Spatial Dynamics of Environmental Health: The Impact of Vegetation Greenness and Heat Exposure on Mental Health Outcomes Across California Census Tracts

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Abstract

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This study examines spatial relationships between environmental factors, socioeconomic conditions, and mental health across California census tracts using a Spatial Durbin Error Model. Analysis of 7,963 tracts revealed significant spatial autocorrelation in mental health distress (Moran's I = 0.4713, $p < 0.001$). Median household income was the strongest predictor of mental health distress (direct effect: $\beta = -0.0000489$, $p < 0.001$; indirect effect: $\beta = -0.0000193$, $p < 0.001$). Vegetation greenness showed a significant protective direct effect ($\beta = -3.8818$, $p <$

0.001) without significant spillover effects, indicating localized benefits. Conversely, maximum temperature demonstrated no significant direct effect but had significant positive indirect effects ($\beta = 0.1022$, $p = 0.0016$), suggesting regional rather than local influence. The substantial spatial error parameter ($\lambda = 0.73511$) and strong spatial autocorrelation in both vegetation ($r = 0.820$) and temperature ($r = 0.992$) validate the spatial modeling approach. These findings enhance understanding of how environmental factors influence mental health through different spatial mechanisms and inform targeted intervention strategies addressing both socioeconomic and environmental determinants of health.

Table of Contents

LIST OF TABLES

List of Figures

GLOSSARY

AIC (Akaike Information Criterion): A statistical measure used to compare different models. Lower AIC values generally indicate a better balance between model fit and complexity.

Direct Effects: In spatial models with lagged independent variables (like SDEM), the impact of a local independent variable on the local dependent variable.

Indirect Effects (Spillover Effects): In spatial models with lagged independent variables, the impact of an independent variable in neighboring areas on the dependent variable in the local area.

Lagrange Multiplier (LM) Tests: Diagnostic tests used to detect the presence of spatial dependence (both spatial lag and spatial error) in the residuals of an OLS model.

Moran's I: A statistic used to measure the degree of spatial autocorrelation in a variable or the residuals of a model. A significant Moran's I indicates non-random spatial patterns.

OLS (Ordinary Least Squares): A common method for estimating the parameters of a linear regression model by minimizing the sum of the squared differences between the observed and predicted values.

Residuals: The differences between the observed values of the dependent variable and the values predicted by the statistical model.

Spatial Autocorrelation: The degree to which values of a variable are similar to or dissimilar from nearby values. Positive spatial autocorrelation means similar values cluster together, while negative spatial autocorrelation means dissimilar values cluster.

Spatial Durbin Error Model (SDEM): A spatial regression model that includes both spatially lagged independent variables and a spatially autocorrelated error term.

Spatial Lag: The weighted average of a variable in neighboring spatial units. It represents the influence of the variable in surrounding areas.

Spatial Error Term: Correlation among error terms in neighboring areas indicating spatially clustered unobserved factors.

Weights List: A specification that defines the spatial relationships between the geographic units in the data, typically based on contiguity or distance.

Spatial Weights Matrix: A mathematical formalization of spatial relationships between geographic units, essential for quantifying interdependence in spatial analyses.

Queen Contiguity: Spatial adjacency criterion where units sharing any boundary component (edges or vertices) are classified as neighbors.

CHAPTER 1: INTRODUCTION

1.1 Background

Mental distress has become increasingly prevalent worldwide, representing a major public health challenge. In 2019, nearly one billion people, including 14% of adolescents, were living with a mental disorder (World Health Organization [WHO], 2022). Global trends such as social inequalities and climate change have been identified as significant stressors that adversely affect mental well-being (WHO, 2022; Cianconi et al., 2020). Researchers now recognize that mental health is not determined by individual factors alone; rather, it is also shaped by the surrounding environment and exposures therein (Cianconi et al., 2020).

Environmental factors, including temperature extremes and access to green space, have been increasingly recognized as significant determinants of mental health outcomes. Research suggests that exposure to extreme heat is associated with heightened psychological distress, increased hospitalizations for mental health disorders, and elevated suicide rates (Burke et al., 2018). In contrast, green space has been shown to have restorative effects, reducing stress and improving overall mental well-being (Beyer et al., 2014; Twohig-Bennett & Jones, 2018).

California's changing environmental landscape, driven by climate change, poses significant risks to mental health. Rising temperatures and increasing extreme heat events have been well-documented across the state. Heatwaves have been linked to heightened anxiety, mood disturbances, and depression, particularly in vulnerable populations (Thompson et al., 2018). Epidemiological studies suggest that individuals with pre-existing mental health conditions are over three times more likely to die during extreme heat events than those without such conditions (Bouchama et al., 2007). In addition to acute heat stress, prolonged droughts, common in

California, contribute to chronic psychological distress, particularly among agricultural workers and rural communities who face economic and environmental uncertainty.

1.2 Statement of the Problem

Despite growing evidence linking environmental factors to mental health outcomes, critical gaps persist in understanding how spatially varying environmental exposures such as heat extremes and vegetation greenness interact to shape mental health disparities in California. Existing studies exhibit two significant limitations in their approach. First, many investigations focus on isolated environmental variables in isolation, such as examining only green space effects. Second, research frequently restricts analysis to localized geographic regions, as demonstrated in studies limited to Los Angeles County (Gonzalez, 2016).

Few studies overcome these limitations by integrating comprehensive spatial analysis with multivariable regression techniques to assess statewide patterns of environmental influence on mental health outcomes. For example, although substantial evidence documents the association between green space access and reduced depression risk (Engemann et al., 2019), the literature presents a significant gap regarding the potential moderating effects of heat exposure on this relationship. The differential impact of green space across varying levels of heat exposure constitutes an underexplored domain in environmental mental health research. Similarly, despite California's 2021 extreme heat events (National Oceanic and Atmospheric Administration [NOAA], 2021), no study has evaluated how temperature extremes interact with socioeconomic vulnerability and vegetation deficits to exacerbate mental health distress at the census tract level.

This gap limits policymakers' ability to design targeted interventions. For instance, while CalEnviroScreen identifies pollution-burdened communities (California Environmental Protection Agency [CalEPA], 2021), it does not explicitly model mental health outcomes or account for vegetation's protective effects. Furthermore, existing geospatial analyses of mental health often prioritize homelessness or acute care utilization (UCLA Health Policy, 2022) rather than environmental determinants.

1.3 Purpose of Study

This study examines the spatial relationships between environmental exposures, socioeconomic conditions, and mental health outcomes across California census tracts using a Spatial Durbin Error Model (SDEM), a statistical approach that accounts for spatial dependencies in regression analysis (LeSage & Pace, 2009). By employing this spatially explicit methodology, the study quantifies how environmental factors (vegetation greenness and heat exposure) influence mental health outcomes through both direct effects within census tracts and indirect spillover effects across neighboring areas. This approach provides more accurate estimates of environmental impacts than traditional statistical methods that often overlook these cross-boundary influences (Anselin, 2013).

Building on this spatial framework, the research identifies compound effects of multiple variables (heat, vegetation, income, and employment) on mental health distress, with particular attention to patterns in geographic hotspots and disadvantaged communities. Through comprehensive spatial analysis, the study identifies high-priority regions where environmental risk factors, socioeconomic challenges, and mental health burden co-occur. These insights directly inform targeted policy interventions such as green infrastructure development, heat mitigation strategies, and mental health resource allocation to address environmental health inequities in the most vulnerable California communities.

1.4 Research Objectives and Questions

1.4.1 Research Objectives

This study employs spatial econometric modeling to investigate the complex relationships between environmental exposures, socioeconomic conditions, and mental health outcomes across California census tracts. By distinguishing between direct effects within tracts and indirect spillover effects across neighboring areas, the research addresses critical gaps in understanding how place-based factors shape population mental health. The first objective examines how vegetation greenness (Enhanced Vegetation Index, EVI) is associated with mental health distress across California census tracts, distinguishing between direct (within-tract) effects and potential spillover (neighboring-tract) effects. The second objective identifies spatial patterns in the relationship between heat exposure and mental health distress at both local and regional scales. The third objective assesses the impact of median household income on mental health distress, including both direct and indirect effects across neighboring census tracts. The fourth objective determines whether the employment rate is a significant predictor of mental health distress once environmental (heat, vegetation) and other socioeconomic (income) factors are taken into account.

1.4.2 Research Questions

This investigation is guided by several key research questions aligned with the stated objectives. Regarding vegetation greenness, the research explores how vegetation relates to mental health distress when considering both local conditions and spillover influences from adjacent areas. For heat exposure, the study examines the role of localized (tract-level) versus regional (multi-tract) heat exposure in explaining variations in mental health distress. Concerning income, the research investigates the extent to which median household income predicts mental health distress within a given tract, and whether higher or lower incomes in surrounding tracts also influence mental health outcomes. For employment, the study considers whether employment rate independently affects mental health distress, or if income is a more dominant socioeconomic determinant when considering environmental exposures. These questions collectively address the spatial nature of environmental and socioeconomic influences on mental health outcomes.

1.4.3 Hypotheses

Based on these research questions and existing literature, several hypotheses are proposed. Regarding vegetation greenness, higher levels of vegetation greenness (EVI) are expected to be associated with lower mental health distress within the same census tract (a direct, protective effect), while spillover (indirect) effects from adjacent tracts' greenness will be minimal or statistically insignificant. For heat exposure, it is hypothesized that heat will primarily influence mental health distress through indirect, cross-tract effects rather than direct local impacts, indicating that regional temperature patterns exert a stronger influence on psychological outcomes than do strictly localized temperatures. Concerning socioeconomic factors, median household income is expected to emerge as the strongest predictor of mental health distress, with higher incomes predicting lower distress through both direct (within-tract) and indirect (neighboring-tract) pathways, suggesting that socioeconomic improvements benefit not only the focal community but also surrounding areas. When controlling for environmental factors and household income, the employment rate is hypothesized to exhibit significant associations with mental health distress, suggesting that not only individual employment status but also the overall employment rate in a community is critical for mental well-being. From a spatial perspective, environmental and socioeconomic variables are expected to exhibit strong spatial clustering, such that lower-income areas may coincide with less green space and higher heat exposure, reflecting potential environmental justice concerns. Finally, significant spatial dependence is hypothesized to remain in mental health distress after accounting for measured predictors, suggesting that additional unmeasured or emergent factors operate across census tract boundaries.

1.5 Theoretical Framework

This research integrates three complementary theories to understand how environmental factors influence mental health across communities. The socio-ecological model (Bronfenbrenner, 1979) serves as the foundation, viewing mental health as shaped by multiple levels of influence from individual to societal factors. Within this framework, environmental conditions like vegetation and heat represent community-level determinants that interact with both individual characteristics and broader social structures (Stokols, 1996).

Building on this foundation, the environmental justice framework (Bullard, 1990) addresses how environmental conditions are distributed unequally across populations. This perspective highlights that green spaces, heat exposure, and other environmental factors often follow patterns of socioeconomic inequality, creating compounded disadvantages in certain communities (Schlosberg, 2007). This theoretical lens directly informs our research questions regarding how environmental factors may disproportionately affect vulnerable populations and communities with limited resources.

The research also incorporates specific environmental health theories that connect to our methodological approach. Stress-Reduction Theory (Ulrich et al., 1991) explains the mechanisms through which natural environments promote psychological restoration and potentially buffer against other stressors, directly supporting our hypotheses regarding vegetation's protective effects.

The spatial analytical approach extends these frameworks by examining how environmental influences operate both within communities and across geographic boundaries. By using a Spatial Durbin Error Model, the study separates direct effects within census tracts from indirect effects across neighboring areas (LeSage & Pace, 2009). This methodological choice directly addresses our research questions concerning spatial spillover effects and provides a more comprehensive analysis of how place shapes mental health across California's diverse communities.

1.6 Significance of the Study

This research makes significant contributions to public health policy, planning practice, and environmental science by identifying specific geographic areas requiring targeted interventions. Through spatial analysis, we identify "hotspots" where heat exposure and vegetation deficits co-occur with mental health challenges. These findings enable evidence-based prioritization of regions for tree-planting initiatives, cooling center implementation, and mental health resource allocation. The results are especially timely given that 53% of Californians report experiencing mental health impacts from climate-related events (Zhao et al., 2024), underscoring the need for policy strategies that buffer climate-related psychological distress through nature-based solutions (Bratman et al., 2019).

The study's integration of environmental and socioeconomic data addresses important health equity concerns with direct policy implications. California's low-income communities face disproportionate barriers to mental health care access. By identifying areas where environmental stressors overlap with socioeconomic vulnerability, this research aligns with and informs the California Environmental Protection Agency's environmental justice objectives (California Environmental Protection Agency, 2021). The findings will guide policymakers toward communities that would benefit most from dual investments in green infrastructure and healthcare access, potentially reducing both environmental and healthcare disparities simultaneously.

Methodologically, this study advances the environmental health literature by merging high-resolution remote sensing data (Enhanced Vegetation Index, air temperature) with sophisticated spatial econometrics (Spatial Durbin Error Models) to disentangle localized environmental effects from regional trends. While previous research has established associations between green spaces and reduced anxiety (Engemann et al., 2019), our approach quantifies how vegetation's protective capacity varies across different environmental and socioeconomic contexts. This represents a novel contribution to both environmental planning and health science by demonstrating how these factors interact across geographic boundaries to influence population mental health outcomes, providing a foundation for more nuanced intervention strategies that account for both local conditions and regional influences (Jerrett et al., 2010).

1.7 Definition of Terms

Mental Health Distress: Frequent mental distress (FMD) as measured through CDC's PLACES data, defined as self-reporting 14 or more mentally unhealthy days during the past 30 days due to stress, depression, or emotional problems (Centers for Disease Control and Prevention [CDC], 2023). This measure serves as the primary mental health outcome in this study and indicates more chronic and severe mental health issues. While related to the Kessler Psychological Distress Scale, PLACES specifically uses the 14+ mentally unhealthy days threshold rather than the K6 scoring system.

Enhanced Vegetation Index (EVI): A sophisticated satellite-derived measure of vegetation greenness calculated from Sentinel-2 imagery. EVI is designed to overcome limitations of traditional vegetation indices by optimizing signal detection while minimizing background soil influence and atmospheric interference. This provides superior sensitivity in high-biomass regions across California's diverse landscapes. EVI effectively captures vegetation presence, density, and health at high spatial resolution, enabling comprehensive assessment of green space distribution across census tracts and robust analysis of vegetation's relationship with mental health outcomes.

Heat Exposure: A measure quantifying thermal burden experienced by populations across California using the Daymet V4 dataset to record maximum air temperature during peak heat season (July-September). This dataset provides daily meteorological parameters at 1-km × 1-km spatial resolution through sophisticated interpolation of weather station observations that incorporate topographic factors including elevation and terrain complexity. The approach captures both magnitude and spatial patterns of temperature extremes across California's diverse geographic regions, providing accurate estimates during periods when heat stress most significantly impacts human physiology and psychological functioning.

Spillover Effects: The influence that conditions in one geographic area exert on outcomes in neighboring areas. In this research, spillover effects represent how environmental conditions in adjacent census tracts affect mental health outcomes beyond their administrative boundaries (Anselin, 2003). This concept is central to the study's spatial analytical approach, recognizing that environmental influences often operate across jurisdictional boundaries and at multiple geographic scales.

Spatial Durbin Error Model (SDEM): An econometric modeling approach that accounts for spatial dependencies in both the dependent variable and error terms while allowing for estimation of both direct effects (within geographic units) and indirect effects (across neighboring units) (LeSage & Pace, 2009). SDEM extends traditional regression by incorporating spatial weight matrices that define the connectivity between geographic areas, providing more accurate estimates of environmental impacts by accounting for spatial autocorrelation in the data.

Census Tract: A small, relatively permanent statistical subdivision of a county designed to be relatively homogeneous with respect to population characteristics, economic status, and living conditions (U.S. Census Bureau, 2020). Census tracts typically contain between 1,200 and 8,000 people, with an optimum size of 4,000, and serve as the primary geographic unit of analysis in this study, offering a granular scale for examining spatial patterns of environmental exposure and mental health outcomes.

CHAPTER 2: LITERATURE REVIEW

This review synthesizes research on environmental determinants of mental health, focusing specifically on vegetation greenness and heat exposure. The chapter examines how these factors interact across diverse populations and geographic contexts, and evaluates the moderating role of socioeconomic variables. Building on spatial analysis frameworks, the review identifies critical research gaps that inform investigations of environmental mental health determinants at the census tract level in California.

2.1 Theoretical Foundation

2.1.1 Environmental Influences on Mental Health Outcomes

Research consistently demonstrates that environmental factors significantly impact mental health through various physiological and psychological pathways. Exposure to high ambient temperatures has been associated with adverse mental health outcomes, with Liu et al. (2021) finding that each 1°C increase in daily temperature corresponds to approximately a 1% rise in mental health-related emergency visits and mortality. These effects are particularly pronounced during extreme heat events, as Thompson et al. (2023) concluded that both absolute temperatures and temperature variability positively correlate with hospital attendance for mental illness.

Conversely, vegetation greenness generally serves as a protective factor for mental health. According to attention restoration theory (Ulrich et al., 1991), natural environments help restore attentional capacity and reduce mental fatigue. Twohig-Bennett and Jones (2018) conducted a systematic review and meta-analysis finding significant associations between greenspace exposure and reduced risk of psychological distress, depression, and anxiety. This protective relationship operates through multiple complementary pathways, including facilitating physical activity, promoting social interaction, and mitigating environmental stressors such as noise, air pollution, and heat (Kuo, 2015).

2.1.2 Stress Reduction and Resilience Theories

Two complementary theoretical frameworks help explain the mechanisms through which environmental factors influence mental health. Stress Reduction Theory (SRT), originally proposed by Ulrich et al. (1991), posits that exposure to natural environments rapidly fosters positive emotions and physiological relaxation, countering stress. According to this framework, viewing or walking in green settings can lower heart rate, muscle tension, and stress hormone levels, thereby improving mood and anxiety. Studies show that people who spend time in natural settings demonstrate rapid decreases in physiological stress markers and self-reported rumination.

Resilience Theory provides another valuable framework, focusing on the capacity to maintain or regain mental health in the face of adversity. A supportive environment can bolster both individual and community resilience to stress. For example, green spaces may act as a buffer against life stressors, helping people cope more effectively. These theoretical frameworks underscore why environmental factors matter: natural settings can diminish stress and build resilience, whereas harsh climatic conditions may overwhelm coping mechanisms.

2.1.3 Environmental Interconnections and Modifying Factors

Environmental exposures rarely occur in isolation, necessitating investigation of interactive effects. Vegetation and heat exposure interact substantially, with green spaces mitigating the urban heat island effect through shading and evapotranspiration. This vegetation-heat interaction may become increasingly valuable as climate change intensifies extreme heat events.

Recent research has highlighted how these interactions operate in real-world settings. For example, Sun et al. (2024) analyzed data from Southern California and found that the effects of heat exposure on postpartum depression were significantly greater among mothers who lived in areas with less green space or more air pollution, suggesting compounding environmental burdens. This demonstrates how multiple environmental factors can interact to either exacerbate or mitigate mental health impacts.

Socioeconomic factors further moderate these environmental relationships. Mitchell et al. (2015) identified green space as an "equigenic" factor that can reduce mental health disparities between high and low-income groups. Employment status also influences environmental exposure patterns, with unemployed individuals potentially experiencing increased exposure to residential environmental stressors due to spending more time at home (Butterworth et al., 2012).

2.2 Current Research in Environmental Health

2.2.1 Vegetation Greenness

Recent studies have reinforced the protective relationship between green space and mental health while providing additional insights into potential effect modifiers and mechanisms. Wang et al. (2024) analyzed data from the UK Biobank cohort and found that long-term exposure to residential greenness was associated with decreased risk of depression and anxiety. The protective effect was more pronounced among individuals with lower socioeconomic status, suggesting that green space may be particularly valuable for populations with fewer resources for alternative coping strategies.

Beyer et al. (2014) examined the relationship between neighborhood green space and mental health using data from the Survey of the Health of Wisconsin. After controlling for individual and neighborhood characteristics, they found that higher levels of neighborhood green space were associated with significantly lower levels of symptoms of depression, anxiety, and stress.

Experimental evidence has strengthened causal claims about greenness and mental health. A landmark cluster-randomized trial in Philadelphia tested this by randomly greening vacant lots in low-income neighborhoods. South et al. (2018) reported striking results: residents near greened lots experienced a 41.5% reduction in feelings of depression and reported 62.8% fewer days of poor mental health compared to a control group. The effect was even stronger (nearly 69% depression reduction) among residents in poverty. This experimental evidence suggests that improving neighborhood greenery can cause tangible mental health improvements, especially in communities burdened by blight.

2.2.2 Heat Exposure and Psychological Wellbeing

More recent research has strengthened connections between heat exposure and mental health, particularly in the context of increasing climate change concerns. A comprehensive systematic review spanning 53 studies found that for each 1°C rise in daily mean temperature, there was an associated increase in mental health-related mortality by about 2.2%, and an increase in mental health morbidity (hospital visits, etc.) by about 0.9% (Ventriglio et al., 2021). In other words, hotter days reliably correspond with more deaths by suicide or other mental health-related causes and more psychiatric emergency room visits.

Heatwaves (sustained extreme heat events) showed especially pronounced effects. Under certain definitions (e.g., >95th percentile temperature for ≥3 days), heatwaves were associated with approximately 6% higher risk of mental health hospitalizations (Ventriglio et al., 2021). High temperatures have been implicated in exacerbating mood and anxiety disorders, increasing aggressive behaviors, and even triggering substance abuse relapses.

Another striking finding comes from studies of suicide: unusually hot periods are linked to notable increases in suicide rates. Burke et al. (2018) found that a month 1°C hotter than average led to a 0.7% increase in the suicide rate in the U.S. (and a 2.1% increase in Mexico). This suggests thousands of additional suicides could occur with projected warming by 2050, underscoring the profound mental health stakes of climate change.

Nori-Sarma et al. (2022) examined emergency department visits for mental health conditions across 2,775 U.S. counties from 2010 to 2019, finding that days of extreme heat (≥95th percentile temperature) were associated with 8% higher rates of emergency department visits for mental health conditions compared to days with more moderate temperatures.

In California specifically, Zhao et al. (2024) found that 53% of respondents reported mental health impacts from climate-related events, including extreme heat. Recent research in Southern California highlighted disparities in heat-related postpartum depression. In a cohort of approximately 430,000 new mothers, higher postpartum temperature exposure was associated with increased risk of postpartum depression (PPD) (adjusted OR ~1.07 per IQR increase in mean temperature) (Sun et al., 2024). The effect appeared strongest for maximum daily temperatures and showed significantly greater impacts among Black, Asian, and Hispanic mothers compared to other demographic groups. These findings suggest that the psychological burden of heat exposure may be particularly pronounced in regions experiencing increasing frequency and intensity of heat waves, with significant disparities across demographic groups.

2.3 Spatial Dimensions in Environmental Mental Health Research

2.3.1 Geographic Dependencies and Spatial Modeling Approaches

The spatial dimension of environmental exposures and mental health outcomes is increasingly recognized as an important consideration in research. Spatial analysis techniques can account for these geographic dependencies and provide more accurate estimates of environmental effects on mental health. Gruebner et al. (2011) used spatial analysis to examine patterns of mental health and found significant spatial clustering of mental health outcomes.

Given that environmental exposures are spatially patterned, scientists are increasingly using spatial regression models to control for location-based autocorrelation and identify true associations. By incorporating geographic information systems (GIS) and high-resolution maps, studies can assess local variations, such as block-level tree cover or neighborhood heat index, and relate them to mental health survey data.

Mennis et al. (2013) applied spatial regression techniques to examine built environment factors associated with depression symptoms among youth. They found that traditional ordinary least squares (OLS) regression failed to account for spatial autocorrelation in the data, potentially leading to biased estimates. The importance of spatial modeling in environmental mental health research is underscored by Anselin (2003), who introduced foundational concepts of spatial econometrics, including spatial lag and spatial error models.

2.3.2 Community-Level Analysis and Regional Patterns

The spatial perspective is particularly relevant for studies examining environmental determinants of mental health at the community level. By employing spatial regression techniques, specifically the Spatial Durbin Error Model, researchers can account for the complex spatial relationships between environmental exposures, socioeconomic conditions, and mental health outcomes. This approach allows for a more accurate assessment of how these factors interact to shape mental health disparities at the local level, with implications for targeted interventions and policies.

Community-level analysis enables the identification of regional patterns in environmental exposures and mental health outcomes that might not be apparent at other geographic scales. These patterns can inform region-specific interventions and policies that address the unique combination of environmental and socioeconomic factors affecting mental health in different areas. By accounting for spatial dependencies and spillover effects, this approach provides a more nuanced understanding of how place shapes mental health, moving beyond individual-level factors to consider the broader geographic context in which people live.

2.4 Methodological Advances

Recent years have seen significant methodological improvements in how researchers study environmental impacts on mental health.

Spatial epidemiology and modeling approaches have improved significantly, with researchers using spatial regression models to control for location-based autocorrelation and identify true associations. By incorporating geographic information systems (GIS) and high-resolution maps, studies can assess local variations in environmental exposures and relate them to mental health outcomes with greater precision.

Improved exposure assessment has enhanced the quantification of environmental exposure. Satellite-derived indices (like NDVI for greenness, land surface temperature for heat) at fine spatial scales are now routinely linked with health datasets. Personal exposure is also better captured through wearable devices and smartphone GPS tracking, providing more granular data on individual environmental exposures (Freymueller et al., 2024).

Longitudinal and quasi-experimental designs have moved beyond cross-sectional studies to infer causality. Some cohort studies track people's mental health over time as they move residences or as environmental conditions change. Quasi-experiments exploit "natural experiments" like urban greening initiatives or climate events to establish causal relationships between environmental changes and mental health outcomes.

Laboratory and field experiments have enriched the evidence on mechanisms. Researchers expose participants to simulated environments and measure acute stress, mood, or cognitive outcomes.

Interdisciplinary data integration has combined information from multiple sources, including environmental sensors, medical records, surveys, brain imaging, and social media, to build a holistic understanding of environmental influences on mental health. This integration enables more precise and causal inferences about the relationships between environment and mental health.

2.5 Research Gaps

Despite growing research on environmental determinants of mental health, several important gaps remain in the existing literature:

First, while numerous studies have examined individual environmental factors, few have investigated the complex spatial relationships between vegetation greenness and heat exposure in relation to mental health. Specifically, the distinction between direct (within-tract) effects and indirect spillover effects across neighboring areas remains underexplored. Understanding these spatial dynamics is crucial for developing targeted interventions that address environmental factors at appropriate geographic scales.

Second, spatial econometric modeling approaches are underutilized in mental health research, potentially leading to biased estimates of environmental effects. By failing to account for spatial dependencies and distinguishing between localized and regional impacts, many studies may misestimate the true relationship between environmental exposures and mental health outcomes at the community level.

Third, although socioeconomic factors like median household income have been identified as important determinants of mental health, more research is needed to understand how employment rates independently contribute to mental health outcomes when controlling for both environmental factors and income. This understanding is essential for developing comprehensive policies that address both economic and environmental aspects of community well-being.

Fourth, causality and long-term effects remain difficult to establish in environmental mental health research. While longitudinal studies and experiments help, they are still relatively few. More natural experiments (such as evaluating mental health before vs. after urban greening, or comparing similar communities with and without heat mitigation) are needed to strengthen causal claims. Additionally, most research has focused on short-to-medium term mental health outcomes; the long-term psychological impacts of chronic exposure to greenness or heat (over decades) are not well understood.

Fifth, few studies have examined how environmental and socioeconomic variables might exhibit spatial clustering patterns that reflect environmental justice concerns. Understanding whether lower-income areas coincide with less green space and higher heat exposure is critical for addressing health disparities across diverse communities.

2.6 Policy Implications

The growing evidence on greenness and heat has timely implications for public health and planning policy. As climate change accelerates, integrating mental health considerations into environmental policies is essential

Planning for green, healthy spaces should be informed by findings that green space promotes mental well-being. Planners and local governments can invest in parks, community gardens, forests, and green roofs, particularly in underserved neighborhoods lacking natural environments. The evidence suggests these interventions may yield larger mental health benefits in low-income areas, helping to reduce disparities (South et al., 2018).

Heat mitigation and climate adaptation efforts should incorporate mental health considerations. Public health officials should include mental health surveillance and services in heat wave response plans. At the policy level, reducing heat islands through cool roofs, reflective pavement, and expanding tree canopy can mitigate the severity of heat exposure (World Health Organization, 2022). Cities such as Los Angeles are beginning to map extreme heat risk and prioritize tree planting in the hottest neighborhoods as an integrated approach to address both climate and mental health concerns.

Cross-sector collaboration between planners, environmental agencies, and mental health professionals is crucial. Tools like health impact assessments can evaluate how proposed developments might affect residents' mental health via changes in green space, walkability, or noise. In California, environmental and health departments are increasingly using data to identify communities with high pollution, heat, and low greenness, guiding targeted investments.

By prioritizing green, resilient environments, policymakers can help reduce stress, depression, and anxiety on a broad scale. This preventive approach can complement clinical services, creating a more holistic strategy to tackle the growing global burden of mental illness.

2.7 Summary

This literature review has synthesized current knowledge on relationships between vegetation greenness, heat exposure, and mental health outcomes. Evidence consistently shows protective effects of vegetation and adverse impacts of heat exposure on mental health. The review highlights the importance of environmental interactions, socioeconomic moderators, and spatial dimensions in understanding these relationships.

Methodological advances, including spatial epidemiology and experimental designs, have strengthened causal evidence. Meta-analyses provide precise effect estimates: each 1°C temperature increase raises mental health-related mortality by 2.2% (Ventriglio et al., 2021).

Advanced spatial modeling approaches, such as the Spatial Durbin Error Model, can examine how environmental and socioeconomic factors interact to shape mental health outcomes across geographic areas. This approach provides a more nuanced understanding of community-level determinants of mental health, informing policies and interventions for promoting well-being, particularly in socioeconomically vulnerable communities facing environmental stressors.

CHAPTER 3: METHODOLOGY

This chapter details the methodological framework for examining relationships between environmental exposures, socioeconomic factors, and mental health outcomes across California census tracts. The methodology integrates spatial epidemiology, environmental science, and econometric modeling to address the study's research questions. Following a cross-sectional observational design, the analysis employs spatial regression techniques to account for geographic dependencies in the data, ultimately selecting the Spatial Durbin Error Model (SDEM) as the optimal approach through rigorous model comparison.

3.1 Research Design

This study employs a cross-sectional, observational design to analyze associations between environmental factors, socioeconomic conditions, and mental health outcomes across California census tracts in 2021. While cross-sectional designs cannot establish causality, they are well-suited for identifying spatial patterns and generating hypotheses about environmental determinants of mental health. The research questions specifically focus on identifying correlational patterns and spatial dependencies rather than causal mechanisms, making a cross-sectional approach appropriate and efficient.

The census tract scale was chosen to capture local variations in environmental exposures and socioeconomic conditions that influence mental health outcomes. This level of analysis allows for identifying spatial patterns that might be obscured in more aggregated studies while remaining large enough to ensure statistical stability in health outcome measures. The selection of 2021 as the temporal focus is justified by the occurrence of extreme heat events in California, providing an opportunity to examine the impact of temperature and other environmental factors on mental health under conditions of environmental stress.

The spatial econometric approach reflects the theoretical understanding that both physical and social environments influence health beyond individual or administrative boundaries (Bratman et al., 2012). The SDEM was selected over traditional regression methods due to California's strong geographic clustering of environmental exposures and mental health outcomes. This design enables quantification of both local effects and spatial spillovers, critical for understanding regional-scale health impacts. The model's dual capacity to handle substantive spatial dependence through lagged independent variables and residual spatial autocorrelation via the error structure makes it particularly suited for analyzing mental health determinants where both observed and unobserved spatial processes operate (LeSage & Pace, 2009).

3.2 Population and Sample

The study initially included all 8,057 California census tracts. After excluding tracts with zero population and isolated polygons without neighbors for spatial analysis, the final analytical sample consisted of 7,963 census tracts, representing 98.8% of the original data. This comprehensive geographic coverage ensures representation of California's diverse urban, suburban, and rural communities.

The neighbor detection process employed queen contiguity criteria in the spatial analysis. Queen contiguity was selected over other approaches (such as rook contiguity or distance-based measures) because it better captures the complex geographical relationships in California's diverse landscape, allowing diagonally adjacent tracts to be considered neighbors. This approach is particularly important in areas with irregular tract boundaries and varying population densities, providing a more comprehensive representation of potential spatial influences. Through this process, 11 isolated tracts (0.14% of initial sample) were identified for removal. These isolated tracts were primarily desert military bases, offshore islands, and newly created census tracts, all of which lacked spatial neighbors necessary for the analysis. The final analytical sample of 7,963 tracts maintains representation of 99.8% of California's population, ensuring the study's findings remain generalizable to the state as a whole.

3.3 Variables and Measurement

3.3.1 Dependent Variable

Mental health data were obtained from the 2023 release of PLACES: Census Tract Data (GIS Friendly Format), a collaborative effort by the Centers for Disease Control and Prevention (CDC), the Robert Wood Johnson Foundation, and the CDC Foundation. The dataset provides model-based prevalence estimates for various health indicators at the census tract level across the United States.

The study's key dependent variable, mental health distress prevalence (MHLTH_CrudePrev), represents the percentage of adults reporting 14 or more days of poor mental health within the past 30 days. These estimates were generated using small area estimation (SAE) methodology, specifically multilevel regression and poststratification (MRP), integrating individual-level data from the Behavioral Risk Factor Surveillance System (BRFSS) with area-level demographic metrics from the American Community Survey (ACS) and U.S. Census Bureau population estimates. Monte Carlo simulations were employed to calculate 95% confidence intervals, ensuring statistical robustness. The prevalence of mental health distress across California census tracts ranged from 6.40% to 34.80%, with a median value of 15.50%.

This measure was selected based on its established use in psychiatric epidemiology as a screening tool for significant psychological distress with potential clinical relevance. While the self-reported nature of the measure introduces some limitations regarding clinical precision, it provides a standardized, population-level indicator that has been validated in previous environmental health studies and is consistently available across all census tracts in the study area.

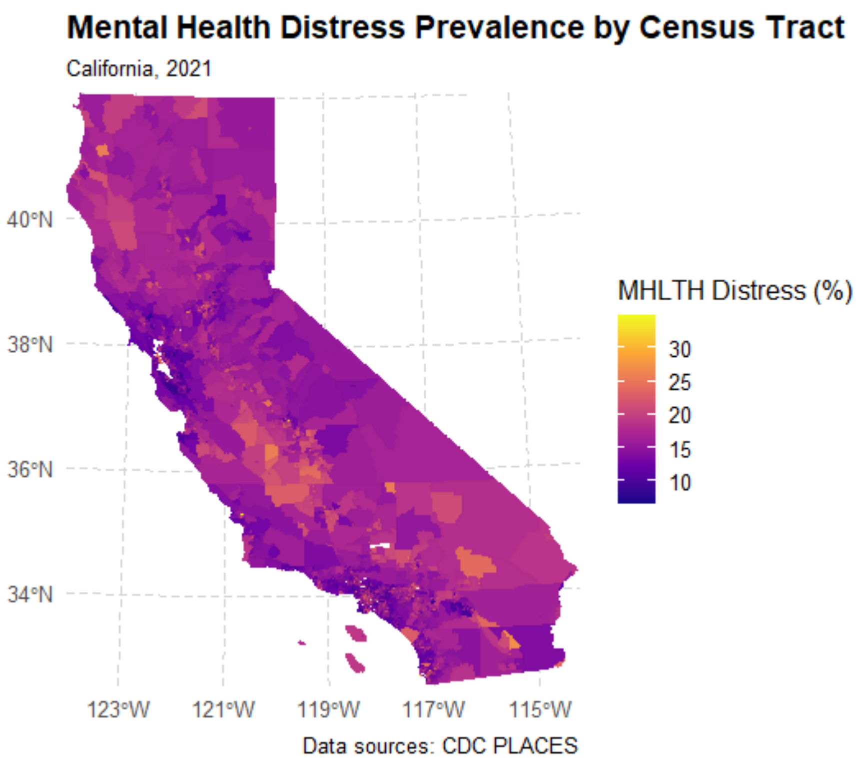

Figure 1: Geographic Distribution of Mental Health Distress Prevalence Across California Census Tracts (2021)

3.3.2 Independent Variables

The study included two key independent variables: heat exposure and vegetation greenness. These variables were selected based on the theoretical framework established in the literature review, which suggests that both built environment characteristics and natural environment exposures influence mental health through multiple pathways, including stress reduction, physical activity facilitation, and physiological responses to environmental stressors.

Maximum air temperature data were obtained from Daymet Version 4, produced by the Oak Ridge National Laboratory. Daymet provides gridded estimates of daily weather parameters for North America at a 1-km spatial resolution. The study used annual maximum temperature as the primary heat exposure metric, which captures the single hottest day recorded in each census tract during 2021. Maximum temperature values ranged from 29.56°C to 54.37°C, with a median of 37.67°C. While Daymet's interpolation methods have known limitations in areas of complex terrain and sparse monitoring stations, validation studies have shown that the dataset provides reliable temperature estimates across most of California (Thornton et al., 2021). Areas of higher uncertainty, primarily in mountainous regions, were identified through confidence interval metrics provided with the dataset and considered during interpretation.

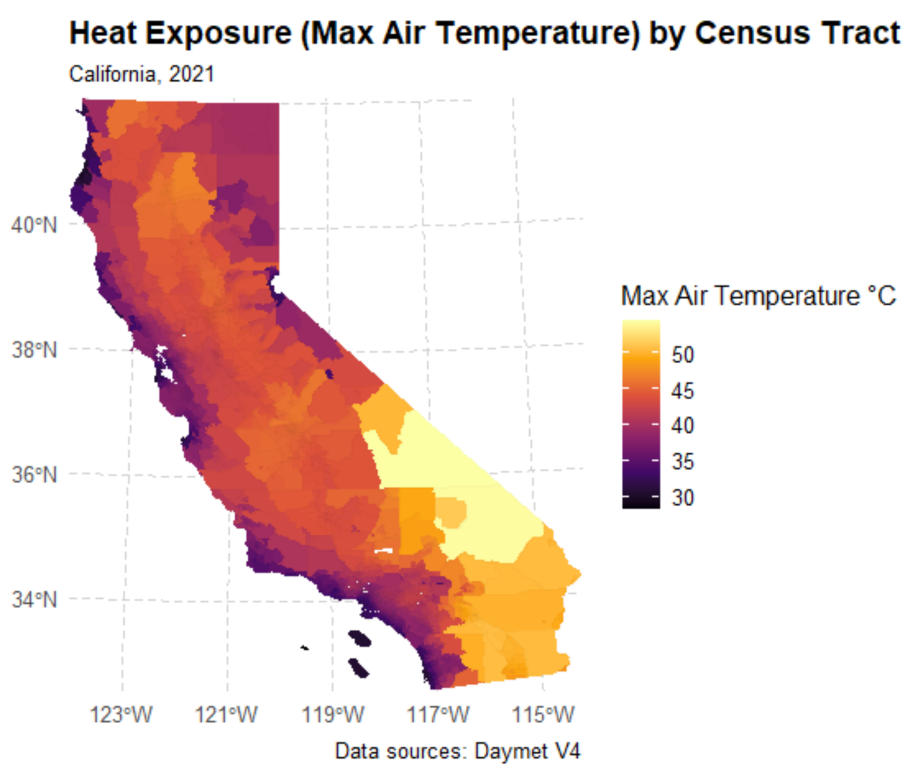

Figure 2: Spatial Patterns of Environmental Exposures in California: Maximum Air Temperature (2021)

Vegetation greenness was assessed using the Enhanced Vegetation Index (EVI) derived from Sentinel-2 satellite imagery via the Google Earth Engine platform. Sentinel-2 provides optical imagery at a 10-meter spatial resolution, allowing for detailed vegetation assessments. EVI values were derived using Band 8 (NIR 842nm), Band 4 (Red 665nm), and Band 2 (Blue 490nm) at 10m resolution, following the formula: $EVI = 2.5 * (B8 - B4) / (B8 + 6 * B4 - 7.5 * B2 + 1)$.

Cloud masking was applied using the SCL layer, and the study calculated median EVI values within each census tract as a proxy for green space exposure. EVI values ranged from -0.03197 to 0.53334, with a median of 0.16719. This approach minimizes the influence of cloud cover and seasonal vegetation changes, though it may underrepresent ephemeral vegetation in some arid regions. The EVI was preferred over other vegetation indices like NDVI because it better accounts for atmospheric conditions and soil background effects, particularly important in California's diverse landscapes. The median value was chosen to represent central tendency while being less sensitive to outliers that might result from classification errors or anomalous pixels.

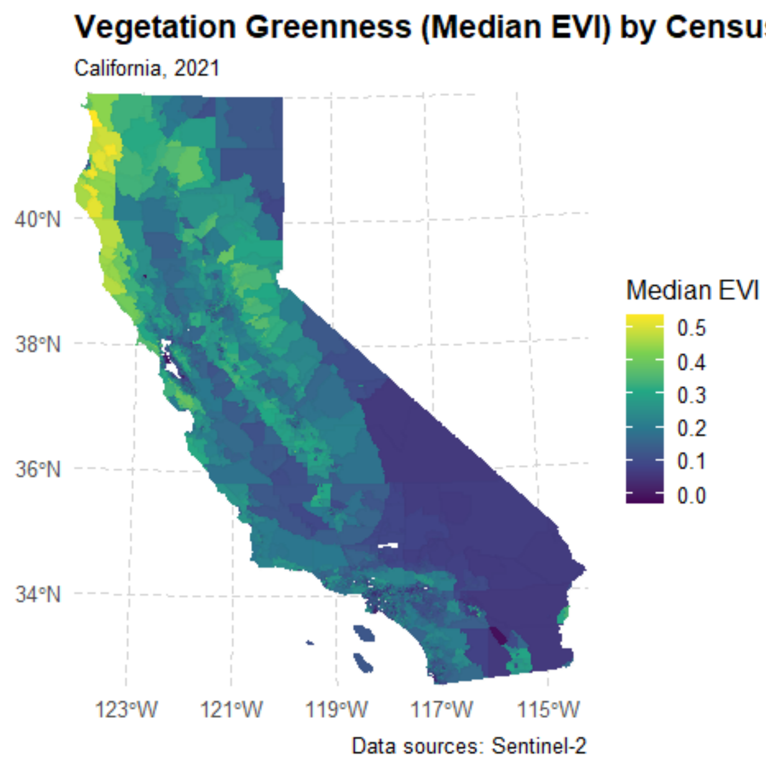

Figure 3: Spatial Patterns of Environmental Exposures in California: Vegetation Greenness (2021)

3.3.3 Covariates

Socioeconomic covariates were included based on extensive evidence from the literature that socioeconomic status strongly influences mental health outcomes and may confound relationships between environmental exposures and health (Hajat et al., 2015). These covariates were obtained from the American Community Survey (ACS) 2015-2019, 5-year estimates and included median household income and employment rate.

Median household income values ranged from $7,461 to $250,001 (median: $73,632). Income serves as a proxy for material resources that can buffer environmental stressors and facilitate access to healthcare and recreational amenities. Mitchell and Popham (2008) demonstrated that socioeconomic factors may moderate the relationship between environmental exposures (particularly green space) and health outcomes, further justifying the inclusion of income as a key covariate.

Employment rate was defined as the proportion of the civilian population aged 16 and older who were employed, with values ranging from 0.007202 to 0.936508 (median: 0.602055). Employment not only provides financial resources but also structures daily activities and social connections that can influence mental health independently of income.

Given the high spatial autocorrelation of temperature (Moran's I = 0.987), a multicollinearity assessment was performed. Variance inflation factors (VIF) for all predictors were calculated, ensuring that no variable exceeded the conventional VIF threshold of 10.

Variable Name	Variable Type	Definition	Time Frame	Granularity	Data Source
Mental Health Distress Prevalence	Dependent	Percentage of adults aged ≥18 years who report 14 or more days during the past 30 days during which their mental health was not good.	2021	Census Tracts	PLACES (Centers for Disease Control and Prevention [CDC], 2023)
Maximum Air Temperature	Independent	Maximum daily air temperature recorded, measured in degrees Celsius.	2021	Census Tracts	Daymet V4 (Oak Ridge National Laboratory, 2024)
Vegetation Greenness (Median EVI)	Independent	Median Enhanced Vegetation Index value, ranging from -1(sparse) to 1(dense).	2021	Census Tracts	Sentinel-2 (Google Earth Engine Catalog, 2024)
Median Household Income	Covariate	Midpoint of the household income distribution within each census tract, measured in dollars.	2015-2019	Census Tracts	American Community Survey (2019)

Employment Rate	Covariate	Proportion of the civilian population aged 16 and over who are employed.	2015-2019	Census Tracts	American Community Survey (2019)

Table 1: Variable Definitions, Measurement, and Data Sources for Mental Health-Environment Analysis in California.

3.4 Data Integration

The research integrates multiple spatial datasets with varying native resolutions to create a comprehensive analytical framework. Data were collected from federal and state agencies, including the U.S. Census Bureau, Centers for Disease Control and Prevention, and European Space Agency.

The data processing workflow involved several stages. First, census tract boundaries were standardized to ensure consistent geographic representation, and environmental data (EVI and air temperature) were aggregated to census tract level using zonal statistics in Google Earth Engine. EVI aggregation process calculated median values for each pixel to minimize the influence of outliers while representing central tendency within each tract. For air temperature data, maximum values were retained to capture extreme heat exposure, which has particular relevance for mental health impacts.

Second, mental health indicators were extracted directly from the PLACES dataset, while socioeconomic variables were calculated from ACS tables. The ACS variables required additional processing to derive employment rates and to enhance the comparability of socioeconomic indicators across diverse California regions.

Third, all datasets were merged using census tract GEOID as the common identifier, and data validation checks were performed to ensure proper alignment of geographic units across datasets in R. These validation procedures included boundary comparisons, attribute matching, and descriptive statistics to identify any potential misalignments or inconsistencies in the integrated dataset.

The data integration process addressed several ethical considerations. Areas with no populations were excluded to prevent potential disclosure of sensitive health information in no populated communities. Moran's I verification was conducted to assess spatial patterns without disclosing specific geographic locations of mental health clusters. All data used in this study were publicly available, aggregated measures with no personally identifiable information, and the research was conducted in accordance with ethical guidelines for spatial epidemiological research as outlined by the U.S. Department of Health & Human Services (2018).

3.5 Statistical Analysis

To address the research questions regarding spatial patterns in mental health outcomes, a spatial econometric approach was employed to account for spatial dependence in the data (Anselin, 1988). Initial exploratory spatial data analysis revealed significant spatial autocorrelation in the dependent variables, indicating that traditional Ordinary Least Squares (OLS) regression would violate the assumption of independent observations. This spatial approach aligns with the theoretical understanding that mental health is influenced by both local conditions and broader regional contexts, with environmental exposures often transcending administrative boundaries.

An OLS model was initially estimated as a baseline: $MentalHealth_i = \beta_0 + \beta_1 Vegetation_i + \beta_2 Temperature_i + \beta_3 Income_i + \beta_4 Employment_i + \varepsilon_i$. Here, β_0 is the intercept term, representing the expected level of mental health distress when all independent variables are zero. The coefficients $\beta_1, \beta_2, \beta_3,$ and β_4 represent the expected changes in mental health distress associated with a one-unit increase in vegetation level, heat, median household income, and employment rate, respectively. Lastly, ε_i represents the error term, capturing unexplained variability in the mental health distress measure across census tracts.

Statistic	Value
Residual standard error	2.102 on 7958 degrees of freedom
Multiple R-squared	0.5893
Adjusted R-squared	0.589
F-statistic	2854 on 4 and 7958 DF
p-value	< 2.2e-16

Table 2: OLS Model Fit Statistics

While this model achieved an adjusted R-squared of 0.589, diagnostic tests revealed significant spatial autocorrelation in the residuals (Moran's I = 0.4713, $p < .001$), confirming the need for spatial regression models (Moran, 1950).

Metric	Value
Moran I statistic	0.4713151
Expectation	-0.0001256124
Variance	0.00004226518
Standard deviate	72.516
p-value	< 2.2e-16
Alternative hypothesis	greater

Note on spatial weights: Queen contiguity was used with row-standardization (style = "W"). Some observations had no neighbors, creating 3 sub-graphs in the neighbor object.

Table 3: Moran's I Test for Spatial Autocorrelation of Residuals

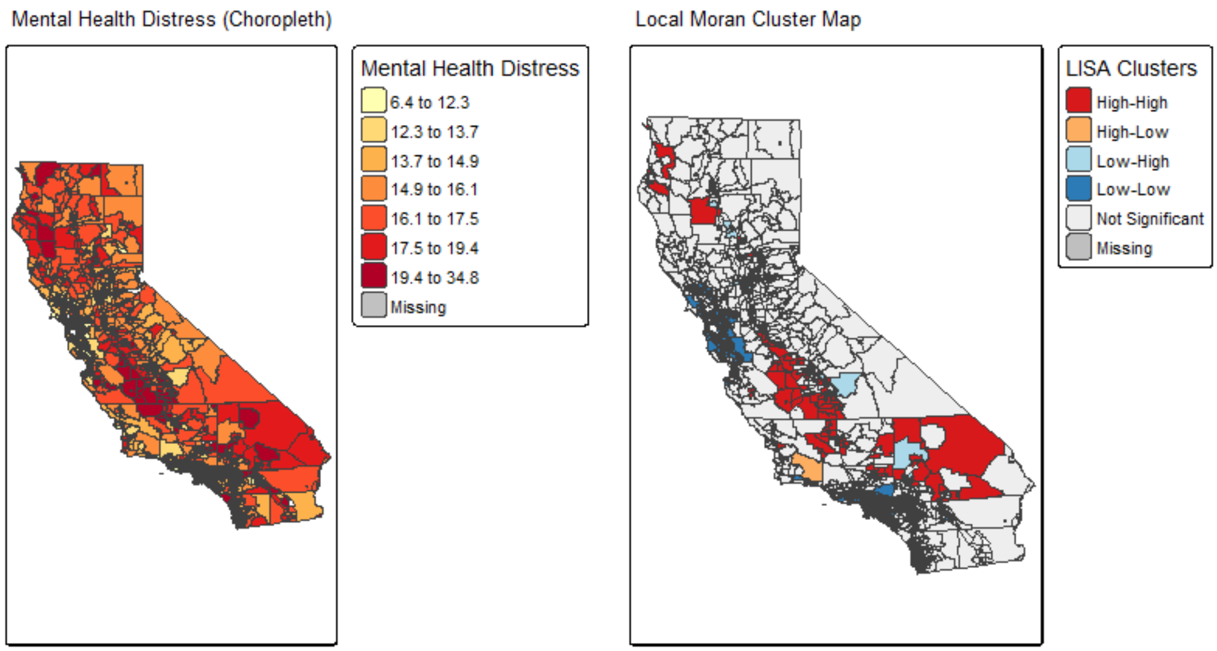

Figure 4: Spatial Regression Model: Moran' I Clustering.

Five spatial regression specifications were systematically tested: Spatial Lag Model (SAR), which includes a spatially lagged dependent variable; Spatial Error Model (SEM), which models spatial dependence in the error term; Spatial Durbin Model (SDM), which combines SAR with spatially lagged independent variables and Spatial Durbin Error Model (SDEM), which combines SEM with spatially lagged independent variables.

To determine the most appropriate model, several diagnostic approaches were employed. Lagrange Multiplier tests on the OLS residuals indicated significant spatial dependence in both the lag and error components (all LM tests $p < .001$), with robust LM tests suggesting that both error and lag specifications could address spatial autocorrelation. Akaike Information Criterion was used for model comparison, with the SDEM achieving an AIC value of 30,553.80, which was only marginally lower than the SDM (30,626.71). Other models showed considerably higher

AIC values. The SDEM effectively eliminated spatial autocorrelation in residuals (Moran's I = -0.0517, p-value = 1.0), confirming its ability to capture the spatial structure in the data.

Test	Statistic	df	p-value	Interpretation
Spatial Error (RSerr)	5250.8	1	< 2.2e-16	Tests for spatial autocorrelation in error terms
Spatial Lag (RSlag)	3914.6	1	< 2.2e-16	Tests for spatial autocorrelation in dependent variable
Robust Spatial Error (adjRSerr)	1516.3	1	< 2.2e-16	Error test robust to presence of spatial lag
Robust Spatial Lag (adjRSlag)	180.04	1	< 2.2e-16	Lag test robust to presence of spatial error
SARMA	5430.9	2	< 2.2e-16	Tests for general spatial dependence (combined lag and error)

Table 4: Lagrange Multiplier Tests for Spatial Dependence

Statistic	OLS	Spatial Lag (SAR)	Spatial Error (SEM)	Spatial Durbin (SDM)	Spatial Durbin Error (SDEM)
AIC	34436.17	31157.06	30711.48	30626.71	30553.80
Log likelihood	N/A	-15571.53	-15348.74	-15302.36	-15265.9
σ^2 (residual variance)	4.42 (approx)	2.7202	2.435	2.4356	2.4032
ρ (Rho)	N/A	0.6007	N/A	0.72498	N/A
λ (Lambda)	N/A	N/A	0.75249	N/A	0.73511
Number of parameters	5	7	7	11	11
Number of observations	7963	7963	7963	7963	7963

Table 5: Model Comparison Statistics

Based on these diagnostics, the Spatial Durbin Error Model (SDEM) was selected as the most appropriate specification for the analysis. The SDEM was preferred because it achieved excellent model fit, effectively eliminated spatial autocorrelation in residuals, overcame numerical issues related to high spatial autocorrelation in predictors, aligned with the theoretical understanding that both unobserved spatial processes and observed spatially lagged effects influence mental health outcomes, and provided a more straightforward interpretation of spatial effects compared to alternative models.

The selected SDEM was specified as: $y_i = \beta_0 + \Sigma(\beta_k \times x_{ki}) + \Sigma\left(\theta_k \times \Sigma\left(w_{ij} \times x_{kj}\right)\right) + u_i, u_i = \lambda\, \Sigma(w_{ij} \times u_j) + \varepsilon_i$, where λ represents the spatial error parameter, estimated to be 0.73511. This parameter quantifies the extent to which unobserved factors in one location are influenced by unobserved factors in neighboring locations.

One notable advantage of the SDEM is its ability to decompose effects into direct, indirect, and total impacts (LeSage & Pace, 2009). Direct impacts represent the effect of a change in an independent variable in area i on the dependent variable in the same area. Indirect impacts (spillovers) capture how changes in independent variables in neighboring areas affect the dependent variable in area i. Total impacts are the sum of direct and indirect impacts. This decomposition provides crucial insights for policy development, as it distinguishes between effects that operate within community boundaries and those that cross such boundaries, informing both localized interventions and regional coordination efforts.

It is important to acknowledge some limitations of the SDEM approach as discussed by Elhorst (2014). The interpretation of spatial spillover effects can be complex and sometimes counterintuitive, particularly when direct and indirect effects have opposing signs. The model also assumes stationarity in spatial relationships, which may not fully capture varying spatial processes across California's diverse regions. Additionally, the queen contiguity weights matrix, while appropriate for this analysis, represents only one possible conceptualization of spatial relationships, and alternative specifications might yield somewhat different results. These limitations were carefully considered during the interpretation phase to avoid overextending conclusions beyond what the data can support.

3.6 Summary

This spatial methodology advances traditional health analyses by explicitly modeling spillover effects, a critical dimension when heat islands and vegetation patterns transcend census boundaries. The approach recognizes that mental health determinants operate at multiple spatial scales, with both local conditions and regional contexts playing important roles. The decomposition of effects in the SDEM provides a more nuanced understanding of the relationships between environmental exposures and mental health outcomes. Direct effects represent the impact of a change in an independent variable within a census tract on mental health outcomes in the same tract. Indirect effects capture how changes in neighboring tracts affect the mental health outcomes in the focal tract.

The comprehensive data integration process brings together diverse environmental, socioeconomic, and health datasets to create a unified analytical framework at the census tract level. The environmental variables capture key dimensions of both natural and built environments that theoretical frameworks suggest influence mental health through various pathways. The inclusion of socioeconomic covariates helps disentangle the complex relationships between environmental exposures and mental health outcomes.

The SDEM's capacity to partition direct and indirect effects provides policymakers with actionable insights for both local interventions and regional coordination. By accounting for both spatial dependence and spatial heterogeneity, the analysis provides robust insights into the research questions regarding spatial patterns and relationships between environmental factors and mental health outcomes. While acknowledging the limitations inherent in cross-sectional spatial analyses, this methodology represents a significant advancement in understanding the geography of mental health and its environmental determinants in California.

CHAPTER 4: RESULTS

This investigation examines the relationships between environmental factors, socioeconomic conditions, and mental health outcomes across California census tracts through comprehensive spatial analysis. Using the Spatial Durbin Error Model (SDEM), the analysis addresses both direct effects within census tracts and indirect (spillover) effects from neighboring areas, addressing significant limitations in previous research on environmental determinants of mental health. Through this analytical framework, the study addresses three fundamental research questions: (1) how environmental factors relate to mental health outcomes, (2) how socioeconomic factors influence mental health and potentially interact with environmental conditions, and (3) how these relationships manifest in spatial patterns across communities. The empirical findings reveal statistically significant associations with substantial implications for public health policy and environmental planning interventions.

4.1 Descriptive Statistics

Mental health distress prevalence across California census tracts exhibits considerable heterogeneity, ranging from 6.40% to 34.80%, with a median value of 15.50% (n = 7,963). This substantial five-fold difference underscores pronounced geographic disparities in psychological wellbeing across California communities. Environmental variables similarly demonstrate significant variation: maximum air temperature ranges from 29.56°C to 54.37°C (median: 37.67°C), reflecting California's diverse climate zones from coastal areas to inland deserts, while vegetation greenness (measured by Enhanced Vegetation Index, EVI) ranges from -0.03197 to 0.53334 (median: 0.16719), capturing the spectrum from heavily urbanized regions to densely forested areas.

Socioeconomic indicators further illustrate California's diverse community contexts. Median household income ranges from $7,461 to $250,001 (median: $73,632), representing one of the nation's widest income gaps. Employment rates vary from 0.007202 to 0.936508 (median: 0.602055), reflecting diverse local economic conditions.

Initial spatial analysis confirms that mental health patterns are not randomly distributed across California. Significant clustering of mental health distress (Moran's I = 0.4713, $p < .001$) indicates that similar mental health outcomes tend to occur in spatial proximity, forming distinct geographic clusters. This substantial spatial autocorrelation justifies the use of spatial regression approaches rather than traditional ordinary least squares regression methods.

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max	Missing Values
Total Population	56	3,369	4,422	4,654	5,660	37,452	0
Mental Health Distress (%)	6.40	13.40	15.60	15.81	17.90	34.80	0
Maximum Temperature (°C)	28.19	34.57	37.67	38.21	41.67	54.37	0
Median EVI	-0.03197	0.13052	0.16711	0.17249	0.20517	0.53334	0
Median Income ($)	7,461	52,459	73,632	81,511	101,346	250,001	41
Employment Rate	0.0000	0.5459	0.6018	0.5913	0.6485	1.0000	2

Table 6: Summary Statistics of Key Variables for Mental Health, Environmental, and Socioeconomic Across California Census Tracts

4.2 Correlation Analysis and Multicollinearity Assessment

4.2.1 Correlation Among Predictors

The correlation matrix of predictors revealed no problematic multicollinearity, with all pairwise correlations below the conventional threshold of concern (|r| > 0.8). Several moderate correlations emerged that provide context for understanding the relationships between environmental and socioeconomic factors. Maximum temperature and employment rate showed a moderate negative correlation (r = -0.355), suggesting that areas with higher temperatures tend to have slightly lower employment rates. Median income and enhanced vegetation index demonstrated a positive correlation (r = 0.275), indicating that greener areas tend to have somewhat higher incomes. As expected, median income and employment rate exhibited a positive correlation (r = 0.298), reflecting the anticipated relationship between community economic indicators.

Overall, the data validation procedures successfully addressed potential multicollinearity concerns, allowing for stable coefficient estimation in subsequent regression models.

Variable	Maximum Temperature	Vegetation Greenness (EVI)	Median Household Income	Employment Rate
Maximum Temperature	1.000	0.188	-0.224	-0.355
Vegetation Greenness (EVI)	0.188	1.000	0.275	-0.114
Median Household Income	-0.224	0.275	1.000	0.298
Employment Rate	-0.355	-0.114	0.298	1.000

Table 7: Correlation Analysis of Environmental and Socioeconomic Variables: Pearson Correlation Coefficients Between Variables

4.2.2 Spatial Autocorrelation in Predictors

Analysis of spatial lags revealed substantial spatial autocorrelation in most predictors, providing strong justification for employing spatial regression techniques. This spatial patterning varied considerably across different types of predictors. Maximum temperature showed extremely high spatial autocorrelation (r = 0.992 with its spatial lag), reflecting the continuous nature of climate patterns across geographic space. Vegetation greenness exhibited high spatial autocorrelation (r = 0.820), indicating that areas with similar vegetation levels tend to cluster geographically. Economic indicators also showed significant spatial patterns. Median income displayed high spatial autocorrelation (r = 0.837), confirming the well-documented tendency for income segregation across neighborhoods, while employment rate showed moderate spatial autocorrelation (r = 0.634), suggesting some clustering of labor market conditions.

These strong spatial dependencies, particularly in temperature and income variables, provided compelling evidence for employing spatial regression models that account for both error dependencies and potential spillover effects. This finding specifically supported the selection of the Spatial Durbin Error Model (SDEM), which explicitly incorporates spatial lags of predictors to capture cross-boundary influences.

Variable	Correlation with Spatial Lag (r)	Interpretation
Maximum Temperature	0.992	Extremely high spatial autocorrelation
Vegetation Greenness (EVI)	0.820	High spatial autocorrelation
Median Household Income	0.837	High spatial autocorrelation
Employment Rate	0.634	Moderate spatial autocorrelation

Note: Spatial autocorrelation measured as Pearson correlation between each variable and its spatial lag using queen contiguity weights matrix. All correlations are significant at $p < 0.001$.

Table 8: Correlation Analysis of Environmental and Socioeconomic Variables: Spatial Autocorrelation of Variables

4.3 Statistical Model Performance

The Spatial Durbin Error Model (SDEM) demonstrated superior performance compared to alternative spatial regression specifications. The SDEM achieved an AIC value of 30,553.80, which was lower than the Spatial Durbin Model (30,626.71) and substantially better than other models. This improvement of 3,882.37 AIC points over the OLS model (34,436.17) provides robust statistical evidence supporting the selection of the SDEM as the preferred model for this analysis.

Formal likelihood ratio testing confirmed that including spatially lagged predictors in the SDEM significantly improved model fit compared to simpler models, which treat spatial spillovers as zero. This result validates the theoretical premise that environmental and socioeconomic factors influence mental health not only within census tracts but also across neighboring areas.

The SDEM effectively addressed spatial dependence in the data, as demonstrated by the non-significant Moran's I test on residuals, indicating successful capture of the spatial structure in mental health outcomes. The significant spatial error parameter ($\lambda = 0.73511$) revealed substantial spatial autocorrelation in unobserved factors affecting mental health, suggesting that unmeasured processes influence mental health outcomes in spatially structured ways. This high lambda value confirms that ignoring spatial relationships would have significantly misrepresented the dynamics in this system and potentially led to incorrect statistical inferences.

Variable	Estimate	Std. Error	z value	p-value
(Intercept)	19.675	0.82115	23.9600	< 2.2e-16 ***
max_temp	-0.04997	0.032803	-1.5233	0.127678
median_EVI	-3.8818	0.47629	-8.1502	4.441e-16 ***
median_income	-0.000048894	7.9008e-07	-61.8850	< 2.2e-16 ***
employment_rate_16plus	0.32059	0.25878	1.2389	0.215387
lag.max_temp	0.10218	0.032412	3.1524	0.001619 **
lag.median_EVI	0.18538	0.96914	0.1913	0.848302

lag.median_income	-0.00001929	1.6219e-06	-11.8934	< 2.2e-16 ***
lag.employment_rate_16plus	0.34693	0.61693	0.5623	0.573879
Lambda	0.73511	N/A	LR=3687.9	**< 2.2e-16 ***

Note: Residual variance (sigma squared) is 2.4032 (sigma: 1.5502); AIC improvement over OLS is 3686.2 points (from 34240 to 30554).

Table 9: Spatial Durbin Error Model (SDEM) Results

Variable	Direct Impact	Indirect Impact	Total Impact
max_temp	-0.0500	0.1022**	0.0522***
median_EVI	-3.8818***	0.1854	-3.6965***
median_income	-0.0000489***	-0.0000193***	-0.0000682***
employment_rate_16plus	0.3206	0.3469	0.6675

Significance codes: *** p<0.001, ** p<0.01, * p<0.05

Table 10: Spatial Durbin Error Model (SDEM):Direct, Indirect, and Total Impacts

Variable	Direct Impact SE	Indirect Impact SE	Total Impact SE
max_temp	0.0328	0.0324	0.0158
median_EVI	0.4763	0.9691	1.0560
median_income	7.901e-07	1.622e-06	1.743e-06
employment_rate_16plus	0.2588	0.6169	0.7284

Table 11: Spatial Durbin Error Model (SDEM): Standard Errors of Impacts

Variable	Direct Impact		Indirect Impact		Total Impact	
	Z-value	p-value	Z-value	p-value	Z-value	p-value
max_temp	-1.523	0.1277	3.152	0.0016**	3.307	0.0009***
median_EVI	-8.150	<0.0001***	0.191	0.8483	-3.500	0.0005***
median_income	-61.885	<0.0001***	-11.893	<0.0001***	-39.125	<0.0001***
employment_rate _16plus	1.239	0.2154	0.562	0.5739	0.916	0.3594

Table 12: Spatial Durbin Error Model (SDEM): Z-values and p-values

4.4 Environmental Factors and Mental Health

4.4.1 Vegetation Greenness and Mental Health

Vegetation greenness demonstrated a significant protective effect on mental health within census tracts. The direct effect coefficient (-3.8818, p < 0.001) indicates that higher EVI values within a census tract are associated with lower mental health distress prevalence, after controlling for other factors. This result aligns with biophilia theory and attention restoration frameworks, which propose that natural environments provide cognitive and emotional benefits that promote psychological wellbeing.

Interestingly, vegetation greenness did not show a significant indirect effect (0.18538, $p = 0.848302$), revealing that the mental health benefits of green space appear confined to the immediate environment rather than producing substantial spillover effects. This finding suggests that the protective influence of vegetation operates primarily at the local level, reinforcing the importance of equitable green space distribution within communities rather than relying on regional green infrastructure to benefit adjacent areas.

The high spatial autocorrelation observed for vegetation greenness ($r = 0.820$ with its spatial lag) further emphasizes the importance of accounting for these spatial dependencies when evaluating its relationship with mental health outcomes.

4.4.2 Heat Exposure and Mental Health

Maximum air temperature exhibited a complex pattern of effects on mental health distress. The direct effect was negative but not statistically significant (-0.04997, $p = 0.127678$), suggesting that temperature within a tract may not independently influence mental health outcomes. However, the indirect effect was positive and significant (0.10218, $p = 0.001619$), indicating that higher temperatures in neighboring areas are associated with increased mental health distress in the focal tract.

The total impact (0.05221, $p < 0.001$) was positive and highly significant, revealing that when both direct and indirect effects are considered, heat exposure appears to contribute to psychological distress. This pattern suggests that temperature influences mental health through regional rather than strictly local mechanisms, potentially related to broader climate patterns, regional heat islands, or interactions with other environmental factors that operate across census tract boundaries.

The extremely high spatial autocorrelation in maximum temperature ($r = 0.992$ with its spatial lag) reinforces the conceptualization of heat exposure as a regional phenomenon rather than a strictly local one. These findings emphasize the importance of considering broader regional climate patterns when evaluating heat-related health impacts.

4.5 Socioeconomic Factors and Mental Health

4.5.1 Income and Mental Health

Median income emerged as a strong predictor of mental health distress in the model, demonstrating powerful effects both within census tracts and across neighboring areas. The direct effect was large and highly significant (-0.000048894, $p < 0.001$), indicating that census tracts with higher median income had substantially lower mental health distress prevalence. While this coefficient appears small, it represents the change in mental health distress percentage per one-dollar increase in income. In practical terms, a $10,000 increase in median household income would be associated with approximately a 0.49 percentage point decrease in mental health distress within the same census tract.

Income also demonstrated a significant negative indirect effect (-0.00001929, $p < 0.001$), indicating that higher income in neighboring areas was associated with reduced mental health distress in the focal tract. This substantial spillover effect suggests that economic conditions influence mental health beyond administrative boundaries, possibly through mechanisms such as shared service infrastructure, regional job markets, or psychological effects of relative socioeconomic position.

The total impact (-0.000068184, $p < 0.001$) confirms the strong protective effect of income on mental health outcomes. These findings suggest that both local and regional economic development can contribute to improved mental health outcomes, with economic improvements in one area potentially benefiting mental health in surrounding communities. The high spatial autocorrelation observed for median income ($r = 0.837$ with its spatial lag) aligns with these strong indirect effects and suggests that income segregation creates distinct spatial regimes of advantage and disadvantage that influence mental health outcomes across geographic boundaries.

4.5.2 Employment and Mental Health

Employment rate did not demonstrate statistically significant associations with mental health outcomes in the model. Neither the direct effect (0.32059, $p = 0.215387$) nor the indirect effect (0.34693, $p = 0.573879$) reached statistical significance. The wide confidence intervals spanning zero for both direct and indirect effects suggest the absence of a reliable linear relationship between employment rate and mental health at the census tract level, after controlling for income and other factors.

This finding indicates that community employment levels may not independently influence mental health outcomes when other socioeconomic and environmental factors are considered. It suggests that income, rather than employment rate alone, may be the more crucial economic determinant of mental health. This pattern could reflect the importance of employment quality, compensation, and stability, factors not fully captured by the employment rate measure, in determining how labor market conditions affect psychological wellbeing.

The moderate spatial autocorrelation observed for employment rate ($r = 0.634$ with its spatial lag) indicates substantial regional clustering of employment conditions, but this spatial patterning does not translate to statistically significant effects on mental health in the comprehensive model.

4.6 Spatial Patterns

4.6.1 Compound Environmental and Socioeconomic Effects

The results suggest potential interactions between environmental and socioeconomic factors in shaping mental health outcomes. The strong negative effect of income combined with the protective effect of vegetation suggests that socioeconomically disadvantaged areas with low vegetation may face dual burdens on mental health, creating potential hotspots of mental health vulnerability. The significant indirect effect for temperature indicates that heat-related impacts may extend beyond administrative boundaries, creating regional patterns of vulnerability that require coordinated intervention strategies.

The correlations between environmental and socioeconomic factors provide additional evidence of potential cumulative vulnerabilities. The moderate negative correlation between maximum air temperature and median income ($r = -0.224$) suggests that heat exposure disproportionately affects lower-income communities, while the positive correlation between vegetation and income ($r = 0.275$) indicates that higher-income areas tend to have more green space. These systematic patterns of environmental inequality, while not proving causal relationships, may contribute to mental health disparities across communities.

4.6.2 Spatial Dependency in Unobserved Factors

The significant spatial error parameter ($\lambda = 0.73511$) indicates substantial spatial dependence in unobserved factors affecting mental health. This large lambda value reveals that after accounting for the measured predictors and their spatial lags, there remains significant spatial structure in the residuals. This suggests additional unmeasured processes, potentially including healthcare access, social capital, air pollution, or neighborhood quality, that influence mental health outcomes in spatially structured ways.

This finding has several important implications for mental health research and policy. First, it confirms that ignoring spatial dependence would lead to incorrect statistical inferences, potentially overestimating some variables' significance while underestimating others. Second, it suggests that even this comprehensive model does not fully capture all spatially structured determinants of mental health. Third, it indicates that mental health outcomes in California exhibit spatial patterns that transcend the explanatory power of measured variables, pointing to broader regional dynamics affecting psychological wellbeing.

The strong spatial dependence in the error term also suggests important social or environmental processes may operate at different spatial scales than those captured by census tract boundaries. Healthcare service areas, school districts, or watershed boundaries might better represent the functional geography of certain mental health determinants.

This strong spatial structure in unobserved factors underscores the importance of spatial approaches in mental health research and cautions against assuming that even comprehensive models fully capture mental health's determinants. Future research could explore alternative geographic scales and boundaries to better understand mental health's spatial dynamics.

4.7 Key Findings

This spatial analysis has revealed several important relationships between environmental factors, socioeconomic characteristics, and mental health outcomes across California census tracts. Statistical model comparison demonstrated the Spatial Durbin Error Model's superior performance compared to simpler spatial models, with a substantial AIC improvement confirming the importance of modeling spatial spillover effects. The significant spatial error parameter ($\lambda = 0.73511$) indicated strong spatial dependence in unobserved factors affecting mental health, validating the spatial modeling approach.

Environmental factors showed complex relationships with mental health outcomes. Vegetation greenness demonstrated a significant protective direct effect on mental health within census tracts (-3.8818, $p < 0.001$), but no significant indirect effect (0.18538, $p = 0.848302$), suggesting that green space benefits are primarily local rather than regional. Maximum temperature showed an interesting pattern with a non-significant direct effect (-0.04997, $p = 0.127678$) but a significant positive indirect effect (0.10218, $p = 0.001619$), indicating that regional heat patterns influence mental health across census tract boundaries.

Socioeconomic factors demonstrated particularly strong relationships with mental health outcomes. Median income emerged as a powerful predictor, with substantial negative effects both within census tracts (-0.000048894, $p < 0.001$) and across neighboring areas (-0.00001929, $p < 0.001$). Employment rate did not show statistically significant associations with mental health (direct effect: 0.32059, $p = 0.215387$; indirect effect: 0.34693, $p = 0.573879$), suggesting that income may be the more crucial economic determinant of mental health.

The significant spillover effects observed for temperature and income indicate that mental health determinants operate beyond administrative boundaries, necessitating coordinated regional approaches to intervention. The direct effect for vegetation suggests the importance of local green space access for mental health, while the strong direct and indirect effects of income underscore the fundamental importance of economic resources for mental health across both local and regional scales.

These findings provide important insights for developing targeted interventions to address geographic disparities in mental health. Effective approaches must consider both local conditions and regional contexts, particularly for factors demonstrating substantial spillover effects. The significant spatial dependencies observed across multiple variables emphasize the importance of coordinated, regional approaches to mental health promotion that address both environmental and socioeconomic determinants.

CHAPTER 5: DISCUSSION

This chapter examines the implications of the study findings, situates them within existing literature, and acknowledges limitations. The discussion highlights how spatial econometric modeling offers insights that non-spatial methods would overlook, emphasizing the multifaceted nature of environmental determinants of mental health and the dominant role of income, while also recognizing the significant contributions of vegetation greenness and heat exposure.

5.1 Interpretation of Findings

5.1.1 Vegetation Greenness and Mental Health

The statistically significant negative direct effect of vegetation greenness (EVI) on mental health distress ($\beta = -3.8818$, $p < 0.001$) reinforces prior findings on the protective influence of green spaces. This result aligns with Attention Restoration Theory and emerging literature on nature's restorative properties. However, this study found no significant indirect effect (spillover) from neighboring areas' vegetation ($\beta = 0.1854$, $p = 0.8483$), indicating that the benefits of green spaces are primarily localized.

While vegetation greenness demonstrates an overall protective effect (total impact: -3.6965, $p = 0.0005$), the lack of significant spillover effects underscores that green space benefits operate at a more localized scale than other environmental factors. These findings refine previous non-spatial analyses by emphasizing that green space interventions likely have their strongest impact on the immediate community where they are implemented, with limited cross-boundary effects on neighboring areas.

5.1.2 Heat Exposure and Mental Health

Interestingly, maximum temperature did not demonstrate statistically significant direct effects on mental health distress within census tracts ($\beta = -0.0500$, $p = 0.1277$). However, the analysis revealed significant positive indirect effects ($\beta = 0.1022$, $p = 0.0016$), indicating that temperatures in neighboring areas exert important spillover effects on mental health outcomes. The total impact of temperature was positive and significant ($\beta = 0.0522$, $p = 0.0009$), suggesting that regional heat patterns do influence mental health despite the absence of significant local effects.

This complex pattern suggests that heat exposure operates through broader regional mechanisms rather than purely local conditions. Several explanations might account for this finding. The relationship between heat and mental health might be mediated by regional adaptation infrastructure; heat effects might operate through complex regional socioeconomic or physiological pathways; or the spatial scale of heat impacts might better align with regional climate patterns than census tract boundaries. This finding highlights the importance of considering regional approaches to heat mitigation strategies when addressing climate-related mental health impacts.

5.1.3 Socioeconomic Factors and Mental Health

Median income emerged as the strongest predictor of mental health distress in the model, demonstrating powerful effects both within census tracts ($\beta = -0.0000489$, $p < 0.001$) and across neighboring areas ($\beta = -0.0000193$, $p < 0.001$). The magnitude of income's effect underscores the profound influence of economic conditions on mental health outcomes. This substantial direct effect indicates that census tracts with higher median income had considerably lower mental health distress prevalence, while the significant negative indirect effect suggests that higher income in neighboring areas was associated with reduced mental health distress in the focal tract.

Employment rate showed no significant direct effect ($\beta = 0.3206$, $p = 0.2154$) or indirect effect ($\beta = 0.3469$, $p = 0.5739$) on mental health distress. These findings suggest that income may be a more reliable indicator of socioeconomic wellbeing as it relates to mental health outcomes, compared to employment rates alone.

5.1.4 Spatial Dependence and Environmental Justice

The significant spatial error parameter ($\lambda = 0.73511$) indicates substantial spatial dependence in unobserved factors affecting mental health. This large lambda value reveals that after accounting for the measured predictors and their spatial lags, significant spatial structure remains in the residuals. This suggests additional unmeasured processes, potentially including healthcare access, social capital, air pollution, or neighborhood quality, that influence mental health outcomes in spatially structured ways.

The Spatial Durbin Error Model demonstrated superior performance compared to simpler models, with a substantial improvement in AIC (from 34436.17 in OLS to 30553.80 in SDEM). This improvement provides robust statistical evidence supporting the inclusion of spatially lagged predictors, confirming that environmental and socioeconomic factors influence mental health not only within census tracts but also across neighboring areas.

The strong spatial dependencies observed across multiple variables emphasize the importance of coordinated, regional approaches to mental health promotion that address both environmental and socioeconomic determinants. The correlations between environmental and socioeconomic factors provide evidence of potential cumulative vulnerabilities. The negative correlation between maximum air temperature and median income ($r = -0.224$) suggests that heat exposure disproportionately affects lower-income communities, while the positive correlation between vegetation and income ($r = 0.275$) indicates that higher-income areas tend to have more green space. These systematic patterns of environmental inequality may contribute to mental health disparities across communities.

5.2 Limitations of the Study

5.2.1 Mental Health Outcome Measures

The tract-level mental health distress estimates rely on model-based methods that smooth variability across larger geographic units. This approach introduces inherent uncertainty, potentially resulting in less precise estimates for less populated or underrepresented communities. The estimates effectively smooth variability across similar demographic groups, which may obscure important localized patterns in mental health outcomes.

Self-reported data also risk stigma-related underreporting or misinterpretation of survey questions. Social stigma surrounding mental health issues or normalization of chronic symptoms may lead respondents to underreport mental health problems. This could result in conservative prevalence estimates, particularly in communities where mental health stigma is more pronounced.

Additionally, these data capture a single year and may not reflect seasonally or historically evolving mental health trends. Acute climate impacts or short-term socioeconomic shifts are likewise not discernible in such a cross-sectional snapshot. This static view limits our ability to detect dynamic relationships between environmental exposures and mental health outcomes over time.

5.2.2 Limitations of Environmental Exposure Data

The dataset used for maximum air temperature provides gridded estimates but can smooth out microclimates, particularly in dense urban areas. Other critical variables influencing heat stress such as humidity, wind, and solar radiation were not included, potentially leading to incomplete representations of the local thermal environment. The data relies on spatial interpolation of weather station observations, introducing greater uncertainty in regions with sparse weather station coverage, complex topography, or coastal environments.

The Enhanced Vegetation Index (EVI) serves as a proxy measure of vegetation. However, aggregating high-resolution data to the census tract level obscures fine-scale greenery features. Furthermore, EVI does not account for qualitative aspects such as accessibility, safety, or maintenance levels that can influence mental health. These qualitative dimensions may modify the relationship between vegetation quantity and mental health outcomes.

5.2.3 Socioeconomic Data Limitations

Data from the American Community Survey (ACS) contain sampling error, particularly for smaller tracts or marginalized subpopulations. ACS estimates for small geographic areas such as census tracts have relatively large margins of error, potentially obscuring true relationships between socioeconomic factors and mental health outcomes.

Additionally, these pooled estimates reflect average conditions and may not align perfectly with recent economic fluctuations or localized shocks. Furthermore, while the study included key socioeconomic indicators (income and employment), it could not account for all potential confounding factors that might influence mental health outcomes, such as social capital, community cohesion, or access to mental health services.

5.2.4 Spatial and Temporal Resolution Considerations

Analyzing data at the census tract level may not represent individuals' actual exposure environments, given that people move beyond their residential neighborhoods for daily activities. Individuals move across tract boundaries for work, recreation, and other activities, potentially experiencing environmental conditions different from those in their residential tract.

Moreover, the study's cross-sectional design precludes establishing causality or identifying temporal lags in the effects of environmental and socioeconomic factors on mental health. The study examines maximum temperature during a specific period but cannot account for long-term exposure patterns or adaptation strategies that may modify the relationship between environmental factors and mental health outcomes.

5.2.5 Statistical Approach Constraints

While the SDEM accounts for local and spillover effects, the choice of spatial weights may not reflect real-world networks. The model assumes that the spatial weights matrix adequately captures the true spatial structure of the data, but alternative specifications might yield different results.

Extreme spatial autocorrelation for temperature ($r = 0.992$) can introduce multicollinearity challenges when both direct and lagged terms are included, potentially affecting the stability of coefficient estimates. This high level of spatial autocorrelation in some predictor variables may compromise the model's ability to distinguish between direct and indirect effects.

In addition, the model cannot fully address potential endogeneity, for instance, the possibility that individuals with mental health conditions might relocate to areas with particular environmental characteristics. While the SDEM accounts for spatial dependence in both the independent variables and error term, it cannot fully address reverse causality or selection bias in residential patterns.

5.3 Implications of Research Findings

5.3.1 Theoretical Implications

The discovered contrasts in direct and indirect effects for different environmental variables reinforce the idea that environmental influences on mental health extend beyond single-level frameworks, echoing multidimensional theories like ecological systems approaches. The findings suggest that environmental factors influence mental health through complex pathways that operate at multiple spatial scales, with vegetation primarily affecting local outcomes and temperature operating through regional mechanisms.

The predominant influence of income corroborates long-standing social determinants of health models, yet environmental factors remained significant after controlling for socioeconomic variables. This underscores the importance of integrated theoretical approaches where both socioeconomics and environmental exposures jointly shape mental health outcomes, supporting environmental justice frameworks that recognize the intersection of social and environmental vulnerabilities.

5.3.2 Practical Implications

The strong association between higher income and lower mental health distress suggests that policies targeting poverty reduction could yield substantial mental health benefits. This finding underscores the value of economic interventions as mental health promotion strategies, particularly in areas with concentrated disadvantage.

The protective effect of vegetation implies that increasing high-quality green spaces can mitigate psychological stress. Urban planning initiatives should therefore prioritize not only increasing green space but ensuring its equitable availability across socioeconomically diverse neighborhoods, particularly focusing on areas with both socioeconomic disadvantage and limited green space.

The significant indirect effects of temperature on mental health highlight the need for regional approaches to heat mitigation. Climate adaptation strategies should consider their potential mental health benefits, particularly in regions experiencing increasing frequency and intensity of extreme heat events.

Spillover effects demonstrate that place-based interventions should consider adjacent tracts' conditions. This spatial dimension requires coordination across municipal boundaries and between different levels of government to effectively address mental health disparities. Interventions that simultaneously improve economic resources and enhance environmental features may have synergistic benefits, particularly in socioeconomically vulnerable areas also burdened by environmental stressors.

5.4 Future Research Directions

Tracking environmental changes and mental health outcomes over time would allow more robust causal inferences. Longitudinal approaches would help disentangle the temporal sequence of environmental exposures, socioeconomic changes, and mental health outcomes, strengthening causal inference beyond what cross-sectional analyses can provide.

Incorporating heat indices (e.g., humidity), qualitative attributes of green spaces, and more nuanced temperature metrics would capture a fuller picture of environmental conditions. Future studies should consider not just the quantity but quality of environmental exposures, including accessibility, perceived safety, and cultural relevance of green spaces, which may modify their mental health benefits.

Combining individual-level data with tract-level measures can illuminate person-environment interactions and reveal psychosocial or behavioral mediators. Multilevel approaches would help bridge the ecological inference gap, allowing researchers to distinguish between compositional and contextual effects and identify how individual characteristics modify environmental influences on mental health.

Future work should explore mechanisms linking environmental exposures to mental health, for example, sleep disruption, social cohesion, or physical activity, to better target interventions. Understanding these mediating pathways would help clarify which aspects of environmental exposures most strongly influence mental health outcomes and inform more targeted intervention approaches.

Examining race, ethnicity, and gender dimensions of environmental exposure can clarify how intersectional vulnerabilities shape mental health outcomes. Future research should explicitly consider how social stratification interacts with environmental exposures to produce differential mental health outcomes across demographic groups, advancing environmental justice approaches to mental health research.

5.5 Conclusion

This study underscores the intertwined roles of vegetation greenness, heat exposure, and income in shaping mental health distress across California census tracts, emphasizing both local and spillover dynamics revealed by a Spatial Durbin Error Model. Despite the inherent limitations of cross-sectional data and ecological indicators, the findings expand upon prior non-spatial research by identifying complex spatial patterns in how environmental and socioeconomic factors influence mental health outcomes.

These conclusions highlight opportunities for policy interventions that address socioeconomic disparities alongside environmental enhancements. They also reinforce spatially explicit perspectives in mental health research, demonstrating that single-tract analyses can miss cross-boundary processes that significantly influence psychological outcomes. Building on these insights, future inquiries should adopt longitudinal, multilevel, and mixed-methods designs to further elucidate causal pathways and effectively target interventions for mental well-being in an increasingly complex and interconnected world.

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