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Methods for Calculating Life Expectancy at Birth for Small Areas: A Systematic Review

Métodos para calcular la esperanza de vida al nacer en áreas pequeñas: una revisión sistemática

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Abstract

Estimating life expectancy at birth for small areas is challenging because of the reduced sample size, which includes small populations and death counts, resulting in high variability and instability in mortality rates. Data deficiencies and imprecision further complicate the task. To address these issues, researchers have used smoothing techniques and data adjustments. In recent decades, significant advances have led to the development of various demographic and/or statistical methods in this field. This systematic review aims to present the state of the art of methods for estimating specific

Keywords

Expectancy at Birth
Small Areas
Methods
Systematic Review
PRISMA Protocol

mortality rates in small areas, with and without data deficiencies. Following the PRISMA protocol, 47 articles were selected. Most of the studies focused on the variability of the estimates, while a few considered the quality of the data before and/or after the smoothing of mortality rates, even in contexts known for poor information quality and underreporting.

Resumen

Las estimaciones de la esperanza de vida al nacer para áreas pequeñas son desafiantes debido al tamaño reducido de la muestra, que incluye una pequeña población y conteos de muertes, lo que resulta en una alta variabilidad e inestabilidad en las tasas de mortalidad. La deficiencia y la inexactitud de los datos complican aún más la tarea. Para abordar estos problemas, los investigadores han utilizado técnicas de suavización y ajustes de datos. En las últimas décadas, avances significativos han llevado al desarrollo de varios métodos demográficos y/o estadísticos en este campo. Esta revisión sistemática tiene como objetivo presentar el estado del arte de los métodos para estimar tasas de mortalidad específicas en áreas pequeñas, con y sin datos deficientes. Siguiendo el protocolo PRISMA, se seleccionaron 47 artículos. La mayoría de los estudios se centró en la variabilidad de las estimaciones, mientras que unos pocos consideraron la calidad de los datos antes y/o después de la suavización de las tasas de mortalidad, incluso en contextos conocidos por la mala calidad de la información y el subregistro.

Palabras clave

Esperanza de vida al nacer
Áreas pequeñas
Métodos
Revisión sistemática
Protocolo PRISMA

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Introduction

Knowing the levels and patterns of mortality by age is essential for understanding demographic dynamics and planning and implementing social policies. In many cases, life expectancy at birth is the key indicator for measuring a population's living conditions. Life expectancy is the average number of years of life expected for a newborn, given the existing mortality pattern in a given location. Its increase represents environmental, health, and public safety improvements.

Life expectancy at birth is obtained from a survival table, which uses specific mortality rates as its primary data, often expressed by five-year age groups and gender.

Estimating specific mortality rates is apparently a simple task, given the data required, which is the total number of deaths and the population by age. However, when it comes to small areas where the sample size or the collected data is not large enough to generate reliable estimates, the literature has shown how variable and unstable the rates are, thus requiring smoothing and adjustments to a more reliable standard.

These difficulties arise mainly from the underreporting of deaths, which occurs when deaths are not correctly registered or when there are errors in the records. Underreporting can be more common in small areas, especially if the registration infrastructure is limited and deaths are not reported or registered correctly.

This problem is exacerbated in regions and localities where data regarding event counting and qualification are not fully reliable, leading to under-registration, under-reporting (sub-collection), errors, and data incompleteness. In small areas of less developed regions, these problems can be even more common due to limitations or even the absence of infrastructure and qualified personnel for record-keeping, resulting in more imprecision in estimates and uncertainties regarding the studied phenomenon (Gonzaga, & Schmertmann, 2016; Queiroz, Lima, Freire, & Gonzaga, 2020).

From the perspective of addressing issues in data quality and undercounting, the indirect method proposed by Brass (1975) is a classic in demography. The method requires data, typically found in demographic censuses, regarding surviving children of women of a certain age, from which it is possible to estimate probabilities of child and youth mortality. These probabilities, in turn, allow the calculation of a complete life table based on a reference table through a relational model. Combining these two steps provides a mortality structure standardized by the reference table and adjusted by the estimated mortality level. Other demographic methods include the family of Death Distribution Methods (DDM), which derive a mortality structure by comparing the age distribution of deaths with that of the population (Queiroz et al., 2020), and indirect standardization, which also generates a structure and adjusts mortality level based on a standard curve (Gonzaga, & Schmertmann, 2016).

Several statistical methods, such as the empirical Bayesian and the Expectation-Maximization (EM) algorithm, allow the estimate of under-

registration of deaths and, when applied to data, provide more reliable estimates of mortality rates (Justino, Freire & Lucio, 2012). Unlike the Brass method (1975), these methods use mortality registration data and census and/or population estimates.

Intending to reduce noise in longevity estimates for small areas in the context of good-quality records, many authors have employed data aggregation. This includes aggregating the number of inhabitants and deaths over a period of time (Congdon, 2014; Eayres, & Williams, 2004; Kulkarni et al., 2011; Tsimbos, Kalogirou, & Verropoulou, 2014), aggregating by geographical areas until a minimum threshold of population size per age group is reached (Kulkarni et al., 2011), or using person-years in the denominators of rates (Gonzaga, & Schmertmann, 2016; Olatunde, White, & Smith, 2010; Talbot, Done, & Babcock, 2018).

Eayres & Williams (2004) evaluated the methodologies for calculating male life expectancy at birth for English electoral districts from 1998-2000. They established the lower limit of 5 000 person-years as an acceptable minimum point for reliably calculating estimates. Kulkarni et al. (2011), on the other hand, when calculating life tables by gender and race for American counties for the years 2000 and 2007, concluded that the lower limit of 7 000 people per county for the application of a Poisson regression is associated with an acceptable estimation error.

Alternative procedures for estimating mortality rates for small areas consist of methods of indirect standardization of these rates, which borrow functions from the specific mortality rates of a population considered to be standard (Sacco, Williams, & Queiroz, 2021), regression (Paredes, & Silva, 2017; Rachet et al., 2015), Bayesian models, which use the power of age, sex, time and space also from a standard population to smooth mortality rates (Congdon, 2014; Gonzaga, & Schmertmann, 2016; Rashid et al., 2021; Sacco et al., 2021; Schmertmann, & Gonzaga, 2018).

The TOPALS (Tool for Projecting Age-specific Rates using Linear Splines) method has also been shown to be effective in estimating and smoothing specific mortality rates for small areas, as demonstrated by Gonzaga & Schmertmann (2016) and Schmertmann & Gonzaga (2018) using data from Brazil. In the first article, the authors point out that the flexibility of the method represents an advance for small area mortality estimates

that require undercount corrections, compared to indirect standardization that imposes a pattern on the curves, usually from the larger area. However, they acknowledge the need for further investigation into the method's results in the context of a large volume of underreporting. In the second, to incorporate the problem of undercounts, they combine TOPALS with the Bayesian model and add the degree of death coverage estimated by other studies as well.

It is worth noting that among the articles evaluated for this systematic review, only the studies by Schmertmann & Gonzaga (2018) and Queiroz et al. (2020) explicitly aimed to both – smooth mortality rates and correct data issues – simultaneously. Queiroz et al. (2020) estimated adult mortality rates for a number of Brazilian regions through TOPALS and adjusted mortality levels via general growth balance adjustment. In both studies, corrections were justified by historical regional disparities in coverage and quality of vital registration in Brazil.

Other articles on mortality rates and life expectancy at birth estimates for small areas in developing and underdeveloped regions (Anggreyani, Indahwati, & Kurnia, 2016; Barman, & Choudhury, 2017; Paredes, & Silva, 2017; Picazzo-Palencia, Flores-Segovia, & Cruz-Maldonado, 2018; Rose, & Nagle, 2017; Sacco, Williams, & Queiroz, 2021; Wakefield et al., 2019) included in this review did not mention any justification for the methods chosen due to deficiencies in microdata. Some authors acknowledged data uncertainties and corrected estimates to some extent by applying mortality rate smoothing techniques. However, this objective was not explicitly stated in the articles. Furthermore, even if such corrections were explicitly stated, smoothing rates do not specify the exact type of inaccuracy that is being corrected.

In this context of diversity in methods and conditions for demographic estimation for small areas, this study aims to conduct a systematic review of methods used to estimate life expectancy at birth. The comprehensive analysis of scientific evidence proposes to investigate whether there are differences in calculation approaches for the longevity indicator and consequently for mortality rates in different localities considered as small areas. Thus, recognizing the importance of this indicator for assessing population living conditions and for policy formulation.

Methods

The systematic review was carried out according to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) protocol (Page et al., 2021), available in Supplementary Material - 1, and registered on the International Prospective Register of Systematic Reviews (PROSPERO) platform under the number CRD42023422418.

The systematic review aims to answer the following question: What methods can be used to calculate life expectancy at birth for small areas? The searches were conducted on April 4, 2023, in the Lilacs, Embase, Web of Science, and Scopus databases. There were no restrictions on time, place, or language. The search terms followed the PICO strategy, an acronym for Population, Intervention, Comparison, and Outcomes. The PICO acronym and search strategy are available, respectively, in Tables A-1 and A-2 of the Appendix. The search terms used were: “expectancy life”, “method”, “small areas” and “demography”.

The references collected were imported into EndNot 20 (Gotschall, 2021) to remove duplicates and transferred to Rayyan for screening (Ouzzani et al.2016). The first selection was based on reading the title and abstract; the selected studies were retrieved completely for reading.

The inclusion criteria for the articles in the first phase were: i) demographic and/or human health studies whose primary or secondary outcome is the calculation of life expectancy at birth; ii) studies whose main or secondary outcome is the calculation of total life expectancy at birth; iii) studies that discuss or apply some statistical or demographic method for calculating life expectancy at birth; iv) studies that include the calculation of life expectancy at birth for small geographical areas, and v) studies that include the calculation of life expectancy at birth for population subgroups.

Studies were excluded if: i) they involved animals and nature; ii) they only calculated life expectancy at birth by cause of mortality as an outcome; iii) they only calculated healthy life expectancy as an outcome, and iv) they were only carried out for large areas, such as countries, states, and regions.

In the second phase of the systematic review, which consisted of reading the articles in full, the inclusion criteria considered were: i) studies that

do not present mortality/life expectancy at birth as an outcome for small areas; ii) studies that calculate but do not present a methodology/calculation for correcting/adjusting/smoothing mortality rates/data for small areas; iii) studies that only consider the quality of information from the death sub-registry, and iv) unavailable full text. The table with the studies by type of exclusion reason can be seen in Appendix A-3.

In all phases, four researchers carried out the screening, and at least two of them assessed each article independently. Differences in assessment for inclusion/exclusion were discussed and resolved by consensus.

Two researchers carried out data extraction in a standardized Microsoft Excel spreadsheet (available in Supplementary Material - 2). The spreadsheet includes information on the general characteristics of the studies, such as authors, country of origin, year of publication, and essential information for qualitative syntheses, such as geographical area of study, minimum population for analysis, type of data, type of study, models used, outcomes observed and kind of disaggregation.

This data allows one to assess the quality and relevance of the studies and compare and synthesize the results. The results were aggregated and categorized in Microsoft Excel, and the figures were generated using R software (version 4.2.3).

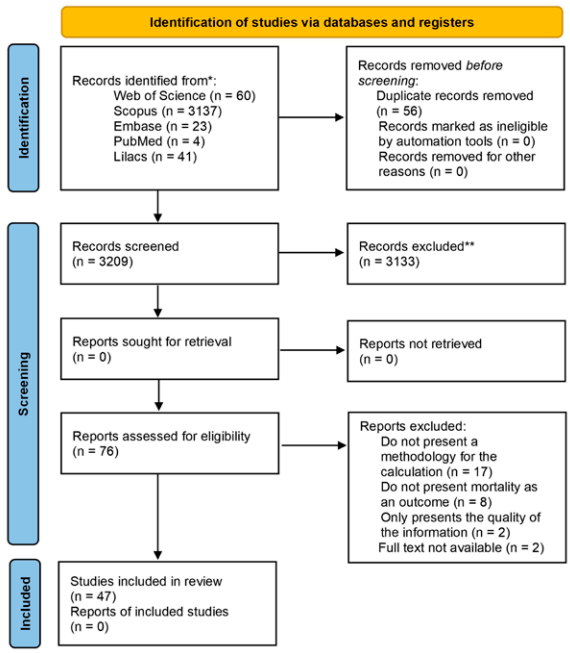
Since no verified instrument assesses study quality, a questionnaire was developed based on the literature to evaluate the quality of study outcomes. The questionnaire includes specific questions for data presentation (Mcarthur, 2020; Munn et al., 2020) (Table A-5 in the Appendix). Two researchers independently assessed the outcomes' quality, and consensus resolved differences.

Results

A total of 3 265 articles were found, 96 % of which were collected from the Web of Science database. In contrast, the remaining 4 % were extracted from other data sources, such as Scopus, Embase, PubMed, and Lilacs (Table A-2 in the Appendix). After removing 56 duplicates, 3 209 references remained to be assessed by reading the title and abstract. Of these, 76 articles were selected for full reading.

According to the pre-established exclusion criteria, 27 studies were removed from the analysis, and two could not be fully retrieved. Thus, 47 articles were included in the final sample (Figure 1). The list of articles included in the analysis is available in Table A-4 in the Appendix.

Figure 1. Flow diagram of the systematic review article selection.



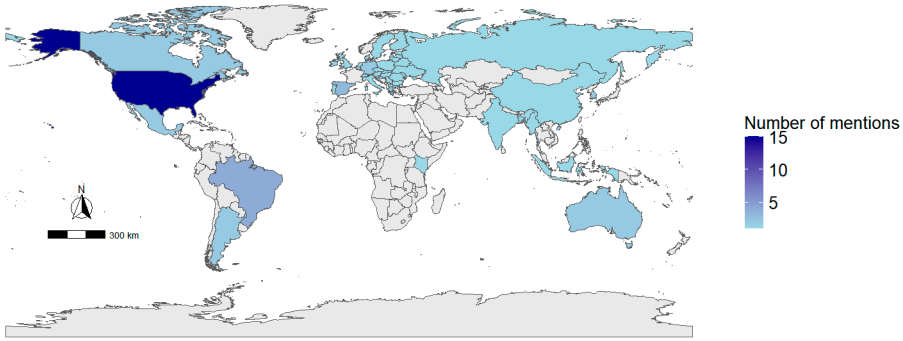
Source: Elaborated based on the model by Page et al., 2021.

Characteristics of the included studies

Of the 47 articles included in the systematic review, 13 (27.6 %) referred exclusively to the United States. Two papers applied techniques using data from the United States and other countries, such as China and France. One article used data from 33 European countries. The other papers covered small areas from Argentina, Australia, Bangladesh, Brazil, Canada, China, Korea, Scotland, Greece, India, England, West Java, Mexico, Myanmar, Kenya, and Taiwan (Figure 2).

Only 36.17 % (n=17) of the studies received financial support. The donors varied significantly between the studies, the most frequent being the Welcome Trust (23.53 %) (Table A-6 in the Appendix).

Figure 2. Number of country mentions in studies included in the systematic review.

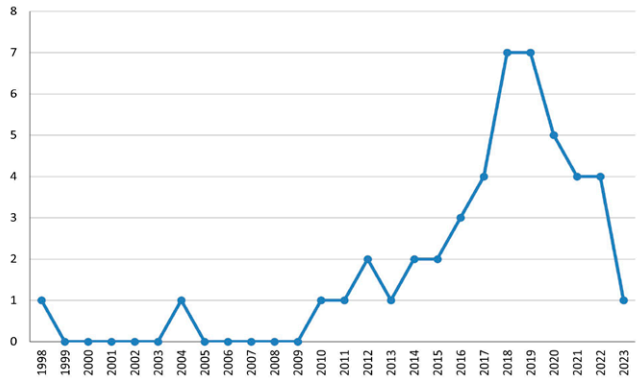


Source: Elaborated by the authors.

Methodological advances regarding mathematical models and computer programming to calculate mortality rates for small areas were made in the 2000s. Still, from the 2010s onwards, epidemiologists played a key role in developing Bayesian models to estimate mortality for regions with low population volumes and, therefore, deaths (Gonzaga, & Schmertmann, 2016).

Figure 3 shows the years of publication of the articles included in this systematic review and the increase in the number of papers over the 2010s.

Figure 3. Number of selected publications over time 1998-2023.*



**Data from the year 2023 is considered up-to-date to April 4, 2023.*
Source: Elaborated by the authors.

Models of empirical studies

To organize the discussions on the techniques adopted by researchers to calculate specific mortality rates for small areas, it was decided to group them into two large groups: parametric and non-parametric models. Table 1 shows the techniques and models found in the systematic review according to this classification.

Table 1. Models covered in the systematic review based on their classifications.

Classification	Method/Model	Does the method explicitly allow adjustments due to data quality issues?
Parametric models	Bayesian	Yes - Small sample size and underreporting of deaths by sex and age
	Generalized linear mixed model	No
	Chiang I and II	No
	Expectation–maximization (EM) algorithm	Yes - Underreporting of deaths by sex and age
	Silcocks	No
	Greville	No
	Reed-Merrell	No
	Mixed-effects Poisson regression	Yes - Small sample size
	TOPALS	Yes - Small sample size and underreporting of deaths by sex and age
	Flexible relational model	No
	Swanson	No
	Beta Binomial	No
	Lee–Carter model	No
	M-model	No
Non-parametric models	Bayesian	Yes - Small sample size and underreporting of deaths by sex and age
	The Brass-type indirect methods	No
	Direct method	No
	Flexible Poisson model	No
	Iterative proportional fitting	Yes - Missing data

Table 1. Continued.

Classification	Method/Model	Does the method explicitly allow adjustments due to data quality issues?
Non-parametric models	Maximum entropy method	Yes - Missing data
	Partial SMR	No
	Penalized maximum entropy model	No
	Standardized mortality ratio	No
	Whittaker graduation method	No

Source: Elaborated by the authors.

Parametric models consider specific parameters to adjust the observed data, in this case, deaths and population in small areas. In this systematic review, the Chiang I, II, Silcocks, Greville, and Reed-Merrell models belong to this group since they seek to smooth specific mortality rates of the population under study based on assumptions about the shape of the distribution of these rates. The models use specific mathematical functions to adjust and estimate the mortality structure using a standard population as a reference. While Chiang I considers fixed values for the fraction of years that individuals live within age intervals between 5 and 15 years, model II assumes that deaths are evenly distributed over an age interval (Chiang, 1968). Silcocks considers the mortality rate constant throughout the age group, resulting in an exponentially decreasing number of survivors (Eayres, & Williams, 2004). Greville assumes constant changes in specific death rates and then applies Gompertez's mortality law to estimate probabilities, while Reed-Merrell is an empirical method based on 33 survival tables from 1910 (Manuel, Goel, & Williams, 1998).

Beta-binomial models, also parametric in nature, often play a role in modeling overdispersion in specific mortality rates in small areas. These models assume that the distribution of rates follows a binomial distribution, in which the event "death" is modeled with two options (survival or not).

The beta-binomial distribution is a probability distribution that combines the properties of the binomial distribution and the beta distribution. This distribution models variability in counting processes, where the number of successes in a fixed number of attempts is not constant and follows a binomial distribution. However, the probability of success in each effort varies according to a beta distribution. This process allows accommodating variability in mortality rates between different areas or periods.

This group also includes linear regression, Poisson, and mixed Poisson models; the former estimates specific mortality rates as a linear function of covariates such as age and gender. For example, Swanson's model (1989), mentioned in some articles in this systematic review, adjusts life expectancy at birth as the dependent variable as a function of the crude mortality rate and the population aged 65 and over.

The second model is applied to shape counts and assumes that the response variable follows a Poisson distribution, i.e., a discrete probability distribution widely used to pattern counts. In this case, the dependent variable is estimated as a function of fixed explanatory variables, unlike the third model, which incorporates random effects and allows the inclusion of grouping or hierarchical structures (Kulkarni et al., 2011; Wang et al., 2013).

Generalized Linear Mixed Models - (GLMM) - are parametric models similar to Poisson mixed models, with the incorporation into their structure of random effects not explained by the predictor variables. The response variable can follow a normal, Poisson, binomial, negative binomial, etc. distribution, and the model allows for the modeling of different covariance structures to accommodate data variability. At the same time, Poisson assumes that the variability of the count is equal to the mean (Anggreyani, Indahwati, & Kurnia, 2016).

The Lee-Carter model has also been used in the literature to estimate specific mortality rates (Wang, Yue, & Chong, 2018; Wang, Yue, & Wang, 2019). It is a combination of a demographic model and a time series model, which uses past information on the structure of mortality to estimate a temporal index of the general level of mortality, which is modeled as a time series.

Bayesian models belong to both categories and are widely used in the studies in this systematic review. They are based on Bayes' theorem to estimate the model parameters and are a more general approach that can be applied to a wide range of modeling problems (Alexander, Zagheni, & Barbieri, 2017).

Bayesian models consider an *a priori* distribution of the parameters to be estimated and, based on the distribution of the observed data, identify an *a posteriori* distribution of the parameters. These models are considered flexible and can accommodate various model structures and error distributions. In addition, they recognize the correlations, known as "forces", between different data (age groups, geographical areas, genders, etc.) and, in the specific case of mortality, borrow these forces to stabilize estimates of life expectancy or mortality rates (Schmertmann, & Gonzaga, 2018).

The two main approaches to this model used in this systematic review stand out: the empirical approach, which is based more on observed data and less on *a priori* information, and the hierarchical approach, which incorporates hierarchical structures in which uncertainty is modeled at different levels, such as larger areas that contain smaller areas (Alexander et al., 2017).

This approach is often used when there is no solid prior knowledge about the model parameters, and it is desired that the data dominate the analysis. The results of the empirical Bayesian model depend heavily on the quality and quantity of the observed data.

The M-model also belongs to the parametric group. It is an autoregressive model that shapes and predicts mortality rates over time, considering autocorrelation between age groups rather than time dependence, as in conventional models. In this systematic review, the M-model estimated probabilities of death rather than mortality rates, as was the case in most of the articles studied (Perez-Panades, Botella-Rocamora, & Martinez-Beneito, 2020).

Finally, the TOPALS model by De Beer (2012), like the other parametric methods presented above, smoothes the age profiles of specific mortality rates. This model smooths the rates using linear splines, segments

polynomial functions that fit data in linear blocks instead of a single polynomial function. This smoothing makes it possible to model changes in mortality rates more flexibly and thus minimize irregular rate fluctuations.

Combining TOPALS with Poisson regression allows for the creation of a more complex model that considers smoothing and its association with other variables (Gonzaga & Schmertmann, 2016).

The second group of models for estimating mortality and life expectancy at birth for small areas refers to non-parametric models used to estimate mortality rates without making assumptions about the data distribution. This group includes the direct method for calculating specific mortality rates, which uses only the ratios between the total number of deaths and the population by age group to estimate probabilities of death directly without making any mathematical or statistical adjustment. The authors have generally aggregated spatially or temporally to reach a minimum population exposed to the mortality risk, given that the idea is to estimate the mortality structure for small areas. It should be noted that this method, given its requirement of grouping raw data in some way, does not provide either individualized or specific estimates, but rather, it provides estimates for a set of years or smaller regions (Congdon, 2014; Eayres & Williams, 2004; Kulkarni et al., 2011).

The indirect estimation of infant mortality by the William Brass method also appeared among the non-parametric methodologies studied for the systematic review. The method uses information on women's age, the number of living children they have had during their lives, the number of births in the last 12 months, and the number of children who have died. This last piece of information is the mortality indicator, which the Brass method transforms into a regular life table indicator (Neupert, Menjivar, & Castilla, 2019).

Indirect standardization is also among the non-parametric models used and has been presented in comparison with other methods (Wilson, 2018). The technique borrows a specific mortality pattern and adjusts the level of the mortality curve. According to Gonzaga & Schmertmann (2016), indirect standardization is used directly to estimate mortality rates in regions where data are reliable. In contexts of uncertainty regarding data coverage and quality, the technique provides inputs for evaluating

the degree and the age pattern of underreporting. In both cases, the authors emphasize the assumption of identity between the age-specific mortality patterns of the region taken as a standard (usually the larger one) and its sub-regions (Kim, Kang, & Khang, 2020a).

The maximum entropy and penalized maximum entropy models also do not specify the functional form of the mortality distribution. Both maximize the entropy (uncertainty) of the probability distribution, and the difference between them lies in the restriction (penalty) imposed in the latter, which reflects the information available, such as averages or known totals. This penalty makes the data fit appropriately to the actual data without rigid assumptions about its distribution (Ruther, Leyk, & Buttenfield, 2017).

The mathematical methods of graduation known as Partial Standard Mortality Ratio (Partial SMR) and Whittaker ratio are also included in the group of non-parametric models. Both methods smooth specific mortality rates based on a reference population, and they were combined with the Lee-Carter model for small area estimation in Taiwan (Yue, Wang, & Wang, 2019).

Finally, Iterative Proportional Fitting is a statistical technique that adjusts mortality rates as totals or specific margins according to specified restrictions (Ruther et al., 2017). Through interactions, the method seeks to ensure that mortality rates are adjusted until a defined parameter value is reached, which can be a population total, population by age group, total deaths, etc.

Qualitative synthesis

In Table 2, the studies were classified according to their primary outcome presented in the body of the article. Most studies (n=12) only reported estimates of life expectancy at birth, the main outcome of this review, and infant mortality rates (n=6). When looking at the studies that estimated joint figures (n =32, representing 68.09 % of the total), it can be seen that the studies took into account the importance of calculating confidence intervals for estimating life expectancy at birth, making it easier to compare methods.

One article had child mortality (smaller than five years old) as an outcome (Wakefield et al., 2019). Another study calculated the variation in the death rates to construct a life table (Swanson, & Tedrow, 2022), while 17 presented the mortality rates as an outcome (36.17 % of all included articles).

The studies varied considerably in terms of estimates, so there is no standard for presenting the results of interest. Most of them used population censuses and administrative data as data sources. Only three (4.26 %) articles used surveys to collect data (Table A-7 in the Appendix).

Table 2. Outcomes produced by the studies (n=47).

Outcome	Number of studies	%	Studies
Child mortality	1	2.13	(Wakefield et al., 2019)
Confidence interval	2	4.26	(Justino et al., 2012; Seaman et al., 2015)
Infant mortality	6	12.77	(Anggreyani et al., 2016; Neupert et al., 2019; Rose and Nagle, 2017; Swanson et al., 2019; Swanson and Baker, 2019)
Life expectancy	2	2.13	(Baffour and Raymer, 2019; Kulkarni et al., 2011)
Life expectancy; mortality rates	1	2.13	(Rachet et al., 2015)
Life expectancy; mortality rates; confidence interval	1	2.13	(Lu et al., 2021)
Life expectancy at birth	10	25.53	(Eayres and Williams, 2004; Kim et al., 2020a; Manuel et al., 1998; Paredes and Silva, 2017; Perez-Panades et al., 2020; Picazzo-Palencia et al., 2018; Puig and Ginebra, 2022; Rashid et al., 2021; Swanson, 1989; Tsimbos et al., 2014)
Life expectancy at birth; rate for the last age group	1	2.13	(Sacco et al., 2021)
Life expectancy at birth; mortality rates	5	10.64	(Alexander et al., 2017; Arias et al., 2018; Congdon, 2014; Hrzic et al., 2023; Wang et al., 2018)
Life expectancy at birth; confidence interval	6	10.64	(Dwyer-Lindgren et al., 2022; Jonker et al., 2012; Melix et al., 2020; Arias et al., 2021; Rodríguez López et al., 2022; Talbot et al., 2018)
Life expectancy at birth; mortality rates; confidence interval	3	8.51	(Barman and Choudhury, 2017; Kim Lim et al., 2020; Schmertmann and Gonzaga, 2018)

Table 2. Continued.

Outcome	Number of studies	%	Studies
Life expectancy at birth; mortality rates; rate for the last age group; confidence interval	1	2.13	(Wang et al., 2013)
Mortality rates	5	8.51	(Ruther et al., 2017; Wang et al., 2008; Gonzaga and Schmertmann, 2016; Wilson, 2018; Yue et al., 2021)
Mortality rates; confidence interval	1	2.13	(Santos et al., 2020)
Rate for the last age group; confidence interval	1	2.13	(Olatunde et al., 2010)
Variance in age at death for a life table	1	2.13	(Swanson and Tedrow, 2022)

Source: Elaborated by the authors.

The results also showed significant variations in terms of the techniques applied. We identified 25 demographic, mathematical, or statistical methods used conventionally or with adaptations to calculate mortality rates, infant mortality rates, and/or estimates of life expectancy or life expectancy at birth. Of the 47 studies, 72.3 % did not compare models, most of which used Bayesian models (Table 3). Around 42.5 % of the studies did not specify which population size was considered when calculating small areas. The smaller population size range presented as small areas was 44 to 536 inhabitants (Anggreyani et al., 2016) (Table A-4 in the Appendix).

Table 3. Number of studies by methodology type and comparison between the methods.

No Comparison	34	72.3%
M-model	1	2.1%
Bayesian	4	8.5%
Bayesian hierarchical	1	2.1%
Bayesian and TOPALS	1	2.1%
Bayesian and filtering models	1	2.1%
Bayesian, Chiang, Silcocks and regression models	1	2.1%
Beta Binomial model and beta-binomial stochastic process	2	4.3%
Beta-binomial random process and indirect estimator	1	2.1%

Table 3. Continued.

No Comparison	34	72.3%
Chiang	1	2.1%
Chiang II and Silcocks	1	2.1%
Direct method with some modification in state-level to specific groups	1	2.1%
Lee–Carter model	1	2.1%
Maximum entropy method	1	2.1%
Mixed effects Poisson regression and Gaussian process regression	1	2.1%
Mixed-effects Poisson regression	1	2.1%
Multiregional life tables	1	2.1%
Small area estimation models	1	2.1%
Standardized mortality ratio	1	2.1%
Swanson	2	4.3%
Taylor	1	2.1%
Indirect method	1	2.1%
Three Generalized Linear Mixed Models (GLMM): negative binomial, quasi-likelihood model and Poisson distribution	1	2.1%
TOPALS	3	6.4%
TOPALS (Bayesian hierarchical framework); Traditional method	1	2.1%
Direct method	2	4.3%
Zero-truncated Poisson model, negative binomial model and a modified version of Chiang	1	2.1%
Comparison	**13**	**27.7%**
Bayesian and Expectation-Maximization algorithm	1	2.1%
Bayesian	1	2.1%
Bayesian, TOPALS and Indirect Standardization Method	1	2.1%
Bayesian and direct method	1	2.1%
Chiang and Silcocks	1	2.1%
Chiang, Greville and Reed-Merrell	1	2.1%
Flexible Poisson and flexible relational model	1	2.1%
Lee-Carter model and Standard Mortality Ratio	1	2.1%
Lee-Carter model, Li-Lee model, Partial Standard Mortality Ratio and Whittaker ratio	1	2.1%
Monte Carlo simulations, Chiang and Silcocks	1	2.1%
National Mortality Rates Aproximation, Standardized Mortality Ratio, mortality surface, indirect model, ratio rate scalen and TOPALS	1	2.1%
Penalized maximum entropy model (P-MEDM) and Iterative Proportional Fitting (IPF)	1	2.1%
Swanson	1	2.1%

Source: Elaborated by the authors.

The estimates for small areas were presented diversely: 59 % of the studies categorized their results by gender, 48.94 % for both, 2.13 % for women, and 8.51 % for men. Concerning age, the majority presented a detailed analysis for various age groups, which allows for a greater understanding of the scenario (87.23 %). A smaller portion (12.77 %) did not carry out such a breakdown. Studies with all age groups were the most reported (n=30), followed by estimates for children under one-year-old (n=6). Few studies addressed differences in race/color (n=1) and ethnicity (n=4). The ethnic groups classified were: i) Chinese, Indian, Australian, British, and New Zealander; ii) White non-Hispanic, black non-Hispanic, Hispanic, or Native American; iii) Non-indigenous, and indigenous, and (iv) White, black, Alaska Native, Pacific Islander, and Latino (Table 4).

Table 4. Attributes of the results of the studies included (n=47).

Item/Component	Number of studies	%
Sex		
No	19	40.43
Yes	28	59.57
Both	23	48.94
Female	1	2.13
Male	4	8.51
Age		
No	6	12.77
Yes	41	87.23
<1 year old	6	12.77
<20 years old	1	2.13
25 years old	1	2.13
65+	1	2.13
All ages	30	63.83
All ages, 65 years old and over	1	2.13
Under 5 years old	1	2.13
Race/color		
No	46	97.87
Yes	1	2.13
White/Black	1	2.13
Ethnicity		
No	43	91.49
Yes	4	8.51

Table 4. Continued.

Item/Component	Number of studies	%
Chineses, Indians, Australians,British and New Zealander	1	2.13
White non-Hispanic, black non-Hispanic, Hispanic or native American	1	2.13
Non-indigenous and indigenous	1	2.13
White, black, Alaska Native, Pacific islander and Latino	1	2.13

Source: Elaborated by the authors.

Quality of the report

The articles met most of the criteria established by the questionnaire for assessing the quality of the outcomes reported. The researchers committed to defining and delimiting their research topics and choosing and applying methods (available in the Supplementary Material). The item with the lowest score on the questionnaire for assessing the quality of outcomes was the description of alternative methodologies (Table A-8 in the Appendix).

Discussion

This article conducted a systematic review to gather information on the methods applied to estimate mortality rates and life expectancy at birth for small areas. Of the 3,209 publications assessed by reading the title and abstract, 76 passed onto the next stage, which was full reading. Of this total, only 47 studies were included in the analysis, given that they met the inclusion criteria.

Knowing the levels and patterns of mortality underlying certain regions is the starting point for thinking about more effective public policies. There is extensive literature on demographic estimates – especially mortality – for small areas. The methods applied are demographic, mathematical, statistical, and combinations of these, which seek to deal with the challenges of the instability and variability of the figures.

The systematic review showed that researchers are getting more concerned about calculating life expectancy at birth for small areas, which

may explain the increased volume of studies from the 2010s onwards. With the advancements of parametric and non-parametric models, it is becoming possible to implement more complex models to estimate mortality patterns and levels in sparsely populated areas.

Despite the complexity of some methods and the simplicity of others, the general main goal is to smooth and complete the mortality structure of small areas, using as parameters information from larger areas that encompass smaller ones, from neighboring regions, or even distant ones, as long as they have similar characteristics. This process allows the incorporation of geographical patterns of different age groups and environmental and spatial influences.

Among the non-parametric models are the direct demographic models, which use strategies to increase the number of population and deaths by age group and then calculate the ratio between them; indirect standardization models, which use the age structure of deaths in a larger region to define a smaller one and then adjust the level of the curve based on a constant factor k, which is the ratio between expected and observed deaths in the smaller region; and the Brass method, which estimates infant and young mortality – an essential input for the construction of survival tables.

The non-parametric group also includes statistical models, such as maximum entropy, which seeks to maximize the uncertainty of death probabilities, and Iterative Proportional Fitting, which adjusts mortality rates so that their aggregation generates the value of the larger area.

Among the more complex models, parametric models stand out. These predominated in the articles in this review, with an emphasis on modeling deaths following a Poisson distribution, occasionally binomial or negative binomial, and the inclusion of demographic and socioeconomic covariates as auxiliaries to the process.

In this group, there are also simpler models, such as the multivariate regression model, which directly estimates life expectancy at birth considering only two predictors in the formula: crude mortality rate and the proportion of people aged 65 and over.

Bayesian regression models are also part of parametric models and have been the most widely used in specialized literature, with some variations in the distribution of variables and the type of data that serves as observed information to establish an *a priori* distribution. These models are recognized as having advantages over frequentist models, especially in regions where there are problems with the coverage of death records and the researcher cannot distinguish between "low mortality rates and high coverage" and "high mortality rates and low coverage". The Bayesian approach makes it possible to use probabilistic information about which coverage probabilities are most likely (*a priori*) to produce probabilistic statements about mortality rates (*a posteriori*).

Some studies have used TOPALS regression to construct complete distributions of the logarithm of specific mortality rates through a relational model between the region of interest and another considered standard.

The model adds a linear spline function with a certain number of parameters to a predefined standard table and estimates it by maximizing a penalized Poisson likelihood function for age-specific deaths, conditional on age-specific exposure (Gonzaga, & Schmertmann, 2016).

It should be noted that in most of the studies, the authors used Chiang's methodology to generate the life tables and, consequently, the life expectancy at birth and the confidence intervals of the estimates. This method traditionally calculates the parameters of the survival table but makes different assumptions compared to Silcocks, Greville and Reed-Merrell to convert the mortality rates observed by age into age-specific probability of death rates. Furthermore, confidence intervals provide a measure of the reliability of the estimates.

A large part of the articles in this systematic review conducted estimates for regions from industrialized countries in the 21st century, which may justify greater concern with smoothing mortality rates in small areas and the search for methodological advancements in this line. Among the studies conducted in the 20th century, Swanson's methodology was used by Swanson (1989) and Manuel et al. (1998). While the first was used for small areas in the U. S., with no mention regarding data quality, the latter was applied in Canada, where the authors acknowledge incorrect classification of residence location in death records, mainly in the city of

Toronto, as the main error in deriving survival tables. Despite this, they calculate life expectancies at birth for 42 public health units in Ontario using the Reed-Merrell, Greville, and Chiang methods, recommending the latter due to lower variability in estimates and given that Reed-Merrell and Greville's methods are respectively less applicable to modern mortality trends and more precise for older ages.

Hrzic et al. (2023), in their study of districts in Germany, reported a problem of underreporting mortality data in some districts during specific periods. The authors noted that between 1997 and 1999, 162 districts did not report death counts for both genders in the age groups of 75-79, 80-84, or 85+. The number of districts having the issue decreased over time, reaching zero after 2006. Alexander et al. (2017), in estimating mortality curves for simulated data from small areas in the U.S. and real data from French departments, explicitly mentioned concerns about the variability of estimates only. To address the challenge, the authors proposed incorporating space-time information within a Bayesian hierarchical framework and highlighted the good calibration of the model based on the confidence intervals. The authors compared the variability measures of life expectancies at birth produced by their work with those estimated by Brass and Loess models, showing lower variability for all population sizes.

Congdon (2014) focused exclusively on the variability and instability of data from small areas in the U.S. and proposed using structured random effects methods that recognize correlations between ages and the adjacent regions to improve the accuracy of life expectancy estimates at birth. Eayres and Williams (2004), also focusing on variability in mortality rates, evaluated the results of life expectancies at birth estimated by Silcocks and Chiang methods for different population sizes, conducting Monte Carlo simulations to infer the distribution of estimates and their standard errors.

However, concerns about data quality were also identified in some studies related to regions from developed countries. That is the case of Arias et al. (2021), who, in calculating complete survival tables including large areas such as the 50 American states and the District of Columbia, acknowledged the possibility of errors in age reporting in deaths and population data, which could affect estimates. The authors addressed

these errors by making proportional adjustments to age-specific mortality and smoothing rates, a procedure that also addresses estimates variability. In addition, Arias et al. (2021) adjusted the estimate of specific mortality rates for ages 66 to 99 using Medicare data, highlighting a particular need to supplement information for older ages. Once these adjustments were made, the authors presented estimates of life expectancy at birth and at age 65, along with confidence intervals, emphasizing greater concern with the accuracy of the forecast. In studies conducted in small areas from the U. S., represented by counties and sub-counties, some authors incorporated concerns about the quality of vital data beyond the mere absence and variability. Two highlighted problems are incorrect classification of ethnicity (i.e., racial miscoding) and discrepancies between the location of a death event and the location of its registration. To address the first problem, both Kulkarni et al. (2011) and Wang et al. (2013) grouped the Asian and Indigenous race groups into a single category. Following this line, Dwyer-Lindgren et al. (2022) estimated rates of incorrect classifications that were incorporated into mortality rates yielded by the chosen model and made corrections to adjust mortality rates according to race and ethnicity misclassification rates, ensuring a more precise analysis and correcting possible data distortions.

Regarding the problem of the actual location of deaths, Talbot et al. (2018), in investigating high life expectancies at birth estimated in sub-counties of New York bordering other states, confirmed the hypothesis of errors in records regarding the location of deaths and made the necessary corrections. In the same direction, the National Center for Health Statistics (2018), faced with difficulties in geolocating deaths that occurred in Puerto Rico, Maine, and Wisconsin, excluded these regions from their analyses. Other challenges regarding data quality were mentioned by Baffour & Raymer (2019), who estimated multi-regional life tables for the Australian population and immigrant groups from the UK, China, and India. The authors encountered a lack of data on specific age mortality and internal migration in Australia and random disturbances added by the Australian Bureau of Statistics to existing data to avoid identification of respondents. They adjusted log-linear models to obtain smoothed estimates of inter-regional migration, leveraging marginal distributions contained in the data to calculate more plausible conditional survival proportions for inter-regional migration. Additionally, they employed spline

smoothing techniques to improve specific age mortality rates. In light of the foregoing, it is clear that in regions where data is reliable, the choice of a method will depend on the variability of estimates, the flexibility of assumptions, and the adherence of results to the reality.

It is worth noting that the complexity or simplicity of the method is also an essential element. According to Green & Armstrong (2015), no evidence shows that more complex techniques provide more accurate estimates. Yet, complexity is a hallmark of many researchers who manage to publish in high-impact journals because this complexity is a reassuring element for a specific audience that does not understand it. Still, in the matter of "simplicity vs. complexity," Talbot et al. (2018) report that, according to their experience regarding New York State, there are audiences that prefer empirically derived health indicators because they consider those derived from models as "black boxes."

Although fewer in number, this systematic review also evaluated studies that focused on data from developing regions, such as Justino et al. (2012), Gonzaga & Schmertmann (2016), Schmertmann, & Gonzaga (2018), Queiroz et al. (2020), and Santos et al. (2020) for Brazil; Anggreyani et al. (2016) for West Java; Barman, & Choudhury (2017) for India, Neupert et al. (2019) for Myanmar; Paredes, & Silva (2017) and Picazzo-Palencia et al. (2018) for Mexico; Rodríguez López et al. (2022) for Argentina; Rose, & Nagle (2017) for Bangladesh and Wakefield et al. (2019) for Kenya. However, not all justified the choice of methods for calculating longevity estimates for small areas due to deficiencies in data.

The focus continued to be on the instability of estimates and, therefore, on smoothing techniques. For example, Barman & Choudhury (2017), although admitting the uncertainty of basic mortality data in developing countries like India, used Silcocks and Chiang methods with Monte Carlo simulations to calculate life expectancy for the Indian districts of Kohima and Dimapur. Since the results were very similar, the authors focused their analysis on standard errors and confidence intervals. Paredes & Silva (2017) used the Swanson method to estimate life expectancy at birth for Mexican municipalities and regions. The authors justified the methodological choice for its simplicity, requiring little demographic information, and precision compared to official results.

Picazzo-Palencia et al. (2018) did not mention information quality as a prerequisite for calculating life expectancy at birth in small Mexican localities; only the instability of mortality rates, which, as they indicate, can be addressed by the model proposed by Swanson. Santos et al. (2020) estimated mortality curves for Brazilian indigenous children and adolescents using the TOPALS method based on the 2010 Demographic Census. They mentioned the limitations of census research for characterizing mortality in the country. Though they did not account for possible underreporting from the survey, the authors presented specific mortality rates and confidence intervals by household situation, indicating the precision of the estimates. Rodríguez López et al. (2022) used a Bayesian adaptation of the TOPALS method to estimate specific mortality rates for small areas in Córdoba City, Argentina, and subsequently to calculate life expectancy at birth. The authors did not mention the quality of microdata as an element for the choice of the method, considering that, according to them, this is not a concern in the country. The results were validated regarding longevity indicator variability, spatial distribution, and socioeconomic characteristics of the studied areas.

Neupert et al. (2019) applied a variation of Brass's indirect method (1975) to estimate infant mortality in small areas in Myanmar. They acknowledged inaccuracies in basic data and random statistical variations as the main errors that may be present in the sample survey. Nonetheless, they showed that the estimates generated are reliable and consistent compared to the classical method, although emphasizing that the technique does not work for very small areas due to the influence of random factors, seasonal changes, and/or specific local factors. In these cases, the authors suggest spatial aggregation of similar contiguous areas or adoption of the rate from an adjacent area with similar characteristics.

Wakefield et al. (2019) estimated mortality rates for children under 5 years of age in Kenya through retrospective birth histories of reproductive-aged women using data from Demographic and Health Surveys. The authors smoothed rates using hierarchical Bayesian models with continuous spatial and discrete temporal components and emphasized the method's superiority regarding Mean Squared Errors (MSE). Rose and Nagle (2017), aiming to test internal and external validation strategies for estimates for small areas, used the iterative Proportional Fitting Method (P-MEDM) to estimate infant mortality rates and other

household indicators in Bangladesh. They related the accuracy of results to the adequacy of sample size and representativeness and emphasized the need for researchers' technical knowledge regarding survey design to identify any potential issues.

Overall, death records and even population data from developing regions are imperfect in terms of underreporting, information incompleteness, and errors in age reporting. Therefore, as pointed out by Schmertmann and Gonzaga (2018), Queiroz et al. (2020), and Sacco et al. (2021), they require corrections and adjustments that go beyond smoothing mortality rates. In this sense, Schmertmann and Gonzaga (2018) and Queiroz et al. (2020), when using TOPALS to estimate mortality rates for small areas in Brazil, incorporated death underreporting into their calculations. Schmertmann and Gonzaga (2018) used the percentages of municipal death underreporting estimated by the active search research project directly in the model equation, while Queiroz et al. (2020) estimated rates in two stages: applying TOPALS first followed by DDM to assess data quality and adjust the level of mortality curves. Sacco et al. (2021), in estimating mortality levels in Argentine departments, made corrections and adjustments to basic data before applying the three considered smoothing methods (Bayesian approach, relational life tables, and indirect standardization), since departmental death data presented incompleteness and some inconsistencies. Although only three studies explicitly stated the need for data correction and incorporated it into calculations, no doubt smoothing mortality rates and/or completing them using information and forces from other (larger, neighboring, similar, etc.) areas adjusts/corrects the pattern and, to some extent, the level of mortality in the studied area. However, for more accurate results, it is ideal to smooth and correct or correct and smooth basic data and mortality estimates. This statement is evidenced by Queiroz et al. (2020) when comparing observed mortality rates for the Southeast mesoregion of Amazonas, Brazil, with those smoothed by TOPALS method and by TOPALS + DDM. The authors demonstrate how relevant smoothing procedures are, especially in adjusting mortality levels in regions with data deficiencies. Schmertmann and Gonzaga (2018) also highlight the effect of incorporating underreports into life expectancy estimates at birth for Brazilian states and show how the indicator is adjusted downward in the Northern and Northeastern regions of the country.

The main outcome analyzed in the 47 articles included in the systematic review was life expectancy at birth, an indicator that can reflect a population's living and health conditions.

The authors point out that life expectancy at birth is an intuitive concept and, therefore, easy to understand since it represents the average number of years a person is expected to live from the moment of birth. This indicator considers the mortality rate in all age groups, providing a comprehensive view of the population's health. It is a significant measure in monitoring changes in health over time and makes it possible to compare different populations, countries, and regions.

The selected studies highlight the relevance of calculating this indicator *per se* and also by population subgroups, such as gender, ethnicity, and race/color to highlight disparities between groups, which are often masked by aggregate estimates for the population as a whole.

Despite this recognition, this review revealed the existence of few studies that disaggregate life expectancy at birth by race/color and ethnicity. These studies are often justified by the difficulty of identifying/declaring these attributes on death certificates and the small number of some populations, making estimates unfeasible.

Another point worth highlighting is the nature and availability of the data used for estimating calculations. Most studies utilized data collected from demographic censuses, such as population and retrospective birth histories of women of reproductive age, as well as administrative data.

Data collected from population censuses have the advantage of providing both numerator and denominator measurements of specific mortality rates. In this sense, the same systematic errors in the population by age can occur in deaths. However, demographic censuses are usually five-yearly or ten-yearly. Therefore, they are not the most suitable for promptly monitoring trends in the structure and level of mortality.

On the other hand, administrative data, such as mortality information systems, have more information on the subject, including the causes of death according to the International Classification of Diseases. In addition,

they make information available monthly and/or annually, making it possible to implement government programs and control and monitor compliance with legal obligations. Still, when combined with population data in the denominator of rates, which can include omissions, duplications, imputation errors, age misreporting, so on and so forth, these factors can amplify the inaccuracies of estimates, as they may contain similar problems to those in the denominator or from a different nature.

In summary, it is concluded that the literature presents different approaches to the challenge of estimating life expectancy at birth for small areas. The choice of method will depend on several aspects. These include: i) the availability of basic data, which can be freely accessible or restricted; ii) the nature of the databases; iii) the quality of information; iv) computational capacity; v) the availability of human capital capable of selecting and operationalizing techniques based on the aforementioned elements, and vi) the adherence of estimates to the studied reality.

References

Alexander, M., Zagheni, E., & Barbieri, M. (2017). A Flexible Bayesian Model for Estimating Subnational Mortality. *Demography*, *54*(6), 2025-2041. https://doi.org/10.1007/s13524-017-0618-7

Anggreyani, A., Indahwati, & Kurnia, A. (2016). Small area estimation for estimating the number of infant mortality in West Java, Indonesia. 080002. https://doi.org/10.1063/1.4940859

Arias, E., Bastian, B., Xu, J., & Tejada-Vera, B. (2021). U.S. State Life Tables, 2018. https://stacks.cdc.gov/view/cdc/101128#:~:text=with%20some%20modifications.,Results%E2%80%94Among%20the%2050%20states%20and%20the%20District%20of%20Columbia,to%2021.1%20years%20in%20Hawaii.

Arias, E., Escobedo, L., Kennedy, J., Fu, C., & Cisewki, J. (2018). U.S. small-area life expectancy estimates project: Methodology and results summary. U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics. https://www.cdc.gov/nchs/nvss/usaleep/usaleep.html

Baffour, B., & Raymer, J. (2019). Estimating multiregional survivorship probabilities for sparse data: An application to immigrant populations in Australia, 1981-2011. *Demographic Research*, 40, 463-502. https://doi.org/10.4054/DemRes.2019.40.18

Barman, P., & Choudhury, L. (2017). Sub-state Life Expectancy Estimation Using the Methodology for Small Population. https://ph02.tci-thaijo.org/index.php/thaistat/article/view/74251

Brass, W. (1975). Methods for estimating fertility and mortality from limited and defective data. Chapel Hill, NC: Carolina Population Center, University of North Carolina.

Chiang, C. L. (1968). Introduction to stochastic processes in biostatistics. 1st Edition, John Willy & Sons, Inc.

Congdon, P. (2014). Estimating life expectancies for US small areas: A regression framework. *Journal of Geographical Systems*, *16*(1), 1-18. https://doi.org/10.1007/s10109-013-0177-4

De Beer, J. (2012). Smoothing and projecting age-specific probabilities of death by TOPALS. *Demographic Research*, 27, 543-592. https://doi.org/10.4054/DemRes.2012.27.20

Dwyer-Lindgren, L., Kendrick, P., Kelly, Y. O., Sylte, D. O., Schmidt, C., Blacker, B. F., Mokdad, A. H. (2022). Life expectancy by county, race, and ethnicity in the USA, 2000-19: A systematic analysis of health disparities. *The Lancet*, *400(*10345), 25-38. https://doi.org/10.1016/S0140-6736(22)00876-5

Eayres, D., & Williams, E. S. (2004). Evaluation of methodologies for small area life expectancy estimation. *Journal of Epidemiology & Community Health*, *58*(3), 243-249. https://doi.org/10.1136/jech.2003.009654

Gonzaga, M. R., & Schmertmann, C. P. (2016). Estimating age- and sex-specific mortality rates for small areas with TOPALS regression: An application to Brazil in 2010. *Revista Brasileira de Estudos de População, 33*(3), 629-652. https://doi.org/10.20947/S0102-30982016c0009

Gotschall, T. (2021). EndNote 20 desktop version. 520. https://doi.org/10.5195/jmla.2021.1260

Green, K. & J. S. Armstrong. (2015). Simple versus complex forecasting: The evidence. *Journal of Business Research*, 68: 1678-1685. https://doi.org/10.1016/j.jbusres.2015.03.026

Hrzic, R., Vogt, T., Brand, H., & Janssen, F. (2023). District-Level Mortality Convergence in Reunified Germany: Long-Term Trends and Contextual Determinants. *Demography*, 10422945. https://doi.org/10.1215/00703370-10422945

Jonker, M. F., Van Lenthe, F. J., Congdon, P. D., Donkers, B., Burdorf, A., & Mackenbach, J. P. (2012). Comparison of Bayesian Random-Effects and Traditional Life Expectancy Estimations in Small-Area Applications. *American Journal of Epidemiology*, *176*(10), 929-937. https://doi.org/10.1093/aje/kws152

Justino, J. R., Freire, F. H. M. D. A., & Lucio, P. S. (2012). Estimação de sub-registros de óbitos em pequenas áreas com os métodos bayesiano empírico e algoritmo EM. *Revista Brasileira de Estudos de População, 29(*1), 87-100. https://doi.org/10.1590/S0102-30982012000100006

Kim, I., Kang, H.-Y., & Khang, Y.-H. (2020a). Life Expectancy in Areas around Subway Stations in the Seoul Metropolitan Area in Korea, 2008-2017. *Journal of Korean Medical Science*, *35*(44), e365. https://doi.org/10.3346/jkms.2020.35.e365

Kim, I., Lim, H.-K., Kang, H.-Y., & Khang, Y.-H. (2020b). Comparison of three small-area mortality metrics according to urbanity in Korea: The standardized mortality ratio, comparative mortality figure, and life expectancy. *Population Health Metrics*, *18*(1), 3. https://doi.org/10.1186/s12963-020-00210-7

Kulkarni, S. C., Levin-Rector, A., Ezzati, M., & Murray, C. J. (2011). Falling behind: Life expectancy in US counties from 2000 to 2007 in an international context. *Population Health Metrics*, 9(1), 16. https://doi.org/10.1186/1478-7954-9-16

Lu, Q., Hanewald, K., & Wang, X. (2021). Subnational Mortality Modelling: A Bayesian Hierarchical Model with Common Factors. *Risks*, *9*(11), 203. https://doi.org/10.3390/risks9110203

Manuel, D., Goel, V., & Williams, I. (1998). The Derivation of Life Tables for Local Areas. https://pubmed.ncbi.nlm.nih.gov/9664025/

Mcarthur, A. (2020). Systematic reviews of text and opinion. In *Manual for Evidence Synthesis* (Vol. 10). https://jbi-global-wiki.refined.site/space/MANUAL

Melix, B. L., Uejio, C. K., Kintziger, K. W., Reid, K., Duclos, C., Jordan, M. M., … Joiner, J. (2020). Florida neighborhood analysis of social determinants and their relationship to life expectancy. *BMC Public Health*, *20*(1), 632. https://doi.org/10.1186/s12889-020-08754-x

Munn, Z.,Moola, S., Lisy K., Riitano D., & Tufanaru C. (2020). Systematic reviews of prevalence and incidence. In E. Aromataris & Z. Munn (Eds.), *Manual for evidence synthesis* (pp. 177-218). JBI.https://doi.org/10.46658/JBIMES-20-06

National Center for Health Statistics (US et al., Health, United States, 2018 [Internet]. https://www.cdc.gov/nchs/index.htm

Neupert, R., Fernandez Menjivar, R. E., & Fernandez Castilla, R. E. (2019). Indirect estimation of infant mortality in small areas. *Revista Brasileira de Estudos de População*, 36, 1–37. https://doi.org/10.20947/s0102-3098a0100

Olatunde, O., White, C., & Smith, M. P. (2010). Life expectancy and disability-free life expectancy estimates for Middle Super Output Areas;

England, 1999-2003. *Health Statistics Quarterly*, *47*(1), 33-65. https://doi.org/10.1057/hsq.2010.15

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan –A web and mobile app for systematic reviews. *Systematic Reviews*, *5(*1), 210. https://doi.org/10.1186/s13643-016-0384-4

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 71. https://doi.org/10.1136/bmj.n71

Paredes, I., & Silva, E. (2017). Estimación de la esperanza de vida a nivel municipal y por marginación sociodemográfica: Una aplicación del método de Swanson para el caso de México, 2010. *Estudios Demográficos y Urbanos, 32*(1), 97-129. https://doi.org/10.24201/edu.v32i1.1711

Perez-Panades, J., Botella-Rocamora, P., & Martinez-Beneito, M. A. (2020). Beyond standardized mortality ratios; some uses of smoothed age-specific mortality rates on small areas studies. *International Journal of Health Geographics*, *19*(1), 54. https://doi.org/10.1186/s12942-020-00251-z

Picazzo-Palencia, E., Flores-Segovia, M., & De La Cruz-Maldonado, M. E. (2018). Análisis regional de la esperanza de vida al nacer en México, por medio del método de regresión. *Revista de Salud Pública, 20*(6), 725-729. https://doi.org/10.15446/rsap.v20n6.35806

Puig, X., & Ginebra, J. (2022). Bayesian spatiotemporal model for life expectancy mapping; changes in Barcelona from 2007 to 2018. *Geographical Analysis*, *54(*4), 839-859. https://doi.org/10.1111/gean.12299

Queiroz, B. L., Lima, E. E. C., Freire, F. H. M. A., & Gonzaga, M. R. (2020) Temporal and spatial trends of adult mortality in small areas of Brazil, 1980-2010. https://doi.org/10.1186/s41118-020-00105-3

Rachet, B., Maringe, C., Woods, L. M., Ellis, L., Spika, D., & Allemani, C. (2015). Multivariable flexible modelling for estimating complete, smoothed life tables for sub-national populations. *BMC Public Health*, *15*(1), 1240. https://doi.org/10.1186/s12889-015-2534-3

Rashid, T., Bennett, J. E., Paciorek, C. J., Doyle, Y., Pearson-Stuttard, J., Flaxman, S., Ezzati, M. (2021). Life expectancy and risk of death in 6791 communities in England from 2002 to 2019: High-resolution spatiotemporal analysis of civil registration data. *The Lancet Public Health, 6*(11), e805-e816. https://doi.org/10.1016/S2468-2667(21)00205-X

Rodríguez López, S., Tumas, N., Bilal, U., Moore, K. A., Acharya, B., Quick, H., ... Diez Roux, A. V. (2022). Intraurban socioeconomic inequalities

in life expectancy: A population-based cross-sectional analysis in the city of Córdoba, Argentina (2015-2018). *BMJ Open*, *12*(9), e061277. https://doi.org/10.1136/bmjopen-2022-061277

Rose, A. N., & Nagle, N. N. (2017). Validation of spatiodemographic estimates produced through data fusion of small area census records and household microdata. Computers, *Environment and Urban Systems*, 63, 38-49. https://doi.org/10.1016/j.compenvurbsys.2016.07.006

Ruther, M., Leyk, S., & Buttenfield, B. (2017). Deriving small area mortality estimates using a probabilistic reweighting method. *Annals of the American Association of Geographers*, *107*(6), 1299-1314. https://doi.org/10.1080/24694452.2017.1320213

Sacco, N., Williams, I., & Queiroz, B. L. (2021). Estimaciones de esperanza de vida al nacer en áreas menores de la región pampeana. *Revista Brasileira de Estudos de População*, 38, 1-41. https://doi.org/10.20947/S0102-3098a0160

Santos, R. V., Borges, G. M., Campos, M. B. D., Queiroz, B. L., Coimbra, C. E. A., & Welch, J. R. (2020). Indigenous children and adolescent mortality inequity in Brazil: What can we learn from the 2010 National Demographic Census? SSM - *Population Health*, 10, 100537. https://doi.org/10.1016/j.ssmph.2020.100537

Schmertmann, C. P., & Gonzaga, M. R. (2018). Bayesian estimation of age-specific mortality and life expectancy for small areas with defective vital records. *Demography*, *55*(4), 1363-1388. https://doi.org/10.1007/s13524-018-0695-2

Seaman, R., Mitchell, R., Dundas, R., Leyland, A., & Popham, F. (2015). How much of the difference in life expectancy between Scottish cities does deprivation explain? *BMC Public Health*, *15*(1), 1057. https://doi.org/10.1186/s12889-015-2358-1

Swanson, D. A. (1989). A state-based regression model for estimating substate life expectancy. *Demography*, *26*(1), 161-170. https://doi.org/10.2307/2061502

Swanson, D. A., & Baker, J. (2019). Estimating the underlying infant mortality rates for small populations: An historical study of US counties in 1970. *Journal of Population Research*, *36*(3), 233-244. https://doi.org/10.1007/s12546-019-09225-w

Swanson, D. A., Kposowa, A., & Baker, J. (2019). Estimating the Underlying Infant Mortality Rates for Small Populations, Including those Reporting Zero Infant Deaths: A Case Study of Counties in California. *Population Review, 58*(2). https://doi.org/10.1353/prv.2019.0005

Swanson, D. A., & Tedrow, L. M. (2022). Taylor's Law and the Relationship between Life Expectancy at Birth and Variance in Age at Death in a Period Life Table. *Population Review*, *61*(1), 31-42. https://doi.org/10.1353/prv.2022.0001

Talbot, T. O., Done, D. H., & Babcock, G. D. (2018). Calculating census tract-based life expectancy in New York state: A generalizable approach. *Population Health Metrics*, *16*(1), 1. https://doi.org/10.1186/s12963-018-0159-3

Tsimbos, C., Kalogirou, S., & Verropoulou, G. (2014). Estimating Spatial Differentials in Life Expectancy in Greece at Local Authority Level. *Population, Space and Place*, *20*(7), 646-663. https://doi.org/10.1002/psp.1800

Wakefield, J., Fuglstad, G.-A., Riebler, A., Godwin, J., Wilson, K., & Clark, S. J. (2019). Estimating under-five mortality in space and time in a developing world context. *Statistical Methods in Medical Research*, *28*(9), 2614-2634. https://doi.org/10.1177/0962280218767988

Wang, H., Schumacher, A. E., Levitz, C. E., Mokdad, A. H., & Murray, C. J. (2013). Left behind: Widening disparities for males and females in US county life expectancy, 1985-2010. *Population Health Metrics*, *11*(1), 8. https://doi.org/10.1186/1478-7954-11-8

Wang, H.-C., Yue, C.-S. J., & Chong, C.-T. (2018). Mortality models and longevity risk for small populations. *Insurance: Mathematics and Economics*, 78, 351-359. https://doi.org/10.1016/j.insmatheco.2017.09.020

Wang, H.-C., Yue, J. C., & Wang, T.-Y. (2019). Do domestic immigrants live longer? An approach for estimating the life expectancy of small populations. *Migration Letters*, *16*(3), 399-416. https://doi.org/10.33182/ml.v16i3.644

Wilson, T. (2018). Evaluation of simple methods for regional mortality forecasts. *Genus*, *74*(1), 14. https://doi.org/10.1186/s41118-018-0040-z

Yue, J. C., Wang, H.-C., & Wang, T.-Y. (2019). Using Graduation to Modify the Estimation of Lee–Carter Model for Small Populations. *North American Actuarial Journal*, *25*(sup1), S410-S420. https://doi.org/10.1080/10920277.2019.1650288

Appendix

Table A-1. Research question in PECO format.

PECO	Description
P – Population	Population residing in small areas
E – Exposure	Life expectancy at birth calculations
C – Comparator	None
O – Outcomes	Demographic and statistical methods

Source: Elaborated by the authors.

Table A-2. Search strategy.

Database	Search strategy	Number of studies
PubMed	((((expectancy life) AND (expectancy life[MeSH Major Topic])) AND (method)) AND (small areas) AND (demography))	41
Lilacs	(‘expectancy life’) OR (method) AND (‘small areas’) AND (demography)	4
Embase	(‘expectancy life’ OR method) AND ‘small areas’ AND demography	23
Scopus	(ALL (“expectancy life”) OR ALL (method) AND ALL (“small areas”) AND ALL (demography)) AND (LIMIT-TO (DOCTYPE , “ar”) OR LIMIT-TO (DOCTYPE , “re”) OR LIMIT-TO (DOCTYPE , “cp”) OR LIMIT-TO (DOCTYPE , “ed”) OR LIMIT-TO (DOCTYPE , “dp”) OR LIMIT-TO (DOCTYPE , “no”) OR LIMIT-TO (DOCTYPE , “sh”))	31,37
Web of Science	method (Tópico) AND small-area (Tópico) AND estimation (Tópico) OR population mortalilty (Tópico) AND demography (Tópico) AND life expectancy (Tópico)	60
Total:		3,265
Total without duplicates:		3,209

Source: Elaborated by the authors.

Table A-3. List of excluded studies in phase II.

Reason	Author's name and year of studies	Title
Studies that do not yield mortality/life expectancy at birth for small areas	(Adebayo and Fahrmeir, 2005)	Analysing child mortality in Nigeria with geoadditive discrete-time survival models
	(Bennett et al., 2015)	The future of life expectancy and life expectancy inequalities in England and Wales: Bayesian spatiotemporal forecasting
	(Bilal et al., 2021)	Life expectancy and mortality in 363 cities of Latin America
	(Carter et al., 2010)	Trends in survival and life expectancy by ethnicity, income and smoking in New Zealand: 1980s to 2000s
	(Castanheira and Monteiro Da Silva, 2022)	Examining sex differences in the completeness of Peruvian CRVS data and adult mortality estimates
	(Checchi et al., 2022)	A method for small-area estimation of population mortality in settings affected by crises
	(Congdon, 1991)	Spatiotemporal models for small-area social indicators
	(Grigoriev and Doblhammer, 2019)	Changing educational gradient in long-term care-free life expectancy among German men, 1997-2012
	(Hanley, 2022)	The (Im)precision of Life Expectancy Numbers
	(Inskip et al., 1983)	Methods for age-adjustment of rates
	(Lankoandé et al., 2022)	Estimating mortality from census data: a record-linkage study of the Nouna Health and Demographic Surveillance System in Burkina Faso
	(Pickle and White, 1995)	Effects of the choice of ageâ€adjustment method on maps of death rates
	(Queiroz, Gonzaga et al., 2020)	Comparative analysis of completeness of death registration, adult mortality and life expectancy at birth in Brazil at the subnational level
	(Queiroz, Lima et al., 2020)	Temporal and spatial trends of adult mortality in small areas of Brazil, 1980-2010
	(Scherbov and Ediev, 2011)	Significance of life table estimates for small populations: Simulation-based study of standard errors
	(Tsimbos et al., 2011)	Life expectancy in Greece 1991-2007: Regional variations and spatial clustering
	(Moser et al., 2014)	What does your neighbourhood say about you? A study of life expectancy in 1.3 million Swiss neighbourhoods
	(Bahk et al., 2017)	Using the national health information database of the national health insurance service in Korea for monitoring mortality and life expectancy at national and local levels
Studies that calculate, but do not provide methodology/ calculation for correction/ adjustment/ smoothing of mortality rates/ data for small areas	(Congdon, 1995)	Life table analysis for areas using vital register data
	(Dwyer-Lindgren, Bertozzi-Villa et al., 2017)	Inequalities in Life Expectancy Among US Counties, 1980 to 2014: Temporal Trends and Key Drivers
	(Dwyer-Lindgren, Stubbs et al., 2017)	Variation in life expectancy and mortality by cause among neighbourhoods in King County, WA, USA, 1990-2014: a census tract-level analysis for the Global Burden of Disease Study 2015
	(Grigoriev and Doblhammer, 2019)	Changing educational gradient in long-term care-free life expectancy among German men, 1997-2012
	(Lo et al., 2016)	Variance models of the last age interval and their impact on life expectancy at subnational scales
	(Mokhayeri et al., 2014)	How within-city socioeconomic disparities affect life expectancy? Results of urban heart in Tehran, Iran
	(Rees et al., 2009)	The estimation of mortality for ethnic groups at local scale within the United Kingdom
	(Singh and Siahpush, 2014)	Widening rural-urban disparities in life expectancy, U.S., 1969-2009
	(Moser et al., 2014)	What does your neighbourhood say about you? A study of life expectancy in 1.3 million Swiss neighbourhoods

Table A-3. Continued.

Reason	Author's name and year of studies	Title
Studies that only consider the quality of information from underreporting of deaths	(Bahk et al., 2017)	Using the national health information database of the national health insurance service in Korea for monitoring mortality and life expectancy at national and local levels
	(Fernand Jubithana and Queiroz, 2019)	Quality of death counts and adult mortality registration in suriname and its main regions
	(Adair and Lopez, 2021)	Generating age-specific mortality statistics from incomplete death registration data: two applications of the empirical completeness method
Complete text unavailable	(Fukawa and Shimizu, 1990)	A Bayesian approach to life table construction for small areas
	(Nikolov 1993)	A simplified method for determining the average life expectancy in the Republic of Bulgaria

Source: Elaborated by the authors.

Table A-4. List of included studies

Author's name and year of studies	Journal name	Objective	Methods	Geographical study area	Year of study	Range of population size	Outcomes
(Alexander et al., 2017)	*Demography*	To estimate mortality at the subnational level.	Bayesian	United States and France	1975-2008 and 1980-2010	1,000-100,000 inhabitants	Life expectancy at birth and mortality rates
(Anggreyani et al., 2016)	*America Institute of Physics Conference Proceedings*	To estimate the number of infant mortality in districts of West Java.	Generalized Linear Mixed Models	West Java	2012	44-536 inhabitants	Infant mortality
(Arias et al., 2021)	*National Vital Statistics Reports*	To present complete period life tables for each of the 50 states and the District of Columbia by sex based on age-specific death rates.	Direct method	United States	2018	Not specified	Life expectancy at birth; mortality rates and confidence interval
(Arias et al., 2018)	*National Center for Health Statistics*	To describe the methodology developed to produce the first set of abridged period life tables for U.S. census.	Zero-truncated Poisson model, negative binomial model Chiang	United States	2010-2015	More than 5,000 inhabitants	Life expectancy at birth and mortality rates
(Baffour & Raymer, 2019)	*Demographic Research*	To develop methods for overcoming irregularities in sparse data on age-specific mortality and internal migration to estimate small area multiregional life tables.	Multiregional life tables	Australia	2001-2006	1,000 to 125,000 inhabitants	Life expectancy

Table A-4. Continued.

Author's name and year of studies	Journal name	Objective	Methods	Geographical study area	Year of study	Range of population size	Outcomes
(Barman & Choudhury, 2017)	*Thailand Statistician*	To estimate the life expectancy at birth along with its standard error for Kohima and Dimapur districts of Nagaland- a smaller tribal state of India.	Chiang and Silcocks	India	2010	More than 1,000 inhabitants	Life expectancy at birth; mortality rates and confidence interval
(Congdon, 2014)	*Demographic Research*	To develop methods for overcoming irregularities in sparse data on age-specific mortality and internal migration to estimate small area multiregional life tables.	Bayesian	Australia	1981-1986 and 2006-2011	1,000 - 125,000 inhabitants	Life expectancy at birth and mortality rates
(Dwyer-Lindgren et al., 2022)	*Lancet*	To estimate life expectancy in the USA annually from 2000 to 2019, stratified by county and racial–ethnic group.	Small area estimation models	United States	2000-2019	More than 1,000 inhabitants	Life expectancy at birth and confidence interval
(Eayres & Williams, 2004)	*Epidemiology and Community Health*	To evaluate methods for calculating life expectancy in small áreas (English electoral wards).	Chiang and Silcocks	England	1998-2000	500-50,000 inhabitants	Life expectancy at birth
(Gonzaga & Schmertmann, 2016)	*Revista Brasileira de Estudos Populacionais*	To propose a more flexible statistical estimation method that combines Poisson regression with the TOPALS relational model to estimate age-specific mortality rates in Minas Gerais small areas (states, mesoregions, microregions and municipalities).	TOPALS	Brazil	2010	Not specified	Life expectancy at birth
(Hrzic et al., 2023)	*Demography*	To examine district-level mortality convergence in the decades since German reunification and, in the process, exploring the role of selected district characteristics.	TOPALS and direct method	Germany	1997–2016	35,000-3,5 millions inhabitants	Life expectancy at birth and mortality rates

Table A-4. Continued.

Author's name and year of studies	Journal name	Objective	Methods	Geographical study area	Year of study	Range of population size	Outcomes
(Jonker et al., 2012)	*American Journal of Epidemiology*	To compare the relative efficiency of traditional method and Bayesian random effects approach and to provide evidence that the second approach can indeed be used to calculate reliable life expectancies for smaller populations than with the traditional approach.	Bayesian and direct method	Europe	2005–2006; 2008-2009	500 -25,000 person-years	Life expectancy at birth and confidence interval
(Justino et al., 2012)	*Revista Brasileira de Estudos de População*	To compare the results of two methods for estimating and correcting unregistered deaths on a municipal level.	Bayesian	Brazil	2000	Not specified	Confidence interval
(Kim et al., 2020a)	*Journal of Korean Medical Science*	To calculate life expectancy in the areas around 614 subway stations on 23 subway lines in the Seoul metropolitan area of Korea.	Direct method	Korea	2008- 2017	Not specified	Life expectancy at birth
(Kim et al., 2020b)	*Population Health Metrics*	To compare three small-area level mortality metrics according to urbanity in Korea.	Standardized mortality ratio	Korea	2013-2017	3,850 - 21,886 inhabitants	Life expectancy at birth; mortality rates and confidence interval
(Kulkarni et al., 2011)	*Population Health Metrics*	To develop life tables for US counties in for each sex, for all races combined, for whites, and for blacks.	Mixed-effects Poisson regression with time, geospatial, and covariate components	United States	2000 and 2007	More than 7,000 inhabitants	Life expectancy at birth
(Lu et al., 2021)	*Risks*	To estimate and project subnational mortality rates based on sparse and/or missing data.	Bayesian	China and United States	1982–2010 and 1999-2018	Not specified	Life expectancy; mortality rates and confidence interval
(Manuel et al., 1998)	*Revista Salud Pública*	To compare three traditional methods of life table construction: Chiang, Greville e Reed-Merrell.	Chiang, Greville e Reed-Merrell	Canada	1988-1992	Not specified	Life expectancy at birth

Table A-4. Continued.

Author's name and year of studies	Journal name	Objective	Methods	Geographical study area	Year of study	Range of population size	Outcomes
(Melix et al., 2020)	*BMC Public Health*	To estimate life expectancy for Floridian census tracts and assess whether or not vulnerability indicators can explain some of the variation on the estimates.	Chiang II	United States	2009-2013	5,000 and more inhabitants	Life expectancy at birth and confidence interval
(Neupert et al., 2019)	*Revista Brasileira de Estudos de População*	To propose an adaptation of the indirect estimation approach that allows estimating infant and child mortality for small áreas.	Indirect methods	Myanmar	2014	32,719-2,456,529 inhabitants	Infant mortality rate
(Olatunde et al., 2010)	*Health Statistics*	To investigate the use of a small area geography, Middle Layer Super Output Areas (MSOAs) for the estimation and comparison of life-expectancy and disability-free life expectancy (DFLE) in England.	Chiang	England	1999- 2003	5,001-15,326 inhabitants	Rate for the last age group and confidence interval
(Paredes & Silva, 2017)	*Estudios Demográficos y Urbanos*	To estimate life expectancy at birth for Mexico, both at the municipal level and by degree of sociodemographic marginalization.	Swanson	Mexico	2010	Not specified	Life expectancy at birth
(Perez-Panades et al., 2020)	*International Journal of Health Geographics*	To make an autoregressive proposal to model the age-specific probabilities of death for each spatial unit, which assumes stronger dependence between closer age groups and spatial units.	M-model	Spain	2014-2017	Not specified	Life expectancy at birth
(Picazzo-Palencia et al., 2018)	*Revista Salud Pública*	To estimate and analyze the regional patterns of life expectancy at birth using multiple regression.	Swanson	Mexico	1990-2010	Not specified	Life expectancy at birth
(Puig & Ginebra, 2022)	*Geographical Analysis*	To build Bayesian models that smooth annual small-area life expectancy estimates for several years.	Bayesian and Chiang	Spain	2007 and 2018	456-57,760 inhabitants	Life expectancy at birth

Table A-4. Continued.

Author's name and year of studies	Journal name	Objective	Methods	Geographical study area	Year of study	Range of population size	Outcomes
(Rachet et al., 2015)	*Public Health*	To evaluate a flexible Poisson and flexible relational model against the Elandt-Johnson approach.	Flexible Poisson and flexible relational model	England	1998–2000 and 1981–1991	47,931-3,000 000 inhabitants	Mortality rates and life expectancy
(Rashid et al., 2021)	*Lancet Public Health*	To estimate trends from 2002 to 2019 in life expectancy and probabilities of death at different ages for all 6791 middle layer super output areas (MSOAs) in England.	Bayesian	England	2002 and 2019	5,760–11, 917 inhabitants	Life expectancy at birth
(Rodríguez López et al., 2022)	*BMJ Open*	To calculate life expectancy for small areas with the help of a Bayesian approach and evaluate the relationship of the estimates with socioeconomic characteristics.	TOPALS	Argentina	2015-2018	Not specified	Life expectancy at birth and confidence interval
(Rose & Nagle, 2017)	*Computers, Environment and Urban Systems*	To produce estimates of infant mortality rate and other household attributes for small areas. The authors also examine methods by which to perform both internal and external validation, and considers issues associated with these validation measures, both in a general sense and specific to the case study.	Penalized maximum entropy model and Iterative Proportional Fitting	Bangladesh	2011	380,000 - 11,800,000 inhabitants	Infant mortality
(Ruther et al., 2017)	*Annals of the American Association of Geographers*	To generate mortality estimates for small-areas based on a probabilistic reweighting method from data for larger geographic areas.	Maximum entropy method	United States	2000-2003	Not specified	Mortality rates
(Sacco et al., 2021)	*Revista Brasileira de Estudos Populacionais*	To estimate mortality levels, using life expectancy at birth, in smaller administrative areas of Argentina called departments.	Bayesian; TOPALS and indirect standardization method	Argentina	2009-2011	1,300; 4,600; 7,000 and 9,000 inhabitants	Life expectancy at birth and rate for the last age group
(Santos et al., 2020)	*SSM - Population Health*	To estimate mortality curves to Indigenous Brazilian children and adolescents and compare them against other races.	TOPALS	Brazil	2010	Not specified	Mortality rates and confidence interval

Table A-4. Continued.

Author's name and year of studies	Journal name	Objective	Methods	Geographical study area	Year of study	Range of population size	Outcomes
(Schmertmann & Gonzaga, 2018)	*Demography*	To propose a Bayesian regression model that specifically addresses the fundamental problems in small-area mortality estimation in countries with potentially defective registration.	Bayesian and TOPALS	Brazil	2010	Not specified	Life expectancy at birth; mortality rates and confidence interval
(Seaman et al., 2015)	*BMC Public Health*	To use the most up-to-date data to compare Glasgow to other Scottish cities and to (i) evaluate whether deprivation could account for lower life expectancy in Glasgow and (ii) explore whether the age distribution of mortality in Glasgow could explain its lower life expectancy.	Direct method and Arriaga	Scotland	2007-2011	Not specified	Confidence interval
(Swanson, 1989)	*Demography*	To construct a regression model to estimate life expectancy using state-level data.	Swanson	United States	1980	Not specified	Life expectancy at birth
(Swanson, 2019)	*Canadian Studies in Population*	To present a method for estimating infant mortality rates for small areas even if there are no reported deaths.	Beta-binomial random process and indirect estimator	Canada	2011	Not specified	Infant mortality
(Swanson & Baker, 2019)	*Journal of Population Research*	To estimate the "underlying" infant mortality rates for areas with small populations.	Beta Binomial model and beta-binomial stochastic process	United States	1970	Less than 1000 births	Infant mortality
(Swanson et al., 2019)	*Population Review*	To estimate infant mortality rates for small areas even if there are no reported deaths.	Beta Binomial model and beta-binomial stochastic process	United States	2009-2011	Not specified	Infant mortality
(Swanson & and Tedrow, 2022)	*Population Review*	To use Taylor's law method to estimate variance in age at death for a life table.	Taylor	United States	1990 and 2010	20,920 and more inhabitants	Variance in age at death for a life table
(Talbot et al., 2018)	*Population Health Metrics*	To present the decisions made and methods used to overcome the challenges in calculating life expectancy at birth using census tracts in New York State.	Bayesian	United States	2008-2012	1,044-25,754 inhabitants	Life expectancy at birth and confidence interval

Table A-4. Continued.

Author's name and year of studies	Journal name	Objective	Methods	Geographical study area	Year of study	Range of population size	Outcomes
(Tsimbos et al., 2014)	*Population, Space and Place*	To estimate life expectancy at birth by gender at local authority level and to explore spatial patterns.	Chiang; Silcocks; regression models and bayesian	Greece	2001	5,000 and more inhabitants	Life expectancy at birth
(Wakefield et al., 2019)	*Stat Methods Med Res*	To estimate mortality rates for children under five years old in Kenyan counties, while accounting for HIV epidemics.	Bayesian	Kenya	2003, 2008, 2009, and 2014	Not specified	Child mortality
(Wang et al., 2013)	*Population Health Metrics*	To estimate mortality rates and life expectancy at birth for men and women by U.S. counties with the use of a statistical model.	Mixed effects Poisson statistical model and Gaussian Process Regression	United States	1985-2010	Not specified	Life expectancy at birth; mortality rates; rate for the last age group And confidence interval
(Wang et al., 2018)	*Insurance: Mathematics and Economics*	To propose a data smoothing method to stabilize mortality estimates for the target population.	Lee–Carter model	Taiwan	1990-2009	10,000-5,000,000 inhabitants	Mortality rates
(Wang et al., 2019)	*Migration letters*	To apply graduation methods and small-area estimation skills to construct county-level life tables and evaluate whether domestic immigrants have lower mortality rates than those who do not migrate.	Lee-Carter model and Standard Mortality Ratio	Taiwan	1995-2014	10,000-20,000 inhabitants	Life expectancy at birth and mortality rates
(Wilson, 2018)	*Genus*	To evaluate eight fairly simple methods of regional mortality forecasting, focusing specifically on the requirements of practising demographers in government and busines.	National mortality rates aproximation; standardized mortality ratio; Mortality surface; Indirect method; ratio rate scale; broad age ratio rate scale; TOPALS	Australia	2006-2016	100,000 -500,000 inhabitants	Mortality rates
(Yue et al., 2021)	*North American Actuarial Journal*	To explore whether graduation methods can be used if the mortality profile of a small population differs from that of the reference population.	Lee-Carter model; Li-Lee model; partial standard mortality ratio and Whittaker ratio	Taiwan	1996-2015	10,000-200,000 inhabitants	Mortality rates

Source: Elaborated by the authors.

Table A-5. Quality assessment tool.

	Questions
1	Is the problem to be solved well defined?
2	Is the definition of the research object clear?
3	Is there discussion of alternative methodologies?
4	Have the methodologies applied by the authors been described in detail?
5	Are the databases used in the paper well specified?
6	Was the question of the paper answered by the methodology used?
7	Can the methodologies used by the authors be replicated? If not, why not?
8	Does the author provide sufficient materials for full reproducibility of the results?*

** "Sufficient materials" in this context means readily available code or spreadsheet.*

Source: Elaborated by the authors.

Table A-6. Studies Funding.

Funding	Number of studies	%
No	30	63.83
Yes	17	36.17
U.S. Department of health and human services - Centers for Disease Control and Prevention National, and Center for Health Statistics National Vital Statistics System	1	2.13
Adur, Arun and Worthing Primary Care Trust and South East Public Health Observatory	1	2.13
Australian Research Council	1	2.13
Capes Foundation	1	2.13
Center on the Economics and Demography of Aging (University of California)	1	2.13
Centers for Disease Control and Prevention (CDC) - National Environmental Public Health Tracking Program	1	2.13
Centers for Disease Control and Prevention Climate-Ready States and Cities Initiative, and Center for Disease Control and Prevention Environmental Public Health Tracking	1	2.13
Korea Health Technology R&D Project through the Korea Health Industry Development Institute (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea	1	2.13
Ministry of Education of China and National Social Science Fund of China	1	2.13
Ministry of Science and Technology (Taiwan)	1	2.13
National Institute on Minority Health and Health Disparities, National Heart, Lung, and Blood Institute, National Cancer Institute, National Institute on Aging, National Institute of Arthritis and Musculoskeletal and Skin Diseases, Office of Disease Prevention, and Office of Behavioral and Social Science Research, National Institutes of Health	1	2.13
State of Washington	2	4.26
Wellcome Trust	1	2.13
Wellcome Trust and the Foundation for Scientific and Technological Development in Health	1	2.13
Wellcome Trust, Imperial College London, Medical Research Council, Health Data Research UK, and National Institutes of Health Research	2	4.26

Source: Elaborated by the authors.

Table A-7. Database used.

Data base	Number of studies	%	Ref
Administrative data	9	19.15	(Hrzic et al., 2023; Jonker et al., 2012; Kim et al., 2020b; Seaman et al., 2015; Swanson, 2019; Swanson & Baker, 2019; Swanson & Tedrow, 2022; Wilson, 2018)
Census	5	10.64	(Baffour & Raymer, 2019; Gonzaga & Schmertmann, 2016; Neupert et al., 2019; Rachet et al., 2015; Santos et al., 2020)
Census and administrative data	25	53.19	(Adair & Lopez, 2021; Alexander et al., 2017; Arias et al., 2021; Congdon, 2014; Justino et al., 2012; Kim et al., 2020a; Kulkarni et al., 2011; Lu et al., 2021; Manuel et al., 1998; Melix et al., 2020; Olatunde et al., 2010; Paredes & Silva, 2017; Perez-Panades et al., 2020; Picazzo-Palencia et al., 2018; Rashid et al., 2021; Rose and Nagle, 2017; Ruther et al., 2017; Sacco et al., 2021; Schmertmann & Gonzaga, 2018; Swanson, 1989; Talbot et al., 2018; Tsimbos et al., 2014; Wakefield et al., 2019; H. Wang et al., 2013)
Not specified	4	8.51	(Puig & Ginebra, 2022; H.-C. Wang et al., 2018; Wilson, 2018; Yue et al., 2021)
Simulation	1	2.13	(Eayres & Williams, 2004)
Survey	2	4.26	(Anggreyani et al., 2016; Barman & Choudhury, 2017)
Survey, and administrative data	1	2.13	(Dwyer-Lindgren et al., 2022)

Source: Elaborated by the authors.

Table A-8. Number of studies per items of the evaluation Quality Assessment.

Items Assessed	Number of studies that	
	Yes	No
Is the problem to be solved well defined?	47	0
Is the definition of the research object clear?	47	0
Is there discussion of alternative methodologies?	26	21
Have the methodologies applied by the authors been described in detail?	44	3
Are the databases used in the paper well specified?	44	2
Was the question of the paper answered by the methodology used?	47	0
Can the methodologies used by the authors be replicated? If not, why not?	47	0
Does the author provide sufficient materials for full reproducibility of the results?*	11	36

** "Sufficient materials" in this context means readily available code or spreadsheet.*

Source: Elaborated by the authors.

References Appendix

Adair, T., & Lopez, A. D. (2021). Generating age-specific mortality statistics from incomplete death registration data: Two applications of the empirical completeness method. *Population Health Metrics*, *19*(1), 29. https://doi.org/10.1186/s12963-021-00262-3

Adebayo, S. B., & Fahrmeir, L. (2005). Analysing child mortality in Nigeria with geoadditive discrete-time survival models. *Statistics in Medicine*, *24*(5), 709-728. https://doi.org/10.1002/sim.1842

Alexander, M., Zagheni, E., & Barbieri, M. (2017). A Flexible Bayesian Model for Estimating Subnational Mortality. *Demography*, *54*(6), 2025-2041. https://doi.org/10.1007/s13524-017-0618-7

Anggreyani, A., Indahwati, & Kurnia, A. (2016). Small area estimation for estimating the number of infant mortality in West Java, Indonesia (No. 080002). https://doi.org/10.1063/1.4940859

Arias, E., Bastian, B., Xu, J., & Tejada-Vera, B. (2021). U.S. State Life Tables, 2018.

Arias, E., Escobedo, L., Kennedy, J., Fu, C., & Cisewki, J. (2018). U.S. small-area life expectancy estimates project: Methodology and results summary. U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics.

Baffour, B., & Raymer, J. (2019). Estimating multiregional survivorship probabilities for sparse data: An application to immigrant populations in Australia, 1981-2011. *Demographic Research*, 40, 463-502. https://doi.org/10.4054/DemRes.2019.40.18

Bahk, J., Kim, Y.-Y., Kang, H.-Y., Lee, J., Kim, I., Lee, J., Yun, S.-C., Park, J. H., Shin, S.-A., & Khang, Y.-H. (2017). Using the National Health Information Database of the National Health Insurance Service in Korea for Monitoring Mortality and Life Expectancy at National and Local Levels. *Journal of Korean Medical Science*, *32*(11), 1764. https://doi.org/10.3346/jkms.2017.32.11.1764

Barman, P., & Choudhury, L. (2017). Sub-state Life Expectancy Estimation Using the Methodology for Small Population.

Bennett, J. E., Li, G., Foreman, K., Best, N., Kontis, V., Pearson, C., Hambly, P., & Ezzati, M. (2015). The future of life expectancy and life expectancy inequalities in England and Wales: Bayesian spatio-temporal forecasting. *The Lancet*, *386*(9989), 163-170. https://doi.org/10.1016/S0140-6736(15)60296-3

Bilal, U., Hessel, P., Perez-Ferrer, C., Michael, Y. L., Alfaro, T., Tenorio-Mucha, J., Friche, A. A. L., Pina, M. F., Vives, A., Quick, H., Alazraqui, M.,

Rodriguez, D. A., Miranda, J. J., & Diez-Roux, A. V. (2021). Life expectancy and mortality in 363 cities of Latin America. *Nature Medicine*, *27*(3), 463-470. https://doi.org/10.1038/s41591-020-01214-4

Carter, K. N., Blakely, T., & Soeberg, M. (2010). Trends in survival and life expectancy by ethnicity, income and smoking in New Zealand: 1980s to 2000s, *Clinical Correspondence*, *123*(1320), 13-25.

Castanheira, H. C., & Monteiro Da Silva, J. H. C. (2022). Examining sex differences in the completeness of Peruvian CRVS data and adult mortality estimates. *Genus*, *78*(1), 3. https://doi.org/10.1186/s41118-021-00151-5

Checchi, F., Testa, A., Gimma, A., Koum-Besson, E., & Warsame, A. (2022). A method for small-area estimation of population mortality in settings affected by crises. *Population Health Metrics*, *20*(1), 4. https://doi.org/10.1186/s12963-022-00283-6

Congdon, P. (1991). Spatiotemporal Models For Small-Area Social Indicators.

Congdon, P. (1995). Life table analysis for areas using vital register data. *European Journal of Population*, *11*(4), 343-369. https://doi.org/10.1007/BF01267725

Congdon, P. (2014). Estimating life expectancies for US small areas: A regression framework. *Journal of Geographical Systems, 16(*1), 1-18. https://doi.org/10.1007/s10109-013-0177-4

Dwyer-Lindgren, L., Bertozzi-Villa, A., Stubbs, R. W., Morozoff, C., Mackenbach, J. P., Van Lenthe, F. J., Mokdad, A. H., & Murray, C. J. L. (2017). Inequalities in Life Expectancy Among US Counties, 1980 to 2014: Temporal Trends and Key Drivers. *JAMA Internal Medicine*, *177*(7), 1003. https://doi.org/10.1001/jamainternmed.2017.0918

Dwyer-Lindgren, L., Kendrick, P., Kelly, Y. O., Sylte, D. O., Schmidt, C., Blacker, B. F., Daoud, F., Abdi, A. A., Baumann, M., Mouhanna, F., Kahn, E., Hay, S. I., Mensah, G. A., Nápoles, A. M., Pérez-Stable, E. J., Shiels, M., Freedman, N., Arias, E., George, S. A., … Mokdad, A. H. (2022). Life expectancy by county, race, and ethnicity in the USA, 2000-19: A systematic analysis of health disparities. *The Lancet*, *400*(10345), 25-38. https://doi.org/10.1016/S0140-6736(22)00876-5

Dwyer-Lindgren, L., Stubbs, R. W., Bertozzi-Villa, A., Morozoff, C., Callender, C., Finegold, S. B., Shirude, S., Flaxman, A. D., Laurent, A., Kern, E., Duchin, J. S., Fleming, D., Mokdad, A. H., & Murray, C. J. L. (2017). Variation in life expectancy and mortality by cause among neighbourhoods in King County, WA, USA, 1990-2014: A census tract-level analysis for the Global Burden of Disease Study 2015. *The Lancet Public Health*, *2*(9), e400-e410. https://doi.org/10.1016/S2468-2667(17)30165-2

Eayres, D., & Williams, E. S. (2004). Evaluation of methodologies for small area life expectancy estimation. *Journal of Epidemiology & Community Health*, *58*(3), 243-249. https://doi.org/10.1136/jech.2003.009654

Fernand Jubithana, A., & Queiroz, B. L. (2019). Quality of death counts and adult mortality registration in Suriname and its main regions. *Revista Brasileira de Estudos de População*, 36, 1-20. https://doi.org/10.20947/S0102-3098a0102

Fukawa, T., & Shimizu, T. (1990). A Bayesian approach to life table construction for small areas, *Jinkogaku kenkyu*, 13, 37-49. https://doi.org/10.24454/jps.13.0_37.

Gonzaga, M. R., & Schmertmann, C. P. (2016). Estimating age- and sex-specific mortality rates for small areas with TOPALS regression: An application to Brazil in 2010. *Revista Brasileira de Estudos de População*, *33*(3), 629-652. https://doi.org/10.20947/S0102-30982016c0009

Grigoriev, O., & Doblhammer, G. (2019). Changing educational gradient in long-term care-free life expectancy among German men, 1997-2012. *PLOS ONE*, *14*(9), e0222842. https://doi.org/10.1371/journal.pone.0222842

Hanley, J. A. (2022). The (Im)precision of Life Expectancy Numbers. *American Journal of Public Health*, *112*(8), 1151-1160. https://doi.org/10.2105/AJPH.2022.306805

Hrzic, R., Vogt, T., Brand, H., & Janssen, F. (2023). District-Level Mortality Convergence in Reunified Germany: Long-Term Trends and Contextual Determinants. *Demography*, 10422945. https://doi.org/10.1215/00703370-10422945

Inskip, H., Beral, V., Fraser, P., & Haskey, J. (1983). Methods for age-adjustment of rates. *Statistics in Medicine*, *2*(4), 455-466. https://doi.org/10.1002/sim.4780020404

Jonker, M. F., Van Lenthe, F. J., Congdon, P. D., Donkers, B., Burdorf, A., & Mackenbach, J. P. (2012). Comparison of Bayesian Random-Effects and Traditional Life Expectancy Estimations in Small-Area Applications. *American Journal of Epidemiology*, *176*(10), 929-937. https://doi.org/10.1093/aje/kws152

Justino, J. R., Freire, F. H. M. D. A., & Lucio, P. S. (2012). Estimação de sub-registros de óbitos em pequenas áreas com os métodos bayesiano empírico e algoritmo EM. *Revista Brasileira de Estudos de População*, *29*(1), 87-100. https://doi.org/10.1590/S0102-30982012000100006

Kim, I., Kang, H.-Y., & Khang, Y.-H. (2020a). Life Expectancy in Areas around Subway Stations in the Seoul Metropolitan Area in Korea,

2008-2017. *Journal of Korean Medical Science, 35*(44), e365. https://doi.org/10.3346/jkms.2020.35.e365

Kim, I., Lim, H.-K., Kang, H.-Y., & Khang, Y.-H. (2020b). Comparison of three small-area mortality metrics according to urbanity in Korea: The standardized mortality ratio, comparative mortality figure, and life expectancy. *Population Health Metrics*, *18*(1), 3. https://doi.org/10.1186/s12963-020-00210-7

Kulkarni, S. C., Levin-Rector, A., Ezzati, M., & Murray, C. J. (2011). Falling behind: Life expectancy in US counties from 2000 to 2007 in an international context. *Population Health Metrics*, *9*(1), 16. https://doi.org/10.1186/1478-7954-9-16

Lankoandé, Y. B., Masquelier, B., Zabre, P., Bangré, H., Duthé, G., Soura, A. B., Pison, G., & Ali, S. (2022). Estimating mortality from census data: A record-linkage study of the Nouna Health and Demographic Surveillance System in Burkina Faso. *Demographic Research*, 46, 653-680. https://doi.org/10.4054/DemRes.2022.46.22

Lo, E., Vatnik, D., Benedetti, A., & Bourbeau, R. (2016). Variance models of the last age interval and their impact on life expectancy at subnational scales. *Demographic Research*, 35, 399-454. https://doi.org/10.4054/DemRes.2016.35.15

Lu, Q., Hanewald, K., & Wang, X. (2021). Subnational Mortality Modelling: A Bayesian Hierarchical Model with Common Factors. *Risks*, *9*(11), 203. https://doi.org/10.3390/risks9110203

Manuel, D., Goel, V., & Williams, I. (1998). The Derivation of Life Tables for Local Areas. https://pubmed.ncbi.nlm.nih.gov/9664025/

Melix, B. L., Uejio, C. K., Kintziger, K. W., Reid, K., Duclos, C., Jordan, M. M., Holmes, T., & Joiner, J. (2020). Florida neighborhood analysis of social determinants and their relationship to life expectancy. *BMC Public Health, 20*(1), 632. https://doi.org/10.1186/s12889-020-08754-x

Mokhayeri, Y., Mahmoudi, M., Haghdoost, A. A., Amini, H., Asadi-Lari, M., & Naieni, K. H. (2014). How within-city socioeconomic disparities affect life expectancy? Results of Urban HEART in Tehran, Iran. 28.

Moser, A., Panczak, R., Zwahlen, M., Clough-Gorr, K. M., Spoerri, A., Stuck, A. E., & Egger, M. (2014). What does your neighbourhood say about you? A study of life expectancy in 1.3 million Swiss neighbourhoods. *Journal of Epidemiology and Community Health*, *68*(12), 1125-1132. https://doi.org/10.1136/jech-2014-204352

Neupert, R., Fernandez Menjivar, R. E., & Fernandez Castilla, R. E. (2019). Indirect estimation of infant mortality in small areas. *Revista Brasileira de Estudos de População*, 36, 1-37. https://doi.org/10.20947/s0102-3098a0100

Nikolov, I. N. (1993). A simplified method for determining the average life expectancy in the Republic of Bulgaria, *Folia Medica*, *35*(3-4), 45-48.

Olatunde, O., White, C., & Smith, M. P. (2010). Life expectancy and disability-free life expectancy estimates for Middle Super Output Areas; England, 1999-2003. *Health Statistics Quarterly*, *47*(1), 33-65. https://doi.org/10.1057/hsq.2010.15

Paredes, I., & Silva, E. (2017). Estimación de la esperanza de vida a nivel municipal y por marginación sociodemográfica: Una aplicación del método de Swanson para el caso de México, 2010. *Estudios Demográficos y Urbanos*, *32*(1), 97-129. https://doi.org/10.24201/edu.v32i1.1711

Perez-Panades, J., Botella-Rocamora, P., & Martinez-Beneito, M. A. (2020). Beyond standardized mortality ratios; some uses of smoothed age-specific mortality rates on small areas studies. *International Journal of Health Geographics, 19*(1), 54. https://doi.org/10.1186/s12942-020-00251-z

Picazzo-Palencia, E., Flores Segovia, M., & De La Cruz-Maldonado, M. E. (2018). Análisis regional de la esperanza de vida al nacer en México, por medio del método de regresión. *Revista de Salud Pública*, *20*(6), 725-729. https://doi.org/10.15446/rsap.v20n6.35806

Pickle, L. W., & White, A. A. (1995). Effects of the choice of age-adjustment method on maps of death rates. *Statistics in Medicine*, *14*(5-7), 615-627. https://doi.org/10.1002/sim.4780140519

Puig, X., & Ginebra, J. (2022). Bayesian Spatiotemporal Model for Life Expectancy Mapping; Changes in Barcelona From 2007 to 2018. *Geographical Analysis*, *54*(4), 839-859. https://doi.org/10.1111/gean.12299

Queiroz, B. L., Gonzaga, M. R., Vasconcelos, A. M. N., Lopes, B. T., & Abreu, D. M. X. (2020). Comparative analysis of completeness of death registration, adult mortality and life expectancy at birth in Brazil at the subnational level. *Population Health Metrics*, *18*(S1), 11. https://doi.org/10.1186/s12963-020-00213-4

Queiroz, B. L., Lima, E. E. C., Freire, F. H. M. A., & Gonzaga, M. R. (2020). Temporal and spatial trends of adult mortality in small areas of Brazil, 1980-2010. *Genus*, *76*(1), 36. https://doi.org/10.1186/s41118-020-00105-3

Rachet, B., Maringe, C., Woods, L. M., Ellis, L., Spika, D., & Allemani, C. (2015). Multivariable flexible modelling for estimating complete, smoothed life tables for sub-national populations. *BMC Public Health*, *15*(1), 1240. https://doi.org/10.1186/s12889-015-2534-3

Rashid, T., Bennett, J. E., Paciorek, C. J., Doyle, Y., Pearson-Stuttard, J., Flaxman, S., Fecht, D., Toledano, M. B., Li, G., Daby, H. I., Johnson, E., Davies, B., & Ezzati, M. (2021). Life expectancy and risk of death in 6791 communities in England from 2002 to 2019: High-resolution spatiotemporal analysis of civil registration data. *The Lancet Public Health*, *6*(11), e805-e816. https://doi.org/10.1016/S2468-2667(21)00205-X

Rees, P. H., Wohland, P. N., & Norman, P. D. (2009). The estimation of mortality for ethnic groups at local scale within the United Kingdom. *Social Science & Medicine*, *69*(11), 1592-1607. https://doi.org/10.1016/j.socscimed.2009.08.015

Rodríguez López, S., Tumas, N., Bilal, U., Moore, K. A., Acharya, B., Quick, H., Quistberg, D. A., Acevedo, G. E., & Diez Roux, A. V. (2022). Intraurban socioeconomic inequalities in life expectancy: A population-based cross-sectional analysis in the city of Córdoba, Argentina (2015-2018). *BMJ Open*, *12*(9), e061277. https://doi.org/10.1136/bmjopen-2022-061277

Rose, A. N., & Nagle, N. N. (2017). Validation of spatiodemographic estimates produced through data fusion of small area census records and household microdata. Computers, *Environment and Urban Systems*, 63, 38-49. https://doi.org/10.1016/j.compenvurbsys.2016.07.006

Ruther, M., Leyk, S., & Buttenfield, B. (2017). Deriving Small Area Mortality Estimates Using a Probabilistic Reweighting Method. *Annals of the American Association of Geographers*, *107*(6), 1299-1314. https://doi.org/10.1080/24694452.2017.1320213

Sacco, N., Williams, I., & Queiroz, B. L. (2021). Estimaciones de esperanza de vida al nacer en áreas menores de la región pampeana. *Revista Brasileira de Estudos de População*, 38, 1-41. https://doi.org/10.20947/S0102-3098a0160

Santos, R. V., Borges, G. M., Campos, M. B. D., Queiroz, B. L., Coimbra, C. E. A., & Welch, J. R. (2020). Indigenous children and adolescent mortality inequity in Brazil: What can we learn from the 2010 National Demographic Census? *SSM - Population Health*, 10, 100537. https://doi.org/10.1016/j.ssmph.2020.100537

Scherbov, S., & Ediev, D. (2011). Significance of life table estimates for small populations: Simulation-based study of estimation errors. *Demographic Research*, 24, 527-550. https://doi.org/10.4054/DemRes.2011.24.22

Schmertmann, C. P., & Gonzaga, M. R. (2018). Bayesian Estimation of Age-Specific Mortality and Life Expectancy for Small Areas With Defective Vital Records. *Demography*, *55*(4), 1363-1388. https://doi.org/10.1007/s13524-018-0695-2

Seaman, R., Mitchell, R., Dundas, R., Leyland, A., & Popham, F. (2015). How much of the difference in life expectancy between Scottish cities does deprivation explain? *BMC Public Health*, *15*(1), 1057. https://doi.org/10.1186/s12889-015-2358-1

Singh, G. K., & Siahpush, M. (2014). Widening Rural–Urban Disparities in Life Expectancy, U.S., 1969–2009. *American Journal of Preventive Medicine, 46*(2), e19-e29. https://doi.org/10.1016/j.amepre.2013.10.017

Swanson, D. A. (1989). A state-based regression model for estimating substate life expectancy. *Demography*, *26*(1), 161-170. https://doi.org/10.2307/2061502

Swanson, D. A. (2019). Estimating the Underlying Infant Mortality Rates for Small Populations, Even Those Reporting Zero Infant Deaths: A Case Study of 66 Local Health Areas in British Columbia. *Canadian Studies in Population*, *46*(2), 173-187. https://doi.org/10.1007/s42650-019-00014-7

Swanson, D. A., & Baker, J. (2019). Estimating the underlying infant mortality rates for small populations: An historical study of US counties in 1970. *Journal of Population Research*, *36*(3), 233-244. https://doi.org/10.1007/s12546-019-09225-w

Swanson, D. A., Kposowa, A., & Baker, J. (2019). Estimating the Underlying Infant Mortality Rates for Small Populations, Including those Reporting Zero Infant Deaths: A Case Study of Counties in California. *Population Review*, *58*(2). https://doi.org/10.1353/prv.2019.0005

Swanson, D. A., & Tedrow, L. M. (2022). Taylor's Law and the Relationship between Life Expectancy at Birth and Variance in Age at Death in a Period Life Table. *Population Review*, *61*(1), 31-42. https://doi.org/10.1353/prv.2022.0001

Talbot, T. O., Done, D. H., & Babcock, G. D. (2018). Calculating census tract-based life expectancy in New York state: A generalizable approach. *Population Health Metrics*, *16*(1), 1. https://doi.org/10.1186/s12963-018-0159-3

Tsimbos, C., Kalogirou, S., & Verropoulou, G. (2014). Estimating Spatial Differentials in Life Expectancy in Greece at Local Authority Level. Population, *Space and Place*, *20*(7), 6466-63. https://doi.org/10.1002/psp.1800

Tsimbos, C., Kotsifakis, G., Verropoulou, G., & Kalogirou, S. (2011). Life expectancy in Greece 1991-2007: Regional variations and spatial clustering. *Journal of Maps*, *7*(1), 280-290. https://doi.org/10.4113/jom.2011.1188

Wakefield, J., Fuglstad, G.-A., Riebler, A., Godwin, J., Wilson, K., & Clark, S. J. (2019). Estimating under-five mortality in space and time in a developing world context. *Statistical Methods in Medical Research*, *28*(9), 2614-2634. https://doi.org/10.1177/0962280218767988

Wang, H., Schumacher, A. E., Levitz, C. E., Mokdad, A. H., & Murray, C. J. (2013). Left behind: Widening disparities for males and females in US county life expectancy, 1985–2010. *Population Health Metrics*, *11*(1), 8. https://doi.org/10.1186/1478-7954-11-8

Wang, H.-C., Yue, C.-S. J., & Chong, C.-T. (2018). Mortality models and longevity risk for small populations. *Insurance:* Mathematics and Economics, 78, 351-359. https://doi.org/10.1016/j.insmatheco.2017.09.020

Wang, H.-C., Yu, J. C., & Wang, T.-Y. (2019). Do domestic immigrants live longer? An approach for estimating the life expectancy of small populations. *Migration Letters*, *16*(3), 399-416. https://doi.org/10.33182/ml.v16i3.644

Wilson, T. (2018). Evaluation of simple methods for regional mortality forecasts. *Genus*, *74*(1), 14. https://doi.org/10.1186/s41118-018-0040-z

Yue, J. C., Wang, H.-C., & Wang, T.-Y. (2021). Using Graduation to Modify the Estimation of Lee–Carter Model for Small Populations. *North American Actuarial Journal*, *25*(sup1), S410-S420. https://doi.org/10.1080/10920277.2019.1650288