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Spatial analysis and modelling of depression relative to social vulnerability index across the United States

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Abstract

According to the Substance Abuse and Mental Health Services Administration, about 21 million adults in the US experience a major depressive episode. Depression is considered a primary risk factor for suicide. In the US, about 19.5% of adults are reported to be experiencing a depressive disorder, leading to over 45,000 deaths (14.0 deaths per 100,000) due to suicides. To our knowledge, no previous spatial analysis study of depression relative to the social vulnerability index has been performed across the nation. In this study, county-level depression prevalence and indicators were compiled. We analysed the geospatial distribution of depression prevalence based on ordinary least squares, geographically weighted regression, and multiscale geographically weighted regression models. Our findings indicated that the multiscale model could explain over 86% of the local variance of depression prevalence across the US based on per capita income, age 65 and older, belonging to a minority group (predominantly negative impacts), and disability (mainly positive effect). This study can provide valuable insights for public health professionals and policymakers to address depression disparities.

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Introduction

According to the World Health Organisation (WHO), depression is a mental health disorder that has substantially contributed to the global health burden of disease (WHO, 2021). The Department of Health and Human Services (HHS) in the US characterises this disorder as a combination of signs and symptoms that can present in various ways, such as irritability, fatigue, pessimism, feelings of guilt or worthlessness, talking or moving slowly, restlessness, oversleeping, difficulty concentrating, weight and appetite changes and suicidal ideation (NHS, 2018). The symptoms should last approximately two weeks to be formally diagnosed by a mental health professional or clinician (HHS, 2018). It is estimated that almost 5% of adults live with depression which makes it a major disability worldwide (WHO, 2021). Every year, this disorder can account for approximately 1 trillion USD in global costs, which is projected to increase to almost 6 trillion USD by 2030 (The Lancet Global Health, 2020). In the US, about 21 million adults (8.4% of adults) experience a major depressive episode (Substance Abuse and Mental Health Services Administration, 2021). In 2018, major depressive disorder (MDD) (*i.e.* major depression, dysthymia, and other signs of depressive disorder) accounted for over 326 billion USD in costs related to the workplace, suicide, and other direct costs in the US (Greenberg *et al.*, 2021). Additionally, there was a significant increase (37.9%) in direct and indirect costs related to MDD between 2010 and 2018 (Greenberg *et al.*, 2021).

Depression is considered a primary risk factor for suicide (Roca *et al.*, 2019). In the US, about 19.5% of adults were reported to be experiencing a depressive disorder (America's Health Rankings, 2021). According to Centres for Disease Control and Prevention (CDC), this has led to over 45,000 deaths (*i.e.* 14.0 deaths per 100,000) due to suicides (CDC, 2020). Individuals between the ages of 18 and 44 years (20.4%), individuals with less than a high school diploma (20.8%), females (23.4%), and those with an annual income of less than $25,000 are at the highest risk of depression in the US (America's Health Rankings, 2021). Among subpopulations, American Indian/Alaska Natives (23.6%) and multiracial people (28.6%) accounted for the highest percentage of depression compared to other races/ethnicities (America's Health Rankings, 2021).

CDC defines the social vulnerability index (SVI), including unemployment, poverty, education, housing stability, and healthcare access, as social factors that aid in identifying needs during a

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natural disaster or public health emergency through geographic distribution (CDC, 2018). According to Nguyen *et al.* (2019), social vulnerability is significantly associated with mental conditions such as depression. Thus, a factor or a combination of these social vulnerabilities might serve as predictors that exacerbate or reduce depression prevalence in specific geographic locations.

Most previous studies have focused on the medical aspects of depression, with little attention paid to its geographic distribution and associations with underlying factors. Spatial analysis and modelling of mental health conditions can provide valuable insights into health disparities and improve health outcomes in communities (Park *et al.*, 2021). Smith-East and Neff (2019) highlight the importance of integrating spatial analysis to identify factors contributing to the spatial variations of depression using geographic information systems (GIS). In the US, they identified three main categories where GIS can be beneficial in addressing mental health care access: type of care (*i.e.* community and integrated), contributions to access (*i.e.* perception of travelling, inequalities, distance, time, cost) and services utilisation. In South Africa, Cuadros *et al.* (2019) conducted a spatial analysis and identified spatial clusters of depression, finding that the high incidence was mostly concentrated in eastern regions of the country. They suggest that the clustering might be influenced by epidemiological (*e.g.*, tuberculosis) and sociodemographic factors, such as educational attainment, employment status, race/ethnicity, household income, marital status, gender, and age.

The findings of this study may support public health measures and strategies to reduce health disparities related to depression, which would be helpful for targeted interventions.

Materials and methods

Data

Depression prevalence data (as response variable) were collected from the CDC Behavioural Risk Factor Surveillance System (BRFSS) at the county level across the US, which is available at https://www.cdc.gov/places. The SVI data (as explanatory variables) for 2018 were also collected at the county level across the US from the CDC (https://www.atsdr.cdc.gov/placeandhealth/svi/index.html). A total of 16 explanatory variables, classified into four themes: socioeconomic status; household composition and disability; minority status and language; housing type and transportation, were included (Table 1). Moreover, the state and county boundary shapefiles were obtained from the US Census Bureau's MAF/TIGER database (https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html). All data were fed into the ArcGIS Desktop 10.8 software (ESRI, Redlands, CA, US) for further spatial analysis and modelling.

Models

To statistically explore the spatial variation of depression prevalence across the US and its association with the SVI variables, we selected the ordinary least squares (OLS) model as baseline model. Further, we compared the OLS with geographically weighted regression (GWR) and multiscale GWR (MGWR) as local models.

Ordinary least squares model

OLS is a global regression model that explores the association between a response variable and explanatory variables. This model assumes a stationary and linear relationship between each SVI variable and depression prevalence (Hutcheson, 2011; Ward and Gleditsch, 2018; Mollalo *et al.*, 2020; Mansour *et al.*, 2021), as follows (Hutcheson, 2011):

$$\gamma_i = \beta_0 + \beta\chi_i + \varepsilon_i \quad (1)$$

where γ_i represents the depression prevalence in the US for county i; β_0 the intercept; β the estimated coefficients vector of SVI variables; and χ_i the selected SVI vector. The model was calibrated by removing highly correlated and insignificant variables.

Geographically weighted regression

Unlike OLS, the GWR model assumes a non-stationary relationship between depression prevalence and each SVI variable (Brunsdon *et al.*, 1996; Mollalo and Tatar, 2021). In GWR, the

Table 1. Characteristics of explanatory variables.

Theme	Explanatory variable	Description
Socioeconomic status	Below poverty	Percentage of persons below poverty estimate
	Unemployed	Unemployment rate estimate
	Income	Per capita income estimate (2014-2018 ACS)
	No high school diplomas	Percentage of persons with no high school diploma (>25 years) estimate
	Uninsured	Percentage uninsured in the total civilian non-institutionalized population estimate
Household composition and disability	Aged ≥65 years	Percentage of persons aged ≥65 years estimate (2014-2018 ACS)
	Aged ≤17 years	Percentage of persons ≤17 years estimate (2014-2018 ACS)
	Civilian with disability	Percentage of civilian non-institutionalized population with a disability estimate (2014-2018 ACS)
	Single-parent household	Percentage of single-parent households with children <18 years estimate (2014-2018 ACS)
Minority status and language	Minority	Percentage minority (all persons except non-Hispanic Whites) estimate (2014-2018 ACS)
	Speaks English 'less than well'	Percentage of persons (>5 years) who speak English 'less than well' estimate (2014-2018 ACS)
Housing type and transportation	Multi-unit structures	Percentage of housing in structures with ≥10 units estimate
	Mobile homes	Percentage of mobile homes estimate
	Crowding	Percentage of occupied housing units with more people than rooms estimate
	No vehicle	Percentage of households with no vehicle available estimate
	Group quarters	Percentage of persons in group quarters estimate

ACS, American Community Survey.

local parameters are estimated through moving kernel-weighted regression centred on the centroid of each county across the study area (Brunsdon *et al.*, 1996). Geographic variations can be seen through this model by showing the distinct parameter variations according to specific counties; which indicates its heterogeneous nature in local variations (Brunsdon *et al.*, 1996; Mathew *et al.*, 2022) as shown by Fotheringham and Oshan (2016):

$$y_i = \beta_{i0} + \sum\nolimits^{m}_{j=1}\beta_{ij}\chi_{ij} + \varepsilon_i,\ i = 1,2,\ldots,n \qquad (2)$$

where y_i represents the prevalence of depression at county i; β_{i0} the intercept for county i; m the number of selected SVI indicators; β_{ij} the jth covariate estimation coefficient; χ_{ij} the jth covariate at county i; and ε_i the error term.

Multiscale geographically weighted regression

MGWR is an extension of the GWR model and allows for examining the relationships of spatial variations at different scales, which is not possible with the GWR model (Oshan *et al.*, 2019; Mollalo *et al.*, 2020). In this model, a specific bandwidth is associated with each variable included in the analysis (Oshan *et al.*, 2019). Therefore, spatial heterogeneity may be more accurately incorporated in MGWR than in GWR (Mollalo *et al.*, 2020). The MGWR equation shown as used by Fotheringham *et al.* (2017) is:

$$y_i = \beta_{i0} + \sum\nolimits^{m}_{j=1}\beta_{bwj}\chi_{ij} + \varepsilon_i \qquad (3)$$

where β_{bwj} represents the estimation of coefficient for county i; bwj the jth optimal bandwidth.

Accuracy assessment

MGWR 2.2 software was utilised to run the global (OLS) and local models (GWR and MGWR) (https://sgsup.asu.edu/sparc/multiscale-gwr). We used the adjusted R^2, the corrected Akaike information criterion (AICc) and the residual sum of squares (RSS) to compare the performance of the models employed. A larger variation in depression prevalence can be explained by a higher adjusted R^2. Moreover, for selecting the most parsimonious model, AICc, and RSS with the lowest values were preferred (Wu *et al.*, 2021). To examine whether the residuals of the models were autocorrelated, Moran's I statistic according to Anselin was used (Kiani *et al.*, 2021). To visually compare multicollinearity in the local models, the local condition numbers were mapped. Local condition numbers below 15 are considered to indicate weak multicollinearity, between 15 and 30 moderate multicollinearity, and above 30 strong multicollinearity (Shrestha, 2020). Moreover, to compare the difference in the goodness of fit of models for different areas, the local R^2 was mapped for both local models. After selecting the best-fitted model, the estimated coefficients for each explanatory variable were mapped to display their effects on depression prevalence across the US. All maps included in this study were produced using ArcGIS Desktop 10.8.

Results

Preliminary descriptive statistics indicated that depression prevalence ranged from 0.0 to 31.2, with a mean of 20.96 and a standard deviation of 3.09 per 100,000 individuals across the US. Figure 1 shows the spatial distribution of depression across the US. According to Figure 1, most counties in Kentucky (KY), Tennessee (TN) and West Virginia (WV) accounted for the highest prevalence of depression ranging from 30.2 to 31.2 per 100,000 individuals. The top five counties in terms of prevalence per 100,000 individuals were Mingo (WV, prevalence =31.2), Logan (WV, prevalence =31.0), Carter (TN, prevalence =30.6), Rowan (KY, prevalence =30.5) and Wyoming (WV, prevalence =30.2). A high concentration of depression was also observed in the Northwest, particularly in Washington, Oregon, and Montana. Conversely, lower rates of depression were concentrated in coun-

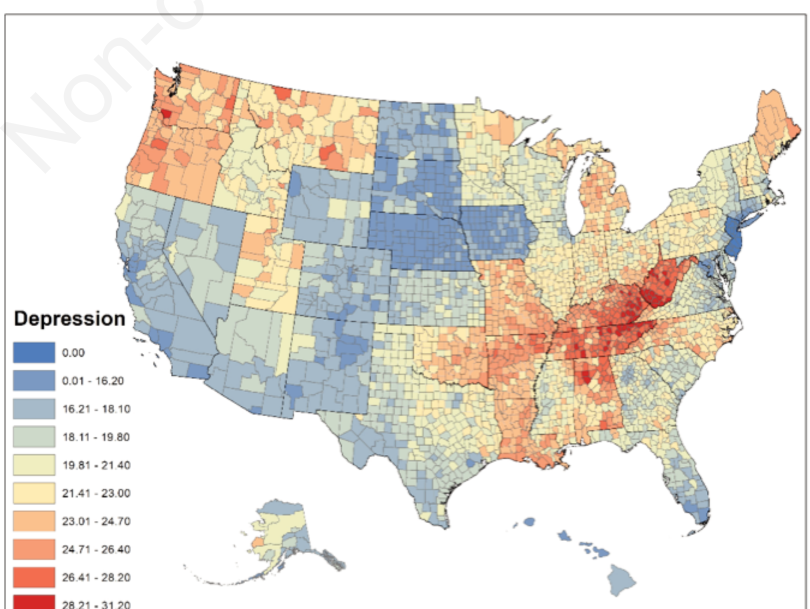

Figure 1. Depression prevalence across the US at the county level. Prevalence given per 100,000 individuals.

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ties in the Midwest, especially in North Dakota, South Dakota, Nebraska and Iowa.

Using the OLS model, only four variables were selected out of the 16 SVI variables, which were per capita income (PCI), persons aged ≥65 years (%), civilian non-institutionalized population with a disability (%) and minority (%). According to the OLS results (Table 2), all selected variables, except for disability (%), had a significant negative association with depression prevalence (P<0.05). Moreover, the variance inflation factor (VIF) for all explanatory variables was less than 3, which shows that multicollinearity was not a concern.

Regarding the goodness of fit of the models, local models showed significant improvements when compared to the OLS. Both local models displayed more than 40% improvements compared to the global model. However, as seen in Table 3, there was a slight difference in adjusted R^2 values between GWR (84.1%) and MGWR (86.4%). MGWR demonstrated a better fit in explaining the variance of depression prevalence based on the selected explanatory variables. Moreover, the OLS had the highest AICc value, an indicator that decreased from GWR to MGWR, *i.e.* showing a better fit for the latter. Similarly, MGWR expressed a lower residual sum of squares (RSS=360.292) when compared to GWR (RSS=411.200) and OLS (RSS=1765.825). Moran's *I* suggested that the MGWR residuals were randomly distributed (Moran's *I*: 0.098, *z*-score: 1.54, P=0.12).

The spatial distribution of local R^2 for GWR and MGWR is shown in Figure 2. These maps display that both models fit the best in California, Florida, Texas, and South Dakota. The local condition numbers in MGWR were between 1.34 and 13.55, while in GWR these numbers ranged between 2.59 and 33.45, indicating possible problematic multicollinearity in this model. However, this was not an issue for MGWR. The spatial distribution of the local condition numbers is also depicted in Figure 2.

GWR utilised an optimal bandwidth of 66 (95% CI: 63.0 - 67.0); whereas MGWR utilised different bandwidths for each explanatory variable ranging from 44 to 3140. Larger bandwidths for 'age≥65 years (%)' and 'minority (%)' suggest that these variables had a more wide-ranging influence on depression compared to the other explanatory variables. Conversely, more local impacts were observed by smaller bandwidth for 'PCI' and 'disability (%).'

We selected the MGWR model as the best-fitted model and mapped the impact of each explanatory variable on depression across the US. The results indicated that 'PCI' had almost persistently negative effects on depression prevalence in the North-west, Central and North-east. 'PCI' also depicted more local variations compared to other explanatory variables, with the most substantial impacts in Kansas, Idaho, Minnesota, Connecticut and Massachusetts. 'Age≥65 years (%)' displayed a steady, negative association with depression prevalence across the US. 'Minority (%)' showed similar results but with a decreasing impact on depression prevalence from north to south. Conversely, 'disability (%)' showed heterogeneous positive effects with the highest impacts on depression in the north-eastern region (Figure 3 and Table 4).

Discussion

Previous studies have shown that mental health disorders are associated with many social factors (Allen *et al.,* 2014; Shyman *et al.,* 2021). We aimed to examine the geospatial relationship between SVI indicators and depression prevalence at the county level across the US. Though we implemented both global and local models, the spatial distribution and regional variations of depression prevalence were best explained by the MGWR model, which showed that in particular four variables: PCI, age ≥65 years, civilian non-institutionalized population with a disability, and minority, could explain over 86% variance in depression prevalence. In contrast, GWR only accounted for the single bandwidth for the same variables included. The MGWR model was thus more accurate in representing county-level neighbouring distribution by applying separate bandwidths for each explanatory variable.

Table 2. Summary statistics of modelling depression in the US with selected variables using the ordinary least squares model.

Variable	Coefficient estimate	Standard error	T (EST/SE)	VIF	P-value
Intercept	–0.000	0.013	–0.000	-	1.000
PCI	–0.261	0.017	–14.918	2.82	0.000*
% Disability	0.451	0.019	23.832	2.43	0.000*
% Persons ≥65 years	–0.371	0.017	–22.450	2.57	0.000*
% Minority	–0.425	0.015	–28.302	2.47	0.000*

PCI, per capita income; VIF, variance inflation factor. *Statistically significant P-value.

Table 3. Ordinary least squares, geographically weighted regression, and multiscale geographically weighted regression in modelling depression in the US.

Criterion	OLS	GWR	MGWR
Adj. R^2	0.437	0.841	0.864
AICc	7118.086	3902.949	3263.302
RSS	1765.825	411.200	360.292
Log-likelihood	–3553.030	–1263.620	–1055.989

OLS, ordinary least squares; GWR, geographically weighted regression; MGWR, multiscale geographically weighted regression; AICc, Akaike information criterion; RSS, residual sum of squares.

The negative association between PCI and depression prevalence in the North-west, Central and North-east of the US and the positive association in counties in Kansas, Idaho, Connecticut, and Massachusetts might be due to systemic issues related to economic disparities and increased distress among populations affected by financial hardships, such as decreased workload and income loss as mentioned by Witteveen and Velthorst (2020). Our findings are consistent with Patel *et al.* (2018), who conducted a systematic review and meta-analysis to explore the association between depression and income inequality. Based on a total of 26 studies in their review, they found a significant association between the risk of depression and income inequality (P<0.05). Moreover, they found that higher income inequality was associated with a greater risk of depression compared to lower-income inequality populations. Frasquilho *et al.* (2015) also performed a systematic literature review. They found that economic crises such as a recession

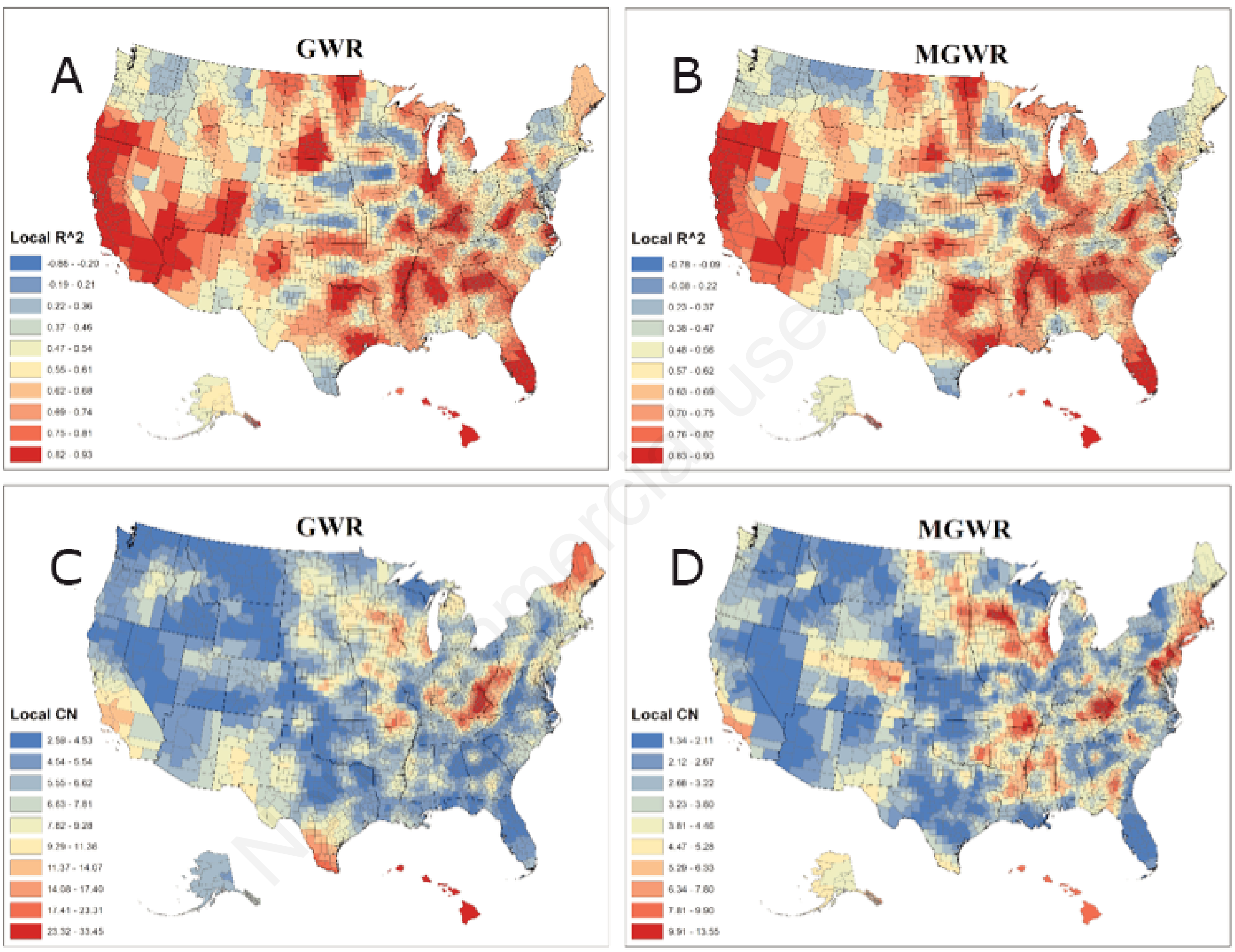

Figure 2. Spatial distributions of local R^2 and the local condition numbers. A) R^2 for geographically weighted regression (GWR); B) R^2 for multiscale GWR (MGWR); C) local condition numbers for GWR; D) local condition numbers for MGWR.

Table 4. Geographically weighted regression and multiscale geographically weighted regression bandwidths comparison.

Bandwidth (95% CI) Model	GWR	MGWR
Intercept	66.0 (63.0, 67.0)	44.0 (44.0, 44.0)
PCI	66.0 (63.0, 67.0)	44.0 (44.0, 46.0)
Disability (%)	66.0 (63.0, 67.0)	44.0 (44.0, 44.0)
Age 65 and older (%)	66.0 (63.0, 67.0)	3140.0 (2690.0, 3140.0)
Minority (%)	66.0 (63.0, 67.0)	1000.0 (774.0, 1226.0)

CI, confidence interval; GWR, geographically weighted regression; MGWR, multiscale geographically weighted regression; PCI, per capita income.

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can increase rates of mental health disorders, suicidal behaviours, and substance-related disorders. Though causality assumptions cannot be made, the results suggest that traumatic events or disasters can give rise to mental health illnesses in specific populations (Goldmann and Galea, 2014).

Our study also showed a significant negative, almost constant association between depression prevalence and the percentage of persons ≥65 years across the US. However, age can be regarded as a confounding variable due to the lack of age group classification for the data included. A possible alternative explanation could be potential social isolation, social disconnectedness, lack of support system and cognitive impairment prevalence among older adult populations (Kok and Reynolds, 2017; Santini *et al.*, 2019). In South Florida, Hames *et al.* (2017) alluded to the importance of understanding the spatial dynamics of medical and social vulnerabilities among older adults. Similarly, a cross-sectional study in rural China explored influential factors and gender-specific prevalence of depression among the elderly (Lin *et al.*, 2021). Their findings highlight the need to screen older adult populations for factors contributing to depression in the ageing population and other comorbidities that may exacerbate those symptoms (Smith and Meeks, 2019). We found a significant negative association between the minority (%) and depression prevalence increasing from north to south. In counties with a lower proportion of minorities, we observed weaker negative impacts, mainly in the northern states. Conversely, there were weak negative impacts observed in the south probably due to the higher proportion of minorities there. In California, Wilderman *et al.* (2021) explored the relationship between mental health prevalence and urban green space. Their results suggest that increased distance to green areas may lead to poorer mental health outcomes, particularly in minority groups (*e.g.*, the proportion of Hispanics in the southern states) and population living below the poverty line. Furthermore, Bailey *et al.* (2019) conducted a study exploring current perspectives of racial and ethnic disparities among those living with depression in the US. They found that minority groups were more likely to experience chronic, severe, and prolonged depression, something that can be debilitating; Caucasians were more likely to experience acute episodes of MDD than other minority groups. Such findings highlight the need to address disparities in depression health outcomes among minority groups, which may be due to underdiagnosis, access to care, and other risk factors.

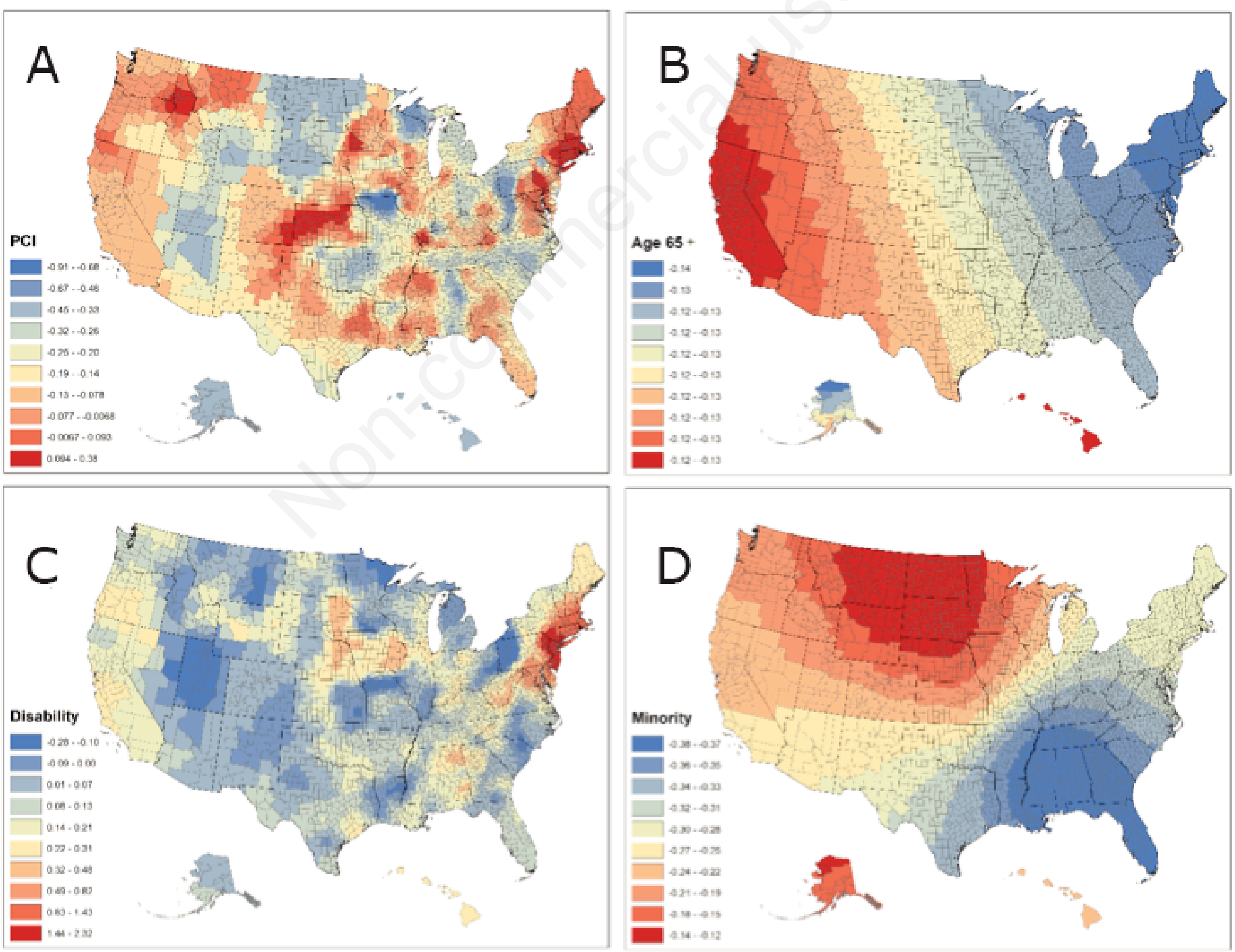

Figure 3. The impacts of: A) per capita income (PCI); B) disability (%); C) age ≥65 years (%); and D) minority (%) on depression prevalence across the US based on the multiscale geographically weighted regression model.

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Disability (%) showed a significant positive impact on depression prevalence in the present study, but mainly in the north-eastern regions. The presence of physical or mental disabilities can exacerbate mental distress, leading to the increased risk of experiencing depression in some populations. Our findings are consistent with the outcomes of a study in South Korea. Jung *et al.* (2021) explored how four types of disability (*i.e*. physical-external, sensory/speech, physical-internal and mental) can predict depressive symptoms.

There were a few limitations to this study. Due to ecological fallacy, we could not make any predictions or assumptions at the individual or sub-county levels (Mollalo *et al.*, 2021). Also, this study does not account for varying types of depression prevalence, such as seasonal affective disorder, perinatal/postpartum depression, persistent depressive disorder or bipolar depression. Future studies can consider separate categories of depression prevalence to understand spatial variability along with other related disorders such as anxiety. Additionally, the future inclusion of other sociodemographic variables, or even environmental factors, could explain the spatial dynamics of mental health. Furthermore, exploring mental health access services, such as therapy, counselling and clinical interventions may aid in better understanding depression disparities across the nation.

Conclusions

SVI data could explain a large variance in depression prevalence in the US. However, future spatial analysis studies are needed to understand the prevalence of depression with other comorbidities and risk factors that may exacerbate or reduce mental health outcomes in specific geographic locations. Moreover, the analysis at finer scales is highly recommended. In addition, public health crises like the COVID-19 pandemic can exacerbate the incidence of depression, among other mental illnesses (Vahratian *et al.*, 2021).

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