Self-reported mental health in the United States: Spatial structure before and after the COVID-19 pandemic across age groups

Carles Comas  
University of Lleida

Angel Blanch  
angel.blanch@udl.cat  
University of Lleida

Research Article

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Abstract

**Purpose.** This study examines the eventual impact of COVID-19 on self-reported mental health in the mainland USA with two main aims. First, to evaluate the pre-pandemic and post-pandemic mental health spatial distribution. Second, to contrast spatial data across three age groups, young (18-44 years), middle-aged (45-65 years), and old (older than 65 years).

**Methods.** We analysed the autocorrelation Moran's $I$ structure with data from the Behavioral Risk Factor Surveillance System (BRFSS). A Monte Carlo approach was applied to evaluate the statistical significance of global and local Moran's I autocorrelation.

**Results.** The main findings indicate a spatial dependence of general mental health before and after the COVID-19. No spatial structure emerged regarding young, middle-aged, and old groups.

**Conclusion.** The spatial structure of the variability in mental health over time from 2019 to 2021, only showed a meaningful configuration for the general population, whereas it was unsupported for young, middle-aged, and old age groups.

Introduction

The COVID-19 global outbreak combines a low predictability with a considerable impact on important areas of human activity such as work, education, and family [1], and including unprecedented deleterious effects on the population general well-being and mental health. Most affected mental conditions and symptoms contemplate post-traumatic stress disorder (PTSD), anxiety, and depression. Moreover, the COVID-19 appears as being more harmful to the most vulnerable people, while bearing notable variations depending on geographical areas and/or countries [2]. Since the COVID-19 inception, several topics have been explored regarding its geographical and spatial distribution. These include spread and transmission mechanisms [3], hospitalised cases and incidence issues [4], mortality rates and associated socio-economic and environmental determinants [5], or the impact of lockdowns on the strain of mental health care units [6].

Whether the COVID-19 has had a meaningful impact on the spatial distribution of mental health, however, has been rather understudied. A recent notable exception highlights that depression and suicidal behaviour increased especially in rural areas within North Carolina during the outbreak [7]. From this perspective, the COVID-19 can be viewed as a natural global experiment whereby to analyse eventual changes in the geographical patterns of mental health after a major epidemic event. In this study, we examined the geographical patterns of mental health across the United States before and after the COVID-19. We analyse data extracted from the Behavioral Risk Factor Surveillance System (BRFSS) in 2019 and 2021, a survey that evaluates self-reported mental health in the United States, among several other factors. The aim of the current study is two-folded.
First, we evaluate whether mental health bears spatial dependence before and after the pandemic. Because self-reported mental health was expected to vary from pre-pandemic to post-pandemic COVID-19, we also evaluate whether the eventual increment or decrement in mental health (i.e., the difference over time) bears any spatial dependence. It can be conceived that the spatial structure of self-reported mental health across USA states could be more robust after the outbreak. For instance, negative impacts of the pandemic have been underlined to occur by enhancing already present mental health disorders and initiating new stress disorders for many people [8]. With an impactful event such as a global pandemic affecting important areas in daily life, we expected to see a higher similarity in mental health across states in 2021, compared with more variable outcomes before the COVID-19 in 2019.

A second interrelated aim involved the evaluation of the spatial distribution of mental health before and after the COVID-19 across different age groups. The elderly endured particularly harsher times than the younger during the COVID-19 by experiencing higher anxiety and stress, although with notable variations regarding race [9]. There were also individual resilience and contextual circumstances that might contribute to the variability in reported mental health [8]. For instance, younger people might have also endured anxious and stressful circumstances, while middle aged individuals might suffer because of increased occupational or family duties and responsibilities. Therefore, we evaluated the spatial dependence of mental health before and after the COVID-19 across three age groups, young, middle-aged, and old. Moreover, we evaluated whether the increment or decrement in mental health underpinned spatial dependence across age groups.

**Methods**

**Dataset**

The data was derived from the Behavioral Risk Factor Surveillance System (BRFSS), a periodic survey implemented by the Centers for Disease Control and Prevention (CDC). Two time points were considered, 2019 prior to the COVID-19, and 2021 after the COVID-19 outbreak. The data was summarized within a .csv file from the America’s Health Rankings® webpage (https://www.americashealthrankings.org), a partnership between the United Health Foundation and the American Public Health Association.

The BRFSS is a comprehensive telephone survey conducted on a yearly basis since 1984 with US residents aged 18 years or older. The BRFSS collects information about health-related risk behaviours, chronic health conditions, access to health care, and use of preventive health services in the 50 states, District of Columbia, Guam, and Puerto Rico. For the current study, we excluded the states of Alaska, Guam, Hawaii, and Puerto Rico (n = 51).

The 2019 survey includes landline (n = 149,047) and cell phone (n = 263,550) interviews, with a median response rate of 49.4% ranging between 37.3 and 73.1%. The 2021 survey includes landline (n = 117,793) and cell phone (n = 322,282) interviews, with a median response rate of 44% ranging between 23.5 and 60.5%.
Mental health

The current study focused on the mental health reported in the 49 mainland states. Mental health described the percentage of people reporting a bad mental health condition during fourteen or more days in the past 30 days. This indicator was considered for the general population, and for three age groups, young (from 18 to 44 years old), middle-aged (from 45 to 65 years old), and old (above 65 years old).

Geographical distances and the weight matrix

The geographical distance between each pair of states was calculated with the great-circle distance using the geosphere R package [10], as the shortest distance in kilometres between the centroid of each state on the surface of a sphere. This distance assumes the spherical shape of the earth and should be considered instead of the Euclidean distance based on a plane surface. With large spatial events throughout a large country, a plausible approach was to analyse the autocorrelation structure between neighbouring states sharing borders regardless of the distance between them.

For the current analyses, a weight matrix was therefore defined by the inverse of great-circle distances between neighbouring states, and values of zero for states with unshared borders and for the elements in the diagonal of this matrix. To facilitate the interpretation of these statistics, this initial matrix of distances was row standardized such as that each weight was divided by its row sum.

Statistical analysis

We analysed the autocorrelation structure of the mental health constructs of choice, assuming the Moran’s $I$ index and related measures, i.e., Moran’s scatter plot, and its local version, assuming a standardized form of the variable under analysis. The supplementary materials provide an overview of the spatial autocorrelation measures used in the current study. The spatial structure of mental health has been introduced in the Moran’s approach by the weight matrix defined earlier in the previous section.

The evaluation of the statistical significance of the Moran’s $I$ and other measures of spatial autocorrelation can be conducted assuming a normal distribution of these statistics under the null hypothesis of spatial independence. This assumption can be inappropriate, however, when the underlying normality assumptions are unsatisfied. Thus, statistical significance was assessed considering a Monte Carlo approach, in which the null sampling distribution of a given variable was generated by simulating this variable several times under the null hypothesis and by comparing this empirical distribution with the resulting statistic of interest [11, 12].

This Monte Carlo procedure was based on randomly permuting the observed values over the fixed spatial locations.

An approximate test to assess the goodness of fit of the proposed null hypothesis was derived from the computation of the rank of the spatial autocorrelation in this null sampling distribution based on $m$.
random permutations. The critical value of this test with an alpha ($\alpha$) significance level corresponded to
the $100 \times (1 - \alpha)^{th}$ percentile, whereby the null hypothesis was accepted with an observed
autocorrelation equal or below this critical value. This procedure generated a pseudo $p$-value to
evaluating the statistical significance of the targeted spatial autocorrelation measure.

For the local measures of spatial autocorrelation, we also considered the Monte Carlo approach with a
conditional permutation of the construct of interest over the fixed spatial locations. In this case, the
permutation procedure considered all the observations except for the value of each $x_i$ fixed at its location
$i$. The remaining $n - 1$ of the $x$ values were then randomly permuted to obtain the null sampling
distribution of these local statistics, which implied the generation of $s$ null sampling distributions.

In particular, the evaluation of the spatial autocorrelation was based on the simulation of 999 null
sampling distributions. These null sampling distributions were obtained by the estimation of the statistic
of interest for the simulated spatial configurations, where the target variables were randomly located
over the fixed locations. This approach resulted in a random attribute spatial distribution based on a
permutation approach.

All statistical analyses were conducted with the R software [10]. The data is available in the
supplemental material, and the code is available from the corresponding author upon request.

Results

Table 1S in the supplemental material shows differences in mental health between 2019 and 2021 for
the general population and the three age groups. Mean values increased very slightly over time, with the
larger difference of 2% for the young age group (18 to 44 years old).

Figure 1 shows the spatial distribution of the general measure of mental health in 2019 and 2021, and
the difference between both years. There were similar spatial structures for the general mental health
under both years and for the differences between these two years. Neighbouring states shared similar
values suggesting a positive dependent spatial structure. For instance, East-Central states had larger
values than the rest of states, especially in 2019. Compared with 2021, this Eastern-Central cluster
appeared even larger. This result is also observed for the difference between 2019 and 2021, where this
difference increased for most states.

Figure 2 shows that for the three age groups and the two years under analysis, neighbouring states
shared similar mental health values, underlining a positive spatial dependence. This distribution of
mental health highlights a dependent spatial structure between neighbouring states regardless of age
group and year (2019, 2021). Hence, states with either large or small values in mental health, were more
prone to be surrounded by states with large and small values, respectively. Note that the specific spatial
configuration of this dependent spatial structure, states conforming a cluster, varied with age group and
year. A general trend or pattern, however, remains uncertain. For the three age groups and the two years,
Central-North and Central-East states showed smaller and larger values compared with the other states,
respectively. The spatial distribution of the difference in mental health between 2019 and 2021 suggests a general increment, with only a few states showing a decrement such as Mississippi, New Mexico, Nevada, and Montana. This outcome was especially notable for young and old age groups.

Table 1. Global Moran's I coefficients with associated \(p\)-values for the general population and three age groups, young, middle-aged, and old.

<table>
<thead>
<tr>
<th></th>
<th>2019</th>
<th>2021</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(I)</td>
<td>(p)</td>
<td>(I)</td>
</tr>
<tr>
<td>General</td>
<td>0.4305</td>
<td>0.0000</td>
<td>0.3257</td>
</tr>
<tr>
<td>Young</td>
<td>0.2717</td>
<td>0.0000</td>
<td>0.1462</td>
</tr>
<tr>
<td>Middle-aged</td>
<td>0.4852</td>
<td>0.0000</td>
<td>0.5325</td>
</tr>
<tr>
<td>Old</td>
<td>0.3939</td>
<td>0.0001</td>
<td>0.2991</td>
</tr>
</tbody>
</table>

Table 1 shows the global Moran's I evaluating the spatial autocorrelation of mental health for the general population and the three age groups. These outcomes confirm statistically significant positive autocorrelation structures for general mental health \((I = 0.4305, p = 0.0000\) in 2019, and \(I = 0.3257, p = 0.0020\) in 2021). Regarding the three age groups in 2019, there were also significant positive autocorrelation structures. In 2021, the autocorrelation was non-significant for the young group only \((I = 0.1462, p = 0.0650\). These outcomes suggest that, except for the young age group, neighbour states shared similar mental health values over the observed period, corroborating the spatial structures shown in Figure 1 and 2.

On the other hand, the Moran's I value for the difference in self-reported mental health symptoms between 2019 and 2021 suggests a spatial dependent structure in the general population only \((I = 0.1623, p = 0.0390\), while there were non-significant global Moran's I measures for age groups highlighting that it was spatially independent for the three age groups. Neighbouring states shared similar mental health values for the general population, with the difference between 2019 and 2021 pointing out to a global increment of the mental health incidence over the observed period.

Figure 3 shows the Moran's scatter plots for the general population in 2019, 2021, and its difference. These distributions suggest positive local dependencies of a given observation with respect to its neighbour states in the lagged construct \((W_2)\). The points cloud increases from left to right, suggesting that neighbouring states held similar construct values. These results agree with the global Moran's I statistic. Figure 4 shows the scatter plots by age group with similar outcomes. Again, the distributions suggest positive local dependencies of a given observation with respect to its neighbour states in the
lagged construct (Wz) in accordance with the global Moran's I statistics (Table 1). The difference in mental health between both years, however, results in scatter plots with a flat point distribution confirming no spatial local dependencies of a given observation with respect to its neighbour states in the lagged construct (Wz). This result agrees with their corresponding global Moran's I statistics.

The Moran’s scatter plots show the distribution of a given observation with respect to its neighbour states in the lagged construct (Wz). States with similar values appear in the High-High and Low-Low scatter plot quadrants, whereas spatial outliers fall within the Low-High and High-Low quadrants (Supplementary materials: Local Moran and scatter plot). However, this visual representation of the spatial structure of the construct under analysis does not provide information about the significance of these spatial clusters and outliers.

To this end, Tables 2S and 3S in the supplementary materials show the local Moran's I indices with their associated statistical significance (p-values) in 2019 (pre-pandemic) and in 2021 (post-pandemic), respectively. These local indices are organized for the general population and for the three age groups, young, middle-aged, and old. These outcomes highlight clusters of these variables with significant positive local Moran's I indices, and outliers with significant negative local Moran's I values, i.e., states with values with a distinct sign of their neighbouring states. For instance, clusters of states with positive values emerge for central North states (North Dakota, South Dakota and Minnesota), particularly for middle and old age groups in 2019 and 2021. Regarding outliers, Florida yields a negative significantly different value compared with its neighbour states in young and old age groups in 2019 and 2021. These clustering and outlier trends remain rather unclear, however, although are in agreement with the observed global autocorrelation structure.

Discussion

In this study, we analysed the spatial autocorrelation structure of self-reported mental health in the United States for the general population and for three age groups, young, middle-aged, and old. Data from the Behavioural Risk Factor Surveillance System (BRFSS) in 2019 and 2021 were used to addressing two main questions. First, we evaluated whether there was a spatial dependence of mental health before and after the COVID-19. Besides, we evaluated whether there was spatial dependence in the observed increments in the reporting of mental health over time.

Main outcomes

The main outcomes indicate that the reported severity of mental health symptoms increased in the observed period, before and after the COVID-19. There was a notable spatial dependence in mental health before the pandemic in 2019, with highly significant Moran's I indices (Table 1). Neighbouring states shared similar levels regarding the mental health in the general population and also across the three age groups, young, middle-aged, and old. After the pandemic in 2021, however, while spatial dependence remained for the general population and for the middle-aged and old age groups, the spatial
dependence was unsupported for the younger age group ($I = 0.1462, p = 0.0650$). Apparently, the spatial structure of mental health remains similar after the COVID-19 (states clusters sharing similar values), while the impact of the pandemic implied a general worsening of mental health for most states.

Despite the fact that the spatial structure for the young age group was statistically non-significant, in general, neighbouring states shared similar values of self-reported mental health regardless of the age group and the year of analysis. This outcome suggests that this spatial structure between neighbouring states could be due to mental health policies that may transcend across these states or even purely geographical aspects that could help understand the presence of these clusters among states. In fact, mental health policies in the USA are multifaceted and often engaging various levels of government, as well as public and private initiatives. As such, this complex framework of mental health policy can result in common strategies for several states. Moreover, visual inspection of the mental health spatial distribution suggests that states sharing similar values (states clusters) can relate to specific geographical locations. For instance, the general mental health in East-Central states displayed larger values than the rest of states over time, 2019 and 2021. It is difficult, however, to establish what more specific geographical factors might favour this spatial configuration. Notice that these tentative reasons for this cluster configuration between states is likely to affect the three age groups analysed in the same way, while holding this spatial dependent structure before and after the COVID-19 outbreak.

The observed difference between pre-pandemic (2019) and post-pandemic (2021) self-reported mental health was spatially dependent for the general population only, whereby neighbouring states shared very similar variations over time. For the rest of age groups, however, the variability over time was spatially independent. This outcome suggests state differences in self-reported mental health after the COVID-19 regardless of state proximities. There was not a clear tendency for neighbouring states to exhibit similarities in self-reported mental health growth or decline. Because most states underwent an increase in mental health deterioration before and after COVID-19, the spatial structure of this difference results in a very similar configuration of spatial values across most states. This could explain the lack of spatial structure for the construct when looking at the three age groups.

Furthermore, this outcome suggests that the spatial configuration of either worsening or improvement in mental health before and after the COVID-19 may not depend on the age group under analysis. For example, socio-economic factors at the area level such as deprivation, unemployment, low income, and education level, have been negatively related with the risk of suicide [13]. Nonetheless, mental health worsening seems to be rather widespread for the three age groups resulting in a general worsening of mental health for most the states regardless of their spatial location.

The analysis of the spatial local structures of self-reported mental health confirms the observed global trends. For the pre-pandemic year 2019, significant Moran's local $I$ statistics reflected a global spatial dependence across the three age groups, suggesting that state clusters bear analogue mental health outcomes. Similar results were observed for the post-pandemic year 2021, where significant global measures also implied significant local clusters of states. This outcome supports the spatial
dependence of mental health resulting in clusters of neighbouring states that shared similar mental health outcomes, regardless of the year of analysis for age groups.

**Study limitations and further research**

These outcomes are based on the BRFSS yearly survey, which is particularly useful to evaluate combined spatial and temporal dimensions addressing disease surveillance problems [14]. However, some questions should be borne in mind concerning the interpretation of the current findings.

The evaluation of the spatial autocorrelation was conducted here with the Moran's $I$, which is interpretable in terms of spatial similarities or dissimilarities. Nonetheless, other available indices allow for the evaluation of spatial relations, such as the Getis-Ord $G^*$ statistic [15], or the Geary’s C index [16], which have also been applied to the spatial analyses of major epidemiological data such as cancer [17], or obesity [18].

Although this analysis has considered the spatial distribution of mental health before and after the COVID-19 pandemic over two years, 2019 and 2021, it might be useful to encompass additional years before and after the COVID-19 pandemic. Analysing the space-time dynamics of COVID-19 over multiple years might provide a more comprehensive understanding of its impact on mental health when comparing space-time structures throughout the COVID-19.

The current dataset provides mental health data categorized within the United States, which offers a broad overview of regional trends. A more detailed comprehension of the problem, however, could be gained from adapting the dataset to include information based on individual postal codes. This finer level of geographical description would allow for a more precise analysis, enabling researchers to pinpoint localized disparities and more specific nuances in mental health outcomes. By incorporating postal code information, analysts would be better able to identify specific areas within states where mental health resources may be lacking or where interventions are most urgently needed [7].

Another related issue involves the measurement of mental health with the BRFSS data. This indicator implied just the percentage of people who reported bad mental health conditions during fourteen or more days in the past 30 days of completing the survey. Mental health, however, is a complex multidimensional construct that implies a variety of individual problems (i.e., stress, depression, anxiety), and that can be activated or inhibited by contextual factors, and at varying spatial dimensions such as counties [19] or even neighbourhoods [20]. Indeed, the unique circumstances implied by the COVID-19 pandemic, have stirred the adaption of psychological assessment methods of mental health [21].

**Conclusions**

The COVID-19 bore an unprecedented impact on people's life and in particular, on mental health. The current study evaluated whether this unique event altered the spatial structure of self-report mental health in the USA for the general population and at different age groups. The current findings indicate that after the COVID-19 pandemic, the spatial structure of mental health remained similar, whereby
neighbouring states shared similar levels of mental health, conforming states clusters regardless of age group. The COVID-19 implied a worsening of mental health for the general population, though the cluster structure between states sharing similar mental health levels remained similar for the two years of analysis.

**Declarations**

**Funding:**

The study received no specific funding.

**Conflicts of interest/Competing interests:**

There are no conflicting/competing interests.

**Author Contribution**

C.C. and A.B. wrote the main manuscript. C.C. conducted the spatial analyses and prepared the Figures. A.B. developed and designed the concept of the study, and collected the initial data. C.C. and A.B. reviewed and edited the final manuscript.

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**Availability of data and material:**

Data is included as supplemental material.

**Code availability:**

Code is available upon request from the corresponding author.

**References**


Figures

![Spatial distributions of general mental health](image)

**2019**

- First quartile
- Second quartile
- Third quartile
- Fourth quartile

**2021**

**Difference**

*Figure 1*

Spatial distributions of general mental health. We assume a discretization of these variables based on their corresponding quartiles to facilitate the interpretation of their spatial distribution.
Figure 2


Figure 3
Moran's scatter plots with line slopes for the general population in 2019 ($I = 0.4305$), 2021 ($I = 0.3257$), and the difference ($I = 0.1623$).

**Figure 4**


**Supplementary Files**

This is a list of supplementary files associated with this preprint. Click to download.

- Supplementalmaterial.docx