

Built Environment, Natural Environment, and Mental Health



Key Points:

- Job sprawl, land mixed use, and green space associate with lower depression risk; the roles of air pollution and precipitation are opposite
- Association of population density and social capital with depression prevalence exhibit significant spatial diversity
- Precipitation and socioeconomic status mainly affect northwestern counties; population demographics plays key role in southeastern counties

Correspondence to:

Y. Wang,
u6039205@utah.edu

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Author Contributions:

Conceptualization: Yehua Dennis Wei, Yu Wang

Formal analysis: Yehua Dennis Wei, Yu Wang, Sungeun Shin

Funding acquisition: Yehua Dennis Wei, David S. Curtis, Ming Wen

Methodology: Yehua Dennis Wei, Yu Wang, Sungeun Shin

Project administration: Yehua Dennis Wei

Resources: Yehua Dennis Wei, David S. Curtis, Ming Wen

Supervision: Yehua Dennis Wei

Visualization: Yu Wang, Sungeun Shin

Writing – original draft: Yehua Dennis Wei, Yu Wang

Writing – review & editing: Yehua Dennis Wei, Yu Wang, David S. Curtis, Sungeun Shin, Ming Wen

Yehua Dennis Wei¹ , Yu Wang¹ , David S. Curtis² , Sungeun Shin¹ , and Ming Wen^{3,4}

¹Department of Geography, University of Utah, Salt Lake City, UT, USA, ²Department of Family and Consumer Studies, University of Utah, Salt Lake City, UT, USA, ³Faculty of Social Sciences, University of Hong Kong, Hong Kong, China, ⁴Department of Sociology, University of Utah, Salt Lake City, UT, USA

Abstract Mental health disorders have become a global problem, garnering considerable attention. However, the root causes of deteriorating mental health remain poorly understood, with existing literature predominantly concentrating on socioeconomic conditions and psychological factors. This study uses multi-linear and geographically weighted regressions (GWR) to examine the associations between built and natural environmental attributes and the prevalence of depression in US counties. The findings reveal that job sprawl and land mixed use are highly correlated with a lower risk of depression. Additionally, the presence of green spaces, especially in urban area, is associated with improved mental health. Conversely, higher concentrations of air pollutants, such as PM_{2.5} and CO, along with increased precipitation, are linked to elevated depression rates. When considering spatial correlation through GWR, the impact of population density and social capital on mental health displays substantial spatial heterogeneity. Further analysis, focused on two high depression risk clustering regions (northwestern and southeastern counties), reveals nuanced determinants. In northwestern counties, depression rates are more influenced by factors like precipitation and socioeconomic conditions, including unemployment and income segregation. In southeastern counties, population demographic characteristics, particularly racial composition, are associated with high depression prevalence, followed by built environment factors. Interestingly, job growth and crime rates only emerge as significant factors in the context of high depression risks in southeastern counties. This study underscores the robust linkages and spatial variations between built and natural environments and mental health, emphasizing the need for effective depression treatment to incorporate these multifaceted factors.

Plain Language Summary This study examines the associations between built and natural environmental attributes and the prevalence of depression in US counties. The findings reveal that greater job sprawl and land mixed use are associated with lower depression prevalence. Additionally, the presence of green spaces in urban area is associated with reduced depression prevalence. Conversely, higher concentrations of air pollutants, such as PM_{2.5} and CO, along with increased precipitation, are linked to elevated depression rates. Associations between population density and social capital with depression prevalence display substantial spatial heterogeneity. Further analysis, focused on two high depression risk clustering regions (northwestern and southeastern counties), reveals region-specific determinants.

1. Introduction

A significant number of US residents experience mental health problems, a burden that has intensified amidst the socioeconomic strains and public health crisis brought about by COVID-19. The impact is substantial, with nearly 10 percent of US adults experiencing major depression each year and a recent global rise in depression rates (Moreno-Agostino et al., 2021). Depression carries a range of socioeconomic and health repercussions, including the reduction of social capacity, a decline in labor productivity, and an increase in disability rates (Garrido-Cumbrera et al., 2018). Notably, it stands as the most widespread psychiatric disorder associated with suicide mortality (Hawton et al., 2013). Given this high prevalence and the substantial costs, identifying place-based risk factors of depression is imperative.

At individual-level, risk of mental health problems is intricately linked to demographic characteristics, encompassing factors like genes, gender, and age, etc. (Silva et al., 2016). Due to biological, familial and sociocultural factors, women experience higher depression rates than men (Parker & Brotchie, 2010). Depressive symptoms in middle-aged adults are significantly higher than in children and older adults (Cuijpers et al., 2020), because they

usually have more anxiety and stress from financial status, work environment, and household relationship (Guan et al., 2022). A higher level of education may expose individuals to greater academic, social, and financial stress, which is linked to poor mental health (McCloud et al., 2023). Cvetkovski et al. (2019) reached the opposite conclusion. Single parents usually have lower income levels and are more likely to experience prejudice in society and mental health problems (Kim & Kim, 2020). Individual socio-economic status can also significantly affect mental health. Individuals with low income disproportionately encounter economic and social stressors and have lower access to health and social resources (Marmot & Wilkinson, 2001). Unemployed people are linked to poor mental health because of financial and mental stress (McKee-Ryan et al., 2005). Black/African Americans report greater psychological distress and more depressive symptoms (Barnes & Bates, 2017). Non-Hispanic white Americans generally experience higher rates of major depressive disorder than African and Mexican Americans (Pamplin & Bates, 2021).

At area-level, extensive research has shown that socioeconomic conditions impact mental well-being (Lorant et al., 2003; Richardson et al., 2015). Places with higher social capital generally have lower rates of mental health disorders, due to emotional support and resources sharing (Thoits, 2011). However, close social ties can limit individual freedom and welfare and lead individuals to engage in health-compromising behaviors such as alcohol consumption (Almedom, 2005). Limited health insurance coverage decreases access to mental health services and elevates mental health problems (Finkelstein et al., 2012). Residing in areas with more crimes reduces physical activity, decreases feelings of safety and increases risk of depression (Ross, 2017; Wei et al., 2021).

In recent years, the exploration of area-level determinants has expanded to encompass physical and natural features within the built environment or urban form due to the acceleration and expansion of urbanization. Evidence indicates that urbanization contributes to psychological distress, and urban areas and larger cities tend to have higher rates of mental disorders (J. Chen et al., 2015). On the other hand, better infrastructure and public services in urban areas may increase residents' life satisfaction, thus improving their mental health (Stier et al., 2021). With the rise of urban sprawl as a global phenomenon, the process and effects of urban sprawl have drawn broad attention. Urban sprawl has been widely criticized for its association with various urban challenges, including imbalanced jobs-housing distribution, traffic congestion, air pollution, diminished social cohesion, sedentary lifestyles, and adverse health outcomes (Wei & Ewing, 2018). Urban sprawl also contributes to residential segregation between different racial, ethnic, or socioeconomic groups, a spatial mismatch between low-income households and suitable employment opportunities, and higher poverty rates among Black/African Americans. Consequently, urban sprawl is often considered a fundamental driver of urban problems in the US and is believed to have negative implications for mental health. The diversity of land use and job opportunities can enhance residents' access to resources, services, and employment opportunities, thereby meeting their daily needs and reducing psychological stress (Van Hooff & Van Hooff, 2014; Wu et al., 2016).

However, a study by Garrido-Cumbrera et al. (2018) found that sprawling areas usually have fewer mental health problems, since households with more socioeconomic resources and lower risk of depression prefer less dense suburban areas with more natural resources (Brueckner et al., 1999; Curtis et al., 2024). Similarly, more dense neighborhoods tend to generate greater mental distress (Wang et al., 2021). Despite the importance of the built environment in shaping mental health outcomes, there is still a limited body of empirical research examining its impact.

Natural environmental conditions also influence mental health and are linked to the built environment. Air pollution, a byproduct of urban sprawl and increased vehicle miles traveled, exacerbates psychological distress (F. Chen et al., 2023; Piracha & Chaudhary, 2022), while green spaces and urban parks are stress-relieving remedies (Richardson et al., 2013; Sturm & Cohen, 2014). Interestingly, the quality of green spaces appears to be more influential than the quantity in terms of their impact on mental health (Astell-Burt et al., 2014). Moreover, the impact of green spaces on mental health has been found to vary between urban and rural areas (Ryan et al., 2024). Exposure to environmental toxins is another area-level factor that heightens the risk of mental health disorders (McLeod, 2017).

Previous studies have investigated the mental health implications of various factors, including demographic characteristics, socioeconomic conditions, the built environment, and the natural environment (Dang et al., 2019; Li & Wei, 2023; Wang et al., 2021). However, a gap persists in terms of an inclusive research framework that integrates these influencing factors. Some argue that the contextual influence on mental health is primarily rooted in area socioeconomic conditions, overshadowing the significance of the built environment (Garrido-Cumbrera

et al., 2018). The role of the urban context in mental health remains inadequately elucidated, and scholars disagree about the definition of urban form or the built environment and their specific impacts on mental health (Clifton et al., 2008). Furthermore, the impacts of the natural environment, including air pollution and green spaces, have not been sufficiently explored (Mantler & Logan, 2015). Thus, we aim to advance the research on mental health by conducting a comprehensive study of the role of the built and natural environments in shaping mental health outcomes. Furthermore, our study contributes to existing knowledge by incorporating spatial perspectives to better grasp the spatial heterogeneity of mental health problems.

This paper provides a comprehensive understanding of the diverse area-level risk factors for depression prevalence rates across US counties by analyzing the effects of built and natural environmental attributes. We ask the following research questions: (a) Where in the US is depression prevalence elevated? (b) How do built and natural environments contribute to variation in depression prevalence rates? (c) Do the predictors of depression prevalence vary across regions? To examine these questions, we compile a large data set that incorporates county-level depression prevalence estimates for 2019 from the CDC Places, along with data from various publicly available sources capturing an extensive array of built and natural environmental attributes. Our analysis aims to shed light on the multifaceted causes of depression, providing valuable insights into the interplay between environmental factors and mental health outcomes.

2. Analytical Framework and Methodology

2.1. Analytical Framework

Building upon the literature review, this study integrates built and natural environments with demographic factors and socioeconomic conditions. The aim is to provide a more comprehensive understanding of the underlying causes of depression across US counties. The analytical framework is presented in Figure 1.

Studies tend to use one or two simple indicators such as population density or urban sprawl index to study the effects of built environment on health. Built environment covers multiple dimensions, and its comprehensive effects on mental health have rarely been thoroughly examined. Research on the effects of cities on human mobility and physical activities has predominantly focused on the built environment, mainly the three Ds (density, distance, and diversity). More recently, two more Ds (destination and design) have been incorporated into measures of urban form. These five Ds provide a comprehensive framework for understanding the influence of the built environment on human mobility, physical activity, and potentially mental health. We thus use a series of indices to represent built environment, including job sprawl index, population sprawl index, land mixed use index, job mixed layout index, job-housing balance index, population density and urban area. Green space, pollutant PM_{2.5} and CO concentrations and precipitation are used to reflect the natural environment. Most studies find exposure to air pollution and increased precipitation are linked to more mental health problems, while green spaces can alleviate negative emotions (F. Chen et al., 2023; Kent et al., 2009; Leslie & Cerin, 2008; Sturm & Cohen, 2014). Our analytical framework also includes those typical natural environmental attributes.

Our research framework also incorporates control variables to reduce inaccurate model estimation due to omitted variables. Individual characteristics such as gender, aging, marital status, race and family structure affect mental health (Cuijpers et al., 2020; Pamplin & Bates, 2021; Parker & Brotchie, 2010). Socioeconomic conditions also play important roles in mental health. Usually, places with larger income segregation, lower job growth, higher unemployment rates, limited access to stores, less social capital, low health insurance coverage, and more crimes tend to have more mental health problems (McKee-Ryan et al., 2005).

2.2. Data Sources

This study uses county level data for the continental US (i.e., excluding Alaska, Hawaii, and the US Territories). The US is among the countries with the most serious mental health related problems, and its cities are characterized by significant sprawling (Behnisch et al., 2022; Tikkanen et al., 2020). County diagnosed depression prevalence among adults came from the Centers for Disease Control and Prevention (CDC) Places, 2021 data release. CDC Places estimates of depression prevalence were derived from the Behavioral Risk Factor Surveillance System 2019 data using small area estimation techniques. County population estimates for subgroups were used to generate model-based estimates of overall county depression prevalence among adults aged at least

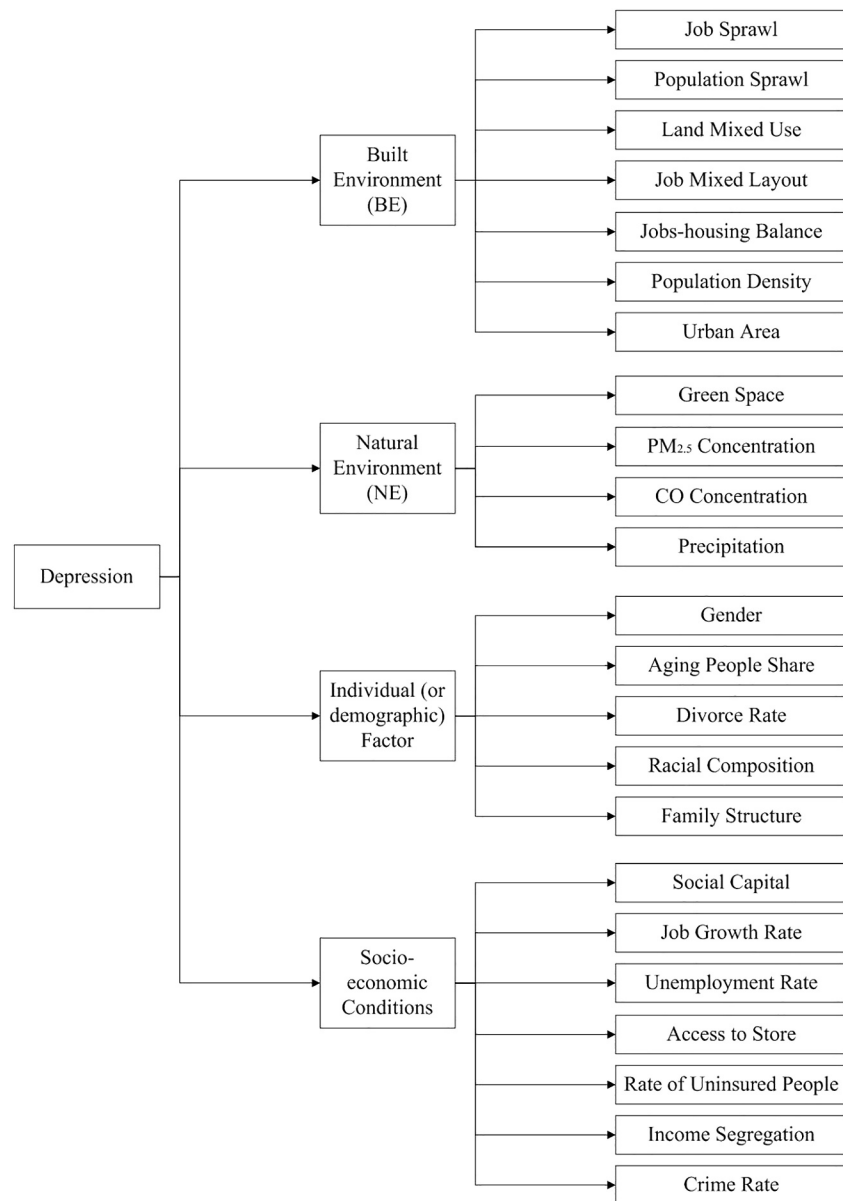


Figure 1. The influencing factors of depression.

18-years-old. The data and modeling approach are described in greater detail in Greenlund et al. (2022). In sensitivity tests, we used an age-adjusted estimate for depression prevalence among adults to test the robustness of our results. Data representing built and natural environments, demographic factors, and socioeconomic conditions come from multiple publicly available sources. Table 1 presents detailed information on variable definitions and data sources. Additionally, we propose hypothesized associations for variables exhibiting relatively consistent findings based on the literature review.

2.3. Hotspot Analysis

Hotspot analysis is a geospatial technique designed to identify clusters of spatial phenomena and their spatial correlations. Hotspots refer to areas with a higher concentration of events compared to the expected events occurring at random. There are many methods to identify the spatial pattern, such as the spatial autocorrelation

Table 1
Variable Selection and Data Sources

Type	Abbreviation	Indicator meaning	Data sources
Depression	Dep	Depression rate. Model-based estimate for crude prevalence of depression among adults aged 18–64 years (2019)	Disease Control and Prevention (CDC)
	Dep2	Age-adjusted depression rate. Model-based estimate for age-adjusted crude prevalence of depression among adults aged 18–64 years (2019)	
Built Environment	Sprawl_J	Job sprawl. Centering coefficient of variation in census block group employment densities (2010). The more variation in densities around the mean, the more centering and/or subcentering exists within the county	Smart Location Database (SLD) Version 2.0
	Sprawl_P	Population sprawl. Centering coefficient of variation in census block group population densities (2010). The more variation in densities around the mean, the more centering and/or subcentering exists within the county	
	Mixed_Land	Land mixed use. 5-tier employment and household entropy. Values were weighted by the sum of block group's population and employment as a percentage of the county total (2010)	
	Mixed_Job	Job mixed layout. 5-tier employment entropy, weighted by the sum of CBG population and employment as a percentage of the county total (2010)	
Natural Environment	Balance_JH	Jobs-housing balance. Working population and actual jobs equilibrium Index, weighted by the sum of block group's population and employment as a percentage of the county total (2010). The closer to one the more balanced the resident workers and jobs in the Census Block Group	
	Density_P	Population density. Gross population density (people/acre) on unprotected land (2010)	
	Urban	Urban area. 1 is urban area, and 0 is non-urban area	
	Green_S	Green space accessibility. Percentage of vegetated land within a census tract, including developed open space, grass, shrub, and forest areas, and excluding those areas for intensive agricultural uses (2001)	Calculated using data from National Land Cover Database (NLCD)
	PM _{2.5}	PM _{2.5} concentration. Average annual outdoor concentration of PM _{2.5} (µg/m ³ , 2010)	Center for Air, Climate, and Energy Solutions
Individual (or demographic) Factors	CO	CO concentration. Average annual outdoor concentration of CO (ppb, 2010)	
	Precipitation	Precipitation level. Average January precipitation at county level (inches, 2010)	National Centers for Environmental Information
	Gender Aging	Female rate. Percent population who are female (%; 2010) Aging population ratio. Percent population who are 67 years old or older (%; 2010)	2011 American Community Survey (ACS)
	Divorce_R	Divorce rate. Average divorce rate between 2010 and 2014 (%)	2014 American Community Survey (ACS)

Table 1
Continued

Type	Abbreviation	Indicator meaning	Data sources
Socioeconomic Conditions	Racial_C	Racial composition. Percent population who are non-Hispanic whites along (%; 2010)	2011 American Community Survey (ACS)
	Family_S	Family structure. The number of households with female heads (and no husband present) or male heads (and no wife present) with own children under 18 years old present divided by the total number of households with own children present (%; 2010)	Opportunity Atlas Database
	Social_C	Social capital index, created using principal component analysis using four factors (voter turnout, census response rate, number of non-profit organizations, and the aggregate of organization such as religious organizations, civic and social associations) (2014)	Northeast Regional Center for Rural Development
	Growth_J	Job growth rate. Average annualized job growth rate (%) over the time period 2004 to 2013	Census Bureau
	Rate_Unemp	Unemployment rate. Average unemployment rate (%) between 2010 and 2014	2014 American Community Survey (ACS).
	Store_A	Access to stores. Percentage of households with low income & more than 10 miles to store (2015). Low value means high access	Food Environment Atlas of USDA Economic Research Service.
	Uninsured_P	Rate of uninsured people. Model-based estimate for crude prevalence of current lack of health insurance among adults aged 18–64 years (2019)	Disease Control and Prevention (CDC)
	Income_S	Income segregation. Average Gini coefficient of income from 2010 to 2014	2014 American Community Survey (ACS)
	Crime_R	Crime rate. Violent crime rate 2010 (per 100,000)	Uniform Crime Reports

analysis and the cluster analysis. For a better understanding of local conditions and spatial autocorrelation, local indicators of spatial association (LISA), such as Gettis-Ord G_i^* statistic, is used to measure to what extent points near a given point have similar values (Anselin, 1995). We also use the Gettis-Ord G_i^* statistic to figure out whether urban sprawl and SWB are spatially autocorrelated.

2.4. Multiple Linear Regression

We use multiple linear regression to identify the association between built and natural environment attributes and depression prevalence, with the following formula.

$$Dep = \theta_0 + \theta_i BE + \theta_j NE + \theta_k ISEC_k + \epsilon$$

where, Dep is our dependent variable, that is, county-level crude prevalence of depression. BE is a vector of built environment variables, and θ_i refers to the coefficients for each variable. NE represents the vector of natural environment variables, and θ_j refers to the corresponding coefficients. The vector $ISEC$ includes the demographic and socioeconomic control variables. θ_0 and ϵ are the intercept and residual term, respectively.

Given our primary interest in the effect of built and natural environments, built environment variables were included in the initial model followed by adding natural environment, individual, and socioeconomic condition variables (Model 1 to Model 4 in Table 2). Considering that green space is more suitable for urban areas rather than rural areas, we also added the *Urban*Greenspace* interaction term in Model 5 to explore whether the relationship between green space and depression is more significant in urban areas. Finally, we used the age-adjusted crude prevalence of depression ($Dep2$) to replace Dep in regressions to prove the robustness of results.

The small area estimation techniques used to derive the CDC Places estimates of county-level crude prevalence of depression incorporate county-level poverty data. We therefore do not include the poverty variable in the regression. Other demographic and socio-economic related data used by the CDC are based on surveys, which is at the individual level rather than the county level. We use county-level data, so the correlation should not be as strong. Furthermore, we are careful with interpreting the effects of population characteristics. Given that the determinants of depression may be highly correlated with each other and cause the results bias due to the multicollinearity in regression, we calculate the correlation coefficients of all variables. All correlation coefficients are significantly less than 0.7, the minimum threshold for high correlation coefficients (Akoglu, 2018). Also, we performed a VIF (variance inflation factor) test to detect potential problem of multicollinearity among independent variables. VIFs in all regression results are less than 2.5, thus no obvious multicollinearity is presented in our regression models.

2.5. Geographically Weighted Regression

Considering that there may be different relationships between variables across regions, a frequently occurring case in geospatial data, we use the geographically weighted regression (GWR) to identify the spatial heterogeneity of determinants in depression. GWR processes operate within a small spatial scale rather than the global scale. The formula for GWR is as follow.

$$Dep_i^{\sim} = \theta_0^{\sim} + \theta_i^{\sim} BE^{\sim} + \theta_j^{\sim} NE^{\sim} + \theta_k^{\sim} ISEC_k^{\sim} + \epsilon^{\sim}$$

where \sim represents counties in the small spatial scale. Dep_i^{\sim} represents the crude prevalence of depression of these counties. BE^{\sim} and NE^{\sim} are vectors of built and natural environment variables respectively. θ_i^{\sim} and θ_j^{\sim} are their corresponding coefficients. The vector $ISEC_k^{\sim}$ indicates demographic and socioeconomic control variables. θ_0^{\sim} and ϵ^{\sim} are the intercept and residual term, respectively. In building GWR model, we used adaptive bandwidths so that roughly the same number of observations is used. Gaussian weights are chosen such that closer points have more weights. We employ cross-validation to test different bandwidth sizes or points.

Table 2
The Effects of Built and Natural Environments on Depression

	Variables	Model 1 Dep	Model 2 Dep	Model 3 Dep	Model 4 Dep	Model 5 Dep
Built Environment	Sprawl_J	0.633*** (0.119)	0.824*** (0.114)	0.584*** (0.0954)	0.447*** (0.107)	0.444*** (0.108)
	Sprawl_P	0.0590 (0.0913)	-0.0434 (0.0837)	-0.0913 (0.0680)	-0.0310 (0.0862)	-0.0324 (0.0863)
	Mixed_Land	-15.44*** (1.181)	-12.08*** (1.095)	-8.123*** (1.032)	-3.632*** (1.113)	-3.698*** (1.113)
	Mixed_Job	-2.625*** (0.790)	-0.239 (0.771)	-4.415*** (0.777)	-2.721*** (0.818)	-2.769*** (0.815)
	Balance_JH	-1.413* (0.725)	-0.239 (0.685)	-0.251 (0.646)	-0.550 (0.631)	-0.588 (0.630)
	Density_P	-0.0971** (0.0484)	-0.138** (0.0598)	-0.0643* (0.0346)	-0.291 (0.183)	-0.287 (0.182)
	Urban	-0.146 (0.124)	-0.557*** (0.116)	-0.662*** (0.104)	-0.398*** (0.108)	-0.0378 (0.200)
Natural Environment	Green_s		-1.849*** (0.302)	-0.336 (0.275)	-0.644** (0.298)	-0.259 (0.350)
	PM _{2.5}		0.254*** (0.0332)	0.167*** (0.0311)	0.150*** (0.0336)	0.145*** (0.0338)
	CO		11.99*** (1.390)	6.679*** (1.167)	5.716*** (1.245)	5.662*** (1.247)
	Precipitation		0.346*** (0.0261)	0.332*** (0.0267)	0.225*** (0.0283)	0.230*** (0.0285)
Individual (or demographic) Factors	Gender			16.04*** (2.075)	21.55*** (2.209)	21.66*** (2.218)
	Aging			-17.20*** (1.480)	-17.90*** (1.951)	-17.78*** (1.955)
	Divorce_R			0.320*** (0.0242)	0.250*** (0.0251)	0.248*** (0.0252)
	Race_C			7.700*** (0.388)	10.47*** (0.528)	10.47*** (0.527)
	Family_S			4.631*** (0.729)	1.905** (0.838)	1.831** (0.837)
Socioeconomic Conditions	Social_C				-0.433*** (0.105)	-0.430*** (0.105)
	Growth_J				-5.753 (3.546)	-5.681 (3.542)
	Rate_Unemp				0.160*** (0.0197)	0.161*** (0.0197)
	Store_A				3.898*** (0.775)	3.830*** (0.772)
	Uninsured_P				0.0510*** (0.0119)	0.0512*** (0.0119)
	Income_S				10.74*** (1.634)	10.91*** (1.640)
	Crime_R				0.000150 (0.000282)	0.000139 (0.000284)
	Urban*Green_S					-0.772** (0.358)
	Constant	31.14*** (0.640)	21.93*** (0.803)	7.244*** (1.199)	-5.758*** (1.529)	-5.925*** (1.538)
	Observations	3,043	3,041	3,040	2,559	2,559
R-squared	0.177	0.287	0.470	0.527	0.528	
VIF	1.49	1.65	1.75	1.99	-	

Note. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3. Results

3.1. Spatial Distribution and Clustering of Depression Prevalence and Predictors

We first conducted the hot spot analysis, which shows that depression prevalence forms geographic clustering across US counties (Figure 2). High depression rates are mainly found in two regions. One is the northwestern region, mainly counties in Washington, Oregon, northern Idaho, and Montana (Figure 3). The other covers parts of the southeastern and midwestern regions, including Alabama (AL), Arkansas (AR), Kentucky (KY), Louisiana (LA), Michigan (MI), Missouri (MO), Oklahoma (OK), Tennessee (TN), and West Virginia. However, low depression rates are found in central United States.

Population density varies widely among US counties (Figure 4). Except for some counties in New York, Chicago, and Los Angeles, etc., the vast majority of counties have relatively low population density. Population clustering and job clustering occur more frequently in the eastern US with limited land rather than the western portion. Levels of land mixed use and job mixed layout are high in north-central US, which tends to have lower depression rates. The distribution of jobs-housing balance is very similar to that of land mixed use and job mixed layout.

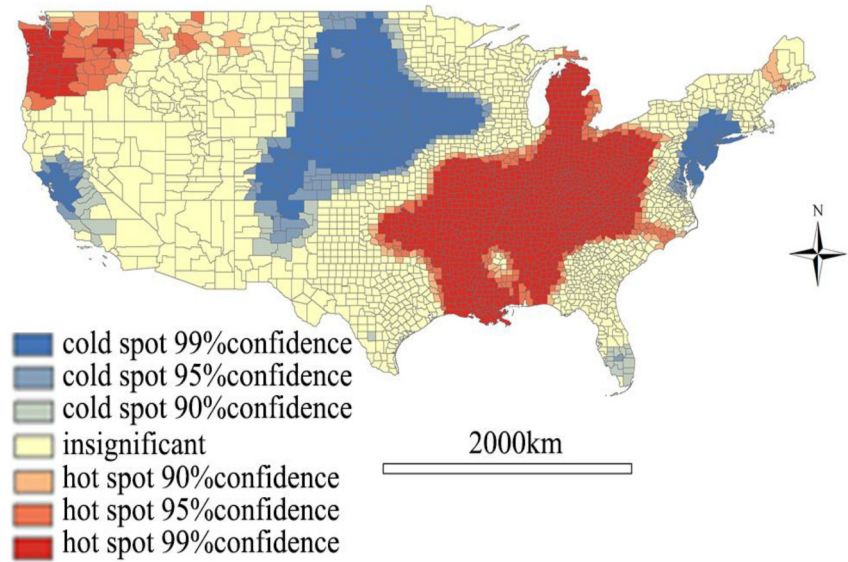


Figure 2. Spatial clustering of depression prevalence.

More urbanization, dense population and developed industries fill much of the eastern US, which has very limited green space and higher $PM_{2.5}$ concentrations (Figure 5). It should be noted that increasing awareness of the effects of green spaces on mental health stems from concerns about declining green space due to urbanization (Byomkesh et al., 2012). Thus, green space is usually defined as urban vegetated space such as parks, grasslands, sports and playing fields and near-road trees, rather than agricultural land (Vanaken & Danckaerts, 2018). Thus, the green space index in our study refers to the percentage of vegetated land within a census tract, including developed open space, grass, shrub, and forest areas, and excluding those areas for intensive agricultural uses. Thus, it more appropriately represents green space in urban areas rather than rural areas. Counties along the Appalachian Mountains, the west bank of the Mississippi River, and the western region of the US have higher CO concentrations. Precipitation is significantly higher in counties along the Pacific coast and in some southeastern states such as Florida and Alabama.

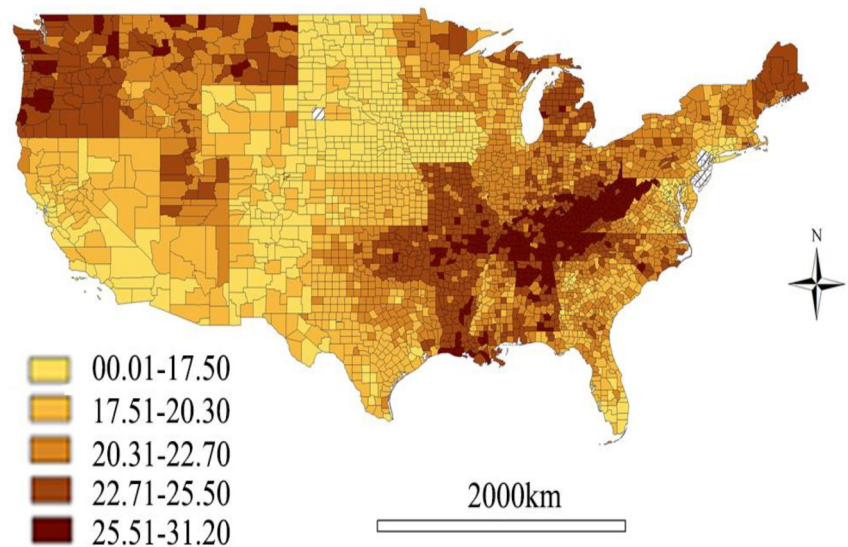


Figure 3. Spatial distribution of the prevalence of depression by county.

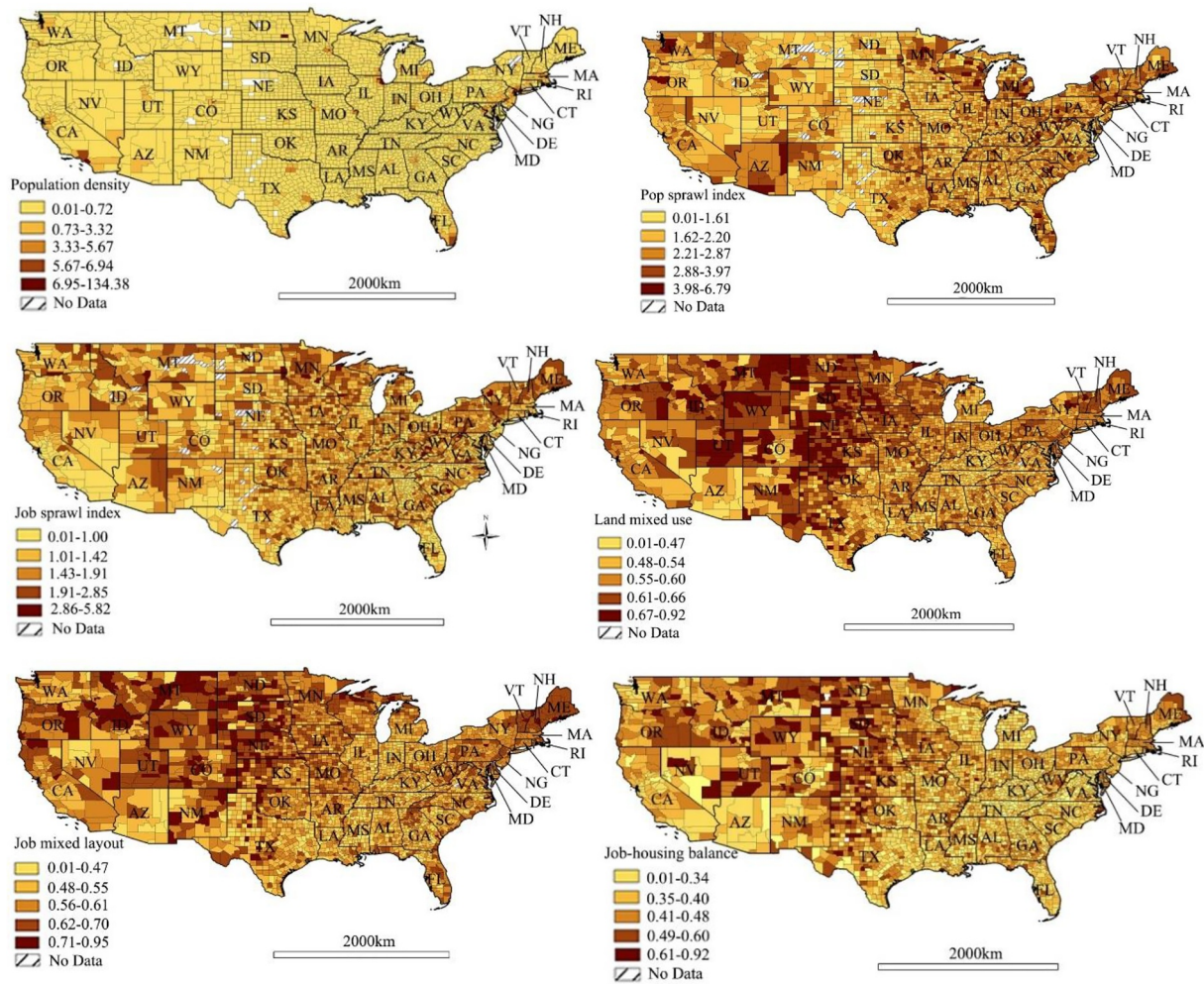


Figure 4. Spatial distribution of built environment factors.

3.2. Built and Natural Environmental Attributes as Predictors of Depression Prevalence

The above mapping analysis provides basis for conducting more rigorous modeling, and we ran a series of regression models to identify place-based predictors of county depression prevalence rates. Model 1 to Model 4 in Table 2 shows that built environment accounts for 17.7% of the variance in depression rates, and the addition of natural environment increases the R^2 to 28.7%. The built and natural environments explain between one-fourth and one-third of depression.

When all control variables are added, job sprawl, land mixed use, job mixed layout and urban areas are significantly associated with depression prevalence (Model 4). Lower values for job sprawl indices indicate greater sprawl or less compact development, thus job sprawl is linked to decreased depression prevalence. Counties with high level of land mixed use and job mixed layout, as well as urban areas are associated to lower depression prevalence. For natural environment, all variables show the same association as our hypotheses. More green spaces, lower level of air pollution, and less precipitation are linked to lower depression prevalence.

For control variables, high proportion of female, divorced people, and non-Hispanic whites, as well as more single-parents families share, are associated with high depression rates, while large share of aging people is usually tied to lower risk of being depression. Counties with high unemployment rate, poor access to store, more uninsured population share, and severe income segmentation are connected to more depression prevalence, while increased social capital is linked to better mental health.

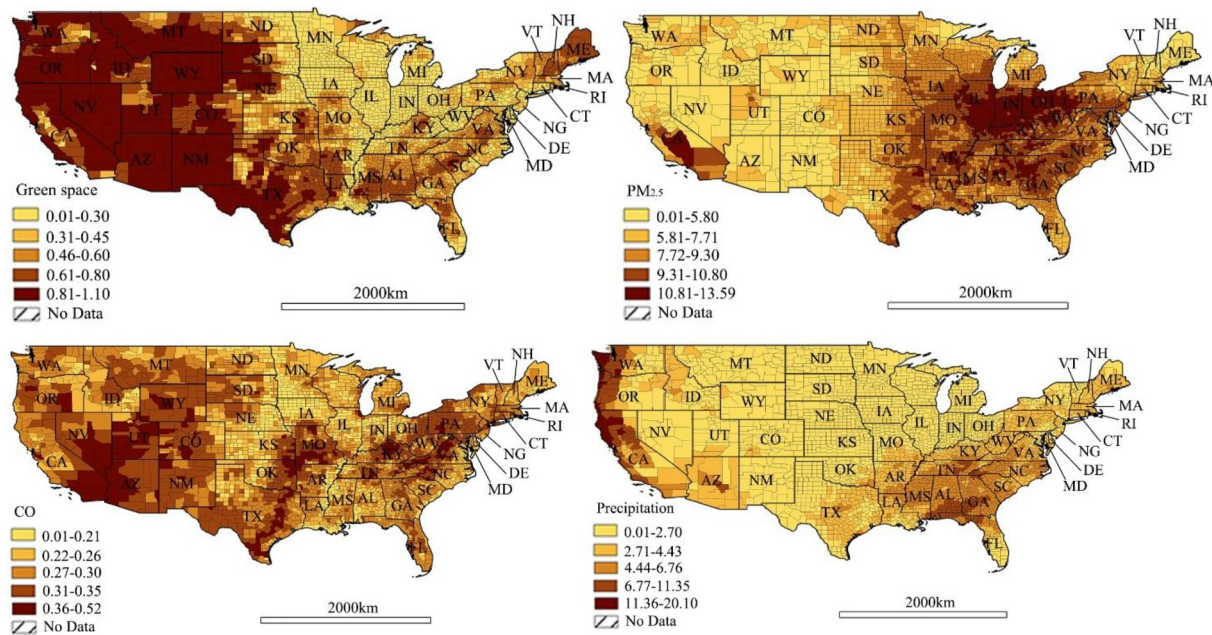


Figure 5. Spatial distribution of natural environmental factors.

We maintain that the relationship between natural environment and mental health also depends on the characteristics of built environment. Therefore, we also examine its interaction with the urban context. The coefficient of *Urban*Greenspace* in Model 5 is negatively significant, implying that the negative correlation between green space and depression prevalence mainly concentrates in urban areas.

3.3. Spatial Heterogeneity of Determinants of Depression

We explore the spatial heterogeneity of the relationship between depression and independent variables by using GWR. The positive and negative ratios are used to measure how these factors have different effects on depression across counties (Table 3). The positive ratio is the proportion of counties with a positive impact on depression (i.e., increasing the depression rate), while the negative ratio is the share of the counties with a negative effect on depression (i.e., decreasing the depression rate). The largest positive ratio for built and natural environment variables is 63.76% (*Sprawl_P*), followed by 62.66% (*Sprawl_J*), meaning that urban sprawl increases depression rates in more than 60% of counties. The largest negative ratio is *Mixed_Land* (62.89%), followed by *Green_S* (61.54%), indicating that mixed land use and green space decrease depression risks in more than 60% of counties. Thus, the associations between built and natural environments and depression are unevenly distributed across counties. Conversely, there are some demographic and SES factors are spatially stationary. Specifically, for more than 80% counties, high female share, more non-Hispanic white population, less aging people, single-parent family structure and income segregation are associated with higher depression prevalence.

We further the above analysis by mapping the correlations of population density and social capital and depression rates, which shows more significant spatial patterns than other variables. Although high population density is linked to less depression prevalence in the vast majority of counties, it shows positive ties with depression risk in a few northeastern metropolitan areas such as the New York and Philadelphia-Camden-Wilmington Metropolitan Areas (Figure 6). Although the positive coefficients are also concentrated in Minneapolis–Saint Paul and Salt Lake City metropolitan areas, the P-value in these regions are larger than 0.1, that is, the coefficients are insignificant in these regions. Thus, we cannot conclude the relationship between population density and depression rates is positive in these regions. Different from the majority of counties, high level of social capital is associated with high depression prevalence in northwestern counties and some counties in the northeastern region (Figure 7). Although some north-central counties show the positive relationship between social capital and depression rates, only coefficients for counties in south Minnesota are significant.

Table 3
Summary of GWR Coefficient Estimates at County Level

	Min.	Median	Max.	Global	Positive ratio (%)	Negative ratio (%)
Sprawl_J	-1.983	0.161	1.565	0.316	62.66	37.34
Sprawl_P	-1.321	0.075	2.023	0.074	63.76	36.24
Mixed_Land	-55.202	-1.521	8.444	-4.707	37.11	62.89
Mixed_Job	-14.087	-0.610	32.266	-2.587	43.64	56.36
Balance_JH	-9.318	0.581	42.082	-0.260	59.64	40.36
Density_P	-2.472	-0.030	3.737	-0.055	47.83	52.17
Urban	-2.882	0.056	3.552	-0.529	52.40	47.60
Green_S	-14.633	-0.638	10.298	0.022	38.46	61.54
PM _{2.5}	-1.997	-0.027	1.060	0.196	43.42	56.58
CO	-42.116	0.829	32.446	2.462	57.52	42.48
Precipitation	-2.600	0.139	3.870	0.251	63.69	36.31
Gender	-194.910	10.621	75.944	12.971	89.25	10.75
Aging	-52.404	-9.846	22.827	-18.382	15.96	84.04
Divorce_R	-148.120	7.199	83.707	23.034	65.59	34.41
Racial_C	-1.955	-0.141	1.819	-0.273	39.81	60.19
Family_S	-8.951	9.246	45.233	15.178	94.53	5.47
Social_C	-3.940	2.858	21.289	6.329	82.75	17.25
Growth_J	-84.316	-5.869	197.080	-3.052	33.22	66.78
Rate_Unemp	-1.064	0.062	0.538	0.157	73.87	26.13
Store_A	-16.051	1.212	114.100	4.292	63.82	36.18
Uninsured_P	-0.329	0.080	1.263	0.173	68.97	31.03
Income_S	-21.860	7.069	34.576	8.387	84.62	15.38

3.4. Determinants of Depression in Northwestern and Southeastern Counties

There are two main high depression prevalence regions in US, that is, northwestern and southeastern counties (Figure 2), which need further examination. Model 1 to Model4 in Table 4 show the multiple linear regression results for northwestern counties. Correlation analysis for northwestern counties shows that there is a high correlation between land mixed use, job mixed layout and jobs-housing balance, which differs from findings based on counties nationwide. Considering high land mixed use tends to have more job mixed layout and high level of jobs-housing balance, we only include land mixed use in our regression. To avoid inaccurate estimation caused by omitted variables, we also included the mean value of three variables (*Mixed index*) in the regression in Model 5. Table 5 shows the regression results for southeastern counties.

After adding all variables, we find that there are fewer variables associated with depression prevalence in northwestern counties. No built environment variable shows significant correlation with depression prevalence (Model 4). Among other variables, socioeconomic variables have made the greatest contribution to R^2 , followed by natural environment. This means socioeconomic conditions and natural environment are the main determinants of depression risks in this region. For southeastern counties, demographic variables are most relevant to the high depression rates, with the highest increased R^2 . The built environment variables also make a significant contribution to R^2 , thus ranking as the second most important predictors.

4. Discussion

There is the high depression prevalence clustering in US northwestern region and US southeastern and midwestern regions, while low depression prevalence mainly clustering in central United States. Compared with other regions, the northwestern regions usually have longer-term gray and rainy weather. Less exposure to sunlight can lead to seasonal affective disorder, a subtype of depression. Southeastern regions like in the Appalachian and Southern

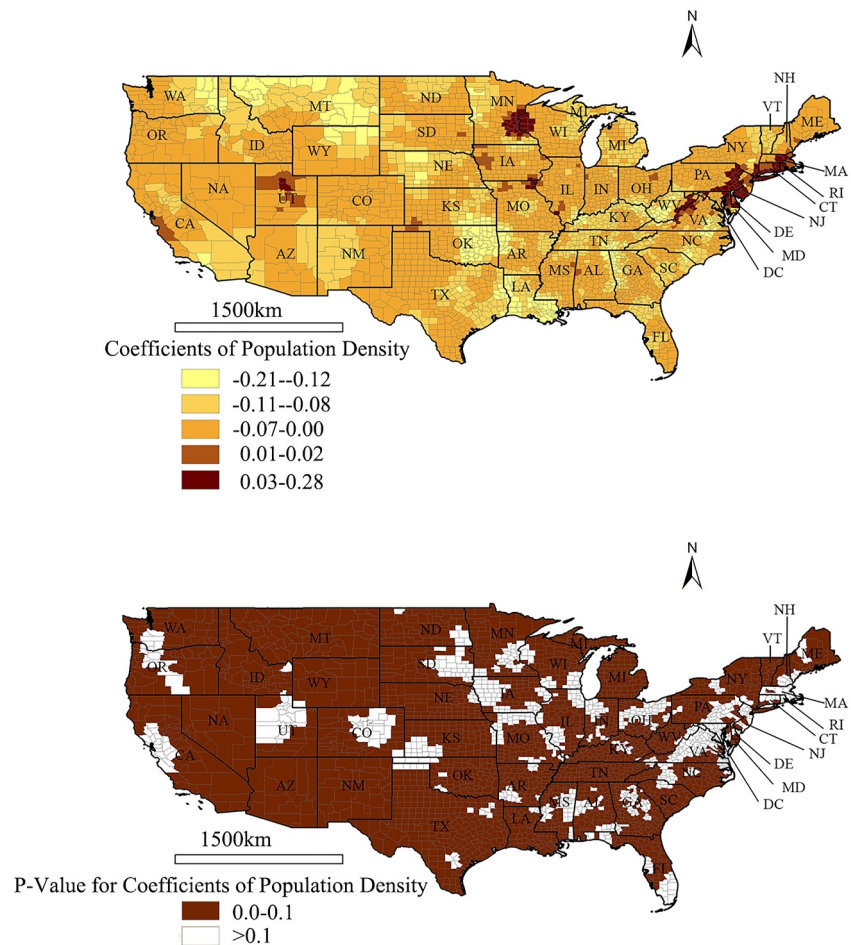


Figure 6. Effects of population density on depression.

Mississippi Valley regions, face many problems such as high poverty rates, limited employment opportunities, and generally more challenging socioeconomic conditions. People in the Great Lakes region and Maine, with cold winter temperature, also suffer more severe depression. Counties in central United States have dry and mild climate, and the adequate sunlight exposure may reduce the risk of depression. There are more rural counties in the central region. Compared to urban counties, rural counties experience fewer social disparities, less pollution, and more connection with the nature, which contribute to higher levels of mental health (Ventriglio et al., 2021).

Job sprawl may result in more open space in urban centers and more job opportunities in suburbs, which can relax people's commute and improve mental health (Garrido-Cumbrera et al., 2018). Land mixed use areas have more access to resources, services and entertainments, which can meet residents' needs and promote more outdoor activities and social interactions (Wu et al., 2016), thereby improving mental health. Job mixed layout enables people to find jobs that interest them, preventing the sense of monotony and boredom and thus reducing risks of being depressed. The more advanced infrastructure and comprehensive healthcare in urban areas enhance people's life satisfaction, therefore urban areas are significantly correlated with good mental health. For natural environment factors, green space is linked to lower depression prevalence by absorbing airborne pollutants and making people feel relaxed (Leslie & Cerin, 2008). Due to the higher population density, more crowded public space, and more serious air pollution caused by transportation and/or industrial production in urban areas, the role of green space is more evident in urban areas. Exposure to $PM_{2.5}$ and CO pollution increases the risk of depression (F. Chen et al., 2023; Liu et al., 2018; Von Lindern et al., 2016). Also, precipitation increases the potential for depression, since it reduces the time people can expose to sunlight and outdoor activities, thereby inhibiting serotonin production (Kent et al., 2009). All significant control variables support our hypotheses in Table 1, except for racial composition. Although some argue that Black/African Americans suffer more mental problems

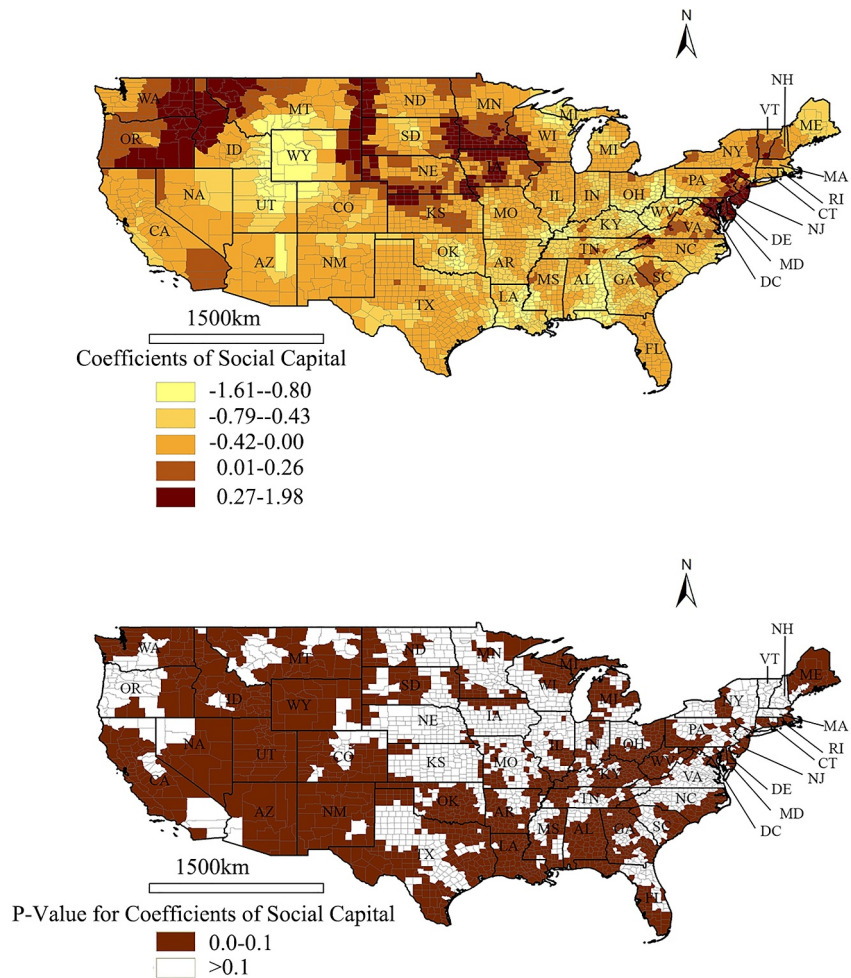


Figure 7. Effects of social capital on depression.

(Barnes & Bates, 2017), LaVeist et al. (2014) find that non-Hispanic whites experience depression more than other racial/ethnic groups, which is supported by our result.

Our study also reveals significant spatial heterogeneity in the association between population density and depression, as well as social capital and depression. Different from the majority of counties, high population density is associated to higher depression prevalence in some northeastern metropolitan areas such as the New York and Philadelphia-Camden-Wilmington Metropolitan Areas. These metropolitan areas are characterized by high population density and limited urban space, which leads to the diseconomies of agglomeration, such as traffic jam, high housing cost, and high crime rates. Northeastern counties and some counties in the northwestern region, as well as counties in south Minnesota, show a different correlation between social capital levels and depression prevalence compared to the majority of counties. Residents in northeastern counties witness large gaps in income levels and employment opportunities, with high concentration of highly paid financial and high-tech jobs. Dense population and intense competition may cause social stress, resulting negative effect of social capital on mental health. For example, the busy lifestyle and high competition in the New York metropolitan area are very likely to make socializing a form of pressure for some people, thus higher levels of social capital are connected with more depression risks. Counties in the northwestern region may have relatively less dense population distribution and have more significant agriculture and manufacturing industries. Increasing social capital may threaten their rural life style and likely causes more depression. Another possible reason is that since the northwest regions have higher depression rates, the depressed people may increase their social interactions to cope with their problem (De Silva et al., 2007). Counties in south Minnesota show the positive relationship

Table 4
Determinants of Depression in Northwestern Counties

	Variables	Model 1 Dep	Model 2 Dep	Model 3 Dep	Model 4 Dep	Model 5 Dep
Built Environment	Sprawl_J	-0.411* (0.212)	-0.279 (0.200)	-0.216 (0.189)	-0.168 (0.176)	-0.166 (0.178)
	Sprawl_P	0.120 (0.199)	-0.0439 (0.184)	-0.116 (0.173)	-0.0506 (0.165)	-0.0408 (0.170)
	Mixed_Land	-8.496*** (2.264)	-6.755*** (2.214)	-5.602** (2.192)	-0.0512 (1.875)	
	Mixed Index					0.380 (2.230)
	Density_P	0.171 (0.217)	-0.0522 (0.236)	-0.134 (0.228)	-0.343 (0.274)	-0.354 (0.277)
	Urban	0.136 (0.258)	0.0366 (0.256)	-0.0384 (0.258)	0.182 (0.227)	0.193 (0.217)
Natural Environment	Green_S		-1.270 (1.037)	-1.223 (0.992)	-1.579* (0.805)	-1.595** (0.805)
	PM _{2.5}		0.270* (0.139)	0.171 (0.143)	0.117 (0.145)	0.115 (0.145)
	CO		7.333* (4.015)	5.789 (3.930)	3.171 (3.378)	3.172 (3.376)
	Precipitation		0.121*** (0.0258)	0.0923*** (0.0272)	0.0567* (0.0300)	0.0569* (0.0295)
Individual (or demographic) Factors	Gender			28.32*** (7.326)	14.78** (6.404)	14.76** (6.330)
	Aging			-5.479 (3.756)	-5.558 (4.831)	-5.586 (4.780)
	Divorce_R			0.0307*** (0.0111)	0.0328*** (0.0107)	0.0332*** (0.0106)
	Race_C			0.856 (1.286)	-0.709 (1.264)	-0.737 (1.313)
	Family_S			4.907*** (1.859)	3.228* (1.875)	3.279* (1.854)
Socioeconomic Conditions	Social_C				-0.312** (0.148)	-0.324** (0.148)
	Growth_J				0.986 (9.705)	0.820 (9.676)
	Rate_Unemp				0.118** (0.0453)	0.118** (0.0453)
	Store_A				1.796 (1.306)	1.798 (1.305)
	Uninsured_P				-0.186*** (0.0317)	-0.188*** (0.0326)
	Income_S				6.210* (3.611)	6.251* (3.575)
	Crime_R				2.64e-05 (0.00111)	4.82e-05 (0.00110)
	Constant	28.59*** (1.585)	24.84*** (2.007)	9.929** (4.357)	15.61*** (4.547)	15.41*** (4.529)
	Observations	167	167	167	162	162
	R-squared	0.170	0.263	0.352	0.557	0.557
VIF	1.51	1.6	1.56	2.16	2.19	

Note. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

between social capital and depression rates. People in these counties face more crime rates and higher income segregation, and higher social capital levels may expose them to more crimes and result in more mental stress.

When the determinants of depression in the northwestern and southeastern counties were further examined, socioeconomic conditions, followed by natural environment factors, play important roles in depression prevalence in northwestern counties, while the role of built environment is insignificant. Northwestern counties, which may be because low density rural counties account for a large proportion of northwestern counties, thus depression prevalence is less associated with built environment. Large income segregation is significant and increases people's psychological stress and mental problems. Although Washington and Oregon are known for their high-tech industry, there are still many counties focusing on agriculture and/or forestry. Counties in some states such as Idaho and Montana are predominantly agricultural, and seasonal unemployment may be a key factor of high depression prevalence. For natural environment, precipitation is associated with high depression rates. Located in a high latitude region, northwestern counties usually go through longer overcast and rainy weather than counties in other regions. High precipitation reduces sunlight and outdoor activities and is a main determinant of depression. US Census Bureau's Household Pulse Surveys in December 2020 and January 2023 report that Seattle is among the 15 largest metro areas with the highest share of adults feeling down, depressed or hopeless.

For southeastern US counties, the high depression prevalence may be derived from demographic factors, then followed by built environment factors. Southeastern US counties have high racial disparities, unemployment rates

Table 5
Determinants of Depression in Southeastern Counties

	Variables	Model 1 Dep	Model 2 Dep	Model 3 Dep	Model 4 Dep
Built Environment	Sprawl_J	0.624*** (0.140)	0.575*** (0.129)	0.370*** (0.105)	0.174 (0.116)
	Sprawl_P	0.256** (0.106)	0.102 (0.0922)	0.147* (0.0816)	-0.0141 (0.101)
	Mixed_Land	-14.37*** (1.313)	-12.07*** (1.160)	-8.164*** (1.035)	-4.126*** (1.325)
	Mixed_Job	0.406 (0.841)	0.625 (0.729)	-2.472*** (0.768)	0.439 (0.628)
	Balance_JH	1.814** (0.915)	2.135** (0.831)	0.766 (0.644)	-0.556 (0.824)
	Density_P	-0.479*** (0.0857)	-0.677*** (0.109)	-0.373*** (0.0809)	-1.660*** (0.393)
	Urban	-0.532*** (0.134)	-0.939*** (0.123)	-0.865*** (0.106)	-0.546*** (0.108)
Natural Environment	Green_S		-3.666*** (0.304)	-0.955*** (0.288)	-0.693** (0.319)
	PM _{2.5}		0.321*** (0.0381)	0.0608* (0.0354)	0.0713* (0.0367)
	CO		13.07*** (1.296)	5.852*** (1.218)	3.626** (1.419)
	Precipitation		0.235*** (0.0301)	0.316*** (0.0282)	0.155*** (0.0368)
Individual (or demographic) Factors	Gender			11.56*** (2.052)	14.85*** (2.295)
	Aging			-14.93*** (1.788)	-13.81*** (2.954)
	Divorce_R			0.00825 (0.0219)	0.0132 (0.0139)
	Race_C			9.554*** (0.424)	9.695*** (0.521)
	Family_S			6.664*** (0.771)	1.212 (0.817)
Socioeconomic Conditions	Social_C				-0.663*** (0.216)
	Growth_J				-7.096* (4.113)
	Rate_Unemp				0.102*** (0.0192)
	Store_A				3.457*** (0.827)
	Uninsured_P				-0.0349** (0.0154)
	Income_S				15.00*** (1.662)
	Crime_R				0.000769*** (0.000246)
	Constant	28.11*** (0.735)	21.36*** (0.818)	11.55*** (1.159)	2.331 (1.634)
Observations	2,043	2,042	2,042	1,672	
R-squared	0.167	0.322	0.509	0.587	
VIF	1.42	1.47	1.60	1.89	

Note. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and poverty segregation, which have brought socioeconomic problems to the region. Study finds that the hopefulness for the future can serve as a safeguard against people from the detrimental impact of adverse ones (Lankarani & Assari, 2017). Compared with African American, non-Hispanic whites usually have less confidence in the future (Bailey et al., 2019). Thus, counties with high proportion of non-Hispanic whites are positively linked to high depression rates. The same as the regression based on all US counties, high female and less aging people proportions are positively connected to high depression risk. The role of built environment is also important. The efficient and proper utilization of land is conducive to leaving more space for leisure and relaxation and relieving the stress of residents. Counties with more land mixed use, higher population density and more urban area are associated with less depression disorders.

Different from the regression result based on all US counties (Model 4 in Table 2), we find some socioeconomic conditions, that is, job growth and crime, only affect depression prevalence in the southeastern counties. As the region with prominent socioeconomic problems, people living there may suffer from high social stress, violence and crime, which increasing their risk of being depressed. The increased job growth rates provide employment opportunities for the unemployed and alleviate socioeconomic problems such as poverty and income segmentation, which reduces people's life pressure. Thus, both high job growth rates and decreased crime rates reduce depression rates. Last, all other significant variables have the same effect with the regression results based on all

US counties, except for the proportion of uninsured people. The high association between high proportion of uninsured people and less depression may be because southeastern counties concentrate the majority of African Americans with high share of adults without health insurance (Sood & Sood, 2021).

5. Conclusion and Limitation

5.1. Conclusion

Our study identifies important variables that may impact mental health across US counties, with the built environment emerging as a significant factor. Urban sprawl is a prominent phenomenon in the US and is widely recognized as a contributor to various urban problems. It has long been associated with increased anxiety and depression, leading to negative impact on mental health (Garrido-Cumbrera et al., 2018). However, our study reveals that job sprawl is linked to lower depression prevalence, potentially due to increased access to job opportunities and open space. Land mixed use reduces commuting and life stress. Additionally, job mixed layouts offer a more diverse range of job opportunities, increasing the likelihood of securing satisfying employment and lowering the risk of long-term unemployment. Thus, these factors exhibit positive associations with overall mental well-being.

It is important to acknowledge that urban sprawl may still contribute to anxiety and depression such as increasing commuting distances (Garrido-Cumbrera et al., 2018). It is crucial to determine the extent to which job sprawl can effectively reduce depression prevalence. Implementing measures such as promoting mixed land use and diverse job layouts can help alleviate the prevalence of depression.

The natural environment is also connected with mental health. We found that the presence of green space is associated with lower depression prevalence, and this connection is particularly significant in urban areas. Increasing green space within urban areas, fostering social connections, expanding employment opportunities, and improving social security and welfare systems play significant roles in mitigating depression prevalence. As expected, PM_{2.5} and CO pollution worsen mental health problems. Air pollution not only induces negative moods but also poses a threat to physical health. Consequently, exposure to PM_{2.5} and CO is negatively correlated with overall mental well-being. Furthermore, our findings indicate that increased precipitation is linked to a higher prevalence of depression.

The presence of social capital, which provides individuals with additional resources and robust social support (Thoits, 2011), is linked to a lower prevalence of mental disorders. However, increasing social capital may also increase peoples' stress in certain geographical contexts. Unemployment, high income segregation, limited store access and insufficient insurance coverage, which have plagued poorer neighborhoods for a long time, tend to exacerbate mental health problems.

Further analysis of influencing factors for the two high depression prevalence areas shows that socioeconomic conditions and natural environment play important roles in changing depression prevalence in northwestern counties. Unemployment, income segregation and precipitation are significantly associated with high depression rates. Depression tends to be further exacerbated by precipitation and seasonal unemployment in these regions. Implementing strategies such as expanding employment opportunities and offering unemployment subsidies can play a crucial role in preventing and alleviating depression. Our examination of the effects of January temperature and its interaction with precipitation on mental health revealed insignificant relationships. Consequently, the cold winter itself does not significantly contribute to increased depression, and winter activities such as skiing are popular and enjoyed in this region.

For southeastern counties, demographic factors, especially the racial composition, play significant roles in influencing depression prevalence. The built environment is also important. Land mixed use, high population density and more urban areas are linked to less mental disorders. It needs to be noted that some socioeconomic factors, mainly job growth and crime, only affect the depression risk in southeastern counties.

5.2. Strengths and Limitations

Our study constructs a more comprehensive analytical framework to explore the correlations between built and natural environments and the prevalence of depression, as well as their spatial heterogeneity. We have identified the various effects of multidimensional urban sprawl on mental health, which has rarely been studied previously.

Moreover, our study has shown that not all dimensions of urban sprawl is bad to mental health. We have provided more nuanced analysis of the effect of natural environment on mental health, and that such effects also vary between urban and rural areas. We also demonstrate that the effect of social capital on mental health depends on places or local context. Further identification was conducted on the determinants of two areas (northwestern and southeastern counties) with high depression prevalence, indicating again the significance of places in the determination of mental health.

Our study also has limitations. In the aftermath of the COVID-19 and associated lockdowns, concerns about mental health have heightened significantly, which has prompted a surge in public awareness and engagement, with more individuals actively participating in outdoor activities as a means to alleviate mental stress (Li & Wei, 2023). The pandemic has thus raised the importance of built and natural environment on mental health. Future research should consider the moderating effect of COVID-19 epidemic on the relationship between built and natural environments and depression. Also, more efforts are need to interpret the locally varied relationships across different places.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All of the data we use is publicly available, see Table 1 Data Sources.

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