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RESEARCH

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Variability of COVID-19 mortality in Honduras: influence of sociodemographic factors

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Abstract

Background In Central America, Honduras experienced a significant increase in SARS-CoV-2 infections between March 11, 2020, and January 26, 2022. Although limited research has been conducted on the impact of the COVID-19 pandemic on populations in Central American countries, this study seeks to contribute to the existing body of knowledge in the region. The objective of this study was to investigate the variability of COVID-19 mortality in Honduras and the impact of sociodemographic factors.

Methods A cross-sectional and ecological study, using data from cases collected by the National Risk Management System (SINAGER) and recorded by the Demographic Observatory of the National Autonomous University of Honduras (ODU) between March 11, 2020, and January 26, 2022. Sociodemographic variables were obtained from the 2013 XVII Population and VI Housing Census by the National Institute of Statistics (INE). Age-adjusted case and COVID-19 mortality rates by sex were calculated. To explain the potential causes of variability, multilevel logistic regression models were constructed, considering individual and contextual variables.

Results A total of 513,416 COVID-19 cases were included, of which 98% (503,176) survived and 2% (10,240) died. The results showed differences in COVID-19 mortality rates between municipalities and departments. The multilevel model revealed that age (OR: 1.0737; 95% CI: [1.0726; 1.0749]) and sex (OR: 0.7434; 95% CI: [0.7027; 0.7841]) were significantly associated with COVID-19 mortality, with men being more likely to die. Among departments, the significant contextual factors were the illiteracy rate and the percentage of the rural population, both of which were associated with higher COVID-19 mortality (OR: 1.0850; 95% CI: [1.0511; 1.1189] and OR: 1.0234; 95% CI: [1.0146; 1.0323]), while the percentage of the active population (working age people) was associated with a decrease in COVID-19 mortality (OR: 0.9768; 95% CI: [0.9591; 0.9944]). The intraclass correlation coefficient (ICC) showed a reduction in variability attributable to the variation between departments, with a final ICC of 0.68%.

Conclusions Differences in COVID-19 mortality were found between the different departments, partly explained by sociodemographic factors. The results of this study show that, in addition to individual characteristics, population-level socioeconomic and educational factors influence COVID-19 mortality. Multilevel analysis is highly useful for providing evidence to improve approaches in future pandemics.

Keywords COVID-19, Standardized rates, Multilevel analysis, Logistic regression, Mixed-effects model

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Background

COVID-19 is a respiratory disease caused by the SARS-CoV-2 virus, which emerged in Wuhan, China, in December 2019 [1]. The disease spread rapidly worldwide, and on January 30, 2020, the World Health Organization (WHO) declared COVID-19 a public health emergency of international concern [2]. Since its emergence, the pandemic has had a devastating impact on public health, the economy, and society. Worldwide, since December 2019, more than 760 million cases and 6.9 million deaths have been reported [3]. In the early months of the pandemic, there was limited knowledge of the virus's dynamics and its short- and long-term effects on health [4]. As the pandemic progressed, health systems worldwide became overwhelmed, leading to millions of additional deaths globally [5, 6]. Authorities implemented various restrictive measures to curb the spread of the virus, such as mobility restrictions and the suspension of economic and social activities, which had a significant negative impact on the global economy [7].

In Central America, Honduras confirmed its first case of COVID-19 on March 11, 2020 [8]. Like other countries, Honduras faced considerable challenges during the pandemic. The spread of the virus across the different departments of the country revealed notable variations in case and COVID-19 mortality rates, making it imperative to study these disparities. In this context, the conceptual framework of this study is based on social epidemiology, which examines how social and economic factors influence public health and how public policies can mitigate these effects.

Social and economic inequalities appear to have a significant impact on COVID-19 infection outcomes. Studies conducted in the early phases of the pandemic have correlated socioeconomic indicators, such as income, poverty, and unemployment, with the risk of hospitalization and disease incidence in countries with low economic inequality [9]. Furthermore, previous research has shown that social vulnerability is associated with higher mortality from COVID-19 [10], and this vulnerability is closely related to marginalization and economic inequality.

Few studies have examined the impact of the COVID-19 pandemic on populations in Central American countries. This study aims to contribute to the existing body of knowledge in the region, particularly in Honduras, which could help inform public health strategies and mitigate the effects of future pandemics. Despite advances in research on the relationship between socioeconomic inequalities and COVID-19 mortality, significant gaps remain in the current knowledge. Many previous studies have primarily focused on high-income countries in Europe, while in Latin America, and particularly in Honduras, there is a limited number of studies that have specifically addressed this issue. Although previous research has identified the relationship between poverty and higher mortality rates, insufficient attention has been given to the differences within countries and the interactions between socioeconomic, geographic factors, and the healthcare system. This gap in the literature highlights the need for more detailed analyses that consider the specific realities of developing countries, such as Honduras. Furthermore, discrepancies have been observed in previous findings regarding the influence of factors such as rurality, access to education, and the Human Development Index on COVID-19 mortality. These discrepancies underscore the importance of continuing to explore how these factors interact differentially across various regions and social groups.

This study has two main objectives: the first is to analyze the variability in case and mortality rates from COVID-19 among the departments of Honduras to identify significant geographical differences; the second is to explore demographics and socioeconomic factors that could explain this variability. For this purpose, the administrative structure of Honduras is considered, which consists of 18 departments (areas), each further subdivided into 298 municipalities (sub-areas). In each of these regions, socioeconomic indicators such as the illiteracy rate, rural population, active population, human development index, and emigration and immigration flows were collected. Based on previous studies, these factors may influence the incidence of COVID-19 cases and related mortality.

Methods

Study population

All COVID-19 cases recorded in Honduras from March 11, 2020, to January 26, 2022, were included in this cross-sectional and ecological study. Sample size was not estimated, since this is a population study. The data were collected by the Demographic Observatory of the National Autonomous University of Honduras (ODU) [11] and published by the National Risk Management System (SINAGER) [12]. No imputation of missing data was performed, only cases with complete information were used. For the calculation of rates, information from the XVII Population and VI Housing Census of 2013 from the National Institute of Statistics (INE) [13] and ODU [11] was also used. The information covers 8,303,778 inhabitants distributed by sex (4,052,324 men and 4,251,454 women) and by urban/rural area. The data used in the analysis are not publicly available, they were specifically requested from the Demographic Observatory of the National Autonomous University of Honduras (ODU) [11], where each report issued by the National

Risk Management System (SINAGER) [12] during the period from March 11, 2020, to January 26, 2022, was recorded, and these were shared only with the university community for research purposes. As for the data from the XVII Population and VI Housing Census of 2013 by the National Institute of Statistics (INE) [13], they are publicly available on the official INE [13] website and also on the official ODU [11] website.

Study variables

At the individual level, for each COVID-19 case, the following information was collected: age, sex, department, municipality of residence, and COVID-19 mortality (deceased/survivor).

At the departmental level, the following contextual variables were collected: percentage of rural population, percentage of illiteracy, percentage of poverty, percentage of active population [14], percentage of housing, Human Development Index (evaluation of wealth, health, and education) in 2019 [15–17], and percentage of emigration and immigration.

Statistical data analysis

Rate Calculation: crude and age-adjusted rates were calculated per 10,000 inhabitants, stratified by sex for the municipalities and departments of Honduras. The cases and deaths from COVID-19 were distributed by sex across 298 municipalities and 18 departments. The adjustment was made using the direct method, applying the age-specific rates of each stratum of the study population to a standard population. For this analysis, the standard population used was the total population of Honduras in 2013, divided into the same age strata.

Multilevel Analysis: multilevel regression models are fundamental tools for analyzing hierarchical data and capturing relationships between variables at different levels [18–21]. These models allow for the decomposition of variance into individual and group components [22], thereby facilitating the estimation of associations at both individual and contextual levels [23–25]. For this study, COVID-19 mortality (deceased/survivor) is considered the dependent variable. The independent variables at the different levels were:

- **Hierarchical Level 1** (Individual Variables): age and sex.
- **Hierarchical Level 2** (Contextual Variables):
  - **Geographic**: department code and percentage of rural population.
  - **Educational**: percentage of illiteracy.
  - **Socioeconomic**: percentage of poverty, percentage of active population (people of working age who are actively involved in the labor market, including both the employed and the unemployed), percentage of housing, and Human Development Index in 2019.
  - **Demographic**: percentage of emigration and immigration.

The Human Development Index (HDI) is a summary measure of human development, composed of three key dimensions: health, knowledge and standard of living. For each region, the HDI reflects the average achievements in these dimensions, as indicated by life expectancy at birth, mean years of schooling, expected years of schooling, and Gross National Income (GNI) per capita in PPP terms (USD) [15–17].

The correlation between the independent variables was explored using Pearson's correlation coefficient, considering those variables highly correlated if the coefficient exceeded 0.8. The relationship between the dependent variable and the independent variables was evaluated using multilevel logistic regression [18–21, 26], calculating odds ratios and 95% confidence intervals for each predictor. Given that the data presented a hierarchical structure, with individuals grouped by departments [23, 27], a multilevel logistic regression analysis was conducted to adequately reflect this structure. First, an empty model was developed to calculate the level 2 variance and the intraclass correlation coefficient (ICC), calculated as:

$$\mathrm{ICC} = \frac{\sigma^2}{\sigma^2 + \frac{\pi^2}{3}} \tag{1}$$

where σ^2 is the variance between groups and $\frac{\pi^2}{3}$ [18, 22, 28] represents the variance at the individual level.

Other measures were also evaluated, such as the proportional change in variance (PCV) [25], calculated as:

$$\mathrm{PCV} = \frac{\sigma_N^2 - \sigma_C^2}{\sigma_N^2} \tag{2}$$

where σ_C^2 and σ_N^2 are the variances of the full model and the null model, respectively.

The Median Odds Ratio (MOR) [29, 30] is calculated as:

$$\mathrm{MOR} = \exp\left(\sqrt{2\sigma^2} \cdot \Phi^{-1}(0.75)\right) \tag{3}$$

where $\Phi^{-1}(0.75) = 0.6745$ is the 75th percentile of a standard normal distribution.

For model selection, the stepwise method was used, applying the likelihood ratio test, calculating deviance, and using the chi-square statistic for model comparison.

To investigate the possible presence of multicollinearity in the final model, the Variance Inflation Factor (VIF) was calculated [31–34].

Statistical software

We used R version 4.1.2 [35]. The graphical representation through maps was created using the **sf** library [36, 37], and the multilevel analysis was conducted with the **lme4** library [38]. The calculation of standardized rates was performed using the software Epidat [39].

Results

After removing incomplete data (3.36%), 513,416 cases were analyzed, distributed across 18 departments and 298 municipalities. Ninety-eight percent of the cases survived (503,176 cases), while 2% died (10,240 cases). The results of the age-adjusted rates of COVID-19 cases and mortality are presented below.

Age-adjusted COVID-19 case and mortality rates by municipality, department and sex

In the male population, the standardized COVID-19 case rates per 10,000 inhabitants were highest in the departments of La Paz, Francisco Morazán and Islas de la Bahía (970.2289, 845.4140 and 774.0990 respectively). In contrast, the lowest rates were found in Copán, Olancho and Lempira departments (321.6849, 293.9932 and 212.9255) (Table 1, Fig. 1).

Regarding mortality, standardized COVID-19 mortality rates per 10,000 inhabitants were highest in the departments of Cortés, Francisco Morazán and Islas de la Bahía (22.0634, 20.8374 and 15.6850 respectively). In contrast, the lowest rates were observed in the departments of Choluteca, Gracias a Dios and Lempira (8.1481, 7.1979 and 7.1598) (Table 2, Fig. 2).

In the female population, the highest standardized COVID-19 case rates were found in the departments of La Paz, El Paraíso and Islas de la Bahía (1207.2091, 919.6344 and 883.3242 respectively). In contrast, the lowest rates were found in Olancho, Copán and Lempira (384.8477, 371.7034 and 266.2186) (Table 1, Fig. 3).

Regarding mortality, the highest COVID-19 mortality rates per 10,000 inhabitants were found in the departments of Cortés, Francisco Morazán and Comayagua (14.3568, 13.0462 and 11.4852 respectively). In contrast, the lowest rates were observed in Ocotepeque, Lempira and and Gracias a Dios (7.0767, 5.2235 and 3.3113) (Table 2, Fig. 4).

Rates for all departments in supplementary material (Tables S1, S2, S3, S4)

Multilevel model

Three multilevel logistic regression models were explored. **Model 0**, or the null model, includes only random effects at the departmental level to capture the variation in COVID-19 mortality between departments. **Model 1** incorporates individual-level characteristics (age and sex), while **Model 2** adds both individual and departmental characteristics. For model 2, a prior correlation analysis between independent variables was carried out. This analysis revealed redundancies between certain contextual variables (e.g. Human Development Index) which were excluded from the model. Therefore, the following variables were kept in the model: percentage of poverty, percentage of illiteracy, percentage of rural population, percentage of active population, percentage of housing, percentage of emigration and immigration.

In Table 3, only the coefficients of the significant variables are presented, while Table 4 shows the corresponding odds ratios, calculated by exponentiating the regression coefficients estimated in Table 3.

In the null model, where we only consider the random effects of the departments and no other predictors, we observe an intercept of -3.9476 which corresponds to $ln\left(\frac{p}{1-p}\right)$, where $p = \frac{e^{-3.9476}}{1+e^{-3.9476}} = 0.0189$, indicating that the probability of a randomly selected individual dying is 1.89%. Furthermore, the variance of 0.1007, indicating that 10% of the variability in COVID-19 mortality between departments is attributable to differences between them (Table 3).

The results of the adjusted models indicate that age and sex are significant predictors of COVID-19 mortality, with higher risks associated with older ages and male sex. In Model 2, contextual variables such as the percentage of the active population, the percentage of illiteracy, and the percentage of the rural population also show significant associations with COVID-19 mortality (Table 3).

The goodness-of-fit metrics (AIC and BIC) decrease with the inclusion of predictors, indicating improved model fit. The likelihood ratio test confirms a significant deviance reduction from the null model to Model 2 ($p < 0.001$), supporting a better fit (Table 3). The ICC between departments drops from 2.97% in the empty model to 1.77% with individual variables and 0.68% with both individual and contextual variables were included. The proportion of explained variance increases by 74.18% in Model 2, while unexplained variance decreases from 0.1007 to 0.0226, highlighting the model's improved ability to explain COVID-19 mortality (Table 3).

By analyzing the odds ratios, we can see that age is significantly associated with COVID-19 mortality (OR 1.0737 [1.0726; 1.0749]) and sex (OR 0.7434 [0.7027;

Table 1 Age-adjusted COVID-19 rates and CI (95.0%) by municipality and department for men and women per 10,000 inhabitants (top 5 and lowest 5 rates)

Sex	Municipality/Department	Age-adjusted Rate	Lower CI (95%)	Upper CI (95%)	Pop. Size	HDI	Poverty (%)
Men	**Age-adjusted covid rates by municipality**						
	LA ESPERANZA	2397.4274	2266.3238	2535.0330	5300	70	7.1963
	POTRERILLOS	2253.3690	2055.6983	2466.3390	2164	60	8.7459
	LA PAZ	1786.6503	1786.6503	1845.6290	20998	70	8.4493
	JACALEAPA	1765.5380	1580.5145	1968.2650	1932	70	10.2144
	PIMIENTA	1729.6377	1640.7615	1822.4580	8871	70	8.9126
	GUARIZAMA	18.8741	7.5466	40.1910	3840	60	9.1646
	SAN FRANCISCO DE OPALACA	18.1792	8.2315	50.1330	5474	50	11.5983
	LA TRINIDAD	17.5036	3.5676	53.1880	2271	50	9.2338
	LAS LAJAS	12.4730	5.3332	27.6590	7107	60	9.6918
	MEAMBAR	5.5880	1.5235	16.0500	6938	50	9.2078
	Age-adjusted covid rates by department						
	LA PAZ	970.2289	950.3702	990.4224	96807	60	8.8650
	FRANCISCO MORAZÁN	845.4140	838.8319	852.0398	719526	70	5.6726
	ISLAS DE LA BAHÍA	774.0990	742.8996	806.6270	30606	70	3.1779
	CORTÉS	720.6843	714.5809	726.8266	750811	70	3.7201
	EL PARAÍSO	688.1799	677.4715	691.1234	223591	60	7.8352
	GRACIAS A DIOS	370.2063	351.6831	389.6043	44274	60	14.1715
	CHOLUTECA	337.9317	330.3199	345.6933	216407	60	7.8994
	COPÁN	321.6849	313.4307	330.1044	183615	60	7.9274
	OLANCHO	293.9932	287.2836	300.8288	257607	60	7.9264
	LEMPIRA	212.9255	205.6609	220.4076	161046	50	11.6845
Women	**Age-adjusted covid rates by municipality**						
	POTRERILLOS	3519.2103	3256.2878	3799.2250	2078	60	8.7459
	JACALEAPA	2368.9937	2160.8403	2594.2250	2033	70	10.2144
	GUINOPE	2192.4928	2050.2782	2342.5490	4204	60	8.8602
	LA ESPERANZA	2178.3936	2065.9088	2296.6040	6331	70	7.1963
	LA PAZ	1956.1075	1899.6528	2014.1200	22982	70	8.4493
	LAS LAJAS	21.7325	11.7714	41.2540	7204	60	9.6918
	LA TRINIDAD	19.9170	4.0987	70.2880	2245	50	9.2338
	PIRAERA	16.8248	7.6024	32.9650	6846	50	11.6215
	SAN MIGUELITO	14.5570	1.7608	83.9190	962	60	11.8848
	MEAMBAR	9.8119	3.1095	24.4890	6124	50	9.2078
	Age-adjusted covid rates by department						
	LA PAZ	1207.2091	1185.3120	1229.4085	102121	60	8.8650
	EL PARAÍSO	919.6344	906.8635	932.5399	220915	60	7.8352
	ISLAS DE LA BAHÍA	883.3242	850.6212	917.3179	31915	70	3.1779
	FRANCISCO MORAZÁN	859.2773	853.0867	865.5015	789383	70	5.6726
	OCOTEPEQUE	719.6000	700.0423	739.5841	74036	60	6.9895
	COLÓN	465.5356	454.2910	477.1088	158202	60	5.4136
	CHOLUTECA	408.0847	399.5592	416.7894	221211	60	7.8994
	OLANCHO	384.8477	377.0464	392.7705	263158	60	7.9264
	COPÁN	371.7034	362.7030	380.8701	187441	60	7.9274
	LEMPIRA	266.2186	257.6685	274.9965	160133	50	11.6845

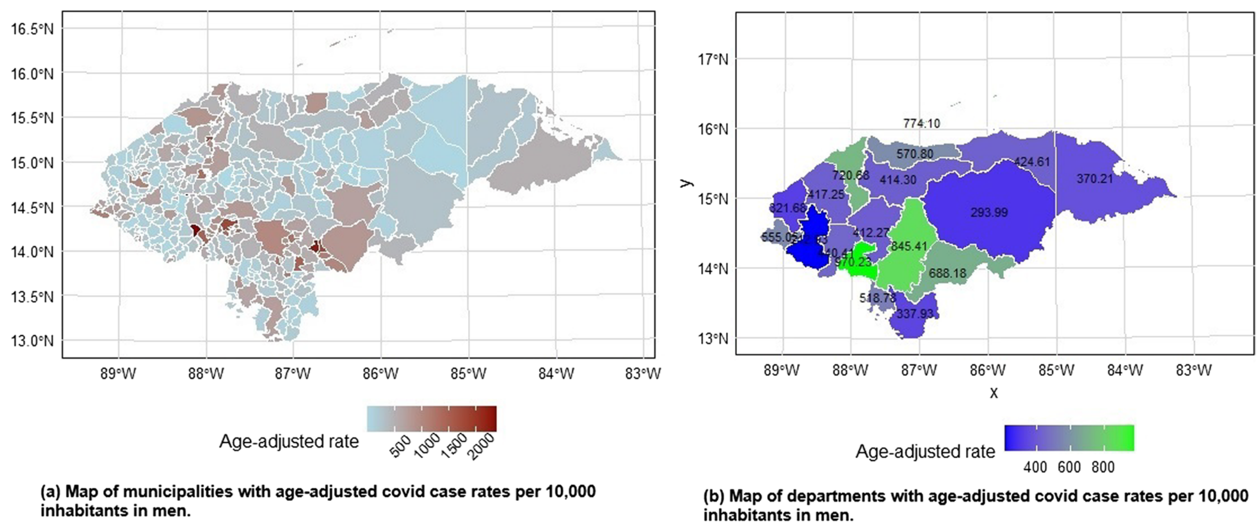


Fig. 1 Age-adjusted covid case rates per 10,000 inhabitants in men **a** by municipality and **b** by department

0.7841]), showing a higher risk of mortality from COVID-19 in men compared to women. In addition, the model that includes contextual variables showed that a higher percentage of employed population is associated with a decrease in COVID-19 mortality (OR 0.9768 [0.9591; 0.9944]). Illiteracy and rurality were also statistically significantly associated with COVID-19 mortality (OR 1.0850 [1.0511; 1.1189] and 1.0234 [1.0146; 1.0323] respectively) (Table 4). The Variance Inflation Factor (VIF) was calculated, with all values falling within the acceptable range, indicating no multicollinearity in the model.

The contextual random effects on the constant in Model 0 and Model 2 show that most departments maintain the same sign in both models, indicating that the departmental effects do not change drastically when adjusting for additional variables in Model 2. However, sign changes are observed in some departments (e.g., Santa Bárbara and Yoro), suggesting that the initially positive effects turn negative after adjusting for additional contextual factors, or conversely, that previously unfavorable departmental effects become favorable (e.g., Intibucá) (Table 5, Fig. 5).

Discussion

The objective of this study was to calculate and compare the rates of COVID-19 cases and COVID-19 mortality across different geographical areas in Honduras, as well as to analyze the sociodemographic factors that may influence the variability of this COVID-19 mortality. Based on 513,416 records from the Demographic Observatory of the National Autonomous University of Honduras, which include 10,240 confirmed deaths, a national COVID-19 mortality rate of 2.0% was observed.

First, we found a clear variability in the age-adjusted rates of COVID-19 cases and mortality at both the municipal and departmental levels, with a notable difference between men and women. The municipalities and departments with the highest rates of cases and COVID-19 mortality reveal that contextual factors such as rurality, illiteracy, and the active population may be influencing the risk of infection and COVID-19 mortality. In particular, municipalities like La Esperanza and Pimienta, as well as departments like Cortés and Francisco Morazán, exhibited the highest rates, suggesting that urbanization and population density may play a significant role in the spread of the virus.

The results also highlight that, at the departmental level, the highest COVID-19 mortality rates were observed in Cortés, Francisco Morazán, Islas de la Bahía, and La Paz. These areas align with those most affected in terms of cases, which may be related to greater exposure due to economic activity or limitations in local health systems.

The multilevel analysis highlights that, in addition to individual factors such as age and sex, contextual factors like the percentage of illiteracy, active population, and rurality play a key role in the variability of COVID-19 mortality. Consistent with the existing literature, we found an increased risk of COVID-19 mortality with advancing age [40, 41]. Additionally, male sex showed a higher risk of death from COVID-19 compared to female, which is consistent with other global studies that have documented a greater vulnerability of men to the virus [42, 43].

Table 2 Age-adjusted COVID-19 mortality rates and CI (95.0%) by municipality and department for men and women per 10,000 inhabitants (top 5 and lowest 5 rates)

Sex	Municipality/Department	Age-adjusted Rate	Lower CI (95%)	Upper CI (95%)	Pop. Size	HDI	Poverty (%)
Men	**Age-adjusted covid mortality rates by municipality**						
	MERCEDES DE ORIENTE	44.8892	1.1346	263.6850	516	50	11.5915
	CANE	39.6523	17.6767	85.3340	1724	70	8.9365
	DULCE NOMBRE	39.0926	20.6826	68.9600	2752	60	9.3458
	SAN JUAN	30.0099	15.8264	55.6480	6620	60	7.6613
	LA ESPERANZA	29.1930	15.6568	50.5870	5300	70	7.1963
	MASAGUARA	1.2922	0.0329	8.6350	7764	50	10.6280
	SANTA ANA DE YUSGUARE	1.2705	0.0324	20.8610	7144	60	9.8528
	VALLADOLID	1.2553	0.0320	28.0280	1826	50	9.1450
	IRIONA	0.9712	0.0248	5.9410	10548	60	8.8572
	ALAUCA	0.9700	0.0247	11.4330	4520	60	9.7815
	Age-adjusted covid mortality rates by department						
	CORTÉS	22.0634	20.9412	23.2345	750811	70	3.7201
	FRANCISCO MORAZÁN	20.8374	19.7796	21.9371	719526	70	5.6726
	ISLAS DE LA BAHÍA	15.6850	11.0931	21.9050	30606	70	3.1779
	LA PAZ	14.3256	11.9646	17.0378	96807	60	8.8650
	VALLE	13.8976	11.6291	16.5020	85125	60	9.6612
	OCOTEPEQUE	9.1413	7.0984	11.6572	72397	60	6.9895
	SANTA BÁRBARA	8.3202	7.2190	9.5584	214131	60	6.9389
	CHOLUTECA	8.1481	7.0219	9.4278	216407	60	7.8994
	GRACIAS A DIOS	7.1979	4.6367	10.8106	44274	60	14.1715
	LEMPIRA	7.1598	5.8538	8.6941	161046	50	11.6845
Women	**Age-adjusted covid mortality rates by municipality**						
	PIMIENTA	28.9052	17.7557	46.9150	9687	70	8.9126
	CANE	28.1960	11.3022	63.8660	1868	70	8.9365
	LA ESPERANZA	24.6152	13.5854	42.6530	6331	70	7.1963
	SAN ISIDRO	22.8276	4.4994	71.7370	2128	50	8.1377
	HUMUYA	22.0691	2.5941	1137.8990	653	60	9.0978
	MAGDALENA	1.4942	0.0381	23.6930	2269	60	11.1442
	CORQUÍN	1.4088	0.0359	19.5310	8319	60	8.4868
	LA JIGUA	1.3881	0.0354	22.4290	4730	50	10.3898
	EL PARAÍSO	1.0337	0.0264	9.2630	9944	50	10.2656
	COLOMONCAGUA	0.9656	0.0246	7.3640	9292	50	9.8545
	Age-adjusted covid mortality rates by department						
	CORTÉS	14.3568	13.4847	15.2783	811586	70	3.7201
	FRANCISCO MORAZÁN	13.0462	12.3033	13.8300	789383	70	5.6726
	COMAYAGUA	11.4852	10.0833	13.0849	252628	60	7.1225
	LA PAZ	11.1971	9.1590	13.5721	102121	60	8.8650
	ATLÁNTIDA	10.8387	9.4807	12.3722	225363	70	4.4938
	CHOLUTECA	8.0981	6.9003	9.4868	221211	60	7.8994
	INTIBUCÁ	7.2217	5.6877	9.0598	118807	60	7.8830
	OCOTEPEQUE	7.0767	5.2693	9.3248	74036	60	6.9895
	LEMPIRA	5.2235	4.0992	6.5789	160133	50	11.6845
	GRACIAS A DIOS	3.3113	1.6173	6.6574	46521	60	14.1715

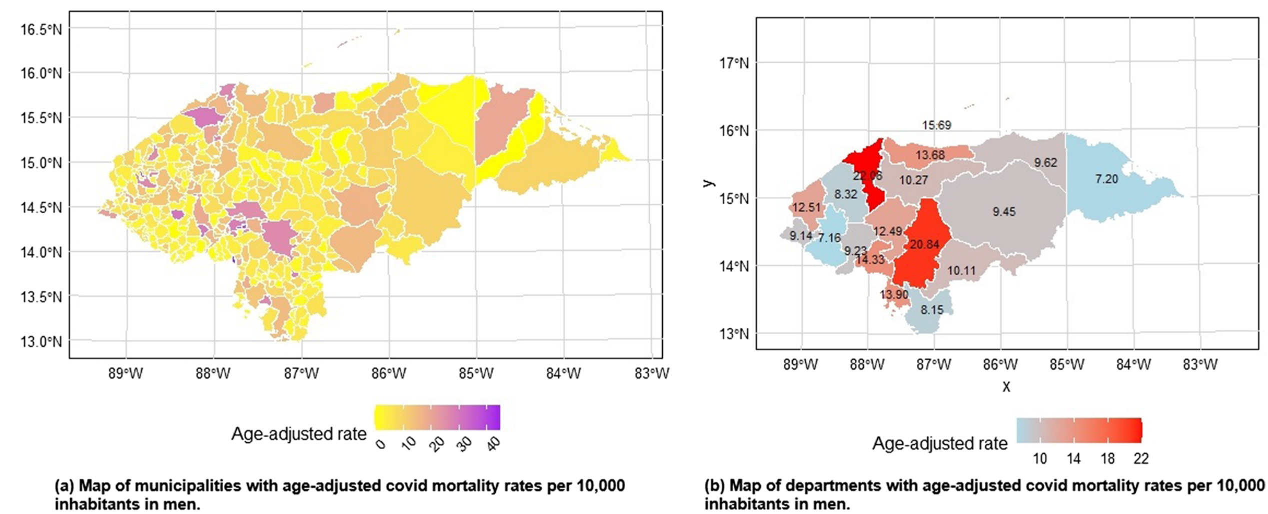


Fig. 2 Age-adjusted covid mortality rates per 10,000 inhabitants in men **a** by municipality and **b** by department

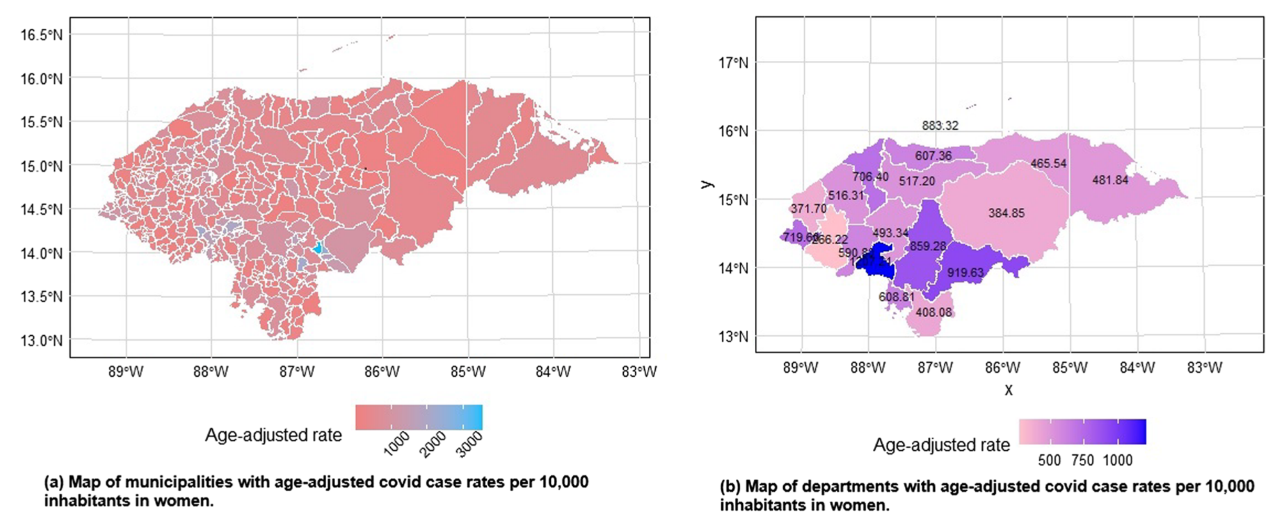
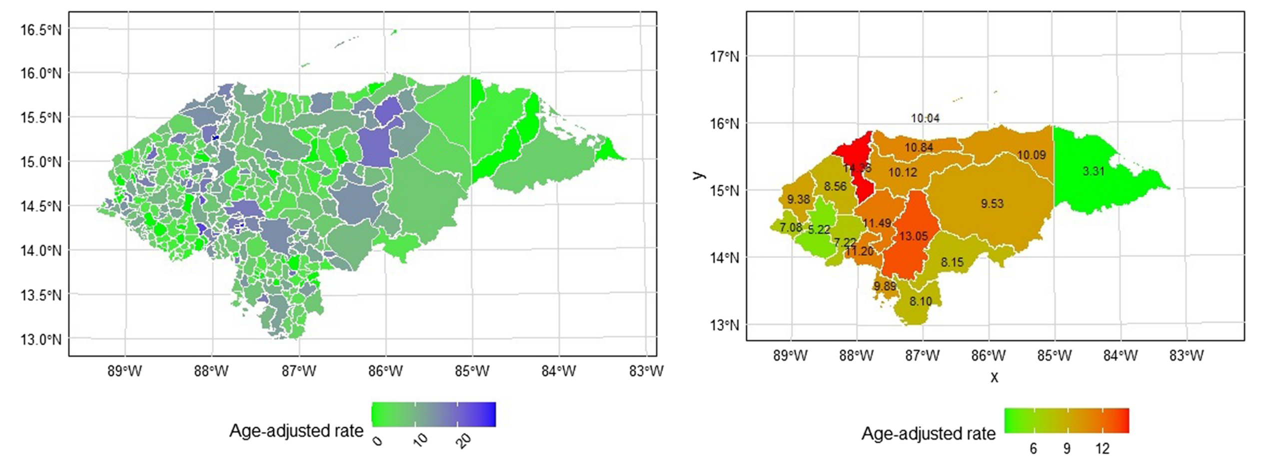


Fig. 3 Age-adjusted covid case rates per 10,000 inhabitants in women **a** by municipality and **b** by department

Our results indicate that socioeconomic variables, such as the percentage of illiteracy, rural population, and active population, were significantly associated with the risk of COVID-19 mortality. This aligns with findings from other studies, which have shown that the geographic region is related to differences in the severity of complications and mortality from COVID-19. Specifically, a higher risk of complications and mortality was observed in geographic areas with higher levels of marginalization (measured by variables such as education rate, rural population, and income level, among others) [44]. Additionally, subsequent studies conducted during the fourth wave of the pandemic consistently demonstrated that rural areas were associated with a higher incidence of COVID-19 cases and mortality, despite having vaccination rates similar to those in urban areas [45].

Along with the influence of socioeconomic factors, other studies have found a reduction of up to 40% in the variability of case rates when including geographical areas in the model [46]. In our case, the model that includes contextual factors (Model 2) showed a substantial improvement in the explanatory capacity of the risk of COVID-19 mortality compared to the null model, reducing the unexplained variance between departments by 74.18%. This finding underscores the importance of considering both individual characteristics and structural determinants in pandemic management.



(a) Map of municipalities with age-adjusted covid mortality rates per 10,000 inhabitants in women.

(b) Map of departments with age-adjusted covid mortality rates per 10,000 inhabitants in women.

Fig. 4 Age-adjusted covid mortality rates per 10,000 inhabitants in women **a** by municipality and **b** by department

Table 3 Factors related to COVID-19 mortality. Results of the multilevel logistic regression models. Regression coefficients and variance components

	Model 0	Model 1		Model 2	
		Estimated coefficients and (s.e.)	*p*	Estimated coefficients and (s.e.)	*p*
(Intercept)	−3.9476 (0.0577)	−7.4203 (0.0698)	< 0.0001	−9.0287 (0.3460)	< 0.0001
Age		0.0711 (0.0006)	< 0.0001	0.0711 (0.0006)	< 0.0001
Reference Category: Female		−0.2967 (0.0207)	< 0.0001	−0.2965 (0.0208)	< 0.0001
Percentage of Active Population				−0.0235 (0.0090)	0.0091
Percentage of Illiteracy				0.0816 (0.0173)	< 0.0001
Percentage of Rural Population				0.0232 (0.0045)	< 0.0001
AIC	100015.3769	82410.2106		82400.7027	
BIC	100037.6745	82454.8060		82478.7446	
Log Likelihood	−50005.6884	−41201.1053		−41193.3514	
Num. obs.	513416	513416		513416	
Num. groups: dept_code	18	18		18	
Var: dept_code (Intercept)	0.1007	0.0592		0.0226	
ICC (%)	2.97	1.77		0.68	
PCV (%)		41.21		74.18	
MOR	1.35	1.26		1.15	

In a multivariate analysis, a $p > 0.20$ value indicates that the variable lacks statistical significance. Standard error (s.e.) in parentheses

In conclusion, the evidence suggests that variability in COVID-19 mortality between departments is partially explained by structural factors, such as unequal access to healthcare services and differences in socioeconomic conditions [47]. Rurality and illiteracy, factors that were significantly associated with a higher risk of COVID-19 mortality, reveal that departments with a higher

Table 4 Factors related to COVID-19 mortality. Results of the multilevel logistic regression models. Odds ratio and 95% confidence interval

	Model 1	Model 2		
	OR and 95% CI	OR and 95% CI	s.e.	*p*
(Intercept)	0.0006 [−0.1362; 0.1374]	0.0001 [−0.6781; 0.6783]	0.3460	< 0.0001
Age	1.0737 [1.0726; 1.0749]	1.0737 [1.0726; 1.0749]	0.0006	< 0.0001
Reference Category: Female	0.7433 [0.7026; 0.7839]	0.7434 [0.7027; 0.7841]	0.0207	< 0.0001
Percentage of Active Population		0.9768 [0.9591; 0.9944]	0.0090	0.0091
Percentage of Illiteracy		1.0850 [1.0511; 1.1189]	0.0172	< 0.0001
Percentage of Rural Population		1.0234 [1.0146; 1.0323]	0.0045	< 0.0001
AIC	82410.2106	82400.7027		
BIC	82454.8060	82478.7446		
Log Likelihood	−41201.1053	−41193.3514		
Num. obs.	513416	513416		
Num. groups: dept_code	18	18		
Var: dept_code (Intercept)	0.0592	0.0226		

CI Confidence intervals in brackets and Standard error (s.e)

Table 5 Comparative random effects between the null model and final model (Model 2)

Code	Department name	Abbreviation	Model 0	Model 2
01	ATLÁNTIDA	AT	0.0728	0.0283
02	COLÓN	CL	0.0996	0.0420
03	COMAYAGUA	CM	0.2727	0.2380
04	COPÁN	CP	0.4893	0.0986
05	CORTÉS	CR	0.1472	0.0446
06	CHOLUTECA	CH	0.1664	0.0533
07	EL PARAÍSO	EP	−0.4635	−0.2920
08	FRANCISCO MORAZÁN	FM	−0.0126	−0.0528
09	GRACIAS A DIOS	GD	−0.4655	−0.0861
10	INTIBUCÁ	IN	−0.1834	0.1525
11	ISLAS DE LA BAHÍA	IB	−0.4029	−0.0370
12	LA PAZ	LP	−0.5057	−0.0228
13	LEMPIRA	LM	0.2963	0.1493
14	OCOTEPEQUE	OC	−0.3540	−0.1934
15	OLANCHO	OL	0.3788	0.1139
16	SANTA BÁRBARA	SB	0.0676	−0.2498
17	VALLE	VL	0.2483	0.0871
18	YORO	YO	0.1840	−0.0528

proportion of rural population and low educational levels face greater vulnerability to the pandemic.

Strength and limitations

This study presents some limitations. First, the demographic data used are based on the 2013 census, which prior to the recording of COVID-19 cases. While this may be a limitation, no more recent data have been published by the Honduran government. We recognize that this is a common issue in ecological studies, where the data analyzed depend on official sources rather than the researchers themselves.

Regarding the data collection system, it is possible that not all cases of COVID-19 infection were captured, particularly in the early stages of the pandemic. This issue may have also occurred in other countries due to the rapid spread of the disease and the urgent actions required by health authorities. However, the overall case rates and COVID-19 mortality rates observed in this study are consistent with those reported by other countries, which makes our results comparable.

Another limitation is the potential presence of individual-level risk factors not included in this study, such as comorbidities. However, the adjustment of rates by age, which significantly influences COVID-19 mortality, helps minimize this limitation. Additionally, we lack contextual variables such as health system factors (number of

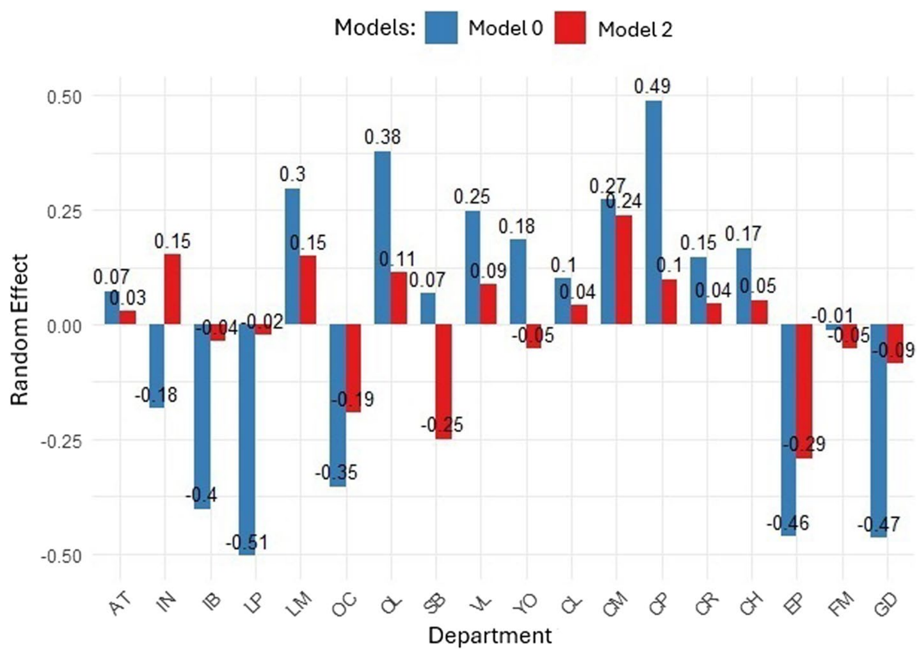


Fig. 5 Comparative graph of random effects by department between the null model and final model (Model 2)

doctors, hospitals, healthcare access) or other government measures (mobility, social contact, mask wearing). This hidden bias is common in observational studies, particularly when the data are analyzed retrospectively.

As a strength, it is worth noting that the databases used are very large in size, with a very low percentage of missing data, making them highly representative of the studied population.

Conclusions

- This study has allowed us to identify the variability of COVID-19 mortality in Honduras, highlighting the influence of sociodemographic factors. The disparities found underscore the need for targeted public health policies, to reduce inequalities and ensure equitable access to health services for the entire population.
- The application of multilevel logistic regression models is suitable for the study of pandemic diseases, contributing to the understanding of the variability in infections and outcomes, as well as exploring the underlying causes of this variability.

Abbreviations

GENYO	Center for Genomics and Oncological Research
SINAGER	National Risk Management System
ODU	Demographic Observatory of the National Autonomous University of Honduras
INE	National Institute of Statistics
WHO	World Health Organization
Pop. Size	Population Size
HDI	Human Development Index
GNI	Gross National Income
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
ICC	Intraclass correlation coefficient
PCV	Proportional change in variance
MOR	Median Odds Ratio
OR	Odds Ratio
CI	Confidence Interval
VIF	Variance Inflation Factor

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12939-025-02407-4.

Supplementary Material 1.

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Not applicable.

Patient and public involvement

Patients or the public were not involved in this study.

Authors' contributions

Escoto-Rodríguez V: Methodology, Software, Formal Analysis, Data Curation, Writting Original Draft, Visualization. Expósito-Ruiz M: Conceptualization, Methodology, Supervision, Review and Editing.

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Data availability
Data will be provided upon written request to the authors.

Declarations

Ethics approval and consent to participate
No ethical approval was needed.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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