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Spatiotemporal associations of mental distress with socioeconomic and environmental factors in Chicago, IL, 2015–2019

Aynaz Lotfata[1] · Alexander Hohl[2]

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Abstract

Mental distress is an epidemic that endangers global well-being and contributes to various illnesses. In the United States, the prevalence of mental distress has risen rapidly in recent years. However, this topic is understudied in spatial information research, as current literature lacks focus on spatially varying relationships between mental distress and relevant factors, which leads to impediment of prevention and mitigation efforts. Therefore, this study aims for investigating the spatiotemporal relationships of mental distress with crime, housing cost, poverty, air quality. Using the space–time scan statistic, we illustrate the spatiotemporal distribution of mental distress in Chicago, IL. In addition, we employ geographically and temporally weighted regression (GTWR) to find the varying relationships between aforementioned factors and mental distress. Lastly, we compare GTWR to a linear ordinary least squares model to assess the effect of spatial and temporal dependence in found relationships. Our findings indicate that, while the crime rate, housing costs, and poverty explain the prevalence of mental distress over time and space, the space–time variation of $PM_{2.5}$ is not a predominant determinant of mental distress in Chicago. The practical implications of our work are that planners and policymakers are encouraged to identify spatiotemporal patterns of mental distress so that resources can be directed to the most vulnerable communities. Spatiotemporal modelling, the identification of geographic patterns and relationships, enables novel understanding of societal issues, and is an integral part of spatial information science.

Keywords Mental distress prevalence · Social determinants of health · Geospatial analysis · Chicago

1 Introduction

In 2020, 21% of U.S. (52.9 million people) adults experienced mental illness [1]. In 2019, 970 million people worldwide suffered from a mental disorder, with anxiety and depression being the most common [2]. Because of the COVID-19 pandemic, the number of people living with anxiety and depression increased significantly in 2020 [3]. Mental health is regarded as an integral and necessary component of health, and the dimension of mental health is explicitly incorporated in the World Health Organization (WHO) definition of health, as stated in its constitution: "Health is a state of complete physical, mental, and social well-being, not merely the absence of disease or infirmity." This definition implies that people should not dismiss common mental problems such as depression, loneliness, anxiety, and stress [4]. Some mental health issues have been identified as a risk factor for suicide, substance abuse, and a variety of conditions such as stroke and coronary heart disease [5, 6].

Mental health issues are not limited to personal health and well-being. They are closely associated with social, environmental and economic issues [7, 8]. Air pollution has been related to behavioral predictors of psychological health. People tend to spend less time outdoors in areas with higher levels of air pollution [9]. Reduced exposure to sunlight and subsequent vitamin D deficiency [10], decreased physical activity [11, 12], and reduced contact with parks and other green space [13] affect the psychological health of the population. Additionally, a key socioeconomic factor affecting

✉ Aynaz Lotfata
alotfata@ucdavis.edu

Alexander Hohl
alexander.hohl@geog.utah.edu

1 Department of Pathology, Microbiology, and Immunology (PMI), School of Veterinary Medicine, University of California, Davis, USA

2 Department of Geography, The University of Utah, Salt Lake City, USA

health is housing [14]. Three essential facets of housing—physical housing conditions, housing affordability, and housing tenure—have received the majority of attention in health research [15]. The main known risk factors for infectious and respiratory disease are poor living circumstances, specifically overcrowding and inadequate ventilation. Although owning a residence offers people a stronger sense of security brought on by their good financial situation, poor living conditions can lead to worry and anxiety, and the inability to afford decent housing is likely to result in mental health issues [16, 17]. Lastly, cost-burdened households have limited resilience to withstand economic crises or job loss, leading to housing insecurity and the household's inability to pay for necessities, such as nutritious food that harm mental health [18].

Furthermore, neighborhoods play a critical role in shaping their residents' physical and mental health [19]. A neighborhood's physical and social infrastructure are critical to its ability to influence the well-being of its residents. Material entities such as buildings, facilities, and technology are examples of physical infrastructure. Community organizations, civic associations, and volunteer groups that foster interpersonal interaction and social engagement in the neighborhood context comprise the social infrastructure. Poverty and crime impact physical and social infrastructures, which act as roadblocks to improving residents' quality of life. Poverty and crime-ridden areas have limited access to urban amenities such as healthcare and green spaces, as well as an unsafe environment that causes stress and discourages physical activity. To illustrate, many studies have found that a variety of mental disorders are associated with poverty [20], with depression 1.5–2 times more prevalent [21] and schizophrenia an eight times greater risk, among low-income groups of a population [22]. Despite the well-established link between social and environmental determinants and mental distress, little is known about the spatial nature, direction, and mechanisms of this relationship.

So far, the existing literature addresses limited studies to spatial varying mental health (e.g. [23–25]). We know little about how social and environmental factors influence the mental distress and how those effects vary over time and space. Spatial and temporal clustering techniques can supplement behavioral maps by identifying statistically high mental distress prevalence areas, allowing researchers to determine whether the observed patterns were caused by chance or not [26]. The spatial and temporal variation of variable relationships was investigated using geographically and temporally weighted regression (GTWR, [27]). Although the GTWR model has been widely used to explain relationships in various fields, including but not limited to urban studies [28, 29], it has not been used to explain the prevalence of mental distress to make informed decisions to reduce health disparities.

The discipline of Urban Studies has a long tradition of viewing problems through a spatial lens, especially by utilizing geographic information systems (GIS, [30]) and Cartography [31]. Examples with focus on mental health include GIS-derived measures of the built environment [32], field-based urban design inventories [33], and the identification of disparities in mental health service provision [34].

Chicago, IL, USA, is ranked 11th out of 51 cities in the United States with the highest levels of mental distress [35]. Therefore, this paper aims to assess spatial and temporal variations of mental distress associated with environmental and social dynamics. It (1) describes the spatial and temporal distribution of mental distress in Chicago; (2) identifies areas of elevated mental distress; (3) describes the social and environmental factors associated with mental distress; and (4) uses publicly available data to suggest priority areas for interventions.

2 Data and method

We obtained model-based estimates of mental distress prevalence ("Mental Distress" Variable) and predictor variables among the population of all 796 census tracts of Chicago, IL for the years 2015, 2016, 2017, 2018, and 2019. The mental distress data, among many other health-related measures, are provided by the PLACES Project of the Centers for Disease Control and Prevention [36] and stem from responses to the Behavioral Risk Factor Surveillance System survey. Mental Distress is defined as the proportion of respondents who frequently feel stress, depression, and problems with emotions. Specifically, respondents aged ≥ 18 years answered, "14 or more" to the following question: "Thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?".

Besides, we collected data for predictor variables that quantify poverty ("poverty" Variable) as the percentage of low-income population, severe rent ("severe rent" Variable) as percentage of the population spending more than 50% of income for housing rent, and the $PM_{2.5}$ ("$PM_{2.5}$" Variable) estimated air quality model provided by the Chicago Health Atlas [37]. We quantified crime ("crime ratio" Variable) using data provided by the Chicago Data Portal [38] as the ratio between the number of crimes and the corresponding census tract population. To conduct spatial analysis and mapping using GIS, we obtained census tract polygon geometries as TIGER/Line Shapefiles from the United States Census Bureau. We joined all our census tract-level variables to the geometries through their 11-digit FIPS codes.

2.1 Spatial distribution of mental distress

To illustrate the spatial distribution of mental distress prevalence in Chicago, we utilize the space–time scan statistic [26] with normal probability model. The space–time scan statistic finds the areas and time periods that most likely exhibit elevated mental distress prevalence. These areas are denoted as "clusters", and stem from a set of candidate clusters. Each candidate z is a cylinder of radius r (the spatial scanning window) and height t (the temporal scanning window), defined by a starting date and an end date. The cylinders are centered on a candidate location, whereas a set of different radii and time periods are tested. The set of candidate locations consists of the centroids of the $N=796$ census tracts in Chicago, and possible start and end dates are the study years 2015, 2016, 2017, 2018, 2019. Therefore, each centroid is the center of multiple candidate clusters of variable radii and heights. Also, all census tracts whose centroid intersects with a cylinder are part of the respective cluster. The null hypothesis (h_0) states that mean mental distress prevalence inside the cluster is equal to outside, whereas the alternative hypothesis (h_a) states that mental distress prevalence inside the cluster is higher than outside. We evaluate both, h_0 and h_a by choosing z to maximize the log of the likelihood ratio (LLR) in Eq. (1):

$$\max_z \left[N\frac{(x_{ij}-\mu)^2}{2\sigma^2} - \frac{N}{2} - Nln ln\left(\sqrt{\sigma_z^2}\right)\right] \tag{1}$$

where $x_{i,j}$ is the mental distress prevalence value at census tract i in year j, μ the global mean, and σ^2 the variance.

We assess statistical significance of clusters using Monte Carlo simulation by randomly permuting the mental distress prevalence values among census tracts 999 times. For each of the 999 simulation runs, we compute LLR for clusters, and if the observed LLR is within the highest 5% among the simulated ones, we deem the cluster as significant at the 0.05 alpha level.

2.2 Spatial correlates of mental distress

Using Ordinary Least Squares (OLS) regression, we identified significant predictors of mental distress. We avoided multicollinearity among predictor variables by computing the variable correlation matrix and ensuring that variance inflation factors were less than the recommended threshold of 2.5, indicating that collinearity among predictors did not cause variance inflation. Poverty, crime ratio, severe rent, and $PM_{2.5}$ were all predictor variables in our regression model. Our regression diagnostics included checking for heteroskedasticity by plotting residuals versus fitted values and checking for normality by the histogram of standardized residuals. We further analyzed our OLS regression model to check for spatial autocorrelation of residuals, which violates OLS assumptions [39]. We tested for the presence of residual spatial autocorrelation using global Moran's I [40].

We developed a GTWR model to deal with the spatial and temporal non-stationarity issues simultaneously [27, 41]. GTWR is an extension of the traditional geographically-weighted regression (GWR) which allows local rather than global parameters to be estimated and assumes spatial heterogeneity of predictor variable effects [42]. While GWR takes into account spatial variation in model effects, it ignores temporal non-stationarity [43]. GTWR incorporates temporal heterogeneity, allowing for the estimation of coefficients that vary across space and time. In GTWR, optimal spatial bandwidth and optimal temporal bandwidth are calculated in the same way that they are in traditional GWR by minimizing the AIC function of the model to obtain a set of local estimates with the best bias-variance trade-off. Once the optimal spatial and temporal bandwidths have been determined, they can be used to build the spatiotemporal weight matrix, which allows for the estimation of local parameters. It should be noted that both spatial and temporal bandwidth optimization require a significant amount of computation because those steps necessitate repeated temporary model calibrations [27].

The GTWR model was used in this paper to address temporal structure in data for mental distress and social-environmental factors ("crime ratio," "severe rent," "poverty," and "$PM_{2.5}$") on an annual basis. Equation (2) describes the general structure of the GTWR model, which was developed to estimate the spatiotemporal relationship between mental distress and tract census-based data.

$$Yi = \beta_0(u_i, v_i, t_i) + \Sigma\beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \tag{2}$$

where (u_i, v_i, t_i) represents the given coordinates of the mental distress i in spatial location $(u_i, v_i,)$ at time t_i; ε_i is the error, and X_{ik} represents the value of the k-th explanatory variable of the sample point i. To estimate the intercept β_0 and the slopes β_k for each variable, a locally weighted least squares method is employed. This assumes that the closer the measurements are to point i in the space–time coordinate system, the greater the weight of the measurements in predicting β_k. Thus, the estimation of coefficients is expressed as Eq. (3):

$$\hat{\beta}(u_i, v_i, t_i) = [X^T W(u_i, v_i, t_i)X]^{-1} X^T W(u_i, v_i, t_i)Y \tag{3}$$

where X is a vector representing the social-environmental factors ("crime ratio", "severe rent," "poverty," and "$PM_{2.5}$"). The space–time weights matrix $W(u_i, v_i, t_i)$ was introduced to measure the importance of sample i to the estimated sample j, with respect to space and time. It implies that a straightforward way of modeling temporal distance is to integrate it directly with spatial distance into the spatiotemporal distance function. Equation (4) defines distance as a linear combination of spatial distance and temporal distance:

$$d_{st} = \mu * d_s + k * d_t \quad (4)$$

where μ and k are scale factors to balance the different effects used to measure the spatial and temporal distance in their respective metric systems. Therefore, if the parameters are adjusted appropriately, d_{st} can be used to measure the extent of 'closeness' in a spatiotemporal space. Equation (5) shows the spatiotemporal weighting function ($W^t_{ijs,T}$) specific for data points located at time t according to a general form of a spatiotemporal kernel function where a spatial kernel function gives weights (k_s) with d_{sij} being the Euclidean distance between the regression point i and a data point j:

$$W^t_{ijs,T} = k_s\left(d_{sij}, b_{St}\right) \times k_T(d_{tij}, b_T) \quad (5)$$

In this study, a time-decay temporal bandwidth is proposed, that is, a temporal bandwidth in which data points located closer in time to the regression point have more influence on local estimates at the regression point i than those located farther away in time. In this study, a set of segregated spatial bandwidths over time which must be estimated along with the temporal bandwidth to fit the data, is applied. Bandwidth can be optimized using AIC. The GTWR model was implemented using an ArcGIS add-in developed by Huang [41]. All our statistical computing was conducted using the R Core Team and R Studio Team, and we used ArcGIS Pro software for cartography.

3 Results

3.1 Spatial distribution of mental distress

From 2015 to 2019, the prevalence of mental distress among adults in Chicago had a relatively clustered spatiotemporal distribution (Fig. 1). While there were no clusters in 2015–2017, we identified 13 statistically significant clusters of high mental distress prevalence in 2018–2019, with the most prominent and strongest cluster (Cluster 1) located on Chicago's west side. It has a mean mental distress prevalence of 17.75% (Table 1), includes multiple industrial corridors, and encompasses 103 census tracts. The second-largest and strongest cluster (Cluster 2) is found south of Chicago, with a mean prevalence of 16.66%, and it encompasses 157 census tracts. Cluster 2 is situated near Englewood Neighborhood, predominantly Black population, and the planned manufacturing corridor. Several additional clusters are found in the northeast part. Table 1 shows important characteristics of the corresponding clusters in Fig. 1.

3.2 Spatial correlates of mental distress

We found that the crime ratio of census tracts ("crime ratio") was high in the southern and western parts of Chicago in 2015 and that it continues to rise in the south and west sides and their surrounding neighborhoods from 2016 to 2019. While severe rent ("severe rent") is highest in downtown's southern, western, and northern, western sides in 2015, extreme rent per census tract shows an incremental decrease during 2016 and 2019. However, the results showed that the poverty rate ("poverty") did not change significantly per census tract during 2015 and 2019. Poverty is primarily concentrated in the city's southern and western neighborhoods. While air pollution ("$PM_{2.5}$") was high in downtown Chicago in 2015, the results show that air quality in Chicago decreased in 2018 and improved in 2019.

The OLS regression model revealed a positive relationship between the crime ratio per census tract, severe rent, and poverty percentage. As poverty, housing costs, and criminal activities increase per census tract, so does the population's susceptibility to mental illness. In contrast, there is no evidence of a link between $PM_{2.5}$ and mental distress (Table 2). Overall, the model fit was moderate, with an R^2 of 0.71. The linear model fit (AIC) was 16,007, and Jarque–Bera Statistic is 5.29 indicating a normal distribution of OLS regression residuals. The spatial analysis of residuals revealed significant spatial autocorrelation in the model. Moran's I test ($I=0.59$, $p=0.00$) confirms the presence of spatial autocorrelation of residuals.

GTWR confirms the OLS result, while the GTWR model (AIC = 12,707) with R^2 of 0.88 was higher than OLS. The GTWR coefficients, as expected, indicated the presence of spatial and temporal variation. The findings show a link between criminal activity and the prevalence of mental distress in Chicago's southeastern and northwestern neighborhoods in 2015 (Fig. 2). During 2016 and 2019, the relationship between criminal ratio and mental distress prevalence dispersed to the nearby areas southeastern and northwestern sides. Our findings show a positive relationship between the crime ratio per census tract and mental distress, which increased on western side in 2019. The positive relationship between rent and mental distress exhibits a stronger increase over time in northwest suburbs, and it gradually disperse along Lake Michigan during 2017 and 2019 (Fig. 3). From 2015 to 2019, the findings show a positive relationship between the poverty ratio and mental distress (Fig. 4). Downtown and nearby neighborhoods, as well as communities in the south and northwest, have seen the greatest increases. Furthermore, while the results show a positive association between $PM_{2.5}$ and mental distress in the southern side of downtown and northwest of Chicago in 2015, a decrease in $PM_{2.5}$ is associated with an increase in

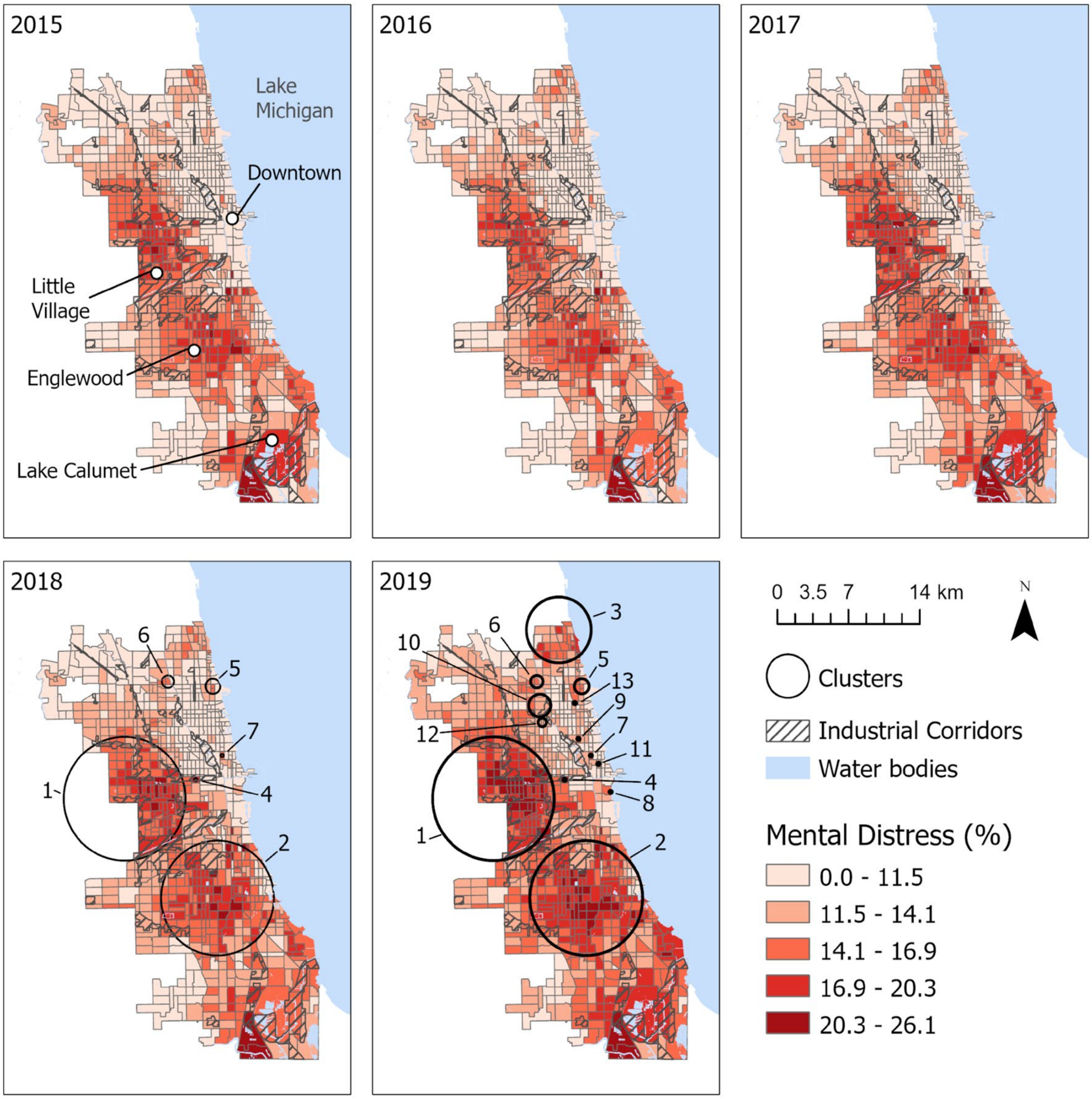

Fig. 1 Clusters from spatial scan statistics

mental distress prevalence across Chicago during 2017 and 2019 (Fig. 5).

4 Discussion

Our study used a spatiotemporal clustering technique and two regression models to examine the spatial and temporal distribution and varying relationships between mental distress prevalence and social- environmental factors. We found that the prevalence of mental distress varies across Chicago, with higher levels in the city's west and south sides, such as Englewood and Little Village, which are surrounded by industrial areas and have high Black and Hispanic populations, respectively (Fig. 1). We identified and described social and environmental factors associated with mental distress as follows: The low-income population is more vulnerable to mental illnesses in the unsafe urban areas along Lake Michigan and the north side of Lake Calumet (Fig. 2). Furthermore, unaffordable housing endangers the population's mental health living in houses with high rents and low income in Chicago's northwest suburbs. The situation worsens, while neighborhoods attract criminal activity in Chicago's southeast (Fig. 2). Additionally, while environmental determinants impact health, air pollutants, specifically $PM_{2.5}$, have no effect on mental distress in Chicago during the 2018–2019 year compared to previous years in both the southern and northern sides (Fig. 5). The findings of this study are consistent with previous research indicating that unaffordable housing contributes to stress and mental

Table 1 Clusters of elevated mental distress

ID	From	To	#tracts	*p* value	Mean inside (μ_{in})	Mean outside (μ_{out})	Variance	LLR
1	2018	2019	103	0.001	17.75	12.90	9.21	730,333.1
2	2018	2019	157	0.001	16.66	12.90	9.45	555,786.1
3	2019	2019	28	0.001	15.13	13.10	10.22	28,102.4
4	2018	2019	1	0.001	20.07	13.12	10.25	7869.2
5	2018	2019	3	0.001	15.16	13.12	10.25	6201.2
6	2018	2019	2	0.001	15.33	13.12	10.25	4676.6
7	2018	2019	1	0.001	15.62	13.12	10.25	2570.2
8	2019	2019	1	0.001	16.50	13.12	10.26	1750.4
9	2019	2019	1	0.001	15.70	13.12	10.26	1499.3
10	2019	2019	6	0.001	13.41	13.12	10.26	101.9
11	2019	2019	1	0.001	13.40	13.12	10.26	30.4
12	2019	2019	2	0.017	13.35	13.12	10.26	13.3
13	2019	2019	1	0.738	13.50	13.12	10.26	8.2

Table 2 OLS model results

Variable	Coefficient	SE	t-statistic	*P* value	VIF
Intercept	16.70	0.30	55.08	0.00	–
Crime	4.29	0.40	10.47	0.00	1.38
Severe rent	0.01	0.002	5.32	0.00	1.42
Poverty	0.18	0.002	67.89	0.00	1.70
PM2.5	−0.68	0.02	−26.89	0.00	1.01

disorders [44]. Similarly, scholars highlight the prevalence of poverty as a major determinant of depression and anxiety [45]. They define poverty as a defining factor of the neighborhood and housing characteristics, such as a lack of access to healthcare and healthy food, as well as poor housing ventilation [46]. In fact, poverty is debated as a multi-dimensional phenomenon in the context of unequal access to resources [47]. One of the critical factors is ecological determinants of mental distress- clean air, water, and access to natural resources- affecting the population's mental health [48]. However, few studies on the subject have been conducted in recent years, notably on air pollution. This study is based on publicly available data and encourages policy-makers and planners to identify the emotional and stressful aspects of the built environment in order to reduce the burden of diseases associated with the risk of mental distress. To improve individual-based mental health, development and renewal practices should include measures to increase housing affordability by taking into account housing costs and neighborhood quality holistically.

5 Conclusion

A mental illness epidemic is endangering the world's health and is a contributing factor in many diseases. In the United States, the prevalence of mental discomfort has significantly increased. This research investigates the spatial and temporal associations between crime rates, high rent, poverty, air pollution, and the rate of mental distress. We propose

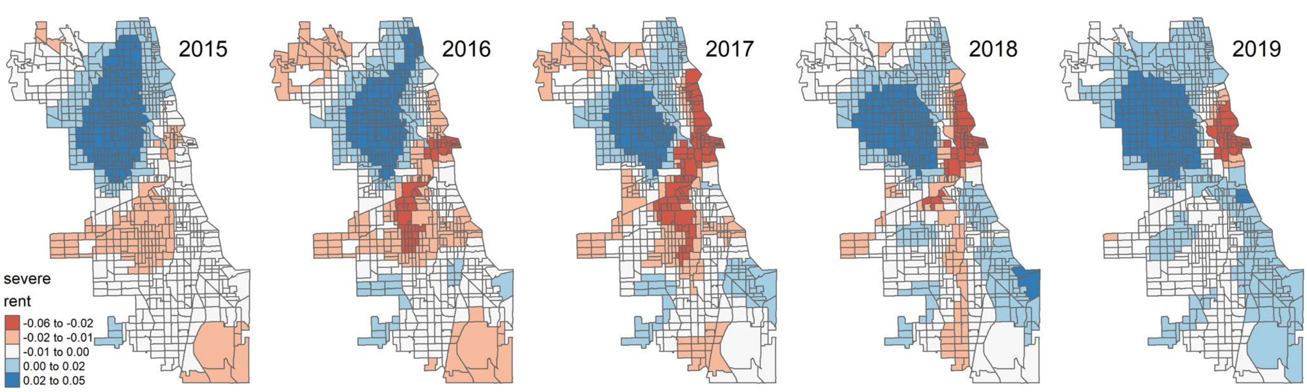

Fig. 2 The spatial distribution of GTWR coefficients: crime

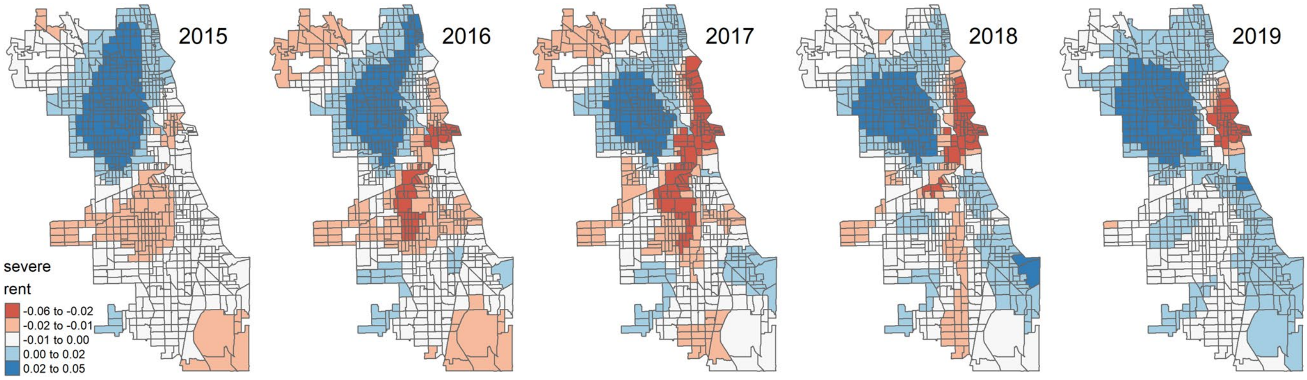

Fig. 3 The spatial distribution of GTWR coefficients: severe rent

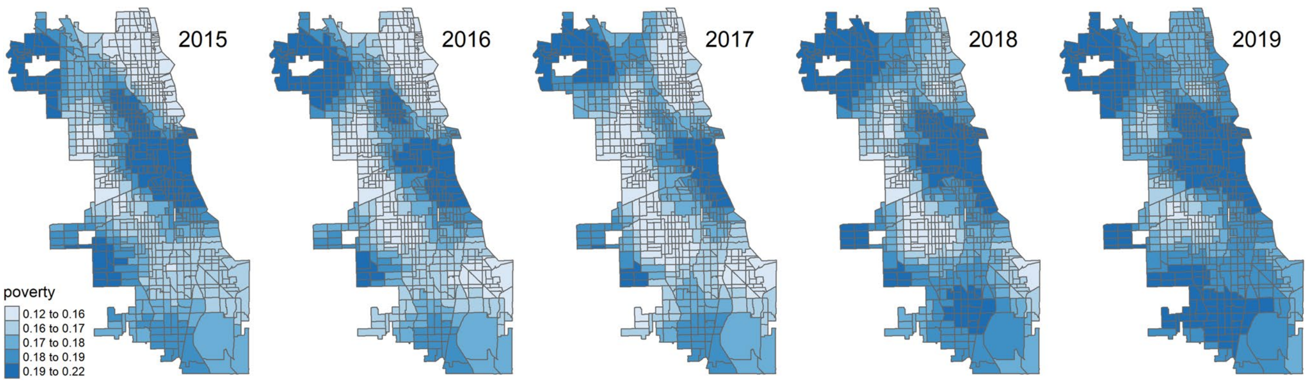

Fig. 4 The spatial distribution of GTWR coefficients: poverty

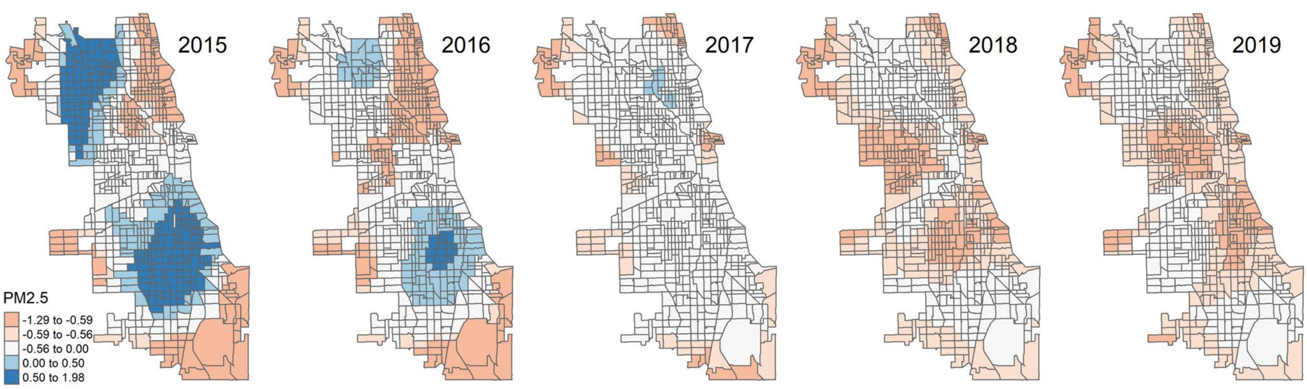

Fig. 5 The spatial distribution of GTWR coefficients: PM 2.5

low-income housing policies in the United States with three main characteristics to improve the housing conditions of low-income households: Rents are regulated, housing units are allocated according to specific rules, frequently targeting low-income households or specific groups such as the elderly, students, or the disabled, and housing units are owned and managed by municipalities or non-profit organizations. Although the Clean Air Act of 1970 resulted in reductions in air pollution in the United States, we propose monitoring pollutant emissions within local services and monitoring air in locals to reduce air pollutants and improve mental healthcare.

This study has five major limitations. The mental distress variable, for example, is based on survey data, which introduces response bias. Second, this study excludes the effects of micro-community environments on mental health. Future research should include housing quality, access to public transportation, parks, and their relationship with the prevalence of mental distress. Third, the spatial scan statistic, which uses clusters of circular shapes, was used. However, in a spatially heterogeneous area of Lake Michigan, the circular cluster assumption may not hold true. Although the spatial scan statistic has been expanded to address this issue, circular clusters are implemented in the SaTScan™ software remain a common practice in spatial analysis. Fourth, while our study may help future research by identifying neighborhoods with high levels of mental distress and their associations with socioeconomic and environmental factors, our ability to identify causal relationships is limited due to the retrospective and longitudinal study design. Fifth, our data is aggregated to census tracts, subject to the modifiable areal unit problem (MAUP).

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Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

Ethical approval The authors declare that the paper does not have conflicts of interest. All applicable international, national, and/or institutional guidelines for the care and use of animals were followed. We did no not use data related to animals or individuals. Data are publishably available data. This article does not contain any studies involving human participants performed by any of the authors. This material is the author's own original work, which has not been previously published elsewhere.

Human and animal rights This article does not contain any studies with human participants or animals performed by any of the authors.

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