# Advanced analysis of depression tendency in China: an investigation of environmental and social factors based on geographical and temporal weighted regression

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## Abstract

The spatiotemporal distribution of depressive tendencies across China from 2011 to 2022 was investigated using the Baidu Depression Search Index (BDSI). We examined key influencing natural factors, such as water pollution, air pollution, and deforestation, along with economic indicators, such as gross domestic product per capita, disposable income per capita, and health professionals per 10,000 population. Geographical and Temporal Weighted Regression (GTWR) was applied to capture the spatiotemporal heterogeneity of the BDSI determinants. The results revealed significant regional disparities, with the China's eastern region consistently exhibiting the highest values reflecting heightened mental health concerns, while the western region were found to have the lowest. The BDSI trends followed different trajectories, all of which peaked in 2019 before a sharp decline in 2020. Water pollution transitioned from negative to positive influence in the East, while deforestation exhibited regionally variable effects. Air pollution, peaking in 2019 and 2022, demonstrated the highest impact variability. The economic indicators showed complex regional and temporal patterns underscoring the need for tailored interventions. Together, these findings provided critical insights into the intricate interplay between environmental, economic, and healthcare factors in shaping mental health that highlighted the necessity of region-specific policies to mitigate depressive tendencies and enhance public mental well-being. These research results offer targeted recommendations for regionally adaptive mental health strategies across China.

## Introduction

Depression is a major public health concern characterized by persistent sadness, cognitive impairment and functional decline (Liu *et al.*, 2020; Marwaha *et al.*, 2023; Y. Zhou *et al.*, 2023). As one of the leading causes of disability worldwide, depression significantly increases the risk of suicide and contributes to a broad spectrum of co-morbidities imposing a substantial burden on individuals and society (Rantala *et al.*, 2018; McKee & Kelly, 2020; Kalin, 2021; Force *et al.*, 2023; Sampogna *et al.*, 2024). The aetiology of depression is complex and multi-factorial, involving genetic predisposition, neurotransmitter imbalance, neuro-inflammation and psychosocial stress (Gao *et al.*, 2023; Cui *et al.*, 2024; Guo *et al.*, 2024). While advances in diagnostic methods, including biomarker-based detection and machine-learning models have improved the identification of depression, early detection and intervention remain the most effective strategies for preventing its progression and mitigating its societal impact (Maier *et al.*, 2021; Y. Zhou *et al.*, 2023; Boby & Veerasingam, 2025).

In clinically diagnosed depression, there is depressive tendency consisting of subclinical manifestations of depressive symptoms or an increased susceptibility to developing depression (H. Zhang *et al.*, 2023; Sun & Chen, 2024). This may include mood instability, heightened psychological distress and mild cognitive impairments and often precede clinical onset serving as early warning signs of mental health deterioration (Y. Liu *et al.*, 2023; Luo et al., 2024). In recent years, the use of Internet search, behaviour as a proxy for mental health assessment has gained considerable attention (Wiljer *et al.*, 2020). In China, the Baidu Depression Search Index (BDSI) has been increasingly utilized to reflect public interest in depression-related topics, offering a large-scale, real-time measure of depressive tendencies. Higher values indicate a higher frequency of depression-related searches, potentially suggesting a greater tendency toward depression, while lower values indicate a lower frequency, potentially suggesting a lower tendency (Yu *et al.*, 2021; W. Zhou *et al.*, 2023). Previous studies have successfully applied BDSI to track mental health responses to major events, including the COVID-19 pandemic, economic recessions and episodes of environmental pollution (He *et al.*, 2020; Chen *et al.*, 2022). Compared to traditional, survey-based epidemiological methods, which often suffer from sample-size limitation, response bias and privacy concerns, BDSI provides a population-wide, continuous and temporally sensitive measure of depressive tendency, making it a valuable tool for mental health surveillance.

Existing research has identified a range of environmental and social determinants influencing depressive tendencies (Remes *et al.*, 2021). Environmental factors such as air pollution—particularly by fine particulate matter ($PM_{2.5}$), sulphur dioxide ($SO_2$), and nitrogen dioxide ($NO_2$)—have been linked to an increased risk of depression through mechanisms involving oxidative stress, neuroinflammation and endocrine disruption (Braithwaite *et al.*, 2019; Kim *et al.*, 2021; Yang *et al.*, 2023). Conversely, exposure to green spaces has been associated with enhanced psychological resilience and reduced stress levels (Z. Liu *et al.*, 2023). Socioeconomic factors, including income disparity, healthcare accessibility and urbanization-related stress also play crucial roles in shaping mental health outcomes (Cuijpers *et al.*, 2019; Daly, 2022). Previous studies have employed time-series models, *e.g.*, Time Weighted Regression (TWR) and spatial models, *e.g.*, Geographically Weighted Regression (GWR) to quantify these associations. However, these models have notable limitations: time-series models primarily capture temporal trends but fail to account for spatial heterogeneity, while spatial models effectively assess regional disparities but often overlook temporal variations (X. Zhang *et al.*, 2023). These methodological constraints hinder a comprehensive understanding of how depressive tendencies evolve across both time and space limiting their utility for targeted mental health interventions.

To address these limitations, this study employed the Geographically and Temporally Weighted Regression (GTWR) model, as itextends traditional spatial regression techniques by incorporating both spatial and temporal heterogeneity in the relationships between depressive tendencies and their influencing factors. Unlike conventional models, GTWR allows regression coefficients to vary dynamically across geographic locations and time periods, capturing localized patterns and temporal fluctuations in mental health determinants. This approach has been successfully applied in research on environmental pollution, urban development and socioeconomic disparities, thereby demonstrating its capacity to uncover complex spatiotemporal relationships (Jiang *et al.*, 2023). By leveraging GTWR, this study aimed to provide a more nuanced understanding of the regional and temporal variations in depressive tendencies, facilitating the development of precision-targeted mental health policies.

This study aimed to investigate the spatiotemporal patterns of depressive tendency in China by utilizing BDSI as a proxy indicator and applying the GTWR model to examine the influence of environmental and social factors. By overcoming the limitations of traditional time-series and spatial models, this study seeks to generate data-driven insights for mental health policymaking and intervention strategies. The findings should contribute to a deeper understanding of how environmental and socioeconomic conditions shape depressive tendencies, ultimately supporting more effective public health initiatives aimed at improving mental well-being.

## Materials and Methods

We investigated the use of some common regression techniques, such as ordinary least squares (OLS), TWR, GWR, and GTWR, finding that the adjusted $R^2$ values for these models were 0.45, 0.76, 0.84, and 0.87, respectively. The latter model was chosen to explore the spatiotemporal heterogeneity of the impact of environmental and social factors on depressive tendencies in China, as it accounts for both temporal and spatial non-smoothness, and also demonstrating the highest accuracy and applicability for this study.

### Introduction to the GTWR model

GWTR provides robust analytical capabilities for capturing spatiotemporal changes and patterns, offering precise insights to support targeted mental health interventions as expressed by the following equation (Eq.):

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p} \beta_k\,(u_i, v_i, t_i) X_{ik} + \varepsilon_i \qquad \text{Eq. 1}$$

where $y_i$ represents the dependent variable; $u_i$,$v_i$, $t_i$ the longitude and latitude coordinates and time of the $i^{th}$ sample point; $\beta_0$ the regression constant of this sample point (*i.e.* the constant term in the GTWR model); $X_{ik}$ the value of the $k^{th}$ independent variable at the $i^{th}$ point; $\beta_K$ the $k^{th}$ regression parameter at the $i^{th}$ point (*i.e.* the value of each explanatory variable in the GTWR model); and $\varepsilon_i$ the residual.

### Data sources

According to the classification criteria of the National Bureau of Statistics (NBS), China's 34 provincial-level administrative units are grouped into five regions: the eastern, central, western and north-eastern regions, as well as Hong Kong, Macao and Taiwan. We utilized data from the China Statistical Yearbook published by the NBS that covers 31 provinces (excluding Hong Kong, Macao, and Taiwan). Panel data were employed for the analysis.

Baidu, the largest Chinese search engine integrates a vast amount of user-search data. Through in-depth processing, these data effectively capture the influence of keywords and the dynamics of information dissemination. Due to its extensive application in academic research, Baidu data demonstrate significant authority and reference value (Lin *et al.*, 2023). We used this search engine to collect search data, with "year" as the time unit covering the period from 2011 to 2022.

## The variables

Building on existing literature, a set of environmental factors influencing depressive tendencies were chosen for the study. They were categorized into natural and social dimensions, were the former included water pollution, air pollution and deforestation and the latter Gross Domestic Product Per Capita (GDP-PC), disposable income per capita (DI-PC) and health staff per 10,000 population (HS-10,000).

The Tree Cover Expansion Area (TCEA) was used as measure of how much natural vegetation in the form of trees and bushes has disappeared; water pollution was expressed as the amount of Chemical Oxygen Demand Emission (CODE) needed to break down organic matter, a key indicator of water quality; and $SO_2$ emission (SO2E), the atmospheric amount of $SO_2$, was used to indicate the level of air pollution. Although here are many other pollutants in water and air, CODE and $SO_2$ were chosen as they have a direct impact on our senses.

In this study, BDSI served as the dependent variable, while natural and social environmental factors were utilized as independent variables. BDSI was employed as an indicator of depressive tendency, with higher index values corresponding to greater likelihood of depression. The definitions of the natural and social environment variables, along with the BDSI are detailed in Table 1, with the descriptive statistics presented in Table 2.

# Results

## Spatiotemporal trends

Figure 1 presents the geographic distribution of BDSI levels across China over the period 2011-2022. Eastern China exhibits the highest BDSI values reflecting greater depression-related concerns there, while the western region shows the lowest values. Table 3 summarizes the mean BDSI values across regions and time, with the trends illustrated in Figure 2. Nationally, BDSI fluctuated upward and peaks in 2019 before a sharp decline in 2020 followed by stabilizations during 2020-2021. The eastern region consistently saw the highest BDSI levels, with a peak at 37.45 in 2019, while the central region showed intermediate values. The western region maintained the lowest BDSI throughout the study and the Northeast experienced smaller fluctuations than the eastern region.

The BDSI evolution was categorized into four phases: i) moderate growth across all regions 2011-2013; ii) 2013-2015, rapid growth 2013-2014 followed by stabilization 2014-2015; iii) volatile increases 2016-2020 with a peak in 2019; and iv) a decline 2019-2020 followed by a slight rebound except in the Northeast, followed by a clear decline across all regions 2021-2022 (Figure 2).

Figure 3 illustrates fluctuations in the impact of environmental and social factors. SO2E exhibits the highest variability, peaking in 2022, while TCEA remained consistently positive. These findings emphasize the need for further spatial analysis of these influences.

Table 4 provides descriptive statistics of GTWR regression coefficients. The variables CODE, TCEA, SO2E, HS-10,000 and DI-PC influenced BDSI positively, whereas GDP-PC exerted a negative effect. These results underscore the necessity of examining spatiotemporal variations of the BDSI determinants.

**Table 1.** Variables and definitions.

| Variable | Unit | Definition |
|---|---|---|
| BDSI | 10,000 times/year | Baidu depression-search index |
| CODE | 10,000 tons/year | Chemical oxygen demand emissions |
| TCEA | 1,000 hectares/year | Tree cover expansion area |
| SO2E | 10,000 tons/year | Atmospheric SO2 emission |
| GDP-PC | CNY | Gross domestic product per capita |
| HS-10,000 | Person | Healthcare staff per 10,000 population |
| DI-PC | CNY | Disposable income per capita |

**Table 2.** Initial descriptive statistics for the variables.

| Variable | Min. | Q1 | Median | Mean | Q3 | Max. |
|---|---|---|---|---|---|---|
| BDSI | 0.95 | 7.41 | 14.95 | 17.48 | 24.82 | 72.12 |
| CODE | 1.76 | 16.83 | 39.42 | 58.83 | 90.68 | 198.25 |
| TCEA | 0.04 | 81.99 | 172.09 | 202.50 | 282.40 | 805.16 |
| SO2E | 0.11 | 8.85 | 20.78 | 36.26 | 54.86 | 182.74 |
| GDP-PC | 16,024 | 37,109 | 50,305 | 58,029 | 68,655 | 189,988 |
| HS-10,000 | 27 | 55 | 63.5 | 65.81 | 76 | 155 |
| DI-PC | 7,510 | 16,799 | 22,714.5 | 25,288.65 | 29,422 | 79,610 |

*Q1 (first quartile) is the value at the 25th percentile; Median is the value at the 50th percentile; Mean represents the average value of all observations; Q3 (third quartile) is the value at the 75th percentile; BDSI, Baidu depression search index. CODE, chemical oxygen demand emissions; TCEA, Tree cover expansion area; SO2E, $SO_2$ emissions; GDP-PC, gross domestic product per capita; HS-10,000 health staff per 10,000 population; DI-PC, disposable income per capita.*

## Specific trends

### *CODE*

Figure 4A reveals significant spatiotemporal heterogeneity in CODE's impact. The eastern region shifted from a negative influence in 2019 to a strong positive effect in 2022. The western region transitioned from negative in 2011 to positive over time. In the central region, the positive influence weakened, while in the Northeast, CODE's impact declined from positive in 2011 to negative in 2015. CODE's heterogeneous effects on BDSI highlight the psychological burden of poor water quality. Targeted pollution control measures should consider regional economic and demographic differences to mitigate this kind of mental health risk.

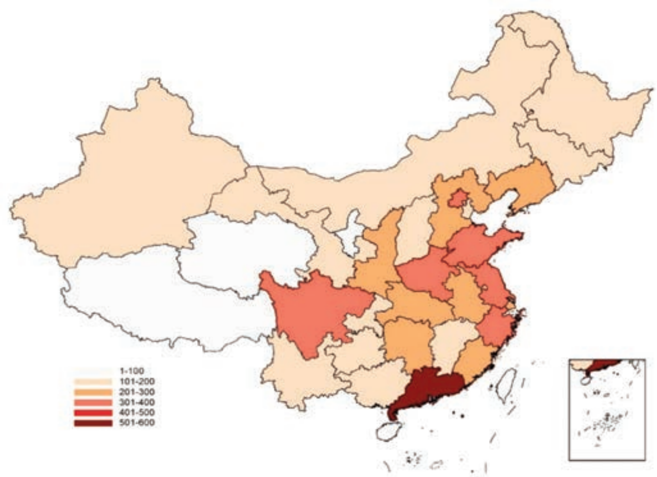


**Figure 1.** Variation of the BDSI level by province from 2011 to 2022. Darker shades indicate higher indices.

**Table 3.** Temporal variation of average BDSI in different regions of China.

| Year | Eastern | Central | Western | Northeast | Nationwide |
|---|---|---|---|---|---|
| 2011 | 7.23 | 5.28 | 3.18 | 5.06 | 5.08 |
| 2012 | 8.16 | 5.61 | 3.46 | 5.31 | 5.57 |
| 2013 | 12.41 | 8.99 | 5.52 | 7.28 | 8.58 |
| 2014 | 22.19 | 16.13 | 9.36 | 12.12 | 15.08 |
| 2015 | 23.13 | 17.14 | 10.21 | 12.86 | 15.98 |
| 2016 | 32.45 | 22.93 | 14.52 | 16.82 | 22.16 |
| 2017 | 31.96 | 24.90 | 14.94 | 17.85 | 22.64 |
| 2018 | 34.05 | 26.75 | 15.99 | 18.88 | 24.18 |
| 2019 | 37.45 | 29.88 | 18.39 | 21.18 | 27.03 |
| 2020 | 29.88 | 25.11 | 15.16 | 17.32 | 22.04 |
| 2021 | 30.13 | 26.41 | 15.87 | 17.53 | 22.67 |
| 2022 | 25.06 | 22.03 | 13.15 | 14.17 | 18.81 |

**Table 4.** Descriptive statistics of GTWR regression coefficients.

| Variable | Min | Q1 | Median | Mean | Q3 | Max |
|---|---|---|---|---|---|---|
| Intercept | -64.58 | -9.87 | -2.06 | -2.96 | 4.11 | 53.19 |
| CODE | -895.15 | -1.24 | 8.14 | 8.75 | 19.95 | 130.35 |
| TCEA | -37.16 | -4.52 | 3.00 | 7.02 | 13.94 | 262.90 |
| SO2E | -188.78 | -3.25 | 8.74 | 46.84 | 61.37 | 688.35 |
| GDP-PC | -332.39 | -63.84 | -11.43 | -16.95 | 17.61 | 1029.37 |
| HS-10,000 | -387.29 | -9.89 | 4.23 | 6.79 | 32.80 | 203.48 |
| DI-PC | -876.13 | -0.005 | 51.93 | 73.48 | 131.91 | 539.45 |

*CODE, chemical oxygen demand emissions; TCEA, Tree cover expansion area; SO2E, $SO_2$ emissions; GDP-PC, gross domestic product per capita; HS-10,000 health staff per 10,000 population; DI-PC, disposable income per capita.*

### *TCEA*

Figure 4B shows regional disparities of impact due to TCEA. It remains positive and increasing in the western part of the country, shifted from negative to positive in the central region, was mostly negative in the East, but followed the opposite trend in the Northeast. These findings suggest that deforestation strategies should align with regional socio-economic conditions and psychological needs to maximize mental health benefits. Further research is needed to understand why deforestation had limited psychological benefits in the western region.

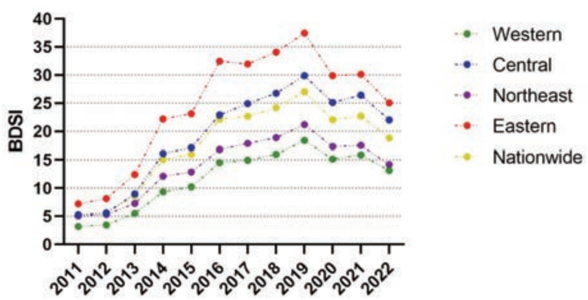


**Figure 2.** Temporal evolution of the average BDSI level by region.

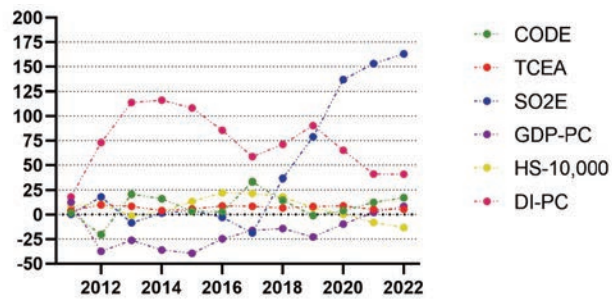


**Figure 3.** Temporal evolution of the influence of social and environmental factors as expressed by BDSI. CODE, chemical oxygen demand emissions; TCEA, Tree cover expansion area; SO2E, $SO_2$ emissions; GDP-PC, gross domestic product per capita; HS-10,000, healthcare staff per 10,000 population; DI-PC, disposable income per capita.

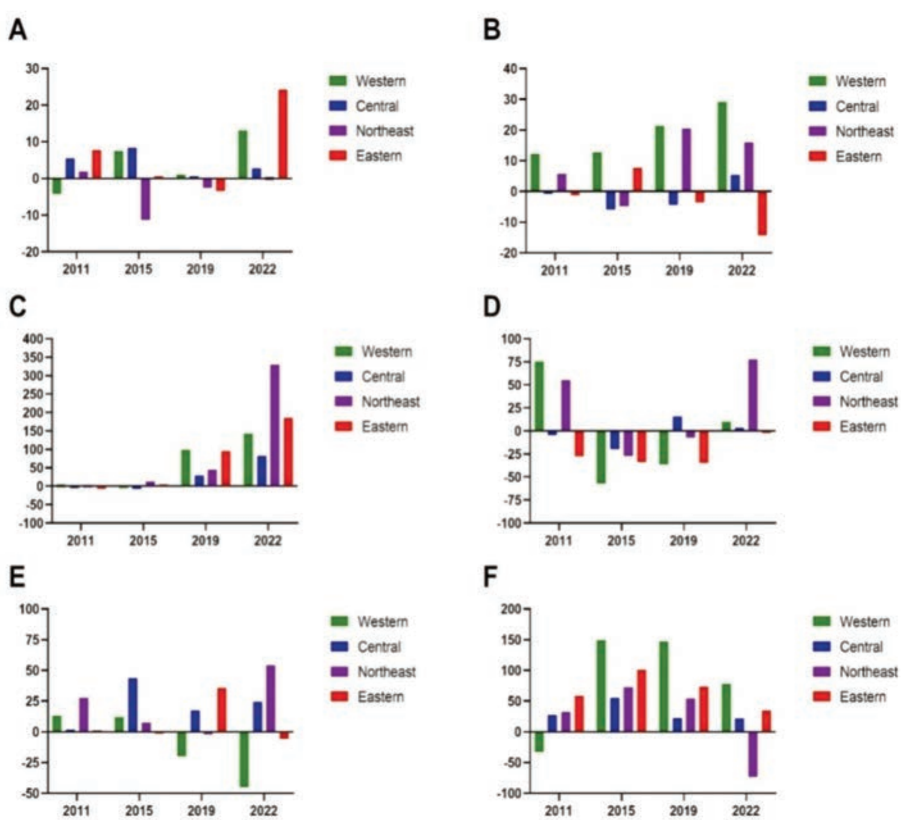


**Figure 4.** Temporal evolution of the influence by the variables investigated on BDSI. **A**) influence of chemical oxygen demand emissions (CODE); **B**) influence of tree cover expansion area (TCEA); **C**) influence of $SO_2$ emissions (SO2E): **D**) influence of gross domestic product per capita (- GDP-PC); **E**) influence of healthcare staff per 10,000 population (HS-10,000); **F**) influence of disposable income per capita (DI-PC).

### *SO2E*

Figure 4C highlights that the impact of SO2E intensified in 2019 and 2022, particularly in the Northeast, while its influence was weaker in 2011 and 2015. This trend may be linked to growing public awareness of pollution and associated stress, especially in industrialized regions. Mitigation efforts should focus on advancing industrial transformation, improving environmental technologies, and promoting psychological support interventions.

### *GDP-PC*

Figure 4D reveals significant spatial and temporal heterogeneity in GDP-PC's influence on BDSI. In the eastern region, it impacted BDSI negatively in 2011, 2015, 2019 and 2022, whereas in the western and north-eastern regions, its effect was positive in 2011 and 2022 but negative in 2015 and 2019. The central region exhibited alternating positive and negative impacts. Economic growth enhances living standards but can also increase stress due to urbanization and competition. Policies should balance economic development with mental health interventions, tailoring strategies to regional conditions.

### *HS-10,000*

Figure 4E reveals the varying regional impact of HS-10,000. The Central region showed a consistently positive effect, while the western region shifted from positive in 2011 and 2015 to negative in 2019 and 2022. The Northeast remained mostly positive, except for a negative effect in 2019. As a further measure of the influence of healthcare, increased resource density suggests that increased medical accessibility improves mental health.

### *DI-PC*

Figure 4F shows that DI-PC had a positive influence in 2015 and 2019, weakening over time. The western region's impact shifted from negative in 2011 to positive later, while the Northeast turned negative in 2022.Income growth initially increased social pressure but later facilitated improved living conditions, reducing depression. Policies should ensure economic benefits translate into mental well-being improvements across regions.

## Discussion

The GTWR model outperformed other regression models, underscoring the importance of considering both spatial and temporal variations in mental health research.Our findings are consistent with previous research highlighting air pollution, economic development, and healthcare accessibility as key factors influencing mental health (Sarris *et al.*, 2014; Wang *et al.*, 2017). For example, the positive association between $SO_2$ emissions and BDSI, especially in 2019 and 2022, aligns with studies suggesting air pollution exacerbates depression via oxidative stress and neuroinflammation (Gladka *et al.*, 2022). However, regional variations suggest that the impact of pollution on mental health may depend on factors, such as industrial structure, public awareness and policy effectiveness. In regions with better pollution control policies and higher public awareness, the negative impact of pollution may be mitigated, a nuance not always captured in traditional models.

Similarly, GDP per capita is typically linked to improved well-being (James & Ferguson, 2023), but our study revealed a more complex relationship. The higher GDP-PC in eastern China appeared to alleviate depressive tendencies, while in the western and north-eastern regions, economic growth correlates with higher BDSI in some years. This pattern may reflect regional differences in the stressors associated with economic growth, such as urbanization pressures and increased social competition.

Our analysis of deforestation reveals that its impact on BDSI varies widely across regions. In the West, as demonstrated in previous studies, deforestation generally exerts a positive impact on mental health (Li *et al.*, 2023), while in other regions, the effects of deforestation were inconsistent and, in some cases, even negative. This could be due to the type and accessibility of green spaces—urban green spaces provide psychological benefits, while large-scale deforestation in rural areas may not have the same effect if it occurs in sparsely populated or ecologically degraded regions.

The influence of water pollution on BDSI illustrates the shifting relationship between environmental factors and mental health. Our results show a transition in this impact from negative to positive in the Eastern and Western regions over time. This shift can likely be ascribed to the burgeoning public awareness of water pollution, whereby concerns regarding poor water quality have exacerbated stress, which is in accordance with the findings of previous research (Sarris *et al.*, 2014). Additionally, the uneven distribution of healthcare resources suggests that while greater medical accessibility improves mental health, its effectiveness is contingent upon regional healthcare infrastructure and public health awareness.

These findings in this study highlight the need to integrate spatial and temporal perspectives into mental health research. The GTWR model offers a more nuanced understanding of how environmental and social factors interact to shape depressive tendencies over time. Unlike static models, GTWR captures the dynamic nature of these relationships, allowing for more region-specific policy recommendations. For instance, regions with high pollution levels may benefit from targeted interventions focused on reducing environmental stressors and enhancing mental health resilience through public education and community-based initiatives. Similarly, economic policies should account for the psychological pressures of urbanization and competition, ensuring that economic growth does not come at the cost of mental well-being.

Future research should explore the causal mechanisms underlying relationships and consider additional psychological and behavioural factors that mediate the impact of environmental and social determinants on mental health. By utilizing advanced spatiotemporal modelling techniques, policymakers can design more effective strategies to mitigate depressive tendencies and promote mental well-being across diverse regions.

## Conclusions

A complex interplay between environmental and socioeconomic factors in shaping depressive tendencies has been shown. The observed regional differences in the effects of pollution, economic development and healthcare accessibility call for tailored interventions that account for local conditions. The high BDSI in eastern China, particularly in urbanized areas, suggests that rapid economic development and industrialization may contribute to mental health challenges. In contrast, the lower BDSI in the western region indicates that while economic disadvantages exist, social and environmental factors may play a different role in shaping mental health outcomes. Temporal fluctuations may reflect external shocks, such as policy changes or global health crises, influencing depressive tendencies. Seasonal variations and public events may also contribute to short-term fluctuations in BDSI, indicating the importance of continuous monitoring.

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