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Xinyuan Gao MS , Yingsi Lai PhD , Weihua Hu MS , Li Wang PhD , Yixuan Liu MS , Jing Liao PhD

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Title page

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Spatial variations and risk factors of multimorbidity in China: A population-based spatial modelling study

Authors

Xinyuan Gao, MS,[1#] Yingsi Lai, PhD,[1,2,3,4#] Weihua Hu, MS,[5] Li Wang, PhD,[1] Yixuan Liu, MS,[1] Jing Liao, PhD [1,2]

Affiliations

[1] Department of Medical Statistics, School of Public Health, Sun Yat-sen University, No.74 Zhongshan 2nd Road, Guangzhou, P.R. China.

[2] Sun Yat-sen Global Health Institute, Institute of State Governance, Sun Yat-sen University, No.135 Xingang West Road, P.R. China.

[3] Health Information Research Center, Guangdong Key Laboratory of Medicine, School of Public Health, Sun Yat-sen University, Guangzhou, 510080, China.

[4] Guangzhou Joint Research Center for Disease Surveillance, Early Warning and Risk Assessment, Guangzhou, 510080, China.

[5] Department of Epidemiology & Biostatistics, School of Public Health, Peking University, Xueyuan Road, Haidian District, Beijing 100191, China.

# Author Xinyuan Gao and Author Yingsi Lai contributed equally to this work and should be considered co-first authors.

Corresponding Authors

Jing Liao, PhD

Address: Department of Medical Statistics, School of Public Health, Sun Yat-sen University, No.74 Zhongshan 2nd Road, Guangzhou, 510030, P.R. China.

Email: liaojing5@mail.sysu.edu.cn

ABSTRACT

Introduction: Multimorbidity burden is likely to vary across China, but relevant evidence is insufficient. The extent to which individual and provincial factors may affect spatial variations of multimorbidity has not been fully examined. This study aims to estimate the provincial multimorbidity burden among Chinese aged 45 and older, identifying which risk factors remain constant and which vary across China.

Methods: This study included 18,561 adults aged 45 and older from the China Health and Retirement Longitudinal Study in 2020. A Bayesian spatial varying coefficients model was adopted to estimate the multimorbidity burden and 95% Bayesian credible intervals, using the Chinese Multimorbidity-Weighted Index (CMWI) as a measurement. Partial correlation coefficients between covariates and CMWI in each region were calculated to investigate the need for varying coefficients. Spatial autocorrelation analyses were used to identify clusters of high and low multimorbidity burden.

Results: The estimated CMWI across the 27 provinces in China ranged from 1.76 (95% BCI: 1.64, 1.89) to 4.42 (95% BCI: 4.16, 4.70). High multimorbidity burden areas were clustered in North and Northeast China, while areas with relatively low burden were in southern China. The top three provinces by median CMWI estimates were Neimenggu, Heilongjiang, and Jilin, whereas Guangdong, Zhejiang, and Beijing were among the lowest CMWI estimates. The

effect of age and sex showed spatial variation across China, while other risk factors showed fixed effects.

Conclusions: The burden of multimorbidity varies across China and not all risk factors associated with multimorbidity are consistent across regions, providing valuable insights for chronic disease management.

Introduction

Multimorbidity, characterized by the coexistence of two or more chronic conditions within an individual[1], poses a significant burden on patients and societies[2]. Previous research estimated the prevalence of multimorbidity (i.e., ≥2 chronic diseases) was 30.4% among Chinese middle-aged and older people[3]. However, the variation in chronic disease burden across China remains unclear[4,5]. A meta-analysis reported higher multimorbidity prevalence in eastern and central China compared to the west[3], while another national survey identified hot spots in the west and north[6]. These estimates may be affected by the heterogeneity in time span, sampling methods, and multi-morbidity categories under consideration.

Applying a comprehensive measure of multimorbidity that incorporates disease impact offers a more informative tool for describing multimorbidity distribution[7]. A study reporting provincial multimorbidity estimates using a Multimorbidity Index (MHI) provided point estimates, and the index was validated only within the developed population and lacked external validation[8]. Uncertainty associated with spatial variation in provincial multimorbidity estimates requires further study. In contrast, the Chinese Multimorbidity-Weighted Index (CMWI)[9] has been validated and performs better than or comparable to other commonly used multimorbidity indices[10,11] (e.g., the Elixhauser comorbidity index and Charlson comorbidity index) in multiple scenarios, including primary care settings[12] and national surveys[13]. Evidence for estimating provincial multimorbidity burden using the generally applicable CMWI is still lacking.

The extent to which risk factors at individual and provincial levels may contribute to spatial variations of multimorbidity has not been fully examined. While most previous studies

assumed spatially constant association between influencing factors and chronic burden throughout the study region[14], such as socioeconomic and lifestyle factors[15,16], this assumption may not hold due to varying provincial characteristics[17]. Previous studies found that the risk effects of influencing factors like smoking and physical activity on breast cancer mortality vary regionally in scale[18]. Identifying which risk factor effects are constant and which vary across the study area is important for accurate estimation of provincial multimorbidity burden in China. Therefore, this study aims to estimate spatial variations in the multimorbidity burden among Chinese middle-aged and older adults and to identify associated individual- and provincial-level factors, using a previously developed and validated CMWI[9]. Understanding the spatial distribution of multimorbidity burden and its risk factors is essential to guiding public health practitioners in targeted chronic disease management.

Methods

Study population

This study utilized data from Wave 5 (2020) of the China Health and Retirement Longitudinal Study (CHARLS)[19]. CHARLS is a national survey of a representative sample of Chinese residents aged 45 years and older, with the sample obtained using multistage stratified probability proportional to size (PPS) sampling. The most recent 2020 wave of CHARLS covered 27 provinces, municipalities, and autonomous regions, involving a total of 19,395 individuals. The inclusion and exclusion criteria for this study were as follows: participants aged 45 or above were included, while individuals with missing variables on any disease's status were excluded. A flow chart of the selection of study population is available in Appendix A. The detailed study design, methods, and response rates have been described previously[19]. According to the seven administrative geographical divisions, mainland China's provinces and municipalities were classified into Northeast, North, Central, East, South, Northwest, and Southwest regions (Appendix B). The studies involving human participants were reviewed and approved by the Ethics Review Committee of Peking University. The CHARLS was approved by the Ethical Review Committee of Peking University (IRB00001052–11015). The authors thank all participants who took part in these studies. The patients/participants provided written

informed consent to participate in this study.

Measures

Multimorbidity was assessed using the CMWI[9]. The CMWI included 14 chronic conditions, including stroke, memory-related disease, cancer or malignant tumour, asthma, arthritis or rheumatism, emotional, nervous, or psychiatric problems, heart disease, chronic lung diseases, hypertension, kidney disease, diabetes or high blood sugar, stomach or other digestive disease, dyslipidaemia and liver disease. The CMWI was calculated as the sum of the weighted scores assigned to each chronic diseases based on respondents' self-reported physician-diagnosed in CHARLS, reflecting their impact on physical functioning. A table detailing the CMWI disease weightings is provided in Appendix C.

Individual and provincial-level factors were considered to comprehensively capture the multiple influences on multimorbidity, as identified in previous studies[6,20]. Individual-level factors included demographic characteristics (i.e., age, sex and type of residence), life conditions related factors (i.e., less education and lower economic status), and unhealthy lifestyle-related factors (i.e., unhealthy behaviours[21] such as smoking, alcohol consumption, and lack of physical exercise, with at least one present; and social isolation[22], including being unmarried, living alone, having less than weekly contact with children, and not participating in any social activities over the last month, with at least one present), information of which obtained from the CHARLS questionnaire. Provincial-level factors included health resources (number of physicians per 10,000 people), environmental factors (green space per capita and PM2.5 concentration), and economic factors, measured using satellite-derived night-time light intensity, a widely used proxy for economic activity and regional development[23], reflecting the spatial distribution of human activity and infrastructure. Provincial-level factors for this study were obtained from open-access databases. Details on the definition and sources of variables can be found in Appendix D. A stratified random forest method[24] was used for the multiple imputations of missing covariates in the data.

Statistical Analysis

The Bayesian spatial varying coefficients (SVC) model[25], which accounts for spatial

heterogeneity in risk factors across provinces, was applied to estimate the provincial multimorbidity burden. Given the characteristics of CMWI as non-negative, right-skewed continuous value, it was assumed that Y_{ik}, the CMWI score of individual k in province i, followed a Tweedie distribution[26]: $Y_{ik} \sim Tw_p(\mu_{ik}, \phi)$, $i = 1, \ldots, 27$. μ_{ik} was the mean CMWI of individual k in province i, ϕ was the dispersion parameter, and p indicates the Tweedie power parameter.

This study modelled covariates using the regression as $log(\mu_{ik}) = \alpha + \sum_{m=1}^{M} \beta X_{ik} + \sum_{n=1}^{N} f_s(\gamma_i X_{ik}) + u_i + v_i,\ N \leq M$. Here, α was the intercept, and β was the fixed effects of the covariates. The covariate's random slope γ_i was assigned a conditional autoregressive (CAR) process[27] as $u_i | u_{j,j\neq i} \sim N\left(\frac{1}{w_{ij}} \sum_{j=1}^{n_i} w_{ij}\, u_{ij}, \frac{\sigma_u^2}{n_i}\right)$, that smoothed the data according to a certain neighbourhood structure that specifies that two areas are neighbours if they share a common boundary. To account for unmeasured spatial confounding, the Besag, York, and Mollié (BYM) model[28] was incorporated, which is commonly used in spatial epidemiology to separate structured and unstructured sources of spatial variation. The model was consisted of two components: spatially structured random effects u_i and unstructured random effects v_i. u_i was commonly assumed to follow CAR process. And $v_i \sim N(0, \sigma_v^2)$ is unstructured random effects following a normal distribution, representing that province i had an independent pattern of CMWI from the adjacent provinces.

To investigate whether covariates should have varying coefficients, the partial correlation coefficient between X_{ik} and Y_{ik} was calculated for each province i. Due to Moran' I method is commonly used to measure the spatial dispersion or correlation of variables[29,30], the Global Moran's I index[31] was employed to identify spatial patterns among the partial correlation coefficients for each variable across 27 provinces[32]. Covariates with significant spatial patterns were assigned varying coefficients, while others were assigned fixed coefficients. Moreover, to obtain the best set of covariates for the model, the all-subsets selection approach was used to identify the best set of covariates for the final model. Additionally, based on previous studies, age, sex and type of residence were identified as the key influencing factors for

multimorbidity[33,34]; hence, the corresponding variables were kept in the models during the whole variable selection process.

To obtain provincially representative CMWI, consistent with previous study on estimating provincial health outcomes[35], provincial sampling weight was applied based on nationally representative sampling weights[36] provided by CHARLS and the National Population Census Data (2020)[37], to adjust for age, sex and residence compositions. Detailed procedures for calculating the weights have been published elsewhere[35]. Individual estimated CMWI from the posterior samples were integrated with provincial sampling weights to derive provincial multimorbidity burden. Global Moran's *I* was used to calculate correlation statistics across all spatial regions and determine if the estimated CMWI in the study area showed clustering. The Local Moran's *I*[38] and Hot-Cold Spots analysis[39] were used to identify geographic clusters of estimated provincial CMWI across 27 provinces. These local indicators enable the identification of provinces exhibiting significantly higher or lower multimorbidity burden relative to neighbouring areas, thereby supporting a more nuanced interpretation of spatial heterogeneity. Additionally, the posterior probability that the CMWI exceeded the average level was calculated for each province.

The Bayesian SVC model was also compared with two commonly used regression models: one including only covariates without accounting for spatial correlation among provinces, and the other not incorporating spatially varying coefficients. The deviance information criterion (DIC)[40] and the Watanabe–Akaike Information Criterion (WAIC)[41] were used to compare the model performances. A detailed analytical flowchart is provided in Appendix E. As insufficient prior information was available on the parameter distributions in the Bayesian models, weak informative priors distributions were adopted as follows: $\log(\sigma_\alpha^2) \sim$ logGamma (1, 0.1), $\log(1/\sigma_\beta^2) \sim$ log Gamma (1, 0.1), $\log(1/\sigma_u^2) \sim$ logGamma (1, 0.05), $\log(1/\sigma_v^2) \sim$ logGamma (1, 0.05), to avoid subjectively selecting unreasonable informative priors. In addition, the sensitivity analysis was conducted on the hyperparameters of the weakly informative priors. Results showed little impact of the prior specification on the posterior estimates of covariates and model fit indices, indicating the robustness of the model (Appendix F). The model was

fitted through the integrated nested Laplace approximations (INLA)[42] approach in a Bayesian framework, using the INLA package in R, and all visualisations were performed with ArcGIS V.10.8.

Results

A total of 18,561 participants (52.86% women) aged 45 and older were included in the analyses. The median of CMWI among the study sample was 2.40 (interquartile range, IQR=0.70-4.70). The demographic characteristics of participants grouped by the seven geographic was presented in Table 1. The prevalence of the 14 chronic conditions included in CMWI in 2020 is provided in Appendix G, illustrating the underlying disease distribution across China. Compared to the other two models (Appendix H), the Bayesian SVC model had the smallest DIC and WAIC, indicating the best fit.

The risk maps of multimorbidity showed obvious geographic variations across China in 2020, with high-burden provinces mainly in Northwest and North China, and low-burden provinces in Southeast and South China (Fig. 1a). The multimorbidity burden across the 27 provinces ranged from 1.76 (95% Bayesian credible intervals, BCI: 1.64, 1.89) to 4.42 (95% BCI: 4.16, 4.70) (see Appendix F). The top three of provinces, ordered by the median estimation of CMWI, were Neimenggu (4.42, 95% BCI: 4.16, 4.70), Heilongjiang (4.15, 95% BCI: 3.76, 4.48) and Jilin (3.84, 95% BCI: 3.49, 4.26). Meanwhile, Guangdong (1.76, 95% BCI: 1.64, 1.89), Zhejiang (2.15, 95% BCI: 2.00, 2.30) and Beijing (2.25, 95% BCI: 1.72, 3.03) ranked among the lowest. High estimation uncertainty was mainly observed in northwest and some eastern areas, particularly in Shanghai, Beijing, Tianjin, and Qinghai (Appendix I). The distribution of random effects, representing the effects of unmeasured factors, is shown in Appendix J, the largest of which were shown in Neimenggu and Heilongjiang, while the smallest in Guangdong, Guangxi, and Fujian. Spatial variance of random effects was 0.028 (95% BCI: 0.007, 0.152). The exceedance probability map reveals that provinces and cities with a 60% or higher probability of exceeding the average level were predominantly concentrated in the northern and western regions, with Heilongjiang, Jilin, Neimenggu, Shaanxi, and Sichuan achieving almost a 100% probability of exceeding the average (Fig. 1b). Consistently, spatial

autocorrelation analysis (Global Moran's *I* statistic=0.28, $P < 0.01$) also showed that provinces with high-risk were mainly aggregated in North China (high–high cluster, local Moran analysis, $P < 0.05$), including Heilongjiang, Jilin and Neimenggu, while regions with low risk were aggregated in South China, with Fujian identified a low-low cluster (local Moran analysis, $P < 0.05$) (Appendix K). A hot spot analysis also demonstrated similar findings (Appendix L).

After variable selection, ten covariates were included in the model. As the partial correlation coefficients of age and sex showed significant spatial patterns (Appendix M), these two variables were assigned varying coefficients, while the others were kept as fixed. The posterior summaries of model parameters are shown in Table 2. At the individual level, age, female, less education, low economic status, unhealthy behaviours and social isolation were positively correlated with CMWI. Per capita green space and night-time light intensity at provincial-level showed a negatively associated with CMWI. The effects of age and sex varied across provinces, as illustrated in Figure 2, with additional details in Appendix N. The spatially varying coefficients for age show higher in central China and lower in the north (Fig. 2a). For sex, provinces with high effects were mainly located in the northern and central China and the ones with lower effects in southern China (Fig. 2b).

Discussion

This study revealed geographic variation in the burden of chronic disease multimorbidity across Chinese provinces. High-burden provinces were mainly concentrated in the Northwest and North, whereas low-burden provinces were clustered in the Southeast and South. Furthermore, associations between CMWI and risk factors were identified, with age and sex showing spatially varying relationships with multimorbidity burden across China. These findings indicated spatial patterns and region-specific risk factors in China.

This study contributes updated evidence on the spatial distribution of provincial multimorbidity burden in China by applying CMWI, incorporating uncertainty estimates, and investigating spatial clustering. The findings show higher burden of multimorbidity in northern and western regions, and lower burden in southern and eastern regions, consistent with previous national survey–based studies[6,8]. However, these results differ from a meta-analysis[3] that reported

higher multimorbidity prevalence in eastern and central China. This discrepancy may reflect differences in study design, sampling strategies, and the broader time span of the meta-analysis (2002–2022)[3] compared with the 2020-based estimates used in this study. Multimorbidity in population-based studies is largely driven by cardiometabolic diseases, like hypertension and diabetes, which are sensitive to lifestyle and dietary factors[43] and exhibit distinct geographic distributions[44]. Regional dietary patterns and contextual exposures[44,45], especially those differing between northern and southern China, may partly explain the observed multimorbidity distribution. Compared with prior studies focusing on individuals aged $\geqslant$60[8], this study extends the evidence base to those aged $\geqslant$45 and incorporates uncertainty estimates. While multimorbidity is more prevalent in older populations[46], including middle-aged adults captures earlier disease accumulation and provides a more comprehensive assessment of population burden. The estimated CMWI ranged from 1.76 to 4.42 across provinces, indicating an approximately 2.5-fold variation. As a relative measure, CMWI reflects both disease accumulation and its impact on physical functioning, with higher values indicating greater impairment[9]. This variation suggests provincial differences in the impact of multimorbidity accumulation on physical functioning, reflecting inequalities in disease burden and functional health.

This study assessed the effects of individual and provincial risk factors on multimorbidity, accounting for spatial heterogeneity. The model incorporates both constant and spatially varying covariate effects, balancing flexibility and parsimony[32] and yielding a better model fit than the other two commonly used models. The results showed that life condition–related factors, particularly lower socioeconomic status, and unhealthy lifestyle behaviors were positively associated with multimorbidity across China. These findings are in line with extensive epidemiological evidence indicating that socioeconomic disadvantage and adverse health behaviors are risk factors for multimorbidity[47,48]. The stable national-level effects of these factors suggest that their influence is largely structural rather than region-specific. Individuals with lower economic status are more likely to have limited access to healthcare[49], lower health literacy[50], and greater exposure to behavioral and environmental risks, all of which

contribute to disease progression. Similarly, unhealthy lifestyle behaviors such as smoking and alcohol consumption promote systemic inflammation and metabolic dysregulation[51], while physical inactivity exacerbates cardiometabolic and musculoskeletal disorders[52], contributing to multimorbidity development. Characteristics of participants, including age and sex, showed spatially varying associations with multimorbidity at the provincial level. Previous studies have shown significant age and sex differences in multimorbidity[53,54] and the observed spatial heterogeneity may help explain geographic disparities. Specifically, stronger age-related effects were found in central China, while women in northwestern provinces faced a relatively higher risk of multimorbidity. The fixed effects of factors capture overall trends, while the spatially varying effects explain local variations. The findings improve the interpretation of provincial multimorbidity burden estimates[55] , provide a more comprehensive understanding of spatial heterogeneity, and support the development of region-specific strategies.

The observed spatial variation and clustering of multimorbidity highlight the policy relevance of these findings for prioritizing prevention efforts and optimizing resource allocation. In particular, the identification of high–high clusters in several northern provinces suggests that these regions should prioritize measures to control multimorbidity. At the national level, the consistent associations of socioeconomic disadvantage and unhealthy lifestyle behaviors with multimorbidity indicates the importance of sustained, nationwide prevention strategies, including tobacco and alcohol control, promotion of physical activity, and interventions to reduce socioeconomic inequalities in health. At the regional level, spatial heterogeneity in age and sex indicates the need for tailored approaches to address subgroup-specific patterns. Regions with stronger age effects may benefit from strengthened geriatric care and integrated chronic disease management, whereas areas with higher risks among women may require sex-specific prevention and screening strategies. Aligning national prevention strategies with region-specific interventions, while prioritizing high-risk populations and high-burden areas, may improve resource allocation efficiency and overall public health outcomes.

To the authors' knowledge, this study provides the first provincial-level application of the validated CMWI in China, offering a comprehensive characterization of the spatial distribution

of multimorbidity burden and its associated risk factors among middle-aged and older adults. By incorporating spatial heterogeneity and uncertainty estimates, the findings highlight the role of population structure in shaping regional health patterns.

Limitations

Some limitations should be acknowledged. First, estimation uncertainty was relatively high in some provinces and municipalities (e.g., Shanghai and Beijing), primarily due to small sample sizes in CHARLS. Pooling multiple CHARLS waves may improve precision. In addition, several regions, including Hainan, Ningxia, and Xinjiang, were excluded due to data unavailability. Second, spatial random effects revealed north–south differences that may indicate unmeasured factors, such as dietary habits[45]. Future studies could integrate complementary data sources(e.g., the Chinese Health and Nutrition Survey[56]) to help clarify these influences. Third, reliance on self-reported or proxy data may introduce recall bias and disease misclassification. Although CHARLS employs standardized procedures[19] and prior waves helped verify disease status, potential underestimation cannot be fully excluded. Previous studies have shown that estimates of self-reported chronic disease prevalence may vary by education level, household registration status, age, and sex[57,58]. Despite adjustment for these factors, residual confounding may remain, and the results should be interpreted with caution. Finally, this study focuses on the cross-sectional spatial distribution of multimorbidity burden using the latest nationwide data in China and does not capture spatiotemporal dynamics. Given that the most recent wave was conducted in 2020, the potential influence of the COVID-19 pandemic should be acknowledged. China implemented stringent containment measures early in the pandemic, which may have limited the spread of COVID-19 largely to localized areas and specific cities[59]. As multimorbidity reflects long-term chronic disease accumulation rather than short-term acute health events, the observed spatial patterns are likely only partly influenced by pandemic-related effects. Future studies using multiple CHARLS waves could further clarify the spatiotemporal trends in multimorbidity and the longer-term impacts of the pandemic.

Conclusions

This study reveals the provincial variations in multimorbidity and its associated risk factors among middle-aged and older adults in China in 2020. High multimorbidity burden areas were clustered in northern and northeastern China, while low multimorbidity burden areas were concentrated in southern China. Age and sex showed spatially varying associations with multimorbidity burden. These findings provide valuable insights for chronic disease management.

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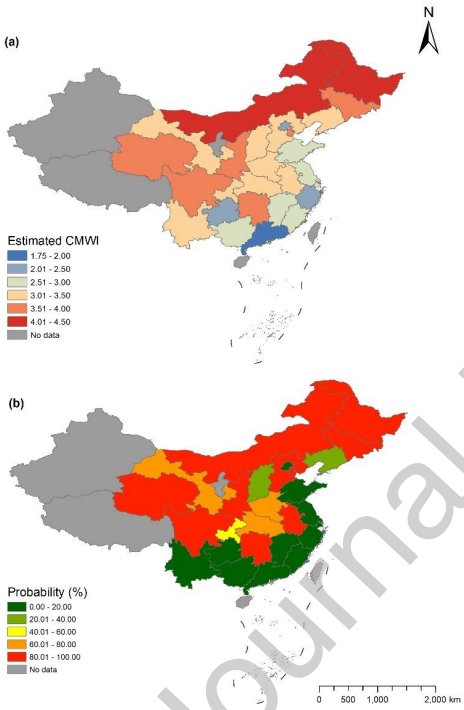

Fig. 1. Model-based multimorbidity burden estimates across China in 2020: (a) Estimated CMWI based on the median of the posterior distribution, and (b) posterior probability (%) of CMWI exceeding the national average.

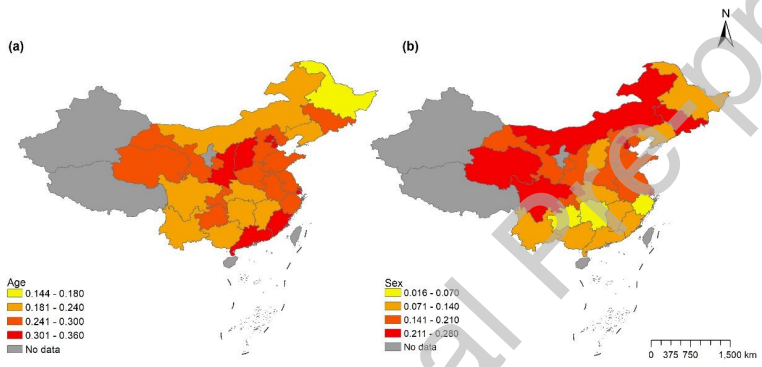

Fig. 2. Spatial varying coefficients of (a) age and (b) sex on CMWI.

Table 1. Characteristics of study participants in CHARLS 2020

Characteristic	Overall (N=18, 561)	Northeast (N=1, 124)	North (N=2, 355)	East (N= 5, 826)	South (N= 1, 602)	Central (N= 2, 949)	Northwest (N= 1, 368)	Southwest (N= 3, 337)
CMWI (Median, IQR)	2.40(0.70,4.70)	2.90(1.00,5.50)	2.90(1.00,5.40)	2.20(0.70,4.20)	1.70(0.00,3.50)	2.5(0.70, 5.0)	2.9(1.08,5.43)	2.9(1.30,4.80)
Age, years (Mean±SD)	63.06±9.93	62.83±9.40	62.20±9.43	63.57±10.10	63.80±10.17	62.52±9.68	61.77±9.54	63.51±10.30
Women	9,811(52.86%)	614(54.63%)	1220(51.80%)	3,081(52.88%)	859(53.62%)	1,549(52.53%)	730(53.36%)	1,758(52.68%)
Rural	11919(64.22%)	582(51.78%)	1309(55.58%)	3759(64.52%)	1068(66.67%)	1889(64.06%)	901(65.86%)	2411(72.25%)
Less Education								
Yes	12,133(65.37%)	592(52.67%)	1,268(53.84%)	3,954(67.87%)	1,067(66.60%)	1,727(58.56%)	854(62.43%)	2,671(80.04%)
No	6,428 (34.63%)	532 (47.33%)	1,087 (46.16%)	1,872 (32.13%)	535 (33.40%)	1,222 (41.44%)	514 (37.57%)	666 (19.96%)
Lower economic status								
Yes	9,278(49.99%)	631(56.14%)	1,238(52.57%)	2,820(48.40%)	653(40.76%)	1,480(50.19%)	682(49.85%)	1,774(53.16%)
No	9,283 (50.01%)	493 (43.86%)	1,117 (47.43%)	3,006 (51.60%)	949 (59.24%)	1,469 (49.81%)	686 (50.15%)	1,563 (46.84%)
Unhealthy lifestyle								
Yes	8,915(48.03%)	593(52.76%)	1,257(53.38)	2,789(47.87%)	693(43.26)	1,390(47.13%)	628(45.91%)	1,565(46.90%)
No	9,646 (51.97%)	531 (47.24%)	1,098 (46.62%)	3,037 (52.13%)	909 (56.74%)	1,559 (52.87%)	740 (54.09%)	1,772 (53.10%)
Social isolation								
Yes	5,045(27.18%)	355(31.58%)	688(29.21%)	1665(28.57%)	488(30.46%)	638(21.63%)	355(25.95%)	856(25.65%)
No	13,516 (72.82%)	769 (68.42%)	1667 (70.79%)	4161 (71.43%)	1114 (69.54%)	2311 (78.37%)	1013 (74.05%)	2481 (74.35%)
NMTP, persons (Mean±SD)	75.48±7.18	78.50±5.99	78.03±8.78	74.56±7.92	68.95±3.86	72.77±1.83	83.52±9.31	76.49±1.26
PGA (Mean±SD) m2/person	14.74±1.98	13.09±0.28	15.83±2.64	15.48±1.55	16.19±2.55	13.63±0.99	13.63±1.18	13.96±1.49
Night-time light intensity (Mean±SD)	10.14±6.42	6.42±3.36	9.17±7.65	15.30±6.25	11.92±4.44	9.66±3.15	4.57±2.54	4.92±1.23

Abbreviations: CHARLS, China Health and Retirement Longitudinal Study; NMTP, persons: Number of physicians per 10,000 people; PGA: Green space per capita; CMWI, Chinese multimorbidity-weighted index;

IQR: Interquartile range.

Table 2. Posterior summaries of fixed effect coefficients

Variable	Posterior median (95% BCI)
Intercept	0.954(0.883, 1.032)
Age	0.262(0.242, 0.282)[a]
Sex	
Men	Ref
Women	0.154(0.115,0.194)[a]
Type of residence	
Urban	Ref
Rural	-0.005(-0.033, 0.028)
Lower Education	
No	Ref
Yes	0.072(0.034, 0.106)[a]
Lower economic status	
No	Ref
Yes	0.046(0.017, 0.076)[a]
Unhealthy lifestyle	
No	Ref
Yes	0.097(0.061, 0.135)[a]
Social isolation	
No	Ref
Yes	0.036(0.005, 0.068)[a]
NMTP, persons (Mean±SD)	-0.026(-0.086, 0.043)
PGA (Mean±SD) m^2/person	-0.072(-0.136, -0.003)[a]
Night -time light intensity (Mean±SD)	-0.082(-0.156, -0.017)[a]

a: Significant effect identified by not including zero in the 95% BCI of posterior distribution of the corresponding coefficient

Abbreviations: NMTP, persons: Number of physicians per 10,000 people; PGA: Green space per capita; CMWI, Chinese multimorbidity-weighted index; IQR: Interquartile range.

Author Contributions – Gao Xinyuan：Conceptualization, Data curation, Formal analysis, Methodology, Writing - original draft, Writing - review & editing. Lai Yingsi: Conceptualization, Methodology, Writing - Review & Editing, Supervision, Funding acquisition. Hu Weihua: Conceptualization, Formal analysis, Methodology, Validation. Wang Li: Data curation, Formal analysis, Visualization. Liu Yixuan: Methodology, Software, Visualization. Liao Jing: Conceptualization, Methodology, Funding acquisition, Supervision, Writing - review & editing.

Declaration of Conflicts of Interest – None.