Social vulnerability and COVID-19 in Maringá, Brazil

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Abstract
This research explores the relationship between COVID-19 and social vulnerability on an intra-urban scale. For this, two composite indicators of social vulnerability have been constructed. The composite indicator constructed by the Benefit-of-the-Doubt considers spatial heterogeneity. It weakly captures the conceptually most significant individual indicator of social vulnerability ($R=-0.39$), as it overestimates the above-average performance sub-indicators. The composite indicator constructed by the Principal Component Analysis considers that the sub-indicators have the same weights in different census tracts, resulting in a highly consistent composite indicator as a multidimensional phenomenon concept ($R=-0.93$).

These findings allow reaching four conclusions. First, the direction and strength of correlations associated with COVID-19 are sensitive to the method employed to construct the composite indicator and not just the geographic scale and space. Second, Medium and High social vulnerability census tracts concentrate 97% of the population but only 93% of COVID-19 cases and deaths. Third, people living in census tracts of None and Low social vulnerability are 3.87 and 2.13 times more likely to be infected or die from COVID-19. Fourth, policies to combat COVID-19 in the study area should prioritize older populations regardless of their social conditions.

Keywords Social Vulnerability · Composite Indicators · COVID-19 · Principal Component Analysis · Benefit-of-the-Doubt

1 Introduction
Studies worldwide show that the relationship between COVID-19 and social indicators depends on space and geographic scale [1]. Richer countries offer better living conditions for the population, increasing the population’s average age and the chances of death from COVID-19 [2–5]. On the national scale, researchers show that the number of cases and deaths from COVID-19 is correlated with income inequality [6] and social vulnerability [7–9] at the...
same time that COVID-19 cases positively correlate with the Gross Domestic Product per capita [10]. In cities in Algeria, Colombia, and the United States, the most socially vulnerable and poor areas have a higher number of cases of COVID-19 [11–13]. Therefore, the relationship between COVID-19 and social indicators must consider the specifics of each space and geographic scale. Ignoring the specifics of each space and geographic scale can result in misguided and inefficient public policies to combat COVID-19.

Several studies explore the relationship between social indicators and COVID-19 at Brazil’s municipal, state, and intraurban scales. At the state scale, studies positively correlate the percentage of poor people with deaths from COVID-19 [14] and social vulnerability with COVID-19 cases [15]. At the municipal scale, Souza, Machado et al. [16] show a positive correlation between COVID-19 and social deprivation. Baggio et al. [17] show that the number of cases of COVID-19 is higher in municipalities with better human development, education, and income. At the same time, the authors reveal that cases of COVID-19 occur in areas of social vulnerability. Souza, Carmo et al. [18] show that cases and deaths caused by COVID-19 are higher in cities with very high social vulnerability. At the same time, the authors bring evidence that cases and deaths from COVID-19 are even higher in cities classified as low, medium, and high social vulnerability. Viezzer and Biondi [19] conclude that socioeconomic and environmental aspects are not strong predictors to explain the cases of COVID-19 in cities. Kong et al. [20] show that social and demographic differences influence countries’ vulnerability to COVID-19 differently. Castro et al. [21] show that correlations between cases of COVID-19 and the human development index in Brazil are space-dependent. At the intraurban scale, Souza et al. [22] show that cases of COVID-19 are negatively correlated with income and positively correlated with the population over 60 years of age. Souza et al. [23] show that COVID-19 cases are positively correlated with the proportion of the elderly population and negatively correlated with income and education.

These studies provide supportive information for elaborating public policies to combat COVID-19. However, studies that relate social indicators and COVID-19 at the intraurban scale have limitations. First, the strength and direction of correlations vary with the indicator, yielding conflicting results. Second, the simultaneous analysis of many indicators is complex, making it difficult to understand the problem. These limitations reflect the individualized analysis of social sub-indicators on the intra-urban scale. This individualized analysis occurs because multidimensional social indicators such as the Human Development Index, the Stringency index, and the Global Multidimensional Poverty Index are unavailable on the intra-urban scale.

This research aims to overcome these limitations to carry out a simplified and complete analysis of the relationship between COVID-19 and social indicators in a Brazilian city. For this, the research uses the operational framework of composite indicators to synthesize the multiple sub-indicators of multidimensional social phenomena such as poverty, inequality, and vulnerability in a one-dimensional measure. Composite indicators are one-dimensional measures, constituted by many sub-indicators, of phenomena with a multidimensional nature that become a valuable tool and are used in practically all fields of knowledge [24–26]. Different methods can be used to build composite indicators, but the operational structure of these methods is similar and always involves scale normalization, weighting, and aggregation of sub-indicators [27]. Although no method is exempt from criticism, the current literature offers several solutions to problems inherent to the operational framework of composite indicators [28]. Robustness and sensitivity analyses are internal validations that verify how much the scores and rankings of the observations vary when the normalized weighting and aggregating of the sub-indicators are changed [29]. Links with other variables allow measuring how much the composite indicator captures the most conceptually important variable in the multidimensional phenomenon [30, 31].

This research carries out this last analysis to define which of the two most popular methods of constructing composite indicators offers the best representation of social vulnerability. In particular, the Principal Component Analysis (PCA) and the Benefit-of-the-Doubt (BoD) methods are analyzed. Then, these composite indicators are related to the number of COVID-19 cases and deaths in urban areas of a Brazilian city.

The structure of this research is organized into four sections: introduction, materials and methods, results and discussions, and conclusions. Data from the study area, such as social vulnerability, demographics, and COVID-19 sub-indicators, are described in subsections 2.1, 2.2, and 2.3. The methods of constructing composite indicators are presented in Subsection 2.4, and the analysis that verifies the consistency of composite indicators is presented in Subsection 2.5. Research results and discussions are presented in Sect. 3, and conclusions in Sect. 4.

## 2 Materials and methods

### 2.1 Social vulnerability in the study area

The study area of this ecological study is Maringá, Paraná, Brazil. The estimated 2021 population of Maringá is 436,472 people [32], which are distributed among 543 urban census
tracts according to the last demographic census [33]. Figure 1 shows the location map of Maringá.

In 2019, the monthly income per person was less than half the minimum wage in 26% of households [32]. The most socially vulnerable populations inhabit the north and central regions and the eastern and western outskirts of the city [30].

The economic dynamism of Maringá and the role that the city plays in the regional urban network attracts young populations looking for work. This attraction results in a younger age structure than Brazilian cities with up to 20,000 inhabitants or European cities. In 2010, 8.2% of the population of Maringá was over 64 years of age, while in small cities, this percentage was 8.9% [33]. Among the 29 member countries of the European Union, the percentage of the population aged over 64 in 2019 was 20.2% [34]. In addition to a relatively young population, Maringá’s Human Development Index is rated “very high.” This implies relatively good living conditions for the population, which includes broad access to health services.

Social vulnerability is a multidimensional social phenomenon that can be represented by a single composite indicator in which different sub-indicators are aggregated [24, 25]. Fifteen sub-indicators were selected to represent five different dimensions of social vulnerability. These five dimensions represent the vulnerability resulting from income deprivation, precarious conditions of housing and the environment, and difficulty accessing public and education services [30]. The sub-indicators of the five dimensions are:

- Demography: inhabitants per household, heads of household between 10 and 19 years old, dependents per head of household, and the number of children up to one year old.
- Economical: heads of households without income, with less than 20 minimum wages and up to two minimum wages.
- Educational: persons 10 up to 14 years of age not literate and illiterate household heads.
- Environmental: Vegetation Coverage.
- Housing: household without bathroom, with less than four bathrooms, without sewage network, without a water network, and rented or leased.

2.2 Demographics of the study area

This research uses population data from the Municipal Dengue Control Program collected in October 2019. Municipal census data refer to geographic recognition carried out in compliance with the National Guidelines for the Prevention and Control of Dengue Epidemics

The municipal census is carried out concurrently with the cycles of inspections carried out by agents of endemic diseases every four to six times a year. The data are compatible with the 34 coverage areas of the Basic Health Units that respect the limits of the IBGE’s census tracts [33]. However, the Basic Health Units contain more than one census tract, and there are populations censused by the municipality that does not belong to any census tract.

Four procedures were performed to update the data from the census tracts correctly. First, equidistant points were created within the polygons of the Basic Health Units. Second, the population data from the Basic Health Units were assigned to the points. Third, the points were associated with the census tracts. Fourth, the sum of the population at each point was calculated.

The population census of the municipality recorded a population 0.4% smaller than that estimated by the IBGE [32]. The population of the census tracts grew by 25% between 2010 and 2019. The error of this estimate is 2.15% for a confidence level of 0.95 with a standard deviation of 0.51. Four census tracts grew more than 100%. The highest population growth in a census tract was 249%.

2.3 COVID-19 in the study area

Data on the number of cases and deaths from COVID-19 were made available by the Health Department of Maringá. The data is not associated with personal identification and is public. According to resolution 510/2016 of the National Health Council, studies that use data with these characteristics do not need prior approval from the Ethics Committee on Research with Human Beings [35].

This study includes data from the first 365 days of the occurrence of COVID-19 in Maringá. Occurrences begin

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1 The national guidelines for the prevention and control of dengue epidemics is available at: http://bvsms.saude.gov.br/bvs/publicacoes/diretrizes_nacionais_prevencao_controle_dengue.pdf.
on March 18, 2020, with the registration of the first case until March 17, 2021. This dataset ensures the quality of the analysis as 92.95% of the population was not vaccinated on March 17, 2021. Besides, 100% of the 26,343 people vaccinated had received only the first dose of the vaccine.

The association of municipal and national census data with COVID-19 data comprises four stages. First, a total of 35,957 records of cases and deaths from COVID-19 from January 2020 to March 2021 were geo-referenced. Second, the geo-referenced data not belonging to the 2010 urban census tracts (rural areas or urban expansion after 2010) were discarded. Third, the 33,495 records in the urban census tracts were associated with the codes of each census tract. Fourth, COVID-19, sociodemographic and composite indicators of social vulnerability data were associated using the census tract code. In this case, data from composite indicators were obtained through Principal Component Analysis (PCA) and Benefit-of-Doubt (BoD).

### 2.4 Principal component analysis (PCA) and benefit-of-the-doubt (BoD)

PCA [36] and BoD [37] were used to construct the composite indicator of social vulnerability. These methods are predominant among researchers and practitioners of the composite indicators field [27]. One of the advantages of these methods is the data-driven weights. Obtaining weights from the data avoids bias and errors in judgment about the sub-indicator weights [24, 30].

The PCA is based on the analysis of an $X_{ij}$ data matrix, where $i = 1, 2, ..., n$ denotes the sub-indicators and $r = 1, ..., m$ denotes the geographic regions. The variance-covariance matrix $\Sigma$ can be decomposed in its auto-structure [36] as follows:

$$\Sigma = \Lambda \Lambda^{\top} \tag{1}$$

where $\Lambda$ is the diagonal matrix of eigenvalues of $\Sigma$; $A$ is the corresponding matrix of eigenvectors of $\Sigma$; superscript $\top$ indicates the transposed matrix. The eigenvalues in $\Lambda$ represent the variance of the principal component $Y_z$ defined as:

$$Y_z = XA_z \tag{2}$$

where $A_z$ is the $Z$-th column of the matrix of eigenvectors $\Lambda$ of $\Sigma$, which represents the contribution of each sub-indicator in $X$ to the $z$-th principal component $Y_z$. The $Y_z$ entries are defined as the scores of the Principal Component. This Principal Component is named the composite indicator.

BoD measures the association between a geographical area’s real performance and its benchmark performance. The considered sub-indicators, using the BoD, must be on the same scale [24]. Otherwise, it is necessary to normalize the scale of the sub-indicators before applying the following model:

$$CI = \max_{w_{ir}} \sum_{i=1}^{n} w_{ir} I_{ir} \tag{3}$$

considering constraints:

$$\sum_{i=1}^{n} w_{ir} I_{ir} \leq 1 \forall i \in \{1, 2, \ldots, n\} \tag{4}$$

$$w_{ir} \geq 0 \forall i \in \{1, \ldots, n\}; \forall r \in \{1, 2, \ldots, m\} \tag{5}$$

where $w_{ir}$ is the corresponding weight of sub-indicator $i$ of region $r$.

The sub-indicators weights are obtained from each geographic region’s reference performance [24]. This weighting for each sub-indicator and geographical area ends up attributing higher weights to sub-indicators with higher performances and lower weights to sub-indicators with lower performances [37]. Consequently, the weights of the sub-indicators vary according to the geographic region. This variation of weights of the sub-indicator according to the area makes any comparative analysis very difficult [28]. It is possible to avoid a reduced or excessive emphasis on sub-indicators by inserting the following additional constraints in (4)-(5):

$$L_{ir} \leq \frac{w_{ir} I_{ir}}{\sum_{i=1}^{n} w_{ir} I_{ir}} \leq U_{ir} i = 1, 2, \ldots, n; r = 1, 2, \ldots, m \tag{6}$$

where $L_{ir}$ and $U_{ir}$ represent the lower and upper limits for the corresponding weight $w_{ir}$.

In this research, the composite indicators of social vulnerability were constructed from the normalized sub-indicators with $L_{ir} = 0$ and $U_{ir} = 0.10$ as a way to reduce the problem of comparability between geographic regions.

The operational structure of the PCA and the BoD makes it possible to represent social vulnerability through two different approaches. First, the maximization of data variance through PCA makes it possible to represent the pattern of social vulnerability. Second, maximizing the weights of the sub-indicators by census tracts through the BoD allows considering the spatial heterogeneity of social vulnerability.

However, the PCA and BoD are not without shortcomings either. Data-driven weights may not adequately reflect...
3 Results and discussions

Social vulnerability maps constructed using PCA and BoD converge with the literature. Figure 2 shows that populations with higher social vulnerability inhabit some census tracts in the central region and the city's suburbs.

Average household income and social vulnerability maps have a similar spatial pattern. Areas of None social vulnerability have higher average household income, while areas of High social vulnerability have lower average household income. The spatial pattern of population distribution does not reveal many similarities with the other indicators.

Maps reveal an important difference. The number of census tracts classified as Low average household income is substantially higher than the number of census tracts classified as High social vulnerability. This difference reflects the allocation of greater weights to sub-indicators that perform above average in the census tract. This overweighting of the best-performing sub-indicators directly impacts the correlation between the composite indicator and the variable used in the consistency check. The correlation between average household income and the PCA Vulnerability Indicator is very strong ($R=0.93$) and weak with the BoD Vulnerability Indicator ($R=-0.39$). These correlation coefficients indicate that the BoD Vulnerability Indicator does not capture the most significant variable to represent social vulnerability satisfactorily. The consistency check of the composite indicators performed through the correlation coefficient indicates that the PCA Vulnerability Indicator offers a good representation of social vulnerability. These results suggest that not every composite indicator of social vulnerability has the phenomenon’s reality [30]. Besides, these methods are very sensitive to the data’s extreme values, outliers, and measurement errors. In PCA, there is an informational loss during constructing the composite indicator [26], which must also present variance extracted and sample consistency above 0.50 and 0.60, respectively [26]. In BoD, the insertion of (6) model does not eliminate that a sub-indicator has different weights in the geographic areas. Assigning different weights to the same sub-indicator makes the composite indicator’s comparability unfeasible [38].

2.5 Composite indicators consistency check

The mentioned shortcomings in PCA and BoD can result in unrepresentative composite indicators. Therefore, the literature on composite indicators suggests analyzing their robustness and verifying their consistency through their correlation with other variables [24]. This correlation verifies how much of the conceptually most significant variable in the multidimensional phenomenon is represented by the composite indicator [30, 31].

The consistency check of the social vulnerability composite indicator was calculated from its correlation with the Average household income indicator. Researchers recognize income as the most significant indicator of social phenomena such as poverty, inequality, social exclusion, and vulnerability [39, 40]. Then, the census tracts were grouped based on the composite indicator scores with the best consistency. The groups were defined by quartile, and the statistical consistency of the classification was verified using the Two Factor ANOVA with Replication.
vulnerability represents the multidimensional phenomenon consistently. Consequently, the relationship between COVID-19 and the BoD Vulnerability Indicator may not adequately reflect what is happening in the study area and produce ineffective public policies to combat COVID-19.

Table 1 shows the histograms and the coefficients, significance level, and scatter plot of the bivariate correlation of five indicators. The PCA Vulnerability Indicator (I_4) presents a negative correlation between the Cases of COVID-19 (I_2) and the Proportion of cases of COVID-19 (I_3). The PCA Vulnerability Indicator presents a positive correlation with the population of the census tracts (I_1). These results contradict the literature that associates the number of cases and deaths from COVID-19 and social vulnerability at the municipal scale.

Table 1 shows that the number and proportion of COVID-19 cases have positive and negative correlations with social indicators and the social vulnerability composite indicators in different intensities. The Population of the census tracts (R = 0.41) and “Average household income” (R = 0.18) indicators show positive correlations with the number of COVID-19 cases. In turn, the number of COVID-19 cases negatively correlates with the PCA vulnerability indicator (R = -0.18). In addition to presenting contradictory directions, the strength of these correlations is negligible or weak. In particular, the BoD vulnerability indicator does not significantly correlate with the number of COVID-19 cases in the study area.

The conclusion on the correlations associated with the Proportion of cases of COVID-19 is not different. The direction of these correlations varies by indicator, and the strength of these correlations is weak or negligible. On the one hand, the “Proportion of cases of COVID-19” is positively correlated with Average household income (R = 0.45) and BoD vulnerability indicator (R = 0.08). On the other hand, the “Proportion of cases of COVID-19” is negatively correlated with the “Population” of the census tracts (R = -0.26) and the PCA vulnerability indicator (R = -0.37). These results indicate that the number of COVID-19 cases is higher in census tracts with higher population density but that the proportion of COVID-19 cases is higher in census tracts with lower population density. This simultaneous analysis of many indicators, which present correlations in different directions and intensities, makes it difficult to understand the relationship between COVID-19 and social indicators.

Composite indicators allow for simplifying these analyses. However, the results reveal that the correlations between the PCA and BoD vulnerability indicators and the other indicators show opposite directions. This contradiction reveals that composite indicators that are not consistent with the concept of the multidimensional phenomenon may not offer an adequate solution to simplify the analysis of the relationship between multiple social indicators and COVID-19. This finding reinforces the need to verify the consistency of the composite indicator by correlating it with other variables of substantial conceptual importance in the multidimensional phenomenon [24, 30, 31]. For this reason, this research correlates COVID-19 with the composite indicator of social vulnerability constructed by the PCA.

Tables 2 and 3 provide information on sociodemography, cases, and deaths by COVID-19 by socially vulnerable groups in Maringá. Cases and deaths from COVID-19 are higher in the groups with the highest scores on the PCA Vulnerability Indicator. The ratio of cases and deaths from COVID-19 is higher in the groups with lower scores on the PCA Vulnerability Indicator. This result shows that the size of the population directly influences the relationship between social vulnerability and COVID-19 in the census tract.

The two-way ANOVA with replication results indicate that the social vulnerability groups are internally similar and externally different. In a sample of five census tracts per group, the test results were p-value less than 0.001, F-value

Table 1  Correlation coefficients between (I_1) Population of the census tracts; (I_2) Cases of COVID-19; (I_3) Proportion of cases of COVID-19; (I_4) Average household income; (I_5) PCA vulnerability indicator; and (I_6) BoD vulnerability indicator

|       | I_1   | I_2   | I_3   | I_4   | I_5   | I_6   |
|-------|-------|-------|-------|-------|-------|-------|
| I_1   | 1.00*** |      |       |       |       |       |
| I_2   | 0.41*** | 1.00*** |      |       |       |       |
| I_3   | -0.26*** | 0.16*** | 1.00*** |      |       |       |
| I_4   | -0.12*** | 0.18*** | 0.45*** | 1.00*** |      |       |
| I_5   | 0.16*** | -0.18*** | -0.37*** | -0.93*** | 1.00*** |       |
| I_6   | -0.14*** | 0.08*** | 0.09*** | 0.33*** | -0.39*** | 1.00*** |

Note: significance level of 0.001***, 0.05** and 0.01*

Table 2  Sociodemography of Maringá by social vulnerability group

|       | Population | Average Age | Elderly Ratio | Average Household Income | PCA Vulnerability Indicator |
|-------|------------|-------------|---------------|--------------------------|---------------------------|
| Group 1 | 596        | 44          | 0.19          | 8,627                    | 0.18                      |
| Group 2 | 10,809     | 43          | 0.17          | 5,705                    | 0.43                      |
| Group 3 | 174,025    | 40          | 0.13          | 2,339                    | 0.67                      |
| Group 4 | 166,277    | 40          | 0.12          | 1,178                    | 0.80                      |

Note: Group 1 (0.00-0.25), Group 2 (0.025-0.50), Group 3 (0.50-0.75) and Group 4 (0.75-1.00)
equal to 56, and F-critical of 2.72. In short, the difference in COVID-19 indicators between the groups are significantly different at a confidence level of 99.9%.

Group 4 comprises census tracts with scores between 0.75 and 1.00 on the PCA Vulnerability Indicator. Infected people from these census tracts have an average of 40 years, 12% are over 60, and have an average household income of R$1,178. Group 3 comprises census tracts with demographic characteristics similar to Group 4. The main similarities are the population size, the average age of the infected people, and the proportion of elderly. Census tracts in Group 3 have scores on the PCA Vulnerability Indicator between 0.50 and 0.75. The average household income in Group 3 is 1.99 times higher than in Group 4, 2.4 times lower than in Group 2, and 3.7 times lower than in Group 1.

It is also possible to state that Groups 1 and 2 are similar and dissimilar to Groups 3 and 4. The average age of infected people is 44 years in Group 1 and 43 years in Group 2. The proportion of the elderly is 19% in Group 1 and 17% in Group 2. Average household income is 1.5 times higher in Group 1 than in Group 2.

Cases and deaths from COVID-19 are proportional to the populations of the four groups. Census tracts in Groups 3 and 4 classified as Medium and High social vulnerability concentrate 97% of the population and 93% of cases and deaths from COVID-19. The relationship between COVID-19 cases and deaths and social vulnerability is reversed when the population of each census tract is considered. The bigger chances of cases and deaths from COVID-19 occur in census tracts with less social vulnerability. Groups 1 and 2 have an average of 3.87 and 2.13 times more chance of cases and deaths from COVID-19 than Groups 3 and 4. These results are compatible with studies that associate the greater chance of cases and deaths from COVID-19 with better living conditions and a higher average population age [2–5, 10].

### 4 Conclusion

Correlations between COVID-19 and social indicators are sensitive to space and geographic scale. In addition, the simultaneous analysis of many social indicators with correlations in different directions makes it difficult to develop public policies to combat COVID-19. This research shows that aggregating multiple social indicators into composite indicators simplify understanding of the relationship between COVID-19 and social phenomena without disregarding its multidimensionality. This simplification favors the elaboration of more effective public policies, especially at the intra-urban scale, due to the lack of data from the Human Development Index, Stringency index, or Global Multidimensional Poverty Index for the Brazilian census tracts.

However, the research reveals that the correlation between COVID-19 and social vulnerability is also sensitive to the method used to construct the composite indicator. The correlations between the number and proportion of COVID-19 cases and the composite indicators of social vulnerability constructed by the BoD and PCA show opposite directions. Correlations with opposite directions reinforce the need to verify if the composite indicator captures the variable of greater conceptual significance in the multidimensional phenomenon. This research shows through this analysis that the consideration of spatial heterogeneity through the BoD method overestimates the positive aspects of each census tract and results in a composite indicator with less consistency. In turn, considering that the weights of the sub-indicators do not vary according to the census tract through the PCA method results in a composite indicator highly consistent with the concept of the multidimensional phenomenon.

The composite indicator of social vulnerability constructed by PCA shows that most of the population of Maringá resides in census tracts classified as “High” and “Medium” social vulnerability. The cases and deaths from COVID-19 in these groups are proportionally higher. However, the chances of cases and deaths from COVID-19 are higher in groups classified as Low and No social vulnerability. The higher average age of infected people and the proportion of elderly in these groups reflect the lower social vulnerability. These results suggest that the decrease in social vulnerability increases the population’s average age, the proportion of older people, and the chances of cases and deaths from COVID-19.

It is possible to assume that the relationship between social vulnerability and the chances of cases and deaths caused by COVID-19 is negative. The average age of the infected population and the proportion of the elderly are important factors in understanding this relationship. These
results suggest that public policies aimed at reducing the number of cases and deaths from COVID-19 should prioritize the elderly population regardless of social status.

The use of municipal census data from 2019 is a limitation of the research since the COVID-19 data are from 2021. However, these data offer more accurate analyses than the vast majority of studies on an intra-urban scale in Brazil, as these studies use data from the last census that took place in 2010. Future analyses by age group can answer other relevant questions, such as: What is the correlation between cases and deaths from COVID-19 and social vulnerability by age group? Are the directions of correlations different by age group? Are the chances of cases and deaths from COVID-19 among the socially more vulnerable and less vulnerable elderly greater, equal, or less?

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Declarations

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References

1. Fatima, M., O’Keefe, K. J., Wei, W., Arshad, S., & Gruebner, O. (2021). Geospatial analysis of COVID-19: A scoping review. International Journal of Environmental Research and Public Health, 18(5), 2336
2. Azarpazhooh, M. R., Morovatdar, N., Avan, A., Phan, T. G., Divani, A. A., Yassi, N., & Di Napoli, M. (2020). COVID-19 pandemic and burden of non-communicable diseases: an ecological study on data of 185 countries. Journal of Stroke and Cerebrovascular Diseases, 29(9), 105089
3. Valev, D. (2020). Relationships of total COVID-19 cases and deaths with ten demographic, economic and social indicators. medRxiv
4. Libório, M. P., Ekel, P. Y., de Abreu, J. F., & Luidares, S. (2021). Factors that most expose countries to COVID-19: a composite indicators-based approach. Geojournal, 1–15
5. Li, W. X. (2021). Worldwide inverse correlation between Bacille Calmette–Guérin (BCG) immunization and COVID-19 mortality. Infection, 49(3), 463–473
6. Benita, F., & asca-Sanchez, F. (2021). The main factors influencing COVID-19 spread and deaths in Mexico: A comparison between Phases I and II. Applied Geography, 102523
7. Khazanchi, R., Beiter, E. R., Gondi, S., Beckman, A. L., Bilinski, A., & Ganguli, I. (2020). County-level association of social vulnerability with COVID-19 cases and deaths in the USA. Journal of General Internal Medicine, 35(9), 2784–2787
8. Karaye, I. M., & Horney, J. A. (2020). The impact of social vulnerability on COVID-19 in the US: an analysis of spatially varying relationships. American Journal of Preventive Medicine, 59(3), 317–325
9. Sung, B. (2021). A spatial analysis of the association between social vulnerability and the cumulative number of confirmed deaths from COVID-19 in United States counties through November 14, 2020. Osong Public Health and Research Perspectives, 13(3), 149–157. doi: https://doi.org/10.24171/jphrp.2020.0372
10. Paez, A., Lopez, F. A., Menezes, T., Cavalcanti, R., & Pitta, M. G. D. R. (2020). A spatio-temporal analysis of the environmental correlates of COVID-19 incidence in Spain. Geographical Analysis, 53(3), 397–421. doi: https://doi.org/10.1111/geoa.12241
11. Kalla, M. I., Lahmar, B., Geullouh, S., & Kalla, M. (2021). Health geo-governance to assess the vulnerability of Batna, Algeria to COVID-19: the role of GIS in the fight against a pandemic. GeoJournal, 1–14. Doi: https://10.1007/s10708-021-10449-8
12. Henao-Cespedes, V., Garcés-Gómez, Y. A., Ruggeri, S., & Henao-Cespedes, T. M. (2021). Relationship analysis between the spread of COVID-19 and the multidimensional poverty index in the city of Manizales, Colombia. The Egyptian Journal of Remote Sensing and Space Science. doi: https://doi.org/10.1016/j.ejrs.2021.04.002
13. Biggs, E. N., Maloney, P. M., Rung, A. L., Peters, E. S., & Robinson, W. T. (2021). The relationship between social vulnerability and COVID-19 incidence among louisiana census tracts. Frontiers in Public Health, 8, 1048
14. Tavares, F. E., & Betti, G. (2021). The pandemic of poverty, vulnerability, and COVID-19: evidence from a fuzzy multidimensional analysis of deprivations in Brazil. World Development, 139, 105307
15. The Lancet Global Health, 9(6), E782-E792
16. Souza, C. D. F., Machado, M. F., & do Carmo, R. F. (2020). Human development, social vulnerability and COVID-19 in Brazil: a study of the social determinants of health. Infectious Diseases of Poverty, 9(1), 1–10
17. Baggio, J. A. O., Machado, M. F., Carmo, D., Armstrong, R. F. C., Dos Santos, A. A., & De Souza, C. D. F. (2021). COVID-19 in Brazil: spatial risk, social vulnerability, human development, clinical manifestations and predictors of mortality—a retrospective study with data from 59 695 individuals. Epidemiology & Infection, 149, doi: https://doi.org/10.1017/S0950268821000935
18. Souza, C. D. F., Carmo, R. F., & Machado, M. F. (2020). The burden of COVID-19 in Brazil is greater in areas with high social deprivation. Journal of Travel Medicine, 27(7), 1–3
19. Viezzier, J., & Biondi, D. (2021). The influence of urban, socioeconomic, and eco-environmental aspects on COVID-19 cases, deaths and mortality: A multi-city case in the Atlantic Forest, Brazil. Sustainable Cities and Society, 69, 102859
20. Kong, J. D., Tekwa, E. W., & Gignoux-Wolfsohn, S. A. (2021). Social, economic, and environmental factors influencing the basic reproduction number of COVID-19 across countries. PLoS one, 16(6), e0252373
21. Castro, R. R., Santos, R. S. C., Sousa, G. J. B., Pinheiro, Y. T. M., Martins, R. R. I. M., Pereira, M. L. D., & Silva, R. A. R. (2021). Spatial dynamics of the COVID-19 pandemic in Brazil. Epidemiology & Infection, 149
22. Souza, C. M. M., Mello, B. J., Florit, L. F., Ramalho, Â. M. C., de Moraes Souza, Y. M., Jeremias, J. T. F., & de Aguiar, P. D. (2021).
Social environmental vulnerability approach on the COVID-19 epoch: a case study in Blumenau (SC), Brazil. Research Society and Development, 10(10), e161101018739–e161101018739

23. Souza, A. P. G. D., Mota, C. M. D. M., Rosa, A. G. F., Figueiredo, C. J. J. D., & Candeias, A. L. B. (2022). A spatial-temporal analysis at the early stages of the COVID-19 pandemic and its determinants: The case of Recife neighborhoods, Brazil. PloS one, 17(5), e0268538

24. Nardo, M., Saisana, M., Saltelli, A., & Tarantola, S. (2005). Tools for composite indicators building. European Comission Ispra, 15(1), 19–20

25. Mazzotta, M., & Pareto, A. (2017). Synthesis of indicators: The composite indicators approach. Complexity in society: From indicators construction to their synthesis (pp. 159–191). Cham: Springer

26. Mazzotta, M., & Pareto, A. (2019). Use and misuse of PCA for measuring well-being. Social Indicators Research, 142(2), 451–476

27. El Gibari, S., Gómez, T., & Ruiz, F. (2019). Building composite indicators using multicriteria methods: a review. Journal of Business Economics, 89(1), 1–24

28. Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. Social indicators research, 141(1), 61–94

29. Saisana, M., Saltelli, A., & Tarantola, S. (2005). Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. Journal of the Royal Statistical Society: Series A (Statistics in Society), 168(2), 307–323

30. Libório, M. P., Martinuci, O. D. S., Machado, A. M. C., Hadad, R. M., Bernardes, P., & Camacho, V. A. L. (2021). Adequacy and Consistency of an Intraurban Inequality Indicator Constructed through Principal Component Analysis. The Professional Geographer, 73(2), 282–296

31. Dialga, I., & Giang, L. T. H. (2017). Highlighting methodological limitations in the steps of composite indicators construction. Social Indicators Research, 131(2), 441–465

32. IBGE (2021). Cidades. Brasil Paraná Maringá. Extracted on December 14, 2021, from: https://cidades.ibge.gov.br/brasil/pr/maringa/panorama

33. IBGE (2010). Censo Demográfico. Extracted on December 14, 2021, from: https://censo2010.ibge.gov.br/resultados.html

34. Eurostat (2019). European Statistical: Recovery Dashboard. Extracted on December 14, 2021, from: https://ec.europa.eu/eurostat

35. Guerriero, I. C. Z. (2016). Resolução nº 510 de 7 de abril de 2016 que trata das especificidades éticas das pesquisas nas ciências humanas e sociais e de outras que utilizam metodologias próprias dessas áreas. Ciência & Saúde Coletiva, 21, 2619–2629

36. Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374(2065), 20150202

37. Cherchye, L., Moesen, W., Rogge, N., & Van Puyenbroeck, T. (2007). An introduction to ‘benefit of the doubt’ composite indicators. Social Indicators Research, 82(1), 111–145

38. Zanella, A., Camanho, A. S., & Dias, T. G. (2015). Undesirable outputs and weighting schemes in composite indicators based on data envelopment analysis. European Journal of Operational Research, 245(2), 517–530

39. Arretche, M. (2018). Paths of inequality in Brazil: a half-century of changes. Springer

40. Libório, M. P., Ekel, P. Y., Martinuci, O. D. S., Figueiredo, L. R., Hadad, R. M., Lyrio, R. D. M., & Bernardes, P. (2022). Fuzzy set based intra-urban inequality indicator. Quality & Quantity, 56(2), 667–687

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