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Spatial pattern of poverty. A new procedure to identify the spatial hierarchy of poverty in Mexico, 2010

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There is no space in a hierarchized society that is not itself hierarchized and that does not express hierarchies and social distances, . . .
Pierre Bourdieu, "Site effects"

A R T I C L E I N F O

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A B S T R A C T

This article presents a new procedure to elaborate a spatial hierarchy of magnitude and intensity of poverty. While the magnitude and intensity refer to absolute and relative data, respectively, each variable may be concentrated or agglomerated in space. Concentration is the presence of high global values, regardless of their location, and agglomeration is the concentration of spatially contiguous high local values. Both agglomeration and concentration are merged through a geographical overlay procedure to create conglomerates of magnitude or intensity of poverty. The intersecting area resulting from the spatial overlay of the map layer for conglomerates of magnitude, on one hand, and the map layer for conglomerates of intensity, on the other hand, contain the highest priority areas. Three different procedures to classify the non intersecting areas of the conglomerates are applied and evaluated: core/periphery, heads/tails and natural breaks. For the first time in the study of the spatial pattern of poverty, the resulting spatial hierarchy is based on the simultaneous combination of the concentration and agglomeration processes measured in relative and absolute terms. The suggested methodology may be easily extended to identify other spatial patterns, such as crime, industry, diseases, or pollution. Briefly, this study suggests an overlay analysis of the concentration and agglomeration processes for variables of magnitude and intensity above statistically supported threshold limit values. The benefits of the procedure for an area based public policy are illustrated by assessing the spatial targeting of poverty in the 2,456 Mexican municipios in 2010.

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Glossary

Agglomeration. Concentration process in neighboring areas.
BCa and Tilting options: Robust resampling alternatives that permit the use of the mean rather the median in asymmetrical distributions.
Case. An entity that displays or possesses the traits of a variable (Argyrous 2011, 3).
Cases beyond the TLV. Cases in the right tail at the 95% percent of confidence with one tail.
Conglomerate of intensity or magnitude. Spatially grouped values of intensity or magnitude resulting from the integration of local high values (from spatial autocorrelation) and contiguous global high values (from bootstrapping).
Cold spot. Low values surrounded by low values (LL).
Concentration. Location of a variable in quite a few areas, regardless of their location.
Core areas. Hot spots (HH) or high values surrounded by low values (HL).
Global high values. Values above the upper limit of the confidence interval of the bootstrapped mean. They are calculated considering the whole array, regardless of the location of each case.
Hot spot. High values surrounded by high values (HH).
Intensity. Local importance (intralocal) of the variable in relative terms, such as rates or location quotients.
LISA. Local indicators of spatial association, such as the local Moran´s Index Ii.
Local high values. Contiguous high values (hot spots-HH) or spatial outliers of the type HL, as defined by LISA. They are identified having as a reference some predefined criteria of contiguity or neighborness.
Magnitude. Interregional presence of the variable in absolute terms or cross-section percentages.
Principle of population independence. Values do not depend upon, or are influenced by, the size of the population (it refers to percentages or relative values).
Priority area. Resulting area from the intersection of conglomerates of intensity and conglomerates of magnitude.
Spatial autocorrelation. Correlation of a variable with itself in space (the surrounding or neighboring areas).
Spatial pattern. Location or geographical distribution of a variable in a specific year (situation) and locational change of the same variable in a given period (process).
Threshold limit value (TLV). The upper class limit of the confidence interval of the bootstrapped mean. In distributions with positive asymmetry, the bootstrapped mean is a conservative criterion (it allows fewer cases to the right) in relation to the median.
Variable. Any construct with more than one value that is examined in research (Urdan 2010, Ch. 1). A condition or quality that can differ from one case to another (Argyrous 2011, 4).

Introduction

The interest in studying the spatial pattern of poverty is increasing, both in academia (Partridge and Rickman 2006) and public policy (Bedi, Coudouel, and Simler 2007, Mexico-CONEVAL nd). The term "spatial pattern" in this research means the location or geographical distribution of a variable in a specific year (situation) and locational change of the same variable in a given period (process).[1] The variable location, in turn, has two characteristics: magnitude and intensity. Magnitude, usually expressed in absolute numbers, refers to the national or interregional presence of the variable (poverty). Intensity, on the other hand, measures the local importance (intralocal) of the variable. In this paper, the analysis of the spatial pattern (or simply, spatial analysis) is focused on the identification of a spatial hierarchy of areas considering both the location and intersection of intensity and magnitude of poverty. The locational change of this variable cannot be addressed with the available information in the Mexican case study.

The identification of the spatial pattern of poverty demands a clear distinction between magnitude and intensity. While the magnitude refers to the amount, number, size or volume of poverty (spatially extended), intensity refers to the degree of severity or seriousness of the problem (spatially intensive) (Goodchild and Lam 1980).

The spatial pattern of the magnitude or intensity can be concentrated and/or agglomerated. The spatially concentrated pattern refers to the hierarchy of areas considering the level or degree of incidence or magnitude of the variable (*i.e.*, Very High, High, Medium, Low), regardless of their geographic location. On the other hand, the agglomerated geographic pattern refers to the classification of areas of similar magnitude or intensity that are spatially contiguous in groups, without considering the array, order, or hierarchy of the whole set of values. Studies on concentration and agglomeration are (or should be) complements, not substitutes. This conclusion, although logical in the light of these definitions, is not explicitly present in the literature reviewed, except for the study of Visvalingam (1983).

The study of the spatial dimension of poverty, in general, and the identification of a spatial hierarchy of poverty, in particular, is important for the following reasons:

a) It is the most efficient way to meet the challenges and problems that have a regional dimension, such as the provision of secondary and higher education or specialized health services.

b) It is a required task in a country of vast territory. The Mexican state of Chihuahua (247,460 km^2), for example, is larger than the United Kingdom (242,900 km^2) and Sonora (179,355 km^2) is larger than Uruguay (176,215 km^2). The provision of social infrastructure in Chihuahua is an effort similar to that for the whole UK.

c) It increases the visibility of poverty by identifying areas where the poor live in adverse socioeconomic and biophysical conditions.

d) It analyzes and incorporates the socioeconomic impact of regional and/or national development strategies.

e) Bearing in mind the above, it is a prerequisite for formulating policies, designing programs, sorting out areas and selecting beneficiaries for social policy.

This research, considering the relevance of studying the spatial pattern of poverty and based on the definitions outlined above, provides a spatial hierarchy of areas of poverty in Mexico in six prongs: The first part approaches the problem of priority areas as

[1] This operative definition is compatible with broader definitions considering the spatial pattern as a material expression or manifestation of essential underlying socioeconomic processes (*i.e.*, spatial simulation in O'Sullivan and Perry 2013, spatial justice in Soja 2010, or uneven development in Gottdiener and Hutchison 2011).

global high values and local high values. The second section presents the overlay analysis suggested in this research within the context of recent literature on spatial patterns of social issues. The third section addresses the need for studying the geographical pattern of poverty in terms of intensity and magnitude. The fourth section contains the substantive steps to set up a spatial hierarchy of areas of poverty. The fifth section applies to the case study the methodology presented in the previous section and finally, the last section highlights the main findings, study limitations as well as suggestions for future research.

Briefly, the paper presents a new procedure to analyze spatial patterns and illustrates it with the Mexican poverty case study. The research identifies a spatial hierarchy of poverty in Mexico simultaneously combining concentration and agglomeration of relative and absolute values. The input data set is the latest information on poverty in Mexico at the municipio level (2010).[2] The study points out that the identification of priority areas can and should be improved and/or validated by criteria of spatial and non-spatial statistics. These two criteria can be integrated with each other by an overlay analysis, as it is presented in the next sections.

1. Approach: Overlay analysis of high global and local values of individual and contiguous areas

The paper highlights two kinds of "high" values: global high values and high values of range (local high values in this research). In general, high values in non-spatial statistics are above the mean or median, for normal or non-normal distributions, respectively. They are "high" in terms of the whole array of the data. On the other hand, high values of range are judged only considering values located within a certain distance (neighbors).[3] High values of range are local high values identified in spatial statistics by permutations. Spatial statistics distinguishes two categories of spatial autocorrelation: spatial agglomerations and spatial outliers (Anselin 1995). On one hand, spatial agglomerations may be hot spots (high values surrounded by high values, HH) or cold spots (low values surrounded by low values, LL). On the other hand, strictly speaking, spatial outliers are high values surrounded by low values (HL), or low values surrounded by high values (LH). For practical purposes, "local high values" in this research are groups of high value areas (HH-hot spots) or high value individual areas (HL) that are statistically different from the neighboring locations. The statistical significance of these high values is detected using local indicators of association or autocorrelation (*Local Indicator of Spatial Association*, LISA) (Zhang *et al*. 2009, 3083). The Moran´s I global index and its local version Ii are the most used indexes to detect local high values (Srinivasan 2008, 615).

As it is explained in detail in the methodology section, global high values are calculated considering the whole data set, regardless of the location of each case. On the other hand, local high values are identified having as a reference some predefined criteria of contiguity or neighborness. As a consequence, some global high values may overlap with local high values, but some others may not. Both global and local high values represent different spatial processes that should be integrated. While global high values

[2] Each Mexican state subdivides into municipios governed by a municipal president. These municipios are the functional equivalent of counties in the US. Huck (2008, 195) uses the word municipalities instead of municipios. This research keeps the Mexican word municipio because it may contain more than one municipality in the US sense. The exception to this terminology is DF, a state subdivided into delegaciones rather than municipios.

[3] These definitions are based on Zhang, *et al.* (2009). I use "high values" instead of "outliers" because this research focuses on significant high values, not on extreme values.

are the result of the concentration process in general, local high values are the consequence of the concentration process in neighboring areas (agglomeration). As an example, the general concentration indicates that poverty is highly concentrated in quite a few areas; the agglomeration process, on the other hand, points out that some of those few areas are contiguous in space.

2. Literature review

In general, five approaches stand out from current literature to identify spatial concentrations and/or agglomerations of social variables, including poverty (Table 1): (a) cutoff approach, (b) Global high values for individual areas, (c) Local high values for contiguous areas, (d) Global high values for individual and contiguous areas, and (e) Overlay analysis.

a) Cutoff approach. It is a controversial method in current literature. In particular, three characteristics define the cutoff approach and identify its main problems (Riguelle, Thomas and Verhetsel 2007, 198): (i) the appropriate cutoff points are obtained through a process of trial and error, guided by local knowledge, (ii) the choice of different thresholds, depending on the study area, limits the comparability between different municipios, and (iii) the selection of a unique threshold for a region prevents the identification of places with greater values than their surrounding areas if they do not reach the fixed threshold.

b) Global high values for individual areas. Places not reaching the threshold limit value defined by parametric or non-parametric statistics are excluded. Based on a specific probability (*e.g.*, p=95%), it does not require full knowledge of the study area and typically uses relative data. It excludes places that do not reach the statistical threshold for the whole data set (*e.g.*, the 90th percentile, as in Ketels and Sölvell 2005).

c) Local high values for contiguous areas. This approach uses spatial autocorrelation to include surrounding areas and identify local high values. It cannot handle more than one variable. Global high values can be ignored, and so they are not calculated. Places not reaching the local threshold limit value (TLV) defined by the Local Indicators of Spatial Association (LISA-Moran´s local index) are excluded, even if they do reach the global TLV. Although absolute values may be used, studies only employ relative variables (*i.e*., Riguelle, Thomas & Verhetsel 2007).

d) Global high values for individual and contiguous areas. A recent study identifies in two stages high global values of both relative and absolute variables (Van Den Heuvel *et al.* 2012, VDH hereafter). In the first stage, areas are selected if their location quotient (LQ) is higher than one, or they are above the mean of the absolute values of the total sample. Unselected areas are discarded. In the second stage, contiguous areas previously selected are grouped for new calculations. Cutoff criteria of the user rather than values based on statistical significance may be applied at this stage (VDH 2012, 8). In their example, the 90^{th} percentile is used as cutoff for absolute values (only the top 10 percent of the areas qualify in this step). For LQ the cutoff value is 2 or the 90^{th} percentile, depending on which one comes first. If LQ =1.9 at the 90^{th} percentile, the cutoff is the last one indicating that LQ = 2 is at a level inferior to the top 10 percent (superior to the 90^{th} percentile). Local values measured by the LQs are expressed in terms of the national framework (global data set). Therefore, it excludes places that do not reach the global statistical threshold (the mean of the original sample or the 90th percentile). It handles more than one variable excluding areas in successive steps. In one of the successive steps, it suggests the mean as a threshold limit value. In statistics it is well documented that the mean is not an appropriate measure for asymmetric distributions.

e) Overlay analysis of high global and local values of individual and contiguous areas (this research). There are mixed versions of previous approaches using overlay analysis (Graw and Husmann 2014). They combine expert judgment and statistically defined criteria for relative and absolute variables. None of them, however, combine the concentration and agglomeration processes. The study by VDH (2012) recognizes the relevance of spatial autocorrelation to check for spatial concentration in neighboring areas (agglomerations in this research). However, it discards the local Moran´s Ii because it cannot handle more than one variable. This research on poverty shows that the use of spatial autocorrelation of several variables is not an issue when it is combined with non-spatial statistics by overlay analysis. Carroll, Reid & Smith (2008) had previously combined relative and absolute measures using cross-tabs for global high values of LQ (a local measure expressed in global-national terms) and local high values of magnitude (LISA). This idea may be extended to several variables if overlay analysis is used instead of cross-tabs. As in previous approaches based on statistics, the same degree of significance can be used for every case and it does not require a full knowledge of the study area.

3. Magnitude *versus* intensity?

Most direct questions about poverty refer to raw data or absolute values: what is the number of people in poverty? How many people in poverty are located in this specific area? These questions call for a number of people in the condition of poverty: there are 33,978 of the poor in Altamirano, Chiapas. Is this a high or low number? It is not possible to answer this question without a general framework in time and space. For this reason, most studies on poverty report results based on rates (Holt 2007, Partridge and Rickman, 2006). Rates are expressed as fractions or percentages of risk or probability to be in poverty. The numerator of the fraction is the number of have-nots and the denominator is the population at risk (of being poor), the total population, for example. Rates are very important in order to compare the information in time (past, present, future) and space (the population in Nuevo León versus DF). These comparisons would be hard or erroneous without using rates. Let’s use as a worked out example the municipios of the state of Aguascalientes.[4] From a quick check of the raw data, it seems that the problem of poverty is higher in the municipio of Aguascalientes than in Asientos since the first one has 242,510 poor and the second one 32,611 (Figure 1). However, expressing the number of the poor in terms of the total population (794,304 and 48,592, respectively) leads to the result that the poverty problem in Asientos is greater than in Aguascalientes: 67.1 cases per hundred people in Asientos against 30.5 cases per hundred people in Aguascalientes (Figure 2). Evidently Figure 1 is notably modified when the raw data (number of people in poverty) are expressed in terms of the total population. The unwritten rule is to use rates to compare the incidence of poverty in different areas (municipios), populations of unequal size, or different years (2000 vs., 2010).

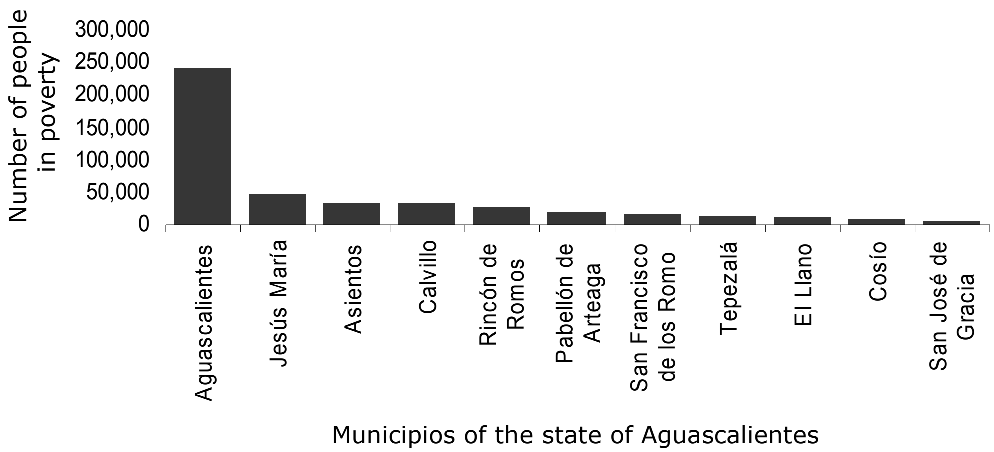
[4] The structure of this example follows the description in Matka (2011).

Table 1. Alternative procedures to identify concentrations of poverty.

Method	Technique	Characteristics & limitations			
Cutoff approach (i.e., Sedesol 2013)	Subjective or expert judgment.	It requires local knowledge. Relative and absolute data.	Limited comparability between different areas.	It prevents the identification of places that do not reach the arbitrary threshold. It cannot handle more than one variable.	Threshold limit values depending on the goal of the user of the method.
Global high values for individual areas (i.e., Ketels and Sölvell 2005)	Parametric/ non-parametric statistics-Aspatial statistics.	It does not require full knowledge of the study area. Relative data.	The same degree of significance can be used in every area.	It excludes places that do not reach the statistical threshold. It handles more than one variable.	Threshold limit values statistically determined (the 90^{th} percentile).
Local high values (i.e., Riguelle, Thomas & Verhetsel 2007)	Spatial statistics.	It does not require full knowledge of the study area. Relative data.	The same degree of significance can be used in every area.	Surrounding areas included. There are not global high values. It cannot handle more than one variable.	Threshold limit values statistically determined (LISA).
Global high values for individual and contiguous areas (i.e., VDH *et al*. 2012).	Aspatial statistics (LQ & mean) and cutoff of the user values for contiguous areas.	It does not require full knowledge of the study area. Concentration of Relative & absolute data.	The same degree of significance can be used in every area.	It excludes places that do not reach the global statistical threshold or the cutoff value of the user. Surrounding areas included in non-spatial calculations. It handles relative and absolute variables.	A cutoff value of the user or threshold limit values statistically determined (mean of the original sample & the 90^{th} percentile).
Overlay analysis of high global and local values of individual and contiguous areas (This research)	Spatial and aspatial statistics overlay.	It does not require full knowledge of the study area. Concentration & agglomeration of relative & absolute data.	The same degree of significance can be used in every area.	Integration of both global and local high values by overlay analysis. It can handle more than one variable.	Threshold limit values statistically determined (bootstrapped mean & LISA).

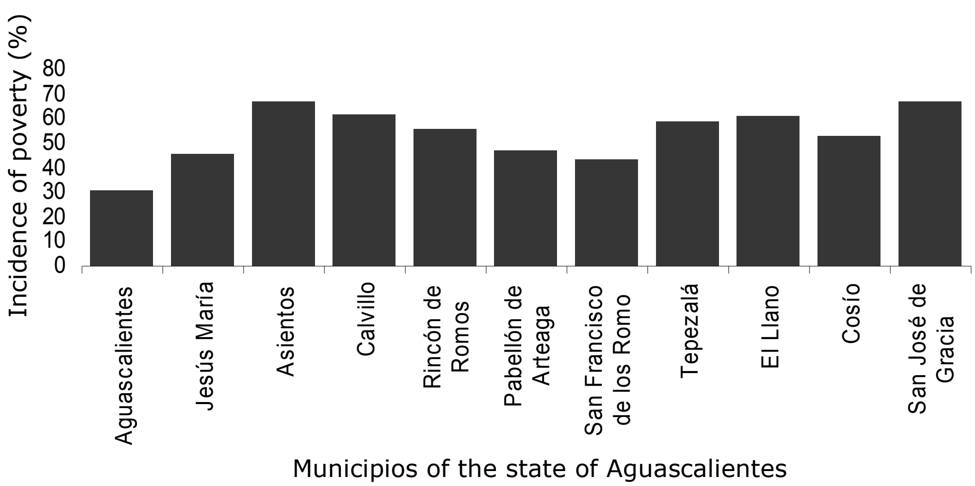
Source: Elaboration by the author.

Figure 1: State of Aguascalientes. Estimated number of people in poverty by municipio, 2010.



Source: Elaboration by the author.

Figure 2: State of Aguascalientes. Estimated percentage of people in poverty by municipio, 2010.



Source: Elaboration by the author.

Using rates demands two comments on spatial smoothing and size:
a. Spatial smoothing. Relative measures such as rates, percentages or location quotients (LQ) create a bias in favor of low populated areas that have most of their population in poverty. These "peaks" or instabilities in relative data may produce inexact or spurious results. The literature on spatial analysis suggests several alternatives to spatially smooth the peaks caused by the large variation in the incidence of poverty among

different municipios (Anselin *et al.* 2004). Among the procedures reviewed in the preparation of the research variable are the empirical Bayes standardization rate, suggested by Assuncao-Reis for the location quotient (excess rate in Geoda) and the Spatial Empirical Bayes Smoothing. It is important to keep in mind two things: (i) To avoid the spatial smoothing of a rate before calculating its spatial autocorrelation. Rate spatial smoothing creates data that are not independent from each other, a required precondition for the ANOVA embedded in several class classification procedures, such as natural breaks. (ii) If rates are used in spatial autocorrelation with the Assuncao-Reis option in Geoda, to be aware that the input data should not be spatially smoothed because they are smoothed by the statistical procedure itself. In this research, incidence is measured by rates or, more specifically, by "excess rates" (location quotients, LQ). The spatial smoothing version of LQ, the Focal LQ (Cromley and Hanink 2012), cannot be classified by conventional statistical procedures, such as natural breaks or deviations from the mean (the FLQ mapping in Liu (2013) is not statistically correct). On the other hand, the Assunçao-Reis option cannot be applied to LQ as input data. In this scenario, there are three alternatives to deal with the spatial smoothing issue:

— To use the raw rate as input data. In this case, the input data in the Assunçao-Reis option are people in poverty in each municipio and the base population is the total population in every municipio. Although this option is easy to apply in Geoda, the identification of the specific spatially smoothed raw rate equal to the national level is unclear. This option is not considered in the case study.

— To use spatial autocorrelation. LISA statistics for traditional LQs, since it creates values based on the pivoting area and its neighbors, operates as a spatial smoother (Liu 2013, 5). In this research, LISA for LQs is reserved to identify core areas of intensity.

— To use bootstrapping to identify the real location of the mean of the rate. This research uses the upper limit of the confidence interval of the bootstrapped mean, at a p= 95%, as a threshold limit value (TLV) for the concentration process. This option is more appropriate than using the mean of the raw data (original sample), not recommended for skewed distributions. At the TLV, the intensity of poverty should be above the national level (LQ>1).

b. Size matters. A high incidence rate does not guarantee the existence of a "critical mass" of poverty. The argument in favor of using rates does not exclude from the analysis the number of people in poverty. There are more poor (also more crime or sales of Coca-Cola) where more population is located. In general, high incidence areas are not the most populous, and vice versa: the most populated areas do not have the highest incidence rates. However, as a product of big numbers, the amount of poor in highly populated municipios with low incidence usually far exceeds the poor (and the total population) of low populated municipios with high incidence of poverty. Municipios not important in relative terms become relevant in absolute terms for the simple reason that the total population at risk of poverty is higher. The possibility exists that heavily populated municipios with a low poverty rate, therefore with a high number of poor, delete from the map municipios with a high poverty incidence but low total population. An example: 97.4 percent (2,196 people) out of the 2,256 residents of the municipio of San Juan Tepeuxila (Oaxaca) live in poverty. At the other extreme, only 8.7 percent (28,653 people) out of the 327,643 inhabitants of the Delegation Benito Juárez in the DF are poor. San Juan Tepeuxila, by the criterion of incidence, would have priority over Benito Juárez. However, the latter, by the criterion of magnitude, with an absolute number of poor 13 times the total municipal population of San Juan Tepeuxila, would have primacy in social policy.

There are no arguments by human rights advocates supporting the preference for incidence over magnitude, or vice versa. However, it should be considered that comparisons in absolute terms are misleading. If the absolute value of the poor in a place does not change in a given period, it could be concluded that social policies have had no effect. This conclusion may be wrong if the absolute number of poor people does not change as the population increases. In this situation, the public policy not only slows down poverty but it also decreases the proportion of people considered poor in the general population (population at risk of poverty). This reasoning explains that most studies on poverty suggest relative measures of poverty. They do not depend upon, or are influenced by, the size of the population (principle of population independence). Relative measures, on one hand, get rid of size related biases but, on the other hand, they overestimate the relevance of poverty in small absolute population areas. The benefits of relative data to compare areas should not rule out the spatial analysis of magnitude, the "localized consistence" as Maggioni and Riggi (2008, 56) call it. Otherwise, social policies to combat poverty would be incomplete because they will only be directed against intensity without considering the magnitude of the problem. All countries face a double challenge: to reduce the incidence as well as the volume of people in poverty.

4. Data and methods

All data on magnitude and intensity of poverty in 2010 come from CONEVAL (Consejo Nacional de Evaluación de la Política de Desarrollo Social). Magnitude is the number of people in poverty and intensity is the percentage of people in poverty within each municipio, as reported in CONEVAL.[5] A familiar measure of intensity, the location quotient, is obtained if the intensity in each municipio is divided by intensity at the national level. Having this information available, the identification of priority areas of poverty is a four-step process:

a. Global high value identification in the concentration process. Bootstrapping. Global high values are aspatial values beyond the upper limit of a confidence interval of the mean, for a determined probability (*e.g.*, p=95% for one tail).[6] Confidence intervals are not reliable if the data distribution is non-normal. After checking results from the usual tests of normality (*e.g.*, the significance of the skewness and the Kolmogorov-Smirnov test), this research applies two robust bootstrapping procedures to deal with problems of symmetry: the *bootstrap bias-corrected accelerated interval* and *bootstrap tilting interval* (BCa and Tilting, hereafter) (Chihara and Hesterberg 2011, 112 and Hesterberg *et al*. 2010, 16-19 and 16-32).

The starting point in bootstrapping is an original sample representing the population.[7] The resampling with replacement of the original sample creates a bootstrapping distribution that should be similar to that obtained with several samples from the original population (sampling distribution). The shape and spread of the bootstrapping distribution should resemble the sampling distribution. Bootstrapping does not solve problems of bias or skewness in the original data. Bootstrap percentile and bootstrap t-

[5] Intensity in this research is not any percentage. For example, the number of people in poverty located in each municipio as a percentage of the nation's population in poverty is a measure of magnitude rather than intensity. Results of calculations with incidence (percentage) or the LQ are the same because the denominator in the latter is fixed.

[6] There are several alternatives to identify global high values in non-normal distributions, such as box-plot charts or modified z-scores based on the median absolute deviation (z-MAD).

[7] Bootstrapping is used as a synonym of resampling with replacement. The metaphor taken from *The Surprising Adventures of Baron Munchausen* supports its meaning as "recovering yourself by your own effort."

intervals are not reliable if the bootstrap distribution is non-normal. Therefore, bootstrapping in general does not solve the problem of non-normality in the original data. Bootstrapping provides two robust options to address non-normal distributions, the BCa and Tilting procedures. The rule is quite simple: if your software provides them and your sample size is large (*e.g*., more than 100 cases), always use the BCa or Tilting for 10,000 resamples or more.[8] Both procedures produce similar results and improve accuracy of the confidence intervals by adjusting the percentiles to correct for bias and skewness (Hesterberg *et al*. 2010, 16-32). In normal distributions, all procedures produce similar results: bootstrap percentile intervals, bootstrap t-intervals, BCa and Tilting. In this research, all values beyond the upper limit at the p= 95% with one tail are considered high values (of magnitude or intensity). Bootstrapping is used in this research to identify global high values in the concentration process.

Why bother with bootstrapping when it is possible to use non-parametric procedures for asymmetric distributions, such as box-plot or z-MAD? Bootstrapping methods in practice usually work significantly better than non-bootstrapping methods. Additionally, bootstrapping makes inferences about the population whereas non-bootstrapping methods center on (are reduced to) the original sample.

b. Local high values (core areas) identification in the agglomeration process. Local spatial autocorrelation. Spatial autocorrelation is a statistical technique that measures the existence and strength of the interdependence between values of a specific variable in reference to the values of the same variable in the surrounding or neighboring areas. It is the correlation of a variable with itself through space, usually measured by the Moran´s I global index of spatial autocorrelation (Burt, Barber and Rigby 2009, 544). A variable is spatially autocorrelated if it exhibits a systematic pattern in its spatial distribution. This pattern may be zero, positive, or negative. Zero spatial autocorrelation is the null hypothesis. It suggests that the spatial pattern is random or the spatial variation of the data is unrelated to its geographic distribution. A positive spatial autocorrelation indicates that similar values (high or low values) tend to be co-located or to be more similar than those more distant. There exists positive spatial autocorrelation if similar data in intensity (or magnitude) are near each other. Negative spatial autocorrelation, on the other hand, indicates that dissimilar characteristics or values, as in a checkboard, tend to be near each other: high values tend to be surrounded by low values, and vice versa. These relationships are the base of the Moran's scatterplot (Anselin 1995, 1996 and Anselin *et al*. 2004). In the Moran's scatterplot, values in the x-axis are in standard deviation units, with mean zero and variance equal to one. In the y-axis are the spatially lagged values (values of the neighboring areas) of the standardized-x variable.

The Moran's scatterplot classifies the spatial autocorrelation in two categories: spatial agglomerations and spatial outliers (they should not be confused with global outliers beyond two standard deviations in descriptive statistics). Each quadrant in the diagram corresponds to a different type of spatial autocorrelation (Figure 3). The lower quadrant to the left (III) and upper quadrant to the right (I) indicate positive spatial autocorrelation, but of a different type. While quadrant III contains low value areas surrounded by low value areas (LL), quadrant I includes high value areas surrounded by high value areas (HH). These differences between quadrants I and III show that agglomerations identified by positive spatial autocorrelation may be hot spots (quadrant I) or cold spots (quadrant (III). In contrast, areas in the upper left (II) and lower right (IV) quadrants suggest negative spatial autocorrelation. Cases in quadrants II and IV are

[8] This study used SPLUS v.8.0 and the bootstrap library that provides BCa and Tilting. SPSS v.22 only provides BCa.

spatial outliers (not necessarily outliers in the two standard deviations sense). While quadrant II contains high values surrounded by low values, quadrant IV includes low values surrounded by high values. This description of spatial autocorrelation shows that local high values may be spatial outliers (HL or LH), hotspots (HH), and/or cold spots (LL).

The local Moran's index (Ii), a LISA measure (*Local Indicators of Spatial Autocorrelation*), provides the statistical significance of the individual observations in the Moran's scatterplot. Ii not only provides information on the statistical significance of cases in the spatial agglomerations (quadrants I and III) and spatial outliers (quadrants III and IV), but it also identifies non-statistically significant cases.

The statistical significance of I and Ii is confronted against the null hypothesis (H_0) of absence of spatial autocorrelation (the variable has a spatial random distribution). H_0 may be rejected or accepted under the NONO principle: NOn-significant, NOt rejected. For example, a *significant* I value at $p < 0.05$ indicates that the absence of spatial autocorrelation (H_0) is *rejected*. It is concluded that the spatial pattern of the variables is agglomerated in space. The software Geoda provides the Moran´s scaterplot and values and significance of the global Moran´s I and local Moran´s Ii.

Adaptation to the case study. All Mexican municipios, considering either their intensity or magnitude, may be allocated in the Moran's scatterplot (Figure 3):

(i) Core areas (hot spots) of poverty. High poverty municipios surrounded by high poverty municipios (HH: High-High),

(ii) Core areas of welfare (cold spots). Low poverty municipios surrounded by low poverty municipios (LL: Low-Low),

(iii) Islands of poverty (spatial outlier of poverty). High poverty municipios surrounded by low poverty municipios (HL: High-Low), and

(iv) Islands of welfare (spatial outlier of welfare). Low poverty municipios surrounded by high poverty municipios (LH: Low-High).

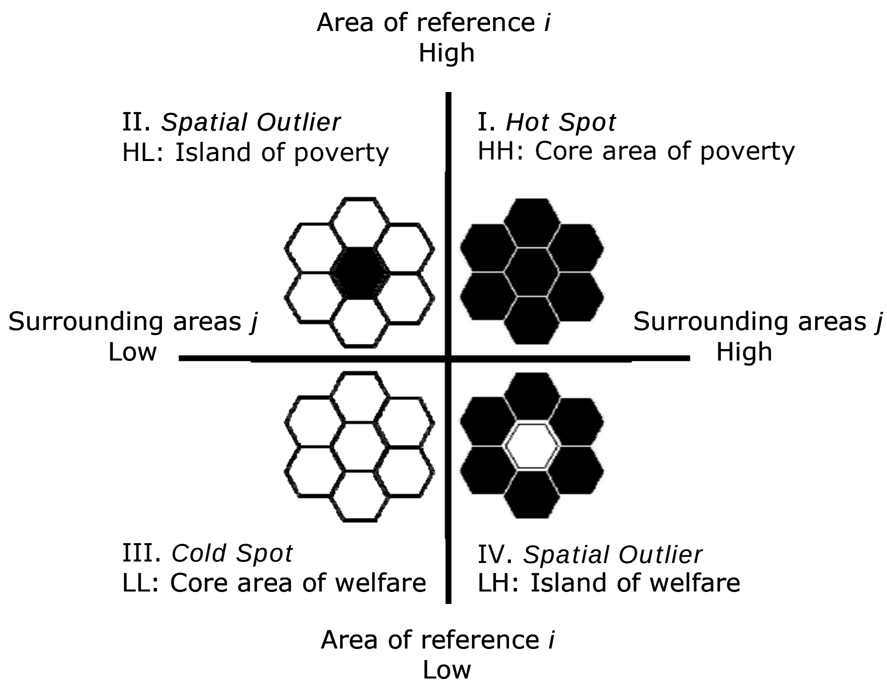
Municipios repeating the same letter in the previous classification (HH or LL) are core areas of high poverty or low poverty (high welfare). Municipios mixing letters (HL or LH) are individual areas different from their neighbors (spatial outliers). There is a fifth category that must be considered in this classification: municipios that are not statistically significant. Since the interest in this study is the identification of priority areas of poverty, the main research focus is on core areas of poverty (HH) and islands of poverty (HL), located in quadrant I and quadrant II, respectively.

c. Identification of conglomerates of intensity or magnitude. Thinking out of the box: overlapping global and local high values. Overlay analysis has already been used to integrate different variables of intensity (*e.g.*, education and poverty in Choudhury and Räder 2014) but, to my knowledge, it has not been used to integrate agglomeration and concentration. This integration is very important considering the fact that high values detected in the concentration analysis (by bootstrapping or descriptive statistics) may be undetected in the agglomeration analysis (by LISA in spatial statistics), and vice versa. High local values from the local viewpoint (spatial autocorrelation) are not necessarily high values from the national perspective (resampling).[9] Using the famous metaphor of the elephant and the six blind men, a recent criticism of spatial statistics illustrates the limitations of local knowledge in these terms: "[T]he mental images of the elephant in the minds of the blind men. . . . reflect local truths, and are indeed correct partially, but they did not reflect the whole of the

[9] It is important to note that the possibility of detecting local high values (hot spots and spatial outliers HL) increases if the original database is smoothed or standardized to decrease the influence of global outliers (Zhang, Luo, Xu and Ledwith 2008).

elephant" (Jiang 2014, 10). However, this criticism neglects that there are high local values undetected from the global perspective.

Figure 3. Daisies for LISA. Spatial taxonomy of poverty: Core areas and islands of poverty and welfare.



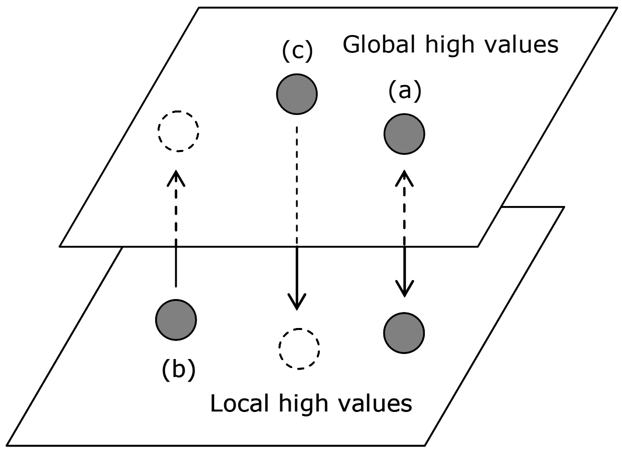
Source: Elaboration by the author based on Anselin (1995). The title "Daisies for LISA" tries to mentally associate the Moran´s scatterplot with LISA indicators.

These observations uncover the limitations of methodologies using only spatial statistics to identify agglomerations, such as the identification of urban centers and subcenters (Baumont, Ertur, and Le Gallo 2004) or only descriptive statistics, such as the identification of industrial clusters (Ketels and Sölvell 2005). They support the need for integrating both procedures (non-spatial statistics-bootstrapping and spatial statistics-spatial autocorrelation) to measure two different geographic processes (concentration and agglomeration) in absolute and relative terms.

Briefly, the approach in this research emphasizes that not all local high values are global high values nor all global high values are local high values (Figure 4). Global high values, identified by bootstrapping, have a statistically defined fixed threshold. On the other hand, local high values, identified with spatial autocorrelation, may exist if values are greater than their surrounding areas, even if they do not reach the global high value threshold. *Not all local high values are global high values because some local high values may not reach the fixed threshold of the global high values. Not all global high values, in turn, are local high values if they are not greater than those in their surrounding areas. This is the case even if global values do reach the global high values threshold*.

In fact, global high values have three potential embodiments (Figure 5): (i) they may be parts of cores if they *overlap* with local high values; (ii) they are the periphery when they are *contiguous* to the core defined by local high values, integrating conglomerates of poverty; and (iii) they may also be *anywhere* in the rest of the country as areas of high concentration of poverty.

Figure 4. Global and local high values spatial mismatch.



(a) Spatial overlapping of global and local high values.

(b) Local high values not reaching the statistical threshold for global high values.

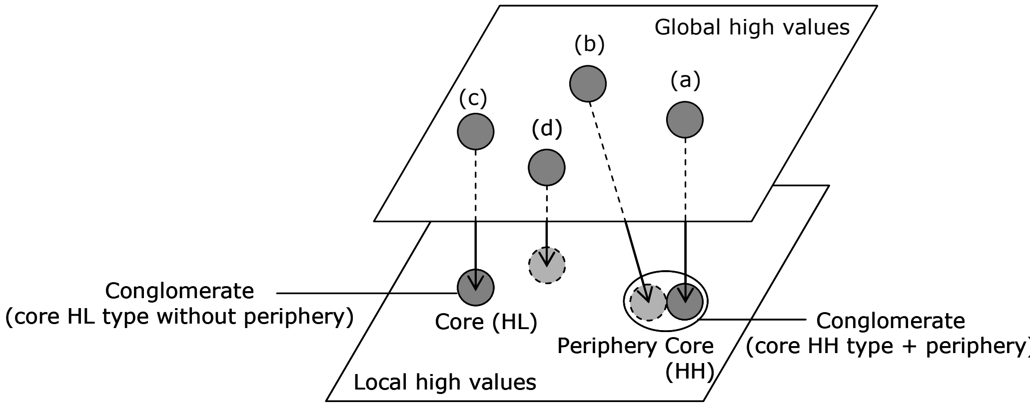
(c) Global high values not greater than those in their surrounding areas, even if they do reach the global high value threshold.

Source: Elaboration by the author.

At this point it is clear that spatial autocorrelation, although it does not require full knowledge of the area of study and the same degree of significance can be used for all regions (Riguelle, Thomas and Verhetsel 2007, 200), does not handle the potential absence of global high values in core areas and islands of poverty. The possibility that global high values are not necessarily local high values [cores (HH) and islands of poverty (HL)], and vice versa, calls for an integration of both spatial processes. It would be absurd to include an area important from the local viewpoint and exclude others that are relevant from the national perspective. The opposite also applies: it is not reasonable to include an area important from the national perspective but exclude another that is relevant from the local viewpoint. The identification of conglomerates of intensity, on one side, and magnitude, on the other side, is accomplished by overlapping global high values and local high values (HH and HL). The overlay analysis in Geographic Analysis Systems mathematically integrates (*e.g.*, by intersection, union) the concentration and core area layers to create a new map layer containing the resulting conglomerates. Core areas (local outliers HH or HL) add to their periphery contiguous global high values to form conglomerates.[10] This procedure is first performed for relative values. Then, as a separate and independent task, the analysis is repeated for absolute values. The literature review in this research presents the high values overlay analysis in comparison to the most common procedures on spatial patterns of poverty (Table 1).

[10] "Conglomerate" is meant to refer to "grouped areas of high values" instead of "agglomeration" (used to describe a spatial process), "hot spot" (reserved for high values surrounded by high values in spatial autocorrelation) or cluster (widely used in productive chains or advanced non-spatial statistics).

Figure 5. Identification of conglomerates combining the concentration and agglomeration processes.



Source: Elaboration by the author.

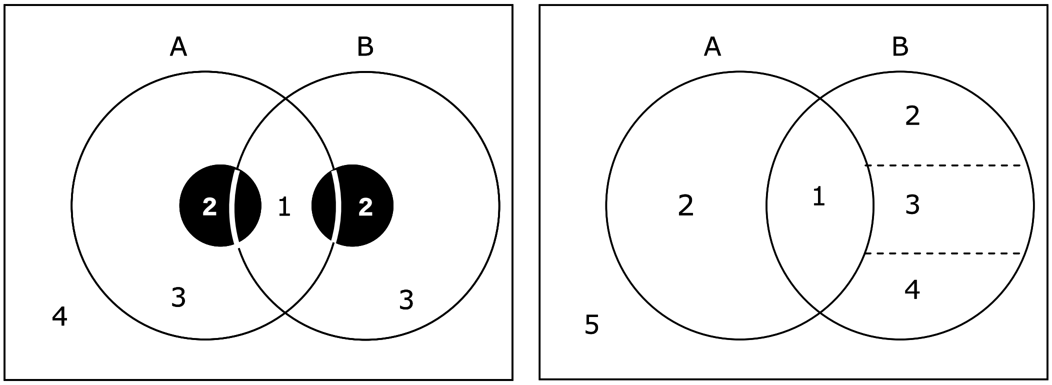
—Global high values are statistically significant cases identified by bootstrapping.
—Local high values are statistically significant cases identified by permutations of the local Moran's I (Ii).
—Global high values may overlap with local high values surrounded by local high values (hot spot or HH type observations, as in case (a)) or spatial outliers (HL type observations, as in (c)).
—Cores areas are HH and HL values; overlapped global high values are also core areas.
—Global high values (not locally significant) may surround HH or HL observations. These global high values are the periphery (as in case (b)). Global high values located anywhere else in the country are just areas of high concentration of poverty (as in (d)).
—Conglomerates may have core & periphery or just core (seldom but possible).

d. Highest priority areas identification by overlapping conglomerates of magnitude and intensity. This step applies Venn diagrams to represent conglomerates of intensity and magnitude. The highest priority areas are where these two subsets intersect with each other (Figure 6). The identified areas contain conglomerated high values in both magnitude and intensity. This is the main reason to give them the highest spatial priority (Priority one).

e. Spatial relevance of non-intersecting areas *within* the conglomerates. Once municipios in the intersection zone are identified, the remaining areas inside each conglomerate may be stratified. This stratification provides a classification of areas complementing the highest priority municipios. Both the identification of the highest priority areas and the stratification of non-intersecting areas provide a spatial hierarchy that may guide the allocation of social resources, decision-making in public policy or future studies on the spatial pattern of poverty.

At least three alternatives to stratify or assign priority to conglomerated areas outside the intersection stand out from the available class classification procedures: core and periphery values, natural breaks, and heads and tails (Figure 6):

Figure 6. Alternative procedures to assign priority values to non-intersecting conglomerates of intensity (A) and magnitude (B). Numbers inside the circles indicate relevance or priority.



(a) Core-Periphery values.

(b) Head and tails procedure or natural breaks. Strata and priority identified with numbers are indicative.

Source: Elaboration by the author.

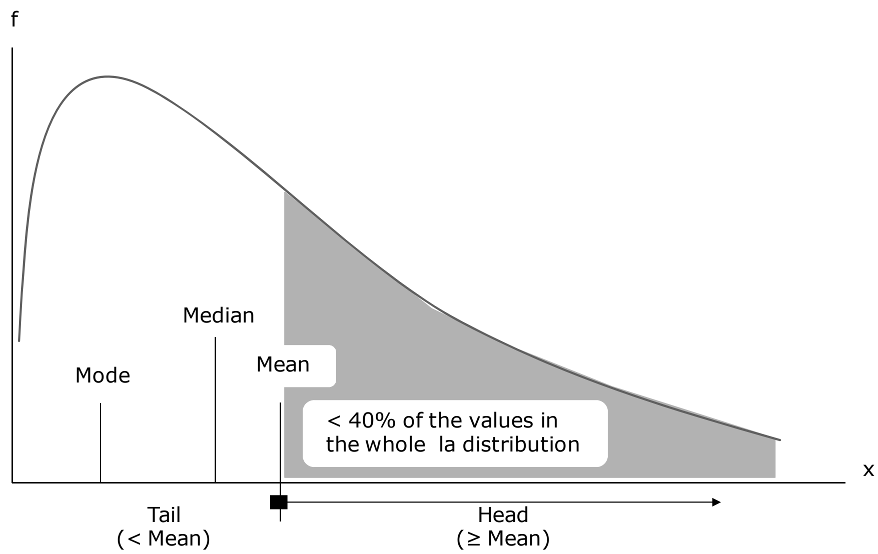
Core and periphery values (Figure 6a). This option is similar (not equal or equivalent) to that suggested in Batey and Brown (2007):
—Priority 1 is for areas in the intersection, as stated above.
—Priority 2 is for areas in the agglomerations of intensity (A) and magnitude (B): areas HH or HL in the conglomerate outside the intersection area (Priority 1). These agglomerated values are identified by spatial autocorrelation.
—Priority 3 is for concentrating (high value) areas not overlapped with priority 2 areas but surrounding them. These concentrating values are identified by bootstrapping.
—Priority 4 is for not conglomerated global high value areas. These are the non-concentrating nor agglomerated values.

Natural breaks or classification of Jenks (Figure 6b). This procedure focuses on the breaks or gaps in the observed data to group the cases in classes. Based on statistical interactions (Jenks' optimization), this method finds the best class classification by minimizing the distance of similar values inside each class and maximizing the distance between classes. Although this method requires a normal distribution, it generally applies to skewed information using a previous data standardization or transformation and temporary manipulation of outliers.

Heads and tails (h/t, Figure 6b), as in Jiang (2014). Main steps in this method specially designed for heavy-tailed distributions are:
—Find the mean of the whole array of (absolute or relative) values. In a right-skewed distribution, values equal to or above the mean are the head and those below the mean are the tail. Notice that the terms "heads" and "tails" refer to the rank-size distribution rather than the probability density function (PDF). The head contains a minority of the large data values whereas the tail a majority of the small data values (Figure 7).

—Values in the head are divided again based on the arithmetic mean in that segment into many small values and a few large values.
—The process continues for every successive head identified in the previous step until the proportion of values in the head and tail become balanced or there are no more values to subdivide.
As a rule of thumb, “the percentages of the heads must be less than 40 percent. This condition can be relaxed for many geographic features, such as 50 percent or even more, if the head retains less than 40 percent in subsequent hierarchical levels” (Jiang and Yin 2013, 8).

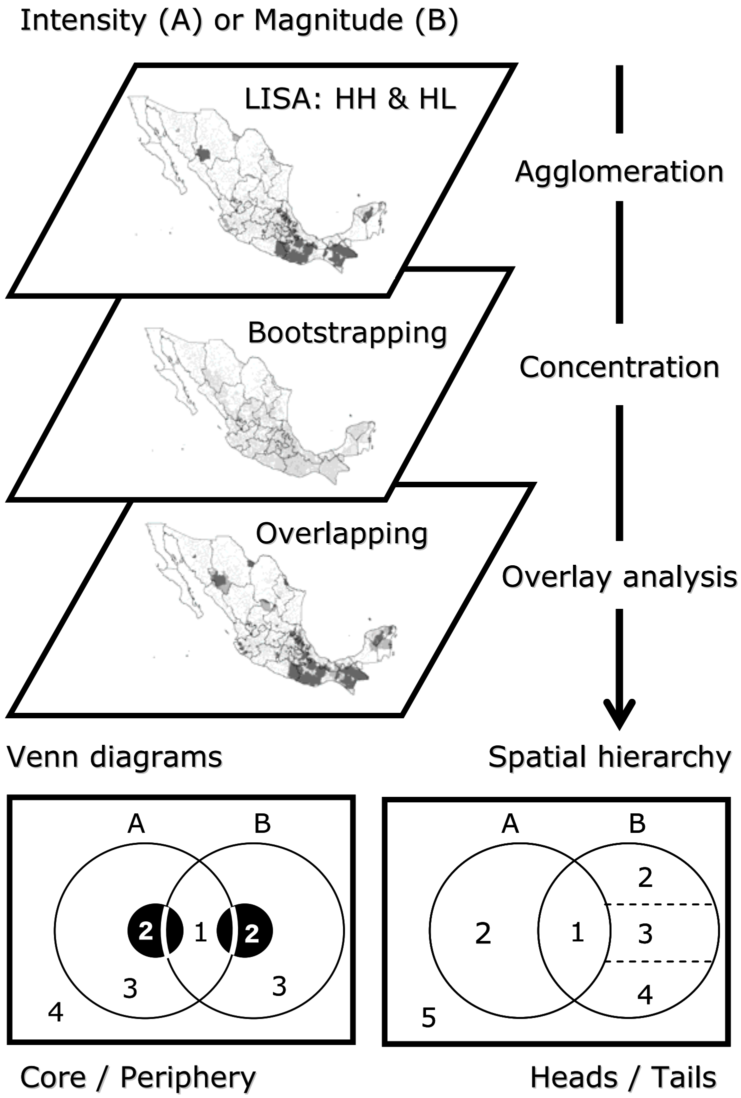
Figure 7. “Heads” and “Tails” in the heads/tails breaks procedure for a right-skewed distribution.



Source: Elaboration by the author based on Jiang (2014). Notice that the “head” in this chart corresponds to the “tail” in the Gaussian distribution.

In the example for the h/t procedure based on the Mexican case study (Figure 6b), the intensity out of the intersection zone is Priority 2 because it is not subdivided into classes. On the other hand, non-intersected conglomerated areas of magnitude are Priority 2, Priority 3, and Priority 4. All remaining areas outside the conglomerates have Priority 5, regardless of their intensity or magnitude values.
In all cases, results may be confronted with cutoff criteria, such as that used by SEDESOL (2013) or mixed criteria (Graw and Husmann 2014). Results also may be compared with some variations of current procedures. As an example, if standardized data had been used in magnitude, the number of core areas may have increased.

Figure 8. Methodological outline to identify the spatial hierarchy of poverty.



Processes and procedures to identify agglomerations of intensity (A) and magnitude (B). Numbers indicate order of priority. Areas located in the intersection area have the highest priority. In the core/periphery diagram, while the black-filled circles are the core, the non-filled area inside each Venn diagram is the periphery. In this example of the non-intersecting area in the heads/tails procedure, while magnitude is stratified in three classes, intensity is classified in one single class.

Source: Elaboration by the author.

5. Case study. This section reports results with the procedure outlined in the methodological section. It has three main parts. Following the steps in Figure 8, intensity comes first. It is expressed by the location quotient (LQ). Bootstrapping is applied to identify the statistically significant global high values of intensity. This statistical procedure identifies global high values regardless of their location, as a result of the concentration process of the poverty. Bootstrapping is applied to all 2,456 observations, as suggested by Tian (2013) in his alternative option to the standardized location quotient (SLQ) procedure suggested by O'Donoghue and Gleave (2004).[11] In the case of the LQ, it does not make sense to consider as "high value" a quotient lower than one. This research verifies that the resulting threshold value of the upper limit of the bootstrapped mean is always higher than one. All bootstrapped LQs reported as high values should be equal to or higher than one.

Spatial autocorrelation identifies the spatial agglomeration of local high values (core areas recognized as HH and HL values). Both global and local high values represent the process of concentration and agglomeration, respectively. Values for these two processes are overlapped to identify conglomerates of intensity. The second part follows the same steps to identify conglomerates of magnitude. The final section overlaps conglomerates of intensity and conglomerates of magnitude creating a spatial hierarchy. The highest priority areas of poverty locate in the intersection zone. The remaining conglomerated areas (those out of the intersection zone) are stratified following the "heads and tails" procedure recently suggested by Jiang (2014). The final product is an integrated territorial order resulting from simultaneously combining concentration and agglomeration of absolute and relative values of poverty.

Magnitude and intensity. As it is observed in the methodology, most people in poverty live in areas of low intensity of poverty (Figure 9). Therefore, it is expected that most clusters of intensity are different from clusters of magnitude. High values of intensity are in low magnitude municipios. In contrast, a large number of populations in poverty live in areas with low or moderate intensity. Areas of high intensity of poverty capture only a small number of people in poverty. As Visvalingam (1983) observed three decades ago, these lines show that spatially targeted policies based solely on intensity (relative measures, such as percentages, proportions or rates) magnify the problem in small populations and neglect the mass of people in poverty. On the other hand, antipoverty spatial policies based only on magnitude (absolute numbers) discriminate against the high proportion of people in poverty of small populations. Hence, area-based policies require simultaneously combining both relative and absolute values in a single territorial classification.

Intensity (LQ). *Agglomeration process and core areas. Spatial autocorrelation*. The global Moran´s index (I) for intensity (LQ), using a matrix of contiguity queen type, does not accept the null hypothesis of randomness (Figure 10). The global index I indicates that the intensity of poverty is spatially concentrated in the country ($I= 0.6796$; $p= 0.0001$; for 9,999 permutations). The local Moran's index (I_i), with a probability of $p < 5\%$, identifies 565 core areas of intensity (HH) and 20 islands of poverty (HL) (Figure 11). Although municipios of the type HH and HL are different, this research refers to both of them as core areas for practical reasons; they are core areas of potential conglomerates of poverty.

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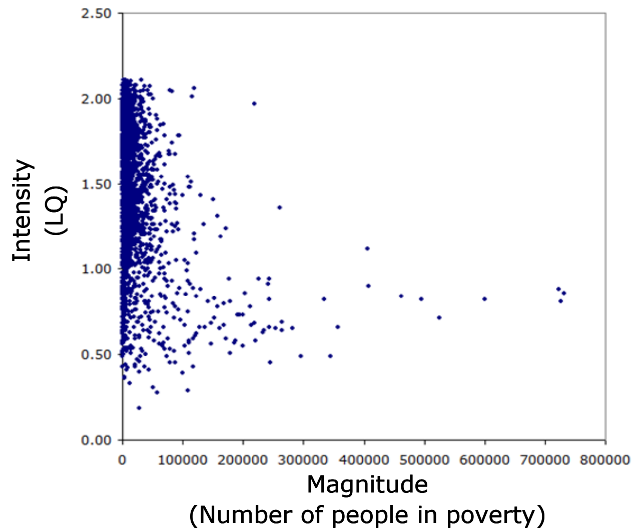
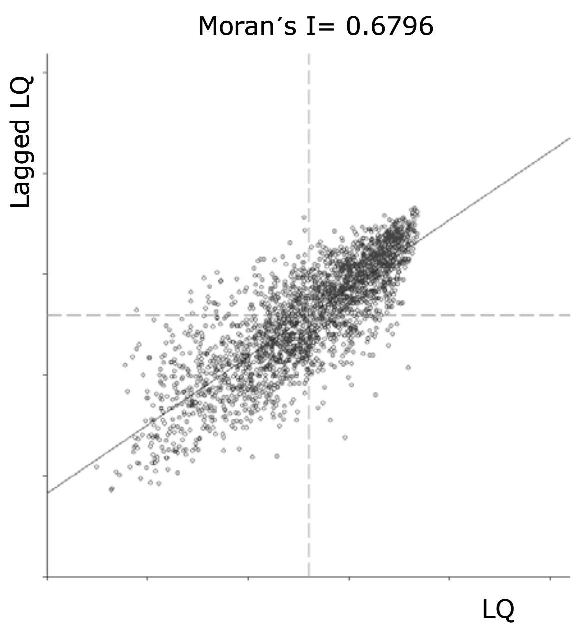
[11] It should be noted that Tian (2013) considers bootstrapping *in general* as an alternative to the SLQ. As stated in the methodology, bootstrapping does not correct skewness in the original sample. The significance for skewed distributions requires using the BCa or Tilting robust options because the bootstrap percentile and bootstrap t-intervals are not reliable for non-normal distributions.

Figure 9. LQ of people in poverty (intensity) against number of people in poverty (magnitude).



Source: Elaboration by the author.

Figure 10. Moran's scatterplot for incidence of poverty.

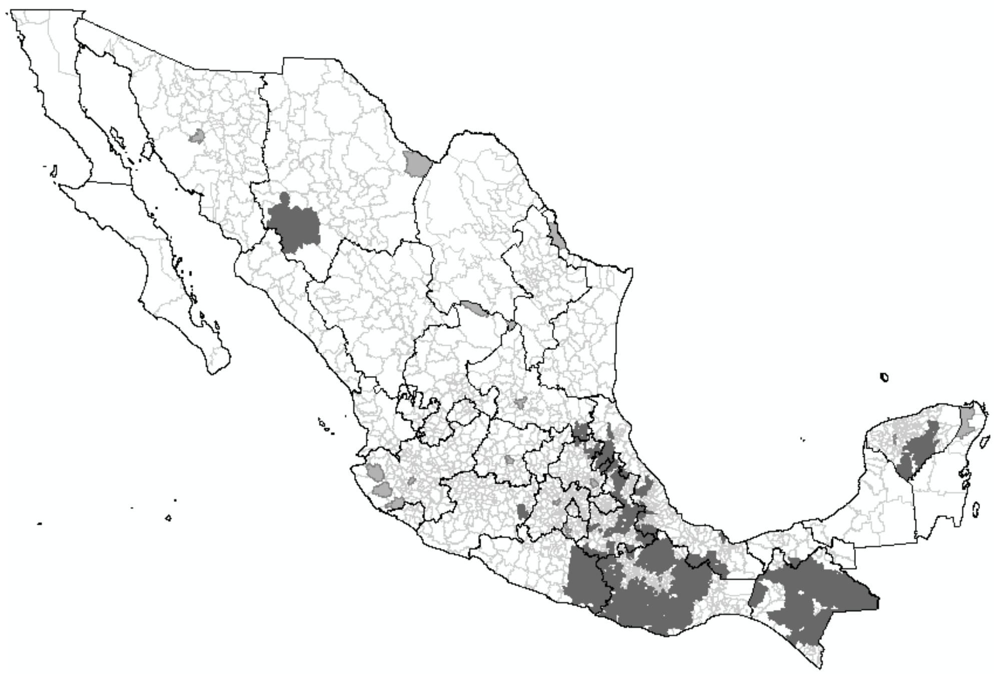


Source: Elaboration by the author.

Most core areas of intensity are located in the South of Mexico, Sierra de Puebla, Sierra Tarahumara and some municipios in the southeast of the country (Figure 11). These areas are the seed or starting point for the identification of conglomerates of intensity.

The periphery of these core areas (and some additional areas not included in conglomerates) is provided by global high values from the concentration process; they are obtained by bootstrapping the mean of the LQ values.

Figure 11. Core areas (HH-dark gray and HL-light-gray) of intensity (LQ).



Source: Elaboration by the author.

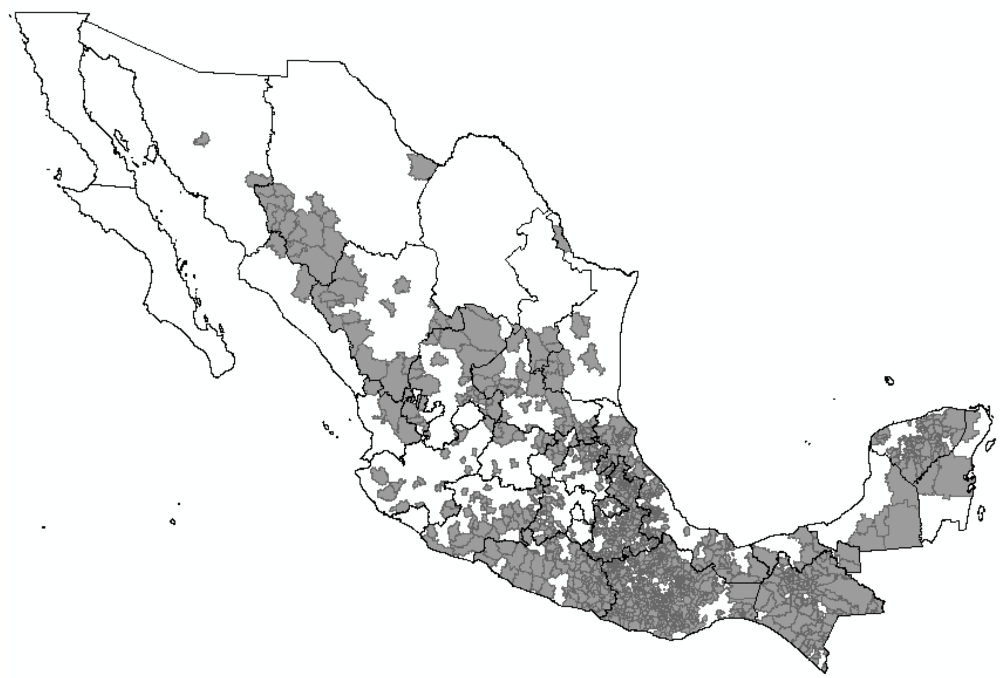
Concentration process. Bootstrapping. Most direct procedures to find the upper limit of the confidence interval of the mean are either BCa or Tilting. Since both values are similar, the case study takes results from Tilting, the most refined option of the two robust procedures. In the case of incidence, the bootstrapping value for Tilting at the 95% in the right tail, for 10,000 replications of the mean of the initial 2,456 cases, is LQ= 1.4705 (Table 2). There are 1,303 municipios above this value (their indicative geographical location is in Figure 12). Some of the global high values match core areas, some others are their periphery or they are merely non-agglomerated high-concentration areas in the rest of the country.

Table 2. Bootstrapping results for intensity of poverty (LQ) for 10,000 replications of the mean.

```
BCa Confidence Intervals:
          2.5%       5%      95%    97.5%
Param 1.441491 1.443803 1.470356 1.473037

Tilting Confidence Intervals:
          2.5%       5%      95%    97.5%
Param 1.441308 1.443891 1.470503 1.473012
```

Source: Calculations by the author.
All 2,456 cases are included. If only cases for LQ ≥ 1 are considered, the critical value is 1.59 at the 95% of confidence in the right tail for the Tilting option. Since the national average (the denominator) in LQ is based on all cases, it is considered convenient to take the result of bootstrapping for the whole dataset rather than just for cases where LQ ≥ 1.

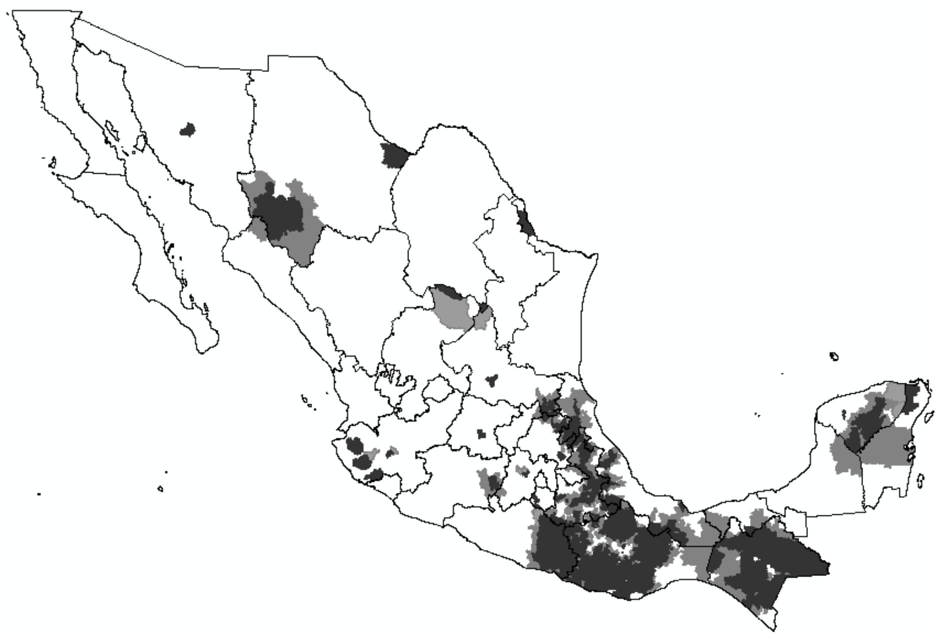
Figure 12. Global high values identified by bootstrapping the mean of intensity (areas with LQ≥ 1.4705).



Source: Elaboration by the author.

Overlapping concentration and agglomeration. The overlay analysis integrates core areas (local high values HH and HL) and global high values to produce conglomerates of intensity (Figure 13). In the overlay analysis, all core areas (HH) create conglomerates but it is not necessarily the case for all islands of poverty (HL). The overlay analysis identifies conglomerates of intensity in two steps (Figure 13):
a. Setting up core areas. Intersection of HH and HL areas with LQ≥ 1.4705. Core areas are defined by the HH and HL values. The map integration identifies global high values that also are core areas because they match to local high values. In this layer overlay unmatched HH and HL values are core areas anyway.
b. Identification of conglomerates. A conglomerate is a set of core areas and their periphery. The periphery is identified by the union of HH and HL areas (dark gray areas in Figure 13) with their neighboring global high value areas (light gray areas, where LQ ≥ 1.4705). As it stated in the previous step, global high values matching HH and HL values are considered core areas.

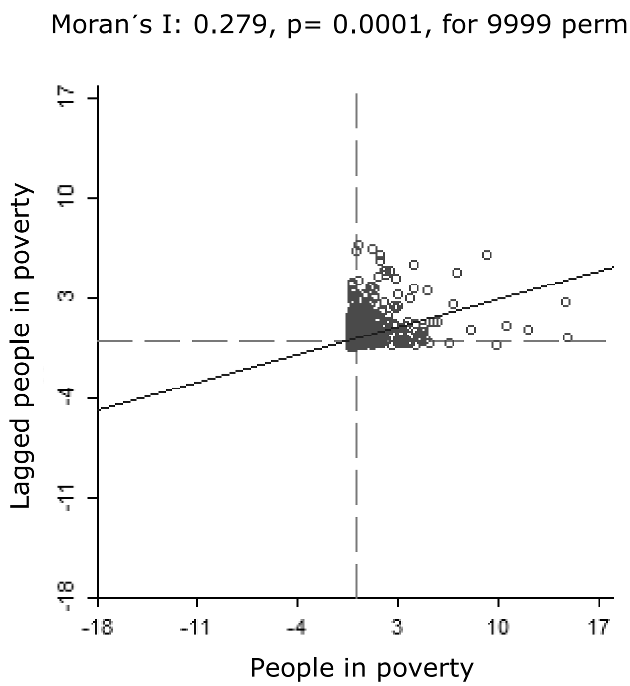
Figure 13. Conglomerates of intensity. Core areas (spatial autocorrelation) and their peripheries (bootstrapping).



Source: Elaboration by the author.
Conglomerates of intensity identified by overlay analysis. Cores (HH and HL) in dark-gray color and peripheries in light-gray color).

Magnitude. *Agglomeration process and core areas. Spatial autocorrelation*. The methodological steps are the same in magnitude and intensity but results at the local level are different. The global Moran's index (I) for magnitude (number of people in poverty), using a matrix of contiguity queen type, does not accept the null hypothesis of randomness (Figure 14). The global index I indicates that magnitude of poverty is spatially concentrated in the country (I= 0.279; p= 0.0001; for 9,999 permutations). The local Moran´s index (Ii), with a probability of p >5%, identifies 146 core areas of magnitude (HH) and 12 islands of poverty (HL) (Figure 15).
Most core areas of magnitude are located in highly populated areas, such as capital cities (Figure 15). The periphery of these core areas (and some additional non-agglomerated areas) is provided by global high values from the concentration process; they are obtained by bootstrapping values of the mean of magnitude (Figure 16).
Concentration process. Bootstrapping. Spatial pattern of magnitude for municipios with population equal or higher to 23,232 persons in poverty. Most direct procedures to find the upper limit of the confidence interval of the mean are either BCa or Tilting. Since both values are similar, the case study takes results from Tilting. In the case of magnitude, the bootstrapping value for Tilting at the 95% in the right tail, for 10,000 replications, is 23,232 (Table 3). As in LQ, bootstrapping calculations are for all 2,456 cases. There are 534 municipios above this value (Figure 16). It is no surprise that the global high values of magnitude are the most populated areas. The result would be the same for Coca-Cola sales or any other variable directly related to population. A similar pattern is confirmed for the agglomeration process of absolute values of poverty. Although these results are redundant, they are a valuable resource in identifying potential intersections between intensity and magnitude.

Figure 14. Moran's scatterplot for magnitude of poverty.



Source: Elaboration by the author.

Table 3. Bootstrapping magnitude of poverty for 10,000 replications for all 2,456 cases.

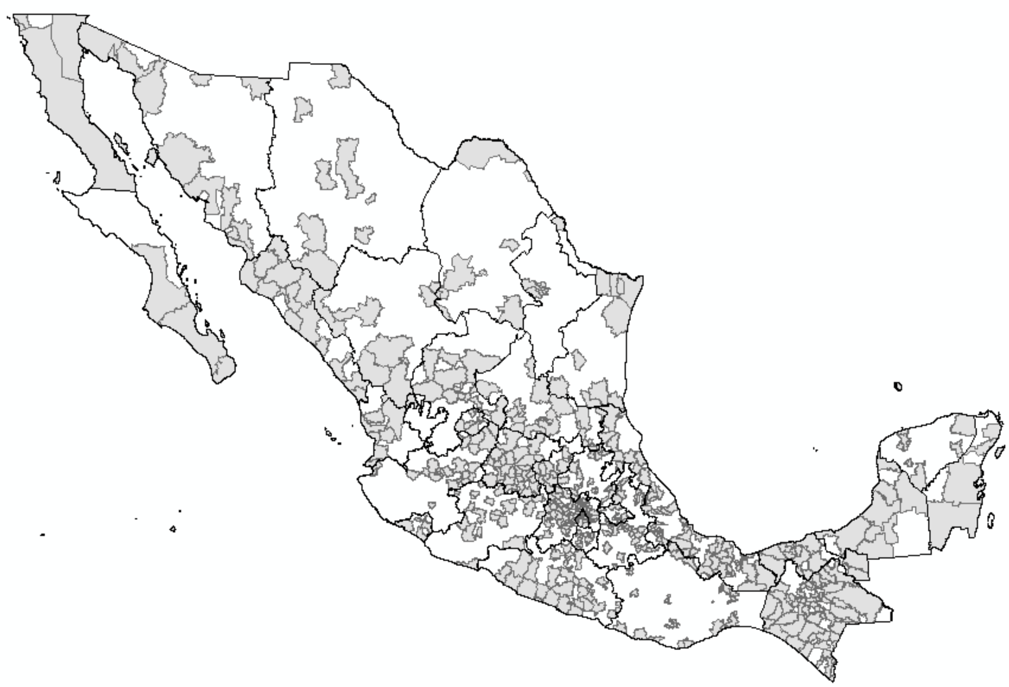
```
BCa Confidence Intervals:
          2.5%       5%      95%    97.5%
Param 19525.34 19791.86 22974.28 23350.45

Tilting Confidence Intervals:
          2.5%       5%      95%    97.5%
Param 19209.42 19581.13 23231.84 23513.95
```

Source: Calculations by the author.

Figure 15. Core areas of magnitude (HH and HL)

Source: Elaboration by the author.

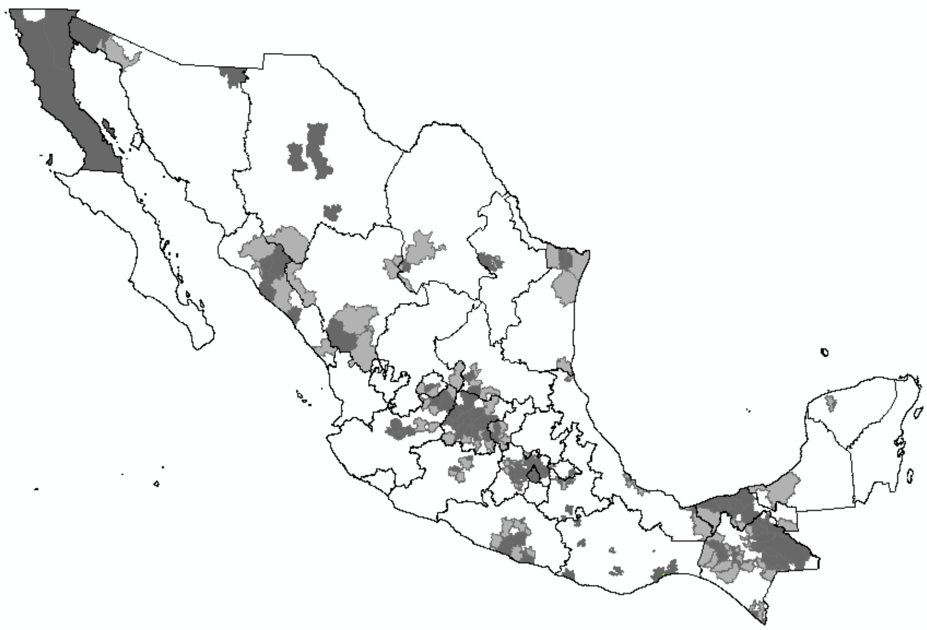
Figure 16. Global high values identified by bootstrapping the mean of magnitude (areas with population in poverty ≥ 23,232).



Source: Elaboration by the author.

Overlapping concentration and agglomeration. The overlay analysis integrates core areas (HH and HL) and global high values to produce conglomerates of magnitude (Figure 17). In the overlay analysis, all core areas (HH) create conglomerates, but this is not always the case for all islands of poverty (HL).

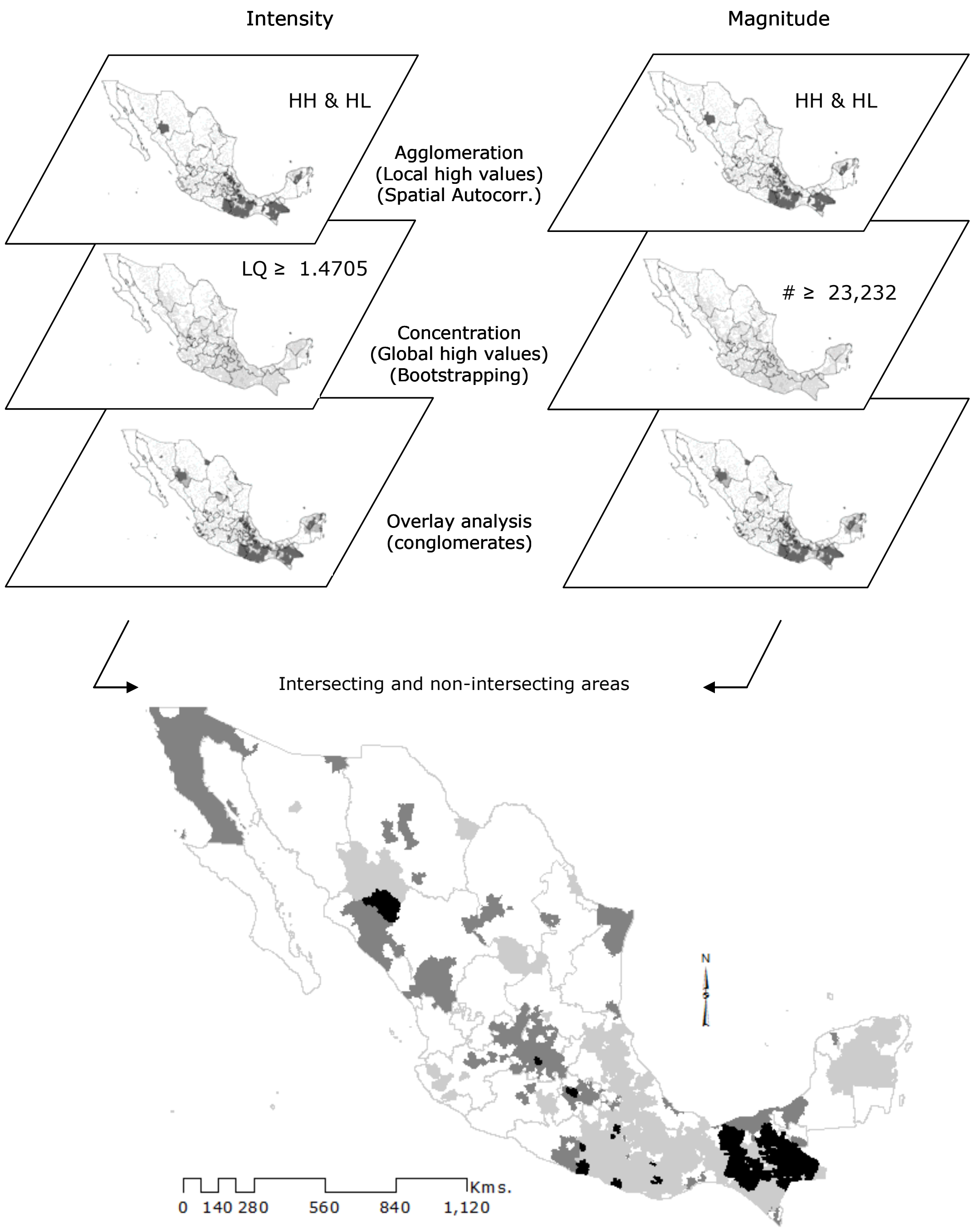
Figure 17. Conglomerates of magnitude. Core areas (spatial autocorrelation) and their peripheries (bootstrapping).



Source: Elaboration by the author.
Conglomerates of magnitude identified by overlay analysis. Cores (HH and HL) in dark-gray color and peripheries in light-gray color).

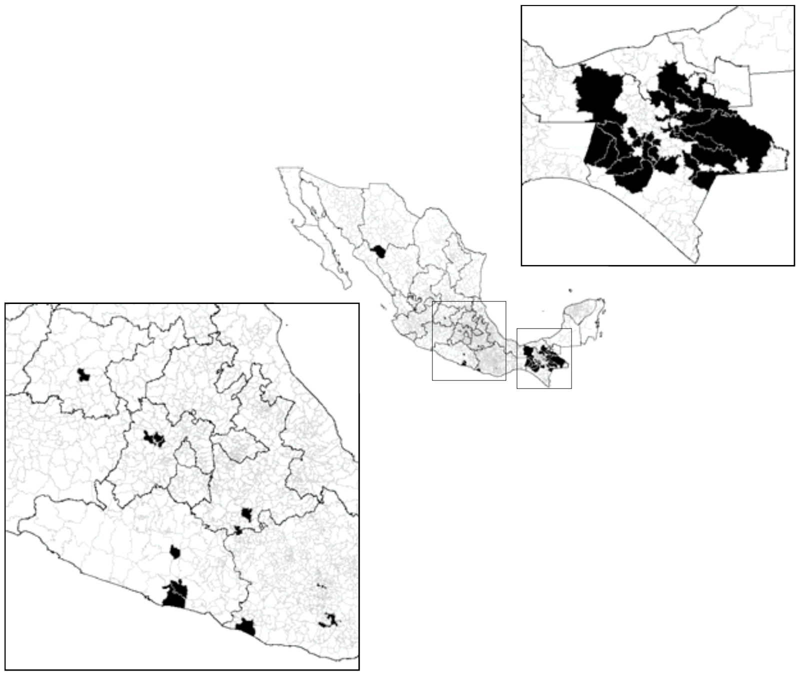
The overlay analysis identifies conglomerates of magnitude in two steps (Figure 17):
a. Intersection of HH and HL areas with the number of people in poverty ≥ 23,232. This step integrates into a single map matching local and global values and unmatched local high values. And,
b. Union of HH and HL areas (dark gray areas) with their neighboring high global value areas (light gray areas, where the number of people in poverty ≥ 23,232).
Highest priority areas. *Overlapping conglomerates of intensity and magnitude*. Once conglomerates of intensity and magnitude are identified, it is possible to identify and sort out areas of poverty. This section overlaps these two conglomerates of relative (Figure 13) and absolute (Figure 17) data to identify the highest priority areas of poverty. The whole procedure is sketched in Figure 18. Results register 44 highest priority areas (Priority 1), located in nine states: Oaxaca, Chihuahua, Veracruz, Guerrero, Guanajuato, Puebla, México, Tabasco and Chiapas (Figure 19 and Table 4). Twenty eight out of the 44 priority municipios are in Chiapas (about 65%). These 28 areas contain 70% (1,874,943) of the population in poverty located in the highest priority areas (2,678,769).

Figure 18. Overlay analysis for conglomerates of intensity and magnitude.



Source: Elaboration by the author.
Conglomerates of magnitude (dark gray color), conglomerates of intensity (light gray color), and areas of intersection of both conglomerates (black color).

Figure 19. Location of the forty-four highest priority areas of poverty in Mexico.



Source: Elaboration by the author.

Non-intersecting areas. In this work, conglomerates are the result of overlapping concentration (non-spatial) and agglomeration (spatial) of high values of intensity or magnitude. These conglomerates *per se* are important areas of (relative or absolute) poverty. It seems reasonable to assign the highest spatial priority for social policy to the intersection area of both conglomerates (urgent areas or priority one). Since remaining municipios (not intersected) in the conglomerates of intensity or magnitude are also significant, they are stratified to suggest some spatial hierarchy for the decision-making process.[12]

Core and periphery (c/p) procedure. Assigning spatial priorities to the Mexican municipios based on the core and periphery values is straightforward. Non-intersecting core or periphery values (priority 2 and 3, respectively) may be directly obtained from the overlapped maps (Figure 20 and Figure 21). As it is expected, core areas of intensity and their peripheries (conglomerates of intensity) cover more area of the country and locate in less populated areas than those of magnitude that include the main metropolitan areas. Non-intersecting cores and peripheries have Priority 2 and Priority 3, respectively, in both intensity and magnitude because both characteristics of poverty are equally important.

Natural breaks and heads and tails (h/t) procedures. These procedures need some previous statistical observations. In the presence of skewness and outliers, the natural breaks procedure (also known as the goodness-of-variance-fit (GVF) method) requires modifications. Outliers should be temporarily excluded in order to apply natural breaks to the previously transformed data (*vgr*., logs, square roots or inverse values). Once the

[12] The database for all non-intersecting areas of magnitude and intensity are available from the author upon request.

class classification is obtained by natural breaks, outliers are reintegrated to the lowest or the highest stratum obtained (Crews and Peralvo 2008, 70). Additionally, if the distribution is skewed, the Goodness of Absolute Deviation Fit (GADF) rather than GVF should be used to evaluate the stratification.

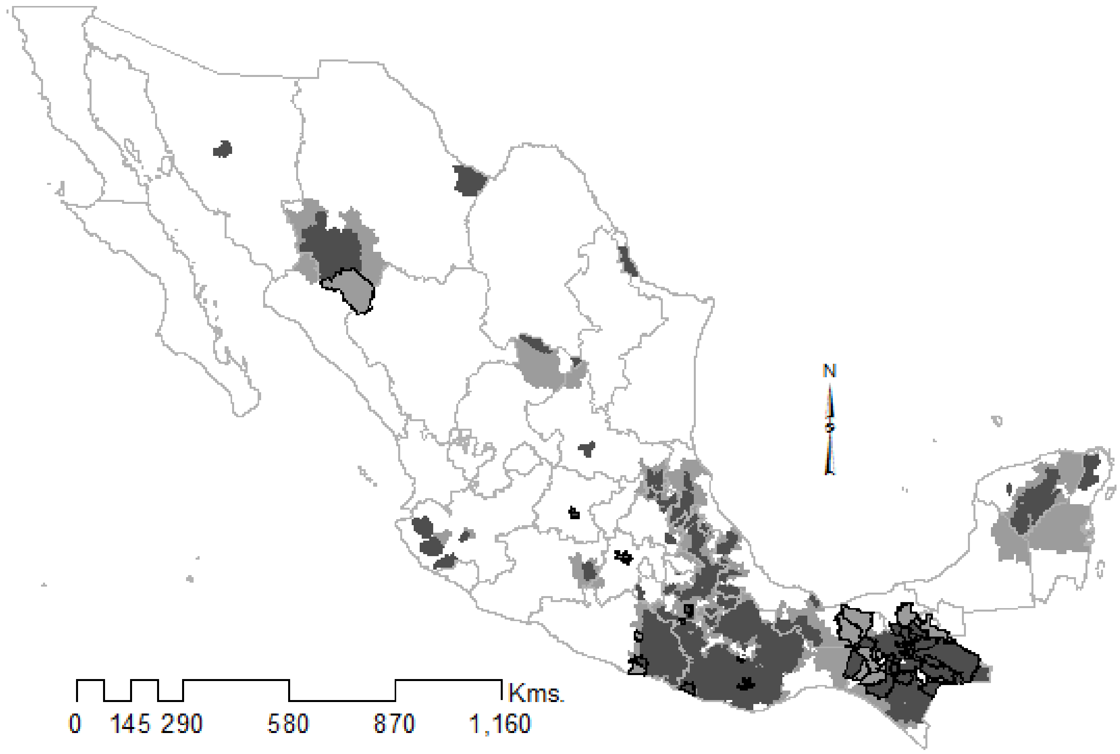
Table 4. List of the forty-four highest priority areas in Mexico.

Priority areas of poverty

Municipality	State
Huimanguillo	Tabasco
Tacotalpa	Tabasco
Macuspana	Tabasco
Temoaya	Mexico
Jiquipilco	Mexico
Ixtlahuaca	Mexico
Acatlán	Puebla
Sta. Cruz de J. R.	Guanajuato
San Marcos	Guerrero
Tecoanapa	Guerrero
Tixtla de Gro.	Guerrero
Las Choapas	Veracruz
Gpe. y Calvo	Chihuahua
V. de Zaachila	Oaxaca
Miahuatlán de P.D.	Oaxaca
S. Pinotepa Nal	Oaxaca
La Trinitaria	Chiapas
Ocosingo	Chiapas
Tuxtla Gutiérrez	Chiapas
Chiapa de Corzo	Chiapas
Tecpatán	Chiapas
San Fernando	Chiapas
Ocozocoautla de Espinosa	Chiapas
Chilón	Chiapas
Chenalhó	Chiapas
Comitán de Domínguez	Chiapas
Altamirano	Chiapas
Acala	Chiapas
San Juan Cancuc	Chiapas
Zinacantán	Chiapas
Yajalón	Chiapas
Villaflores	Chiapas
Villa Corzo	Chiapas
Venustiano Carranza	Chiapas
Tenejapa	Chiapas
Simojovel	Chiapas
Salto de Agua	Chiapas
Palenque	Chiapas
Oxchuc	Chiapas
Las Margaritas	Chiapas
Ixtapa	Chiapas
Tila	Chiapas
Jiquipilas	Chiapas
Cintalapa	Chiapas

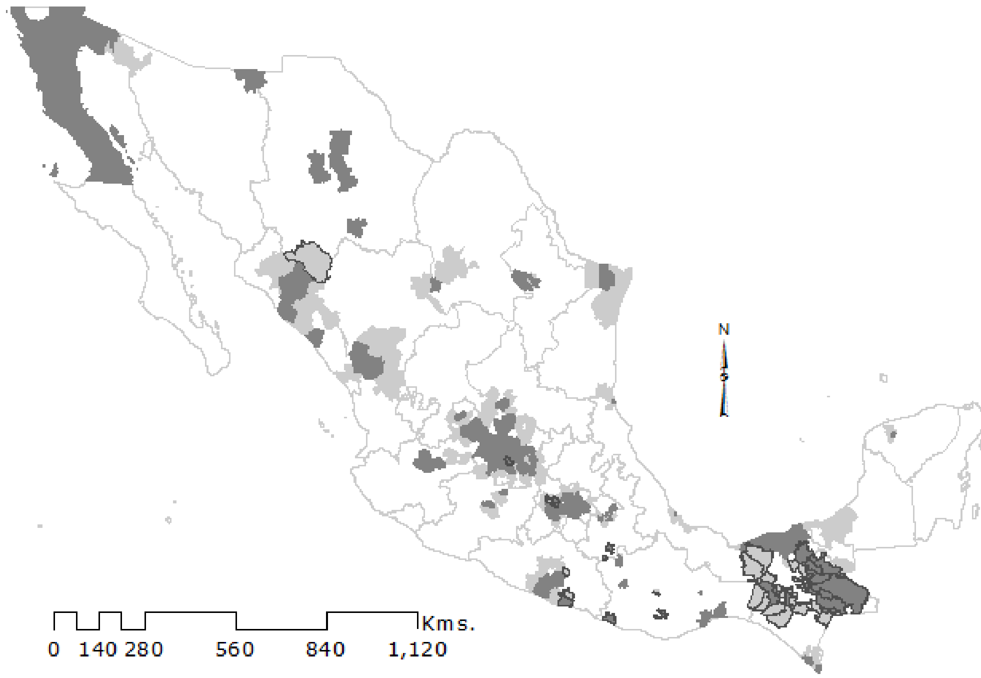
Source: Elaboration by the author.

Figure 20. Core and periphery (c/p) procedure for intensity of poverty.



Source: Elaboration by the author.
Municipios in the area of intersection of the conglomerates of intensity and magnitude are outlined in black color (Priority 1). Core areas of intensity are in dark gray color (Priority 2). Peripheral areas of intensity are in light gray color (Priority 3).

Figure 21. Core and periphery (c/p) procedure for magnitude of poverty.



Source: Elaboration by the author.
Areas in the intersection of the conglomerates of intensity and magnitude are outlined in black color (Priority 1). Core areas of magnitude are in dark gray color (Priority 2). Peripheral areas of magnitude are in light gray color (Priority 3).

Descriptive statistics show that the distribution of values in non-intersecting areas, either of magnitude or intensity, is skewed. In magnitude, skewness of the 215 non-intersecting absolute values is 3.065 and the standard error of this skewness is 0.166. Replacing terms in the formula (Eq. 1):

$$z = \frac{Skewness}{Standard\ Error\ of\ Skewness} \qquad \text{(Eq. 1)}$$

The resulting z-value to evaluate skewness is 18.46, above the 1.96 limit value of significance at the 5% level with a two-tailed test. Both box-plot charts in ArcGis 10.2 and the z-MAD standardization report outliers in this distribution. The outlier threshold is 241,325 or 191,029 people in poverty for box-plot or z-MAD, respectively. The K-S test rejects the hypothesis of normality at the 5%. Magnitude is skewed and presents outliers.
On the other hand, there are 902 non-intersecting values of intensity with a skewness of -0.290 and a standard error of skewness of 0.081. The resulting z-value is -3.58, beyond the -1.96 required to be statistically significant at the 5% level with a two-tailed test. The K-S test rejects the hypothesis of normality at 5%. Box-plot charts and z-MAD values do not report outliers. Intensity is skewed without outliers.
The heads and tails (h/t) method is specially designed for asymmetric distributions. It is a robust procedure for skewed distributions with outliers. The number of strata in the h/t procedure may be identified by an empirical rule or a methodological condition (Jiang and Yin 2013, 8). Applying the empirical rule that “heads must be less than 40 percent,”

magnitude has three strata. If the condition that most (though not necessarily all) hierarchical classes meet the principle of "far more small things than larger ones" is applied, there are five strata (Table 5).

Table 5. Non-intersected magnitude. Information of the Heads and Tails procedure to determine the number of strata.

Obs. Total (#)	Heads (#)	Tails (#)	Heads (%)	Tails (%)	Mean
215	62	153	28.84	71.16	101809.95
62	22	40	35.48	64.52	236467.71
22	8	14	36.36	63.64	384471.55
8	4	4	50.00	50.00	573043.75
4	3	1	25.00	75.00	695746.50

Note: Heads= Values ≥ mean; Tails= Values < mean. Calculations verified with the h/t software available at https://www.dropbox.com/sh/k2aaoip1y888r45/AAACV2jsvP8s0y8a-5reRgrda (August 05, 2014).

Next lines in this research are based on the three strata classification obtained by the 40% rule in the h/t procedure (Table 6 and Figure 23). A similar number of strata is identified by natural breaks for comparative purposes, including and excluding outliers (Table 7).

Table 6. Non-intersected magnitude. Heads and tails classification for the 40% rule.

Stratum	Class limits	Priority
1	23271 – 101809	4
2	101810 – 236467	3
3	236468 – 732154	2
GADF	0.5382	

Source: Elaboration by the author based on Table 5.

Table 7. Non-intersected magnitude. Natural breaks classification.

Stratum	Class limits	
	With outliers	Without outliers (*)
1	23271 – 134177	23271 - 53987
2	134178 – 356328	53988 – 103550
3	356329 – 732154	103551 – 732154
GADF	0.5506	0.4846

Source: Elaboration by the author with the program ArcGis 10.2
* Outliers identified as modified z-scores (z-MAD) > |3.5|. They were temporarily excluded and reintegrated in the upper stratum. Class limits are the same with absolute raw values or their equivalent z-MAD.

Since the h/t procedure suggested by Jiang and Yin (2013) is very recent, natural breaks is the most common procedure to classify (with some adaptations) skewed distributions *with* outliers. The basic adaptation of the procedure suggests a data standardization to fulfill the normality requirement and identify potential outliers.[13] After the standardization, outliers are temporarily excluded to perform the Jenks stratification and reintegrated to the lowest or highest strata, depending on their extreme values.

In the natural breaks option for magnitude, the research standardizes the raw data to z-MAD scores to deal with skewness and temporarily excludes outliers. This option, however, does not generate strata of similar amplitude to those obtained by the heads and tails procedure (Table 6 and Table 7).

The GVF (Goodness of Variance Fit) evaluation does not apply to the h/t procedure because it is not based on the normal distribution of values. The GADF (Goodness of Absolute Deviation Fit) values, the robust alternative to GVF to evaluate stratifications in skewed distributions, suggest that the number of classes in magnitude identified by the h/t method should increase (until reach a GADF of 0.8, at least) (Table 6 and Table 7). Having in mind the superiority of the h/t over the natural breaks (a.k.a. GVF or Jenks) method to classify skew distributions (Jiang and Yin 2013), these results show that the GADF does not seem appropriate to compare the efficiency of both procedures. On the other hand, under the 40% rule for the heads, the h/t procedure classifies all non-intersected values of intensity into a single stratum. Therefore, no comparative natural breaks classification is used in intensity. All non-intersected values of intensity are Priority 2 (Figure 22 and Venn diagram B in Figure 8).

Once the natural breaks method is replaced by the h/t procedure, the spatial hierarchy of the conglomerates of magnitude and intensity may follow two directions, depending on the research or decision-making problem: (a) if the interest is on agglomerated local high values, such as the identification of stigmatized areas of poverty (*i.e.*, Wacquant 2004 and 2007), the core/periphery (c/p) classification may be useful. (b) If the public policy interest is in conglomerates of high values, regardless of whether they are global or local values, the heads and tails (h/t) stratification is the best option for asymmetric spatial distributions, such as poverty. These two classifications (c/p and h/t) may also be merged, but a clear conceptual and convincing justification is necessary to give a sense or provide direction to the resulting spatial taxonomy.

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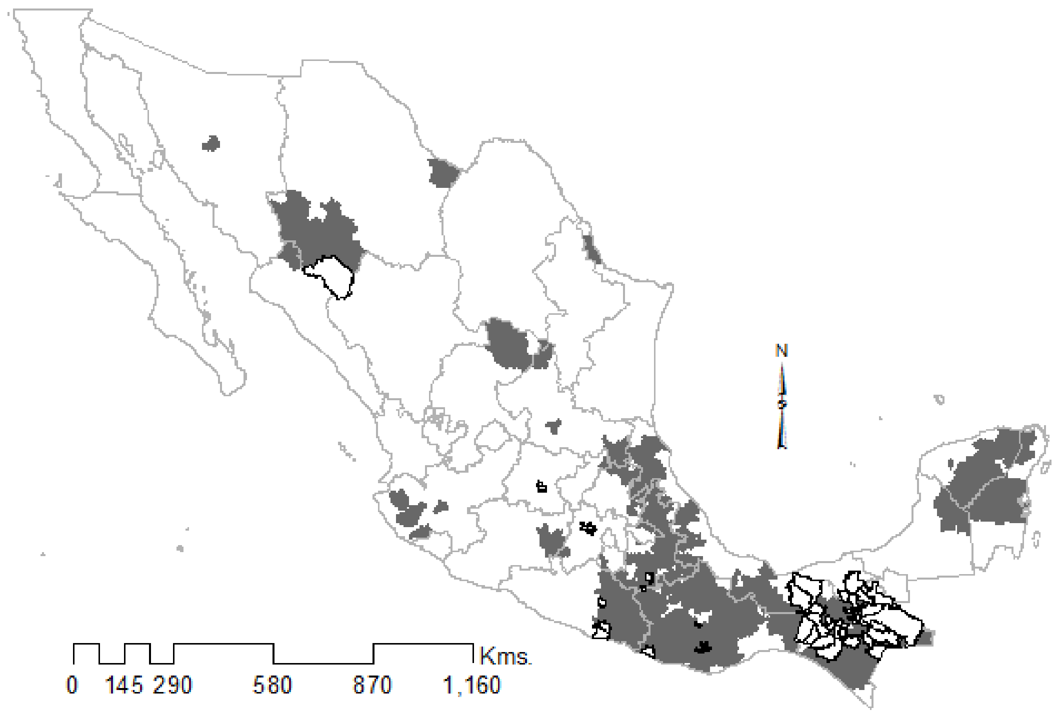
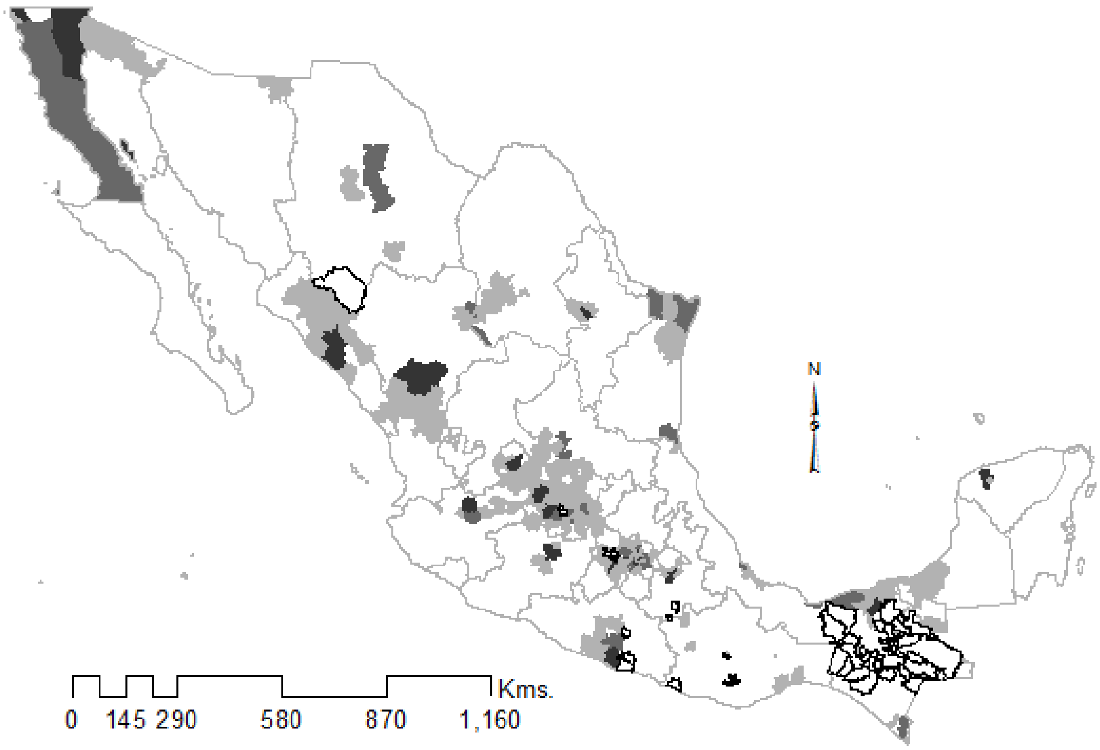
[13] In this research, standardization is not transformation. The standardization of data (z-scores or z-MAD values) re-scales the information and it does not change the shape of the original distribution; skewedness remains the same and outliers, if they exist, stay. Z-MAD standardization, based on the median, is recommended for skewed distributions because it is less sensitive to extreme values than the z-score, based on the mean. In skewed distributions, z-MAD detects more outliers than z-scores. On the other hand, the transformation of values, such as log, square root or Box-Cox transformation, changes the shape of the distribution and modifies (or disappears) the number of outliers.

Figure 22. All non-intersecting areas of intensity have Priority 2 (they are not stratified).



Source: Elaboration by the author based on the heads and tails procedure explained in the text. Intersected areas of magnitude and intensity are outlined in black and filled with no color.

Figure 23. Stratification of non-intersecting areas of magnitude.



Source: Elaboration by the author.
The darker the color, the highest the priority (from 2 to 4), as indicated in the class limits of Table 6. Intersected areas of magnitude and intensity are outlined in black and filled with no color.

6. Concluding remarks and future research guidelines

This research presents a new procedure to identify important areas of magnitude and intensity of poverty in Mexico. The study, by the principle of population independence, first focuses on intensity. It identifies concentrations of poverty and integrates them with agglomerations (cores) to form conglomerates of intensity (cores and peripheries). Here, concentration refers to the location of high global values in some few municipios in Mexico, regardless of their geographic location. Agglomeration, on the other hand, refers to the location of high local values in contiguous municipios. Global high values, identified by bootstrapping, may locate anywhere. They create conglomerates when their location is contiguous to agglomerations, identified by spatial autocorrelation.

On the other hand, considering that size matters, all methodological steps to create conglomerates of intensity are replicated to form conglomerates of magnitude. This research builds upon the explicit differentiation between concentration and agglomeration (Arbia 2001) and references to old (Linge 1960) and recent (Van den Heuvel 2012) works combining relative and absolute values. However, in order to set up a spatial hierarchical order of areas, this study, for the first time in the spatial analysis literature, simultaneously combines concentration and agglomeration of relative and absolute values of poverty using overlay analysis. Venn diagrams are used to identify the intersecting area between conglomerates of magnitude and intensity. Areas in this intersection have Priority 1. Outside the intersection area there are the subsets of non-intersecting areas of intensity and magnitude.

As expected in most social issues, the Mexican case study does not accept the null hypothesis (H_0) of randomness and it concludes that intensity and magnitude, in different sets of calculations, have a concentrated and agglomerated spatial pattern. Forty-four Mexican municipios locate at the intersection area of these conglomerates of absolute and relative values (Priority 1). Sixty-five percent out of these forty-four municipios contain 70% of the poverty in the highest priority areas and it fully locates in the state of Chiapas. Ocosingo, Chiapas, has “the highest of the highest” values of magnitude and intensity. It should have the highest priority in the public policy against poverty in Mexico.

Once the intersection area of the two conglomerates is identified, the study suggests two spatial orders of classification for the non-intersecting areas. The first one is the core/periphery procedure. In descending order, municipios in the intersecting area between the conglomerates of magnitude and intensity have the highest priority (Priority 1). Then, considering either intensity or magnitude, cases in cores and peripheries in the non-intersecting area have Priority 2 and Priority 3, respectively. Finally, areas outside the two conglomerates have Priority 4.

The second procedure also provides a spatial hierarchy. As in the core/periphery procedure, the intersecting area between intensity and magnitude receives the highest priority. The non-intersecting areas of intensity and magnitude are classified by the heads and tails procedure (h/t). As demonstrated by Jiang and Yin (2013), results from natural breaks are not close to those obtained by the h/t procedure. Considering the highly skewed distributions of magnitude and intensity, the h/t procedure is the most appropriate option to classify values in the non-intersecting areas of the conglomerates. The h/t procedure generates three strata for magnitude and only one stratum for intensity. Both intersecting and non-intersecting stratified areas provide a spatial hierarchy of poverty in Mexico in 2010.

This study presents three main contributions:

1. It integrates a comparative conceptual body to identify areas of poverty with hierarchical levels of priority. This framework is relevant for designing spatially targeted policies, and it may be an input into subsequent explanatory models (OLS, Spatial regression and GWR). At the statistical level, for example, the existence of agglomerations and conglomerates is evidence of spatial heterogeneity (spatial regimes) to be taken into account in spatial regression models.
2. Conceptually and empirically it articulates two spatial processes (concentration and agglomeration), two complementary statistical techniques (bootstrapping and spatial autocorrelation), one GIS procedure (overlay analysis), one recent class classification procedure (heads and tails procedure), and two different kind of data (relative and absolute values) to set up a spatial hierarchy of poverty.
3. It reassesses basic concepts *(i.e.*, spatial pattern, concentration, agglomeration) and reviews measures of intensity and magnitude that can be applied to the identification and explanation of diverse geographical patterns, such as poverty, human development, infant mortality, teenage fertility, industry, diseases or crime patterns. Results also need to be assessed in light of results from other case studies.

It is expected that the methodology in this paper helps to create a spatial hierarchy useful for social programs. The two variables in this research (intensity of poverty and number of people in poverty) may be replaced by those in SEDESOL programs such as the Crusade against Hunger (people in extreme poverty and people in food poverty) or Prospera. The research also presents objective criteria that do not require familiarity with case study and provides statistically supported cut-off values.

As any other method, the suggested spatial methodology has its own shortcomings:

—It depends on the desegregation and the accuracy of the unit of analysis (*e.g.*, census tracts, blocks, municipios).

—Results may not be the same for the time-space smoothed data. Besides using the spatial smoothing rates in this research, if available, studies may also use the statistical mean for a time period (*i.e*., the poverty rate average of 2003-2012) or moving mean averages in time. Unfortunately, the spatial disaggregated database for poverty in the Mexican case study only exists for the year 2010.

—It leaves populations in poverty without social program entitlements if they are not located in the selected areas. Regional adjustments based on common history, culture and economy are necessary. Regions and their municipios usually share similar natural settings, common social factors and community experiences. As an example, 23 municipios integrate the Tarahumara region, but only some of them are included in the Tarahumara conglomerate of intensity of poverty.[14] Therefore, it is necessary to visit the region and check what happens there to find out if the inclusion/exclusion of municipios has local support. This task is beyond the possibilities of the case study and remains as an assignment to be included in subsequent studies.

The main results of this research are not comparable or compatible with those in related official documents, such as CONEVAL or SEDESOL. In the case of CONEVAL:

—While this research simultaneously includes magnitude (absolute number of people in poverty) and intensity (LQ) in its classification, CONEVAL does not include

[14] Fourteen municipios locate at the highest altitude of the mountain: Balleza, Bocoyna, Carichi, Cusihuirichi, El Tule, Guachochi, Guadalupe y Calvo, Guerrero, Madera, Matachi, Nonoava, Rosario, San Francisco de Borja, Temósachi. In the lower levels, but still in the Tarahumara sierra the remaining 9 municipios are situated: Batopilas, Chínipas, Guazapares, Maguarichi, Morelos, Moris, Ocampo, Urique, Uruachi.

magnitude. It only uses incidence (percentage of people in poverty) to stratify the Mexican municipios.
—Unlike this research, CONEVAL does not consider agglomerations in its classification.
On the other hand, although the municipal selection of the Crusade against Hunger in SEDESOL includes the criteria of magnitude and intensity, it uses food poverty, a different variable. Food poverty is a subset of the multidimensional poverty dataset generated by CONEVAL and used in this research.

Bibliography

Anselin, L., Kim, Y. W., & Syabri, I. (2004). Web-based analytical tools for the exploration of spatial data. *Journal of Geographical Systems*. doi:10.1007/s10109-004-0132-5

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Dordrecht: Kluwer Academic Publishers.

Anselin, L. (1995). Local indicators of spatial association-LISA. *Geographical Analysis*, *27*(2), 93-115.

Anselin, L. (1996). The Moran scatterplot as an ESDA tool to assess local instability in spatial association. In M. M. Fischer, H. J. Scholten, & D. Unwin (Eds.), *Spatial analytical perspectives on GIS* (pp. 111-125). London: Taylor & Francis.

Arbia, G. (2001). The role of spatial effects in the empirical analysis of regional concentration. *Journal of Geographical Systems*, *3*, 271-281. doi:10.1007/PL00011480

Argyrous, G. (2011). *Statistics for research: With a guide to SPSS* (3rd ed.). London: SAGE.

Batey, P., & Brown, P. (2007). The spatial targeting of urban policy initiatives: a geodemographic assessment tool. *Environment and Planning A*, *39*, 2774-2793. doi:10.1068/a38519

Baumont, C., Ertur, C., & Gallo, J. L. (2004). Spatial Analysis of Employment and Population Density: The Case of the Agglomeration of Dijon 1999. *Geographical Analysis*, *36*(2), 146-176. doi:10.1353/geo.2004.0001

Bedi, T., Coudouel, A., & Simler, K. (2007). *More than a pretty picture: Using poverty maps to design better policies and interventions*. Washington, DC: World Bank.

Bourdieu, P. (2000). Site effects. In P. Bourdieu, A. Accardo, & P. Parkhurst Ferguson (Eds.), *The Weight of the World: Social Suffering in Contemporary Society*. Stanford, CA: Stanford University Press.

Burt, J. E., Barber, G. M., & Rigby, D. L. (2009). *Elementary statistics for geographers* (3rd ed.). New York: Guilford Press.

Carroll, M. C., Reid, N., & Smith, B. W. (2008). Location quotients versus spatial autocorrelation in identifying potential cluster regions. *Annals of Regional Science*, *42*, 449-463.

Chihara, L., & Hesterberg, T. (2011). *Mathematical statistics with resampling and R*. Hoboken, NJ: Wiley.

Choudhury, N. Y., & Räder, C. (2014). Targeting the Poorest and Most Vulnerable: Examples from Bangladesh. In J. Von Braun & F. W. Gatzweiler (Eds.), *Marginality: Addressing the Nexus of Poverty, Exclusion and Ecology*. Dordrecht: Springer Netherlands.

Crews, K. A., & Peralvo, M. F. (2008). Segregation and Fragmentation: Extending Landscape Ecology and Pattern Metrics Analysis to Spatial Demography. *Population Research and Policy Review*, *27*, 65-88. doi:10.1007/s11113-007-9054-5

Cromley, R., & Hanink, D. (2012). Focal location quotients: Specification and applications. *Geographical Analysis*, *44*, 398-410.

Goodchild, M. F., & Lam, N. S. (1980). Areal interpolation: A variant of the traditional spatial problem. *Geo-Processing*, *1*, 297-312. Retrieved from http://www.geog.ucsb.edu/~good/papers/46.pdf

Gottdiener, M., & Hutchison, R. (2011). *The new urban sociology*. Boulder, CO: Westview Press.

Graw, V., & Husmann, C. (2014). Mapping Marginality Hotspots. In J. Von Braun & F. W. Gatzweiler (Eds.), *Marginality: Addressing the Nexus of Poverty, Exclusion and Ecology* (pp. 69-83). Dordrecht: Springer Netherlands.

Hesterberg, T., Moore, D. S., Monaghan, S., Clipson, A., Epstein, R., Craig, B. A., & McCabe, G. P. (2010). Bootstrap Methods and Permutation Tests. In D. S. Moore, G. P. McCabe, & B. A. Craig (Eds.), *Introduction to the practice of statistics* (7th ed.). New York: W. H. Freeman.

Holt, J. B. (2007). The topography of poverty in the United States: a spatial analysis using county-level data from the Community Health Status Indicators project. *Preventing Chronic Disease*, *4*(4), 1-9.

Huck, J. D. (2008). *Mexico: A global studies handbook.* Santa Barbara, CA: ABC-CLIO.

Jiang, B., & Yin, J. (2014). Ht-index for quantifying the fractal or scaling structure of geographic features. *Annals of the Association of American Geographers*, *104*(3), 530-541.

Jiang, B. (2013). Head/tail breaks: A new classification scheme for data with a heavy-tailed distribution. *The Professional Geographer*, *65*(3), 482-494.

Jiang, B. (2014). Geospatial analysis requires a different way of thinking: the problem of spatial heterogeneity. *GeoJournal*. doi:10.1007/s10708-014-9537-y

Ketels, C., & Sölvell, Ö. (2005). Clusters in the EU 10 New Member Countries. *Europe INNOVA*. Retrieved from http://www.europe-innova.eu [09/15/14]

Linge, G. J. (1960). The Concentration and Dispersion of Manufacturing in New Zealand. *Economic Geography*, *36*(4), 326-343.

Liu, Z. (2013). Global and Local: Measuring Geographical Concentration of China's Manufacturing Industries. *The Professional Geographer*. doi:10.1080/00330124.2013.784953

Maggioni, M. A., & Riggi, M. R. (2008). High-tech firms and the dynamics of innovative industrial clusters. In C. Karlsson (Ed.), *Handbook of research on innovation and clusters: Cases and policies*. Cheltenham, UK: Elgar.

Matka, E. (2011). Uses and Abuses of Crime Statistics. *Crime and Justice Bulletin. Contemporary Issues in Crime and Justice*, (153). Retrieved from http://feedback.lawlink.nsw.gov.au/lawlink/bocsar/ll_bocsar.nsf/vwFiles/cjb11.pdf/$file/cjb11.pdf [30/04/2013]

Mexico. SEDESOL. (2013). *Procedimiento de selección de los 400 municipios prioritarios de la Cruzada Nacional Contra el Hambre*. Retrieved from http://www.sedesol.gob.mx/work/models/SEDESOL/Cruzada/4_NOTA_TECNICA_DEL_PROCEDIMIENTO_DE_SELECCION_DE_LOS_400_MUNICIPIOS_PRIORITARIOS_DE_LA_CNCH.pdf [30/04/2013]

Mexico-CONEVAL. (n.d.). *Medición de la Pobreza. Pobreza a nivel municipio 2010*. Retrieved from http://www.coneval.gob.mx/Medicion/Paginas/Medici%C3%B3n/Medicion-de-la-pobreza-municipal-2010.aspx [10/may/2014]

Moore, D. S., & McCabe, G. P. (2010). *Introduction to the practice of statistics* (7th ed.). New York: Freeman.

O'Donoghue, D., & Gleave, B. (2004). A Note on Methods for Measuring Industrial Agglomeration. *Regional Studies*, *38*(4), 419-427. doi:10.1080/03434002000213932

O'Sullivan, D., & Perry, G. L. (2013). *Spatial simulation: Exploring pattern and process*. Chichester, West Sussex: John Wiley & Sons Inc.

Partridge, M. D., & Rickman, D. S. (2006). *The geography of American poverty: Is there a need for place-based policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Riguelle, F., Thomas, I., & Verhetsel, A. (2007). Measuring urban polycentrism: a European case study and its implications. *Journal of Economic Geography*, *7*, 193-215. doi:10.1093/jeg/lbl025

Soja, E. W. (2010). *Seeking spatial justice*. Minneapolis: University of Minnesota Press.

Srinivasan, S. (2008). Local and Global Spatial Statistics. In S. Shekhar & H. Xiong (Eds.), *Encyclopedia of GIS*. New York: Springer.

Tian, Z. (2013). Measuring Agglomeration Using the Standardized Location Quotient with a Bootstrap Method. *Journal of Regional Analysis and Policy*, *43*(2), 186-197.

Urdan, T. C. (2010). *Statistics in Plain English, Third Edition*. Hoboken: Taylor & Francis.

Van den Heuvel, F. P., De Langen, P. W., Van Donselaar, K. H., & Fransoo, J. C. (2012). Identification of Employment Concentration Areas. *European Planning Studies*. doi:10.1080/09654313.2012.741573

Visvalingam, M. (1983). Area-based social indicators: Signed chi-square as an alternative to ratios. *Social Indicators Research*, *13*(3), 311-329. doi:10.1007/BF00318102

Wacquant, L., Slater, T., & Borges Pereira, V. (2014). Territorial Stigmatization in Action? *Environment & Planning A, special issue on "Territorial Stigmatization"*, *46*(6), 1270-1280.

Wacquant, L. (2007). Territorial stigmatization in the age of advanced marginality. *Thesis Eleven*, (91), 66-77.

Zhang, C., Luo, L., Xu, W., & Ledwith, V. (2008). Use of local Moran's I and GIS to identify pollution hotspots of Pb in urban soils of Galway, Ireland. *Science of The Total Environment*, (398), 212–221. doi:10.1016/j.scitotenv.2008.03.011

Zhang, C., Tang, Y., Luo, L., & Xu, W. (2009). Outlier identification and visualization for Pb concentrations in urban soils and its implications for identification of potential contaminated land. *Environmental Pollution*, (157), 3083–3090. doi:10.1016/j.envpol.2009.05.044

Statistical appendix

A.1 Islands of poverty creating/not-creating conglomerates of intensity

Islands of poverty creating conglomerates (HL-conglomerates)	Islands of poverty that remain as such (HL-Islands)
Melchor Ocampo, Zac El Salvador, Zac Villa Purificación, Jal Chiquilistlán, Jal Temoaya, Mex Singuilucan, Hgo Coronango, Pue Nuevo Zoquiápam, Oax Lázaro Cárdenas, QRoo	San Miguel de Horca, Son Manuel Benavides, Chi Guerrero, Tam Armadillo de los Infantes, SLP Santa Cruz de Juventino Rosas, Gto Talpa de Allende, Jal Cuautitlán de García, Jal Miacatlán, Mor Puente de Ixtla, Mor San Agustin Yataren, Oax Timucuy, Yuc

A.2 Data of population and poverty for the forty-four municipios selected as priority areas of poverty.

State	Municipio	Total Population (a)	Magnitude (People in Poverty) (b)	Incidence (b/a) *100
Guerrero	San Marcos	53513	42455	79.3
Guerrero	Tecoanapa	46262	38277	82.7
Guerrero	Tixtla de Guerrero	40101	28533	71.2
México	Temoaya	69224	49309	71.2
México	Jiquipilco	56997	39128	68.6
México	Ixtlahuaca	121464	83745	68.9
Chihuahua	Guadalupe y Calvo	48406	43474	89.8
Chiapas	La Trinitaria	80023	68239	85.3
Chiapas	Ocosingo	241505	219582	90.9
Chiapas	Tuxtla Gutiérrez	521096	225392	43.3
Chiapas	Chiapa de Corzo	71825	49202	68.5
Chiapas	Tecpatán	44427	37620	84.7
Chiapas	San Fernando	34637	27061	78.1
Chiapas	Ocozocoautla de Espinosa	84570	69670	82.4
Chiapas	Chilón	124017	118180	95.3
Chiapas	Chenalhó	38891	37192	95.6
Chiapas	Comitán de Domínguez	131367	87182	66.4
Chiapas	Altamirano	36801	33978	92.3
Chiapas	Acala	29423	23980	81.5
Chiapas	San Juan Cancuc	32538	31648	97.3
Chiapas	Zinacantán	43476	41259	94.9
Chiapas	Yajalón	33148	29285	88.3
Chiapas	Villaflores	97782	76426	78.2
Chiapas	Villa Corzo	75011	63887	85.2
Chiapas	Venustiano Carranza	66486	57721	86.8
Chiapas	Tenejapa	47390	45373	95.7
Chiapas	Simojovel	46765	43578	93.2
Chiapas	Salto de Agua	55014	46396	84.3
Chiapas	Palenque	113458	93402	82.3
Chiapas	Oxchuc	49819	46571	93.5
Chiapas	Las Margaritas	123998	115205	92.9
Chiapas	Ixtapa	27753	24488	88.2
Chiapas	Tila	86780	81727	94.2
Chiapas	Jiquipilas	35448	25730	72.6
Chiapas	Cintalapa	72731	54969	75.6
Tabasco	Huimanguillo	163384	114178	69.9
Tabasco	Tacotalpa	42542	30510	71.7
Tabasco	Macuspana	161492	110167	68.2
Oaxaca	Villa de Zaachila	37503	28536	76.1
Oaxaca	Miahuatlán de Porfirio Díaz	42664	32551	76.3
Oaxaca	Santiago Pinotepa Nal	47832	35042	73.3
Guanajuato	Santa Cruz de Juventino Rosas	66462	45321	68.2
Veracruz	Las Choapas	76133	58657	77.0
Puebla	Acatlán	32463	23943	73.8