fundamental causes of the distribution of risk factors in the whole population (Rose, 1985). These fundamental causes were called mass influences by Rose (Rose, 1985) and are mostly environmental or social factors at several levels. There is a large and renewed interest in these fundamental causes, especially at the urban context where people live and work and particularly at neighbourhood level (Franco *et al*., 2015; Hirsch *et al*., 2014). Understanding contextual determinants of obesity creates opportunities for policy development at the local level that may bring obesity and other associated chronic diseases down.

The regulation of body weight depends on multiple factors such as physical activity and healthy eating, among others (Bethlehem *et al*., 2014). The contextual determinants of physical activity are complex and multifaceted, but can be roughly classified into transport-related physical activity and leisure-time physical activity influences. The determinants of active transportation relate to walking and biking and include features such as quality of pavements, safety, mix land use, destinations and connectivity (Pikora *et al*., 2003). Contextual influences of leisure-time or recreational physical activity include sports facilities and green spaces. Contextual determinants of healthy eating include all aspects of the local food environment that influence dietary behaviours (Franco *et al*., 2015).

The literature on the associations between contextual determinants of physical activity and healthy eating has been quite mixed. The diversity of methodologies used and the results obtained (Feng *et al*., 2010; Leal & Chaix, 2011) highlight the complexity of the chain of causation linking contextual factors and different chronic diseases, as well as the challenges inherent to measuring complex social phenomena (Glass & McAtee, 2006). Among these challenges there is the intertwining of environmental features: physical activity environments and food environments are not created in isolation but are rather the result of social forces that affect neighbourhoods (Guthman, 2013). Much of the previous research has focused solely on one factor in isolation, such as walkability (Owen *et al*., 2007) or healthy food availability (Glanz, *et al*., 2005). Moreover, the strong correlation between physical activity and dietary behaviours calls for strategies that tackle sedentarism and unhealthy diets concurrently (Economos *et al*., 2015; Meyer *et al*., 2015; Jones *et al*., 2007). Interventions may be ineffective if only focused on promoting physical activity, ignoring a food environment which may promote the consumption of unhealthy foods (Economos *et al*., 2015). Thereby, there is a need of an integrated approach to understand contextual factors of both environments.

A potential promising avenue to operationalize the contextual determinants of obesity is to aggregate measures of both physical activity and diet determinants. Previous studies have aggregated urban context indicators in a synthetic index, finding significant correlation with health outcomes (Feng *et al*., 2010; Kelly-Schwartz *et al*., 2004). For instance, Kelly-Schwartz *et al*., (2004) found significant association between a composite index (county sprawl index) and obesity, but not between its components and health outcomes.

Our objective is to design a multivariable tool based on Geographic Information Systems (GIS) to integrate information from the physical activity and food environment to better characterize obesogenic environments in urban areas. GIS are rapidly becoming a relevant part of the panoply of methods adopted in Public Health

Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
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Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

research (Matthews *et al.*, 2009). GIS is a well-suited tool to define healthy urban environments allowing to integrate data from different sources and scales, both spatial and non-spatial.

2. METHODS

This study was conducted within the multidisciplinary Heart Healthy Hoods project (http://www.hhhproject.eu/). The main objective of this European project is to analyse the impact of the physical and social urban environment in relation to residents' cardiovascular health in Madrid, Spain.

2.1   Study area

According the 2014 Health Report of Madrid City Council (Díaz-Olalla & Benítez-Robredo, 2015), 41.2% of the population presents overweight or obesity, 30.1% and 11.2% respectively. Although these values are below the national measures, 38.4 of overweight 18.2% of obesity conforming the last National Health Survey, they values remain alarmingly high. Regarding risk factors, the Risk Factors Surveillance System Associated with Noncommunicable Diseases in Adult Population of 2013 (or SIVFRENT-A in Spanish) (Díez-Gañán, 2013), indicated that 49.2% of Madrid citizens affirm to be sitting most of their working time and 73% are inactive at leisure time. Regarding diet, Madrid citizens eat in average 1.2 rations of fresh fruit and 1.1 rations of vegetables per day. These rates are far from the recommendations of 5 rations per day.

We selected a study area of 12 contiguous census sections (Figure 1) using the Median Neighbourhood Index (MNI). This method computes a composite score of the mean Euclidean rank distances to the median census section of the city in four key sociodemographic and urban form domains: population aging (%> 65), educational level (% with <8.9 years of education), immigration (% foreign-born) and population density (inhabitants/km^2).

Figure 1. Study area, type of food stores and streets audited. Coloured areas represent census sections within the pilot study area. Source: Prepared by the authors.

2.2   Characterizing the urban environment

FOOD ENVIRONMENT: 40 retail food outlets located within the 12 selected census sections were identified by on field observation. All stores were classified into corner stores (small stores with a low variety of items and generally no fresh products), grocery stores (mid sized stores with higher variety and presence of fresh products), supermarkets (large stores with highest variety and presence of fresh products), specialty stores (fruit and vegetable stores, butcheries, fishmongers and bakeries), gas stations and convenience stores (long opening hours and no presence of fresh products).

Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

All food outlets were audited by a trained data collector using an abbreviated version of the Nutrition Environment Measures Survey in Stores (NEMS-S) (Glanz *et al*., 2005), a standardized observational tool with high degrees of inter-rater and test-retest validity (Glanz et al., 2005). The abbreviated version was developed by the Johns Hopkins Center for a Livable Future for an assessment of Baltimore's Food Environment (Behrens, *et al*., 2015). It collects data on milk, juice, fruits, vegetables, lean red meat, chicken, seafood, canned, dry, frozen and packaged goods, whole-grain bread and low-sugar cereal. From this data a Healthy Food Availability Index (HFAI) was computed, ranging from 0 to 27.5 (higher scores representing higher availability of healthy foods). The data collection instrument in Behrens *et al*., (2015) shows details on the scoring system.

A trained data collector visited all food stores in the study area to assess the availability of healthy food choices using an adapted version of the NEMS-s, were the item "% lean" and "% fat" in the measure of "meat" was changed for the single item "beef"; and the food item "corn tortillas", not consumed in Spain, was removed from the scoring system.

PHYSICAL ACTIVITY ENVIRONMENT: The Systematic Pedestrian and Cycling Environment Scan (SPACES) (Pikora *et al*., 2002) is an observational audit of features of the built environment that can influence walking and cycling along a street network. We adapted this audit tool to the Madrid (M-SPACES) environment and conducted a validity and reliability study before (Gullón *et al*., 2015). For the purposes of this study, and due to the residual use of bikes in the area, only walkability measures were considered.

A trained researcher audited all street segments of the study area (n=145 segments) by foot. A street segment is defined as one section of a street that runs between two intersections. It is often used as the basic observation unit in neighbourhood or community analysis. Items of the M-SPACES tool are then added up to four domains: functionality, safety, aesthetics and destinations. These, in turn, can be added to compute a walkability score for each street segment (ranging from 0, least walkable, to 1, most walkable) Main audited characteristics were functionality, safety, aesthetics and destinations. More details on this audit tool and its measurements properties have been published before in Gullón *et al*., (2015).

SPATIAL DATASETS: Contextual information on the study area was collected from the Spanish National Mapping Agency (IGN) and Spanish National Spatial Data Infrastructure (IDEE), allowing us to generate a georeferenced database to integrate and map the results from the food and physical activity environment assessment. Administrative boundaries (district and census sections) and street networks were collected in vector polygon and line formats, respectively. We also used orthophotograpy of the study area obtained from the Orthophotography Air National Plan (PNOA).

ArcGIS 10.1 software was used to integrate, standardize and manage these datasets. First, all information was projected to a common system (ETRS89 UTM 30N). The physical activity environment data (collected with the M-SPACES tool) was associated with the street network layer by a relational join. The food environment data (collected with the abbreviated NEMS-S tool) was integrated in the system using a point-based layer with a relational join. All other layers (administrative boundaries, blocks and orthophotos) were introduced to the final maps as reference information.

Sociodemographic data was obtained from Statistical National Agency at census section level to characterize the populations living in the areas established by the proposed method

2.3   Geospatial analysis

The aim of this study was to integrate data on the physical activity and food environment in characterizing the urban environment by using Geographic Information Systems. Figure 2 summarizes our approach. In summary, we converted line and point data into a whole study area surface area (one for each environment), followed by map algebra to combine both measurements and a categorization of the final results .to ease interpretation.

First, we extended line data (walkability index for each street segment) and point data (healthy food availability index for each food store) to the whole study area using Kernel Density Estimation (KDE). KDE fits a

Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

mathematical surface (composed of pixels) with a normal distribution over each point based on (a) the value empirically collected for each point, and (b) the distance from each location in the surface to all points in the area within defined radius or bandwidth. Essentially, the value of each point is smoothed over the study area producing a density value that will be the highest at the location of every point, and decaying from there with distance using a defined bandwidth (Carlos *et al.*, 2010).

We use de KDE integrated in ArcGis 10.1 software which employs the quadratic Kernel function of Silverman (Silverman, 1986):

$$\hat{f}(x) = \frac{1}{nh} + \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

Where K is the quadratic Kernel function defined by K(x)= 3/4 (1-x^2), x≤1, "x" is the point at which density is estimated, "xi" is the value of the variable in the case "i", "n" is the number of cases and "h" is the bandwidth. The basic idea consists calculated for specific points, the averaged sum (hence the estimator involves summing over "n" and then divide by this value) of Kernels centered on the observations.

Figure 2. Development of continuous KDE variables from direct observation data. On the left, is depicts the calculating for the food environment starting with the location of all stores, continues with the Healthy Food Availability Index (HFAI) score for each one, and the next is the KDE surface weighted by HFAI score. On the right, the development for the physical activity environment. Above the location of all the street segments, continues with Pedestrian and Cycling Environment Scan (SPACES) score by each one. And in front the KDE weighted by the SPACES.

This spatial analysis allows weighting each element by their associated attributes, in our case the HFAI and SPACES scores. For example, if the element has associated value attribute equal to 3, the case counts as 3 cases. Thus, density value in each pixel of the output image is calculated summing the values of all overlapping Kernel surfaces. All surfaces were generated with a pixel size of 3 meters. We used a bandwidth of 100 meters, given that the average distance from one food store to the closest food store was around half that length (improving smoothing). A static bandwidth was used because of the small study area and the homogeneous population density distribution (Carlos, *et al.*, 2010).

Figure 2 shows the development of both continuous density surfaces: one from the food stores layer weighted by the value of HFAI; and the other from the street segments layer weighted by the scores obtained from the M-SPACES audit.

After generating both surfaces, we performed a map algebra analysis. The operation adopted for map algebra was a local average that computes an average of pixels at the same location in both the physical activity and

Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

food environment surfaces, generating the synthetic index. To fully integrate the synthetic index into the geographic context of the area, we assigned each census section an obesogenic (synthetic index) value. For this, we used zonal analysis that calculates a single output value for each census section averaging all pixels that fall within each area. To improve the interpretability of our results, we categorized census sections into four classes according to their value in the synthetic index (high, medium-high, medium-low and low). For this, we used the Jenks intervals approach that reduce the variance within classes, while maximizing the variance between them.

3. RESULTS

Figure 2 represents the calculated KDE surface obtained for the food environment, with an important concentration of food sales scored with high HFAI values in the North and South ends of the study area, with patches of medium-high density distributed throughout the area. Most stores ranked with high HFAI were quite close to each other and mostly located along important roads, creating "islands" of healthy foods. Stores with low HFAI were distributed more evenly and gave form to "healthy food deserts" The surface resulted from the M-SPACES showed highest values at streets intersections, on streets with wide sidewalks, and in the surroundings of squares and parks. The greater the number of intersections, the greater the walkability of the area.

Figure 3. Continuous synthetic index surface. This surface is the local average of the pixels of walkability KDE and the pixels of food availability KDE. The size of pixel is 3x3 meters and the bandwidth selected to the smoothing was 100 meters.
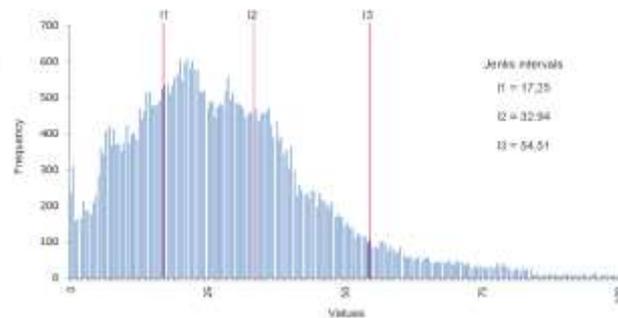
Figure 4. Histogram of the synthetic index surface. It depicts the frequency of pixel values of the study area with a range from 0 to 100 with higher scores indicating a healthier environment. The red lines represent the intervals defined by Natural Jenks to categorize the 12 census sections of the study area in high, medium-high, medium-low and low healthy areas.

The synthetic index surface resulted from the averaging of walkability, and healthy food environment surfaces, is depicted in Figure 3. The values obtained range from 0 to 100 with higher scores indicating a healthier environment. Observing the distribution of data in the frequency histogram of Figure 4, a 75% of the area is below 36.8 of the index score and half of the area below 25.5.

Figure 5 shows the results of the characterization of the obesogenic environment in terms of diet and physical activity at census section level. For representation purposes, natural breaks (or Jenks intervals) were adopted. The classes defined to characterize how healthy is the urban environment of the study area follows a range of high to low with respect to themselves. If we take into account the extent of the study area, 36.5% of its surface is characterized by low values. Only 7.4% of the area is classified within a high value in both cases. The

Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

majority of surface (56.1%) is characterized as medium-high and medium-low rating, 22.4% and 33.7%, respectively.

Considering population in each census section and the characterization of the pilot area, the results show that 4.2% of the population live in areas characterized as "healthy" environments, while 41.0% of the residents live in an area with the lowest rating. In turn, the majority of population (52.8%) live in a medium score environments, 29.1% medium-high and 26.6% medium-low. Analysing the results by sex, 40.7% of women have lower scores than men (41.5%). 4.6% of women and 3.7% of men live in a section with high score. In the case of foreign-born residents, 54.7% of them live in the unhealthiest areas and 4.4% in the healthier. If results are studied by age, the majority of young people live in a census section with low score (51.13%) as well as adult people (44.43%) but in the case of elderly people, they live in a medium-high healthy space (32.9%). Only the 1.9%, 3.5% and 7.0% of young, adult and elderly people respectively live in a healthy section.

Figure 5. Final characterization of census section level of the pilot area. Depicts the result of zonal analysis of each administrative area having in account all the pixels of the local analysis within each area.

4. DISSCUSSION

This paper documents the development of an innovative method to assess the obesogenic environment by a synthetic index integrating continuous measures of both food and physical activity environments, generated by KDE. The results show a heterogeneous distribution of obesogenic determinants in the study area. 36.5% of the census sections are classified as low healthy, followed by medium-low healthy (33.7%), and medium-high (22.4%). Only one census section is classified as high healthy, a 4% of the study area surface.

This high healthy census section is delimited by main streets of the neighbourhood, where healthiest food stores were present. Main streets are also designed to be more walkable. Moreover, the only park located in the study area, was also located within this census section.

In order to understand the obesogenic environment it is necessary to consider the interrelations between the food and physical activity environments, as built environment metrics are correlated with each other. The use of composite indices reduces collinearity and over-adjustment, confers ease of interpretation, and may reduce measurement errors (Feng *et al*., 2010). Besides, integrating different indicators within an index can detect associations not previously found (Kelly-Schwartz *et al*., 2004). In our case, systematic observation of a built

Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

environment, using validated audit tools, provided high detailed spatial data. This also ensured variability on measures of both constructs and statistical power. The use of a detailed sampling strategy to maximize the variation between environmental factors reduced the sample sized needed to assess associations between built environments and obesity outcomes (Frank *et al.*, 2012).

Previous studies have integrated both physical activity and food environments to characterize high and low environmental obesogenity (Frank *et al.*, 2012; Meyer *et al.*, 2015). These integrations have been used to evaluate their relation with diabetes incidence (Christine *et al.*, 2015) or cardiometabolic risk factors (Paquet *et al.*, 2014). The methodology designed in our work considers variables studied in these studies, such as food store density, food store type, street intersection density, parks or street aesthetic, among others. The majority of these studies used GIS to integrate all information from diverse sources, mostly from secondary databases. But we also consider other variables as variety of healthy foods captured by NEMS-s or the aesthetic or safety by SPACES tool, very difficult to assess from secondary database. Therefore, and as indicated in the previous paragraph, we consider as strength of our study having gathered, by direct observational measures, new data and new information not available in secondary databases.

Moreover, the presented index can be enriched with other variables and refined when scientific advances provide evidence. The first priority to improve the measuring and impact of the urban environment on health behaviours is to identify relevant environmental factors to measure and the relative importance of each of them over health outcomes. This work has not considered the relative importance of domains, so that both environments were weighted with equal weight.

In Spain, the least aggregated administrative data publicly available is at census section level, composed of ≈1500 people. Therefore, the outcomes obtained are represented at this level of aggregation. The area of this study is made up of 12 census sections, but the methodology used to evaluate the obesogenic environment is replicable at larger units: municipalities as Madrid, or countries as Spain. Reproducing this methodology to characterize the obesogenic environment of Madrid, would allow assessing the relationship with other indices, such as the one developed by the project "Mortality in Spanish small areas and socio-Economic and Environmental Inequalities" (MEDEA) (Domínguez-Berjón *et al.*, 2008). This project built a deprivation index based on census data in large Spanish cities to study its association with excess mortality risk.

Current methodology presents several limitations, especially regarding primary data collection through systematic observation. This is an expensive and time consuming process. Thanks to advances in Geographic Information Technologies, these costs can be drastically reduced, by using available secondary databases with spatial information, and new geographic remote devices to collect geocoded primary data. In addition, despite possible objections to the variables considered, the general approach can be adapted to other circumstances. Thus other relevant urban built environments can be measured with the methodology proposed. Moreover, as scientific literature has not yet fully quantified the proportion of food or physical activity responsible for current obesogenic conditions, we adopted a local average. In the future, when scientific evidence is made available, this local average could be weighted accordingly.

A general limitation of research environments and health is the lack of information about the cumulative exposure to different environments and duration of exposure to such environments (Chaix *et al.*, 2012; Feng *et al.*, 2010). Considering that population is only exposed to environmental factors around their residential area implies an underestimation and fails to recognize the high heterogeneity among the spatial behaviour of individuals living in the same neighbourhood. People cross borders of several administrative boundaries and are exposed to the influence of contextual factors of different environments beyond their residential area (Kwan, 2015).

Therefore new perspectives are emerging as the one proposed by Zenk *et al.*, (2011). Zenk found that residents´ activity spaces were larger than residential neighbourhoods and found also a statistically significant relationship between activity space environmental features and dietary behaviours. In order to measure exposure to contextual factors, it is necessary to consider the daily mobility patterns of individuals. Not

Aplicaciones de las Tecnologías de la Información Geográfica (TIG) para el desarrollo económico sostenible
XVII Congreso Nacional de Tecnologías de Información Geográfica, Málaga, 29, 30 de junio y 1 de julio 2016
Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

considering individual's intimate connections to multiple geographic locations is one of the main limitations of studies on public health adopting the neighbourhood as their unit of analysis.

We developed a synthetic index integrating data on physical activity and food environments at census section level. This methodology was able to capture inter-relations between both domains of the urban environment that did not emerge when they have been studied in an isolated way. The index obtained and the cartography associated are necessary to inform recommendations in environments to support healthy physical activity and nutrition related behaviours. A residential environment that encourages active transportation and with a wide access to healthy foods, would support residents' healthier behaviours.

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Caracterización del entorno urbano saludable centrado en actividad física y alimentación: un método basado en SIG, pp. 51-61
Alba Cebrecos-Eguren, Julia Díez-Escudero, Pedro Gullón-Tosio, Manuel Franco-Tejero, Francisco Escobar-Martínez

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