International Journal of Applied Earth Observations and Geoinformation 117 (2023) 103219

Contents lists available at ScienceDirect

International Journal of Applied Earth Observations and Geoinformation

journal homepage: www.elsevier.com/locate/jag

National variation in patterns of bone disease treatment-seeking behaviors: A study of more than 50,000 hospital admissions between 2008 and 2021

Yanchao Tang [a,b,c], Yongze Song [d,*], Yongqiang Wang [a], Shengjie Lai [e,f], Victor A. Alegana [g], Xiaoguang Liu [a,h,*]

[a] Department of Orthopaedics, Peking University Third Hospital, Beijing, China
[b] Beijing Key Laboratory of Spinal Disease Research and Engineering, Beijing, China
[c] Research Center of Bone and Joint Precision Medicine, Ministry of Education, Beijing, China
[d] School of Design and the Built Environment, Curtin University, Perth, Australia
[e] WorldPop, School of Geography and Environmental Science, University of Southampton, Southampton, UK
[f] Institute for Life Sciences, University of Southampton, Southampton, UK
[g] World Health Organization (WHO) Africa Region, Brazzaville, Republic of Congo
[h] Health Science Center, Peking University, Beijing, China

ARTICLE INFO

Keywords:
Treatment-seeking behavior
Bone diseases
Remote sensing
Geospatial big data modeling
Public health management

ABSTRACT

Understanding disease treatment-seeking behaviors is a fundamental issue for national and regional healthcare management. However, treatment-seeking behaviors are complex and affected by various factors, including disease incidence, healthcare resources, and population accessibility to hospitals. Geospatial analysis is a practical approach to investigating treatment-seeking behaviors. Still, methods and cases are limited due to the lack of long-term data, interdisciplinary knowledge, and data analytic techniques. We develop a new paradigm for investigating spatial patterns and factors affecting bone disease treatment-seeking behaviors. We leverage consecutive long-term records of over 50,000 nationwide bone disease patients outside Beijing who had surgeries in a prestigious hospital in Beijing, China. Five categories of patient individual-level geographical and environmental variables are derived from multi-source remote sensing and geospatial data to explain treatment-seeking behaviors. First, we develop a scaling approach to assess the relationships between bone patients and population migration. Next, we develop a treatment-seeking index to measure treatment-seeking behaviors and develop spatial models to identify their regional disparities, i.e., hotspots and coldspots. Finally, we develop spatial heterogeneity models to explore the complex factors affecting treatment-seeking behaviors. Results show that the developed paradigm is effective in examining national variations of the patterns of disease treatment-seeking behaviors. We find that (i) population migration is an effective predictor of the treatment-seeking behaviors of bone patients, (ii) significant hotspots and coldspots are identified for informing regional disparities, and (iii), multiple types of factors affecting the treatment-seeking behaviors through a geospatially overlapped approach. This study pioneers the development of geospatial models and implementation of patient individual-level data derived from satellite remote sensing for large-scale disease treatment-seeking behaviors assessment. The proposed paradigm provides solid evidence for previous and future policies and actions to address the regional inequality of disease treatments.

1. Introduction

Understanding disease treatment-seeking behaviors affect decision-making in national and regional healthcare management (Alegana et al., 2018, Willcox et al., 2018). Disease treatment-seeking behavior reveals the patients' efforts in seeking effective healthcare resources within their cognitive scopes, with available healthcare facilities, and under specific situations of geography, environment, economy, transport, education, and socio-cultural context (Tanner and Vlassoff, 1998, Jowett et al., 2004, Das et al., 2018). Disease treatment-seeking behavior is a complex issue, and it is associated with various factors, including the incidence of disease in different regions, healthcare

* Corresponding authors.
E-mail addresses: yongze.song@curtin.edu.au (Y. Song), xglius@vip.sina.com (X. Liu).

https://doi.org/10.1016/j.jag.2023.103219
Received 17 November 2022; Accepted 1 February 2023
Available online 8 February 2023
1569-8432/© 2023 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

resources for the specific diseases, and population accessibility to healthcare facilities (Ruebush et al., 1995, Adhikari et al., 2019, Kane et al., 2019, Kenangalem et al., 2019). Mapping disease treatment-seeking behaviors is an essential interdisciplinary issue and provides solid evidence for large-scale decision-making.

Recent research highlights the importance of quantitative analysis of treatment-seeking behaviors in increasing treatment opportunities. For instance, a community-based study of the treatment-seeking behaviors of the prevalence of lower urinary tract symptoms (LUTS) with 644 male respondents in Singapore revealed that a large number of moderate-to-severe LUTS did not seek medical support for treatment (Chong et al., 2012). This study suggested that public awareness and variability of treatment options should be improved. A study about the treatment-seeking behaviors of psychiatric disorders of 31,464 older adults in India indicated that less than a half of patients would seek treatment, and patients from the most senior group, females, and certain regions had a low probability of seeking treatment (Srivastava et al., 2021). It is suggested that more attention is required for high-risk, psychologically distressed, and rural patients. In addition, spatial disparities and geographical factors have been essential components of understanding disease treatment-seeking behaviors. In the geographical information science (GIS), the assessment of spatial association widely has contributed to the characterization of spatial patterns and disparity, geographical factor exploration, spatial prediction, and geographical decision making (Song, 2022; Song and Wu, 2021). Geographical conditions are closely associated with patients' living environment, distance to hospitals, and groups of residents, such as income, education, gender equality, etc (Ghosh, 2004, Wangroongsarb et al., 2011, Alegana et al., 2017). However, bench-making cases of large-scale mapping of disease treatment-seeking behaviors are limited due to the lack of long-term tracking datasets, interdisciplinary knowledge, and data analytic techniques. More importantly, almost none of the previous studies mentioned treatment-seeking behaviors for bone diseases.

We leverage consecutive records of hospital admissions, i.e., the long-term data of the nationwide bone disease patients who have had surgeries in a prestigious hospital, the Peking University Third Hospital (PUTH), in China, to investigate variation patterns and factors affecting bone disease treatment-seeking behaviors. A series of potential factors are collected to characterize groups of bone patients, geographical conditions, healthcare resources, socio-economic, climate, and environmental conditions. We develop a treatment-seeking index to map bone disease treatment-seeking behaviors and employ advanced geospatial models to estimate the impacts of different categories of factors on treatment-seeking behaviors. Therefore, the primary motivation of the study is to demonstrate the capacity of interdisciplinary knowledge and geospatial data analytic techniques in the assessment and management of treatment-seeking behaviors for bone diseases. Our findings suggest that population migration effectively predicts bone disease treatment-seeking behaviors. The identified hot-spot and cold-spot regions demonstrate the spatially clustered regions that treatment strategies should be improved from stakeholders' perspectives, including patients, the public, hospitals, and healthcare management agencies. We also find that the geographical distance to the PUTH, patient age groups, and regional population density are essential factors affecting bone disease treatment-seeking behaviors. Our findings highlight the importance of large spatial scale mapping of disease treatment-seeking behaviors in health care management.

2. Materials and methods

2.1. Data and pre-processing

2.1.1. Bone disease patients

This study collects consecutive long-term records of the nationwide relatively severe bone disease patients who have had surgeries in the 14 years from 2008 to 2021 in the prestigious hospital, the Peking University Third Hospital (PUTH), in Beijing, China. The bone patients are geocoded for geospatial analysis using their residential addresses. As a result, the dataset consists of 106,411 geocoded bone patients during the 14 years, where 52,229 (49.1 %) bone patients from cities outside Beijing are used for the analysis in this study. In the study, explanatory variables are computed for each patient, and then both patient and explanatory variables data are summarized at a city level.

Table 1
Summary of explanatory variables of bone disease treatment-seeking behaviors.

Category	Variable	Code	Description and unit
Groups of bone patients	Gender	male	Percentage of males
	Age	age	Mean age
	Elders	elder	Percentage of elderly people (aged 60 years or older)
Geography	Distance to PUTH	dputh	Average distance of patients to hospital PUTH (km)
	Distance to cities	dcity	Average distance of patients to the nearest provincial capital city (km)
Healthcare resources	Local hospitals	hcr	Hospitals per million persons
	Distance to local hospitals	dhosp	Average distance of patients to the nearest hospitals (km)
Socio-economic	Economy	gdp	GDP per capita (USD)
	Population	pop	Population density (/km^2)
Climate and environment	Sunshine	solar	Solar radiation: direct normal irradiation (kWh/m^2/day)
	Temperature	temp	Temperature (°C)
	Precipitation	prec	Precipitation (mm/year)

2.1.2. Population migration

The population migration data are computed using the open-access Baidu Mobility Data stored in the Harvard Dataverse (China Data Lab, 2020). The dataset provides daily inflows and outflows of population movement intensity between any cities in China, which are collected from the location-based service by Baidu in terms of the global positioning system (GPS) and a large number of apps on mobile devices (Lai et al., 2020). The Baidu Mobility Data has been applied in diverse research areas, such as COVID-19 research (Hu et al., 2020, Liu et al., 2020, Han et al., 2021), and air pollution exposure and population migration during the Chinese New Year (Shen et al., 2021). Recent studies demonstrate a significant linear relationship between the Baidu Mobility Data and the actual population migration with a coefficient of $k = 3.24 \times 10^{-5}$ (Wang and Yan, 2021). Therefore, in this study, the annual population migration (m) from other Chinese cities to Beijing is calculated as:

$$m = k \bullet h \bullet 365 \quad (1)$$

where h is the average daily inflows of the population movement intensity from other cities to Beijing.

2.1.3. Explanatory variables

The five categories of potential explanatory variables of the treatment-seeking behaviors of bone patients are listed in Table 1. Except for the socio-economic variables, local GDP per capita, and population density, all explanatory variables are computed for each patient and then summarized at a city level. The group of bone patients, including gender, age, and the percentage of older adults, are sourced from the bone disease treatment records in the PUTH. The locations of hospitals are sourced from the Points of Interest (POIs) of the OpenStreetMap (https://planet.openstreetmap.org) and the HealthSites.io projects (https://healthsites.io/map), which include 9360 hospitals across China. The gridded GDP per capita data and population density data are sourced from the Chinese kilometer grid datasets of GDP (Xu, 2017a) and population (Xu, 2017b) spatial distributions, respectively. The solar radiation is measured by the direct normal irradiation, sourced from the World Bank Global Solar Atlas 2.0 dataset with a spatial

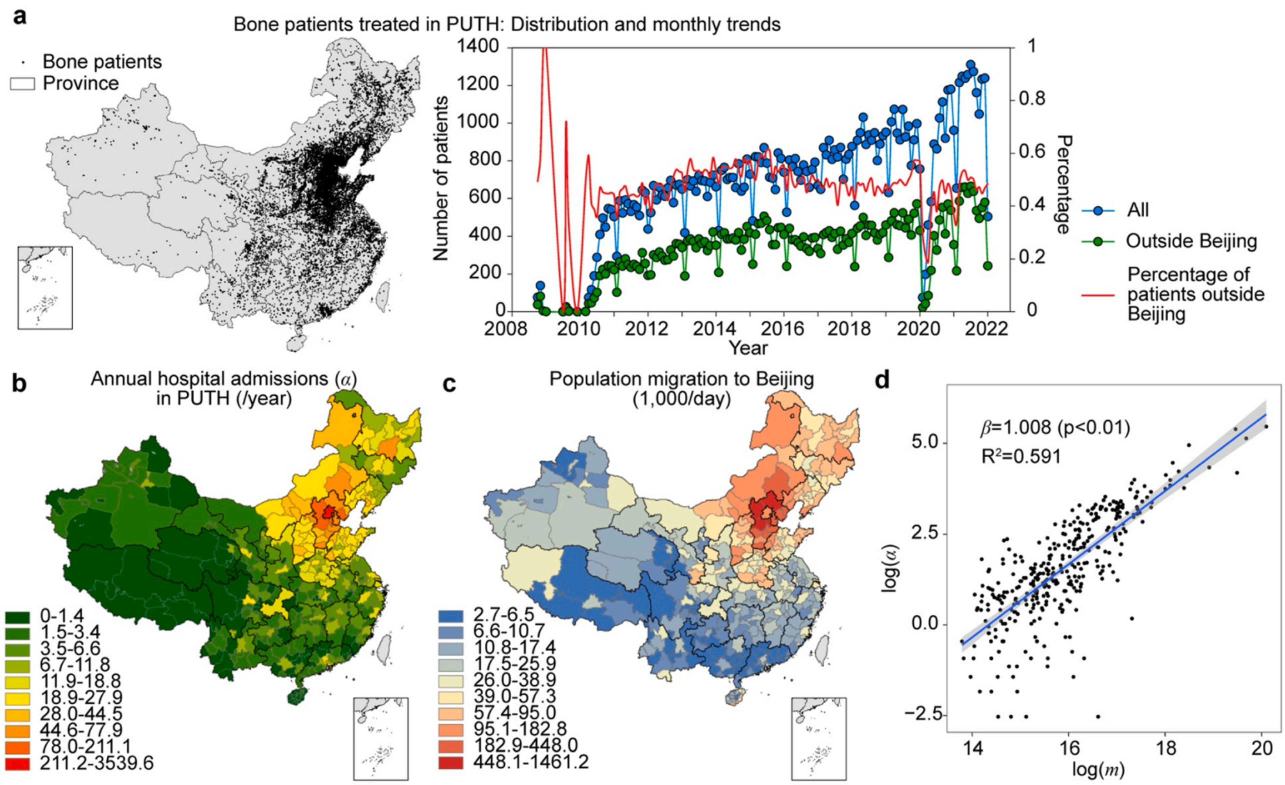

Fig. 1. Bone disease patients treated in the Peking University Third Hospital (PUTH) from 2008 to 2021 and the population migrated to Beijing. a. Spatial distributions and monthly trends of bone disease patients; b. Annual average bone patients (α); c. Population migration to Beijing; and d. Relationship between annual population migration to Beijing (m) and α.

resolution of 250 m (The World Bank, 2020). The datasets of temperature and precipitation used in this study are sourced from the Network Common Data Form (NetCDF) at https://doi.org/10.5281/zenodo.3185722 for temperatures and https://doi.org/10.5281/zenodo.3114194 for precipitation (Peng et al., 2019), respectively.

2.2. Scaling relationships

The scaling relationship between the treatment-seeking behavior of bone patients and population migration is explored to test if patterns of treatment-seeking behaviors are consistent across space. The scaling relationship analysis will provide quantitative evidence that it is reasonable to develop a treatment-seeking behavior index using the patients and population migration data. The relationship between annual bone patients treated in the PUTH (α) and the annual population migration to Beijing (m) is assessed using a power-law scaling function:

$$\alpha(u) = c_0 m(u)^{\beta} \tag{2}$$

where u is a city outside Beijing, c_0 is a normalization constant, and β is the exponent coefficient revealing the scaling relationships between $\alpha(u)$ and $m(u)$.

2.3. Mapping treatment-seeking behavior index

We develop a bone disease treatment-seeking behavior index γ to reveal the spatial disparity, map and analyze treatment-seeking behaviors:

$$\gamma = \frac{\alpha}{m \bullet 10^{-6}} \tag{3}$$

Thus, γ means the treated bone patients in the PUTH per million migration population. The spatial clustering regions, including the hotspots and coldspots, are identified using the local indicators of spatial association (LISA), a geographically local autocorrelation and clusters identification approach (Anselin, 1995). A hotspot city means that the γ values are relatively high in both this city and its surrounding cities, and a coldspot city means that the γ values are relatively low in both this city and its surrounding cities (Ge et al., 2017). The hotspot or coldspot cities at adjacent and close locations are labeled as hotspot or coldspot regions, i.e., hotspots or coldspots (Song et al., 2018, 2021).

2.4. Contributions of geospatial variables

The contributions of individual, regional, and geographically combined variables to γ are calculated using a pioneered geospatial method, the geographically optimal zones-based heterogeneity (GOZH) model (Luo et al., 2022). GOZH is an effective model for exploring geospatial factors and measuring spatial association based on the spatial stratified heterogeneity (Guo et al., 2022, Luo et al., 2022). GOZH describes the spatial association by comparing regional variance values at spatial zones determined by explanatory variables and the variance of data across the whole study area (Wang et al., 2010, 2016, Song et al., 2020, 2021). GOZH has the following advantages in geospatial factor exploration. First, GOZH is a flexible model, and no statistical assumptions are required, which is similar to other spatial stratified heterogeneity-based models, such as the widely used optimal parameters-based geographical detector (OPGD) (Song et al., 2020) and robust geographical detector (RGD) (Zhang et al., 2022) models. In addition, the maximum spatial association is explored through an optimization algorithm that identifies geographically optimal zones with the minimum intra-area variance and the maximum inter-area variance (Luo et al., 2022). Finally, compared with other optimization and machine learning algorithms, GOZH can effectively visualize the entire tree-structure spatial discretization process and geographically optimal zones.

In GOZH, the power of determinants of explanatory variables is

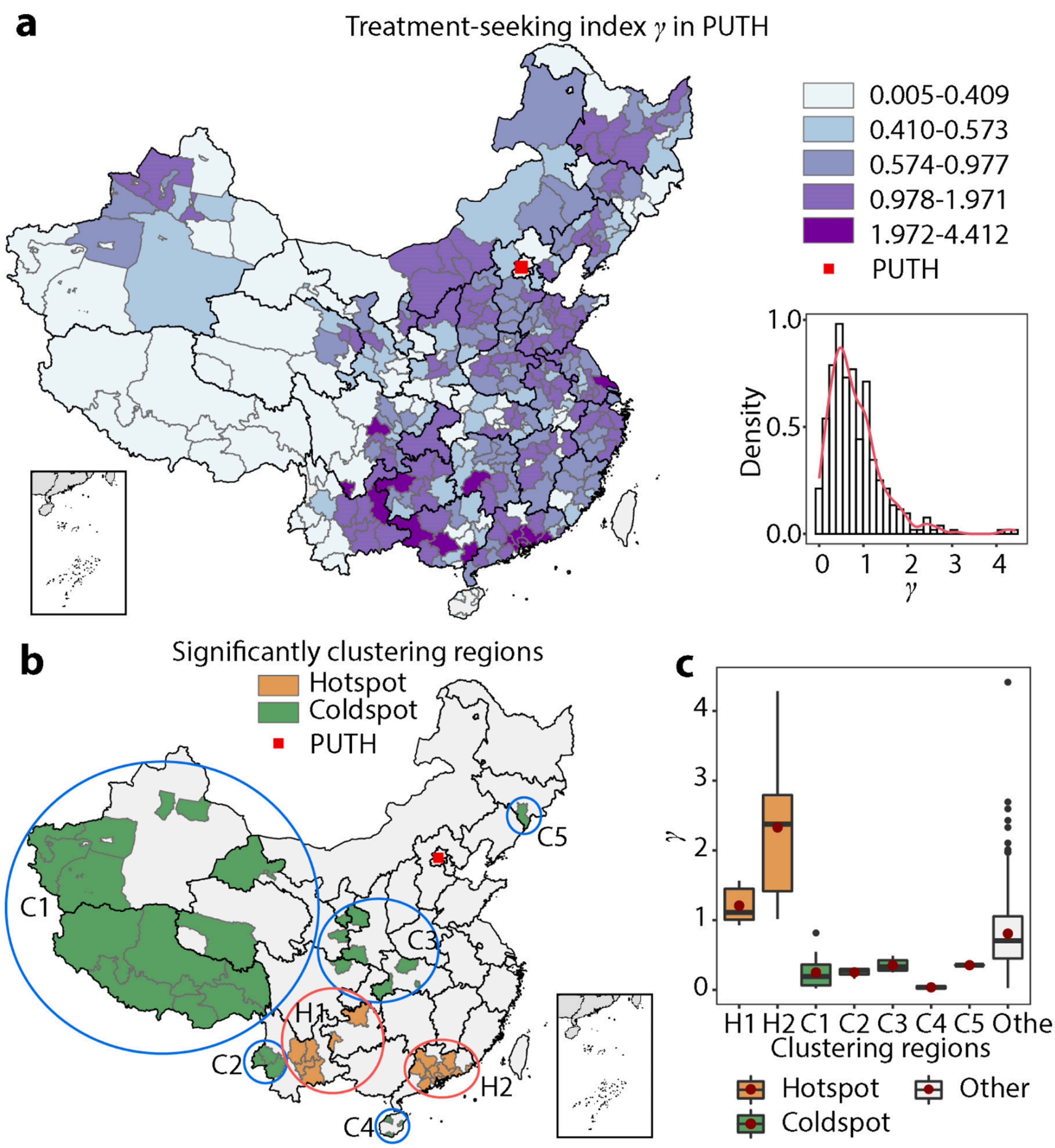

Fig. 2. Spatial distribution of bone disease treatment-seeking index γ in PUTH (a) and identified clustering regions of γ, including hotspots and coldspots (b).

calculated as:

$$\Omega = 1 - \frac{\min\left(\sum_{z=1}^{s} N_z \sigma_z^2\right)}{N\sigma^2} \tag{4}$$

where Ω is the maximum contribution of explanatory variables, $N_z(z = 1, \ldots, s)$ and σ_z are the number and standard deviation of data within a zone z, which is determined by one or multiple spatial explanatory variables, and N and σ are the number and standard deviation of data in the whole study area, respectively. The Ω enables the minimum intra-zone variance and the maximum inter-zone variance, and the optimization process is converted as:

$$min\left(\sum_{z=1}^{s} N_z \sigma_z^2\right) = min\left(\sum_{z=1}^{s} \sum_{j=1}^{N_z} \left(y_{z,j} - \overline{y}_z\right)^2\right) \tag{5}$$

where $y_{z,j}$ is the j th ($j = 1, \ldots, N_z$) observation at the zone z, and $\overline{y}_z$ is the mean of data at the zone z. The detailed optimization process to derive Ω can be found in (Luo et al., 2022). The GOZH is modeled using the R software packages "GD" (Song et al., 2020) and "rpart" (Therneau et al., 2010, Therneau et al., 2015, Milborrow, 2016).

Further, we develop a series of spatial comparison experiments to assess the regional contributions of factors to Ω. In the spatial comparison experiments, the regional contribution of factors to Ω at a hotspot or coldspot region is calculated by comparing Ω values in areas between the combination of hotspot/coldspot and non-hotspot/non-coldspot regions and the hotspot/coldspot region. The calculation equation is:

$$\Delta\Omega = \Omega(\mathrm{A} + \mathrm{B}) - \Omega(\mathrm{B}) \tag{6}$$

where $\Delta\Omega$ is the contribution of factors to Ω at a hotspot or coldspot region A, $\Omega(\mathrm{A} + \mathrm{B})$ is the contribution of factors at the combined region of the non-hotspot and non-coldspot region (region B) and the region A, and $\Omega(\mathrm{B})$ is the contribution of factors at the region B.

3. Results

We analyze bone disease treatment-seeking behaviors using advanced geospatial models and multi-source spatial and remote sensing data. First, we assess the relationship between long-term geocoded bone

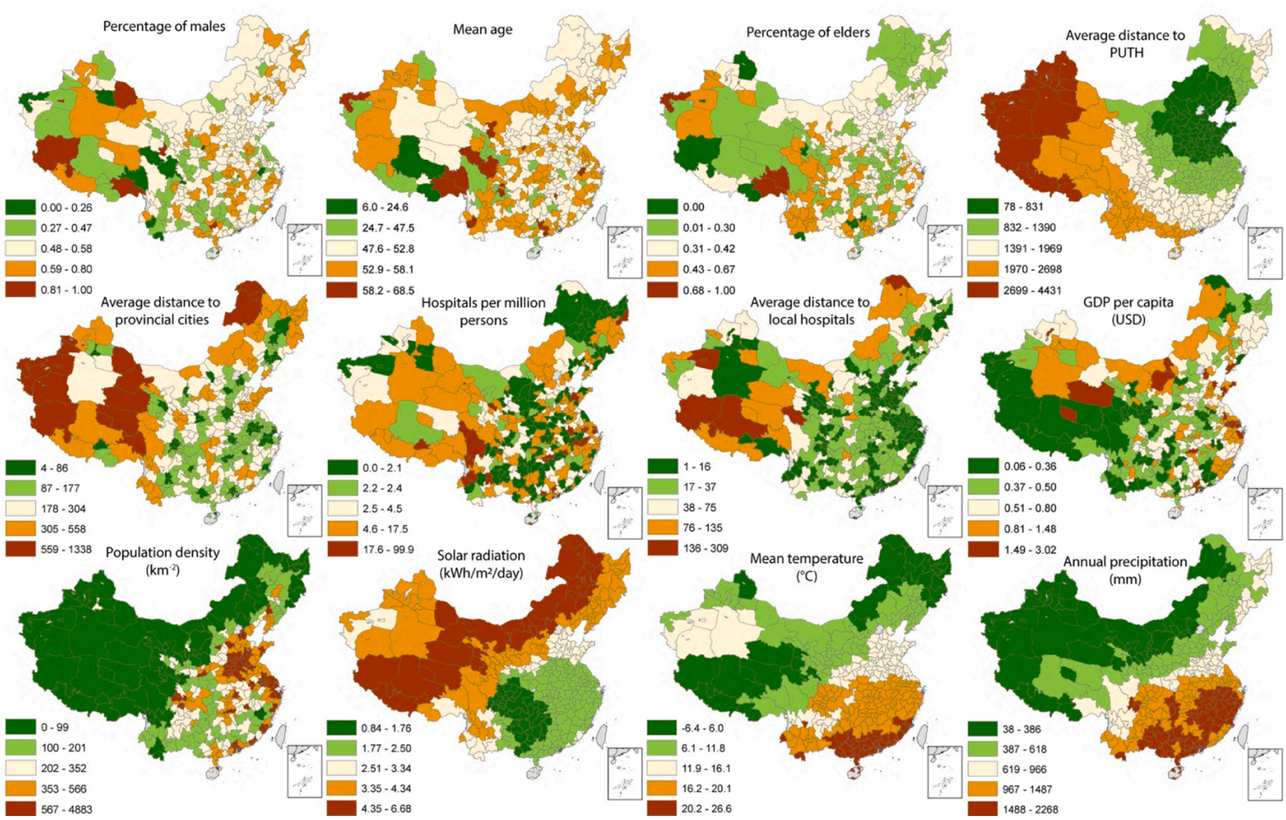

Fig. 3. Maps of explanatory variables of γ computed using geospatial approaches and multi-source spatial big data and Earth observations.

disease patients and population migration. We propose that the population migrated from other cities to Beijing is an effective predictor of the bone patients who travel from other cities to the PUTH in Beijing. Second, we develop a treatment-seeking behavior index using the bone patients and population migration data for mapping and identifying regional hotspots and coldspots of treatment-seeking patients. Finally, we explore the individual, regional, and geographically combined factors affecting the spatial disparities of treatment-seeking behaviors.

3.1. Bone disease patients and population migration

Fig. 1 shows the relationships between bone disease patients treated in the Peking University Third Hospital (PUTH), Beijing, China, from 2008 to 2021, and population migration to Beijing. Fig. 1a provides a descriptive view of the spatial distribution of 106,411 geocoded bone patients treated in the PUTH, including 52,229 (49.1 %) bone patients outside Beijing, and the temporal variations from 2008 to 2021, respectively. Fig. 1b shows the spatial distribution of a city-based summary of annual bone patients (α) of bone patients in the PUTH, showing that α gradually decreases from cities near Beijing to cities far from Beijing. Fig. 1c maps the city-based population migration to Beijing, which shows a similar spatial pattern with the distribution of α. Fig. 1d shows the relationship between annual population migration (m) to Beijing and the annual bone patients in the PUTH, i.e., $\log(\alpha)\ \ \log(m)$. The results show that they are significantly correlated, and the population migration is an effective predictor of the annual bone patients with a coefficient of $\beta = 1.008(p < 0.01)$.

3.2. Mapping treatment-seeking behaviors

Fig. 2a shows the spatial and statistical distributions of γ. The average value of γ is 0.820. The maps demonstrate that the high γ values are primarily distributed in southern and southwestern China, and the low γ values are located in western, central, and northeastern China. To further understand the spatial patterns of γ, the significantly clustering regions, i.e., hotspots where both γ values of a city and surrounding cities are high, and coldspots where both γ values of a city and surrounding cities are low, are identified using spatially local autocorrelation models (Fig. 2b). According to the geographical locations of cities, the clustering regions are divided into two hotspots, consisting of 6 cities in hotspot region 1 (H1) with an average γ of 1.208 and 12 cities in hotspot region 2 (H2) with an average γ of 2.330, and 5 coldspots, accounting for 5.3 % and 8.8 % of all cities in China, respectively. Fig. 2c presents a statistical summary of γ values in the hotspot, cold spots, and other regions, showing that γ in hotspots is much higher than in the different areas, and γ in coldspots is lower than in other areas. This means the identified clustering regions effectively demonstrate regions with relatively high or low γ and spatially clustering characteristics.

3.3. Factors affecting treatment-seeking behaviors

We have collected a series of variables from multi-source datasets, such as satellite remote sensing data and geospatial modeling data, to explore factors affecting γ. Table 1 shows the five categories of potential factor data, including 12 variables of the groups of bone patients, geography, healthcare resources, socio-economic conditions, and local climate and environment. Descriptions and sources of the data are presented in Section 2. Fig. 3 maps the spatial distributions of the 12 variables, which are used to explore the impacts of individual, regional, and geographically combined factors on γ as follows.

3.3.1. Individual factors

Fig. 4a shows the contributions (Ω values) of individual variables to the spatial pattern of γ, where only variables with statistically significant ($p < 0.05$) spatial association with γ are shown in the figure. The distance to the hospital PUTH and local population density have much

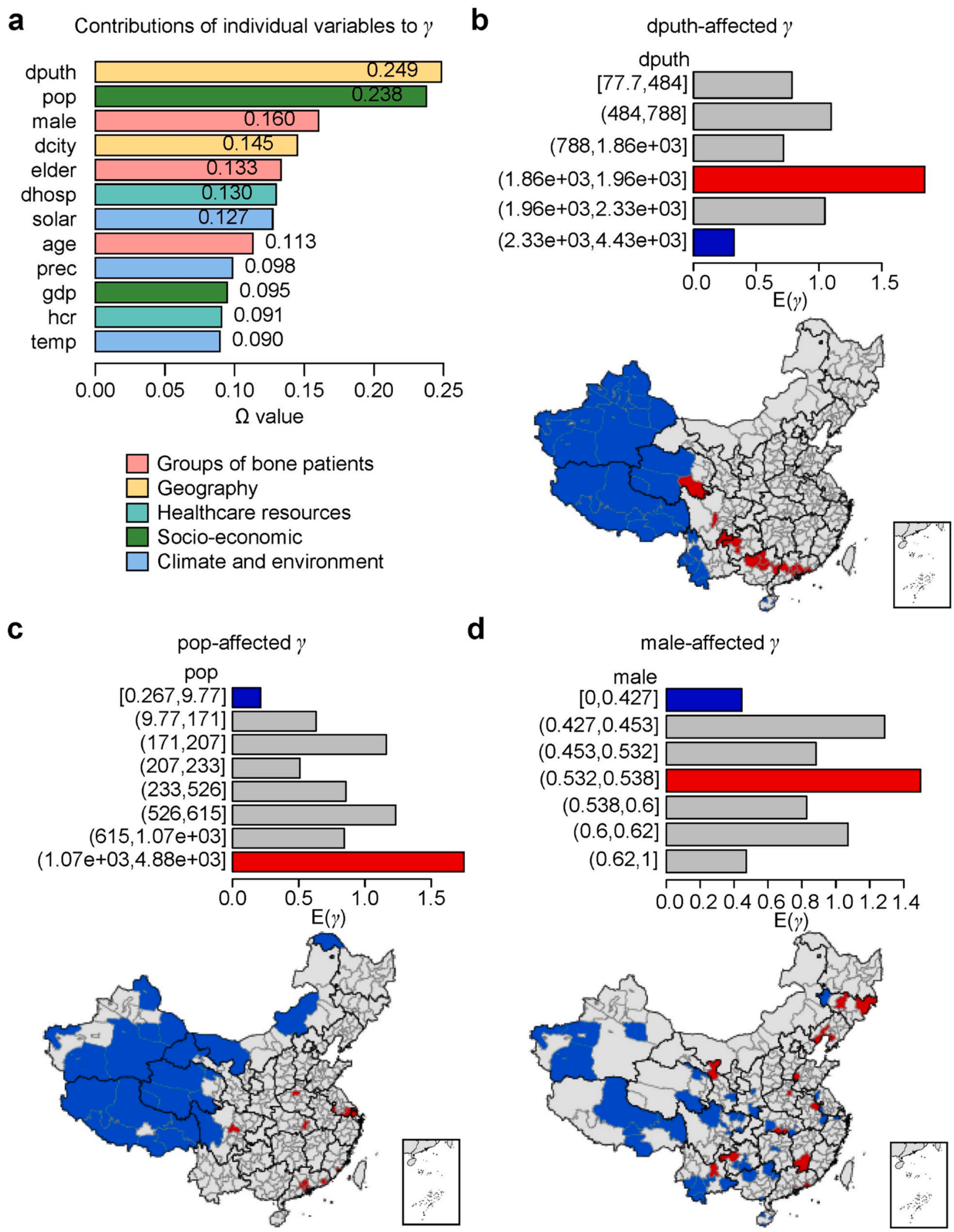

Fig. 4. Contributions (Ω values) of individual variables to the pattern of γ (a), and nonlinear and spatial association between γ and the top three contributors, including distance to PUTH (b), population density (c), and percentage of males (d).

higher contributions to γ than other variables, with Ω values of 0.249 and 0.238, respectively. The following factors that have more than 10 % of contributions in terms of Ω values are the gender of patients (Ω = 0.160), the average distance to the nearest provincial capital cities (Ω = 0.145), percentage of elder patients (Ω = 0.133), the average distance to the nearest hospitals (Ω = 0.130), solar radiation (Ω = 0.127), and mean age of patients (Ω = 0.113).

Fig. 4b–d show the spatial and nonlinear impacts of the top three factors on γ, including the distance to the hospital PUTH, local population density, and gender of patients. Results show that the distance to the hospital PUTH has both significant spatial and nonlinear impacts on γ. Bone patients from cities where the distances between cities and the hospital PUTH range from 1859 km to 1960 km have the highest treatment-seeking behavior index, which is defined as the high-γ regions related to the distance to the PUTH. The locations of the distance to the PUTH-related high γ regions are generally consistent with the hotspots identified in Fig. 2b. When the distance is lower than 1859 km or higher than 1960 km, the treatment-seeking behavior index γ is

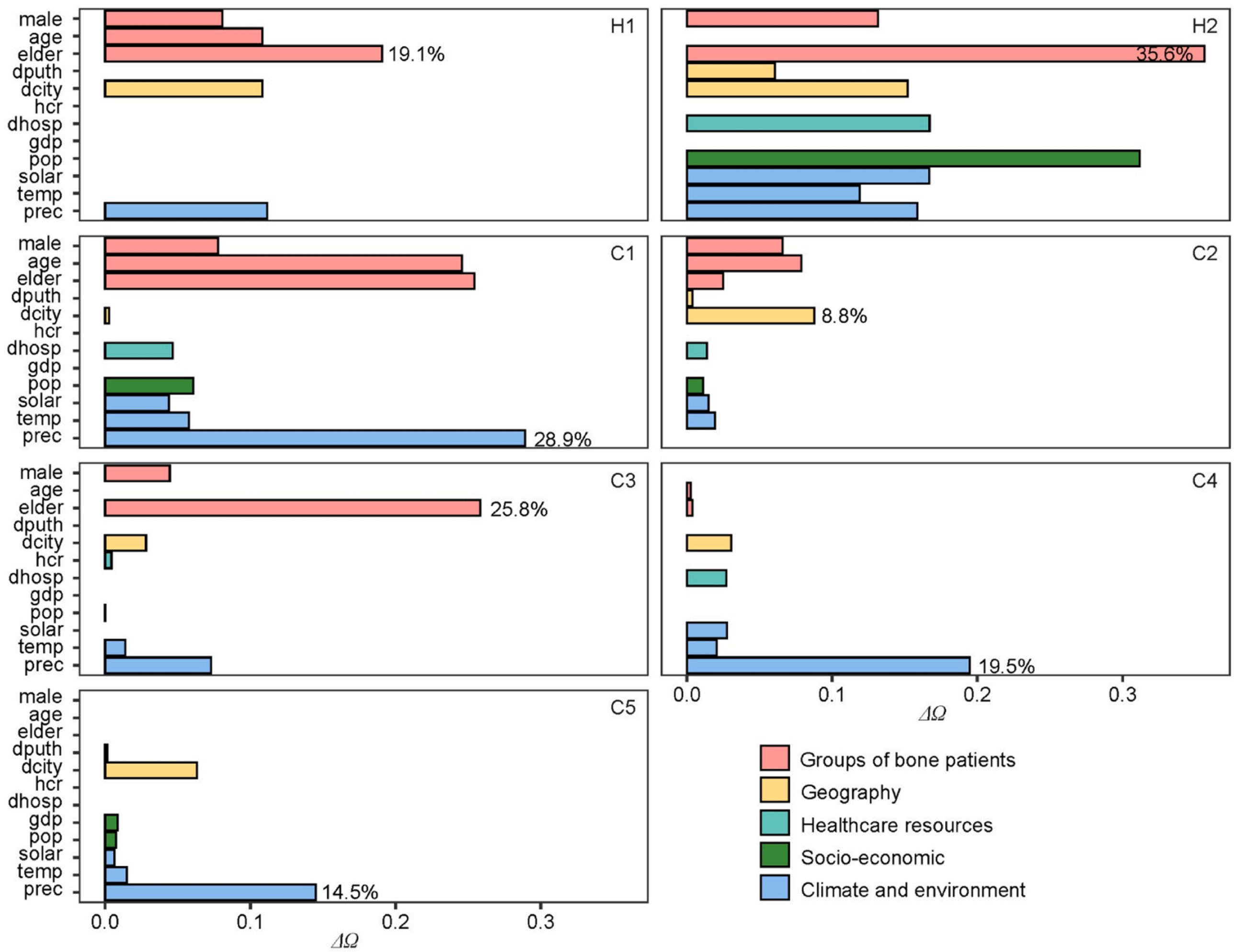

Fig. 5. Regional contributions (ΔΩ) of factors to the pattern of γ in the hotspot (H1 and H2) and coldspot (C1, C2, C3, C4, and C5) regions.

much lower than the distance to the PUTH-related high- γ regions. When the distance is longer than 2327 km, patients have the lowest treatment-seeking behavior in terms of γ.

In addition, results show that γ is generally linearly increased with local population density. Bone patients from cities with a population density higher than 1073/km^2 have the highest γ. In the population density-related high-γ regions, the available healthcare resources may be higher than in other areas. Still, they are not enough to treat many patients, especially for bone patients, which requires professional doctors, devices, and medicine. The relatively tight medical resources in densely populated cities cause more bone patients to seek treatment at the hospital PUTH, one of the most prestigious hospitals for bone disease treatment in China. The gender of bone patients, measured by the percentage of males among patients, also has a nonlinear impact on γ. When the percentage of male patients is similar to the percentage of female patients, i.e., the rate of male patients is between 53.2 % and 53.8 %, bone patients have the highest γ. When the gender of local bone patients is unbalanced, i.e., the percentage of male patients is much lower or higher than the percentage of female patients, the γ is very low.

3.3.2. Regional factors

Fig. 5 shows the results of the spatial comparison experiments to assess regional contributions of factors to γ. Results show that the primary factors in hotspot regions tend to be similar, but they are varied in coldspot regions. The inconsistency of the regional factors may be related to the number and prevalence of bone patients, their regional varied human mobility patterns, and regional environmental and socio-economic factors. In the two hotspot regions, H1 and H2, the percentage of elderly patients is the primary factor of γ with contributions of 19.1 % and 35.6 %, respectively. Therefore, it is essential to pay more attention to the elderly bone patients in the hotspots to improve their treatment-seeking behavior. In the coldspots, precipitation is the primary factor of γ in three coldspot regions, including C1, C4, and C5, where the contributions of precipitation are 28.9 %, 19.5 %, and 14.5 %, respectively. Precipitation is probably related to bone patients' incidence and bone disease treatment-seeking behavior in the coldspots. In coldspot *C*2, the distance to the nearest provincial capital cities is the primary factor contributing 8.8 %. In coldspot C3, the percentage of elderly patients is the primary factor contributing to 25.8 %.

3.3.3. Geographically combined factors

Fig. 6 shows the structure and spatial distribution of the total contribution of all geographically combined factors. The structure of combined factors (Fig. 6a) indicates that the overall γ is related to eight factors, meaning that factors are spatially overlapped in affecting γ. Fig. 6b shows that the geographically combined factors-related high-γ regions include southern, southwestern, and eastern China. The geographically combined factors-related low- γ regions are primarily located in western China. From a spatial perspective, the overall contribution of all combined factors is 39.1 %. The contribution also indicates the complexity of assessing the nationwide bone disease patient treatment-seeking behaviors. The combined variable of geography has the highest contribution (30.2 %) among the five categories of combined variables, followed by groups of bone patients, socio-

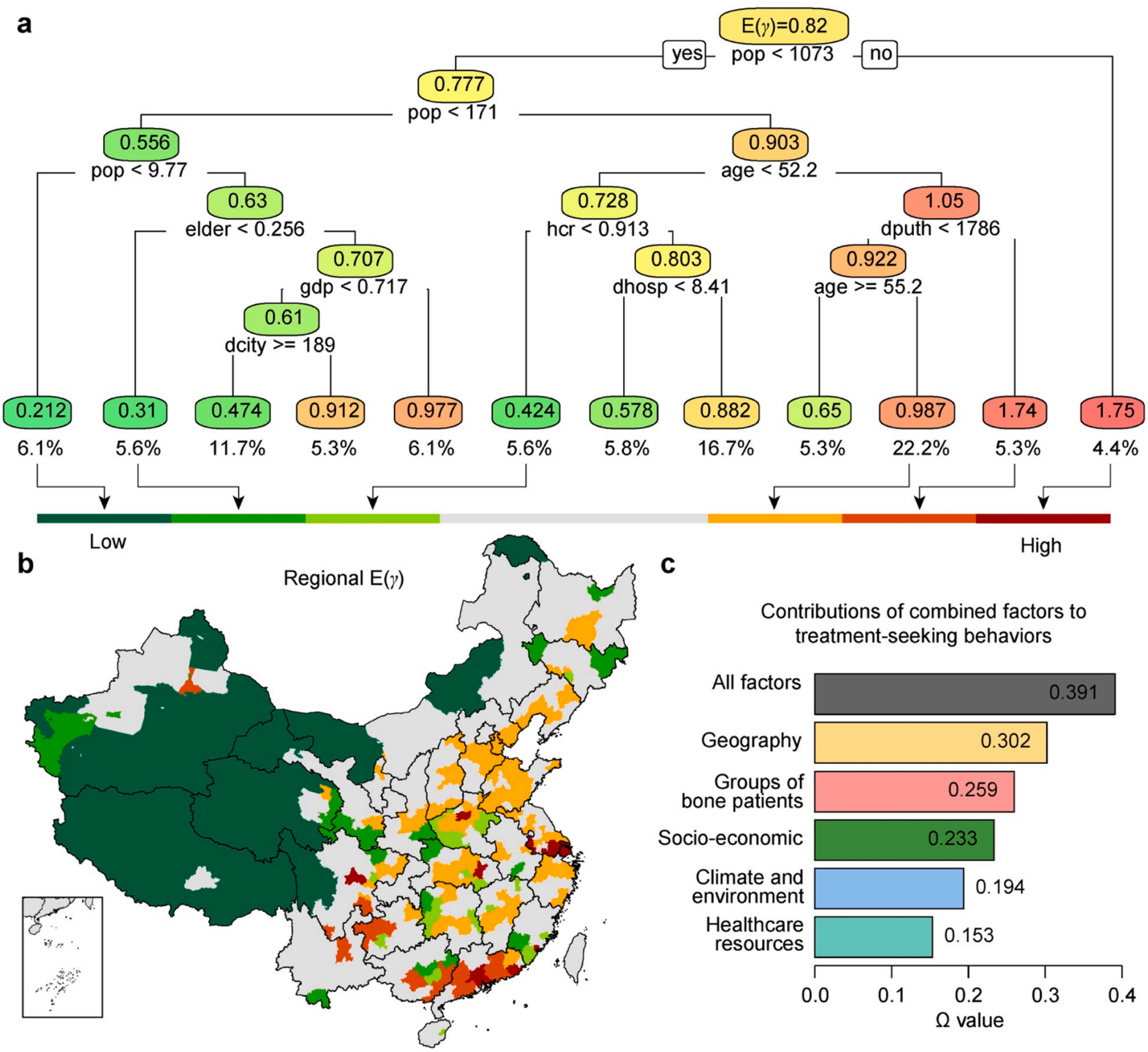

Fig. 6. Geographically combined impacts of factors affecting γ. a. Nonlinearly combined impacts of factors; b. Distributions of regions with relatively high and low γ values affected by combined factors; and c. Contributions of different categories of combined factors.

economic factors, climate and environment, and local healthcare resources, which contributes 25.9 %, 23.3 %, 19.4 %, and 15.3 %, respectively, to γ.

4. Discussion

4.1. Findings of bone disease treatment-seeking behaviors

Factors affecting the treatment-seeking behaviors of bone patients are complex. The primary potential factors may include the incidence of bone patients, gender and age components of patients, tight or loose medical resources, and the patients' accessibility to health care resources, especially professional bone treatment resources. In this study, five categories of variables are collected from remote sensing and big spatial data to characterize the potential factors affecting the treatment-seeking behaviors of bone patients. The five categories of variables can effectively describe bone patients' gender and age characteristics, local healthcare resources and socio-economic conditions, patients' accessibility to hospitals, and climate and environmental conditions that may influence the incidence of bone patients and patients' travel to hospitals.

This study has the following findings. First, from a spatial perspective, population migration is an effective predictor of treatment-seeking behaviors of bone patients. The distance to the admission hospital, i.e., the PUTH in this study, and local population density are primary factors affecting treatment-seeking behaviors. Second, significant regional disparities are found in the treatment-seeking behaviors of bone patients. The regional disparities are assessed by identifying hotspots and coldspots and regionally varied factors affecting treatment-seeking behaviors. Finally, treatment-seeking behaviors of bone patients are complex in a nationwide and large-scale study and consist of relatively high uncertainty, as the overall contribution of the collected five categories of variables is 39.1 %. The treatment-seeking behaviors are closely associated with multiple variables, and the variables affect the treatment-seeking behaviors through a geospatial overlapped and combined approach.

4.2. Contributions to academics and management

This study provides a new paradigm for understanding bone disease treatment-seeking behaviors using consecutive long-term hospital admissions data, remote sensing, spatial big data, and advanced geospatial models. The approaches of developing geospatial models and implementing remote sensing and spatial big data in this study have the potential to address issues of treatment-seeking behaviors for both bone diseases and other health studies. In addition, findings from this study provide solid and quantitative evidence for both previous and future policies and actions for addressing the regional inequality of bone disease treatment-seeking behaviors.

On one hand, spatial patterns and factors of bone disease treatment-seeking behaviors examined in the study demonstrate that locations of previous medical aid programs of bone diseases are generally consistent with the regions with high requirements. For instance, the Chinese government has initiated policies since the 1990 s to support hospitals and doctors from developed regions to develop medical aid programs to treat patients in undeveloped areas, such as the Medical Aid Xinjiang Program launched in 1997 and the Medical Aid Tibet Program launched in 2015 (National Health Commission of the People's Republic of China, 2015, 2016a, 2016b, 2018). In the last two decades, the bone doctors team from the PUTH stayed in the undeveloped western regions have been to many undeveloped areas, such as Qinghai, Xinjiang, Inner Mongolia, and Tibet, to treat bone patients, including congenital spinal disorders, Kashin-Beck disease, spinal deformities, Lumbar disc herniation, etc. (National Health Commission of the People's Republic of China, 2009, 2014, 2016a, 2016b). On the other hand, according to the findings of this study, more reasonable medical aid programs can be developed in the future, i.e., different assistant approaches, policies, actions, and budget allocations should be designed for various regions and diverse groups of patients, such as the hotspot regions and elder groups of patients identified in the study.

4.3. Limitations and future recommendations

There are still limitations in this study, and future studies are recommended in the following aspects in terms of the new paradigm for understanding treatment-seeking behaviors and findings. First, spatial and temporal analysis of treatment-seeking behaviors is recommended to explore temporal variations and inform changes in spatial characteristics. Second, a specific type of bone disease may be analyzed in future studies, such as spinal deformities or Lumbar disc herniation. Third, data on individual patients' income or economic conditions might be collected to investigate the relationships between treatment-seeking behaviors and patients' income. In this study, city-wide average GDP per capita is used to describe the local economic conditions, which may not be entirely consistent with the economic conditions of individual patients due to the inequality of economic conditions within cities. Finally, the developed new paradigm of using remote sensing and spatial big data, and advanced geospatial models for investigating treatment-seeking behaviors can be implemented in studies of other diseases and health issues.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (No. 81972103).

References

Adhikari, B., Phommasone, K., Pongvongsa, T., Koummarasy, P., Soundala, X., Henriques, G., Sirithiranont, P., Parker, D.M., von Seidlein, L., White, N.J., 2019. Treatment-seeking behaviour for febrile illnesses and its implications for malaria control and elimination in Savannakhet Province, Lao PDR (Laos): a mixed method study. BMC Health Serv. Res. 19 (1), 1–16.

Alegana, V.A., Wright, J., Pezzulo, C., Tatem, A.J., Atkinson, P.M., 2017. Treatment-seeking behaviour in low-and middle-income countries estimated using a Bayesian model. BMC Med. Res. Method. 17 (1), 1–12.

Alegana, V.A., Maina, J., Ouma, P.O., Macharia, P.M., Wright, J., Atkinson, P.M., Okiro, E.A., Snow, R.W., Tatem, A.J., 2018. National and sub-national variation in patterns of febrile case management in sub-Saharan Africa. Nat. Commun. 9 (1), 1–7.

Anselin, L., 1995. Local indicators of spatial association—LISA. Geographical analysis 27 (2), 93–115.

China Data Lab, 2020. Baidu Mobility Data.

Chong, C., Fong, L., Lai, R., Lau, W.K.O., Hartmann, M., Chia, S.E., 2012. The prevalence of lower urinary tract symptoms and treatment-seeking behaviour in males over 40 years in Singapore: a community-based study. Prost. Cancer Prostat. Dis. 15 (3), 273–277.

Das, M., Angeli, F., Krumeich, A.J., van Schayck, O.C., 2018. The gendered experience with respect to health-seeking behaviour in an urban slum of Kolkata, India. Int. J. Equity Health 17 (1), 1–14.

Ge, Y., Song, Y., Wang, J., Liu, W., Ren, Z., Peng, J., Lu, B., 2017. Geographically weighted regression-based determinants of malaria incidences in northern China. Trans. GIS 21 (5), 934–953.

Ghosh, S., 2004. Gender differences in treatment-seeking behaviour during common childhood illnesses in India: Does maternal education matter? In: 18th European Conference on Modern South Asian Studies University of Lund, Sweden.

Guo, J., Wang, J., Xu, C., Song, Y., 2022. Modeling of spatial stratified heterogeneity. GISci. Rem. Sens. 59 (1), 1660–1677.

Han, X., Xu, Y., Fan, L., Huang, Y., Xu, M., Gao, S., 2021. Quantifying COVID-19 importation risk in a dynamic network of domestic cities and international countries. Proc. Natl. Acad. Sci. 118(31).

Hu, T., Guan, W.W., Zhu, X., Shao, Y., Liu, L., Du, J., Liu, H., Zhou, H., Wang, J., She, B., 2020. Building an open resources repository for COVID-19 research. Data Inform. Manage. 4 (3), 130–147.

Jowett, M., Deolalikar, A., Martinsson, P., 2004. Health insurance and treatment seeking behaviour: evidence from a low-income country. Health Econ. 13 (9), 845–857.

Kane, J.C., Elafros, M.A., Murray, S.M., Mitchell, E.M.H., Augustinavicius, J.L., Causevic, S., Baral, S.D., 2019. A scoping review of health-related stigma outcomes for high-burden diseases in low-and middle-income countries. BMC Med. 17 (1), 1–40.

Kenangalem, E., Poespoprodjo, J.R., Douglas, N.M., Burdam, F.H., Gdeumana, K., Chalfein, F., Thio, F., Devine, A., Marfurt, J., Waramori, G., 2019. Malaria morbidity and mortality following introduction of a universal policy of artemisinin-based treatment for malaria in Papua, Indonesia: a longitudinal surveillance study. PLoS Med. 16 (5), e1002815.

Lai, S., Bogoch, I.I, Ruktanonchai, N.W., Watts, A., Lu, X., Yang, W., Yu, H., Khan, K., Tatem, A.J., 2020. Assessing Spread Risk of Wuhan Novel Coronavirus Within and Beyond China, January–April 2020: A Travel Network-based Modelling Study. MedRxiv.

Liu, D., Clemente, L., Poirier, C., Ding, X., Chinazzi, M., Davis, J.T., Vespignani, A., Santillana, M., 2020. A Machine Learning Methodology for Real-time Forecasting of the 2019–2020 COVID-19 Outbreak Using Internet Searches, News Alerts, and Estimates from Mechanistic Models. arXiv preprint arXiv:2004.04019.

Luo, P., Song, Y., Huang, X., Ma, H., Liu, J., Yao, Y., Meng, L., 2022. Identifying determinants of spatio-temporal disparities in soil moisture of the Northern Hemisphere using a geographically optimal zones-based heterogeneity model. ISPRS J. Photogramm. Rem. Sens. 185, 111–128.

Milborrow, S., 2016. Plotting rpart trees with the rpart. plot package. Search in.

National Health Commission of the People's Republic of China, 2009. Beijing-Inner Mongolia Autonomous Region Medical Counterpart Aid Program.

National Health Commission of the People's Republic of China, 2014. The Four Key Tasks of Counterpart Support for Urban and Rural Hospitals.

National Health Commission of the People's Republic of China, 2015. The Initial Work of the First Batch of the Medical Aid Tibet Program Teams from Beijing.

National Health Commission of the People's Republic of China, 2016. Medical Aid Tibet Program: The Counterpart Relationship between Recipient Hospitals and Support Provinces and Cities.

National Health Commission of the People's Republic of China, 2016. A Series of Reports on the Bone Disease Aid Activities of the Peking University Third Hospital.

National Health Commission of the People's Republic of China, 2018. Briefs on the Medical Aid Xinjiang and Tibet Programs, 2015–2018.

Peng, S., Ding, Y., Liu, W., Li, Z., 2019. 1 km monthly temperature and precipitation dataset for China from 1901 to 2017. Earth Syst. Sci. Data 11 (4), 1931–1946.

Ruebush, T.K., Kern, M.K., Campbell, C.C., Oloo, A.J., 1995. Self-treatment of malaria in a rural area of western Kenya. Bull. World Health Org. 73 (2), 229.

Shen, H., Shen, G., Chen, Y., Russell, A.G., Hu, Y., Duan, X., Meng, W., Xu, Y., Yun, X., Lyu, B., 2021. Increased air pollution exposure among the Chinese population during the national quarantine in 2020. Nat. Human Behav. 5 (2), 239–246.

Song, Y., 2022. Geographically optimal similarity. Math. Geosci. 1–26.

Song, Y., Long, Y., Wu, P., Wang, X., 2018. Are all cities with similar urban form or not? Redefining cities with ubiquitous points of interest and evaluating them with indicators at city and block levels in China. Int. J. Geogr. Inf. Sci. 32 (12), 2447–2476.

Song, Y., Wang, J., Ge, Y., Xu, C., 2020. An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: cases with different types of spatial data. GISci. Rem. Sens. 57 (5), 593–610.

Song, Y., Wu, P., 2021. An interactive detector for spatial associations. Int. J. Geogr. Inf. Sci. 35 (8), 1676–1701.

Song, Y., Wu, P., Hampson, K., Anumba, C., 2021. Assessing block-level sustainable transport infrastructure development using a spatial trade-off relation model. Int. J. Appl. Earth Observ. Geoinf. 105, 102585.

Srivastava, S., Sulaiman, K.M., Drishti, D., Muhammad, T., 2021. Factors associated with psychiatric disorders and treatment seeking behaviour among older adults in India. Sci. Rep. 11 (1), 1–13.

Tanner, M., Vlassoff, C., 1998. Treatment-seeking behaviour for malaria: a typology based on endemicity and gender. Soc. Sci. Med. 46 (4–5), 523–532.

The World Bank, 2020. Global Solar Atlas 2.0.

Therneau, T.M., Atkinson, B., Ripley, M.B., 2010. The rpart package. R Foundation for Statistical Computing, Oxford, UK.

Therneau, T., Atkinson, B., Ripley, B., Ripley, M.B., 2015. Package ‘rpart’. Available online: cran. ma. ic. ac. uk/web/packages/rpart/rpart. pdf (accessed on 20 April 2016).

Wang, J.-F., Li, X.-H., Christakos, G., Liao, Y.-L., Zhang, T., Gu, X., Zheng, X.-Y., 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China. Int. J. Geogr. Inf. Sci. 24 (1), 107–127.

Wang, C., Yan, J., 2021. An inversion of the constitution of the Baidu migration scale index. J. Univ. Electron. Sci. Technol. China 50 (4), 616–626.

Wang, J.-F., Zhang, T.-L., Fu, B.-J., 2016. A measure of spatial stratified heterogeneity. Ecol. Ind. 67, 250–256.

Wangroongsarb, P., Satimai, W., Khamsiriwatchara, A., Thwing, J., Eliades, J.M., Kaewkungwal, J., Delacollette, C., 2011. Respondent-driven sampling on the Thailand-Cambodia border. II. Knowledge, perception, practice and treatment-seeking behaviour of migrants in malaria endemic zones. Malaria J. 10 (1), 1–12.

Willcox, M.L., Kumbakumba, E., Diallo, D., Mubangizi, V., Kirabira, P., Nakaggwa, F., Mutahunga, B., 2018. Circumstances of child deaths in Mali and Uganda: a community-based confidential enquiry. Lancet Glob. Health 6 (6), e691–e702.

Xu, X., 2017. The Chinese Kilometer Grid Dataset of GDP Spatial Distributions.

Xu, X., 2017. The Chinese Kilometer Grid Dataset of Population Spatial Distributions.

Zhang, Z., Song, Y., Wu, P., 2022. Robust geographical detector. Int. J. Appl. Earth Observ. Geoinf. 109, 102782.