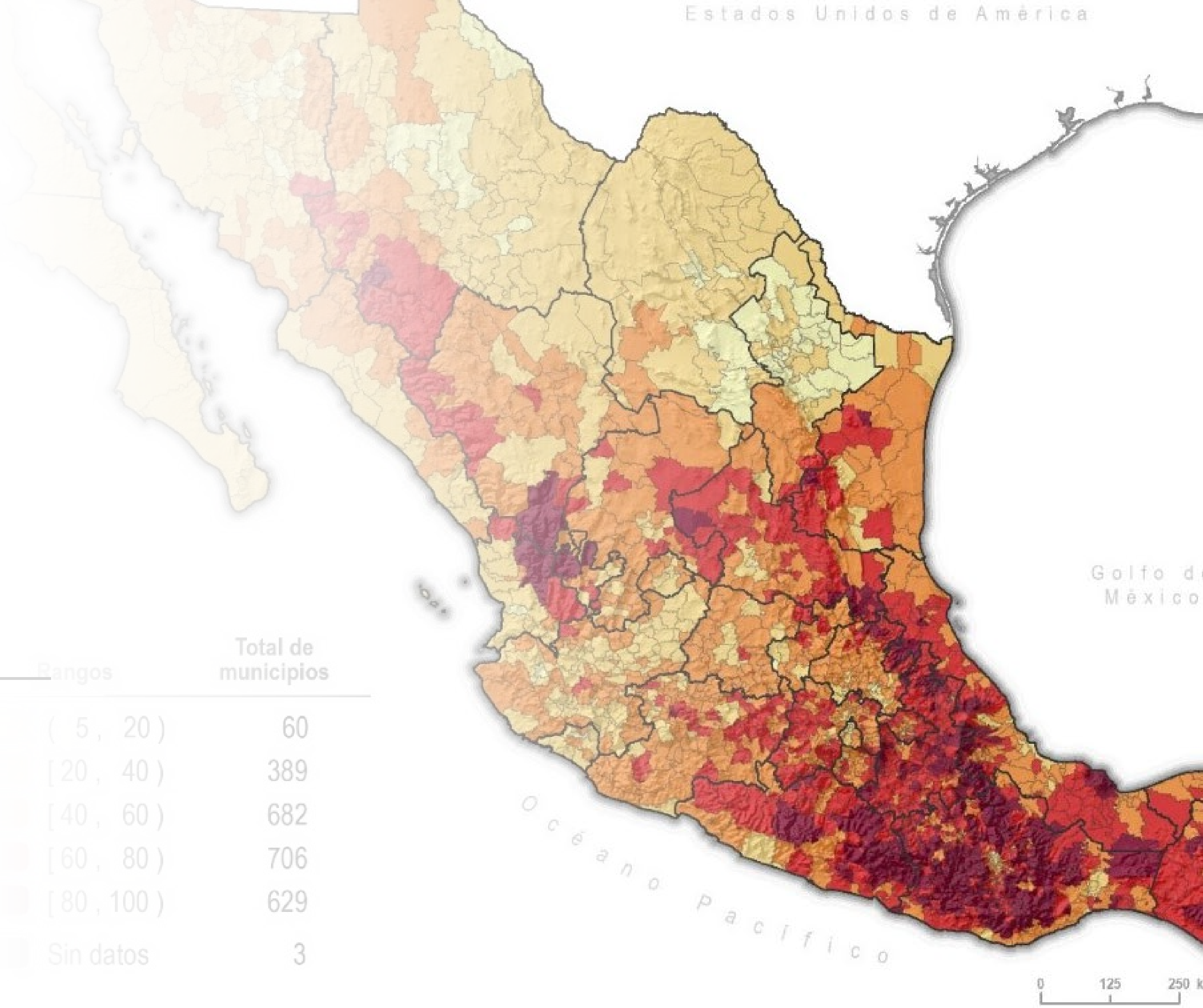
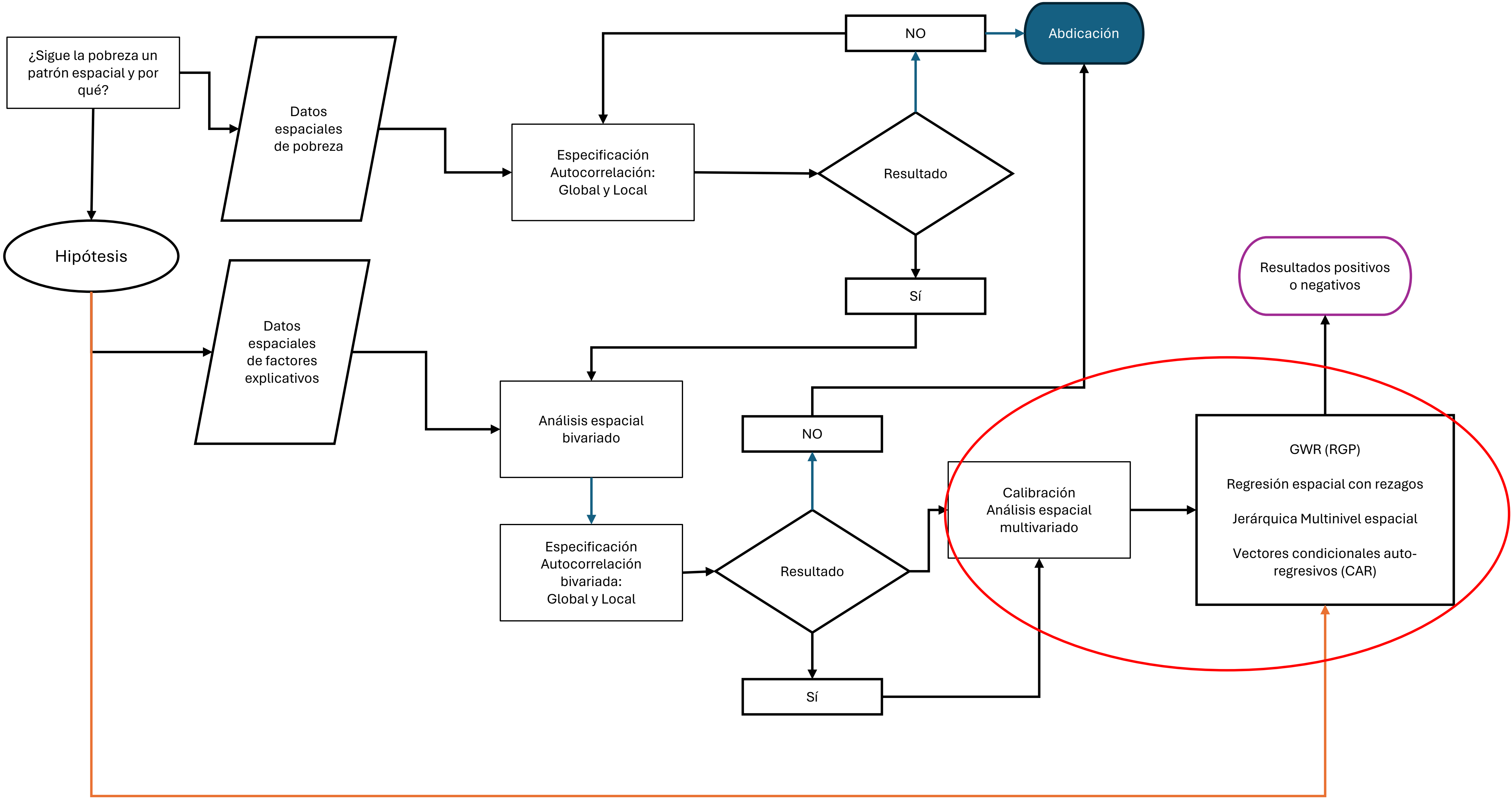
Análisis empírico de la geografía de la pobreza




¿Sigue la pobreza un patrón espacial y por qué?
Datos espaciales de pobreza
Especificación Autocorrelación: Global y Local
Resultado
NO
Abdicación
Sí
Hipótesis
Datos espaciales de factores explicativos
Análisis espacial bivariado
Especificación Autocorrelación bivariada: Global y Local
Resultado
NO
Sí
Calibración Análisis espacial multivariado
GWR (RGP)
Regresión espacial con rezagos
Jerárquica Multinivel espacial
Vectores condicionales auto-regresivos (CAR)
Resultados positivos o negativos

Predictores de la pobreza intergeneracional

- Desigualdad social: Sexo, condición indígena, clase social
- Capital: Educación de las personas adultas en el hogar
- Contextual:
    - Municipio de nacimiento
    - Inversión en infraestructura social básica en el municipio
    - Proximidad a áreas urbanas del municipio

En grupos…

¿Qué diseño analítico se les ocurre para contestar esta pregunta?

- ¿Qué tipo de datos?
- ¿Qué tipo de método?
- ¿Cómo lucirían los resultados?

Tipo de inferencia

- Unidad: Hogares / personas
- Dominios: AGEB / Localidad / Municipio
- Mixto: Unidad y dominio

Problemas en inferencia

GLOSSARY

A glossary for multilevel analysis

A V Diez Roux

J Epidemiol Community Health 2002;**56**:588–594

Multilevel analysis has recently emerged as a useful analytical technique in several fields, including public health and epidemiology. This glossary defines key concepts and terms used in multilevel analysis.

Multilevel analysis, originally developed in the fields of education, sociology, and demography, has received increasing attention in public health and epidemiology over the past few years. This glossary defines key terms and concepts in multilevel analysis. The intent is to provide conceptual explanations of basic concepts, particularly those that are fundamental, that have been used inconsistently or that lend themselves to confusion. Selected terms and concepts more broadly related to the presence of multiple levels of organisation (such as group level variables and inferential fallacies) are also included. Although the glossary often refers to individuals nested within groups, multilevel analysis is applicable to a broad range of situations involving units at a lower level (or micro units) nested within units at a higher level (or macro units) (including for example, persons nested within studies as in meta-analysis, and measures over time nested within individuals as in the analysis of repeat measures). References to terms that have their own specific entry are in SMALL CAPITALS.

AGGREGATE DATA

Term used to refer to data or variables for a higher level unit (for example, a group) constructed by combining information for the lower level units of which the higher level unit is composed (for example, individuals within the group). Examples of aggregate data include summaries of the properties of individuals comprising a group, for example, the percentage of persons in a neighbourhood with complete high school or the mean income of state residents. Implicit in most uses of the term aggregate data is the idea that aggregate variables are merely summaries of the properties of lower level units and not measures of higher level properties themselves (although this is not necessarily true in all cases, see DERIVED VARIABLES).

two variables at the individual level may differ from associations between analogous variables measured at the group level. For example, a study of individuals may find that increasing individual level income is associated with decreasing coronary heart disease mortality. If it is inferred from these data that at the country level, increasing per capita income is associated with decreasing coronary heart disease mortality, the researcher may be committing the atomistic fallacy (because across countries, increasing per capita income may actually be associated with *increasing* coronary heart disease mortality). The sources of the atomistic fallacy are similar to those of the ECOLOGIC FALLACY. In the atomistic fallacy, the conceptual model being tested corresponds to the higher level, but the data are collected for a lower level.[1 2] The atomistic fallacy has sometimes been referred to as the INDIVIDUALISTIC FALLACY.[3 4]

COMPOSITIONAL EFFECTS

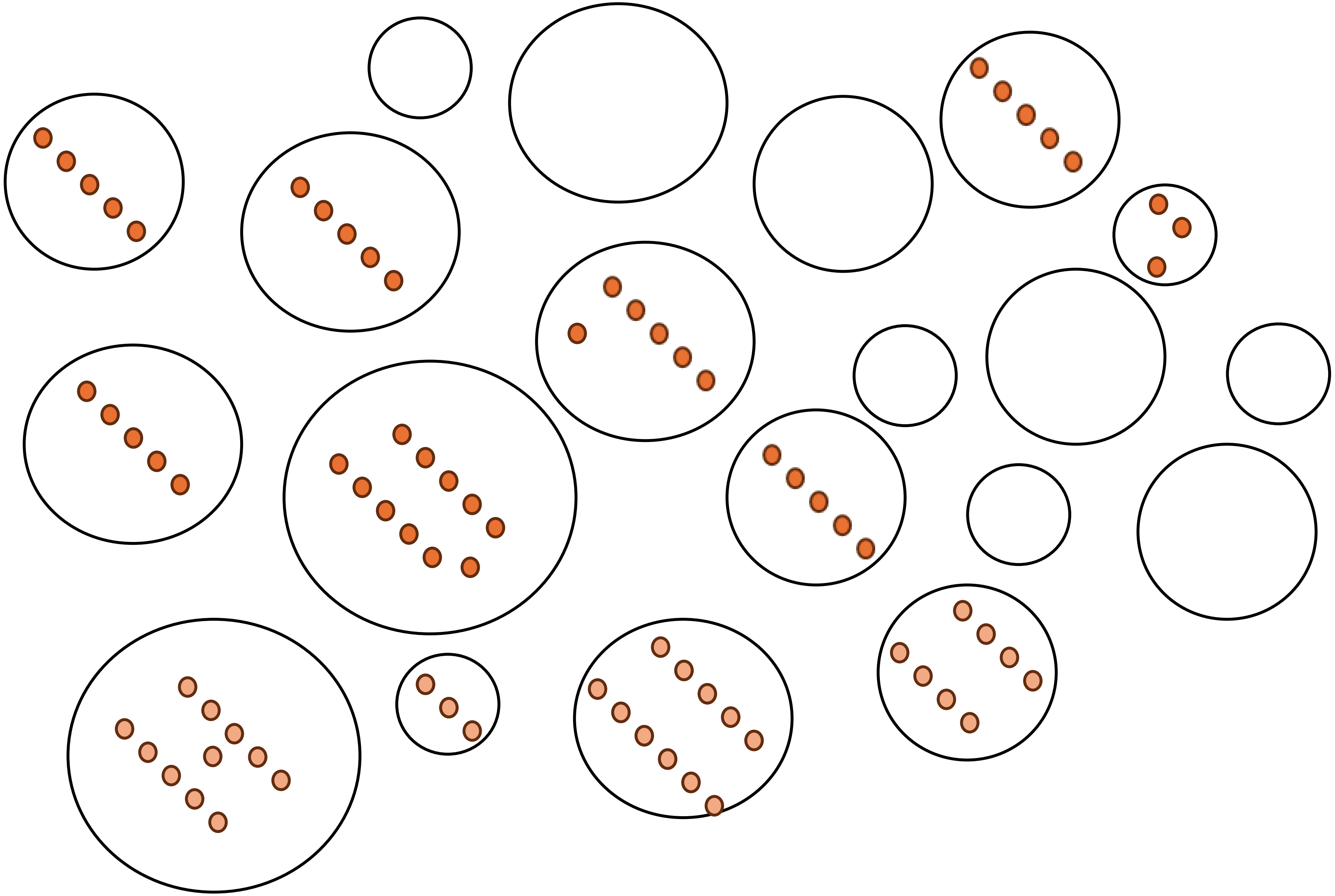
When inter-group (or inter-context) differences in an outcome (for example, disease rates) are attributable to differences in group composition (that is, in the characteristics of the individuals of which the groups are comprised) they are said to result from compositional effects.[5] On the other hand, when group differences are attributable to the effects of GROUP LEVEL VARIABLES or properties, they are said to result from CONTEXTUAL EFFECTS.

CONTEXTUAL ANALYSIS

An analytical approach originally used in sociology to investigate the effect of collective or group characteristics on individual level outcomes.[4 6 7] In contextual analysis, group level predictors (often constructed by aggregating the characteristics of individuals within groups) are included together with individual level variables in standard regressions with individuals as the units of analysis (CONTEXTUAL EFFECTS MODELS). This approach permits the simultaneous examination of how individual level and group level variables are related to individual level outcomes. It thus allows for macro processes that are presumed to have an impact on individuals over and above the effects of individual level variables.[6] The terms "contextual analysis" and MULTILEVEL ANALYSIS have sometimes been used synonymously,[8–10] and both approaches

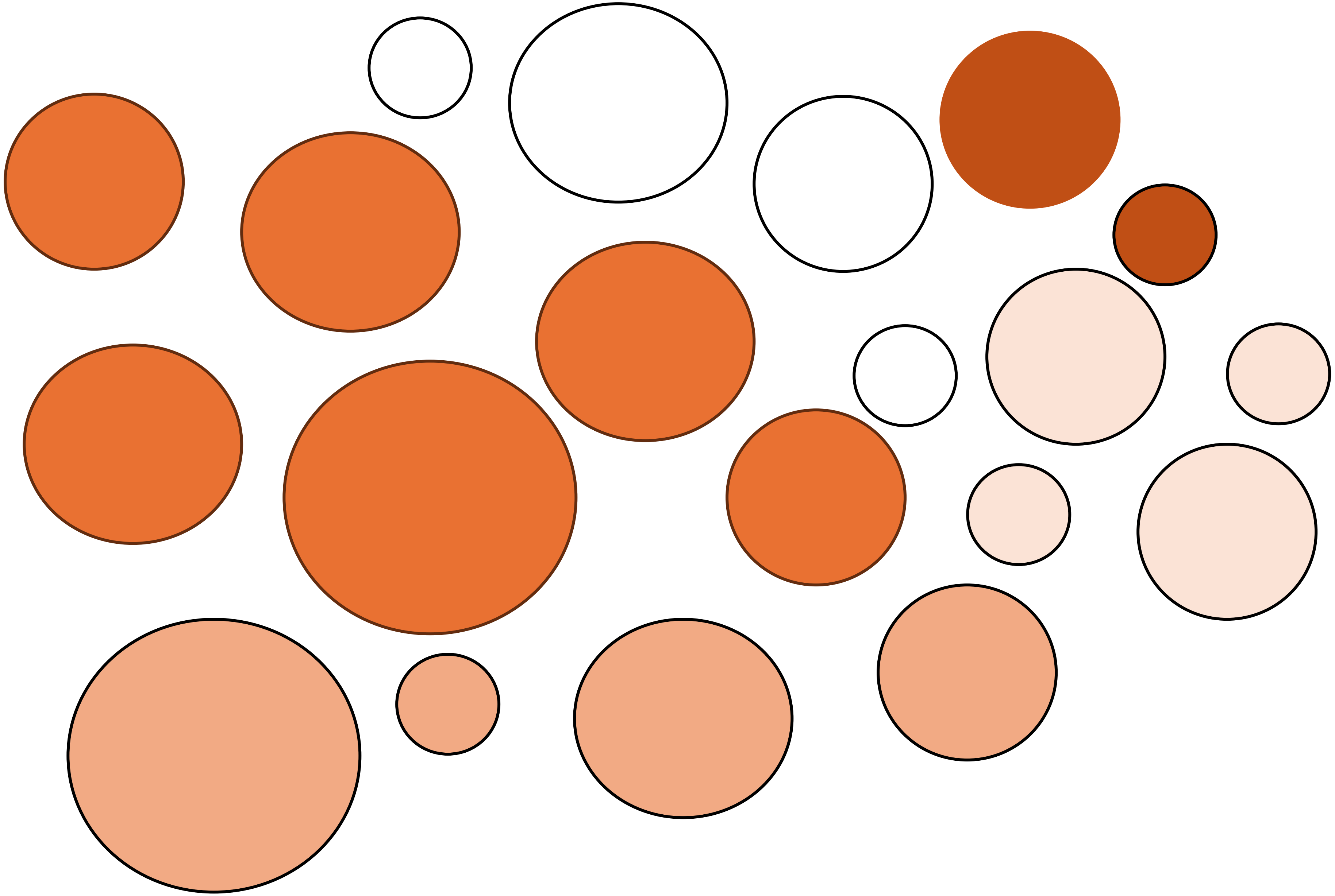
https://jech.bmj.com/content/jech/56/8/588.full.pdf

Falacia atomística



Falacia atomística:

Concluir que el resultado agregado es una función perfecta de lo que ocurre individualmente



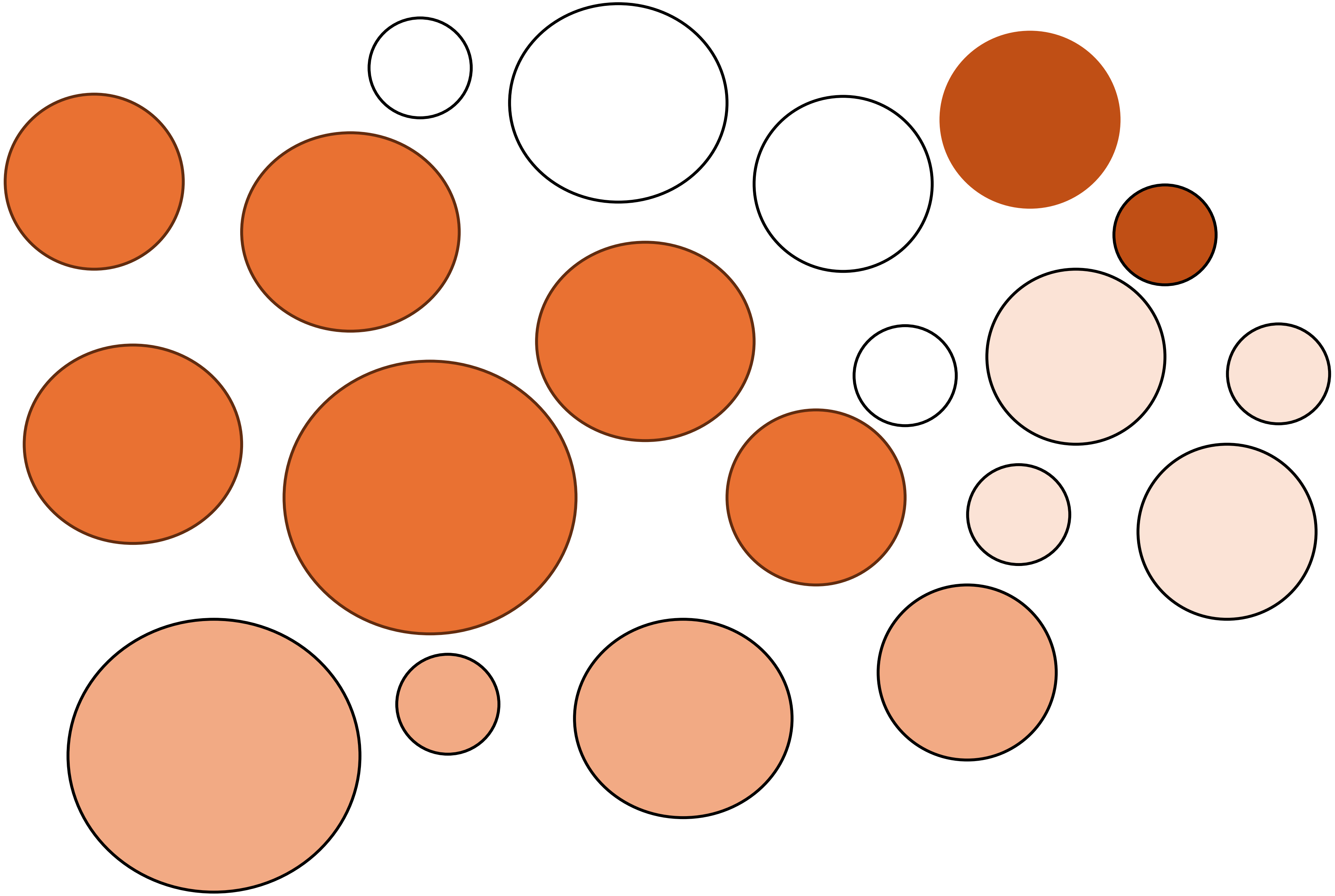
Falacia atomística:

Concluir que el resultado agregado es una función perfecta de lo que ocurre individualmente

Encontramos que el riesgo de vivir en pobreza aumenta para la población indígena:

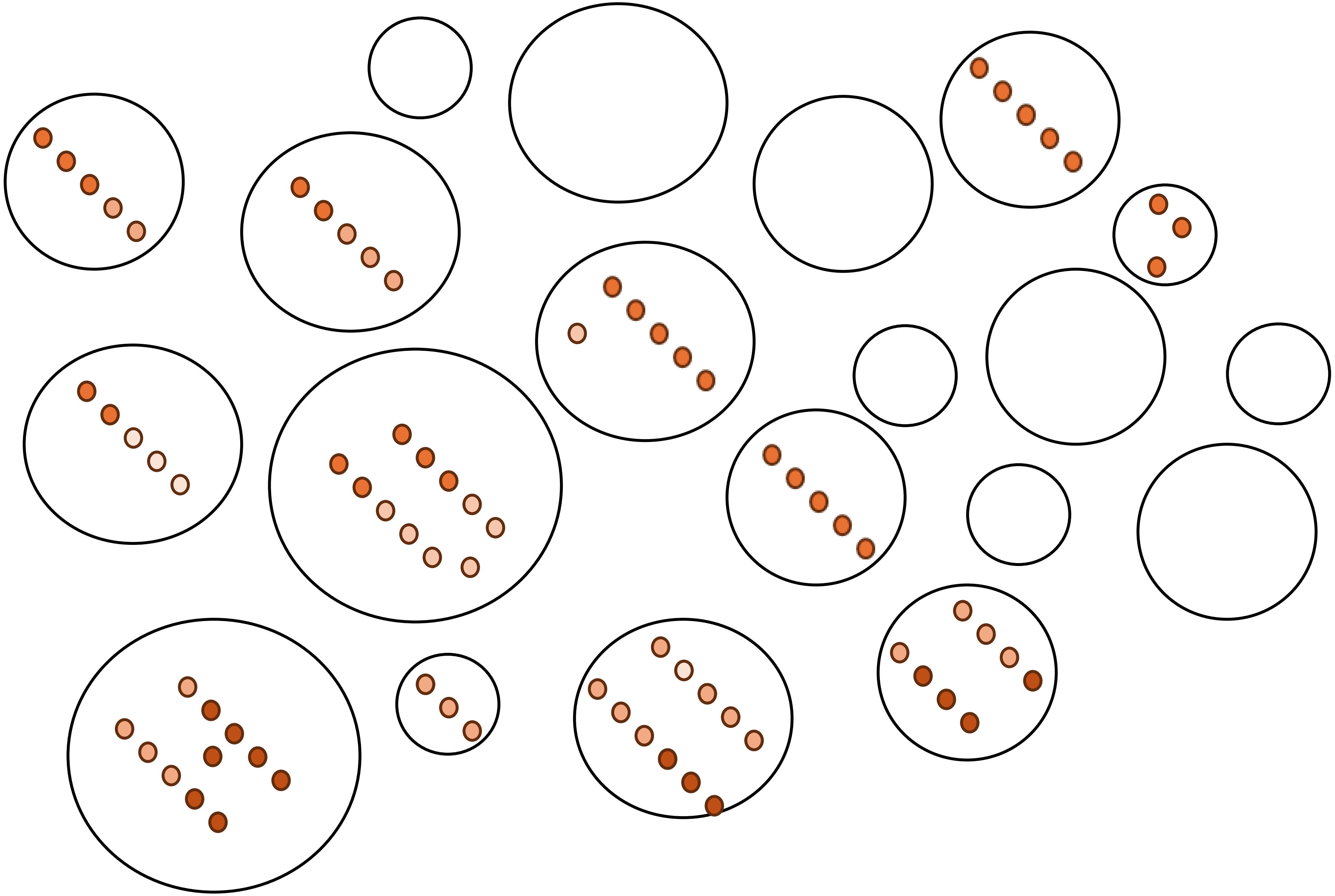
¿Podemos concluir que los municipios con mayoría de población indígena siempre serán mayormente pobres?

Falacia ecológica



Falacia ecológica:

Concluir que el resultado individual es representativo de lo observado en el agregado



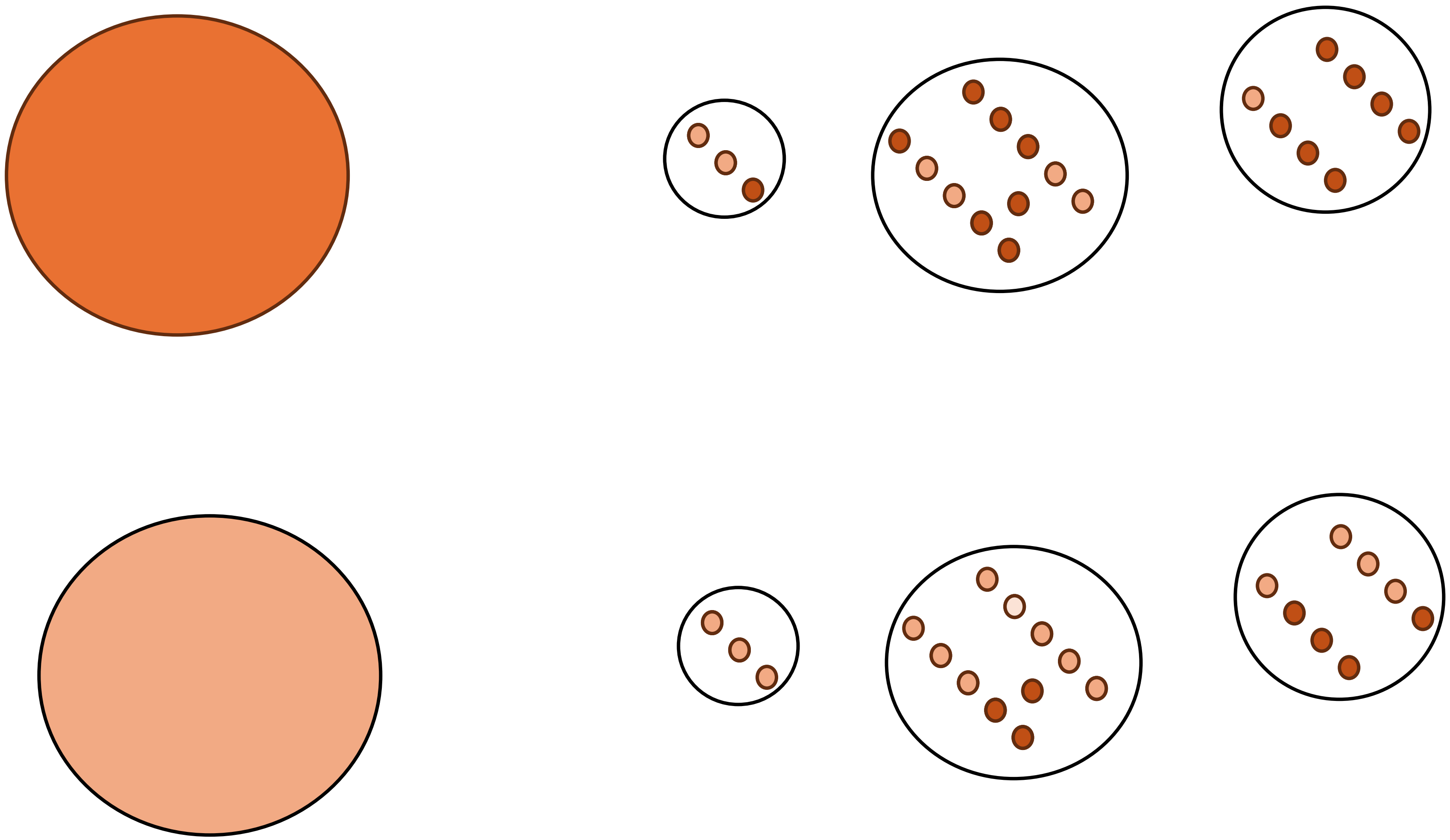
Falacia atomística:

Concluir que el resultado agregado es una función perfecta de lo que ocurre individualmente

Encontramos que los municipios con mayoría de población indígena tienden a ser mayormente pobres :

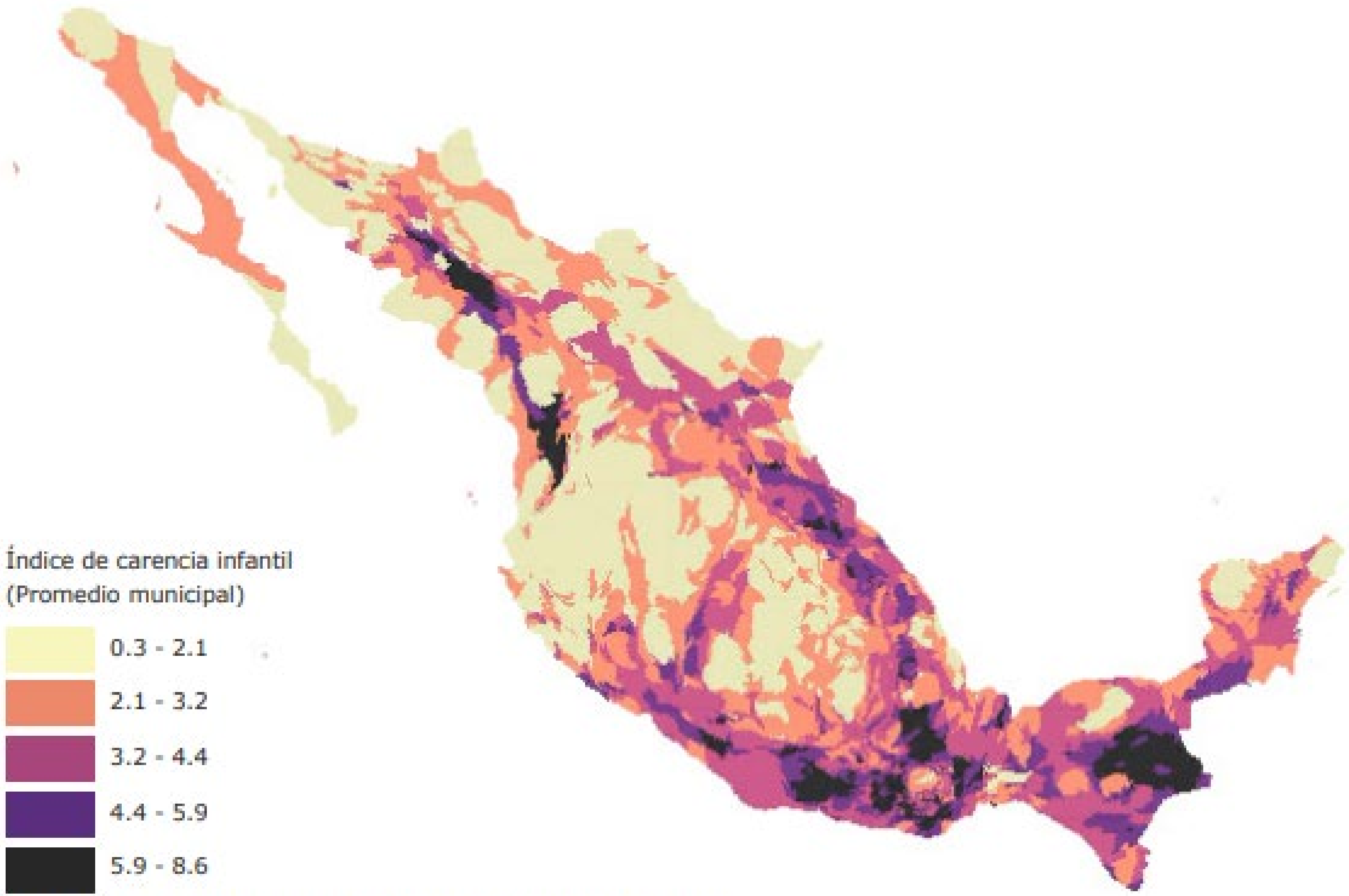
¿Podemos concluir que una persona indígena dada tiene mayor riesgo de vivir en pobreza?

Control de daños: Multinivel



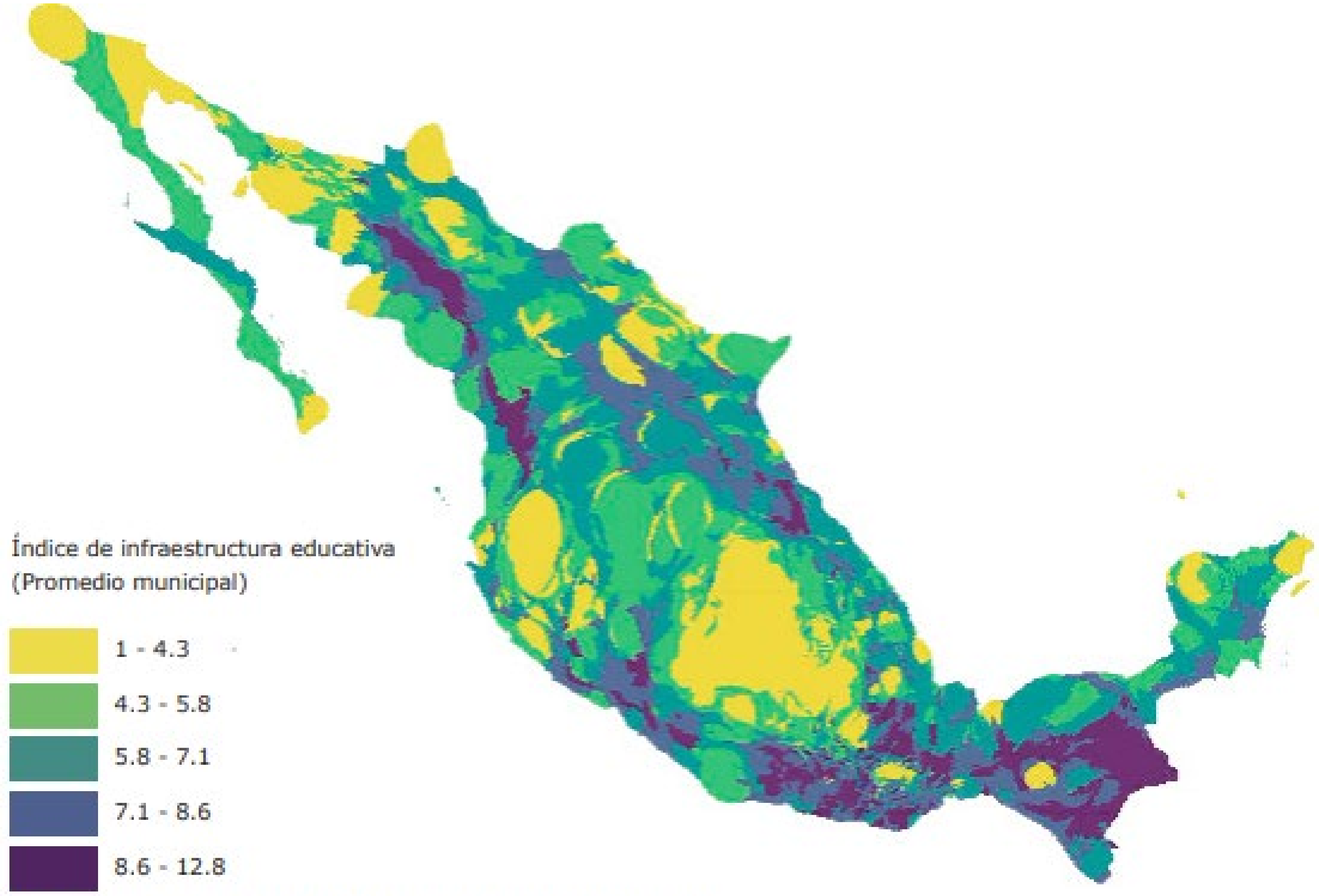
La variabilidad individual es condicional en la contextual y viceversa

Algunos ejemplos



Nota: El índice «I de Moran» de autocorrelación espacial (p<.01).

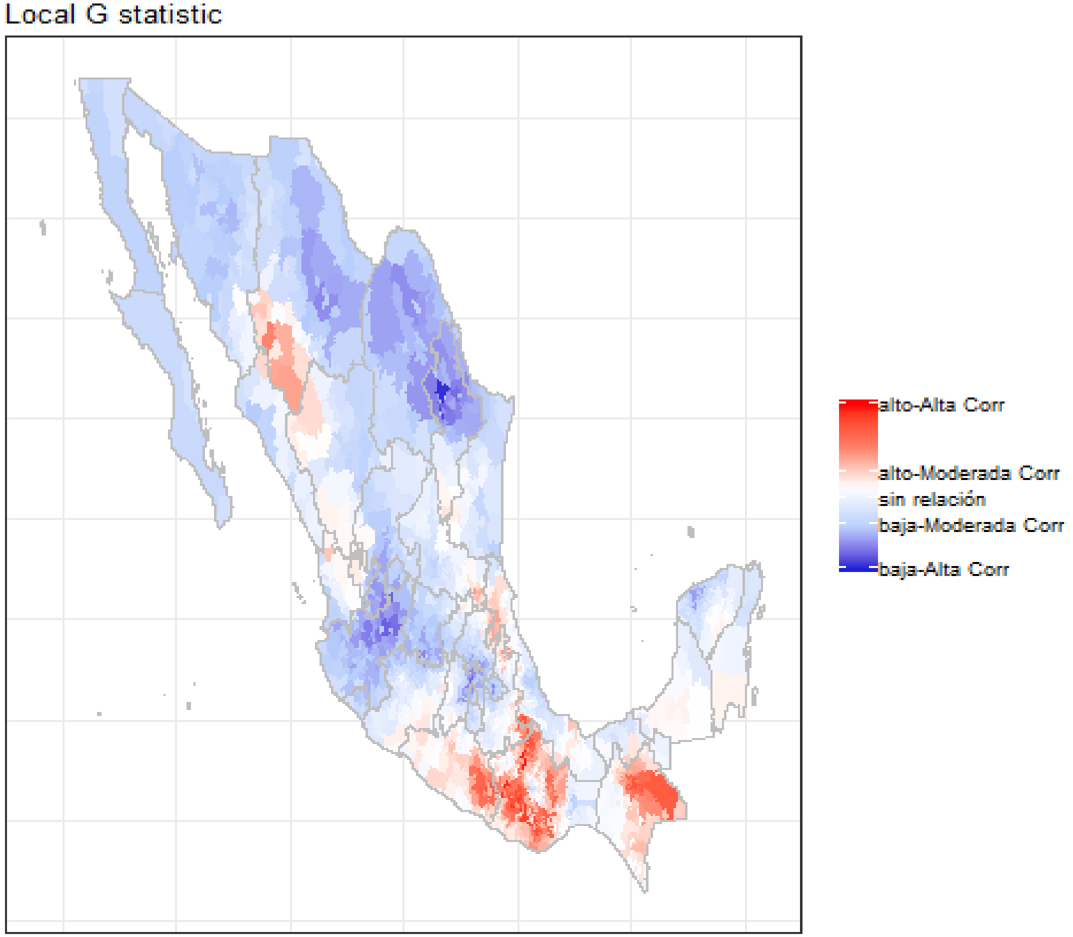
Fuente: Elaboración propia con datos de la Encuesta Intercensal 2015, INEGI, (2015).



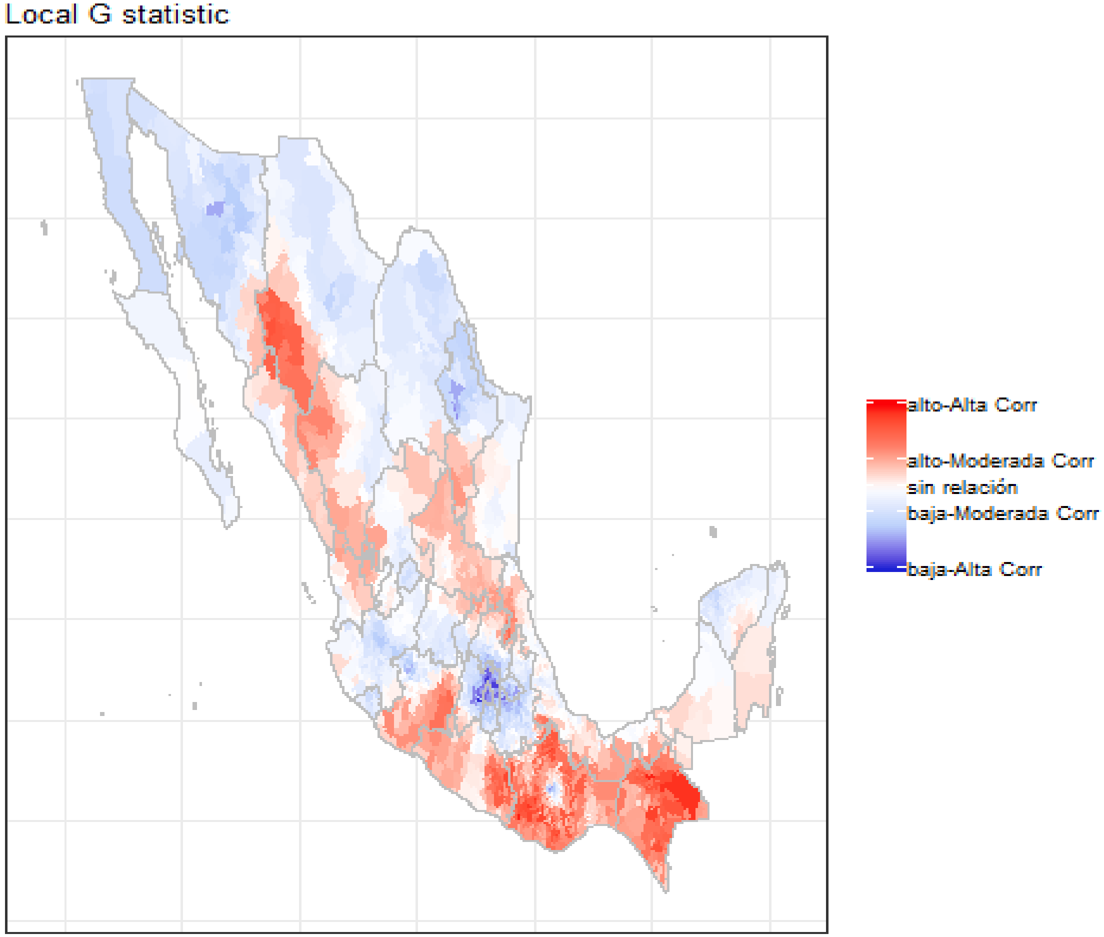
Nota: El índice «I de Moran» de autocorrelación espacial (p<.01).

Fuente: Elaboración propia con datos del Censo Educativo, INEGI-SEP, (2014).

Áreas de concentración de alta y baja carencia infantil

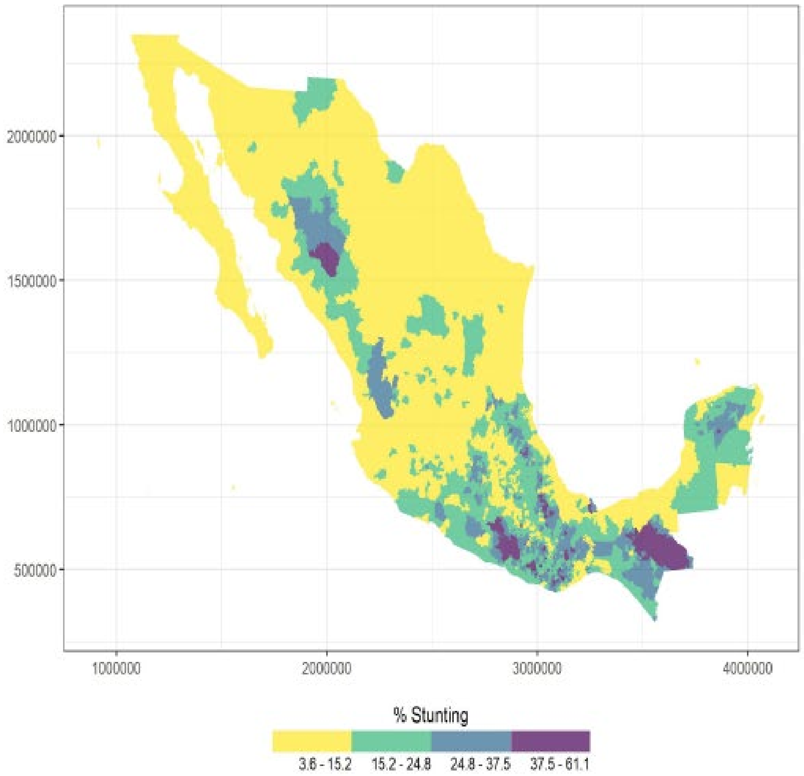


Áreas concentración de alta y baja calidad de infraestructura educativa

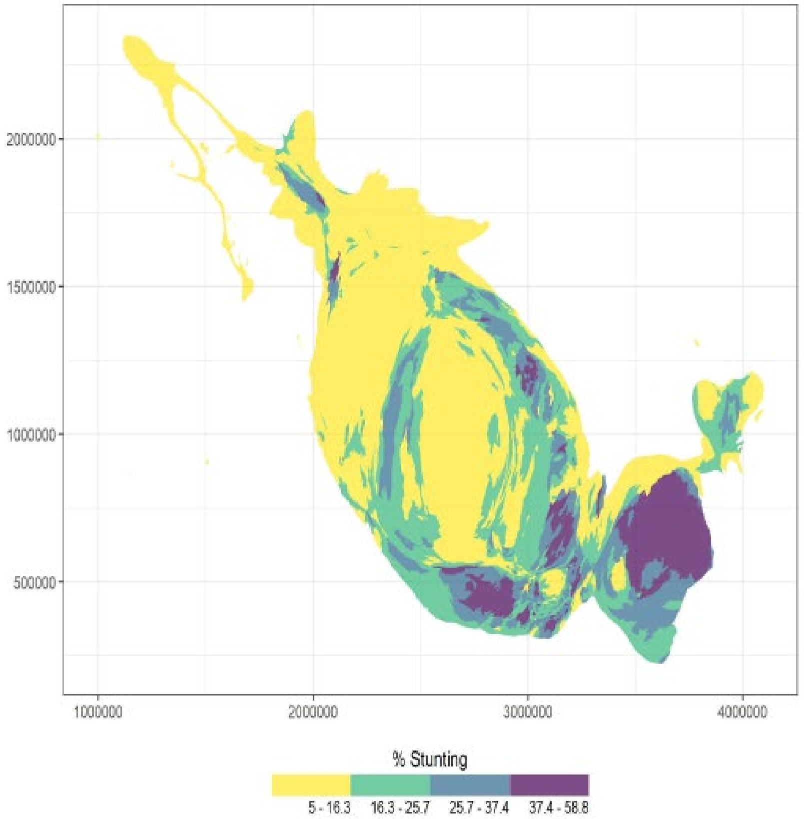


Segundo ejemplo

Figure 5: State-level stunting prevalence direct HHB census estimates 2010. Based on ENSANUT



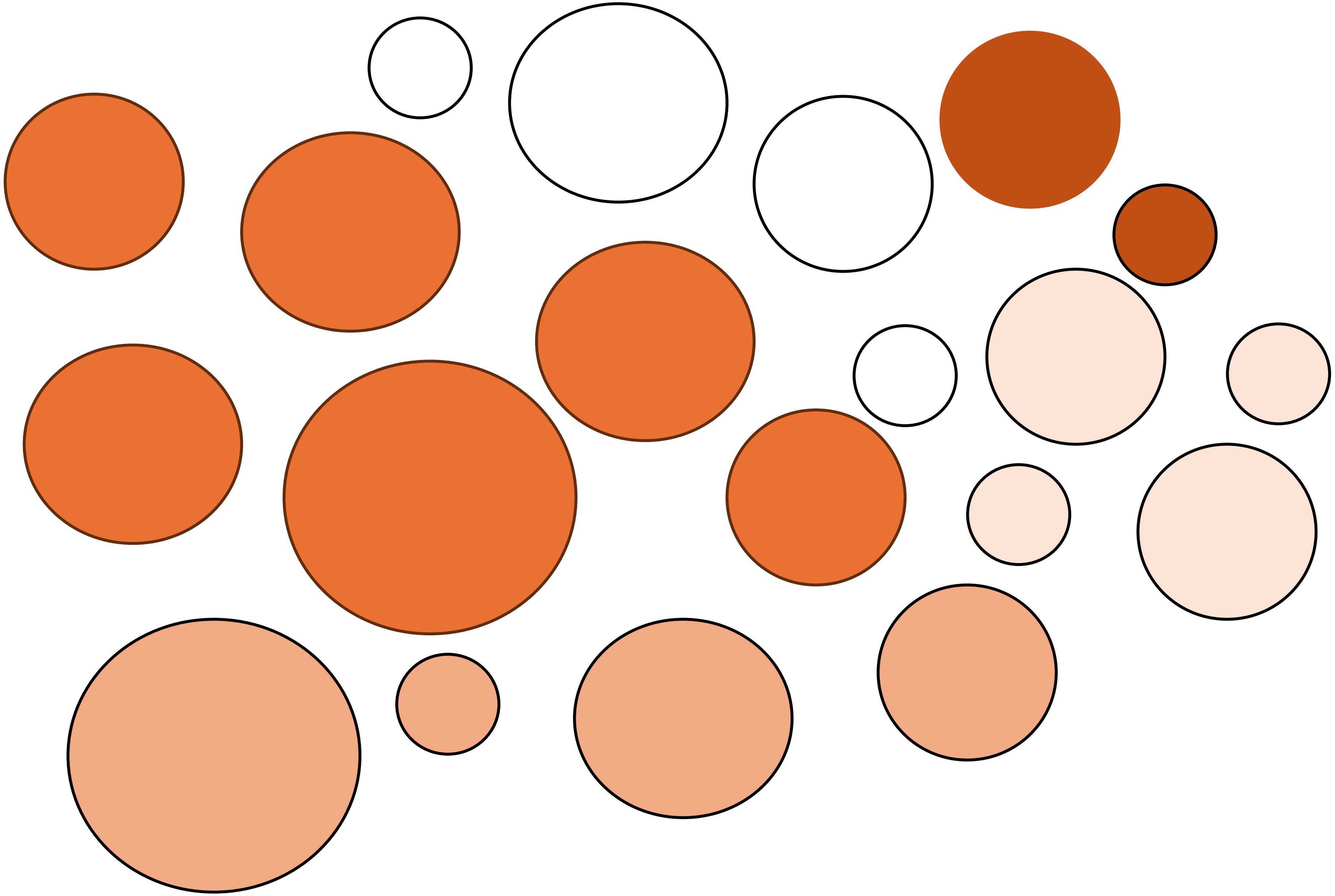
(a) % of Stunting. HHB estimates. Mexico 2010. Municipalities

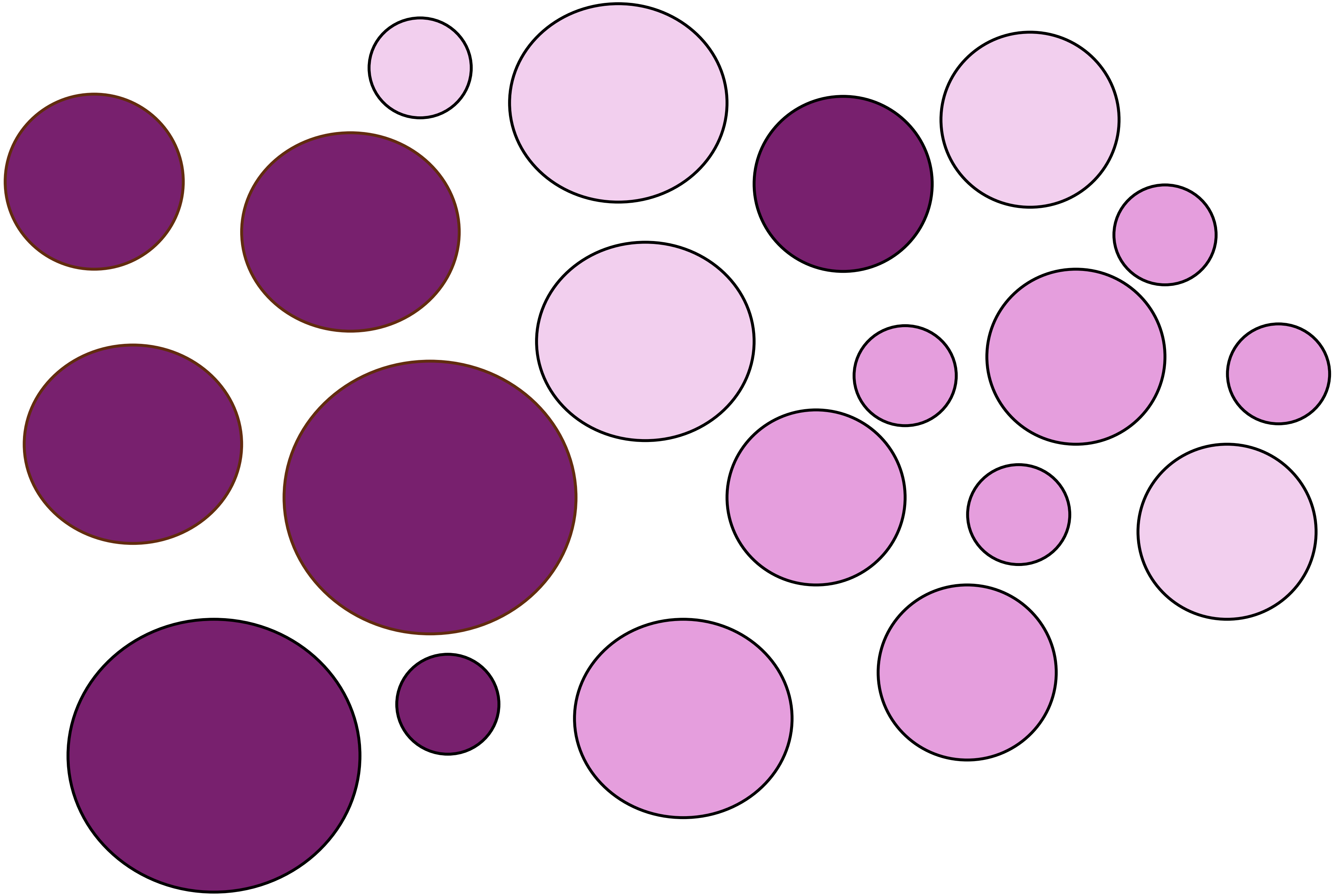


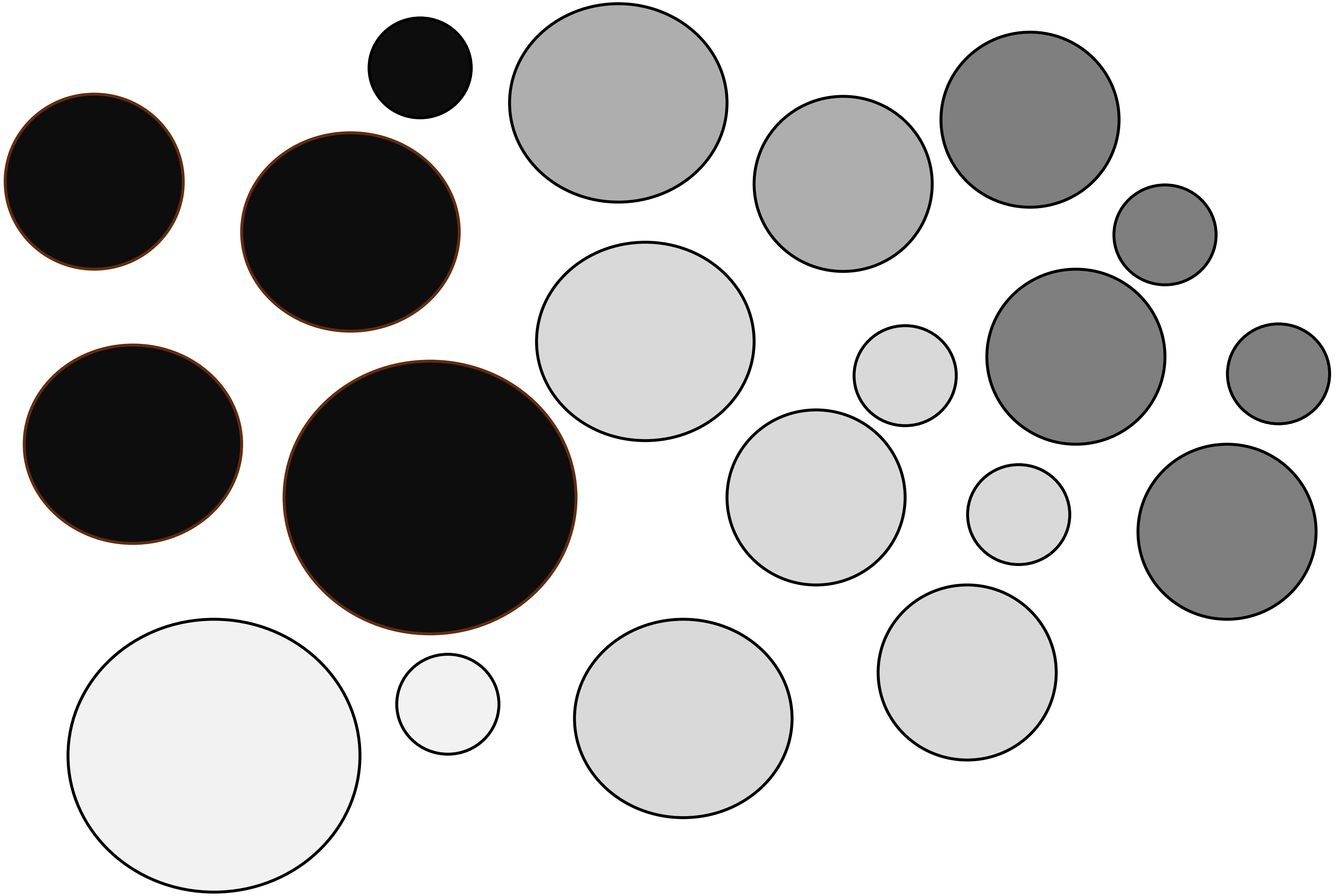
(b) % of Stunting. HHB estimates. Mexico 2010. Cartogram: Number of Children

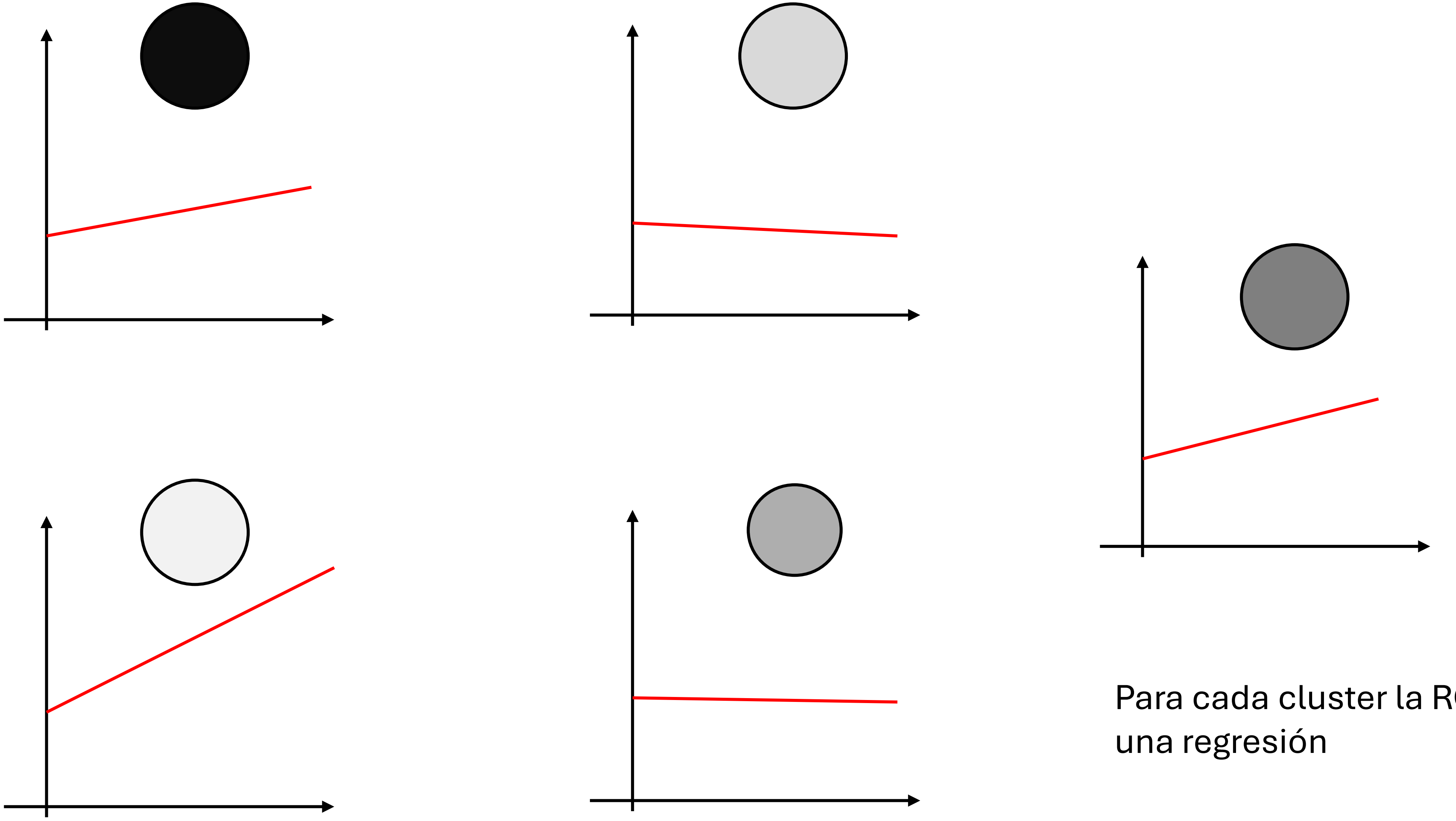
¿Hay alguna relación local entre la proporción de infantes con desnutrición crónica y la proporción de inseguridad alimentaria?

Intuición detrás de la RGP

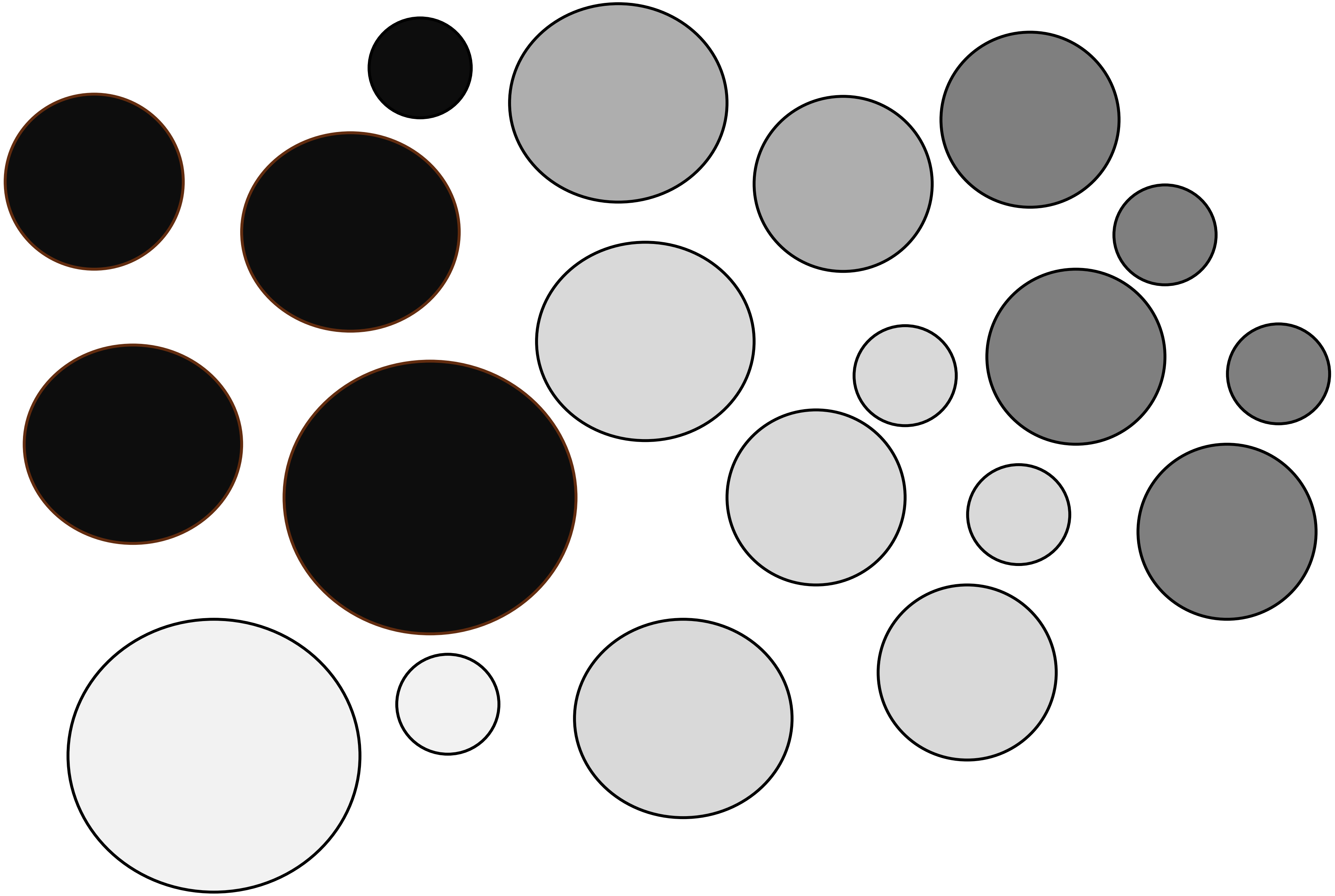


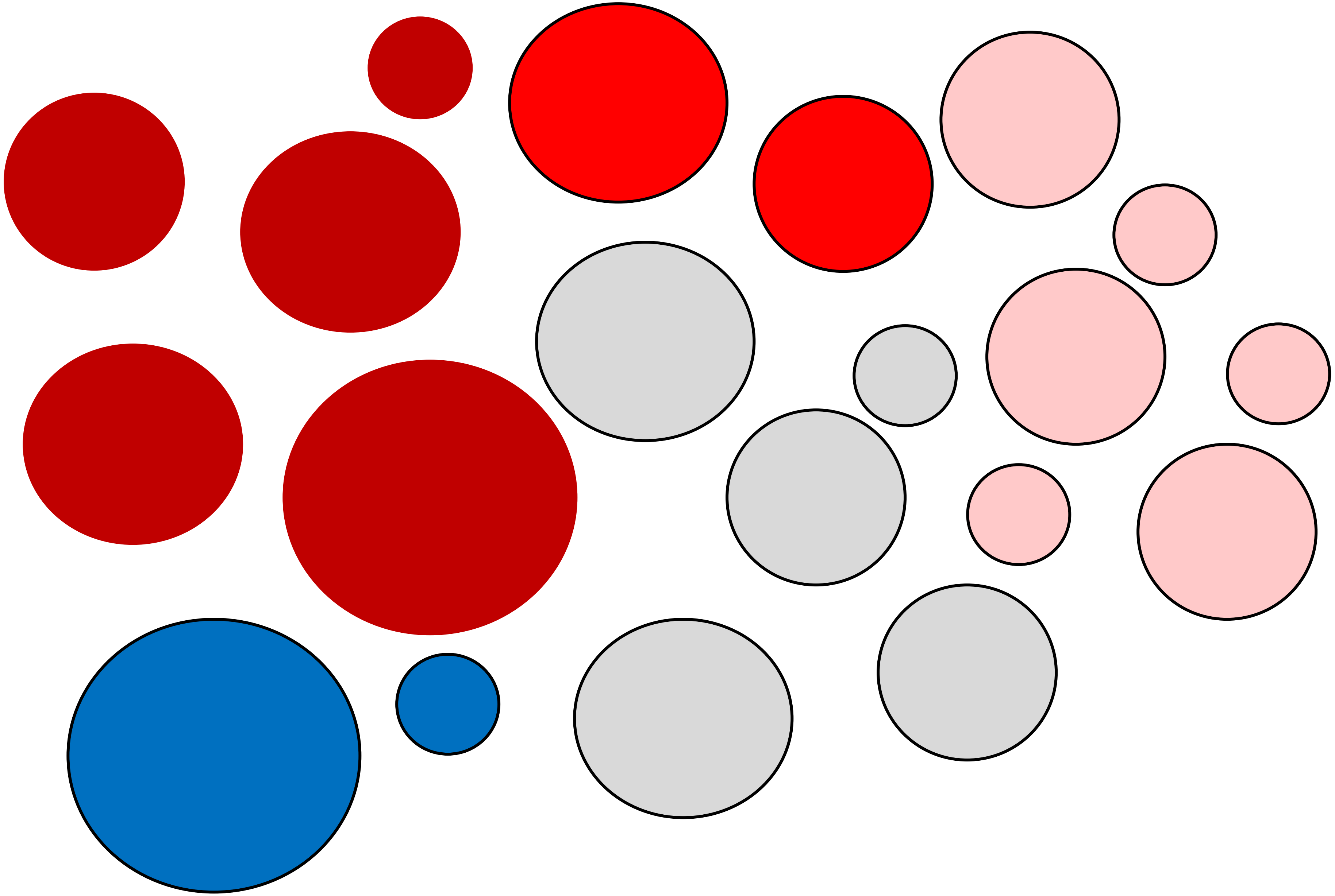






Para cada cluster la RGP estimará
una regresión





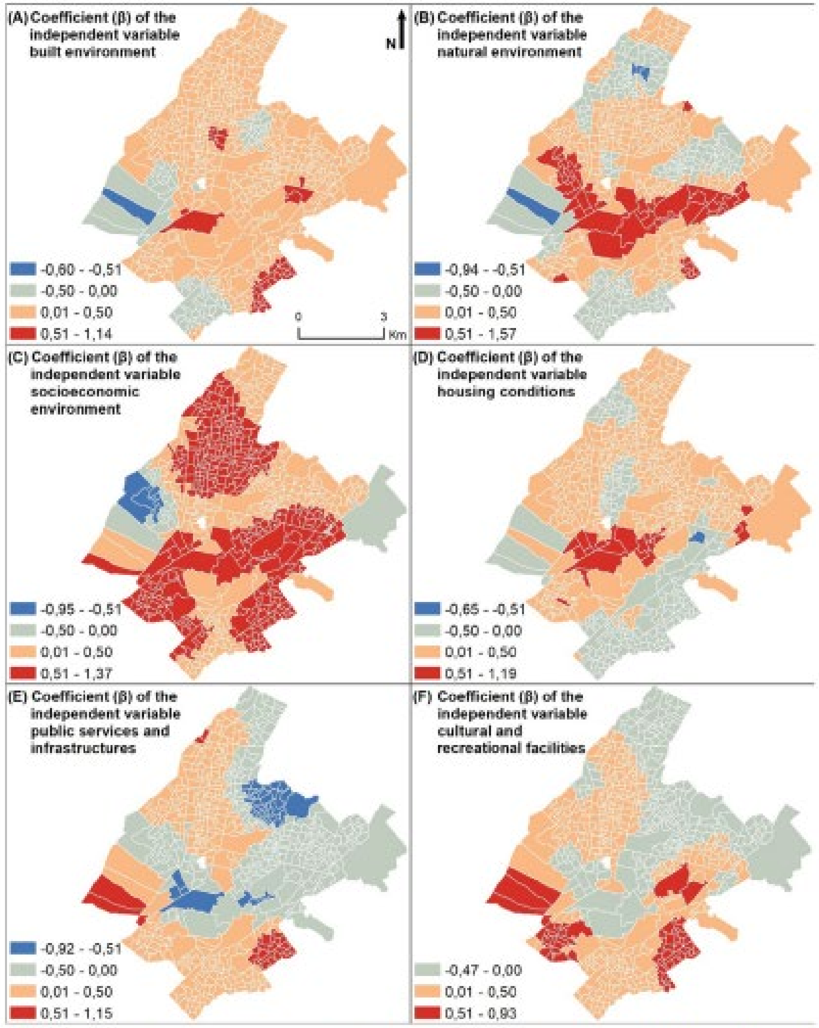


FIGURE 2.3 The spatial variation of the QoL criteria coefficient from GWR modeling. (A) Built environment, (B) natural environment, (C) socioeconomic environment, (D) housing conditions, (E) public services and infrastructures, (F) cultural and recreational facilities. *GWR*, Geographically Weighted Regression; *QoL*, quality of life.

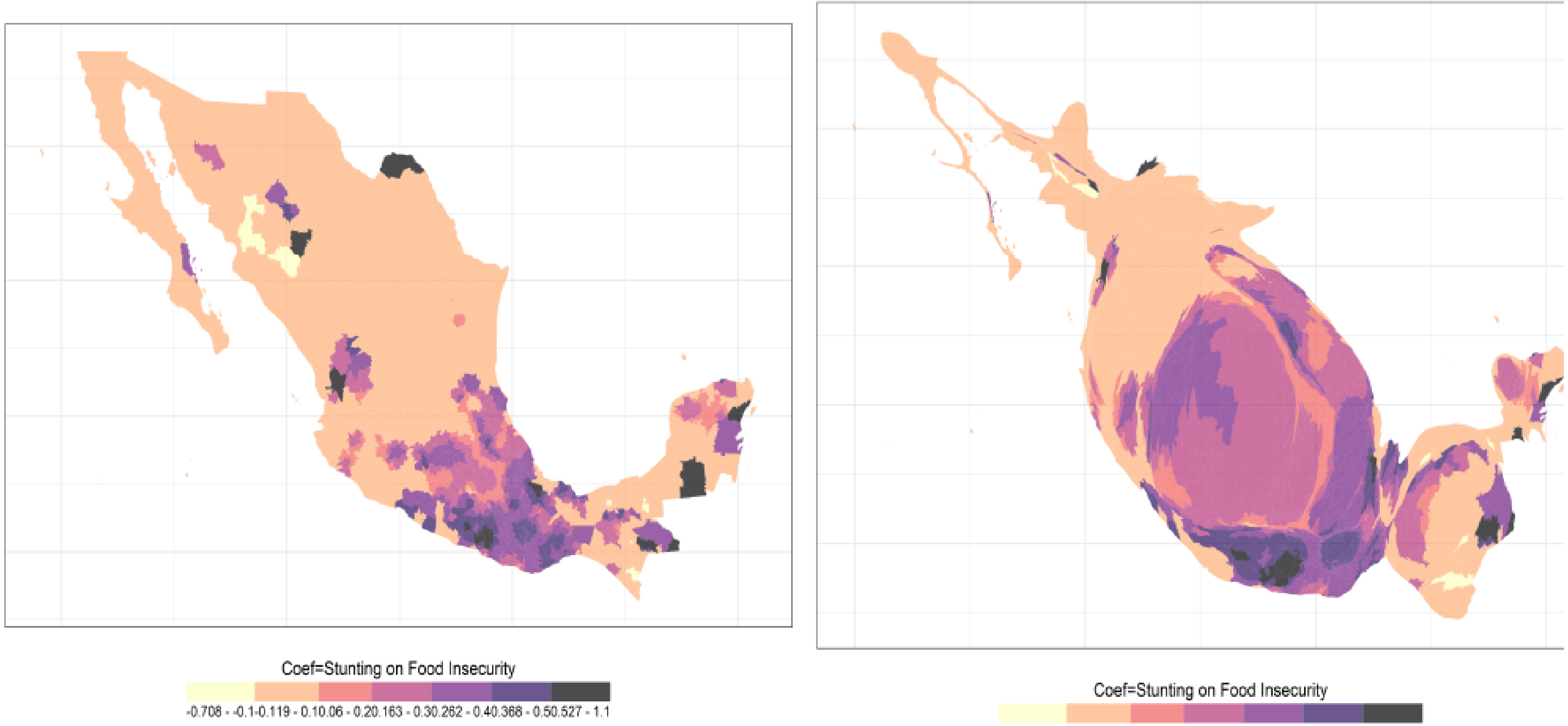
Chapter 2

Quality of life in Athens, Greece, using geonformatics

Antigoni Faka[1], Kleomenis Kalogeropoulos[2] and Christos Chalkias[1]

[1]Department of Geography, Harokopio University of Athens, Athens, Greece, [2]Department of Surveying and Geoinformatics Engineering, University of West Attica (UniWA), Athens, Greece

Figure 6: State-level stunting prevalence direct HHB census estimates 2010. Based on ENSANUT



(a) % of Stunting. HHB estimates. Mexico 2010. Municipalities

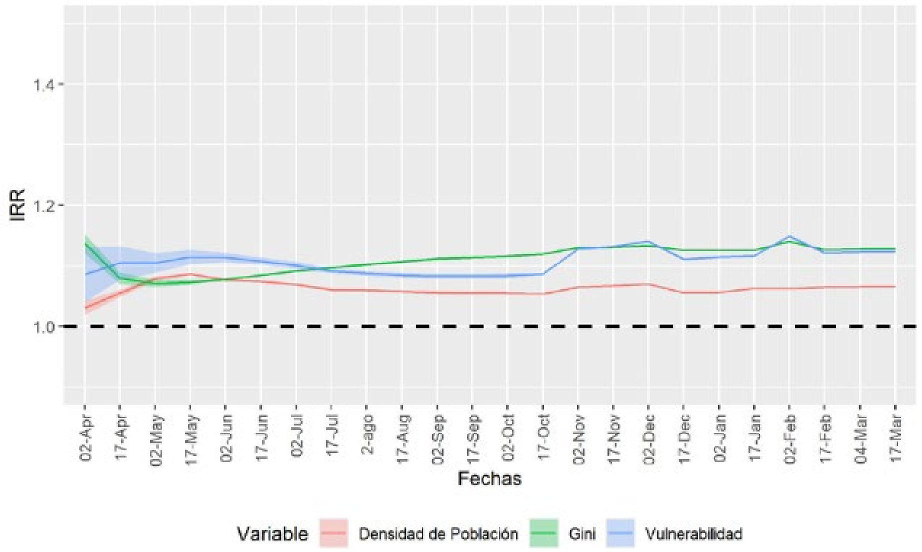
(b) % of Stunting. HHB estimates. Mexico 2010. Cartogram: Number of Children

Tercer ejemplo

Predictores ecológicos a nivel municipal del número de contagios de COVID-19 en México

Figura 1. Razones de momios de los contagios por covid en los municipios de México. Abril de 2020 a marzo de 2021

(a)



(b)

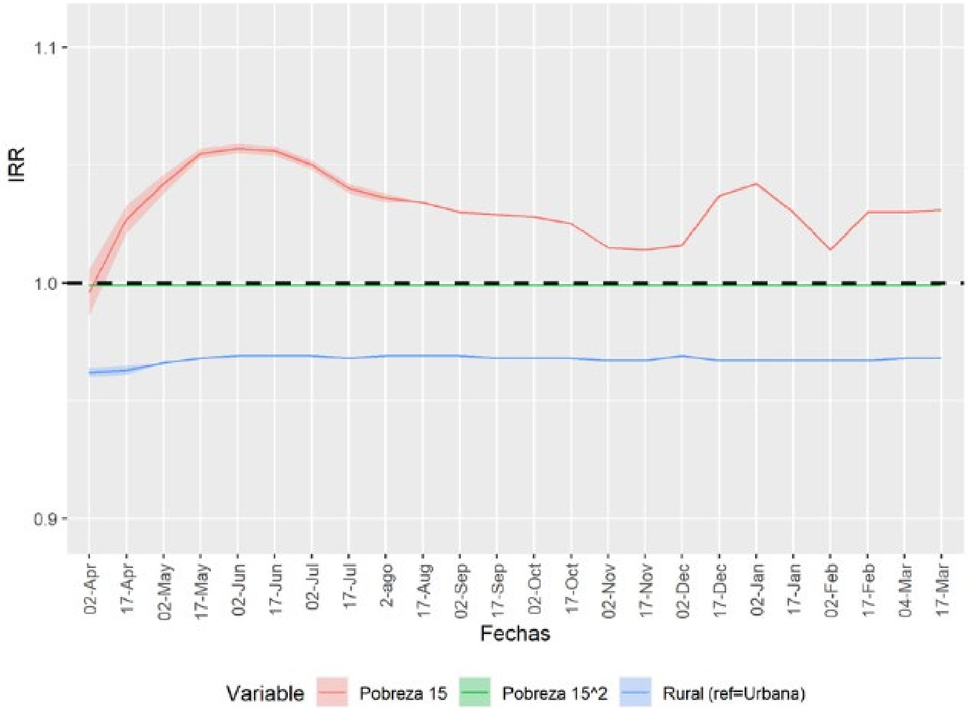


Figura 2. Comparación de la predicción de casos del modelo multinivel con los casos observados

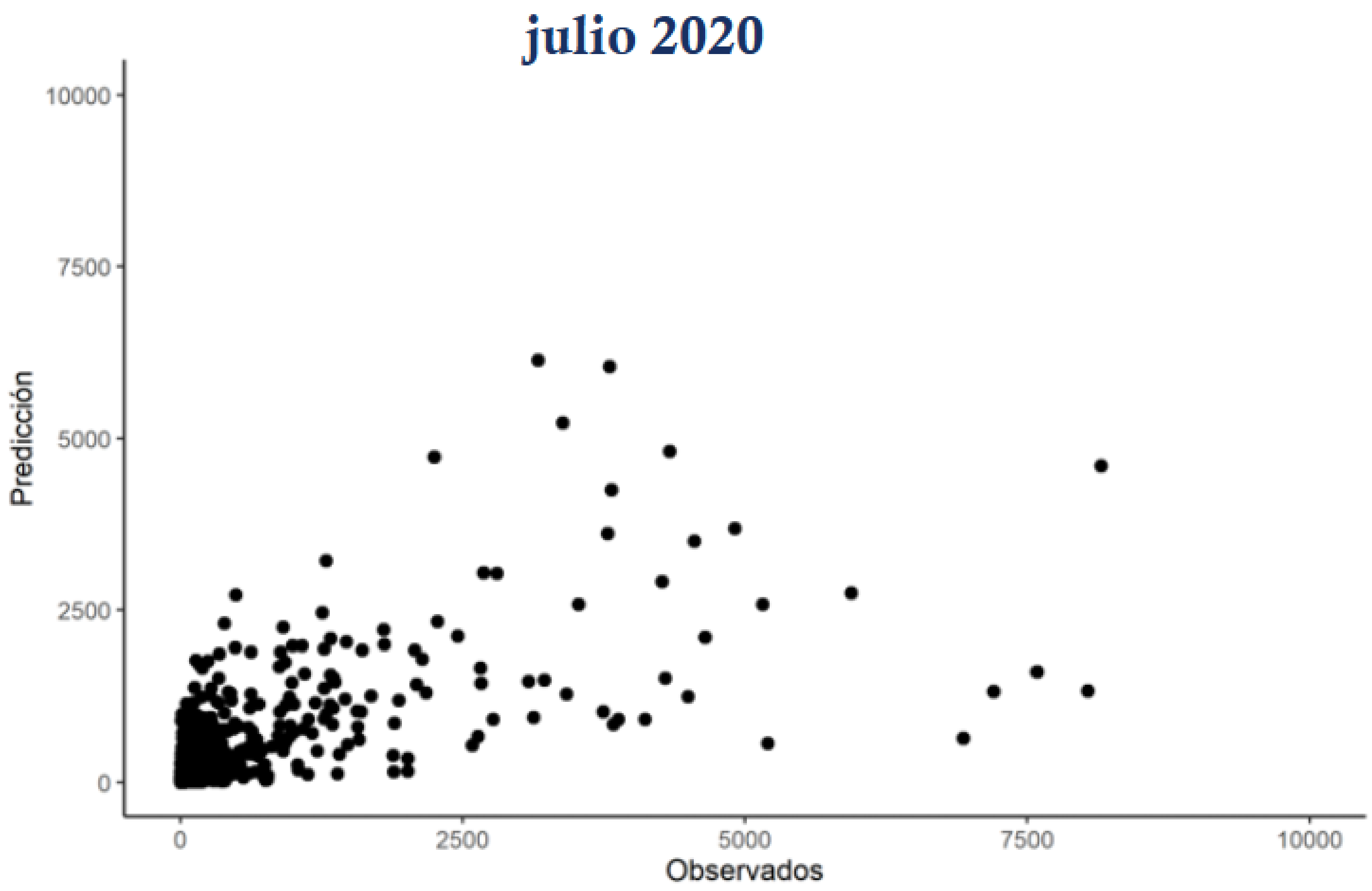
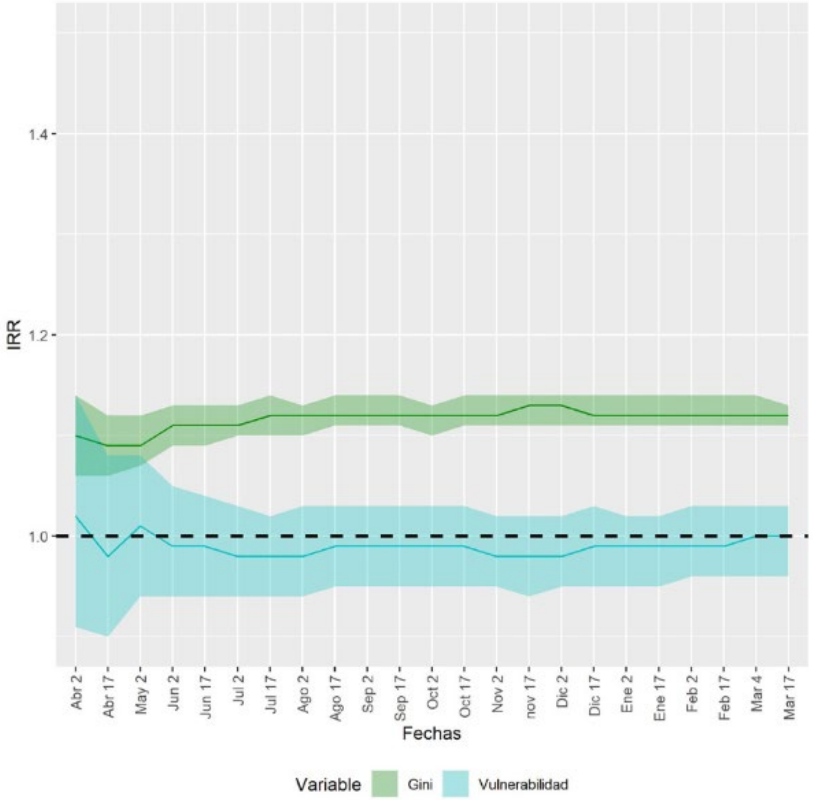


Figura 3. Evolución de los coeficientes (IRR) de las variables Gini y Vulnerabilidad, y de la densidad de población

(a)



(b)

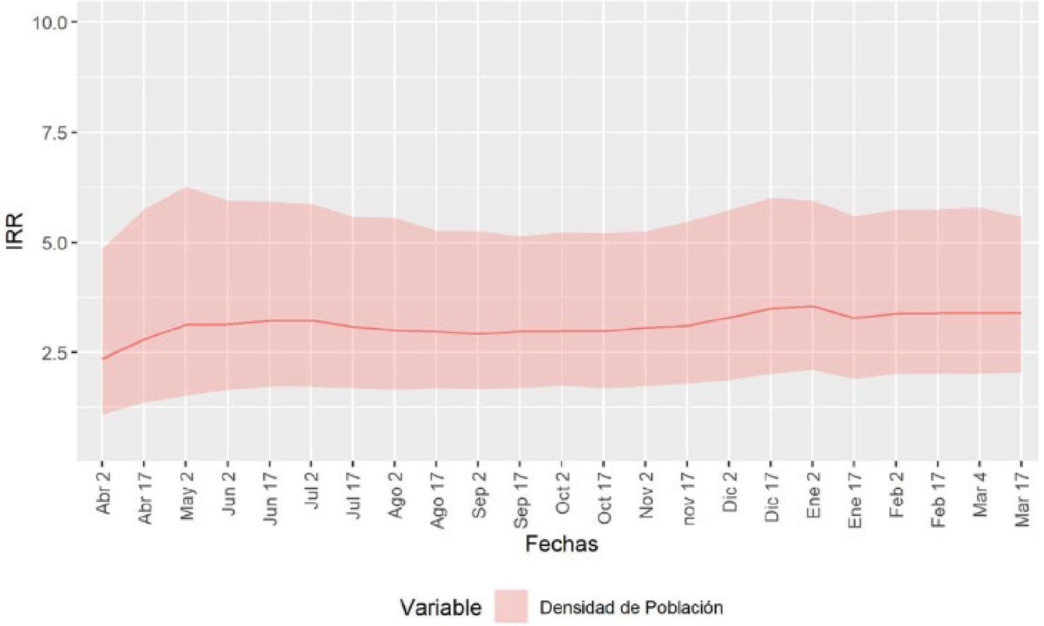
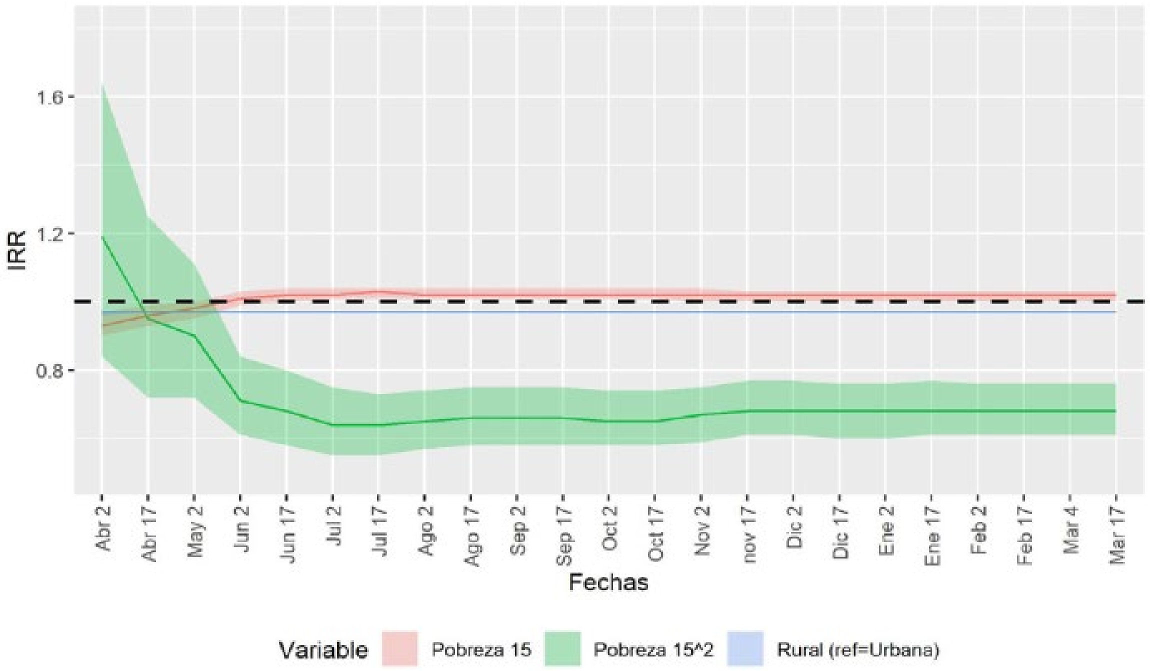


Figura 4. Evolución de los coeficientes (IRR) de la pobreza multidimensional, pobreza multidimensional al cuadrado, ruralidad y ordenada al origen

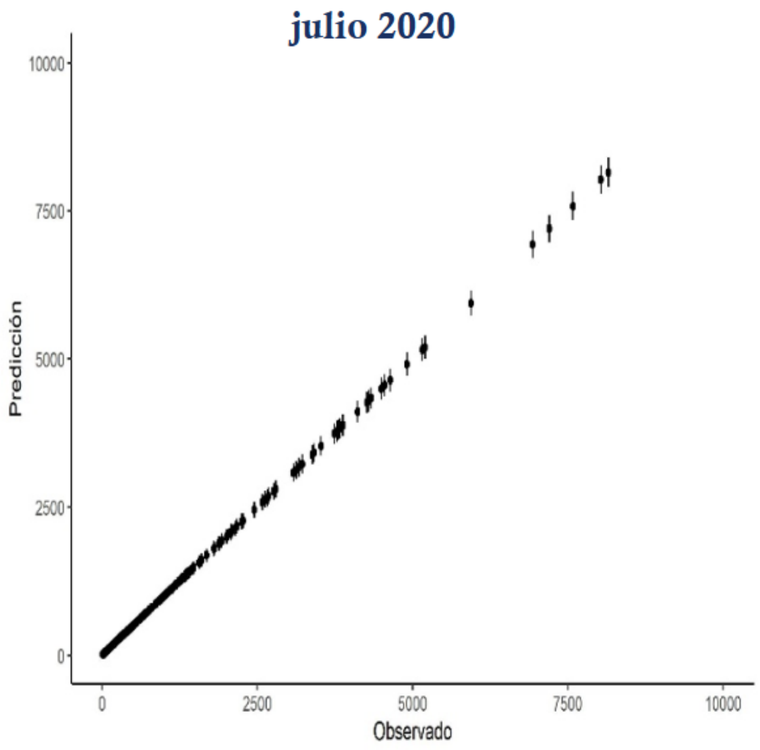
(a)



La relación entre pobreza y el número de casos tiene la forma de una parábola:

a muy baja y muy alta pobreza corresponde un bajo número de contagios, pero a niveles moderados de pobreza se observa un elevado número de contagios; esto al controlar el efecto lineal de las variables restantes incluidas en el modelo

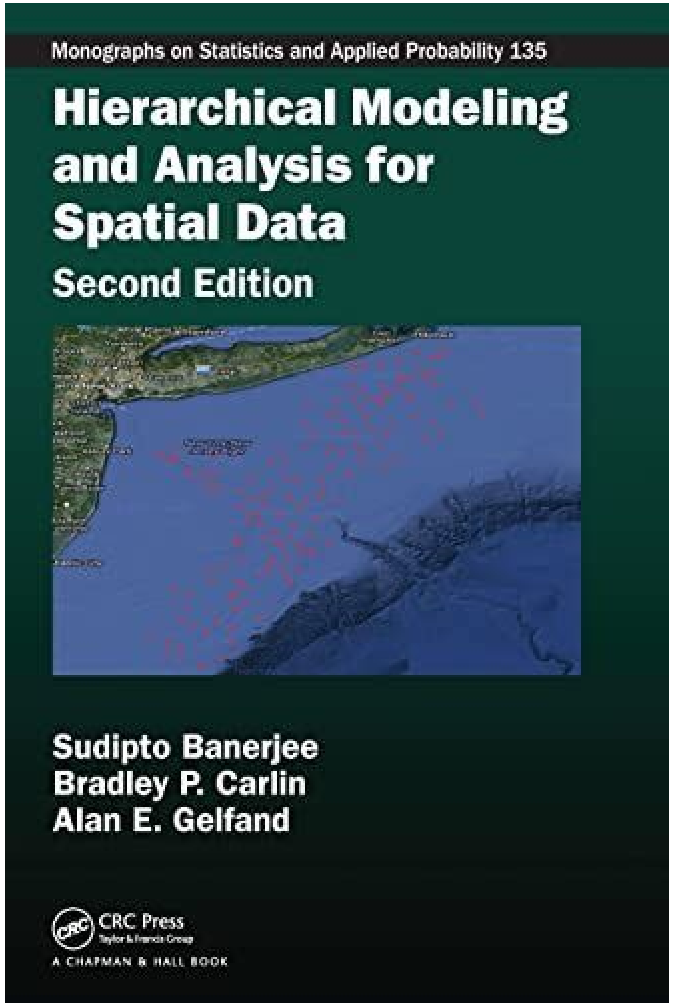
Figura 5. Comparación de la predicción de casos modelo CAR Bayes con los casos observados



El modelo global muestra una relación lineal positiva del índice de vulnerabilidad con el volumen de contagios por covid-19. Sin embargo, cuando se incorporan las variables que dan cuenta de la ubicación del municipio en el territorio, dicha relación desaparece.

Este resultado lleva a concluir que el volumen de contagiados por el virus en los municipios se debe principalmente a su ubicación geográfica y no tanto a su vulnerabilidad

Algunas referencias



Chris Brunsdon, A. Stewart Fotheringham and Martin E. Charlton

Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity

Spatial nonstationarity is a condition in which a simple "global" model cannot explain the relationships between some sets of variables. The nature of the model must alter over space to reflect the structure within the data. In this paper, a technique is developed, termed geographically weighted regression, *which attempts to capture this variation by calibrating a multiple regression model which allows different relationships to exist at different points in space. This technique is loosely based on kernel regression. The method itself is introduced and related issues such as the choice of a spatial weighting function are discussed. Following this, a series of related statistical tests are considered which can be described generally as tests for spatial nonstationarity. Using Monte Carlo methods, techniques are proposed for investigating the null hypothesis that the data may be described by a global model rather than a non-stationary one and also for testing whether individual regression coefficients are stable over geographic space. These techniques are demonstrated on a data set from the 1991 U.K. census relating car ownership rates to social class and male unemployment. The paper concludes by discussing ways in which the technique can be extended.*