

Article

Integrating Spatial and Non-Spatial Dimensions to Evaluate Access to Rural Primary Healthcare Service: A Case Study of Songzi, China

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Abstract: Access to rural primary healthcare services has been broadly studied in the past few decades. However, most earlier studies that focused on examining access to rural healthcare services have conventionally treated spatial and non-spatial access as separate factors. This research aims to measure access to primary healthcare services in rural areas with the consideration of both spatial and non-spatial dimensions. The methodology of study is threefold. First, the Gaussian two-step floating catchment area (G-2SFCA) method was adopted to measure spatial access to primary healthcare services. Then, a questionnaire survey was conducted to investigate non-spatial access factors, including demographic condition, patient's household income, healthcare insurance, education level, and patient satisfaction level with the services. After that, a comprehensive evaluation index system was employed to integrate both spatial and non-spatial access. The empirical study showed a remarkable disparity in spatial access to primary healthcare services. In total, 78 villages with 185,137 local people had a "low" or "very low" level of spatial access to both clinics and hospitals. For the non-spatial dimension, the results depicted that Songzi had significant inequalities in socioeconomic status (e.g., income, education) and patient satisfaction level for medical service. When integrating both spatial and non-spatial factors, the disadvantaged areas were mainly located in the eastern and middle parts. In addition, this study found that comprehensively considering the spatial and non-spatial access had a significant impact on results in healthcare access. In conclusion, this study calls for policymakers to pay more attention to primary healthcare inequalities within rural areas. The spatial and non-spatial access should be considered comprehensively when the long-term rural medical support policy is designated.

Keywords: spatial access; non-spatial factors; primary healthcare; rural areas; GIS



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1. Background

Primary healthcare services provide the initial point of contact for individuals seeking healthcare and are focused on preventing illness, promoting health, and offering professional care for common health problems. These services are typically provided by various facilities, such as clinics, and general hospitals. Accessible primary healthcare services are essential to high-quality services and better health outcomes [1]. Numerous studies have consistently shown that rural primary healthcare services are comparatively less accessible when compared to those in other areas [2,3]. Therefore, enhancing comprehension of access to primary healthcare services in rural areas can aid healthcare planners and decision makers in improving health resource deployment and service efficiency in rural areas.

As a multi-dimensional concept, access to healthcare services has been extensively explored by scholars across various disciplines, such as geography, public policy, and sociology [4–6]. From a spatial perspective, access to healthcare can be differentiated between spatial and non-spatial access, where the former mainly concentrates on spatial/geographic costs (e.g., distance or travel time) between healthcare providers and patients [7]. The latter emphasizes non-geographical characteristics such as demographic factors, socioeconomic status, patients' satisfaction level or healthcare insurance that can influence the ease of acquiring healthcare services [8]. Based on the utilization perspective, access can be classified as potential and revealed access, where the former represents the opportunity to reach the service provider but does not guarantee that patients can use the service immediately. The latter emphasizes when patients can actually use such services [9].

Various studies have confirmed that spatial and non-spatial access are both critical to evaluating the quality of healthcare services. On the one hand, spatial access affects health outcomes by influencing the ability of individuals to quickly reach appropriate healthcare facilities and utilize medical resources. Thus, it plays a critical role in determining whether people can reach healthcare services when they need it, ultimately impacting their health status and well-being. For example, Wang [10] indicated that better spatial access to primary healthcare remarkably decreased the potential risk of late diagnosis for breast cancer patients living outside Chicago, IL, USA, and they suggested that good spatial distribution of primary care resources is essential to prevent breast cancer.

Non-spatial access also plays a vital role in affecting whether patients can effectively access the healthcare services they need, often influenced by differences in demographic and socioeconomic characteristics [11–13]. Wan et al. [14] found that demographic factors such as disadvantaged population groups rather than spatial access had an increased risk of colorectal cancer mortality. Similarly, socioeconomic disadvantages (e.g., poverty, poor education and low insurance levels) influence an individual's ability to afford and effectively navigate the healthcare system. Wang and Luo [8] grouped those demographic and socioeconomic factors that affected healthcare access into three categories, including socioeconomic disadvantages, high healthcare needs and sociocultural barriers. In addition to objective factors linked to demographic and socioeconomic dimensions, patients' subjective perceptions, such as their satisfaction with the services, constitute a crucial factor in evaluating healthcare access [15,16].

During the last few decades, various methods have been developed to evaluate access to health services. Three types of methods are frequently implemented, including proximity-based measures, provider-to-population ratios (PPRs) and gravity-based models. The proximity-based measures focus on the distance or travel time between a patient's location and their facility, which has been widely used in the healthcare field [17]. PPRs are always estimated by aggregated data within geographic/spatial scales such as catchment areas of healthcare services or administrative boundaries. Gravity-based models integrate the above measures with the consideration of potential interactions between healthcare demands and providers, which often incorporates with a distance decay function. The most popular gravity-based models are the two-step floating catchment area (2SFCA) [9] and its improved version named the Gaussian-based 2SFCA (G-2SFCA) [18]. Among those methods, the 2SFCA and G-2SFCA are comparatively more widely used in the healthcare field because the availability of medical resources and geographical costs are the two essential issues that healthcare planners face [19].

Geography should not be limited to spatial thinking alone, but should pay more attention to the trend of combining geography with social and political processes [20], reflecting on the association with social phenomena, going beyond simple descriptions and explanations of the spatial nature of social phenomena, and incorporating them into normative evaluation dimensions [21]. One limitation is that spatial and non-spatial access are always considered separately among the relevant studies [6,22,23], though many studies have indicated that both aspects can influence an individual's ability to afford and effectively navigate the healthcare system [16]. Few efforts have tried to consider both

dimensions of healthcare access, and non-spatial factors are frequently intertwined with secondary data on local demographic factors such as age, race, and gender [8,14], as well as local socioeconomic characteristics [11,13]. However, first-hand data about patients' household incomes, insurance, education levels and satisfaction levels with medical services are always ignored by current studies, which makes it difficult to yield valuable insights into the healthcare seeking process and help to uncover subtle disparities within healthcare systems [15]. Thus, one contribution of this study is to measure primary healthcare access involving both spatial and non-spatial dimensions, with the consideration of first-hand data about rural patients, to gain a more profound understanding of access to the primary healthcare system.

Another limitation is that inequalities in primary healthcare access inside of rural areas are rarely studied, even if such problems are widespread globally. Existing scholars often investigate such inequalities from national [24,25], regional [26], municipal [27,28] or individual [23] levels, identifying areas with insufficient healthcare services and proposing policy implications for future healthcare planning. After continuous efforts by governments and decision makers, some studies have found varying degrees of alleviation in healthcare access disparities, especially between urban and rural areas [29]. However, inequalities in healthcare access inside of rural areas have received little attention. This may lead to increasing healthcare inequalities inside rural areas, even though urban–rural fairness has improved. Although Agbenyo et al. [30] focused on spatial access to healthcare in rural areas, non-spatial factors were ignored. Therefore, another contribution of this study is to fill this gap by investigating the extent of inequalities in access to primary healthcare services within rural areas, providing decision making support for policymakers to reach the goal of healthcare equalization.

This study investigates potential access to rural primary healthcare services by integrating spatial and non-spatial factors. The case study area, Songzi, is a rural area of Jingzhou City, Hubei, China. In detail, the aim of this research is threefold: (1) measure spatial access to the healthcare system based on the G-2SFCA method; (2) use a questionnaire survey to obtain data related to non-spatial access, including demographic, socio-economic characters, and patients' level of satisfaction with medical services; (3) evaluate access to rural primary healthcare services by integrating both spatial and non-spatial factors. Songzi's economic and social development is at the middle position of rural China, exhibiting a more universal character comparable to those of well-developed rural areas. Understanding the healthcare challenges faced by Songzi can contribute to helping address similar rural issues encountered in China and other developing countries worldwide.

This paper is structured as shown in Figure 1. The next section introduces methods of measuring access to healthcare services, mainly including the G-2SFCA and the entropy weight method. The empirical results related to spatial and integrated access are presented and described in Section 3. Section 4 discusses the significant findings of this study and the policy implications, concluding with the existing limitations of this research and further study.

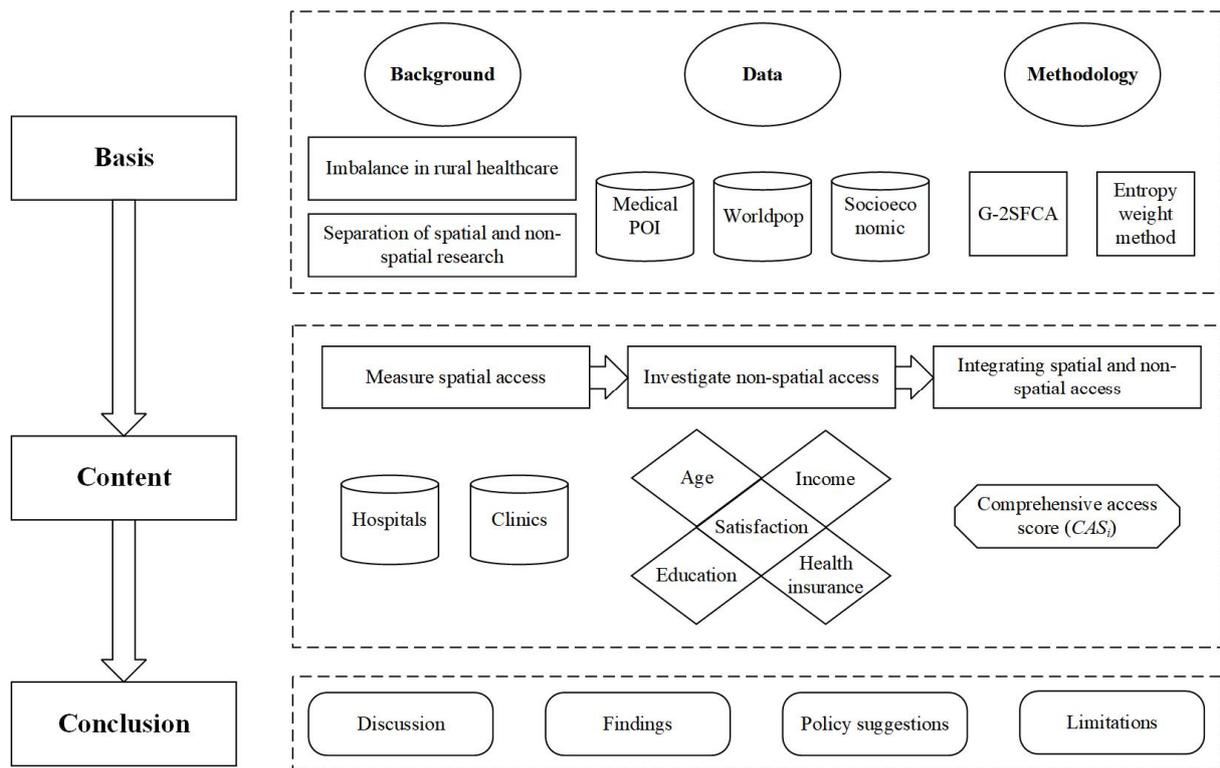


Figure 1. The framework of this study.

2. Materials and Methods

2.1. Study Area and Data

The study area, Songzi, is located in the southwest of Hubei Province, China ($110^{\circ}14'$ – $112^{\circ}03'$ E to $29^{\circ}53'$ – $30^{\circ}22'$ N). Songzi is the rural area of Jingzhou city, and the transition area from Jiangnan plain to Western Hubei Mountain, covering an area of 2177 km² with a population of 0.64 million at the start of 2022 [31]. Songzi has an important geographical location, located at the intersection of Jiaoliu Railway and Yangtze River, with convenient transportation. The terrain of Songzi is dominated by hills and plains, accounting for 59.5% and 37.7% of the total area, respectively. The economy of Songzi is diverse and primarily based on agriculture, while the fertile lands along the Yangtze River support the cultivation of rice, tea, and various other crops. Additionally, the industrial and tourism sectors have grown significantly in recent years, contributing to local economic development.

Songzi has a total of 16 districts with 278 villages, and the local government is in Xinjiangkou district, which is the most economically developed local town. The village constitutes the most diminutive rural administrative entity within China, encompassing a specific geographical region characterized by intimate social interactions. Furthermore, it also represents the most granular spatial level at which census population data are accessible. The average number of people in each district is 2523.3. Among all districts, the most populous district is Xinjiangkou, with a population of 127.4 thousand, but Xiejiaping has the smallest population, only 15.0 thousand. Hospitals that provide primary healthcare services can be classified into three hierarchical categories, including Grade I, II and III. Grade I hospitals are also called community healthcare centers or clinics. General hospitals are grouped into Grade II or III. In general, Grade III hospitals have comparatively the highest medical capacities. The service threshold is 15 min travel time for Grade I hospitals but 30 min for Grade II and III hospitals. Patients in rural China can choose to enter any level of hospital to seek primary care according to their needs and actual conditions. In 2022, Songzi City has a total of 382 medical institutions. Per thousand people, there are 5.54 hospital beds and 2.27 doctors. The socio-economic overview of various districts in Songzi can be found in Table 1.

Table 1. Economic and social overview of each district.

District	Population Density (People/km ²)	Number of Villages	Per Capita Annual Income (RMB yuan)	Number of Hospitals	Number of Clinics
Xinjiangkou	1587	10	8820	10	83
Shadaoguan	460	6	5149	0	2
Wanshi	352	17	4106	0	3
Babao	436	17	5400	0	14
Laocheng	368	17	4892	0	4
Chendian	234	12	3253	0	5
Nanhai	316	21	2896	1	6
Weishui	223	25	4040	0	13
Liujiachang	225	21	6500	1	20
Jieheshi	441	14	3345	0	10
Wangjiaqiao	266	21	3557	0	5
Sijiachang	279	13	3895	0	1
Wanjia	358	8	3085	1	5
Zhichanghe	321	12	2548	1	8
Yanglinshi	337	13	3350	0	2
Xiejiaping	133	8	4800	0	2

The data employed in this research can be classified as spatial and non-spatial data. For the spatial dimension, the population distribution and demographic structure data were derived from Worldpop (<https://www.worldpop.org/>, accessed on 20 August 2023), which is structured by classes with a 5 year age range and different genders (male/female), represented by 100 m × 100 m lattices. The total population of each village is calculated by summing the number of people located in the lattices of the area. As shown in Figure 2, which shows the spatial distribution of the population in the study area, the densely populated areas were mainly distributed in the northern area, the southwest area and the seat of government. The location information of healthcare facilities was collected from Baidu Map (<https://map.baidu.com/>, accessed on 1 August 2023), which included 183 Grade I hospitals, 13 Grade II and 1 Grade III hospitals. Spatial data related to Songzi administrative boundaries were obtained from the Geographical Information Monitoring Cloud Platform (<http://www.dsac.cn/>, accessed on 15 July 2023), which serves as the predominant source for spatial, geographical, natural resource, and socioeconomic databases in China. For non-spatial data, we conducted a questionnaire survey in all levels of hospitals across 16 districts in Songzi, involving 1760 primary care patients, to gain a deeper understanding of individuals' demographic and socio-economic condition as well as their subjective perceptions of healthcare services. All information related to patient privacy has been desensitized.

2.2. Research Methods

2.2.1. Measure Spatial Access

This study utilizes the gravity-based G-2SFCA model to assess spatial access, as it incorporates both accessibility and the availability of medical resources. This method has gained widespread acceptance for measuring primary care access, including clinics (Grade I hospitals) and general hospitals (Grade II or III hospitals). The G-2SFCA improves the previous 2SFCA by adding a Gaussian function to present the distance decay effect of seeking healthcare services [18], which is also a population-based measure method. The G-2SFCA consists of two successive steps, and the detail can be expressed as follows:

$$G(d_{kj}, d_0) \begin{cases} e^{(-\frac{1}{2})} \times \left(\frac{d_{kj}}{d_0}\right)^2 - e^{(-\frac{1}{2})} & \text{if } d_{ij} \leq d_0 \\ 0 & \text{if } d_{ij} > d_0 \end{cases} \quad (1)$$

where $G(d_{kj}, d_0)$ is the Gaussian function. d_{kj} is the travel distance/time from the patient's location i to the hospital j , and d_0 is the certain threshold travel distance/time that is pre-defined.

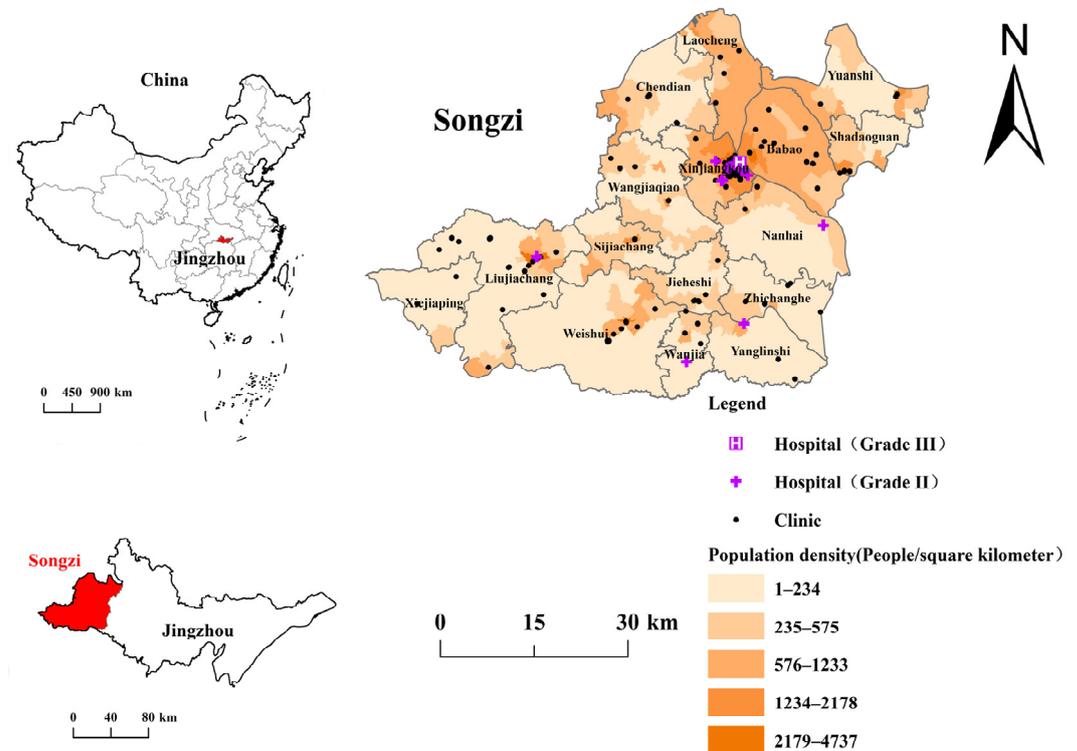


Figure 2. Location of study area.

Step 1: evaluate supply-to-demand ratio within a certain distance/travel time (e.g., 10 km or 15 min) of each primary healthcare provider.

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} G(d_{kj}, d_0) D_k} \quad (2)$$

where R_j is the supply-to-demand ratio at the hospital location j . S_j is the supply capacity (i.e., number of inpatient beds) at the hospital j , and D_k is the volume of potential demand.

Step 2: sum up all the supply-to-demand ratios of all healthcare providers within the pre-defined distance/travel time of each potential demand location.

$$A_i = \sum_{j \in \{t_{kj} \leq t_0\}} G(d_{kj}, d_0) R_j \quad (3)$$

where A_i is the access score at the demand location i , and a higher value represents better spatial access.

With respect to the values of the parameters, the threshold travel time (d_0) is 15 min for Grade I hospitals (i.e., clinics) and 30 min for Grade II and III hospitals (i.e., general hospitals), which meet the healthcare service requirements for different levels of hospitals [32]. S_j is defined by the number of inpatient beds in hospital, which can be found in each hospital's official website. D_k is defined as the total number of residents in the village k .

2.2.2. Investigate Non-Spatial Access

Five dimensions of non-spatial factors are involved in this study, including demographic variables, income, education, healthcare insurance and satisfaction levels of healthcare service. Demographic variables (i.e., sex and age) influence the need for primary

healthcare. In general, three population groups are often considered as having a high need for primary healthcare services, including children aged 0–4, females aged 15–44 and seniors with aged over 65 [8]. The spatial distributions of those groups can be obtained from the Worldpop dataset. Cooperating with the demographic data obtained from Worldpop, the ArcGIS 10.7 was employed to calculate the high healthcare needs ratio (HHNR) in each village, calculated by the following equation.

$$\text{HHNR} = \frac{\text{Children}(0-4 \text{ ages}) + \text{female}(15-44 \text{ ages}) + \text{seniors}(65 + \text{ages})}{\text{total population}} \quad (4)$$

In order to investigate non-spatial factors related to patients themselves, this study conducted a two-month questionnaire survey in 16 districts in Songzi (from August to October 2019), assessing income levels, education levels of primary healthcare patients and health insurance, as well as their satisfaction degree with local medical services. The major questions about those dimensions are shown in Table 2. During the survey period, we selected hospitals at all levels in each district and surveyed 110 patients from each. In total, 1760 questionnaires were collected, with 1609 questionnaires considered valid, resulting in an effective response rate of 91.4%.

Table 2. Non-spatial factors related to access to primary healthcare services.

Non-Spatial Factors	Collected Way	Question	Rank	Indicator Character
Age	Worldpop Dataset	None	None 1: Above 10 k; 2: 10–30 k; 3: 30–50 k; 4: 50–80 k; 5: 80–150 k; 6: Above 150 k (Unit: RMB)	-
Income	Questionnaire	What is your annual income range?	1: Primary school or Below; 2: Junior high school; 3: Senior high school; 4: Junior College; 5: University degree or Above	+
Education level	Questionnaire	What is your highest educational degree?	1: Yes; 0: No	+
Health Insurance	Questionnaire	Do you have a health insurance?	1: Great dissatisfaction; 2: Dissatisfaction; 3: Not bad; 4: Satisfaction; 5: Great satisfaction	+
Satisfaction level	Questionnaire	How satisfied you are with local medical services		+

2.2.3. Integrating Spatial and Non-Spatial Access

The entropy weight method is a commonly used method in decision analysis, mainly used for multi-attribute decision making problems to determine the weights of each attribute [33]. The basic principle of the entropy weight method is based on the concept of information entropy. Information entropy is an indicator that measures the degree of information concentration, representing the maximum amount of information in a random variable when the sum of probabilities of each value appearing is 1. The entropy weight method determines the weight of each indicator by calculating the information entropy of each indicator, reducing the influence of subjective factors.

In this study, an indicator system of the comprehensive access score (CAS_i) is constructed to integrate various indicators of spatial and non-spatial factors, the entropy weight method was employed to determine the weights of various indicators for the spatial access score (A_i) and above non-spatial factors.

Due to the different data units of the indicators, the indicators need to be dimensionless and processed by the standardized formula. The standardized formula of positive indicators is as shown in Equation (5):

$$Y_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} \quad (5)$$

The standardization formula of negative indicators is as follows:

$$Y_{ij} = \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} \quad (6)$$

Then, the method of information entropy is applied in this paper to calculate the weight of each spatial and non-spatial factor in comprehensive access evaluation. The information entropy formula of each group of data is as follows:

$$E_j = -\ln(N)^{-1} \sum_{i=1}^N p_{ij} \ln p_{ij} \quad (7)$$

Among them:

$$p_{ij} = \frac{Y_{ij}}{\sum_{i=1}^N Y_{ij}} \quad (8)$$

According to the calculated information entropy, we calculated the weight W_j of each group of data:

$$W_j = \frac{1 - E_j}{K - \sum E_j} (j \in K) \quad (9)$$

where N is the total number of demand areas, and K is the total number of indicators. X_{ij} represents the actual value of the j -th indicator at the i -th demand location, and Y_{ij} is the standardized value of X_{ij} . The information entropy of j -th group of data is represented as E_j . Among them, P_{ij} is the proportion of Y_{ij} to all values in the j -th indicator, which is equivalent to defining a certain probability that will have a significant impact on entropy E_j . $\max(X_{ij})$ is the maximum value of X_{ij} and $\min(X_{ij})$ is the minimum value of it. By substituting the index data into the above formula, the weight of the j -th indicator (W_j) can be calculated.

After the weights of all indicators have been evaluated, the comprehensive access score at the i -th location (CAS_i) is calculated by Equation (10).

$$CAS_i = \sum_{j=1}^K W_j X_{ij} \quad (10)$$

3. Results

3.1. Spatial Access to Primary Healthcare Services

The variations in standardized G-2SFCA access scores for clinics (Grade I hospitals) and general hospitals (Grade II and III hospitals) are depicted in Figure 3a,b, with a range of values from 0 to 1, respectively. For access to clinics, the average standardized access value is 0.18, and over 85% of the villages have scores under 0.3. The average clinic access score in Liujiayang is the highest among all districts, standing at 0.4 (see Figure 3a). As the township of Songzi, the clinic access score of Xinjiangkou ranks second among all regions at 0.30. However, the lowest clinic access scores among all districts is Wanshi (0.04); thus, local residents have the most difficult-to-reach clinics. Regarding access to general hospitals (see Figure 3b), the standardized scores are relatively high, with 78% of villages having a value score higher than 0.3, with a mean of 0.5. Specifically, the highest mean value of hospital access scores points to Xinjiangkou, with a value of 0.89. The average hospital

access score in Nanhai is 0.79, ranking second among all districts (see Figure 3b). However, Xiejiaping and Wanshi districts have the lowest access scores in all regions, at 0.09 and 0.1, showing a severe shortage of hospital services compared to other areas in Songzi (see Figure 3b).

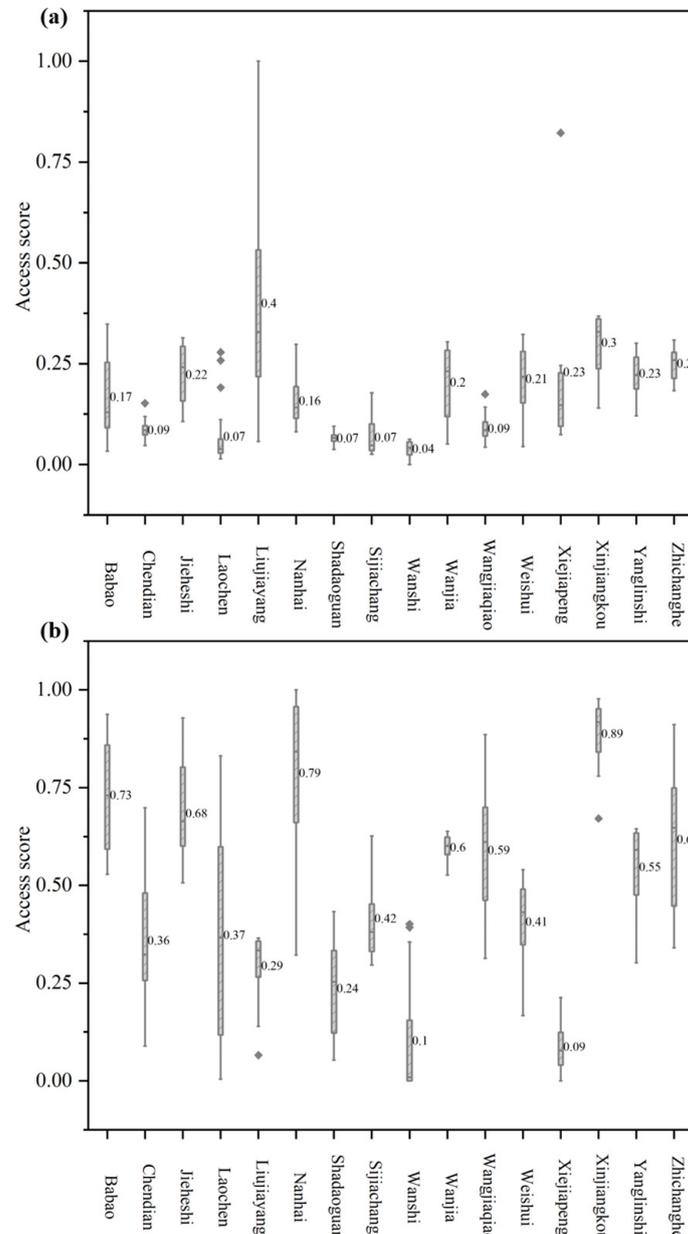


Figure 3. Boxplots of spatial access scores to primary healthcare services: (a) clinic access; (b) hospital access.

Figure 4a,b show the spatial distribution of access scores relative to clinics and hospitals, respectively. Access scores of villages are classified into five categories (i.e., very high, high, medium, low and very low) using the Natural Breaks method. According to Figure 4a, 44.5% of the villages have a “high” or “very high” level of clinic access. The areas with a “very high” level of clinic access are located in the west area (i.e., the north of Xiejiaping and Liujiachang). Areas around the seat of government (i.e., the township) and the south of Songzi have a “high” level of clinic access. It is worth noting that while the western areas do not have as many clinical medical resources as the township, the lower patient demand resulted in a higher level of access score for clinics. The villages with a “very low” level of clinic access are distributed in the north and the middle area. Figure 4b describes

that the spatial distribution of access levels to hospitals exhibits a core-periphery declining pattern, gradually decreasing from the township (i.e., Xinjiangkou) to the peripheral areas. In detail, 52 villages have the “highest” level of hospital access scores, accounting for 18.7% of the total villages, which are distributed in the central part of Songzi. In contrast, those areas with a “very low” level of hospital access are observed at the northeastern, northern, and southwestern peripheries.

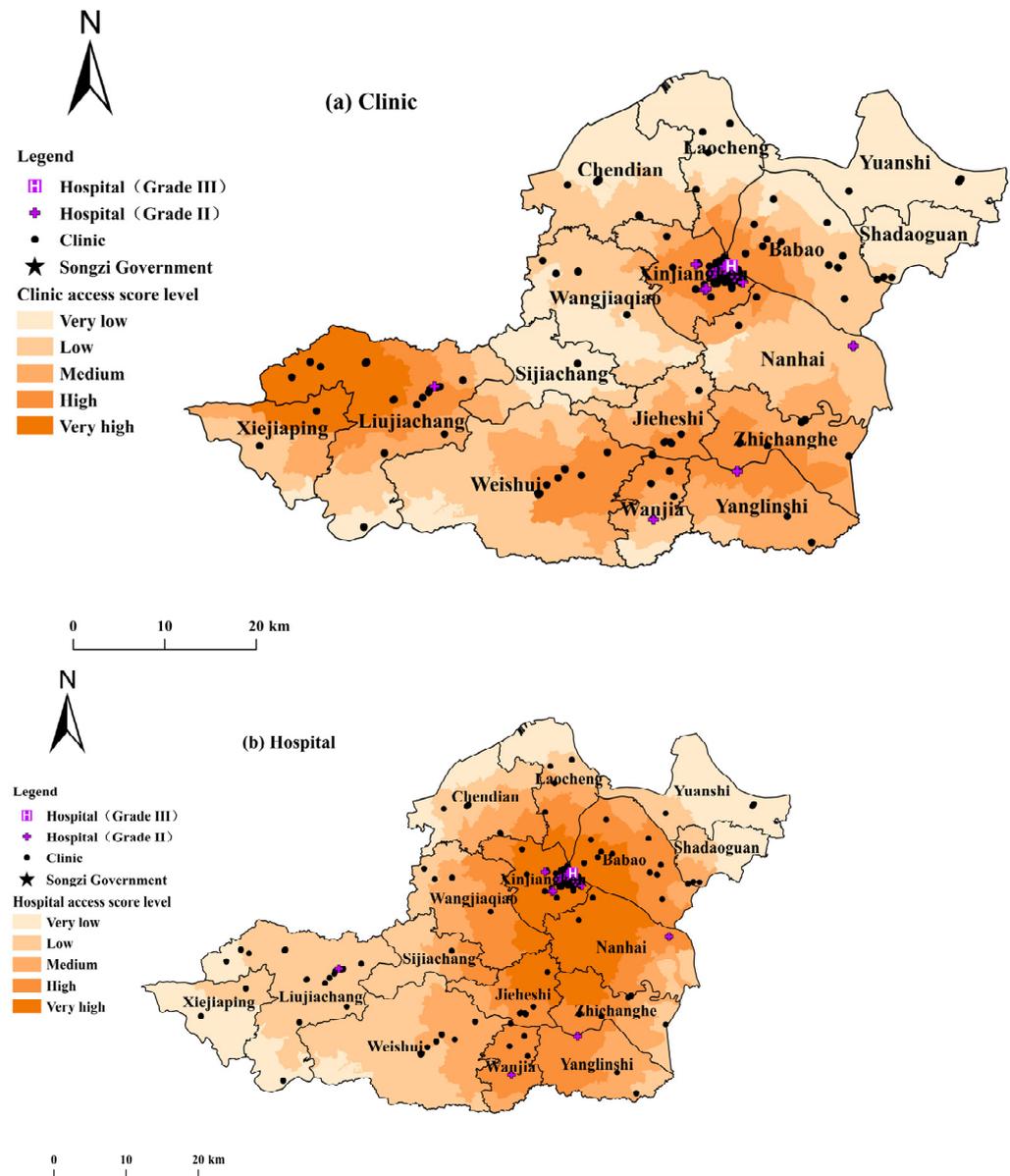


Figure 4. Distribution of levels of access to (a) clinics and (b) hospitals.

Figure 5 highlights that 78 villages have a “low” or “very low” level of access to both clinics and hospitals, accounting for 23.4% of the total villages with 185,137 people. Those villages are distributed in the northern, western and southwestern peripheral areas. Comparatively, 39 villages with 176,799 residents have a “high” or “very high” level of access to both types of facilities, and those areas are mainly distributed around the Xinjiangkou and the south of Songzi. According to the above three figures, inequalities in spatial access to clinics and hospitals clearly exist, and more primary care resources should be allocated in the north and southwest of peripheral areas (i.e., Chendian, Weishui).

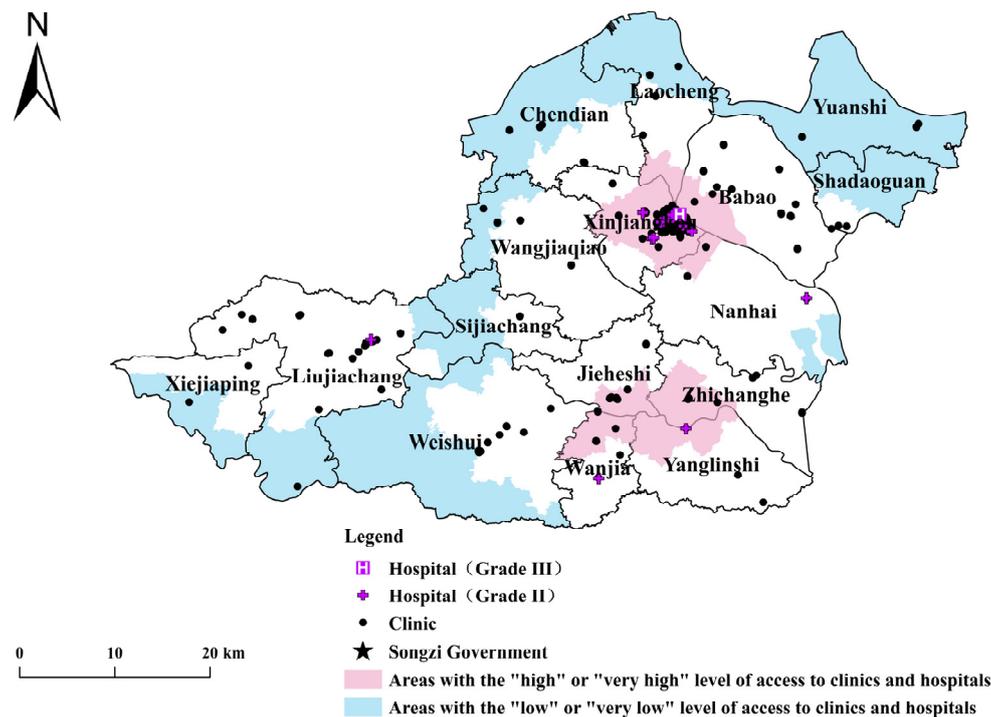


Figure 5. Spatial distribution of highlighted areas.

3.2. Integrating Spatial and Non-Spatial Factors

This section aims to compute comprehensive access scores to primary healthcare access using a comprehensive evaluation index with the integration of both spatial and non-spatial factors. Figure 6a–e show distributions of different non-spatial factors based on districts. Their ranks are also classified into five levels, the same as the Section 3.1. In detail, the spatial differences in healthcare insurance and demographic factors are faint (see Figure 6a,c). On the contrary, there are substantial spatial disparities in economic, medical service satisfaction and education levels, as shown in Figures 6b, 6c and 6d, respectively. Table 3 outlines the analysis of information entropy that has yielded valuable information about the weighting of spatial and non-spatial factors influencing primary care access. Specifically, spatial factors make up 36.5% of the total weight, with 23.0% allocated to clinic access and 13.5% to hospital access. Comparatively, the top two non-spatial factors, education level and household income, hold significant weight, contributing 29.0% and 25.5% to the overall total, respectively. Notably, patients' satisfaction degree is assigned a weight of 7.9%, while demographic factors carry the lowest weight among all factors at just 1.0%.

Figure 7 shows the average value of CAS_i for each district in Songzi, with a range from 0 to 1. The CAS_i in Xinjiangkou surpasses all other districts, with a lead of 0.37 points over Liujiayang, which holds the second position. The average CAS_i in six districts is above 0.3, and there are three districts under 0.1. Nanhai and Zhichanghe have the lowest and second-lowest CAS_i among all districts. Figure 8 depicts the spatial distribution of CAS_i classified into five levels by the Natural Breaks method. The spatial disparities in CAS_i are clear; while the districts with "high" or "very high" level of CAS_i are located in the north part and west parts of Songzi, the areas with "low" or "very low" levels of CAS_i are located in the middle and the east parts. It is worth noting that good spatial access cannot ensure equally good CAS_i . For example, the majority of villages in Zhichanghe district have a "high" level of clinic and hospital CAS_i or above. However, when non-spatial factors are considered, the CAS_i in those areas decreases remarkably.

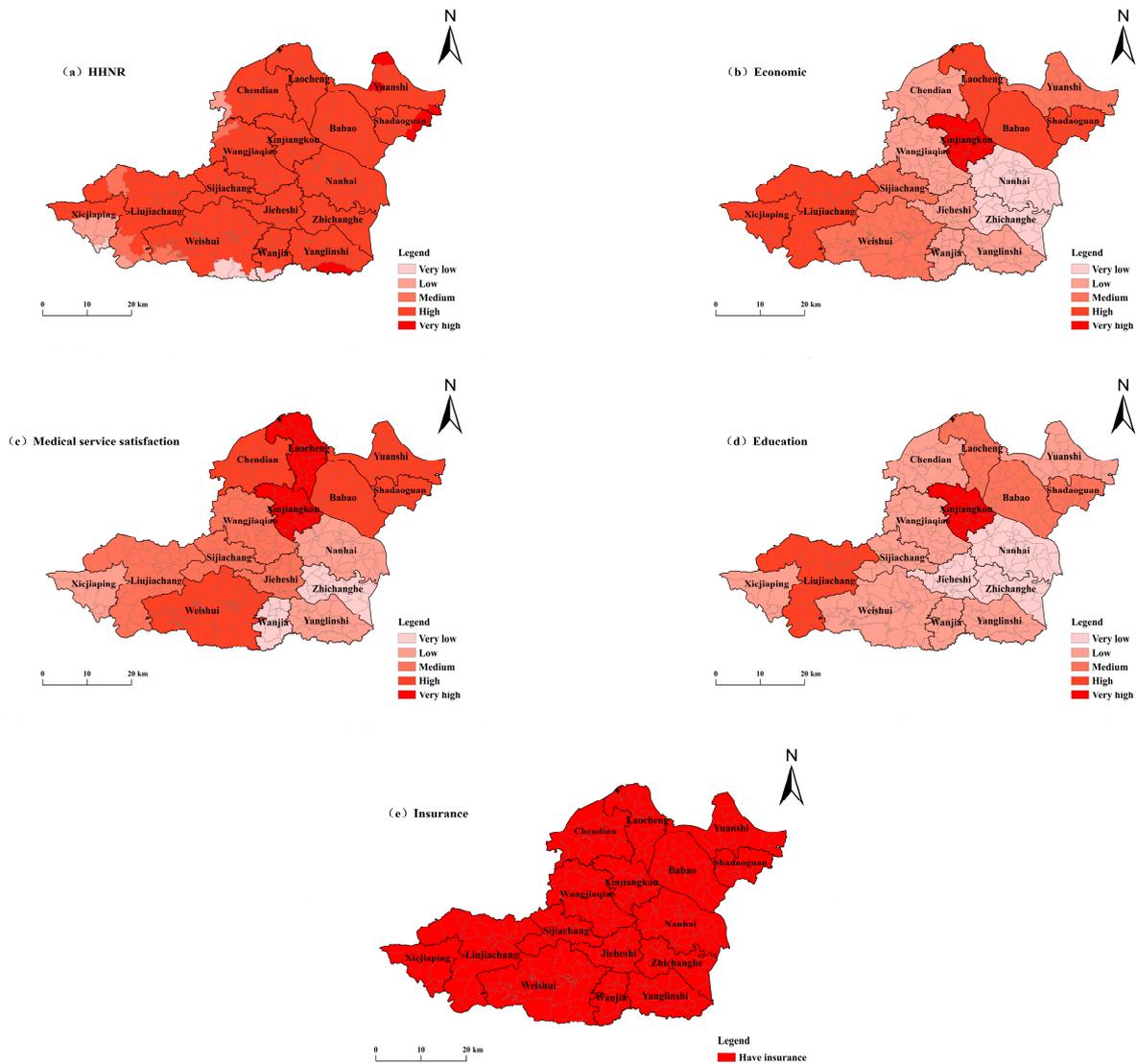


Figure 6. Levels of different factors related to non-spatial factors: (a) demographic factor—HHNR; (b) household income; (c) medical service satisfaction; (d) education level; (e) healthcare insurance.

Table 3. Weights of spatial and non-spatial factors related to primary healthcare access.

	Indicators	Indicator Character	Weight	Remark
Spatial factors	Accessibility of clinic	Positive	0.2298	Clinic’s G-2SFCA scores
	Accessibility of hospital	Positive	0.1354	Hospital’s G-2SFCA scores
	Age	Negative	0.0102	HHNR (children aged 0–5, women aged 15–44, and elderly people aged 65 and above) to the total population
Non spatial factors	household income	Positive	0.2545	Per capita annual income of residents
	Medical service satisfaction	Positive	0.0792	Residents’ satisfaction with medical facilities and services
	Healthcare insurance	Positive	0.0000	Whether residents have health insurance (1—Yes; 0—No)
	Education	Positive	0.2908	Education level of residents (1–5 indicates education level from low to high)

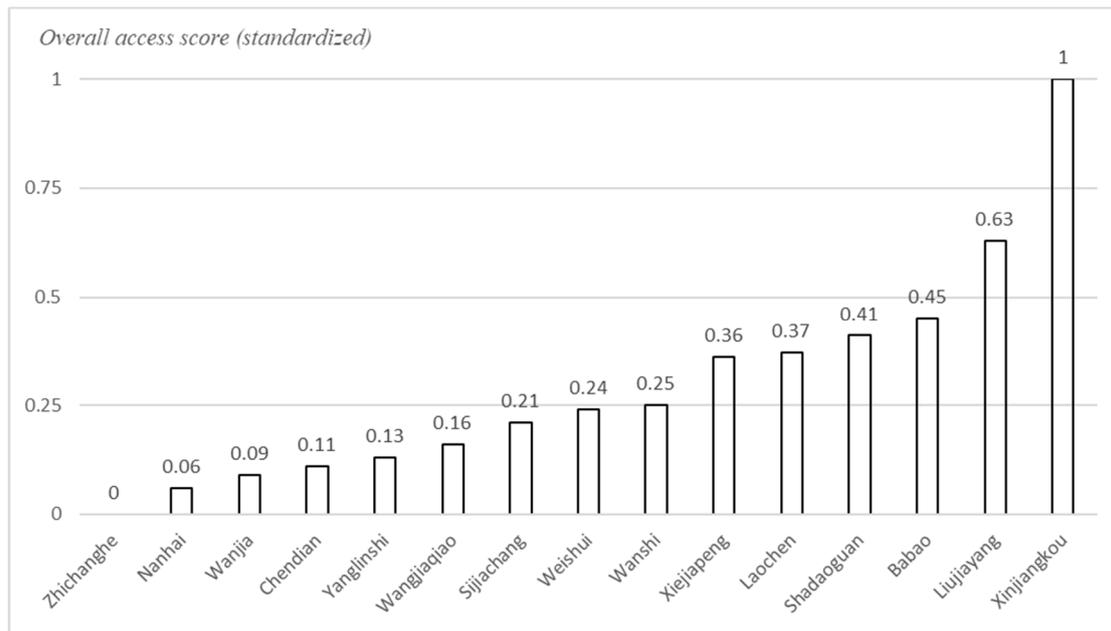


Figure 7. Average comprehensive (overall) access scores for each district in Songzi.

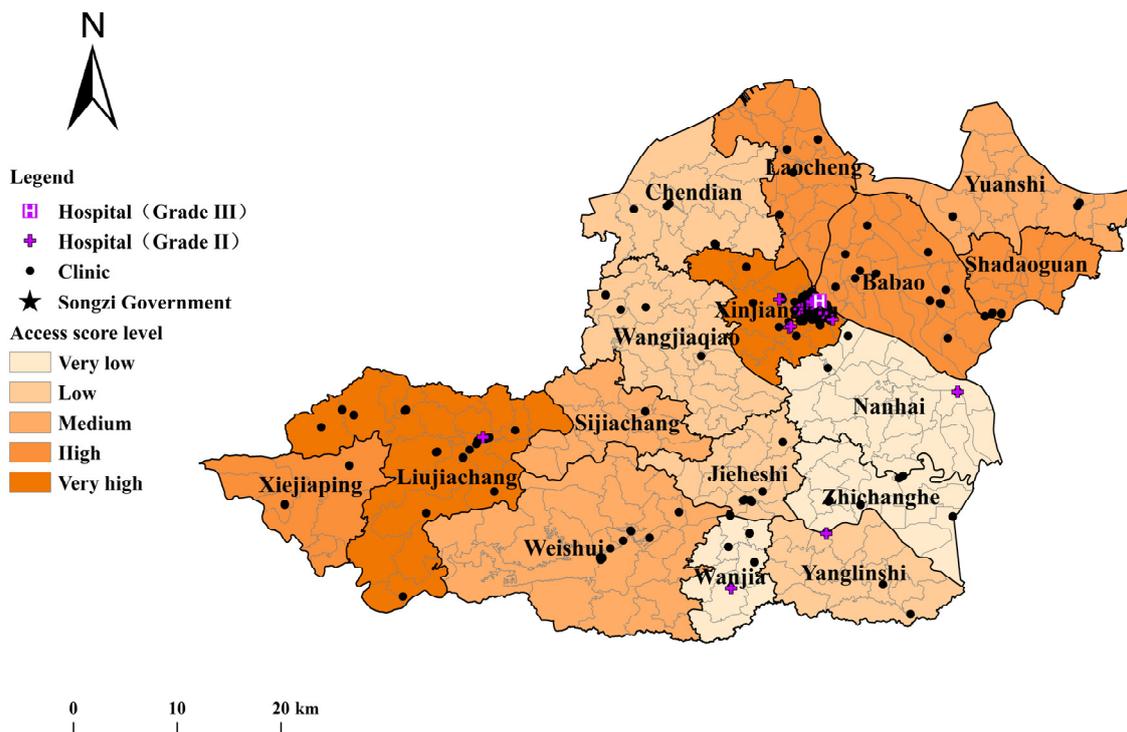


Figure 8. Distribution of levels of average comprehensive access.

4. Discussion

The research results indicate that there are disparities in access to primary healthcare for both spatial and non-spatial factors. Regarding measuring spatial access using the G-2SFCA, clinic access scores in the southern and central areas are much higher than those in the northern and western regions, and the spatial distribution of hospital access has a declining trend from the center to the periphery areas. In total, 78 villages with 185,137 local people had a “low” or “very low” level of spatial access to both clinics and hospitals, but only 39 villages with 176,799 residents had a “good” or “very good” level of spatial access

to both facilities. For non-spatial factors, there are significant spatial inequalities in the education level and household income. In general, the eastern areas tend to exhibit poorer socioeconomic status and a lower level of satisfaction with medical services. It is worth noting that the healthcare insurance and population structure exhibit faint spatial variations, with an aging trend. When combining spatial and non-spatial factors using the entropy weight method, it becomes evident that the northern and southwestern areas of Songzi have the highest level of access to primary healthcare services, while the eastern region experiences the lowest access level.

Considering both spatial and non-spatial factors has a notable impact on the evaluation results of access to primary healthcare services and might find different spatial distribution characteristics. This is because areas with a high level of spatial access cannot guarantee equally good levels of non-spatial access such as local socioeconomic status or level of satisfaction with medical services. For example, although the level of spatial access to clinics and hospitals in the east of Songzi (i.e., Nanhai and Zhichanghe districts) is obviously above average, the low levels of socioeconomic status and patients' satisfaction with medical services result in the lowest comprehensive access scores among all districts. In contrast, an area with a high level of comprehensive access does not mean it has equally good spatial access to primary healthcare services. For instance, Laocheng district, located in the northern part of Songzi and characterized by low spatial access, sees a substantial increase in its comprehensive access score when spatial and non-spatial factors are integrated. Whether a comprehensive consideration of spatial and non-spatial factors is needed depends on health planning priorities and policymakers' focus areas. Suppose there is a need to establish new primary healthcare facilities in a short period of time (i.e., one year), measuring spatial access can identify underserved areas so that the best locations for new facilities can be found. Conversely, for policymakers aiming to formulate long-term healthcare planning policies (i.e., ten-year planning), a more holistic understanding of the local healthcare landscape necessitates the integration of both spatial and non-spatial factors.

Regarding policy implications, first, the empirical results can aid in making public policies in primary healthcare management and planning. For example, Figure 5 shows that areas around the north and southwest boundaries need to allocate more medical resources in the future due to the poor spatial access to both clinics and general hospitals. Second, spatial optimization models can be further adapted to investigate the optimal spatial configurations of clinics and general hospitals when medical resources are limited so that primary healthcare facilities can cover as many potential patients as possible under the defined travel time constraint (i.e., 10 or 15 min travel time). A similar method can be applied to investigate how to calculate the minimum number of facilities required to serve all demands within a certain time [34]. Accordingly, the spatial layout of medical resources (e.g., physicians or inpatient beds) can be reallocated to more appropriate places so that the equality and efficiency of the healthcare system can be improved [27]. Third, having good spatial access in a place cannot guarantee that the area will be equally good for non-spatial access, and vice versa. To improve non-spatial access, the governments need to provide affordable healthcare services for disadvantaged areas, enhance health literacy among individuals with lower education levels, and offer pre-service and on-the-job training for healthcare professionals. Fourth, a Chinese healthcare insurance system, named the New Rural Cooperative Medical System, has been launched, which offers financial support to rural residents for seeking healthcare services. Benefited by this, most rural residents in China have participated in the New Rural Cooperative Medical System. In this study, all respondents have participated in the insurance systems, which reflects that the policy has been well implemented in rural areas of Hubei Province. In addition, although the empirical research was carried out in Songzi, China, the study could also have implications for the rest of the world. The G-2SFCA model utilized in this study has been widely used in other relevant studies [35]. The input parameters used, which have been validated in various contexts, are not exclusive to Songzi. Non-spatial data can be obtained using a

questionnaire survey with similar questions. In the context of profound changes in the current world and rural society, where we are in a risk society, the organizational structure and class of rural areas are also undergoing significant changes. Improving the medical and health conditions of rural residents, as well as the spatial imbalance of education, economy and other factors, is conducive to alleviating social exclusion in rural areas and promoting class identity [36,37].

This study has some limitations that future research should address. First, due to constraints in survey time and funding, the questionnaire survey focused on non-spatial factors was collected at the district level rather than the level of individual villages. This may result in a need for more precision in the spatial distribution of non-spatial access. Thus, a future study is necessary to conduct more refined data collection on the non-spatial dimension to improve the accuracy of results of primary healthcare access, integrating both spatial and non-spatial factors. Second, given the absence of actual medical data, such as mortality or hospital discharge rates, this study is not complex enough to draw definitive findings regarding the genuine influence of spatial and non-spatial access on the health outcomes of local people. In future research, there should be a collaboration with local healthcare authorities to acquire actual medical data and delve deeper into exploring the relationship between various access factors and local residents' health outcomes. Third, this study only focused on whether the patients had medical insurance but did not pay attention to the type of and difference between medical insurance. Therefore, future research needs to refine the types of medical insurance to achieve a better distinction on healthcare affordability. In addition, only a driving-based travel mode is considered in this study. However, patients might select various modes of transportation to seek healthcare services, such as walking, cycling or public transport, which needs to be considered in further work.

5. Conclusions

Primary healthcare services are essential elements of the rural healthcare system and play an irreplaceable role in protecting people's health and safety. As a primary indicator to evaluate the efficiency and equality of the primary healthcare system, access has been widely studied in the past few decades. This study contributes to the existing literature by integrating both spatial and non-spatial access with the consideration of first-hand data about patients. The empirical study focused on the primary healthcare services in Songzi, China. According to the results, we found apparent spatial inequalities in primary healthcare access with respect to both spatial and non-spatial dimensions. In addition, good spatial access cannot necessarily guarantee good non-spatial access or comprehensive access, and vice versa. This study calls for policymakers to pay more attention to intra-rural health inequalities. Meanwhile, spatial and non-spatial access should be considered comprehensively when the long-term rural medical support policy is implemented.

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