A Method for Assessing the Fairness of Health Resource Allocation Based on Geographical Grid

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Abstract: The assessment of the fairness of health resource allocation is an important part of the study for the fairness of social development. The data used in most of the existing assessment methods comes from statistical yearbooks or field survey sampling. These statistics are generally based on administrative areas and are difficult to support a fine-grained evaluation model. In response to these problems, the evaluation method proposed in this paper is based on the query statistics of the geographic grid of the target area, which are more accurate and efficient. Based on the query statistics of hot words in the geographic grids, this paper adopts the maximum likelihood estimation method to estimate the population in the grid region. Then, according to the statistical yearbook data of Hunan province, the estimated number and actual number of hospitals in each grid are analyzed and compared to measure the fairness of health resource allocation in the target region. Experiments show that the geographical grid population assessment based on hot words is more accurate and close to the actual value. The estimated average error is only about 17.8 percent. This method can assess the fairness of health resource allocation in any scale, and is innovative in data acquisition and evaluation methods.

Keywords: Health resource allocation, fairness assessment, geographical grid, hot words.

1 Background

The fairness of health services means that citizens should have equal or similar access to health services resources. According to the current research literatures, the research on the fairness of health services is mainly divided into four aspects: the fairness of health resource allocation, the fairness of health service utilization, the health equity and the equity in health financing. To be specific, the fairness of health resource allocation refers to the fairness of the distribution of population, finances and facilities used to provide health services, that is, the distribution of hard health resources; the fairness of health service utilization is the fairness and accessibility of health services provided to the public; the health equity means that different social groups should have equal or similar health levels,

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and health status is balanced; the equity in health financing is the fairness of different social groups in health financing, divided into horizontal fairness and vertical fairness.

Since the fairness of health services involves the vital interests of every member of modern society and is also an important part of the overall fairness of modern social development and construction, Domestic and foreign scholars have conducted a lot of research on it. At present, the research on the fairness assessment of health services mainly focus on process faireness. The data sources of most studies are generally based on data published by the government. Among these research, Zere et al. [Zere, Mandlhate, Mbeeli et al. (2007); Zere, Moeti, Kirigia et al. (2007)] used principal component analysis to calculate the asset index using data from the Namibian Demographic and Health Survey in 2000, combined with asset and health-related variables. Then, based on these asset indices, a regional weight recommendation basic model of a demand-based resource allocation formula is established. It used quintile ratios and concentration curves in the analysis of trends in health care equity in Malawi to analyze data from the 1992, 2000 and 2004 Demographic and Health Surveys to understand inequalities in health care. Burström et al. [Burström, Burström, Nilsson et al. (2017)] found that since 2010, the new PHC institutions established in Sweden had been located in the large cities and urban areas, with better socio-economic conditions.

Chinese scholars drew on foreign researches on fairness, and most of them also adopted the process fairness method [Fan and Huang (2018)]. Data acquisition is also generally obtained from the yearbook data or questionnaires. Hou et al. [Hou, Shi and Yang (2018)] used the China Healthy Statistics Yearbook 2008-2014 data in the study of China's health resource allocation in 2008-2014, and found that the fairness of resource allocation by population is greater than the allocation of resources according to geographical area; the fairness of resources is distinct among different regions. Liu et al. [Liu, Liu, Twum et al. (2016)] found that although the level of health resource fairness in China is much better than before, the inequalities in the eastern region are still quite significant. Li et al. [Li, Zhang, Xia et al. (2019)] collected data about the number of medical institutions, the health human resources and the number of beds through surveys, and analyzed the regional fairness of health resource allocation through analysis and research. In addition to direct research on fairness, Ren et al. [Ren, Ding, Song et al. (2018)] applied data envelopment analysis (DEA) to evaluate the operational efficiency of health services in various communities, and reflected the rational allocation of health resources from the side. Tao et al. [Tao, Henry, Zou et al. (2014)] collected six methods for measuring the fairness of health resource allocation. Through comparative analysis, it is considered that the Lorenz curve and the Gini coefficient have the disadvantages of uncertainty and incompleteness.

A major problem of the current studies for fairness of health services is the data source for fairness assessment. In summary, there are two sources on the data subject used in the assessment of health service fairness in the existing researches. One is the yearbook, and the other is the questionnaire survey or field survey. The annual geography vector data released by the state data can only be specified to the county level, and its accuracy is difficult to support the needs of some health services fair research, such as access to health services, fairness of health resources distribution, etc. It is difficult to achieve a fine-grained assessment of health resource statistics, and it is not possible to assess health services equity across regions. The use of field research collection or questionnaire surveys clearly has problems such as high cost, low efficiency, and limited coverage area.

Therefore, the data source in the health service fairness assessment study is a very intractable issue. In view of the data source problem of the above assessment, this paper adopts a new way to obtain the data source needed for the assessment, namely the geographical grid hot words statistics. Geographical grid is the grid data related to geographic information, and has spatial information and attribute information. It is formed by the geographic information system to the target area according to certain specifications, such as the set latitude and longitude interval or the length of small geographical area. Early researches on geographic grids mainly focused on the grid model of geographic grids [Lee and Samet (2000); Kimerling, Sahr, White et al. (1999)]. Since human economic and social activities are always inseparable from geographical environment, in recent years, an increasing number of studies combine geographic information to analyze and evaluate human social and economic activities [Yang and Mu (2015); Kundakci (2014); Feng, Wang, Bi et al. (2018); Sun, Gao and Cui (2018)]. However, most of these evaluation studies are based on administrative geographical divisions, so far, this paper has not found an evaluation method based on geographical grids. The hot words statistics refer to statistical data such as buildings and business entities that are queried based on a certain keyword in a geographical area. Hot words statistics are widely used in geographic service systems, such as surrounding hospitals, gas stations, restaurants, etc. Although the number of health resources such as hospitals in the geographical grid can be obtained from the hot words query, not all the data needed for the health service fairness assessment can be obtained directly from the hot words query, such as the regional population.

However, because the hot words in the geographical grid are all kinds of entities in the region, these entities are generated by the population of the region through economic and social activities. Hence, the number of hot words is closely related to the population of the region. Therefore, based on the hot words statistics, this paper proposes a method based on the maximum likelihood estimation to estimate the population in the geographical grid, and then combines the query results of hospital hot words in the geographical grid to achieve a specific region assessment of the fairness of health resource allocation.

2 Geographical grid-based assessment method for health resource allocation fairness

2.1 Health resource allocation fairness assessment model

The evaluation model used in this paper assumes that the fairness of health resources is equal to or approximate to the health resources that each community is supposed to obtain. Therefore, the method for assessing the fairness of health resource allocation in this paper is to estimate the average number of hospitals assigned to per 10,000 people in the target area. For example, the average number of hospitals assigned to per 10,000 people in a j-level city is calculated as follows:

$$\overline{X}_p = \frac{N_j}{P_j} \tag{1}$$

$\overline{X}_p$ represents the average number of hospitals allocated to each 10,000 people in a certain prefecture-level city, that is, the theoretical per capita hospital resource allocation density; P_j represents the actual population of the j-level city, and this paper uses the number of permanent residents at the end of the year to calculate; N_j is the number of hospitals in the scope. The number of hospitals evenly distributed per 10,000 people is then calculated for each geographical grid within the assessment area, calculated as follows:

$$\overline{X}_{pr} = \frac{N_{jr}}{P_{jr}} \tag{2}$$

$\overline{X}_{pr}$ means the number of hospitals that are evenly distributed per 10,000 people on a grid, that is, the actual population resource allocation density; P_{jr} is the population of the grid calculated by the representative model; N_{jr} represents the total number of hospitals in the grid. From Eqs. (1) and (2), the actual hospital per capita density in a geographical grid and the theoretical per capita hospital resource allocation density can be obtained. There must be a certain difference between the two average density indices. By accumulating the density difference between the two hospital resource allocations of all the grids in the assessment area and then dividing the sum by number of evaluation area grids, the health resource allocation unfairness index F in the area to be evaluated is obtained. As shown in Eq. (3):

$$F = \frac{\sum|\Delta_i|}{n} \tag{3}$$

F is the assessment of regional health resource allocation unfairness index, Δ_i represents the difference between the actual population resource allocation density $\overline{X}_{pr}$ of i grid and the theoretical population resource allocation density $\overline{X}_p$; n represents the total number of grids in the assessment area.

2.2 Estimation of geographic grid population data based on maximum likelihood estimation

As mentioned above, the health resource allocation fairness evaluation model used in this paper mainly relies on two data: one is the number of hospitals in each geographical grid, and this data can be directly obtained through the hot grid words query statistics of the geographical grid; the other is the number of people in each geographical grid. This data cannot be directly obtained through the hot words of the geographical grid. In this regard, this paper uses the geographic grid population data estimation method based on maximum likelihood estimation. The entities corresponding to the hot words formed in the geographical grid are formed by the economic and social activities of the population within the geographical grid. Therefore, the number of entities corresponding to hot words is closely related to the population. It is thus possible to achieve a quantitative assessment of the geographic grid population by the number of hot words that are closely related to the population. In this paper, a linear model is used to simulate the population and hot words, and the representative hot words in each geographical grid are analyzed. The specific estimation analysis process is as follows:

Let A_m be the degree of association between the population and the keyword m, that is, the probability that each individual will generate relevant keywords, then

$$P(N_{mj} = k) = C_{P_j}^{k} \times A_m^k \times (1 - A_m)^{P_j - k} \tag{4}$$

where: A_m represents the linear correlation coefficient between the population and the keyword corresponding to the keyword m; P_j represents the actual population of the j-level city; and N_{mj} is the theoretical quantity of the keyword m in the j-level city. Now use the maximum likelihood estimation method to find A_m.

$$\mathrm{L_m} = \prod_{\mathrm{j}} \mathrm{P(N_{mjr} = N_{mj}, A_m)} \tag{5}$$

where L_m is a likelihood function, and N_{mjr} is the actual number of keywords m in the actual j-level city. Take the logarithm of (2), there is

$$lnL_m = \sum_j lnC_{P_j}^{N_{mjr}} + N_{mjr} lnA_m + (P_j - N_{mjr}) ln\,(1 - A_m) \tag{6}$$

Take derivative of $\sum_j \frac{N_{mjr}}{A_m} + \frac{P_j - N_{mjr}}{A_m - 1} = 0$ then obtain:

$$A_m = \frac{\sum_j N_{mjr}}{\sum_j P_j} \tag{7}$$

The population estimates for each grid are:

$$P_{jr} = \frac{N_{mr}}{A_m} \tag{8}$$

N_{mr} represents the number of queries for the hot words m within each grid. Rasterization is a conversion process that accompanies information loss, with some details being ignored, and can only convey a rough message [Bai, Liao and Sun (2011)]. And the correlation between different hot words and population is inconsistent. Therefore, the estimation method needs to query statistics through multiple hot words, and then it is necessary to further clarify which hot words can be most accurately used to estimate the population population, as described in the following formula:

$$D = \frac{\left|\sum_j P_{jr} - P_j\right|}{P_j} \tag{9}$$

D represents the percentage of the difference between the estimated population of a prefecture-level city and the actual population of that city in the actual population of that city.

2.3 Implementation process of the evaluation method in this paper

1. Obtain the Digital Elevation Model (DEM) of the research map, resample it in ArcMap, and set the division criteria of the geographic grid (in this study, select the area every 5 km×5 km). And then generate a grid partition model of the study area;

2. Call the external data interface of Baidu map, develop the crawler tool, search and query in each grid range, select 30 hot words including hospital, community, village, school, etc., as keywords to get the query, get hot words quantity vector in each grid;

3. For each prefecture-level city, calculate the distribution density of the theoretical per capita hospital resources of each prefecture-level city by using the number of hospitals and the population of each city in each statistical yearbook;

4. By using the maximum likelihood estimation method described above, make each hot words quantity vector to evaluate the grid population, and compare the evaluation results with the prefecture-level demographic data to calculate the error and get the most accurate hot words. And use the hot words to calculate the grid population;

5. Calculate the distribution density of actual per capita hospital resources using the number of populations within each grid and the number of hospitals;

6. Bring the theoretical and actual per capita hospital resource distribution density into the fairness assessment model and calculate the unfair distribution index of health resources.

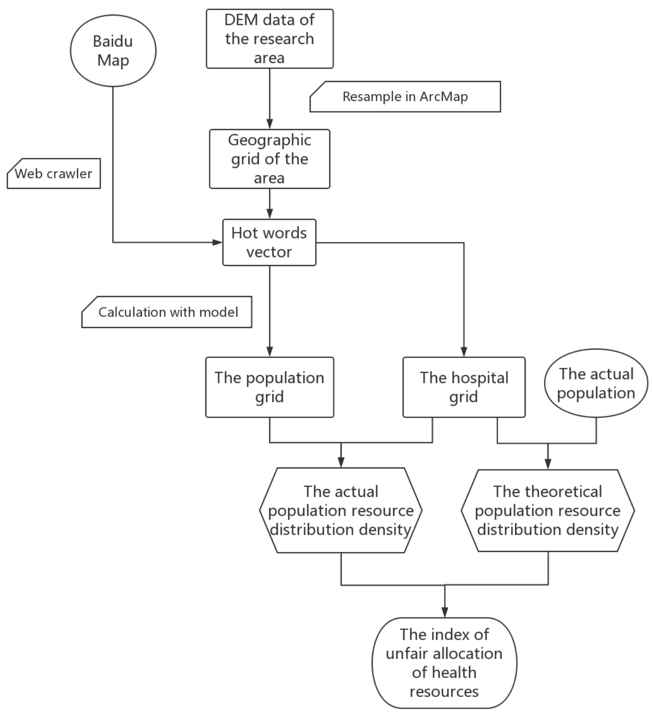

Figure 1: Realization process

3 Evaluation experiment

3.1 Assessment of the population of geography grid in Hunan

Using the health resource allocation fairness assessment model described above, this paper conducts an assessment of the fairness of health resource allocation in Hunan province. Firstly, according to the evaluation process of this paper, ArcGIS software is used to segment the geographical division of Hunan province. The size of each grid is 5 km×5 km, and a total of 8470 geographical grids are obtained. Afterwards, we further develop a crawler program using the query interface of Baidu map hot words, and use it to search and query each grid range.

In this paper, a total of thirty hot words are used in the hot words query statistical experiment, which respectively comprises:

Hospital, community, restaurant, university, school, shopping mall, restaurant, express, business hall, KTV, parking lot, ancestral hall, canteen, village, pond, village, mountain, company, supermarket, internet cafe, internet cafe, bus stop, police station, Vegetable market, hotel, park, gas station, forest farm, hotel, tire repair

And we get the hot words quantity vector of each grid, as shown in Tab. 1.

Table 1: Grid of hot words vector (part)

Grid number	Hospital	District	Restaurant	University	School	Shopping mall
3981	2	243	24	8	72	1
3982	36	720	193	6	108	5
3983	5	104	30	1	27	1
3984	0	5	0	0	1	0
3985	0	14	30	1	6	0
3986	25	474	468	3	107	2
3987	11	440	265	5	93	4
3988	3	34	84	0	13	0
3989	0	0	0	0	1	0
3990	0	0	0	0	1	0

The actual population data of 13 prefecture-level cities and 1 autonomous prefecture in Hunan province are derived from Hunan Statistical Yearbook 2018. As shown in Tab. 2, this paper extracts the number of resident population at the end of each year in each city and state in 2017.

Table 2: Hunan province 2017 population data

Area	Permanent residence end of the
Changsha	791.81
Zhuzhou	402.15
Xiangtan	285.24
Hengyang	720.53
Shaoyang	737.54
Yueyang	573.33
Changde	584.48
Zhangjiajie	153.16
Yiyang	439.2
Binzhou	473.16
Yongzhou	547.97
Huaihua	496
Loudi	391.76
Xiangxi	263.82

We retrieve the hot words in each gird with the method of web crawler and then construct the hot words vectors from the thirty dimensions of the 8470 grids. Finally we obtain each number of thirty hot words throughout Hunan province.

In the "Hunan Statistical Yearbook 2018", we can get the total population of Hunan province. The total population and the total number of the 30 hot words were used respectively to put into the population estimation model to calculate correlation coefficient between each hot words and population with (5) and (7).

Then, each grid is classified according to the city to which it belongs, and each grid is divided into the prefecture-level city to which it belongs to count the number of each hot words in each prefecture-level city. The correlation coefficient between each hot words and the population we get from the above is brought into the formula (4) to calculate the theoretical population of each prefecture-level city.

Then calculating the absolute value of the difference between the theoretical population of the prefecture-level city and the actual population of the prefecture-level city in the Hunan Statistical Yearbook 2018. We calculate the estimation error of each hot words, as shown in the following table:

Table 3: Population estimation and error of hot words in various cities and states in Hunan province

City (State)	Hospital	District	Restaurant	Cun	Vegetable Market	School	Shopping mall	Hotel	Express	Park
Changsha	1213.27	1842.57	2982.96	758.27	3357.61	1690.90	2307.29	2198.25	2981.97	2263.46
Changsha (Error)	421.46	1050.76	2191.15	33.54	2565.80	899.09	1515.48	1406.44	2190.16	1471.65
Zhuzhou	408.07	494.36	727.55	505.80	357.60	463.61	453.07	449.32	355.72	279.55
Zhuzhou (Error)	5.92	92.21	325.40	103.65	44.55	61.46	50.92	47.17	46.43	122.60
Xiangtan	324.27	475.34	390.58	295.00	248.39	396.46	226.53	263.29	267.76	297.59
Xiangtan (Error)	40.47	191.54	106.78	11.20	35.41	112.66	57.27	20.51	16.04	13.79
Hengyang	641.25	604.27	394.17	686.20	364.03	639.99	486.63	432.49	537.08	414.82
Hengyang (Error)	79.28	116.26	326.36	34.33	356.50	80.54	233.90	288.04	183.45	305.71
Shaoyang	522.83	375.14	187.87	683.34	291.22	529.15	495.02	341.73	316.80	288.57
Shaoyang (Error)	307.25	454.94	642.21	146.74	538.86	300.93	335.06	488.35	513.28	541.51
Changde	632.14	541.49	523.41	489.10	462.53	492.20	495.02	477.99	378.29	459.91
Changde (Error)	47.64	43.01	61.09	95.40	121.97	92.30	89.48	106.51	206.21	124.59
Zhangjiajie	191.28	164.00	82.09	183.82	44.97	125.62	176.19	427.99	81.73	180.36
Zhangjiajie (Error)	21.67	5.61	87.52	14.21	124.64	43.99	6.58	258.38	87.88	10.75
Yiyang	351.59	274.84	131.15	460.70	269.81	273.73	352.39	287.46	391.53	432.85
Yiyang (Error)	87.61	164.36	308.05	21.50	169.39	165.47	86.81	151.74	47.67	6.35

Binzhou	561.09	454.69	448.74	468.69	241.97	463.29	327.22	379.17	337.82	703.39
Binzhou (Error)	89.99	16.41	22.36	2.41	229.13	7.81	143.88	91.93	133.28	232.29
Huaihua	544.70	386.18	115.59	547.47	175.59	329.63	385.95	336.28	334.70	243.48
Huaihua (Error)	48.70	109.82	380.41	51.47	320.41	166.37	110.05	159.72	161.30	252.52
Xiangxi	287.83	166.66	38.77	321.83	111.35	172.53	100.68	403.58	77.06	243.48
Xiangxi (Error)	174.32	53.15	74.74	208.32	2.16	59.02	12.83	290.07	36.45	129.97
Yueyang	471.83	495.28	393.21	402.90	492.51	545.21	444.68	439.60	298.12	523.03
Yueyang (Error)	96.28	72.83	174.90	165.21	75.60	22.90	123.43	128.51	269.99	45.08
Loudi	286.01	223.00	174.95	385.06	201.29	288.51	151.02	151.43	190.70	198.39
Loudi(Error)	167.16	230.17	278.22	68.11	251.88	164.66	302.15	301.74	262.47	254.78
Yongzhou	435.39	373.71	280.49	683.34	252.68	460.72	469.85	282.96	322.25	342.68
Yongzhou (Error)	112.58	174.26	267.48	135.37	295.29	87.25	78.12	265.01	225.72	205.29

Due to the differences among different regions, different hot words show great distinctions in population assessment errors in different regions. As the provincial capital of Hunan province, Changsha has the highest level of urbanization. Therefore, there are many infrastructures such as shopping malls and parks, increasing estimation errors of these hot words. For some villages, the settlement of village forms is named after “jie” and “tun”, and it will also have more or less influence on the evaluation results of hot words such as “village”. It can be seen from the error line chart of each city and state (Fig. 2) that when the hot words is “village”, the error is concentrated in a low value range and the degree of fluctuation is small.

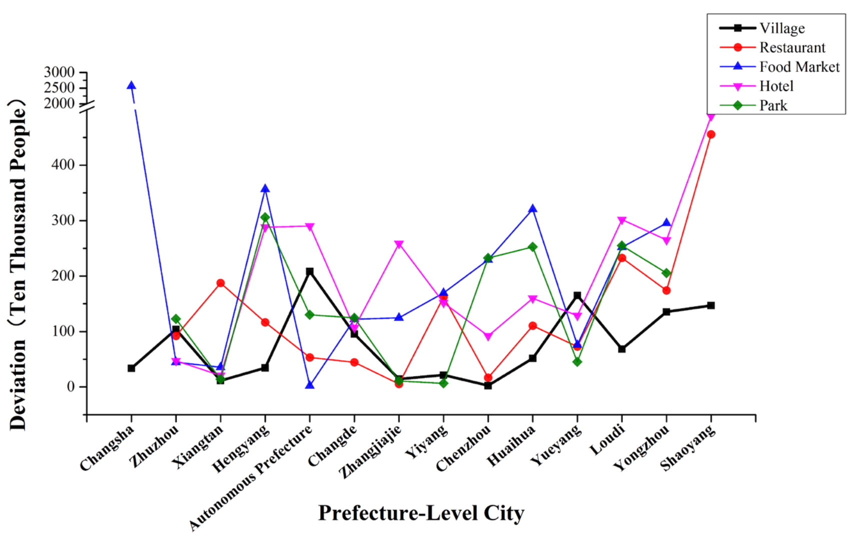

Figure 2: Model estimation error line chart of cities and states in Hunan (Part of hot words)

It can be seen in Fig. 2 that after the accuracy evaluation of the results from model calculation of each hot words, when the hot words is "cun", the population estimation value is the most accurate, and the average error is only 17.8%, which can explain that the population and economic data extracted by our method have certain accuracy.

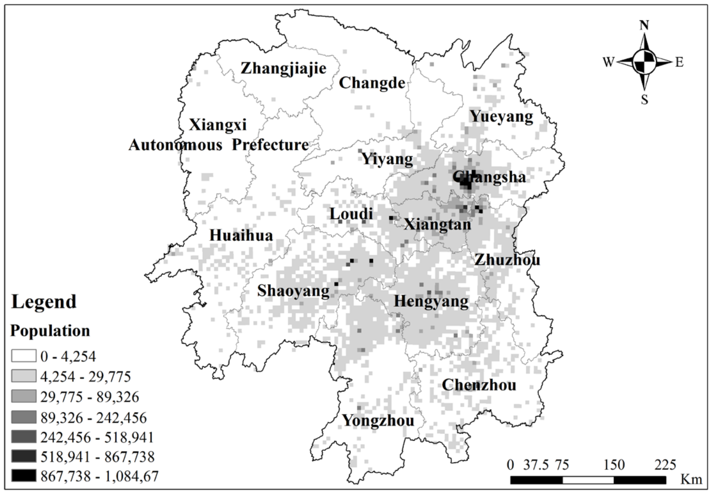

Figure 3: City and state population grid in Hunan

Fig. 3 shows the geo-grid population assessment results from the experiments, which are mapped to the map of Hunan province by interval division. From Fig. 3, Densely Inhabited District is well matched with the actually economically developed regions where the population is concentrated, that is, the evaluation of the geographical grid population in our research is roughly consistent with the actual situation. It is also verified the accuracy of the evaluation model to some extent.

3.2 Calculation of regional unfairness index in Hunan province

According to the unfairness indicator table of each city and state in Hunan province (Tab. 4), the regional unfairness degree of Changde is the most serious, with the unfairness index of 3507.96, and the unfairness index of Zhangjiajie is also at a high level, reaching 2228.57; while Xiangtan has the smallest value with 16.12, indicating that the distribution of medical resources in Xiangtan is relatively balanced. For the average number of hospitals assigned to per 10,000 people, Changsha is the highest, indicating that Changsha has gathered more medical resources in Hunan province so that the allocation of health service resources is excessive. The average numbers of hospitals per assigned to 10,000 people in Loudi and Shaoyang are only 4.81 and 4.42 respectively, which is only one fifth of Changsha.

Table 4: Fairness indicators of cities and states in Hunan province

Prefecture-Level City (State)	Provincial inequality indicators (F_j)	Average number of hospitals per 10,000 people
Changsha	232.35	22.76
Zhuzhou	565.31	12.02
Xiangtan	16.12	16.38
Hengyang	105.45	8.20
Shaoyang	439.79	4.42
Changde	3507.96	9.06
Zhangjiajie	2228.57	9.46
Yiyang	707.90	6.12
Binzhou	538.68	9.44
Huaihua	831.90	7.61
Xiangxi Tujia and Miao Autonomous Prefecture	1456.16	14.36
Yue Yang	1457.13	8.53
Loudi	158.30	4.81
Yongzhou	352.87	6.67

As shown in Fig. 4, the resource allocation in the whole province is totally out of balance in the north part, while the central region is relatively better. Especially in Hengyang and Xiangtan, the unfairness index is in a lower extend.

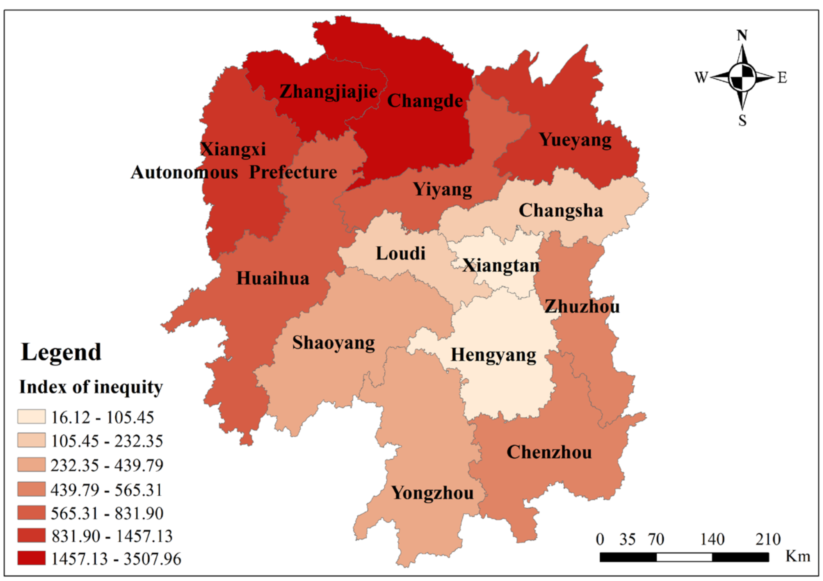

Figure 4: Unfairness index of health resources allocation in various cities and states in Hunan Province

As shown in Fig. 5, the health and medical resources of Hunan province are mainly concentrated in Changsha. The per capita medical resources of Xiangxi Tujia and Miao Autonomous Prefecture are also abundant. While the per capita health care resources in the central and western regions are relatively scarce, and the pressure on medical facilities is relatively high.

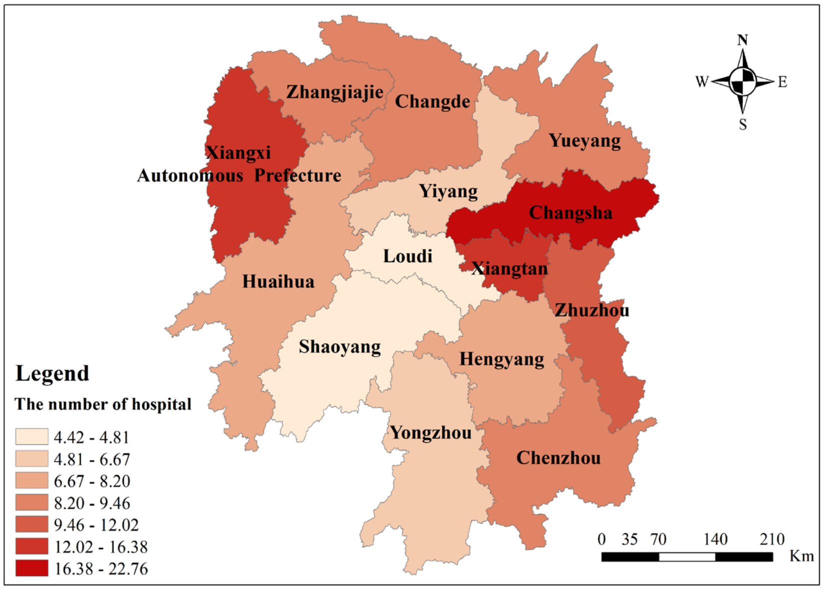

Figure 5: Statistics of the number of hospitals assigned to per 10,000 people in various cities and counties in Hunan Province

4 Summary and recommendations

What research method proposed in this paper can obtain more detailed assessment data for the study area of health resource allocation fairness. Unlike other similar studies, this program can not only assess the fairness of health resource allocation in small-scale areas, but also provide improving suggestions for the study area.

By analyzing the distribution of health resources in Hunan province, we have found that there is a large regional difference in the fairness of health resource allocation in Hunan province. It has a serious distribution imbalance in the north area while the situation is better in the central and southwestern regions. Relevant government agencies should pay more attention to the northern region in the future, and give priority to improving the medical resource allocation structure in the north.

The health and medical resources in Hunan province are mainly concentrated in Changsha which is the provincial capital of Hunan. As a result, the difference between Changsha and other cities which have a relatively lower per capita medical resources is vast. Therefore, to develop Hunan, the government agencies should consider more about the establishment of hospitals and other health services in the central and western regions to meet these people's health needs.

There is a large regional difference of the health resource allocation fairness in Hunan province. When relevant departments make decisions, they should fully consider local conditions, combined with local development, and formulate targeted policies and regulations based on the specific conditions of each city and state.

Health is considered a collective interest, so providing health care has become an integral part of determining human dignity [Lichtman (1987)], and everyone should have the equal right of health protection. At present, there is a widespread imbalance in resource allocation in China. It is common that where medical resources are scarce in some areas. The issue of health resource allocation is an urgent problem to be solved today. It requires government agencies to try their best to promote rational medical and health construction and take practical and effective measures based on the actual background.

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