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Desigualdades espaciales en la esperanza de vida al nacer en los municipios de México, 2010 a 2020: un análisis bayesiano ecológico de la pobreza y la cobertura de seguridad social

Spatial inequalities in life expectancy at birth across Mexican municipalities, 2010 to 2020: An ecological Bayesian analysis of poverty and social security coverage

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RESUMEN

Antecedentes: Las desigualdades municipales en longevidad pueden quedar ocultas en los promedios nacionales. Se examinó la asociación entre pobreza por ingresos y esperanza de vida al nacer en municipios mexicanos, así como su variación según un indicador municipal indirecto de cobertura de seguridad social.

Métodos: Se analizó un panel ecológico de 7.313 observaciones municipio-periodo correspondientes a 2.466 municipios en 2010, 2015 y 2020. Se ajustaron siete especificaciones gaussianas bayesianas con covariables socioeconómicas y efectos aleatorios espaciales y espaciotemporales mediante aproximación de Laplace anidada integrada. Como sensibilidad, se reincorporaron 56 observaciones extremas de esperanza de vida.

Resultados: La esperanza de vida municipal media fue de 77,33 años en 2010, 78,20 en 2015 y 73,43 en 2020. En el modelo más flexible, un incremento de una desviación estándar de la pobreza por ingresos se asoció con 1,07 años menos (intervalo de credibilidad [ICr] del 95 %: −1,41 a −0,73) con cobertura media. La interacción pobreza-cobertura fue de −0,187 (ICr del 95 %: −0,369 a −0,005), pero incluyó el cero en el análisis de sensibilidad. La dependencia espaciotemporal fue importante y el error predictivo aumentó en municipios menos poblados.

Conclusiones: Una mayor pobreza por ingresos se asoció de forma consistente con menor esperanza de vida municipal. El indicador indirecto de cobertura no atenuó robustamente esta asociación. Los patrones espaciales reflejan heterogeneidad latente y no demuestran efectos causales.

Palabras clave: esperanza de vida; pobreza por ingresos; desigualdades espaciales; seguridad social; análisis bayesiano.

ABSTRACT

Background: Municipal inequalities in longevity may be obscured by national averages. We examined whether income poverty was associated with life expectancy at birth in Mexican municipalities and whether a municipal social-security coverage proxy modified that association.

Methods: A repeated ecological panel included 7,313 municipality-period observations across 2,466 municipalities in 2010, 2015, and 2020. Seven Bayesian Gaussian specifications combined socioeconomic covariates with spatial and spatiotemporal random effects, fitted using integrated nested Laplace approximation. Robustness was assessed by restoring 56 extreme life-expectancy observations.

Results: Mean municipal life expectancy was 77.33 years in 2010, 78.20 in 2015, and 73.43 in 2020. In the most flexible model, a one-standard-deviation increase in income poverty was associated with 1.07 fewer years (95% credible interval [CrI]: −1.41 to −0.73) at average coverage. The poverty-by-coverage coefficient was −0.187 (95% CrI: −0.369 to −0.005), but its interval included zero in the sensitivity analysis. Spatiotemporal dependence was substantial; predictive error was greater in less populated municipalities.

Conclusions: Higher income poverty was consistently associated with shorter municipal life expectancy. The area-level coverage proxy did not robustly attenuate this association. Geographic patterns reflected latent heterogeneity, not identified causal effects.

Keywords: life expectancy; income poverty; spatial inequalities; social security; Bayesian analysis.

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1. INTRODUCTION

Life expectancy at birth condenses age-specific mortality into a summary of prevailing survival conditions. Its geographic distribution is therefore informative about how material resources, public institutions, and environmental risks are organised across territory. Within-country differences are not simply demographic noise, they can reflect unequal exposure to preventable mortality, unequal access to care, and uneven protection from economic shocks (World Health Organization, 2008). In Mexico, state-level averages obscure substantial municipal heterogeneity in poverty, labour-market formality, infrastructure, violence, and access to social protection.

Various theoretical approaches suggest a socioeconomic gradient in longevity. Preston's (1975) account separates the contribution of income from broader gains in public health and medical knowledge. Fundamental-cause theory argues that money, knowledge, power, and social connections remain adaptable resources as disease profiles and technologies change (Link & Phelan, 1995; Phelan et al., 2010). Ecosocial and place-based perspectives further locate those resources within historically produced environments, neighbouring municipalities may share labour markets, referral networks, transport constraints, environmental hazards, and state capacity (Krieger, 2001; Macintyre et al., 2002; Cummins et al., 2007). Spatial clustering is thus substantively relevant, not only a nuisance that invalidates independent-error models.

Social security could alter the poverty–longevity gradient through access to medical care, continuity of treatment, income replacement, and financial risk pooling (Arrow, 1963; Grossman, 1972). Yet a deprivation complement is not equivalent to effective protection. Mexico's health and social-protection systems remain segmented by employment status and institution, with marked territorial variation in resources and service capacity (Knaul et al., 2012; Becerril-Montekio et al., 2024). The inverse care law is pertinent, formal entitlement can coexist with weak local provision precisely where need is greatest (Hart, 1971). Consequently, a municipal percentage resulting from a lack of Social Security coverage may reflect a combination of formal employment, urbanization, and institutional reach, rather than the quality or ease of access.

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Previous Mexican research has documented disparities in life expectancy by state, socioeconomic position, and social security status (Agudelo-Botero et al., 2023; Gómez-Ugarte & García-Guerrero, 2023; García-Hernández et al., 2026). Less is known about whether the association between income poverty and longevity varies with municipal social security coverage after allowing for dependence between neighbouring municipalities and persistence across periods. Municipal analysis can disclose within-state contrasts, but it also raises measurement and inferential problems, small-area life expectancy may be imprecise; municipal boundaries and populations change; ecological associations cannot be transferred to individuals; and spatial random effects can absorb both omitted context and measurement error (Diez Roux, 2001; Wakefield, 2008).

We therefore estimated a sequence of Bayesian spatial and spatiotemporal models for Mexican municipalities in 2010, 2015, and 2020. The primary question was whether higher income poverty was associated with lower municipal life expectancy. A secondary, explicitly associational question was whether the poverty slope differed across levels of a derived area-level social-security coverage proxy. We expected a negative poverty coefficient and a positive interaction, which would indicate a less adverse poverty gradient at higher proxy values. We also evaluated whether residual heterogeneity followed municipal contiguity, persisted over time, and varied across municipalities. The design defines no intervention, exchangeability condition, or causal estimand; all regression coefficients are interpreted as adjusted ecological associations.

2. METHODOLOGY

Study design and analytical unit

This repeated ecological analysis examined municipal-period observations for 2010, 2015, and 2020, the years aligned with municipal poverty measurements (Consejo Nacional de Evaluación de la Política de Desarrollo Social [CONEVAL], 2021, 2022). The life-expectancy series covered 2,467 municipal identifiers; according to the study procedures, municipal estimates were constructed using actuarial life tables with official registered deaths from the General Directorate of Health Information (DGIS) and midyear population estimates from the National Population Council (CONAPO). The analytical panel used the three years aligned with the social indicators.

Municipal codes were aligned using five-character identifiers. The analytical sample comprised 2,466 municipalities after record-level quality controls: 2,394 contributed three waves, 59 contributed two, and 13 contributed one (7,313 municipality-period records). The 2020 spatial graph was held fixed across waves; consequently, this harmonisation provides a consistent model index but does not establish historical boundary equivalence for every municipality.

Data sources and variables

The outcome was municipal life expectancy at birth, expressed in years and derived from mortality and municipal population records using actuarial life tables. These estimates entered the Bayesian Gaussian likelihood with a common observation variance. The model did not separately propagate estimation uncertainty for each municipality, an assumption that may be consequential for sparsely populated areas (Eayres & Williams, 2004).

Municipal socioeconomic indicators were obtained from the CONEVAL municipal poverty series for 2010, 2015 and 2020 (CONEVAL, 2021, 2022; Supplementary Table S1). Income poverty was the percentage below the Income Poverty Line rather than multidimensional poverty, which includes social-security deprivation. The coverage proxy equalled 100 minus the percentage lacking access to social security; it is an aggregate complement, not a direct measure of formal affiliation, care quality, use, or effective financial protection. Educational deprivation and lack of basic housing services were prespecified adjustment covariates. Health-care deprivation was not adjusted for because of its potential intermediate relationship with the proposed pathway. All four covariates were standardised over the analytical sample: one standard deviation corresponded to 19.22, 15.45, 10.51 and 30.25 percentage points for poverty, the coverage proxy, educational deprivation and lack of basic housing services, respectively.

Data quality and missingness

The initial three-wave file comprised 7,401 records. We flagged 56 life-expectancy values below 40 or above 100 years (18 in 2010, 25 in 2015, and 13 in 2020). The primary analysis excluded these observations without replacement or imputation; a sensitivity analysis restored them. After that exclusion, 32 records lacked complete covariates, yielding 7,313 observations from 2,466 municipalities. The sensitivity sample contained 7,367 observations after 34 incomplete records were removed. The thresholds functioned as quality-

control rules rather than clinically validated cut points. Because extreme estimates may reflect both error and genuine local mortality, the comparison of analysesnot the exclusion alone governed interpretation.

Statistical models

Let y_{it} denote life expectancy for municipality i in period t. We assumed $y_{it} \sim \text{Normal}(\mu_{it}, \sigma^2)$. The fixed portion of the linear predictor included period indicators, standardised income poverty (P_{it}), the standardised social-security coverage proxy (S_{it}), their product, educational deprivation (E_{it}), and lack of basic housing services (B_{it}):

$\mu_{it} = \alpha + \gamma_t + \beta P\ P_{it} + \beta S\ S_{it} + \beta PS(P_{it} \times S_{it}) + \beta E\ E_{it} + \beta B\ B_{it}$ + spatial terms.

At a given proxy value s, the conditional poverty association is $\beta P + \beta PSs$. A positive βPS would be consistent with attenuation of the negative poverty gradient as the proxy rises; a negative value implies a more negative gradient. This parameter is a statistical interaction between area-level variables and is not an individual-level or causal effect modifier.

Seven nested or alternative specifications were fitted (Supplementary Table S2). M0 included period, education and basic-services deprivation; M1 added poverty; M2 added the coverage proxy; and M3 added their interaction. M4 added a scaled Besag–York–Mollié (BYM2) municipal intercept with queen-contiguity structured and independent components. M5 replacednot accumulated on top ofthe static M4 field with period-specific BYM2 fields linked by first-order autoregressive (AR1) dependence. M6 retained the M5 spatiotemporal field and additionally included an intrinsic conditional autoregressive municipal deviation from the overall poverty slope. The structured effects were scaled and sum-to-zero constraints were used for identifiable decomposition (Besag et al., 1991; Riebler et al., 2016; Sørbye & Rue, 2014).

The neighbourhood graph was generated from INEGI 2020 municipal polygons and kept constant for all three observations per municipality (Instituto Nacional de Estadística y Geografía [INEGI], 2021). The fitted graph contained 2,466 nodes in a single connected component with no isolates; queen-contiguity neighbour counts ranged from 1 to 22 (median 6). Three geometries in the initial cartographic processing were not represented in the final graph. The graph corresponds to the 2,466-municipality analytic index, not to all source records or polygons. Using fixed 2020 geometries stabilised model indexing, but does not

correct historical territorial revisions or identify administrative changes that may affect longitudinal comparability.

Priors, computation, and model assessment

The BYM2 and spatial-slope precision parameters were assigned penalised-complexity priors with Pr(standard deviation > 1) = 0.01; the BYM2 mixing prior used (0.5, 0.5). Fixed effects had diffuse Gaussian priors with precision 0.001 and the intercept an improper flat prior. The reported fitting configuration retained INLA defaults for Gaussian observation precision and AR1 correlation. INLA technical documentation describes a log-gamma(1, 0.00005) prior on Gaussian observation precision and a normal(0, 0.15) prior for the AR1 logit-transformed correlation, $\log[(1 + \rho)/(1 - \rho)]$ (R-INLA Project, 2026a, 2026b). Exact settings are version- and model-configuration dependent. Their sensitivity was not assessed, so temporal-dependence inference across three periods may be prior-sensitive (Simpson et al., 2017).

Posterior marginals were approximated using the simplified Laplace strategy with INLA (Lindgren & Rue, 2015; Rue et al., 2009). Analyses used R 4.6.1 (R Core Team, 2026), INLA 26.08.07, sf 1.1-2 (Pebesma, 2018), and spdep 1.4-2 (Bivand & Wong, 2018).

Models were compared using the deviance information criterion (DIC), the widely applicable information criterion (WAIC), and conditional predictive ordinates (CPO); lower values denote better scores within this dataset (Spiegelhalter et al., 2002; Watanabe, 2010). Pointwise uncertainty estimates for paired differences in WAIC were not computed, and the available results do not support a formal uncertainty interval for ΔWAIC or ΔDIC. We therefore use these criteria descriptively rather than as definitive hypothesis tests (Vehtari et al., 2017). In-sample posterior predictive checks used 100 joint posterior samples on model-specific random subsets of 3,000 observations; RMSE values across models are not paired and cannot rank their predictive accuracy.

Further diagnostics included mean absolute error, bias, 95% predictive-interval coverage, CPO-based probability integral transforms (PIT), CPO failures, and period-specific residual Moran's I (Held et al., 2010; Moran, 1950). A post hoc analysis grouped M6 errors and interval coverage by municipal population quartile. PIT uniformity, comparable coverage across municipality sizes, and spatial residual independence were assessed as calibration targets, not assumed.

The analysis used aggregated, publicly available municipal indicators and no identifiable individual records. On that basis, the study did not constitute human-participant research requiring informed consent. No causal estimand was specified. Time-varying confounding, exposure and outcome measurement error, selective missingness, changing municipal composition, and reverse causation remain plausible; spatial adjustment cannot by itself resolve them. We therefore use 'association', 'difference', and 'prediction' throughout.

3. RESULTS

Analytical sample and temporal pattern

The primary sample included 7,313 municipal-period observations. Mean municipal life expectancy was 0.87 years higher in 2015 than in 2010 and 4.77 years lower in 2020 than in 2015 (Table 1). Over the same intervals, mean income poverty, educational deprivation, and lack of basic housing services were lower, while the coverage proxy was somewhat higher. These are unweighted municipal cross-sections with slightly different composition across waves; they describe the typical observed municipality rather than within-municipality change or the average Mexican resident.

Table 1.

Municipal characteristics by observation period

Year	n	Life expectancy, mean (SD)	Income poverty, %	Social-security coverage proxy, %	Educational deprivation, %	Lack of basic services, %
2010	2,438	77.33 (7.36)	70.16	24.42	31.44	47.14
2015	2,422	78.20 (7.20)	69.19	26.09	27.82	45.89
2020	2,453	73.43 (6.51)	65.83	27.66	25.59	39.95

Note. Unweighted means across municipalities in the primary analytical sample. SD = standard deviation. Sample size differs because of outcome flags and incomplete covariates. Figure 1 displays pronounced within-state contrasts in municipal life expectancy in 2020. The lower mapped values are concentrated across large parts of northern Mexico, whereas higher values appear in parts of the centre and Pacific south. These are estimated point values and the map does not display their measurement precision. The corresponding municipal poverty map (Supplementary Figure S1) shows particularly high percentages in the south and

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southeast (CONEVAL, 2022). Poverty correlated with lack of basic housing services (r = 0.745) and educational deprivation (r = 0.642), indicating substantial collinearity among adjusted predictors.

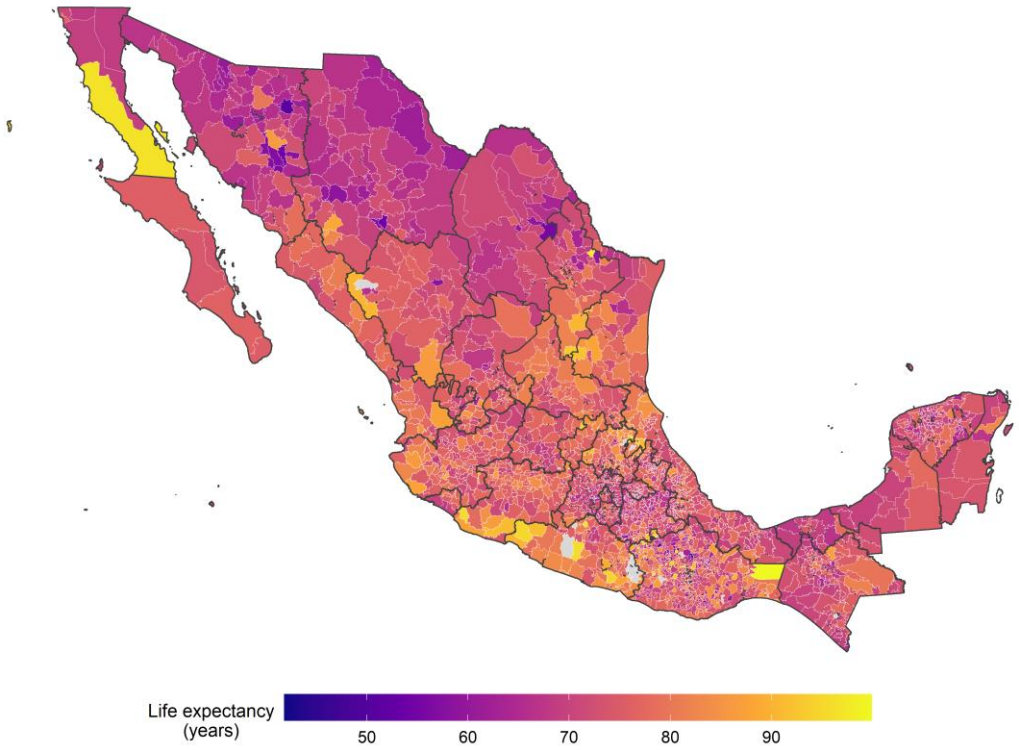


Figure 1. Municipal life expectancy at birth in 2020. Note. n = 2,453 municipalities. Grey polygons denote missing analytical values. Source: own estimates of life expectancy; 2020 INEGI boundaries in Mexico ITRF2008 / Lambert conformal conic projection. The sequential legend reports years. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

Model comparison

Among non-spatial specifications, adding the social indicators produced comparatively small changes in information criteria. The largest change occurred when a static spatial field was replaced with temporally evolving fields: WAIC decreased from 49,013.4 (M4) to 44,530.1 (M5; Table 2). Model complexity also increased sharply (pWAIC 10.5 in M4 versus 2,216.9 in M5). M6 had the lowest observed WAIC (44,512.2), 17.94 points below M5, and a DIC difference of 18.39 points. However, no paired uncertainty estimate for those differences was

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obtained. The information-criterion preference for M6 was therefore provisional, particularly in light of the outcome-threshold sensitivity analysis.

Table 2.

Model fit, effective complexity, and in-sample checks

Model	DIC	pD	WAIC	pWAIC	Mean −log(CPO)	RMSE
M0	49,126.5	6.0	49,127.6	7.0	3.359	6.90
M1	49,118.8	7.0	49,120.1	8.3	3.358	7.03
M2	49,025.6	8.0	49,027.2	9.6	3.352	7.07
M3	49,015.9	9.0	49,017.7	10.8	3.351	7.02
M4	49,011.9	9.0	49,013.4	10.5	3.351	6.84
M5	44,433.2	2,681.8	44,530.1	2,216.9	3.089	3.38
M6	44,414.8	2,681.6	44,512.2	2,217.1	3.088	3.45

Note. pD and pWAIC are effective parameter counts. Lower DIC, WAIC, and mean −log(CPO) indicate better values within this dataset. Each RMSE used 100 posterior draws and a different random subset of 3,000 observations; RMSE values are in-sample checks and are not directly comparable across models. Pairwise standard errors for WAIC differences were unavailable.

Fixed associations and the coverage interaction

In M6, adjusted life expectancy was 0.76 years higher in 2015 than in 2010 and 4.09 years lower in 2020 relative to 2010 (Table 3). At average proxy coverage, an additional standard deviation of income poverty (19.22 percentage points) was associated with 1.07 fewer years of life expectancy (95% credible interval [CrI]: −1.41 to −0.73). Educational deprivation also had a negative partial association, whereas the main coverage-proxy coefficient was compatible with zero. The positive conditional coefficient for housing-services deprivation does not indicate benefit; it is vulnerable to collinearity, spatial confounding, and omitted-variable bias.

Table 3.

Posterior fixed associations from M6

Term	Posterior mean	95% CrI	Conditional interpretation
Intercept	77.974	77.702, 78.247	2010; all standardised predictors at their means
2015 vs 2010	0.759	0.489, 1.029	Adjusted period difference
2020 vs 2010	−4.094	−4.397, −3.791	Adjusted period difference
Income poverty	−1.070	−1.408, −0.731	Per 1 SD at mean proxy
Social-security coverage proxy	−0.205	−0.452, 0.041	Per 1 SD at mean poverty
Educational deprivation	−0.438	−0.765, −0.112	Per 1 SD
Lack of basic services	0.458	0.114, 0.801	Per 1 SD; direction not given a causal reading
Poverty × coverage	−0.187	−0.369, −0.005	Change in poverty association per 1-SD higher coverage

Note. CrI = credible interval; SD = standard deviation. Estimates are adjusted ecological associations. The main effects are conditional on the interacting predictor being at its sample mean; the coverage variable is a deprivation-derived area-level proxy.

The poverty-by-coverage coefficient was negative rather than positive, contrary to the hypothesised attenuation. The estimated conditional poverty gradient became more negative across the observed proxy range (Supplementary Figure S2); this does not indicate that actual access to social security worsens poverty-related mortality. The proxy correlated with poverty (r = −0.619) and may reflect formal employment, municipal composition, selective migration, or institutional resources. Its interpretation is further limited by the sensitivity analysis, in which the interaction interval included zero.

Spatial heterogeneity

The posterior mean BYM2 mixing parameter was 0.768 (95% CrI: 0.685, 0.831), indicating that most variance within the M6 BYM2 latent component was allocated to the structured rather than independent part. The AR1 correlation was 0.761 (0.699, 0.811), consistent with persistence of the latent spatial surface between adjacent five-year observations. These parameters do not reveal which omitted processeshealth-system capacity, violence,

migration, environmental exposure, registration quality, or other conditionsproduced the pattern.

Posterior mean local poverty slopes ranged from approximately −4.04 to 3.39 years per standard deviation (Supplementary Figure S3); 1,882 of 2,466 means were negative. Sign certainty was much narrower: from 800 joint draws, 875 municipalities had at least 95% posterior probability of a negative local association, whereas eight had probabilities at or below 5% (Supplementary Figure S4). Positive posterior means are not evidence of protective local mechanisms, and unadjusted sign-probability maps are not a multiplicity-corrected set of municipality-specific discoveries. Both surfaces depend on smoothing and the specified adjacency graph.

Predictive checks and sensitivity

M6 posterior predictive means followed the central outcome distribution but shrank extreme values toward the fitted surface (Supplementary Figure S5). In its random 3,000-observation diagnostic subset, RMSE was 3.45 years, mean absolute error 2.53 years, mean bias 0.005 years, and nominal 95% interval coverage 97.6%. No CPO failures were reported. PIT averaged 0.494 but departed visibly from uniformity; a Kolmogorov–Smirnov test yielded $p < 0.001$ (Supplementary Figure S6), so predictive calibration cannot be described as complete.

Predictive performance depended strongly on municipality size. In the smallest-population quartile, RMSE was 4.85 years and 95% interval coverage 93.3%; in the largest quartile, RMSE was 2.16 years and interval coverage 99.9%. Absolute error correlated inversely with log population ($r = −0.338$). These differences suggest that the common-residual-variance likelihood did not adequately represent the differing precision of small-area life-expectancy estimates. Wide overall intervals can conceal undercoverage in small municipalities and overcoverage in large ones; precision-sensitive local ranking is therefore not supported.

Residual Moran's I was negative and statistically distinguishable from its null expectation in 2010 (−0.075; $p < 0.001$), 2015 (−0.045; $p < 0.001$), and 2020 (−0.026; $p = 0.035$). The flexible specification removed pronounced positive residual clustering present in simpler models but did not achieve independence. Residual contrasts may reflect overcorrection, a misspecified graph, or unmodelled measurement heterogeneity; thus mapped latent effects should be treated as exploratory.

When the 56 flagged life-expectancy observations were restored, M5 replaced M6 as the WAIC-preferred specification (Table 4). The negative poverty coefficient persisted (−0.733; 95% CrI: −1.094 to −0.372), but the interaction was compatible with zero (−0.118; 95% CrI: −0.304 to 0.069). The evidence shared by both analyses is an average negative poverty association and strong modelled spatiotemporal dependence; the interaction and geographically varying poverty slope do not demonstrate comparable robustness.

Table 4.

Primary analysis and outcome-threshold sensitivity analysis

Analysis	n	Selected model	WAIC	Income poverty, mean (95% CrI)	Poverty × coverage, mean (95% CrI)
Primary: values <40 or >100 excluded	7,313	M6	44,512.2	−1.070 (−1.408, −0.731)	−0.187 (−0.369, −0.005)
Sensitivity: extreme values retained	7,367	M5	47,121.1	−0.733 (−1.094, −0.372)	−0.118 (−0.304, 0.069)

Note. Predictors are standardised. The selected model minimised WAIC within each analysis. A different model and non-excluding interaction interval in the sensitivity analysis limit claims about effect modification and spatially varying slopes.

4. DISCUSSION

Principal findings

Across specifications, income poverty had a stable negative association with life expectancy. Spatial dependence was not a minor residual feature: allowing the spatial field to change across periods produced the largest improvement in information criteria, and the structured component represented most of the M6 BYM2 variance. The derived area-level coverage proxy did not attenuate the poverty gradient as hypothesised. Its main coefficient was imprecise, the interaction was small and negative in the primary analysis, and the interaction interval included zero when extreme outcomes were restored.

The first finding is consistent with social-determinants and fundamental-cause accounts. Income poverty constrains nutrition, housing, transport, preventive care, and the capacity to

absorb illness-related costs; it also clusters with educational and infrastructural disadvantage (World Health Organization, 2008; Link & Phelan, 1995). The estimate should not be read as the effect of transferring a fixed amount of income to a municipality. A one-standard-deviation contrast represents a bundle of social conditions, and the observed panel lacks the design features required to separate that bundle from unmeasured confounding.

Why the coverage proxy did not buffer poverty

The absence of a protective interaction does not demonstrate that social protection is ineffective. It shows that the municipal complement of social-security deprivation did not behave as a robust buffer after conditioning on correlated deprivation measures and latent spatial fields. This proxy does not measure affiliation, service availability, continuity, effective coverage, benefit adequacy, or financial protection. In a segmented system, those dimensions can differ (Knaul et al., 2012; Becerril-Montekio et al., 2024). The proxy is also tied to formal employment and urban labour markets. Conditioning on poverty, education, housing services, and spatial effects may therefore compare municipalities with uncommon covariate combinations and amplify measurement error.

The negative interaction could arise from at least four non-exclusive mechanisms: (1) compositional differences between municipalities at the same measured poverty level; (2) poorer quality or congestion in nominally covered populations; (3) selective migration and labour-market sorting; or (4) residual spatial confounding. The data do not discriminate among them. Interpreting the coefficient as evidence that expanding social security would shorten life would invert the inferential logic of this design. A more informative test would replace entitlement with indicators of effective access, waiting time, provider density, continuity, catastrophic spending, and benefit use, and would specify a temporal ordering compatible with the hypothesised mechanism.

Place, persistence, and the 2020 discontinuity

The gain from the period-specific BYM2 field and the AR1 estimate is compatible with spatially organised context that was not measured. Municipalities are embedded in transport systems, labour markets, referral networks, environmental regions, and state administrative structures; proximity indexes part of that shared context (Macintyre et al., 2002; Cummins et al., 2007). The latent field, however, is not a measured institutional capacity index. It may also absorb misspecified functional forms, spatially patterned errors in life

expectancy, and omitted variables. The probability map is a model-based summary for further study, not a basis for ranking local governments or assigning causal responsibility.

The adjusted 2020 difference was −4.09 years relative to 2010, following a positive 2015 difference. The timing is compatible with the mortality shock of the COVID-19 period, but the design cannot allocate the decline to the pandemic. Only one pandemic-year observation is included, and changes in registration, health-service disruption, violence, migration, and outcome estimation may contribute. The result demonstrates a sharp temporal break in the supplied series; it is not an interrupted-time-series estimate of a pandemic effect.

Model diagnostics and robustness

M6 should not be presented as fully calibrated. Although pooled predictive intervals were conservative, population-stratified coverage showed the opposite errors at either end of the municipality-size distribution; PIT was nonuniform and residual Moran's I remained significantly negative. A common Gaussian observation variance may attribute estimation noise in small municipalities to latent geography, exaggerate local contrasts and distort local posterior uncertainty. The differences in RMSE cannot rank M5 and M6 because they were calculated on different observations. Moreover, the M6 information-criterion advantage was not robust to restoring the extreme outcomes.

A direct robustness check would replace common residual variance with municipality-specific life-expectancy sampling variances, or estimate age- and sex-specific death counts with population offsets and propagate their uncertainty through the life-table calculation. These analyses require the original mortality extracts, denominators and outcome-estimation code. Other priorities are paired pointwise estimates for information-criterion differences, geographically blocked validation, alternative adjacency structures, and sensitivity to AR1, observation-precision and spatial-slope priors. Until these tests are available, local prediction, the slope map and the small M5–M6 score difference warrant restrained interpretation.

Strengths, limitations, and implications

The analysis combines near-national municipal coverage, harmonised poverty measurements, explicit spatial and temporal dependence, transparent comparison of seven specifications, and a sensitivity analysis that materially changed the interpretation. The maps separate posterior magnitude from posterior sign probability, and the interaction

plot incorporates joint posterior uncertainty; these choices make it harder to mistake smoothed estimates for observed local facts.

Ecological associations cannot be assigned to individuals. The municipal life-expectancy estimates were analysed without observation-level standard errors, despite substantially higher predictive error in small municipalities. The three-wave panel is unbalanced; five-character identifier matching and a fixed 2020 contiguity graph do not fully resolve earlier boundary revisions. The coverage proxy does not measure effective care or financial protection. Omitted spatially structured factors may include violence, migration, rurality, environmental exposures, health-service capacity and registration quality. Correlated deprivation indicators further weaken interpretation of individual partial coefficients. All reported averages are municipality-weighted rather than population-weighted.

5. CONCLUSION

Income poverty was consistently associated with shorter municipal life expectancy across 2010, 2015 and 2020. Allowing for geographically structured and temporally persistent latent heterogeneity improved model fit, but those latent components do not identify specific contextual causes. The municipal complement of social-security deprivation showed no robust attenuation of the income-poverty gradient, and the interaction became compatible with zero when extreme life-expectancy estimates were retained. These results support associational, not causal, interpretations.

The findings motivate further evaluation of material deprivation and of social protection measured through effective access, continuity and financial risk protection. Evidence for precise municipal rankings or policy effects requires reproducible life-table estimates, uncertainty-aware outcome modelling, and independently validated spatial predictions. The observed geographic pattern should be understood as residual spatial heterogeneity, not as proof that territory itself causes differences in longevity.

BIBLIOGRAPHIC REFERENCES

Agudelo-Botero, M., Dávila-Cervantes, C. A., Velasco-Calderón, O., & Giraldo-Rodríguez, L. (2023). Divergences and gaps in life expectancy and health-adjusted life expectancy in Mexico: Contribution analysis of the Global Burden of Disease Study 2019. *PLOS ONE, 18*(11), e0293881. https://doi.org/10.1371/journal.pone.0293881

Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. *American Economic Review, 53*(5), 941–973. https://www.jstor.org/stable/1812044

Becerril-Montekio, V., Meneses-Navarro, S., Pelcastre-Villafuerte, B. E., & Serván-Mori, E. (2024). Segmentation and fragmentation of health systems and the quest for universal health coverage: Conceptual clarifications from the Mexican case. *Journal of Public Health Policy, 45*(1), 164–174. https://doi.org/10.1057/s41271-024-00470-9

Besag, J., York, J., & Mollié, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics, 43*(1), 1–20. https://doi.org/10.1007/BF00116466

Bivand, R. S., & Wong, D. W. S. (2018). Comparing implementations of global and local indicators of spatial association. *TEST, 27*(3), 716–748. https://doi.org/10.1007/s11749-018-0599-x

Consejo Nacional de Evaluación de la Política de Desarrollo Social. (s. f.). *Programas de cálculo y bases de datos a nivel municipio 2010, 2015 y 2020* [Conjunto de datos]. Recuperado el 6 de septiembre de 2026, de https://www.coneval.org.mx/Medicion/Paginas/Programas_BD_municipal_2010_2020.aspx

Consejo Nacional de Evaluación de la Política de Desarrollo Social. (2021). *Metodología para la medición de la pobreza en los municipios de México, 2020*. https://www.coneval.org.mx/Medicion/Documents/Pobreza_municipal/2020/Metodologia_pobreza_municipal_2020.pdf

Consejo Nacional de Evaluación de la Política de Desarrollo Social. (2022). *Informe de pobreza en los municipios de México 2010–2020*. https://www.coneval.org.mx/InformesPublicaciones/Paginas/Mosaicos/Informe_Pobreza_Municipios_Mexico_2020.aspx

Cummins, S., Curtis, S., Diez-Roux, A. V., & Macintyre, S. (2007). Understanding and representing 'place' in health research: A relational approach. *Social Science & Medicine, 65*(9), 1825–1838. https://doi.org/10.1016/j.socscimed.2007.05.036

Diez Roux, A. V. (2001). Investigating neighborhood and area effects on health. *American Journal of Public Health, 91*(11), 1783–1789. https://doi.org/10.2105/AJPH.91.11.1783

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

García-Hernández, H., Salinas-Escudero, G., Agudelo-Botero, M., & Reyes-Morales, H. (2026). Life expectancy and healthy-adjusted life expectancy in Mexico by social security status. *Gaceta Sanitaria, 40*(Suppl. 2), Article 102632. https://doi.org/10.1016/j.gaceta.2026.102632

Gómez-Ugarte, A. C., & García-Guerrero, V. M. (2023). Inequality crossroads of mortality: Socioeconomic disparities in life expectancy and life span in Mexico between 1990 and 2015. *Population Research and Policy Review, 42*, Article 57. https://doi.org/10.1007/s11113-023-09806-x

Grossman, M. (1972). *The demand for health: A theoretical and empirical investigation*. National Bureau of Economic Research. https://www.nber.org/books-and-chapters/demand-health-theoretical-and-empirical-investigation

Hart, J. T. (1971). The inverse care law. *The Lancet, 297*(7696), 405–412. https://doi.org/10.1016/S0140-6736(71)92410-X

Held, L., Schrödle, B., & Rue, H. (2010). Posterior and cross-validatory predictive checks: A comparison of MCMC and INLA. En T. Kneib & G. Tutz (Eds.), *Statistical modelling and regression structures: Festschrift in honour of Ludwig Fahrmeir* (pp. 91–110). Physica-Verlag. https://doi.org/10.1007/978-3-7908-2413-1_6

Instituto Nacional de Estadística y Geografía. (2021). *Marco Geoestadístico. Censo de Población y Vivienda 2020* [Conjunto de datos]. https://www.inegi.org.mx/app/biblioteca/ficha.html?upc=889463807469

Knaul, F. M., González-Pier, E., Gómez-Dantés, O., García-Junco, D., Arreola-Ornelas, H., Barraza-Lloréns, M., Sandoval, R., Caballero, F., Hernández-Ávila, M., Juan, M., Kershenobich, D., Nigenda, G., Ruelas, E., Sepúlveda, J., Tapia, R., Soberón, G., Chertorivski, S., & Frenk, J. (2012). The quest for universal health coverage: Achieving social protection for all in Mexico. *The Lancet, 380*(9849), 1259–1279. https://doi.org/10.1016/S0140-6736(12)61068-X

Krieger, N. (2001). Theories for social epidemiology in the 21st century: An ecosocial perspective. *International Journal of Epidemiology, 30*(4), 668–677. https://doi.org/10.1093/ije/30.4.668

Lindgren, F., & Rue, H. (2015). Bayesian spatial modelling with R-INLA. *Journal of Statistical Software, 63*(19), 1–25. https://doi.org/10.18637/jss.v063.i19

Link, B. G., & Phelan, J. (1995). Social conditions as fundamental causes of disease. *Journal of Health and Social Behavior, 35*(Extra Issue), 80–94. https://doi.org/10.2307/2626958

Macintyre, S., Ellaway, A., & Cummins, S. (2002). Place effects on health: How can we conceptualise, operationalise and measure them? *Social Science & Medicine, 55*(1), 125–139. https://doi.org/10.1016/S0277-9536(01)00214-3

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika, 37*(1–2), 17–23. https://doi.org/10.1093/biomet/37.1-2.17

Pebesma, E. (2018). Simple features for R: Standardized support for spatial vector data. *The R Journal, 10*(1), 439–446. https://doi.org/10.32614/RJ-2018-009

Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social conditions as fundamental causes of health inequalities: Theory, evidence, and policy implications. *Journal of Health and Social Behavior, 51*(Suppl.), S28–S40. https://doi.org/10.1177/0022146510383498

Preston, S. H. (1975). The changing relation between mortality and level of economic development. *Population Studies, 29*(2), 231–248. https://doi.org/10.1080/00324728.1975.10410201

R Core Team. (2026). *R: A language and environment for statistical computing* (Version 4.6.1) [Software informático]. R Foundation for Statistical Computing. https://doi.org/10.32614/R.manuals

R-INLA Project. (2026a). *Autoregressive model of order 1 (AR1)* [Documentación técnica]. https://www.inla.r-inla-download.org/r-inla.org/doc/latent/ar1.pdf

R-INLA Project. (2026b). *Gaussian likelihood* [Documentación técnica]. https://inla.r-inla-download.org/r-inla.org/doc/likelihood/gaussian.pdf

Riebler, A., Sørbye, S. H., Simpson, D., & Rue, H. (2016). An intuitive Bayesian spatial model for disease mapping that accounts for scaling. *Statistical Methods in Medical Research, 25*(4), 1145–1165. https://doi.org/10.1177/0962280216660421

Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society: Series B (Statistical Methodology), 71*(2), 319–392. https://doi.org/10.1111/j.1467-9868.2008.00700.x

Simpson, D., Rue, H., Riebler, A., Martins, T. G., & Sørbye, S. H. (2017). Penalising model component complexity: A principled, practical approach to constructing priors. *Statistical Science, 32*(1), 1–28. https://doi.org/10.1214/16-STS576

Sørbye, S. H., & Rue, H. (2014). Scaling intrinsic Gaussian Markov random field priors in spatial modelling. *Spatial Statistics, 8*, 39–51. https://doi.org/10.1016/j.spasta.2013.06.004

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology), 64*(4), 583–639. https://doi.org/10.1111/1467-9868.00353

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing, 27*, 1413–1432. https://doi.org/10.1007/s11222-016-9696-4

Wakefield, J. (2008). Ecologic studies revisited. *Annual Review of Public Health, 29*, 75–90. https://doi.org/10.1146/annurev.publhealth.29.020907.090821

Watanabe, S. (2010). Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. *Journal of Machine Learning Research, 11*(116), 3571–3594. https://www.jmlr.org/papers/v11/watanabe10a.html

World Health Organization. (2008). *Closing the gap in a generation: Health equity through action on the social determinants of health*. https://www.who.int/publications/i/item/9789241563703

CONFLICT OF INTEREST

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