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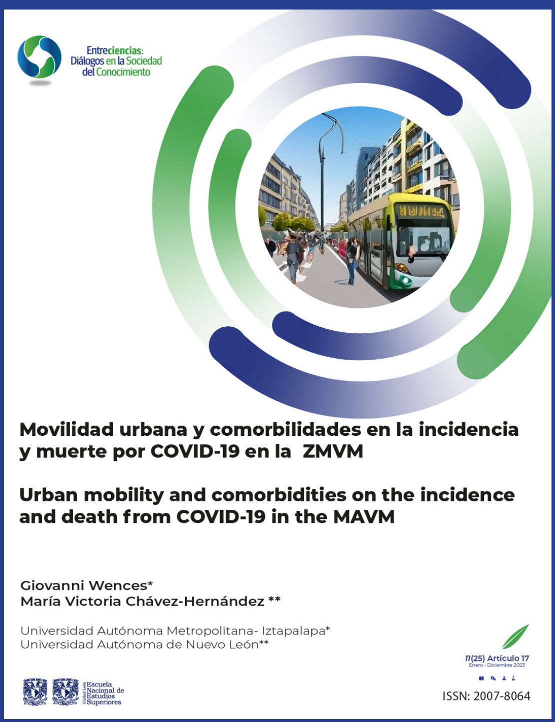


# Movilidad urbana y comorbilidades en la incidencia y muerte por COVID-19 en la ZMVM

# Urban mobility and comorbidities on the incidence and death from COVID-19 in the MAVM

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## Resumen

**Objetivo:** identificar y cuantificar, por una parte, el efecto de los modos de transporte en la tasa de contagios por COVID-19 y, por otra parte, el efecto de las comorbilidades en la tasa de muertes por COVID-19 en la Zona Metropolitana del Valle de México durante la primera ola de la pandemia del coronavirus.
**Diseño metodológico:** se ajustaron dos modelos de regresión lineal múltiple considerando como variables dependientes las tasas de incidencia y de mortalidad por COVID-19. Como variables explicativas se consideraron factores de transporte, demográficos y sanitarios. Se usó el número de arribos a un municipio utilizando cualquier medio de transporte para identificar el efecto de estos en la tasa de contagios de COVID-19 además de la prevalencia de atención a la salud para determinar las comorbilidades, incluidas en el modelo, que están más relacionadas con la tasa de muertes por COVID-19.
**Resultados:** a mayor número de viajes realizados en vehículos de transporte público pequeños, más significativamente aumenta la tasa de incidencia. Los viajes realizados caminando afectan negativamente a la tasa de incidencia de COVID-19. La prevalencia de diabetes y neumonía está altamente asociada con el aumento de muertes por COVID-19.
**Limitaciones de la investigación:** este estudio se realizó considerando un escenario hipotético donde las medidas de confinamiento no afectaron el número de viajes en la zona de estudio.
**Hallazgos:** los hombres tienen más probabilidad de infectarse que las mujeres. Las comorbilidades además de estar relacionadas con la mortalidad por COVID-19, también son factores de riesgo para contraer la enfermedad.


*Palabras clave: COVID-19, movilidad urbana, comorbilidades, incidencia, mortalidad.*


## Abstract

**Purpose:** To identify and quantify, on one hand, the effect of public transportation modes on the incidence rate of COVID-19 infections and, on the other hand, the comorbidities more related to the rate of COVID-19 deaths in the Metropolitan Area of the Valley of Mexico during the first wave of the coronavirus pandemic.
**Methodological design:** Two multi-linear regression models were fitted, considering the COVID-19 incidence rate and COVID-19 death rate as dependent variables. Transport, demographic, and healthcare variables were also considered as explanatory. The number of arrivals to a municipality using any mode of transportation was considered to identify the effect of public transportation modes on the incidence rate of COVID-19 infections, and the prevalence of healthcare was considered to determine which comorbidities (included in the model) are more related to the rate of COVID-19 deaths.
**Results:** The greater the number of trips made using small public transport vehicles, the more significantly the incidence rates increase. The number of trips done by walking negatively affects the incidence rate of COVID-19. The prevalence of diabetes and pneumonia is highly associated with increased COVID-19 deaths.
**Research limitations:** This study was carried out considering a hypothetical scenario where the containment measures did not affect the number of trips made in the study area due to the difficulty of obtaining updated data.
**Findings:** Men are more likely to be infected than women. Not only are the comorbidities related to mortality due to COVID-19, but they are also risk factors for contracting the disease.


*Keywords: COVID-19, urban mobility, comorbidities, incidence, mortality.*

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## INTRODUCTION

The SARS-CoV-2 coronavirus, which caused the COVID-19 disease and was originated in China in 2019, has dramatically impacted the world. It caused many infections and deaths.

During the first five months after the World Health Organization (WHO) declared the pandemic, Mexico became the fourth location with the most deaths caused by this coronavirus, at least during the first wave of infections. Mexico reported 79, 791 deaths up to 27 August 2020, and 592, 495 infected cases as of the same date (Worldometer, 2021). Mexico, like other countries, adopted non-pharmaceutical interventions (*e.g.*, social-distancing measures) to reduce the spread of the COVID-19 pandemic and its effects; that is why it is crucial to identify factors that increase the spread of the disease.

For the reasons mentioned above, it is unsurprising that since the start of the pandemic, many researchers have turned their attention to exploring the different risk factors for both the spread of the disease and its mortality rate.

In the absence of information regarding the impact of mobility on the spread of the disease, the risk of contagion remains only as a perception for individuals, causing them to avoid using some public transport modes or to ignore the recommendations by governments (Chen *et al.*, 2022). Hörcher, Singh and Graham (2022) affirm that mixed messages have been disseminated to travelers on the risk of infections and safety in public transport, so they discussed five potential approaches to social distancing in public transport and concluded that multiple demand management measures would have to be implemented simultaneously.

Motivated by the lack of research in terms of mobility and the spread of COVID-19, this paper explores the association of five modes of transportation as well as other poverty indicators with the incidence rate of COVID-19 in the Metropolitan Area of the Valley of Mexico (MAVM) within the period that includes the first wave of the outbreak. The purposes of this work are two. The first one is to identify and quantify the effect of public transportation modes on the incidence rate of COVID-19 infections in a hypothetic scenario where the trips using public transport were not affected. The second purpose is to identify and quantify the comorbidities that are more related to the death rate of COVID-19 in a zone of the Metropolitan Area of the Valley of Mexico during the first wave of the coronavirus pandemic.

In this paper two hypotheses were tested: if the number of arrivals to each zone, using any transit mode considered, is significantly associated with the incident rate of cases, and if the comorbidities are significantly associated with the rate of death caused by COVID-19.

This study is made on a borough level considering 26 municipalities of the State of Mexico and the 16 boroughs of Mexico City. A multi-linear regression model was used to analyze and quantify the effect of the control variables and data from the Health Ministry. The number of reported cases of infection and death due to COVID-19 was considered since the first case in Mexico City up to August 27, 2020.

It is important to emphasize that due to the shortage of mobility data corresponding to the study period, a hypothetical scenario was considered in which no containment measures would affect the number of trips made in the study area and then visualize the results that this situation would lead us to. Although the results obtained in this work should be interpreted under that consideration, this study could be relevant to gain experience and identify the factors that are most important in the COVID-19 incidence and have greater control in the future.

This article is organized as follows: first, the literature review is presented, where some studies that were carried out using data from different areas of Mexico were incorporated. Next, the methodology used in this research is described, indicating the sources of the data used and redefining the variables into consideration. After that, the two models proposed to investigate the relationship between variables through a functional form were introduced and the three assumptions of a linear regression in the two models studied were reviewed, namely, normality, homoscedasticity and non-autocorrelation of the errors. Then, the results obtained from the models are presented. After that, a discussion of the results is done, and some conclusions are made. Finally, this work is complemented with Appendix A, where local spatial clusters are shown using a bivariate local indicator spatial association analysis (LISA).

## LITERATURE REVIEW

Among the different available investigations on the identification of factors that impact COVID-19 incidence and deaths through the first wave of the coronavirus pandemic, the work of Sannigrahi *et al.* (2020) can be found, where spatial regression models (geographically weighted regression (GWR), spatial error model (SEM), spatial lag model (SLM), ordinary least square (OLS), partial least squares (PLS) and principal components regression (PCR) are used. There, the association between income, poverty, and total population, is analyzed with the number of people infected and the number of deaths due to COVID-19. There are 31 European regions considered as a study area with data up to 29 April 2020.

In Ehlert (2021) the association of socioeconomic, demographic, and health-related variables at the regional level with COVID-19-related cases and deaths in Germany through the first wave of the coronavirus pandemic is explored. A comparison of spatial auto-regressive SAR, SEM, and spatial auto-regressive combined (SAC) models is done there. Also, there are some explanatory variables considered like income, age, employment, population, gender, heart conditions, such as chronic obstructive pulmonary disease (COPD), and the number of people in healthcare.

In Stojkoski *et al.* (2020), 31 factors are included, such as employment, age, income, population, hospital beds, and international influence on social interactions to explain the outcome of the first wave of the coronavirus pandemic.

In other studies, like the one by Irawan *et al.* (2022), the relationship between different variables of travel behavior and individual characteristics is studied. The role of the behavior of humans in protecting themselves from contracting COVID-19 disease in Indonesia is particularly analyzed. A structural model is proposed, which was adjusted using SEM. It is shown that the more people perceive the severity of the disease, the more they try to reduce their activities outside the home. Table 1 summarizes the models and some variables considered in each study mentioned above.

**Table 1. Models and variables considered in the literature**

| Author | Sannigrahi *et al.* (2020) | Ehlert (2021) | Stojkoski *et al.* (2020) | Irwan *et al.* (2021) |
|---|---|---|---|---|
| Regression model | GWR, SEM, SLM, OLS, PLS and PCR | SAR, SEMand SAC | BMA | SEM |
| Variable | | | | |
| Income | X | X | X | X |
| Poverty | X | | | |
| Age | | X | X | X |
| Personal services | | X | | |
| Employment | | X | X | X |
| Population | X | X | X | |
| Gender | | X | | X |
| Hypertension | | X | | |
| COPD | | X | | |
| Physicians | | X | X | |
| Hospital beds | | X | X | |
| Daily trips | | | X | X |
| Region | 31 European Regions | 401 countries in Germany | 106 countries including Mexico | Indonesia |

Source: Author´s own elaboration.

### Literature in Mexico

The literature in Mexico on factors that increase COVID-19 deaths includes the study carried out by González *et al.* (2021), where the risk of death in the pediatric population infected with SARS-COV2 is investigated. It was found that the presence of comorbidities in babies is strongly associated with mortality caused by COVID-19. Another study that evaluates the risk factors associated with mortality in Mexican children with COVID-19 was carried out by Rivas *et al.* (2020), where it turns out that the development of pneumonia is the main risk factor for mortality. Table 2 summarizes the models and some variables considered in each study.

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**Table 2. Models and variables considered in the literature in Mexico**

| Author | González *et al.* (2021) | Rivas *et al.* (2020) | This work |
|---|---|---|---|
| Regression model | Logistic | Logistic | OLS |
| Variables | | | |
| Income | | | x |
| Poverty | | | x |
| Age | x | x | |
| Personal services | | | |
| Employment | | | |
| Population | | | x |
| Gender | x | x | x |
| Housing occupancy | | | x |
| Hypertension | x | x | x |
| Diabetes | x | x | x |
| Immunosuppression | x | x | |
| Obesity | x | x | |
| Chronicrenal/ kidney disease | x | x | |
| Asthma | | x | |
| COPD | | | |
| Tobacco use | | x | x |
| Physicians | | | |
| Hospital beds | | | |
| Pneumonia | | x | x |
| Daily trips | | | x |
| Region | Mexico City | Country of Mexico | MAVM |

Source: Author´s own elaboration.

In addition, in the literature of studies in Mexico on comorbidity factors and COVID-19 death rates, four diseases are explored to investigate their association with the rate of contagion and the rate of death due to COVID-19 in the MAVM.

Other studies in the literature also evaluate the incidence and mortality rates of COVID-19. For example, Phannajit *et al.* (2021) carried out a meta-analysis of data from 216 countries to estimate the global burden and the mortality rate. They explored different associated factors such as geographical variations, the economic situation of the country, health spending, and performance of medical care. Medeiros *et al.* (2021) studied the incidence and mortality rates in an ecological study that used epidemiological, demographic, environmental, and variables on the structure of health services. Studies such as those by Martínez-Martínez, Valenzuela-Moreno and Coutiño (2021), and Djaharuddin *et al.* (2021) only consider health variables and factors such as age and sex associated with the death rate. Others, like Valero *et al.* (2022), evaluate the influence of meteorological and geographical factors in Spain.

Although some of the studies mentioned above consider the interactions between personnel in charge and older adults and children, they do not evaluate the use of transportation in the incidence of COVID-19 cases, which seems to be an essential factor for the spread of pathogens. Recently, Prieto *et al.* (2022) incorporated the daily mobility of people in Mexico City into a partial differential equations model to forecast the spread of the coronavirus; their model uses Bayesian inference to estimate critical epidemiological characteristics associated with the coronavirus spread. Since the COVID-19 disease is transmitted by physical contact and aerosols, it is expected that contagion will occur inside transport vehicles and transit stations.

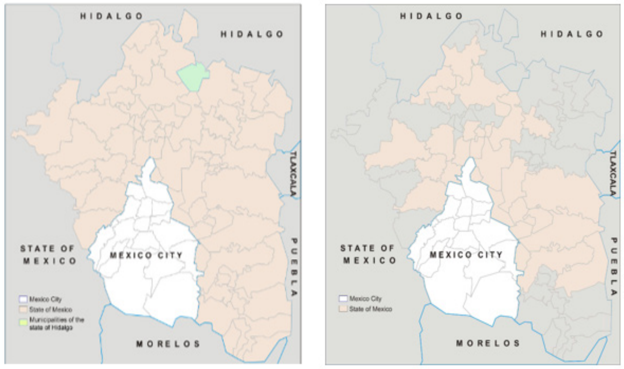
## MATERIALS AND METHODS

### Mobility in the area considered

This work was focused on the conurbation around Mexico City, known as the Metropolitan Area of the Valley of Mexico (MAVM), described by the National Population Council (CONAPO, 2015). It comprises the 16 boroughs of Mexico City, 59 municipalities of the State of Mexico, and one municipality of the state of Hidalgo. The MAVM is the most populated area in the country, it is home to more than 18 million inhabitants, and has the highest concentration of resources and national institutions. According to the National Institute of Statistic and Geography (Inegi), in 2020, around 21.8 million people lived in the MAVM in 7,866 km$^2$. It has many offices and an extensive transport network, with more than 20 different modes of transport.

Although the federal government made available a database regarding the COVID-19 disease during the first year of the pandemic, the database was incomplete or had some inconsistencies. Due to the unavailability of data for some explicative variables considered in our model, 34 municipalities were not considered in this study. Figure 1 (a) shows the MAVM; the remaining 42 boroughs considered can be seen in (b), 16 from Mexico City (in white) and 26 from the State of Mexico in (light orange).

**Figure 1. Area of study**




(a) Metropolitan Area of the Valley of Mexico. (b) Boroughs considered in this work.

Source: Author´s own elaboration.

The origin-destination movements in Mexico City are usually obtained every ten years from surveys; the last was carried out in 2017 (Inegi, 2017). According to this survey, in 2017, about 52.7 million trips were carried out in the MAVM on a weekday. During the first months of the pandemic, there was great interest by the Mexico City government in estimating the reduction in trips made in the city using some modes of transportation; however, it was not clear what the reference value was, and there was no information about all modes of transportation or the surrounding municipalities.

This paper considered the information obtained from the 2017 origin-destination survey carried out by the Inegi. Also, it is assumed that no significant changes were made until 2020. So, in this analysis, a hypothetical scenario is contemplated where the containment measures did not affect the number of trips. The number of weekly trips for each transport mode that originated in the MAVM and ended at each of the municipalities in the study area is used.

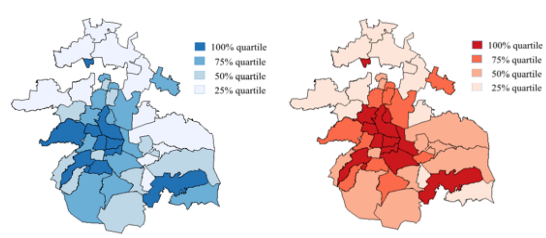
In the MAVM more than twenty different transport modes operate; however, using the selection method forward and backward stepwise, the final model includes collective/micro, bus, walk, taxi, and subway transit modes. Here, collective/micro refers to small public transport vehicles such as microbuses and other vehicles with a maximum capacity of 18 people.

### Dependent variables

The first case of COVID-19 in Mexico was reported on February 27, 2020; since then, the Health Ministry daily reported the number of infected people. Likewise, the reported cases were tracked at the municipality level nationwide. In this work, each municipality of the MAVM was considered as the observation unit; however, as mentioned before, because of the absence of data for some variables included in the model, 34 municipalities in the area were eliminated from the study, leading to 42 municipalities for the analysis. The study period for the number of people infected with COVID-19 comprehends from the first day of contagion in Mexico until August 22, 2020. The reported deaths due to the infection are considered from the first death in MAVM to August 22, 2020.

One of the proposed regression models contemplates the incidence rate as a dependent variable; it is the number of people infected with COVID-19 in the 42 municipalities mentioned above during the described period. This incidence rate is constructed by dividing the total number of people infected with COVID-19 (from February 27 to August 22, 2020) by the total population of each municipality, provided by the Inegi (2020b). Similarly, the other proposed regression model contemplates the rate of death caused by the disease, given by the number of deaths reported divided by the total population of each municipality. Figure 2 shows the spatial distribution of the incidence and death rates in the study area. In both cases, the high levels of infected and dead people are focused on the north of Mexico City and the south of the State of Mexico.

**Figure 2. COVID-19 incidence and death rates classified in quartiles**




(a) Incidence (b) Deaths

Source: Author´s own elaboration.

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### Explanatory variables

The model proposed in this paper for the incidence rate of COVID-19 considers the trips done by using collective/micro, bus, taxi, and subway, or by walking, which are the most commonly used transport modes in the study area. The variable for each mode of transport is defined as the number of trips that arrive on a weekday in the municipality using that mode of transportation. The data for these variables were obtained from the origin-destination survey of the MAVM (Inegi, 2017).

The socioeconomic and demographic explanatory variables considered in the model are population density, percentage of the male population, and percentage of the population over 45 years old in each municipality. In addition, the housing occupancy index and the social backwardness index are also considered. These data were collected from the platform of the Inegi (2020b). The housing occupancy index gives us an idea of how many people live in the same dwelling house; it is computed by dividing the total number of dwellings by the total population for each municipality. The social backwardness index incorporates education indicators, access to health services, essential services, and quality and space in the home; it is a weighted measure that summarizes four indicators of social deprivation. The data were obtained from the National Council for evaluating the social development policy (Coneval, 2020).

Another variable incorporated into the proposed models is the percentage of the population of the observed municipality that receives less than twice the minimum wage. The most updated data was obtained from the inter-census in 2015 (Inegi, 2015). Also, healthcare-related variables for the following diseases were contemplated: pneumonia, diabetes, hypertension, and smoking. For each condition, the variable was defined as the prevalence rate for each municipality in the study area.

For both models, the COVID-19 incidence rate and COVID-19 death rate, the same explanatory variables were examined, except for those related to transportation modes, which were not contemplated in the model of the COVID-19 death rate. Next, the transportation, demographic, and health-related variables considered in the proposed models for each municipality are listed.

Dependent variable for each model:

$I_r$ : Incidence rate.

$D_r$ : Death rate.

Explanatory variables:

$t_{cm}$: The number of arrivals made using collective/micro.

$t_b$: The number of arrivals made using bus.

$t_w$: The number of arrivals made walking.

$t_x$: The number of arrivals made using taxi.

$t_s$: The number of arrivals made using subway.

$p_d$: Population density.

$p_m$: Percentage of the male population.

$p_{45}$: Percentage of the over 45 years old population.

Table 3 shows an overview of the data. In the first column the name of the variable is shown; from the second to the fifth column the mean, the standard deviation, the minimum value, and the maximum value of the data are shown respectively.

**Table 3. Descriptive statistics of the variables**

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| $I_r$ | 1.3975 | 0.491 | 0.7021 | 2.6978 |
| $D_r$ | 0.0009 | 0.0003 | 0.0004227 | 0.0018681 |
| $t_{cm}$ | 290471 | 258570.9 | 14247 | 1271612 |
| $t_b$ | 16155.36 | 16155 | 354 | 57829 |
| $t_w$ | 551289.40 | 551289 | 32833 | 2417808 |
| $t_x$ | 31777.19 | 31777 | 292 | 137771 |
| $t_s$ | 93774.40 | 93774 | 105 | 724095 |
| $p_d$ | 6677.6 | 5394.926 | 302.9 | 17522.7 |
| $p_m$ | 48.04 | 0.791117 | 45.85 | 49.38 |
| $p_{45}$ | 27.48 | 5.711542 | 16.03 | 39.33 |
| $p_{dw}$ | 0.2834 | 0.031 | 0.2413 | 0.4055 |
| $p_b$ | -1.1886 | 0.1938797 | -1.5501 | -0.8062 |
| $p_w$ | 57.79 | 6.555822 | 47.19 | 77.76 |
| $h_p$ | 0.001429 | 0.000519 | 0.000557 | 0.003104 |
| $h_a$ | 0.000621 | 0.000249 | 0.000263 | 0.0013 |
| $h_t$ | 2.07e-04 | 8.97e-05 | 6.13e-05 | 4.67e-04 |
| $h_d$ | 0.000561 | 0.000206 | 0.000212 | 0.001122 |

Source: Author´s own elaboration.

## THE MATHEMATICAL MODEL

In the regression analysis, the relationship between variables through a functional form is investigated. This relationship is approximated by a model of the form:

$$Y = f(X_1, X_2, \ldots, X_p) + \varepsilon,$$

where $Y$ is the dependent variable (output), $X_0, X_1, \ldots, X_n$ are the independent variables (explanatory), and ε is a random error representing the discrepancy in the approximation. Next, an example of a functional form is shown:

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon,$$

where $\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients/parameters to be estimated from data. The estimation allows evaluation of the importance of each explanatory variable by knowing its effects on the dependent variable when changes are present. The most used method to estimate these parameters in regression analysis is the ordinary least squares (OLS) method, which, under specific hypotheses, produces estimates with desirable properties. Other superior methods are used when any of those hypotheses are not met. An important issue in regression analysis is to specify the functional form that will relate the response variable to the set of explanatory variables. Functional forms can be linear in the parameters, which, in turn, can be classified as linear or non-linear in the variables.

In this work, simple functional forms for the models were proposed. That allowed us to interpret the estimated coefficients without significant difficulties. The method used to estimate the parameters in each proposed model is ordinary least squares.

### Incidence rate model for COVID-19 infected people

The incidence rate of infected people is modeled by using a multilinear regression with some explanatory variables log transformed. Model (1) was obtained after adjusting well-known functional forms such as linear, log-linear, and log-log, among others.

$$\begin{aligned} \ln(I_r) = {} & \beta_0 + \beta_p d_w \ln(p_{dw}) + \beta_{p_b} p_b + \beta_{p_d} \ln(p_d) + \beta_{p_w} p_w + \beta_{p_m} p_m + \\ & \beta_{p_{45}} p_{45} + \beta_{t_{cm}} \ln(t_{cm}) + \beta_{t_b} \ln(t_b) + \beta_{t_w} \ln(t_w) + \beta_{t_x} t_x + \\ & \beta_{t_s} t_s + \beta_{h_p} \ln(h_p) + \beta_{h_a} \ln(h_a) + \beta_{h_t} \ln(h_t) + \beta_{h_d} h_d \end{aligned} \tag{1}$$

Model (1) was fitted using OLS, and then the multicollinearity of the variables was investigated. For this, the variance inflation factor (VIF) of each explanatory variable was calculated and then compared with the global VIF of the fitted model. The VIF more significant values than the global VIF imply that the relationship between the explanatory variables was more significant than between the response and the predictors, indicating multicollinearity. Some variables resulted in a VIF more significant than the global VIF in the adjustment. In addition, the tolerance coefficient was calculated for each variable, and those whose tolerance coefficient was greater than or equal to 0.1 were eliminated from the

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model. The step() function of the R package was used to find the best model based on the Akaike Information Criterion using the stepwise forward regression approach to overcome the multicollinearity problem. The fitted model with selected variables is the following:

$$\ln(I_r) = \beta_0 + \beta_{p_m} p_m + \beta_{p_d} \ln(p_d) + \beta_{t_{cm}} \ln(t_{cm}) + \beta_{t_b} \ln(t_b) + \beta_{t_w} \ln(t_w) + \beta_{h_p} \ln(h_p) + \beta_{h_a} \ln(h_a) + \beta_{h_t} \ln(h_t) \tag{2}$$

**Death rate model due to COVID-19**

Analogously to model (1), for the relationship between the rate of deaths due to COVID-19 and the health and demographic variables, the next model was proposed:

$$\ln(D_r) = \delta_0 + \delta_{p_{dw}} \ln(p_{dw}) + \delta_{p_b} p_b + \delta_{p_d} \ln(p_d) + \delta_{p_w} p_w + \delta_{p_m} p_m + \delta_{p_{45}} p_{45} + \delta_{h_p} \ln(h_p) + \delta_{h_a} \ln(h_a) + \delta_{h_t} \ln(h_t) + \delta_{h_d} \ln(h_d) \tag{3}$$

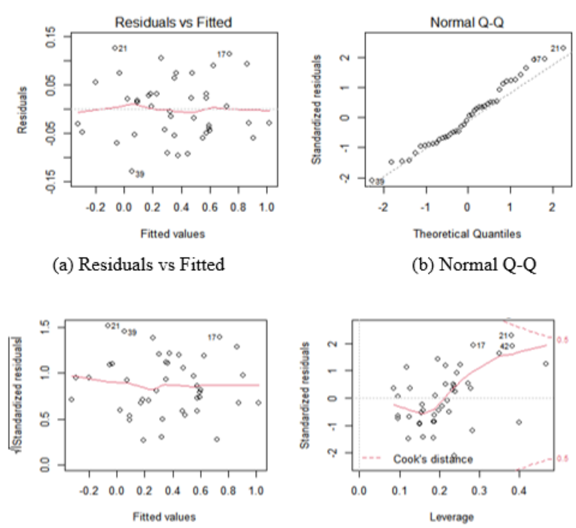
A regression analysis to model (3) was also performed, similarly to what was done with model (1). Using the VIF and the tolerance criteria to investigate the multicollinearity and the stepwise forward regression approach, the resulting model is the following:

$$\ln(D_r) = \delta_0 + \delta_{p_{dw}} \ln(p_{dw}) + \delta_{p_d} \ln(p_d) + \delta_{p_w} p_w + \delta_{h_p} \ln(h_p) + \delta_{h_d} \ln(h_d) \tag{4}$$

**Analysis of linear regression assumptions**

The three assumptions of a linear regression in the two models studied were reviewed, namely, normality, homoscedasticity, and non-autocorrelation of the errors (Rao, 2009). First, it was verified that model (2) does not present multicollinearity problems obtaining a coefficient of determination of 0.9532. The F-value is 108.6 with p-value lower than 2.2e-16. The hypotheses under which the linear regression model is governed using OLS were also verified. Through the Breusch-Pagan test (Kennedy, 2003), no evidence of heteroscedasticity was found at a confidence level of 99.9% and the value of the Breusch-Pagan statistic equal to BP=5.2889. The normality of the errors was verified using the Shapiro-Wilk test (Kennedy, 2003) at a confidence level of 99.9% and with the value W=0.97681 for the Shapiro-Wilk statistic. Finally, no evidence of error correlation was found using the Durbin-Watson test at a confidence level of 99.9% and the Durbin Watson statistic equal to DW = 1.7187 (Chaterjee and Hadi, 2012). The results were visually corroborated by Figure 3.

**Figure 3. Graphic diagnosis for model (2)**



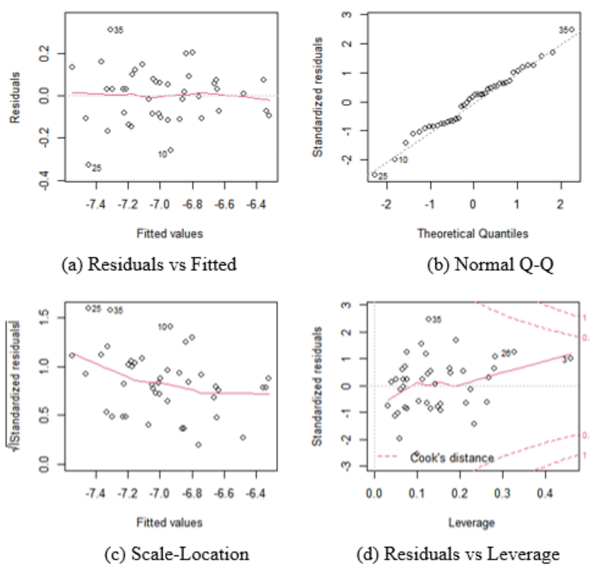

(a) Residuals vs Fitted (b) Normal Q-Q

(c) Scale-Location (d) Residuals vs Leverage

Source: Author´s own elaboration.

For model (4), $R^2$= 0.8544 and the F-value =42.26 with p-value < 4.39e-14 were obtained. Through the Breusch-Pagan test, no evidence of heteroscedasticity was found at a confidence level of 99.9% and the value of the Breusch-Pagan statistic equal to BP=6.1759. The normality of the errors was verified using the Shapiro-Wilk test at a confidence level of 99.9% and with the value W=0.98452 for the Shapiro-Wilk statistic. Finally, no evidence of error correlation was found using the Durbin-Watson test at a confidence level of 99.9% and the Durbin Watson statistic equal to DW = 2.0388. The results were visually corroborated by Figure 4.

**Figure 4. Graphic diagnosis for model (4)**




Source: Author´s own elaboration.

## RESULTS

With the methodology described above, the results were interpreted and the effect of the significant explanatory variables in the incidence of COVID-19 was inferred.

Table 4 shows the coefficients estimated by OLS. There can be seen for the three considered modes of transport in the model (2): the $\ln(t_{cm})$ has a positive coefficient, indicating that the greater the number of trips made using collective/micro, the greater the increase in the incidence rates. More precisely, its coefficient, $\beta_{t_{cm}} = 0.14560$, indicates that for every 1% of increase in $t_{cm}$, the incidence rate, $I_r$, increases by 0.14560%. $\ln(t_b)$ also has a positive sign and its coefficient, $\beta_{t_b} = 0.03485$, indicates that for every 1% of increase in the number of trips made using a bus $t_b$, the incidence rate, $I_r$, increases 0.03485%. In addition, $\ln(t_w)$, had a negative coefficient, which means that the number of trips done by walking negatively affects the incidence rates of COVID-19, that is, its coefficient, $\beta_{t_w} = -0.22369$, indicates that for every 1% increase in $t_w$, the incidence rate decreases by 0.22369%. The transport mode collective/micro has the highest effect on the $I_r$ for the transport mode-related variables since it has the biggest coefficient. The variable $p_m$ was significant with a positive coefficient, indicating that the higher the percentage of the male population in the municipality, the higher level of incidence rate was observed. Its coefficient, $\beta_{p_m}$=0.09683, indicates that for each unit increase in *Pm* the incidence rate, $I_r$, increases by 9.683%. The variable $\ln(p_d)$ was significant with a positive coefficient $\beta_{p_d}$=0.04170, which indicates that the higher the population density, the higher the incidence rate of COVID-19, and for every 1% increase in $p_d$, the incidence rate, $I_r$, increases 0.04170%.

**Table 4. Coefficients estimated to model the incidence rate (2)**

| Variable | Coefficient | Std. Error |
|---|---|---|
| Intercept | 4.02637*** | 1.05559 |
| $\mathbf{P_m}$ | 0.09683*** | 0.01854 |
| $\ln(p_d)$ | 0.04170* | 0.01592 |
| $\ln(t_{cm})$ | 0.14560** | 0.04773 |
| $\ln(t_b)$ | 0.03485* | 0.02000 |
| $\ln(t_w)$ | −0.22369*** | 0.05361 |
| $\ln(h_p)$ | 0.51038*** | 0.05510 |
| $\ln(h_a)$ | 0.26514*** | 0.07081 |
| $\ln(h_t)$ | 0.19527** | 0.06378 |
| $R_a^2 = .9545$ | | |

Source: Author´s own elaboration.

Note: OLS estimators are used. ***,**,* indicate significant at .1, 1, and 5 level, respectively.

Regarding the three comorbidity variables considered, all significantly positively affect the incidence rate $I_r$. The coefficient $\beta_{h_p}$=0.51038 indicates that, for every 1% increase in $h_p$, the incidence rate increases by 0.51038%. The variable $\ln(h_a)$ has a coefficient $\beta_{h_a}$=0.26514, which indicates that for every 1% increase in $h_a$, the variable $I_r$ increases 0.26514%. For the variable $\ln(h_t)$, its coefficient $\beta_{h_t}$=0.19527, indicates that for every 1% increase in $h_t$, there is an increase of 0.19527% in $I_r$. It can be observed that the effect of the prevalence of pneumonia on the incidence rate of COVID-19 is greater than the effect of the prevalence of hypertension, and this in turn has a greater effect than the prevalence of smoking.

As well as model (2), model (4) does not present multicollinearity problems. In addition, homoscedasticity,

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non-autocorrelation, and normality were investigated and verified using the same tests used for the model (2). This allows us to make inference and quantify the effects of significant independent variables on the dependent variable. With model (4), it is proven that the comorbidity variables, $\ln(h_p)$ and $\ln(h_d)$ are significantly associated with the COVID-19 death rate.

Table 5 shows the estimated coefficients by OLS for model (4); also in this case, all the variables are significant. The coefficient of $\ln(h_p)$, $\delta_{h_p}$=0.28116, indicates that for every 1% increase in pneumonia prevalence rate, $h_p$, the death rate, $D_r$, increases by 0.28116%. While the coefficient of the variable $h_d$, $\delta_{h_d}$=1034.71408, indicates that for each unit increase in diabetes prevalence rate, $h_d$, the rate of deaths due to COVID-19 disease increases by 103471.08%. Regarding the variable $\ln(p_{dw})$, its coefficient $\delta_{p_{dw}}$=−1.26979, indicates that for a 1% increase in $p_{dw}$, the variable $D_r$ decreases 1.26979%. The population density variable with a coefficient $\delta_{p_d}$ =0.05472, indicating that for every 1% of increase in population density, there is an increase of 0.05472% in the rate of deaths due to COVID-19 disease. Also, it can be seen that $p_w$ is significant and its coefficient $\delta_{p_w}$ =0.01460 indicates that for every unit of increase in the percentage of the population that earns less than twice the minimum wage, the rate of death due to COVID-19 disease increases by 1.460%.

**Table 5. Coefficients estimated to model the death rate (4)**

| Variable | Coefficient | Std. Error |
|---|---|---|
| Intercept | −8.60908*** | 1.13499 |
| $\ln(p_{dw})$ | −1.26979** | 0.35781 |
| $\ln(p_d)$ | 0.05472* | 0.02431 |
| $p_w$ | 0.01460** | 0.00517 |
| $\ln(h_p)$ | 0.28116* | 0.10594 |
| $h_d$ | 1034.71408** | 1.96586 |
| $R_a^2$ =.8342 | | |

Source: Author´s own elaboration.

Note: OLS estimators are used. ******,****,* indicate significant at .1, 1, and 5 level, respectively.

## DISCUSSION AND CONCLUSIONS

This paper examined both associations of transport variables with the incidence rate of COVID-19 and the comorbidity variables with the COVID-19 death rate. The two studies were carried out during the first wave of infections. The hypotheses were tested using mathematical models with log-transformed variables. It was found that the number of trips to the municipalities using some modes of transport is significantly associated with COVID-19 incidence rates, and some comorbidities are significantly associated with COVID-19 deaths. The signs of the significant variable coefficients in both models resulted as expected.

It is important to highlight that the magnitude of the transport variable coefficients is consistent with reality. For example, the fact that the variable related to the collective/micro transport mode will result in a higher coefficient than the coefficient of the variable $t_b$ could be explained by saying that the public transport vehicles corresponding to the collective/micro mode have no control over their capacity because people can travel very close to each other and stand for long periods, so the social distancing is almost impossible in them; contrary to the bus mode of transport, where all passengers are assigned to a seat. The problem with the bus mode of transportation is that they have no natural ventilation, making it easy for the pathogen to spread. We also find a negative coefficient for the transport variable related to the trips made by walking $t_w$, which is also consistent with reality since it allows social distancing and natural ventilation, so this mode of transport contributes to the reduction in the incidence rate of COVID-19. Comparing the effects of the transport variables quantitatively, it turns out that the impact of the variable related to the trips made by walking is more significant than the other variables related to collective/micro and bus transport modes.

Regarding the comorbidity variables, to our knowledge, it is a novel finding that not only the comorbidities are related to mortality due to COVID-19, but they are also risk factors for contracting the disease. This may be because people with these types of diseases go to hospitals more frequently; therefore, they have greater exposure to people infected with COVID-19. It has been shown that more men than women are dying (of COVID-19), potentially due to sex-based immunological or gendered differences, such as patterns and prevalence of smoking (Wenham *et al.*, 2020), here our estimation on the coefficient of the variable $p_m$ suggests that men are more likely to be infected than women.

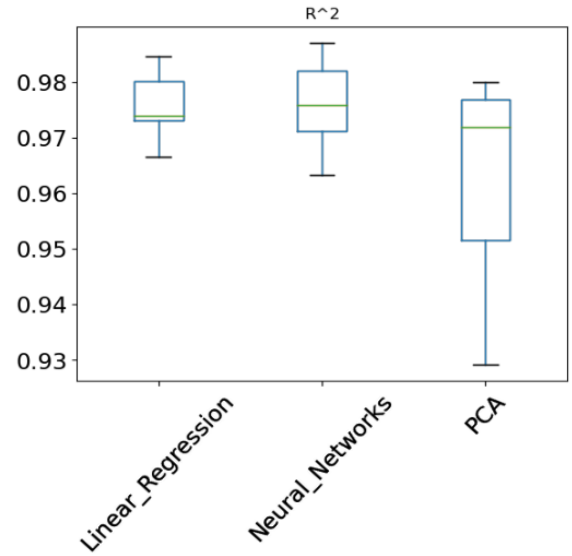
Ejaz *et al.* (2020) showed that comorbidities lead the COVID-19 patient into a vicious infectious cycle of life and are substantially associated with significant morbidity and mortality; thus, our findings on the association of comorbidities with the increase in the rate of COVID deaths are consistent with the studies carried out. Also, in Gasmi *et al.* (2021), it is shown that comorbidities contribute to the prognosis of acute disease and the increased risk of severe symptoms, where it is observed that 70% of the patients in intensive care have comorbidities. In our study, it is shown that the prevalence variables of diabetes and pneumonia are associated with the increase in the rate of COVID-19 deaths, the rest of the comorbidities do not appear in the model since they present multicollinearity.

With respect to the home occupancy rate variable, it is consistent with reality since the lower the saturation in dwelling homes, the less probability of contagion is expected, and therefore, it could imply less mortality.

Two machine learning models were also fitted to justify the models presented in this paper. The models based on ordinary least squares (OLS) were compared to neuronal network regression and principal component regression (PCA) models. The coefficient of determination $R^2$ was used as a performance measure. It can be consulted at Hernández and Wences (2023) for a more detailed explanation of the comparison analysis used here.

Concerning model (2), for each machine learning algorithm, 10, 30, 50, 100, 300, 500 and 1000 iterations were performed. In Figure 5, the box plot for the performance measure is shown.

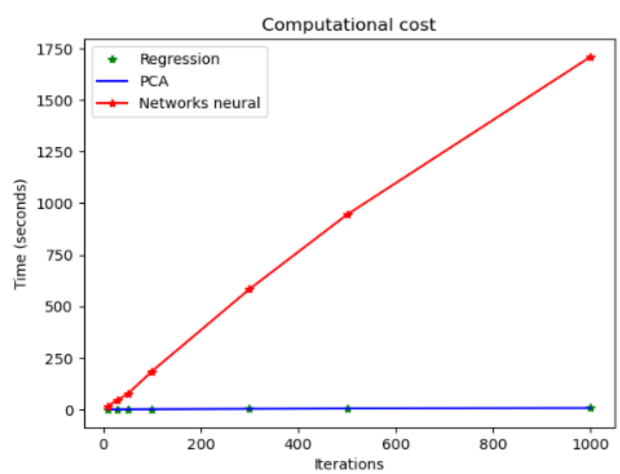
**Figure 5. Box Diagram for the $R^2$ in the models of incidence rate**




Source: Author´s own elaboration.

It can be observed that the models are equivalent with respect to the performance measure since the whiskers in the box plot intersect each other. Figure 6 presents the graphs of the times, as a function of the number of iterations, for each model. The graphs for principal component regression (PCA) and OLS regressions overlap, and the computational cost is considerably cheaper for PCA and OLS than for neuronal network regression.

**Figure 6. Computational cost for each model in incidence rate**




Source: Author´s own elaboration.

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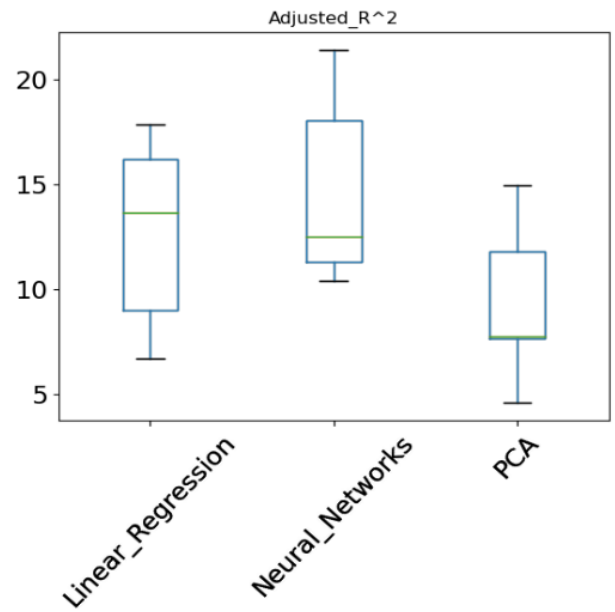
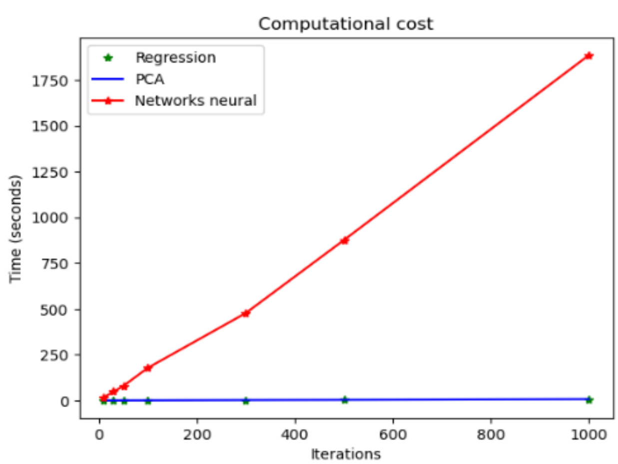
For model (4), it is also proven that the two machine learning models, neuronal network regression and principal component regression, are equivalent to model (4), see Figure 7. Figure 8 shows the computational cost for the three models. The results are similar to the previous case.

**Figure 7. Box Diagram for the $R^2$ in the models of death rate**




Source: Author´s own elaboration.

**Figure 8. Computational cost for each model in death rate**




Source: Author´s own elaboration.

Let us recall that this study was carried out considering a hypothetical scenario where the containment measures did not affect the number of trips made in the study area due to the difficulty of obtaining updated data. Although this could be a limitation in our research, the importance of this analysis is to assess the effects that would have occurred if mobility in the MAVM would not had been restricted. Also, let us notice that, according to Prieto *et al.* (2022), the mobility trends were similar for all the transit modes considered in this work. So, it may be expected that if current data were available, the study could be repeated, and the results may be proportional to the observed data.

Despite the limitations of this work, the models presented had a good fit with high determination coefficients. They fulfilled the multilinear regression hypotheses, which allowed us to perform statistical inference since the ordinary least squares estimators are of minimum variance in the whole class of unbiased estimators. So, through models, which could be considered simple, the change in the incidence and death rates of COVID-19 in the study area has been explained. Future work that could be carried out with available data would be to consider variables related to environmental factors in a model and explain the indirect impact on incidence and death rates.

This study is complemented by Appendix A, where local spatial associations between the COVID-19 incidence/mortality rate variables are shown. Each variable was found to be significant in the proposed models by computing the bivariate local Moran's I value. It is worth mentioning that, in this work, we use the I Moran test to determine the spatial autocorrelation, generating the matrix of spatial weights using the Queen criterion. Geographically speaking, two municipalities are neighbors if they share a point on their borders; however, the test returned a p-value beyond 0.01. This means that the hypothesis of non-autocorrelation of errors is not rejected, so we did not find enough evidence of spatial autocorrelation. Other criteria could be sought for future work to build the weight matrix and investigate spatial autocorrelation. For example, in Naveen and Gurtoo (2022), passenger clusters are considered based on their travel dynamics to guide those responsible for transport planning to provide a more efficient service, in the presence of COVID-19, rather than control access.

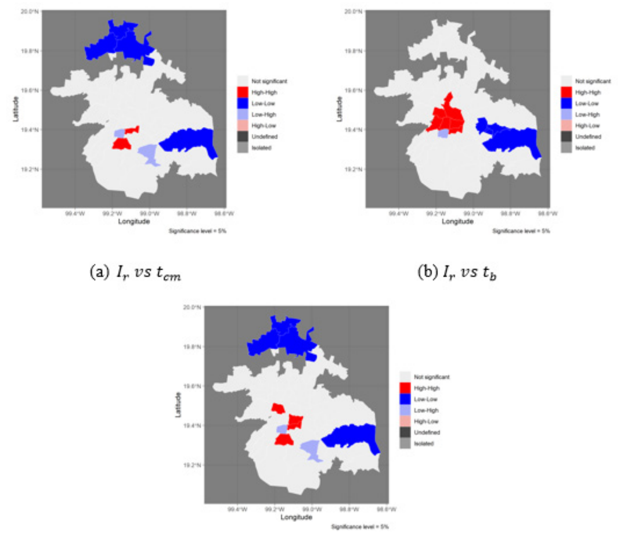
In Iacus *et al.* (2021), they define the concept of Mobility Functional Areas as the geographic zones highly interconnected according to the analysis of mobile positioning data and affirm that they can be used to inform local transportation, spatial planning, and health and economic policies.

## APPENDIX A LOCAL SPATIAL ASSOCIATIONS

In this appendix, local spatial associations between variables COVID-19 incidence/death rate are shown; each of the variables found to be significant in the proposed models by computing the bivariate local Moran's I value, also known as Local Indicators of Spatial Association (LISA; Anselin, 1995). These associations are shown through LISA cluster maps that reveal local spatial clusters that are valuable tools to answer critical questions, for example, where these groups can be found or what they look like. Next, the clusters obtained through the bivariate LISA for the $I_r$ and $D_r$ variables with each significant variable are shown, considering a 5% significance level.

Figure 9 shows the clustering for $I_r$ and the transport-related variables. It can be seen that the municipalities conforming a high–high cluster are located near the center of Mexico City. Meanwhile, the municipalities conforming a low–low cluster are located in the periphery, and the municipalities conforming a low–high cluster are located somewhere close to the high-high cluster. A significant spatial relationship between the rest of the municipalities was not found. Here, a high(low)–high(low) cluster means that if the number of trips made by using a transport mode increases (decreases), then the number of COVID-19-infected people increases (decreases). Notice that a cluster high-low was not found, which could indicate the increase in the number of trips is not related to the reduction in the incidence rate.

**Figure 9. Map clusters of incidence rate of COVID-19 versus the explanatory variables related to transport modes using the LISA bivariate method**

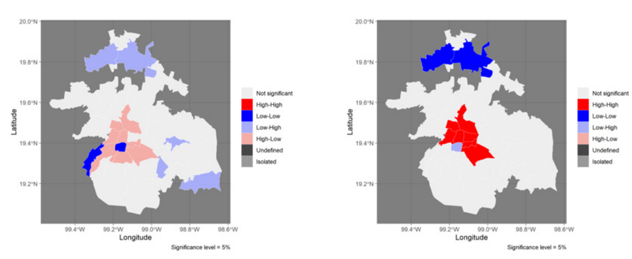


(a) $I_r$ *vs* $t_{cm}$ (b) $I_r$ *vs* $t_b$ (c) $I_r$ *vs* $t_w$

Source: Author´s own elaboration.

Figure 10 shows the clustering for $I_r$ and the demographic variables. Figure 10 (a) shows the presence of high(low)-low(high) clusters indicating that, in those areas, the incidence rate decreases (increases) while the male population increases (decreases). Meanwhile, Figure 10 (b) shows that the incidence rate increases/decreases as well as the density of the population.

**Figure 10. Map clusters of the incidence rate of COVID-19 versus the demographic explanatory variables using the LISA bivariate method**



(a) $I_r$ *vs* $p_m$ (b) $I_r$ *vs* $p_d$

Source: Author´s own elaboration.

Figure 11 shows the clustering for $I_r$ versus the health-related variables. It can be seen that the clustered mu-

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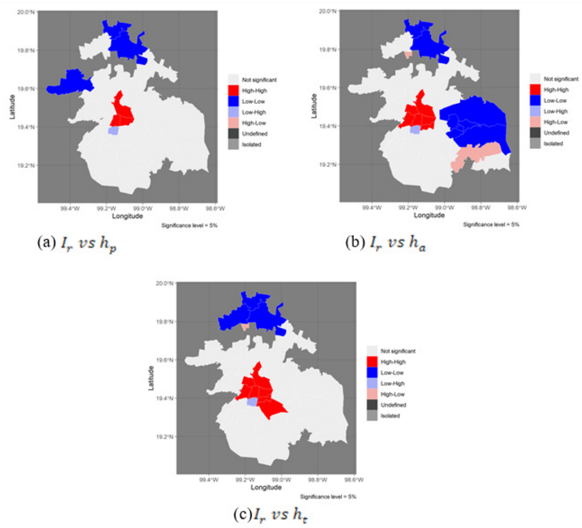
nicipalities conforming a high–high cluster are located near the center of Mexico City. Meanwhile, the low-low cluster is located in the periphery. This could indicate that the greater the population with comorbidities, the larger the prevalence of COVID-19.

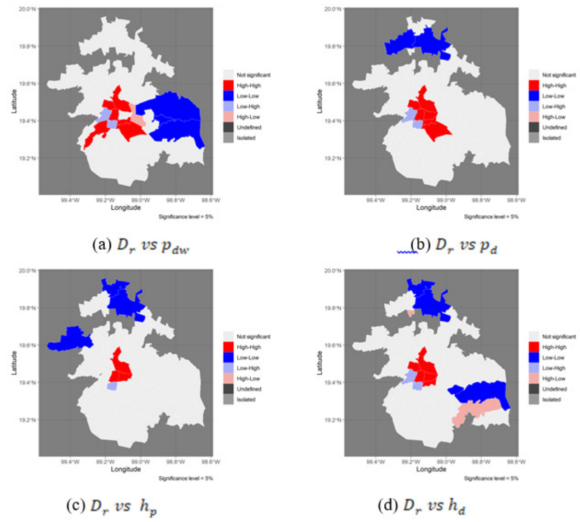
**Figure 11. Map clusters of the incidence rate of COVID-19 versus the health-related explanatory variables using the LISA bivariate method**




Source: Author´s own elaboration.

Figure 12 shows the clustering for $D_r$ versus the demographic and health-related variables. The municipalities conforming a high–high cluster are also located near the center of Mexico City, and the low-low clusters are located in the periphery. Observe that the death rate mostly increases (decreases) with the increase (decrease) of the dwelling occupancy rate (a), population density (b), and the prevalence of pneumonia (c) and diabetes (d).

**Figure 12. Map clusters of the death rate of COVID-19 versus the demographic, (a) and (b), and health-related, (c) and (d), explanatory variables using the LISA bivariate method**




Source: Author´s own elaboration.

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