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Bayesian spatial modeling of COVID-19 case-fatality rate inequalities

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ABSTRACT

The ongoing outbreak of COVID-19 challenges the health systems and epidemiological responses of all countries worldwide. Although preventive measures have been globally considered, the spatial heterogeneity of its effectiveness is evident, underscoring global health inequalities. Using Bayesian-based Markov chain Monte Carlo simulations, we identify the spatial association of socioeconomic factors and the risk for dying from COVID-19 in Colombia. We confirm that from March 16 to October 04, 2020, the COVID-19 case-fatality rate and the multidimensional poverty index have a heterogeneous spatial distribution. Spatial analysis reveals that the risk of dying from COVID-19 increases in regions with a higher proportion of poor people with dwelling (RR 1.74 95%CI = 1.54–9.75), educational (RR 1.69 95%CI = 1.36–5.94), childhood/youth (RR 1.35 95%CI = 1.08–4.03), and health (RR 1.16 95%CI = 1.06–2.04) deprivations. These findings evidence the vulnerability of most disadvantaged members of society to dying in a pandemic and assist the spatial planning of preventive strategies focused on vulnerable communities.

1. Introduction

The ongoing outbreak of COVID-19 challenges health systems and epidemiological responses of all countries worldwide since its first report in Wuhan City, Hubei Province of China (WHO, 2020a). Several mitigation measures oriented to reduce the severity, named case-fatality rate (proportion of persons with COVID-19 who die from this disease), have been considered by various governments, as the household-based prevention model, which usually includes remote work and self-isolation (Britton et al., 2020). Apparent differences in the COVID-19 case-fatality rate between regions (WHO, 2020a) and variations concerning the basic reproduction number R_t (Weber et al., 2020; Polo et al., 2018a) are indicators of the spatial heterogeneity of the preventive measures and their effects. Indeed, the effectiveness of the mitigation measures depends on the time of its implementation (Tuite et al., 2020), and presumably, on other factors, such as the proportion of individuals unable to work remotely, e.g., socioeconomically disadvantaged people who depend on informal activities.

Besides the dependence of COVID-19 on biological, clinical, and epidemiological aspects (Zhang et al., 2020), even in populations under similar mitigation or contingency measures, the COVID-19 case-fatality rate can be spatially heterogeneous (Bambra et al., 2020). This heterogeneity can intuitively be associated with barriers to health services, such as hospitals and intensive care units, however, other social and economic aspects related to poverty may be involved (Mpofu et al., 2016; Dégano et al., 2017).

Poverty is understood as a multidimensional phenomenon that must be measured with multiple monetary and non-monetary indicators (Nolan and Whelan, 2011; Alkire et al., 2015). The Multidimensional Poverty Index (MPI), developed by Alkire and Santos (2010, 2014) in collaboration with the United Nations Development Program and the Oxford Poverty and Human Development Initiative, systematically implements the most comprehensive counting-based measure of multidimensional poverty for developing regions. This index has been adopted by different countries worldwide, including Colombia, for the strategic establishment and monitoring of public policies (Battiston et al., 2013; DANE, 2020).

The MPI in Colombia comprises five dimensions: health, educational, childhood/youth, employment, and dwelling, in turn, composed of fifteen indicators (lack of health insurance, barriers to health services, illiteracy, low educational attainment, school non-attendance, school lag, barriers to childhood care services, child labor, informal employment, economic dependency, lack of access to safe water, inadequate disposal of human feces, poor floor/walls construction, and critical overcrowding). Concerning the health dimension, the MPI considers the definition of barriers to health services, as the proportion of individuals who do not attend a health service due to an illness that does not require hospitalization (DANE, 2020).

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The educational and childhood/youth dimensions in Colombia are mainly associated with access to education, the level of schooling, school backwardness, and child labor (DANE, 2020). Regarding these indicators, previous research shows that people with less educational resources are more vulnerable to poor health and mortality from different causes (Drefahl et al., 2020; Selvan, 2020; Hummer and Lariscy, 2011; Cutler et al., 2011). In addition, regarding human-to-human transmission diseases, poor people could be at greater risk due to the impossibility of working remotely and the exigency to go out to work daily in informal activities (Henao-Cespedes et al., 2021). Furthermore, conditions associated with the dwelling such as the provision of safe water, sanitation, and waste management are essential for preventing and protecting human health during the COVID-19 outbreak (WHO and UNICEF, 2020). Basic prevention measures for the human-to-human transmission of COVID-19, such as handwashing (Desai and Patel, 2020), depend directly on the practice of hygiene measures in communities, homes, schools, marketplaces, and healthcare facilities (WHO and UNICEF, 2020).

In this sense, we provide quantitative evidence of the importance of socioeconomic factors in COVID-19 inequalities, i.e., the systematic, avoidable, and unfair differences in health outcomes that can be observed between populations, social groups within the same population, or as a gradient across a population ranked by social position (McCartney et al., 2020). Identifying factors causing inequalities on the COVID-19 case-fatality rate and its distribution over space (Polo et al., 2018b) is fundamental to reduce the COVID-19 impact on vulnerable communities and enhance the effectiveness of population-level strategies. Thus, our findings assist policy-makers in the spatial planning of strategies focused on preventing case fatalities in the most vulnerable communities and preparing for future pandemics by progressively reducing the factors that generate syndemic conditions (Horton, 2020).

2. Data

2.1. COVID-19 data

We use the COVID-19 death official reports by the National Institute of Health of Colombia - INS available in a public domain (Instituto Nacional de Salud, 2020). Colombia has a population of around 50 million people distributed in 32 administrative units called departments and Bogotá D.C as the capital district. The 33 administrative units that are part of the Colombian Territorial Health Directorates, have an average area size of 34 678 km^2 [Min = 52, Max = 110 029], and an average population of 1 526 437 inhabitants [Min = 44 712, Max = 7 743 955] (Table 1). Nevertheless, the distribution of resources is not proportional to the number of inhabitants of each department, so there are socioeconomic and sociocultural differences (i.e., possible mechanisms connecting poverty and COVID-19 fatality) between the administrative units. Notwithstanding, the INS and the National Administrative Department of Statistics (DANE) report, collect, analyze, and publish health, demographic, and socioeconomic data considering these administrative units. Furthermore, the formulation and implementation of public policies is done, based on national guidelines, on a departmental scale, expressed, for instance, in the departmental development plans, which include health and social aspects.

The first death by COVID-19 in Colombia was reported on March 16, 2020, and in total, 126 425 people have died, as the INS report of October 04, 2021. Data summarizing population-level deaths were aggregated to a set of 33 non-overlapping areal units for the study period from week 11 (March 16) to week 40 (October 04) of 2020.

On March 18, 2020, the Colombian government released Decree 420, stopping national and international land and air travel, closing schools and universities, canceling in-person activities, and imposing self-isolation for people over 70 years of age (Ministerio del Interior, 2020). These regulations were eased the first week of May with the reactivation of some economic activities and finished the first week of September. From this time, the national Decree 1168 stipulated the self-isolation exclusively of infected individuals (Ministerio del Interior, 2020). COVID-19 Decrees in Colombia are national and therefore must be adopted by all the administrative units. In this way, there are no evident political differences that explain the heterogeneity in COVID-19 health outcomes at the department level.

Table 1
Area, population, observed (Y) and expected (E) deaths, case-fatality rate (CFR) and standardized case-fatality (SCFR) rate for each administrative unit from March 16 to October 04 of 2020.

Department	Area[a]	Pop.	Cases	Y	E	CFR	SCFR
Amazonas	109665	79020	2746	120	93	4.37	1.29
Antioquia	63612	6677930	120270	2793	4070	2.33	0.69
Arauca	23818	294206	1938	68	65	3.53	1.04
Atlántico	3388	2722128	67961	3133	2297	4.64	1.36
Bogotá DC	1775	7743955	274587	7345	9296	2.69	0.79
Bolívar	25978	2180976	29447	817	996	2.79	0.82
Boyacá	23189	1242731	7938	196	268	2.49	0.73
Caldas	7888	1018453	6494	177	218	2.76	0.81
Caquetá	88965	410521	8745	345	295	3.97	1.17
Casanare	44640	435195	2641	72	89	2.74	0.81
Cauca	29308	1491937	9989	322	336	3.26	0.96
Cesar	22905	1295387	20943	727	708	3.49	1.03
Chocó	46530	544764	4034	161	136	4.02	1.18
Córdoba	25020	1828947	25562	1613	827	6.63	1.95
Cundinam.	22633	3242999	34756	1127	1176	3.26	0.96
Guainía	72238	50636	960	18	33	1.88	0.55
Guaviare	53460	86657	944	20	32	2.13	0.63
Huila	19890	1122622	12697	491	429	3.89	1.14
La Guajira	20848	965718	8320	380	282	4.58	1.35
Magdalena	23188	1427026	15591	896	568	5.79	1.70
Meta	85635	1063454	16785	464	568	2.78	0.82
Nariño	33268	1627589	18745	741	633	3.98	1.17
Norte Sant.	21658	1620318	16540	1012	558	6.16	1.81
Putumayo	24885	359127	3876	193	145	5.00	1.47
Quindío	1845	555401	4247	145	144	3.42	1.01
Risaralda	4140	961055	11806	335	399	2.85	0.84
San Andrés	52	63692	1504	28	51	1.87	0.55
Santander	30537	2280908	32582	1548	1101	4.78	1.41
Sucre	10917	949252	14029	620	474	4.45	1.31
Tolima	23562	1339998	12864	423	434	3.32	0.98
Valle Cauca	22140	4532152	65045	2532	2197	3.92	1.15
Vaupés	54135	44712	863	12	29	1.40	0.41
Vichada	100242	112958	556	8	19	1.44	0.42

[a] km^2

2.2. Standardized case-fatality rate

Metrics describing the impact of the ongoing outbreak of COVID-19 in a given population can be biased due to underreported cases, delays to case resolution, unrealistic transmission modeling, and other countless unknown factors. For instance, the case-fatality rate (CFR), usually expressed in terms of the number of detected cases C and observed deaths Y, i.e.,

$$\mathrm{CFR} = \frac{Y}{C}, \quad (1)$$

has a bias due to delays to case resolution during an ongoing outbreak. Restricting the analysis to resolved cases mitigates most of these biases (the sum of observed deaths Y and reported recovered cases $\mathcal{R}$) (WHO, 2020b). The CFR is then redefined as WHO (2020b),

$$\mathrm{CFR} = \frac{Y}{Y + \mathcal{R}}. \quad (2)$$

Additionally, the possible heterogeneity in the underreporting of cases, partially related to the presence of asymptomatic individuals, can induce a bias in the spatial distribution of the CFR. Thus, we have evaluated the spatial distribution of the positive rate (the ratio between positive detected cases and the number of tested individuals) in the study period (from March 16 to October 04 of 2020). We find that the positive rate is almost constant among all departments (i.e., between

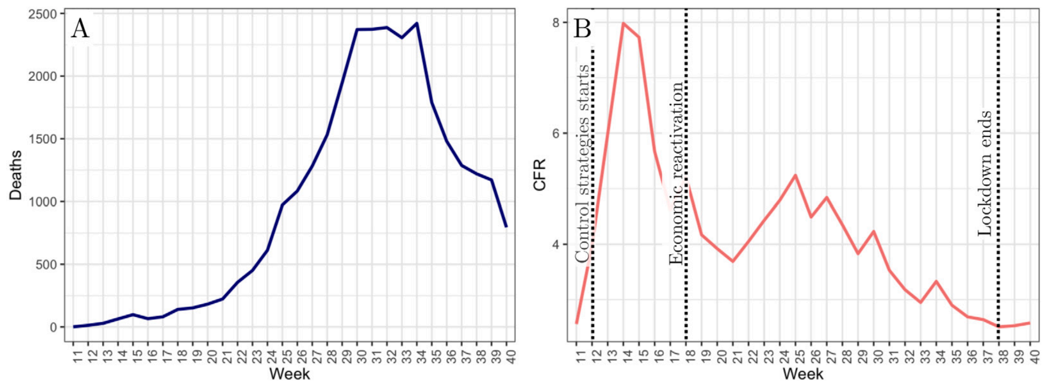

Fig. 1. COVID-19 deaths (A) and case-fatality rate (B) in Colombia from March 16 to October 04 (weeks 11 to 40) of 2020.

2.6 and 6.9, with an average of 4.2 and standard deviation of 1.2), indicating that the underreporting is almost homogeneous in Colombia (Table 1 Supplementary Material). In other words, no bias in the heterogeneity of the CFR is caused by the spatial distribution of asymptomatic or mild flu-like symptoms individuals.

To better understand the association between CFR and socioeconomic factors across the Colombian administrative units, we consider the standardized CFR (SCFR). In our analysis, this metric corresponds to the CFR for each department k, CFR(k), divided by the NCFR. The SCFR can be rewritten in a more suitable way for the Bayesian modeling discussed in the next sections, i.e.,

$$\mathrm{SCFR}(k) = \frac{Y_k}{E_k}, \tag{3}$$

where E_k is the number of expected resolved cases ($E_k = (Y_k + \mathcal{R}_k)$NCFR), Y_k is the observed deaths, and $\mathcal{R}_k$ is the number of reported recovered cases for each department k (Lee, 2020; Souris and Gonzalez, 2020). These parameters are described in Table 1. An SCFR equal to 1 means that the CFR in the specific department is equal to the national CFR.

In Colombia, the number of reported deaths from March 16 to October 04 of 2020 was 28 882, and the number of recovered individuals was 821 495, so the national CFR (NCFR) was equal to 0.034 (or 3.4%). Fig. 1 shows COVID-19 deaths and case-fatality rates in Colombia from week 11 (March 16) to week 40 (October 04) of 2020. The highest number of deaths was reported by the INS between weeks 30 (July 20, 2020) and 34 (August 23, 2020). The highest CFR (approximately 8%) was observed at the beginning of the outbreak. However, a clear downward trend in the CFR over the 29 week study period is evident from week 14 (March 30, 2020) onwards. The CFR was in a range of 1.4 and 6.6, with a standard deviation of 1.3, which evidences the large variation of the CFR across the departments, despite the homogeneity of the control measures.

2.3. Covariates

As proxy socioeconomic covariates, we consider the Colombian Multidimensional Poverty Index (MPI) database calculated by the National Administrative Department of National Statistics considering a departmental level (DANE, 2020). The MPI comprises five dimensions: educational (EMPI), childhood/youth (YMPI), employment (WMPI), health (HMPI), and dwelling (DMPI) poverty conditions containing information on 15 variables (EMPI: illiteracy, low educational attainment; YMPI: school non-attendance, school lag, barriers to childhood care services, child labor; WMPI: informal employment, economic dependency; HMPI: lack of health insurance, barriers to health services; DMPI: lack of access to safe water, inadequate disposal of human feces, poor housing construction, and critical overcrowding). Variables definition of the MPI can be found in Table 2 of Supplementary Material. The MPI reflects the percentage of deprivations poor people experience,

Table 2
Dimension percent contribution to the Colombian poverty index in each department.

Department	HMPI	DMPI	EMPI	WMPI	YMPI
Amazonas	1.6	6.3	10.5	11.1	5.3
Antioquia	1.4	2.6	5.6	4.9	2.6
Arauca	3.9	4.9	9.5	8.8	4.6
Atlántico	3.6	2.0	5.7	5.3	3.4
Bogotá DC	0.8	0.3	1.2	1.4	0.7
Bolívar	3.2	5.8	10.8	8.2	4.4
Boyacá	1.9	1.6	5.9	4.9	2.2
Caldas	1.7	1.2	5.7	4.5	2.1
Caquetá	2.7	3.4	9.6	8.1	4.8
Casanare	2.8	1.9	6.1	5.1	3.2
Cauca	3.2	3.5	10.1	7.6	4.2
Cesar	5.1	4.2	10.4	8.3	5.3
Chocó	3.7	8.5	15.5	11.4	5.9
Córdoba	2.5	6.9	13.5	9.2	4.6
Cundinamarca	1.7	0.9	3.9	3.4	1.6
Guainía	3.1	15.8	17.8	20.4	7.9
Guaviare	3.4	6.4	10.3	9.0	4.4
Huila	1.6	2.0	6.7	5.6	3.3
La Guajira	6.0	11.3	15.8	11.8	6.6
Magdalena	5.4	6.1	12.2	9.4	5.4
Meta	2.0	1.5	5.1	4.5	2.5
Nariño	4.9	4.3	11.1	8.3	4.8
Norte Santander	6.1	3.2	9.2	8.2	4.7
Putumayo	2.1	3.6	8.3	7.5	3.5
Quindío	2.9	0.7	5.6	4.8	2.1
Risaralda	1.4	0.9	4.5	3.6	2.1
San Andrés	7.6	2.8	5.8	2.6	6.3
Santander	1.5	1.2	4.6	3.8	1.9
Sucre	4.7	5.5	14.6	9.6	5.2
Tolima	3.4	2.2	7.8	6.3	3.6
Vaupés	1.2	14.3	15.9	21.4	6.5
Valle del Cauca	2.2	0.9	4.3	3.8	2.3
Vichada	3.4	13.4	15.4	15.2	7.3

as a share of the possible deprivations that would be experienced if all people were deprived in all dimensions (Alkire et al., 2020) for each department. Thus MPI is calculated as:

$$\mathrm{MPI}_k = H_k \times A_k \tag{4}$$

where H_k is the percentage of people who are poor in department k, and A_k is the average deprivation score for each dimension, in which poor people are deprived. The departmental MPI for each dimension is shown in Table 2.

In order to focus on the spatial variation and spatial heterogeneity, rather than time-dependent factors (e.g., unemployment), we consider the CFR in the complete study period. This intrinsically addresses problems associated with the strong CFR daily and weekly variation. Indeed, the above-mentioned components of the Multidimensional Poverty Index are constant during the pandemic, since no variation is reported by the Colombian Territorial Health Directorates.

3. Methods

3.1. Bayesian modeling

A bayesian spatial model and Markov chain Monte Carlo (MCMC) simulations were used to describe the variation in the SCFR, considering prior distributions for spatial random effects (Lee, 2013). This kind of model is usually proposed to analyze epidemiological aspects of disease dynamics (Aidi and Djuraidah, 2017; Kandhasamy and Ghosh, 2017; Ver Hoef et al., 2018; Amsalu et al., 2019; Aswi et al., 2020; Lee, 2020).

Initially, a Poisson log-linear model was formulated as:

$$\begin{aligned} &Y_k \sim \text{Poisson}(E_k R_k) \quad \text{for } k = 1, \dots, 33. \\ &\ln(R_k) = \beta_0 + \beta_1(\text{HMPI})_k + \beta_2(\text{EMPI})_k \\ &+ \beta_3(\text{WMPI})_k + \beta_4(\text{DMPI})_k + \beta_5(\text{YMPI})_k \\ &\boldsymbol{\beta} \sim \text{N}(\boldsymbol{\mu}_\beta, \Sigma_\beta), \end{aligned} \tag{5}$$

where R_k is the SCFR relative to E_k, in the department k. The number of deaths is denoted by $\mathbf{Y} = (\mathbf{Y}_1, \dots, \mathbf{Y}_N)_{K\times N}$, where $\mathbf{Y}_k = (Y_1, \dots, Y_K)$ denotes the $K \times 1$ column vector of observed deaths for all K departments. The vector of covariate regression parameters is denoted by $\boldsymbol{\beta}$, and a multivariate Gaussian prior was assumed with mean μ_β and diagonal variance matrix Σ_β.

To check for the null hypothesis of spatial independence we used the Moran's I statistic based on 10 000 random permutations of the data given by:

$$I = \frac{K \sum_{k=1}^{K} \sum_{j=1}^{K} w_{kj}(r_k - \bar{r})(r_j - \bar{r})}{(\sum_{k=1}^{K} \sum_{j=1}^{K} w_{kj}) \sum_{k=1}^{K} (r_k - \bar{r})^2} \tag{6}$$

where $\bar{r}$ is the mean of each MPI, r_k denotes MPI's for the kth department and r_j denote MPI's at another department j. $W = (w_{kj})$, is a $K \times K$ neighborhood matrix, where $w_{kj} = 1$ if departments (k, j) share a common border, and $w_{kj} = 0$, otherwise.

Finally, we considered a spatial structure through a latent component for the department k by ψ_k, encompassing spatially autocorrelated random effects (Amsalu et al., 2019). Thus, adjusting Eq. (1),

$$\begin{aligned} \ln(R_k) = \beta_0 &+ \beta_1(\text{HMPI})_k + \beta_2(\text{EMPI})_k \\ &+ \beta_3(\text{WMPI})_k + \beta_4(\text{DMPI})_k + \beta_5(\text{YMPI})_k \\ &+ \mathbf{O}_k + \psi_k \end{aligned} \tag{7}$$

where a vector of known offsets is denoted by $\mathbf{O} = (\mathbf{O}_1, \dots, \mathbf{O}_N)_K$. Then, the model was concluded by considering (Leroux et al., 2000):

$$\begin{aligned} &\psi_k = \phi_k, \\ &\boldsymbol{\phi}_k | \boldsymbol{\phi}_{-k}, \mathbf{W}, \tau^2, \\ &\rho \sim \text{N}\left(\frac{\rho \sum_{i=1}^{K} w_{ki}\phi_i}{\rho \sum_{i=1}^{K} w_{ki} + 1 - \rho}, \frac{\tau^2}{\rho \sum_{i=1}^{K} w_{ki} + 1 - \rho} \right) \\ &\tau^2 \sim \text{Inverse-Gamma}(a, b), \\ &\rho \sim \text{Uniform}(0, 1). \end{aligned} \tag{8}$$

where ρ is a spatial dependence parameter taking values in the unit interval, specifically $\rho = 1$ corresponds to the intrinsic CAR model and $\rho = 0$ corresponds to independence ($\phi_k \sim \text{N}(0, \tau^2)$). The spatial autocorrelation is induced by the neighborhood matrix $\mathbf{W}$. The prior specification for τ^2 is conformed by (a = 1,b = 0.01).

We generated MCMC samples from three independent Markov chains. Each chain was run for 2 200 000 samples, of which 200 000 were removed as the burn-in period and the remaining 2 000 000 samples were thinned by 1000 to remove correlation amongst the samples. This leaves 1000 samples for inference from each chain. All analyzes were conducted in R Version 1.3.959 (R Core Team, 2020), using the 'CARBayes' package version 5.1 (Lee, 2013).

The effects of each MPI on the COVID-19 SCFR were quantified as relative risks, for a fixed increase ξ in each covariates value. For instance, the relative risk for a ξ increase in HMPI is computed by:

$$\begin{aligned} &RR(\text{HMPI}, \xi) = \frac{\text{Risk if HMPI increases by } \psi}{\text{Risk given the current value of HMPI}} \\ &= \frac{\exp(\beta_0 + \beta_1(\text{HMPI}_k + \xi) + \boldsymbol{\beta}\text{MPI}_k + \psi_k)}{\exp(\beta_0 + \beta_1\text{HMPI}_k + \boldsymbol{\beta}\text{MPI}_k + \psi_k)} \\ &= \exp(\beta_1 \xi), \end{aligned} \tag{9}$$

and equivalently calculated for EMPI, WMPI, DMPI and YMPI. To compute these relative risks we construct a matrix of the MCMC samples for the regression parameters from all chains. We use the standard deviation of each covariate as the increase ξ, because it represents a realistic increases in each covariates value (Lee, 2020). We tested the performance of the fitted model on an independent test composed of the case-fatality rate data for the weeks between March 16, 2021, and October 4, 2021 (Figure 1 Supplementary Material).

4. Results

4.1. Standardized case-fatality rate

Fig. 2A shows the SCFR for the 33 Colombian administrative units from week 11 (March 16) to week 40 (October 04) of 2020. An SCFR equals 1 means that the case-fatality rate is equal to the national CFR. Córdoba (index 13), Norte de Santander (index 20), Magdalena (index 17), Putumayo (index 21), Santander (index 24), and Atlántico (index 3) represent the departments with the highest SCFR. Córdoba exhibited the highest SCFR (SCFR= 1.95), which corresponds to an increase of 95% in the observed COVID-19 deaths compared to the national CFR value over the 29 weeks study period. Vaupés (index 32), Vichada (index 9), San Andrés (index 33), Guainía (index 31), Guaviare (index 29), Antioquia (index 2), Boyacá (index 6) and Bogotá DC (index 4) were the departments with the lowest SCFR. Vaupés exhibited the lowest SCFR (SCFR= 0.41), which corresponds to a decrease of 59% in the observed COVID-19 deaths compared to the national CFR value over the 29 weeks study period.

The MPI of each dimension i.e health, dwelling, employment, and educational dimensions is shown in Figs. 2B–2F. As shown in Fig. 2B, the highest proportion of poor people with deprivations of the health dimension (lack of health insurance and barriers to health services) is located mainly in the Caribbean region (northern Colombia) and the Pacific coast (western Colombia). These regions, as well as eastern Colombia have the highest proportion of poor people with educational deprivations (Fig. 2C). As shown in Figs. 2D–2F, the central region of the country has the lowest proportion of poor people with deprivations of dwelling (lack of access to safe water, inadequate disposal of human feces, poor housing construction, and critical over-crowding), employment (informal employment, and economic dependency) and childhood/youth (school non-attendance, school lag, barriers to childhood care services, and child labor) dimensions. The relation between the variation of MPI's for each dimension and the SCFR is not visually apparent. For instance, Vichada (index 9) and Córdoba (index 13), which have one of the lowest (SCFR=0.33) and highest (SCFR= 1.80) SCFR, respectively, are characterized by a similar proportion of poor people with deprivations of the education (Fig. 2C) and dwelling dimensions (Fig. 2D). In contrast, Antioquia (index 2) and Vaupés (index 32), which have a similar SCFR (e.g., approximately 0.55), have a different proportion of poor people with deprivations related to health (Fig. 2B) and dwelling dimensions (Fig. 2D).

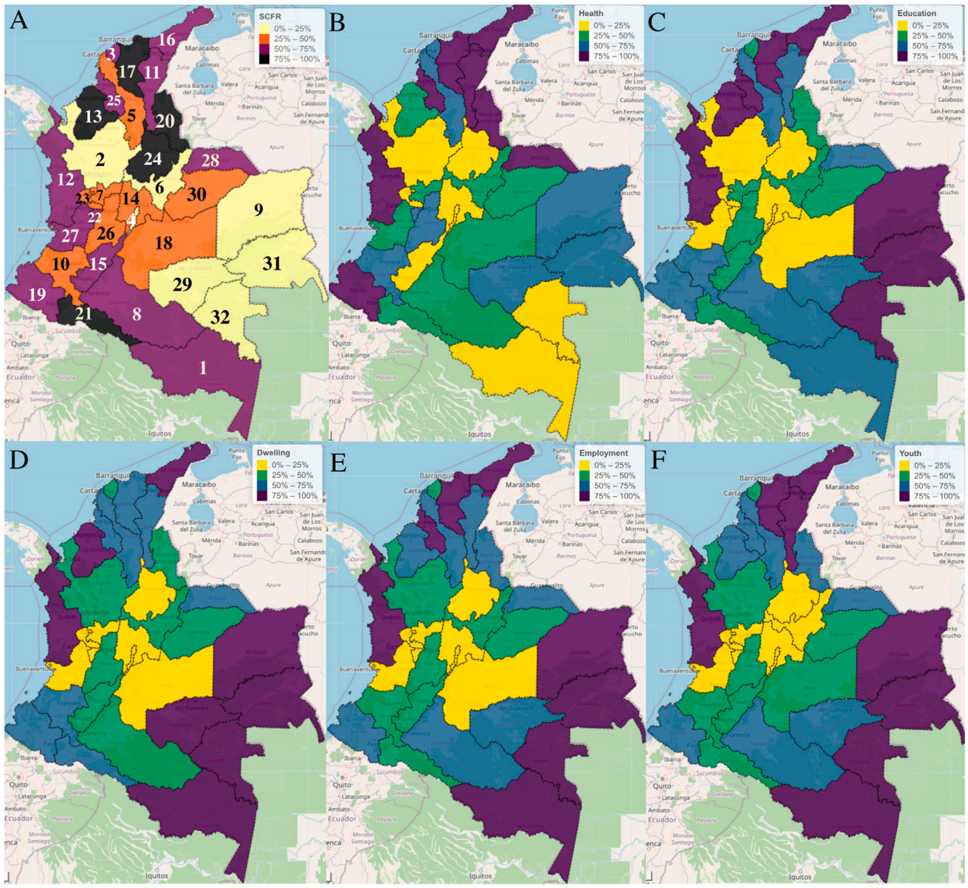

Fig. 2. Spatial distribution of the (A) SCFR from week 11 (March 16) to week 40 (October 04) of 2020 at department level, (B) health, (C) educational, (D) dwelling, (E) employment and (F) childhood/youth poverty dimensions of the Multidimensional Poverty Index. Indexes correspond to 1:Amazonas, 2:Antioquia, 3:Atlántico; 4:Bogotá DC.; 5:Bolivar; 6:Boyacá; 7:Caldas; 8:Caquetá; 9:Vichada; 10:Cauca; 11:Cesar; 12:Chocó; 13:Córdoba; 14:Cundinamarca; 15:Huila; 16:La Guajira; 17:Magdalena; 18:Meta; 19:Nariño; 20:Norte de Santander; 21:Putumayo; 22:Quindio; 23:Risaralda; 24:Santander; 25:Sucre; 26:Tolima; 27:Valle del Cauca; 28:Arauca; 29:Guaviare; 30:Casanare; 31:Guainía; 32:Vaupés; 33:San Andrés.

Table 3
Posterior quantities for selected parameters and DIC of the autoregressive CAR model.

	Median	2.5%	97.5%	n.effective	Geweke.diag
(Intercept)	0.260	−0.998	0.54 5	189.4	0.7
HMPI	0.142	0.015	0.214	225.8	−0.1
DMPI	0.636	0.228	0.901	116.2	0.5
EMPI	0.056	0.011	0.215	241.1	0.6
WMPI	−0.055	−0.183	0.097	227.1	−1.0
YMPI	0.060	0.037	0.534	703.5	−0.7
ρ	0.612	0.219	0.782	843.2	−0.3

DIC: 320.79.

4.2. Bayesian spatial modeling

Before incorporating spatial autocorrelated random effects into the model, we modeled the data with a Bayesian multivariate Poisson log-linear model (Table 3 Supplementary Material). To quantify the presence of spatial autocorrelation in the residuals from this model, we compute the Moran's I statistic and conduct a permutation test to assess its significance. Based on 10 000 random permutations of the data, Moran's I statistic suggests that the residuals contain substantial positive spatial autocorrelation ($p < 0.05$). Table 3 describes the results of the spatial Bayesian model with the lowest criteria deviance information criterion (DIC) after considering all possible permutations of the MPI covariates.

In addition to the median and 95% confidence intervals, Table 3 contains the effective number of independent samples (n.effective), and the result of Geweke diagnostic (Geweke, 1992), an MCMC convergence diagnostic that should lie between −2.0 and 2.0 to indicate convergence. The output shows that the health, dwelling, educational, and childhood/youth dimensions, exhibits positive relationships with the SCFR. Furthermore, the spatial ρ dependence parameter exhibit that autocorrelation is present in these data after adjusting for the effects of the covariates. Additionally, the prior related to the work dimension (WMPI) is near zero, indicating that this dimension does not contribute (i.e., it is not relevant) to the spatial heterogeneity of the SCFR. On the other hand, the most relevant dimension is the dwelling (DMPI) with a weight of about 0.9, which potentially means that for an increase of 0.1 in the DMPI, the SCFR would then increase by 9%. In other words, if the contribution of the DMPI to the total MPI increases by 10%, then the SCFR would then increase by 9%. Note that this interpretation assumes that there is no relationship between changes in one dimension and variations in the other dimension, however, since the proposed Bayesian model is multivariate, such a condition is not always valid. The Bayesian model also reveals that the health and educational dimensions equally contribute to the spatial variation of the SCFR (≈ 0.214), where a variation of 10% of these dimensions induces an increase of at least 2% in the SCFR. The childhood/youth dimension (YMPI) has almost half of the weight of the DMPI (Table 3).

Note also that each dimension is in turn composed of another set of variables (socioeconomic factors) related to poverty. For instance, DMPI (i.e., dwelling) is described by the lack of access to safe water, inadequate disposal of human feces, poor floor/walls construction, and critical overcrowding. These subdivisions of each dimension imply that the establishment of a causal relationship between a given socioeconomic factor (or human behavior) with the SCFR is not directly explicit in the Bayesian model. In other words, despite the model providing a hierarchy of the importance of the dimension can be used to infer the

Table 4
Posterior median relative risk estimates for the CAR model.

	RR	2.5%	97.5%
DMPI	1.74	1.54	9.75
EMPI	1.69	1.36	5.94
YMPI	1.35	1.08	4.03
HMPI	1.16	1.06	2.04
WMPI	1.02	0.80	3.06

relative effect of the dimensions, one cannot have access to the weight for each feature composing a specific dimension.

Estimated relative risks for the regression parameters show that the posterior relative risk for the DMPI dimension was 1.74 (Table 4). Thus, departments with a higher proportion of poor people with deprivation of the dwelling dimension (lack of access to safe water, inadequate disposal of human feces, poor housing construction, and critical overcrowding) have 74% higher risk of dying from COVID-19. The posterior relative risk for the EMPI dimension was 1.69, thus, in administrative units with a higher proportion of poor people with deprivation of the educational dimension (illiteracy, low educational attainment), the risk of dying from COVID-19 is higher by 69%. Furthermore, in administrative units with a higher proportion of poor people with deprivation of the childhood/youth dimension (school non-attendance, school lag, barriers to childhood care services, child labor), the risk of dying from COVID-19 is higher by 35%. Moreover, the posterior relative risk for the HMPI dimension was 1.16, suggesting that departments with a higher proportion of poor people with deprivation of the health dimension (lack of health insurance, barriers to health services) have 16% higher risk of dying from COVID-19. Finally, the posterior median relative risk for the employment dimension (informal employment, economic dependency) was approximately 1 (RR 1.02 95%CI = 0.80–3.06), thus employment is not significantly related to COVID-19 mortality risk as the 95% credible interval contains the null risk of 1.

Fig. 3A shows the spatial pattern of the relative risk of dying from COVID-19 from week 11 (March 16) to week 40 (October 04) of 2020 among the Colombian departments adjusted to the dimensions of the MPI. This pattern obtained from the Bayesian modeling describes in a remarkably accurate way the SCFR (Fig. 2A). In a simple direct visual comparison, one can infer a relatively good agreement with the SCFR obtained from the reported data for death and recovered individuals (Eq. (2)). To better characterize the performance of the Bayesian model, we plot the observed SCFR as a function of the predicted relative risk (i.e., the SCFR predicted by the Bayesian model) on the right side of Fig. 3A. The relatively small average error of 0.012 can be visualized in the almost perfect agreement of the predicted and observed SCFR, i.e., a line with a slope of almost 45 degrees.

According to the Bayesian model, in Colombia, people are not at equal risk of dying from COVID-19, and the people most at risk are those poor with deprivation of the dwelling, educational, childhood/youth, and health MPI dimensions. For specific departments, the Bayesian predicted SCFR is numerically close to the observed values. Specifically, the risk of dying from COVID-19 in the study period was higher in the department of Córdoba (94% higher risk), followed by Norte de Santander (81% higher risk), Magdalena (69% higher risk), Putumayo (44% higher risk), Santander (40% higher risk), Atlántico (36% higher risk), La Guajira (34% higher risk), Sucre (31% higher risk), Amazonas (24% higher risk), Chocó (18% higher risk), Nariño (17% higher risk), Caquetá (16% higher risk), Valle del Cauca (15% higher risk), and Huila (13% higher risk) when compared to the national. The lowest risk of dying from COVID-19 was observed in the departments of Vaupés (56% lower risk), Guainía (46% lower risk), Vichada (45% lower risk), Antioquia (31% lower risk), Guaviare (28% lower risk), Boyacá (25% lower risk) and Bogotá DC (21% lower risk).

Fig. 3B shows the results of testing the performance of the fitted model and the validation of the predictions against the case-fatality

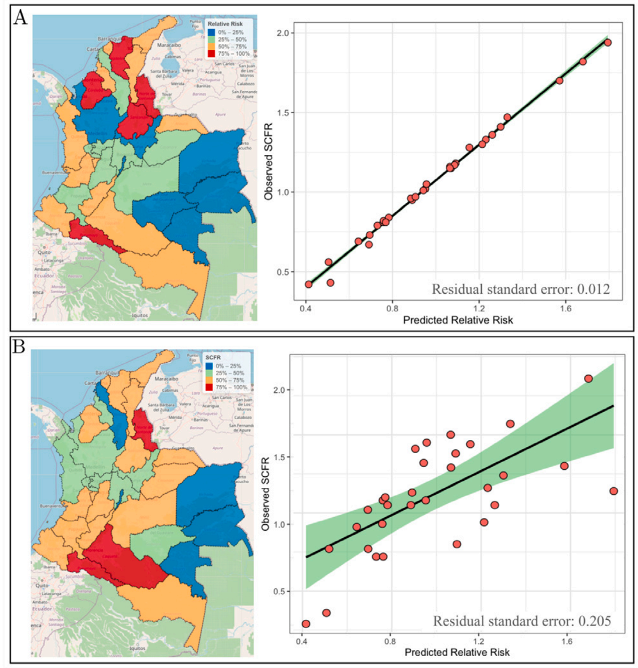

Fig. 3. Relative risk of dying from COVID-19 in Colombia among the Colombian departments adjusted to the dimensions of the MPI and model performance. (A) Spatial pattern of the relative risk of dying from COVID-19 from March 16 to October 30 of 2020 among the Colombian departments adjusted to the dimensions of the MPI, and difference between the observed SCFR and the estimated Relative Risk. (B) Spatial pattern of the relative risk of dying from COVID-19 from March 16 to October 30 of 2021 and difference between the observed SCFR (from March 16 to October 30 of 2020) and the estimated RR (from March 16 to October 30 of 2021).

rate data from week 11 (March 16) to week 40 (October 04) of 2021 based on the model fitted with data of the same period but a previous year (i.e., 2020). On the left side of the figure, the spatial pattern is presented, meanwhile, the right side shows the observed SCFR in 2021 (study period) against the predicted SCFR by the model depending on the components of the MPI. The Bayesian model reproduces the SCFR pattern obtained between March 16, 2021, and October 4, 2021 (i.e., the next year) in the departments with extreme SCFR values, such as the case of low-risk departments such as Bogotá (residual: 0.09), Vaupés (residual: 0.16), Vichada (residual: −0.21), Guainia (residual: 0.23), and high risk such as Norte de Santander (residual: 0.19), Putumayo (residual: −0.21). On the other hand, the comparison of observed and predicted cases indicates an average residual standard error of 0.205. Although there are some departments in which the SCFR is overestimated, in general, the prediction is reasonable enough to guide public actions.

5. Discussion

We provide a comprehensive study of socioeconomic risk factors for dying from COVID-19 in Colombia, using the multidimensional poverty index and the official COVID-19 death reports of the Colombian National Institute of Health. Our results corroborate that people living in more socioeconomically disadvantaged regions have higher rates of the known clinical risk factors that increase the case-fatality risk of COVID-19 (Bambra, 2016; Bambra et al., 2020).

We consider the official COVID-19 dataset even containing biases inherent to underreporting and the number of diagnostic tests performed. However, we contemplated the spatial isotropic underreporting rate (Instituto Nacional de Salud, 2020), which implies that although the values found for the case-fatality rate are not definite, the described spatial trend is expected to continue. We verify that a spatially homogeneous increment in the observed cases generates an adjustment of the intercept, however, maintaining the importance of each MPI dimension, as shown in the results of this work.

We evidence that health, dwelling, educational, and childhood/youth MPI dimensions are risk factors for dying from COVID-19. In Colombia, the health dimension of the MPI considers the definition of barriers to health services, as the proportion of individuals who do not attend a health service due to an illness that does not require hospitalization (DANE, 2020). In this sense, COVID-19 case-fatality rate heterogeneity could be mainly related to the level of self-reporting, since social groups with low socioeconomic indicators usually have lower self-reporting morbidity rates (Jivraj, 2020; Akhtar et al., 2020). Therefore, as HMPI is linked to the lack of health insurance and self-reporting, we strengthen the importance of public strategies promoting the prompt self-reporting of symptoms associated with COVID-19 as a fundamental measure for the prevention of fatal cases.

The educational and childhood/youth dimensions are also risk factors for dying from COVID-19 in Colombia. Similarly, previous research shows that people with less educational resources are more vulnerable to mortality from different causes (Drefahl et al., 2020; Selvan, 2020; Hummer and Lariscy, 2011; Cutler et al., 2011). Similarly, Yoshikawa and Asaba (2021) reported in a two-sample Mendelian randomization study that educational attainment decreases the risk of COVID-19 severity in the European population. Additionally, an increased risk of dying from COVID-19 has been reported in people with the inability to understand information, practice preventative measures, and communicate symptoms of illness (CDC, 2020). We verified that although the average COVID-19 testing turnaround time is similar across the country, the time from symptoms onset and the official notification/diagnostic is longer in social groups with low educational indicators (r = .6, p <.005). However, more research is needed to understand all the mechanisms behind low-income and low-educated individuals' excess COVID-19 case-fatality.

The provision of safe water, sanitation, and waste management are essential for preventing and protecting human health during the COVID-19 outbreak (WHO and UNICEF, 2020). In this way, populations with poverty associated with dwelling have greater difficulty in applying the necessary biosecurity measures to prevent COVID-19, such as handwashing (Bekele et al., 2021). Other measures, especially those related to wastewater treatment are fundamental and urgent when it is contemplated that the fecal–oral transmission of SARS-CoV-2 is possible (Hindson, 2020) and even more so than wastewaters from hospitals or quarantine centers dedicated to COVID-19 treatments may contain SARS-CoV-2 RNA particles (Adelodun et al., 2020).

The employment dimension associated with informal work and economic dependency was not significantly related to COVID-19 dying risk, despite the large proportion of socioeconomically disadvantaged people who are dependent on informal activities in all Colombian departments. At the beginning of the COVID-19 outbreak in Colombia, the Colombian government declared a national measure of Mandatory Preventive Isolation, canceling, among others, informal work activities, despite the absence of social and labor security protection for these workers and the impossibility of working remotely (Romero-Michel et al., 2021). This measure of confinement of informal workers along with the staying-at-home pattern of economically dependent people could generate the prevention of these populations getting infected and dying from COVID-19. Persons working in production and transportation have been reported as predictors of deaths from COVID-19, possibly because many of these occupations offer below-average salaries and lack paid sick leave (Harrington, 2020).

In a given population, age and race/ethnicity can drastically affect the COVID-19 fatality, indicating that these can be natural factors to explain the spatial heterogeneity of the SCFR. However, this relation is not necessarily direct. For instance, the heterogeneity of the case fatality risk cannot be related to a homogeneous variable, indicating that a spatially homogeneous density of elderly or race/ethnicity cannot be statistically related to the SCFR. Additionally, it is also possible that in a department with a high MPI, an individual of a specific population group (Afro-descendant or elderly) has drastically more risk for dying from COVID-19 than an individual from an area with better socioeconomic conditions, i.e., there is a spatial variation of the density of elderly or race/ethnicity, but it is not relevant (or statistically significant) to the spatial distribution of the case fatality risk. We find that in the specific case of Colombia, the contributions of the dimensions describing the MPI are more relevant than the age or the ethnic group populations. The comparison of the spatial distribution of both populations older than 60 years and the Afro-descendant population with the SCFR can be found in the Supplementary Material.

Results from previous spatial modeling of COVID-19 have found an association between COVID-19 morbidity and socioeconomic factors. In the United States, Mollalo et al. (2020) compiled 35 variables grouped into five different themes (socioeconomic, environmental, behavioral, topographic, and demographic), affirming that the median household income, income inequality, percentage of nurse practitioners, and percentage of black female population explain the variability of the COVID-19 incidence. Moreover, DiMaggio et al. (2020) reported a nearly five-fold increase in the risk of a positive COVID-19 test associated with the proportion of African American residents, residents older than 65 years, housing density, and the proportion of residents with heart disease. Older adults, African American, and Hispanic-Latina populations living in high-density environments have also been found as an important risk factor for the spread of COVID-19 (Wong and Li, 2020; Hou et al., 2021). However, although the risk in terms of morbidity is evident, the association of these factors with the risk of dying from COVID-19 has not been thoroughly studied.

In Europe, demographic and socio-economic components, including total population, poverty, and income, have been reported as key factors in regulating the overall casualties of COVID-19 (Sannigrahi et al., 2021). In England, for example, spatial variations of the COVID-19 mortality rate were mainly attributable to socioeconomically disadvantaged areas (Sun et al., 2021) and specifically to people living in deprivation (Sartorius et al., 2021). On the other hand, in Asia, it has been reported that urbanized, highly connected provinces with older population structures and higher average temperatures are the most susceptible to present a higher number of COVID-19 cases (Ramírez-Aldana et al., 2020).

Our findings have direct relevance to Colombia and provide valuable insight for Latin American countries preparing for the challenges associated with the COVID-19 syndemic (Poteat et al., 2020; Polo et al., 2022), and a better understanding of potential alternative scenarios for countries, with similar health systems.

6. Conclusions

We provide evidence that in Colombia, people are not at equal risk of dying from COVID-19. The multidimensional poverty index significantly affects the inequalities in the COVID-19 case-fatality risk. Dwelling, childhood/youth, educational and health factors such as lack of access to safe water, inadequate disposal of human feces, poor housing construction, critical overcrowding, child labor, illiteracy, low educational attainment, lack of health insurance, barriers to health services, were robust and consistent aspects associated to a high risk of dying from COVID-19 in Colombia at the department level. These findings assist policy-makers in the spatial and temporal planning of strategies focused on mitigating fatalities in most vulnerable communities and preparing for future pandemics by progressively reducing the factors that generate health inequality.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement

Data supporting the findings of this study are freely available within the article and its supplementary materials.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.sste.2022.100494.

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