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Analysis of the Spatial Distribution of Health Posts in Senegal

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Abstract

Health infrastructure is a major socioeconomic and territorial equity issue, as its availability improves both local population living conditions and makes their areas attractive. The results of our study have provided insights into the various types of spatial distribution of health facilities and the local spatial relationship connecting them to the population. We used data from the general census of population and housing of Senegal and the ANAT in 2023. While the use of centrographic measures allowed the description of the overall spatial distribution, the use of the chi-square statistic enabled us to verify the existence of a preferential direction of spatial distribution. Using the Ripley statistic therefore facilitated the verification of the existence of a spatial structure of the health post seeding. Local indicators of local spatial association have been used to measure and visualize the clusters of local spatial association between health posts and the population. Our results can be useful in land use planning, spatial resource allocation policies and in combating spatial disparities in access to health infrastructure. Indeed, the identification of different types of spatial aggregates and the highlighting of the preferred directions of the spatial distribution of health posts constitute important information for this purpose.

Keywords

Spatial Distribution, Local Indicators of Spatial Association, Ripley's Statistic, Centrographic Measures

1. Introduction

For several decades, Senegal, like many West African countries, has been subject to the structural adjustment and neoliberalism policies imposed by donors, which have drastically reduced public spending, particularly that allocated to the construction of infrastructure, equipment, and basic services [1]-[4].

However, since the 2000s, the State of Senegal has implemented several programs for the construction of infrastructure, equipment and basic services (National Rural Infrastructure Project—PNIR, Drinking Water for All Project and Support for Community Activities, the National Rural Electrification Program—PNER of Senegal) (ASER/Senegal, 2020; Ministry of Agriculture and Hydraulics/Senegal, 2006) [5] [6]. In the specific field of health, several programs/projects for the equipment of health infrastructure have been initiated to reduce inequalities of access [7]. We therefore note on the part of the State of Senegal, a revival for the development of infrastructure, equipment and basic services, particularly health infrastructure.

Health infrastructures stand as a significant socio-economic and territorial equity issue [8]. Indeed, the availability of these infrastructures has not only allowed the possibilities to improve the living conditions of populations, but it has made territories attractive and has allowed territorial development to be driven [9] [10].

Undoubtedly, the spatial distribution of health infrastructure issue has long preoccupied researchers and professionals. Some authors emphasize density at the territorial scale or access time. The work of the National Agency of Statistics and Demography (ANSD) of Senegal [11] [12] on the distribution of health structures in Senegal at the regional level in 2016 and at the departmental level in 2015 can be cited as an example. The work of Walter T. F. [13] also focuses on the analysis of the densities of health structures at the territorial level or the distance to the nearest structure. Other authors [14] put the emphasis on the distance between structures.

The literary review has also showed that cartographic visualization and frequency table analysis has been used as a method to analyze the spatial distribution of health facilities. The work of Muganzi Z. and Obudho R., A [15] on the spatial distribution of health facilities in urban centers of Keynia is an illustration of this. Belarem, M. *et al.* [16], in their study on the distribution of health facilities and the level of access to them in the city of Jeddah in Saudi Arabia, emphasized the visualization of inequalities in spatial distribution. Thus, these authors used buffers around health facilities, then counted the population within these buffers and finally compared the population size of them. Authors like Nieto M. A. and Márquez S. N. [17] have paid more attention to the analysis of the adequacy between the spatial distribution of health facilities and that of the population.

These studies have certainly made all the possibility to determine first the density of health structures at the territorial level, the distance or time of access, then measure inequalities of access, and at last analyse the similarity between the spatial distribution of health structures and that of the population. However, these upsaid studies do not allow the analysis of the spatial structure of the distribution of health centres in a continuous space. Yet, the analysis of this structure is important for the fight against spatial disparities and regional planning. Indeed, it highlight the forms of spatial distribution, the preferred directions and clusters of spatial association of structures. In addition, so far, we have ignored, we have ignored the application of methods of analysis of the spatial structure in the analysis of the spatial distribution of health infrastructures in Senegal.

We are then wandering about the spatial distribution structure of health facilities in Senegal. The use of several complementary spatial analysis methods will helps us bring a response to this question. The advantage of this approach is that it can reveal the spatial disparities in the distribution of health facilities, assess the spatial relationships between the locations of these facilities and infer the spatial processes at work. This includes describing the centre of gravity, dispersion/concentration, the orientation of the sowing of the facilities and testing the presence of spatial association clusters in the distribution of these facilities.

Our work therefore has the main objective of highlighting the spatial distribution structure of health posts in Senegal in a continuous space. The choice of health posts is justified by the fact that they play a strategic role in the health system of Senegal.

2. Materials and Methods

2.1. Study Area

Senegal covers an area of 196,712 km^2 and is bordered to the west by a coastline of over 700 km. It is bordered to the north by Mauritania, to the east by Mali, to the south by Guinea-Bissau and the Republic of Guinea, and finally by Gambia, which is almost entirely landlocked within its territory (**Figure 1**). Senegal is divided into 14 regions, 45 departments, 123 districts, and 557 communes. According

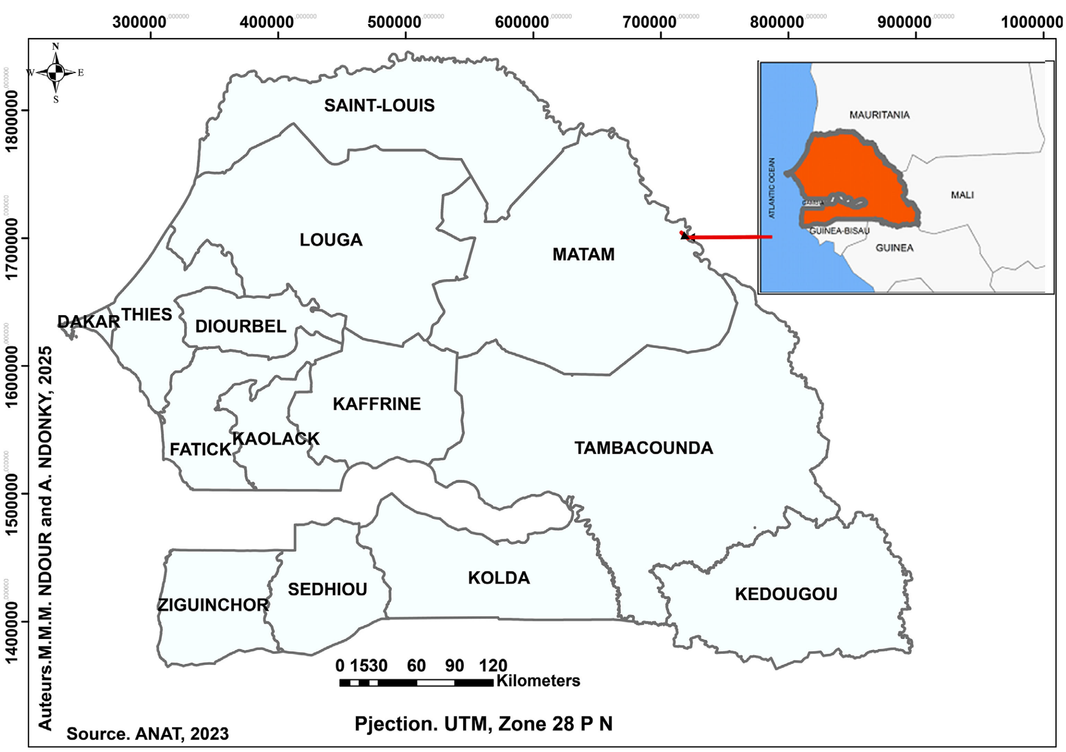

Figure 1. Map of the study area.

to the National Agency of Statistics and Demography, the population of Senegal is expected to be 18,126,390 in 2023 [18]. This population was 13,508,715 in 2013. It therefore experienced an average annual intercensal growth rate of 2.9%, which remained constant between the two intercensal periods.

Northern Senegal has a desert climate, while the south has a tropical savannah climate. There are two main seasons: a dry season (November to June) and a rainy season (June to October), marked by monsoons. The terrain is essentially flat, consisting of plains and plateaus, with some hills and sandy coastal areas. The plains and plateaus are located in the center, the hills in the southeast, and the Senegal River valley in the north.

2.2. Data

The data used come from the ANSD and the National Agency for Territorial Planning (ANAT). The ANSD provided us with data on the population and spatial location (in latitude and longitude) of health facilities collected during the 2023 general population and housing census. The administrative division maps used were collected from the ANAT in 2023.

2.3. Description of the Spatial Distribution Structure

2.3.1. Centrographic Measurements to Describe Overall Spatial Distribution

The objective is to measure the overall spatial dispersion of the health post pattern and clearly visualize its orientation. To do this, we use the mean point, the standard distance, and the standard deviation (or dispersion) ellipse. These centrographic measurements allow us to globally display the spatial distribution patterns of a phenomenon [19] [20], providing information on the degree of spatial concentration or dispersion and its orientation.

The mean point was used to measure and visualize the center of gravity of the health post pattern, as it allows the spatial distribution to be summarized. Its x_g and y_g coordinates are calculated as follows:

$$x_g = 1/N \sum_{i=1}^{N} x_i \quad y_g = 1/N \sum_{i=1}^{N} y_i \tag{1}$$

with *N*: number of points, x_i: longitude of given point *i*, and y_i: latitude of given point *i*.

To determine the overall spatial dispersion of health centers around the mean point, we used standard distance. This is a statistic that measures the average variability of point positions around the center of gravity. Its formula is as follows:

$$\sigma_{x,y} = \sqrt{1/N \sum \left(x_i - x_g\right)^2 + \left(y_i - y_g\right)^2} = \sqrt{\sum 1/N \left(d_{iG}^2\right)} \tag{2}$$

with *N*: number of points, x_i: longitude of point *i* and y_i: latitude of point *i*; x_g: longitude of the mean point and y_g: latitude of the mean point; *d*: distance between point *i* and the mean point.

The use of the dispersion ellipse made it possible to clearly visualize the orien-

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tation of the spatial distribution of health posts, which is not readily apparent on the map. This ellipse represents the intensity of the minimum and maximum dispersion of a series of points relative to their mean center [21]. The two standard deviations (σ_x and σ_y), in the X and Y directions, are orthogonal and, by construction, form an ellipse showing the distribution orientation of the phenomenon. These are calculated, one along the transposed X axis and the other along the transposed Y axis [22] as follows:

$$\sigma_x = \frac{\sqrt{\sum_{I=1}^{n}\left(\left(X_i - \overline{X}\right)\cos\vartheta - \left(Y_i - \overline{Y}\right)\sin\vartheta\right)^2}}{N-2} \quad \sigma_y = \frac{\sqrt{\sum_{I=1}^{n}\left(\left(X_i - \overline{X}\right)\sin\vartheta - \left(Y_i - \overline{Y}\right)\cos\vartheta\right)^2}}{N-2} \tag{3}$$

where N is the number of points, θ is the rotation angle of the Y axis relative to the horizontal (X axis), X_i: longitude of the given point i and Y_i: latitude of the given point $\overline{X}$: longitude of the mean point and $\overline{Y}$: latitude of the mean point.

2.3.2. Chi-Square Statistic to Confirm the Existence of a Preferential Distribution Direction

Centrographic measurements certainly offer the possibility of producing indicators that can be projected onto a map and thus visualize the preferential direction of the spatial distribution of the phenomenon. However, they do not allow statistical confirmation of the existence of this direction. Therefore, we used directional statistics (**Figure 2**). Using this statistic required the following steps. First, we segmented the study area into four angular sectors representing four cardinal directions, based on the average point of the health post pattern. Then, in each direction, we counted the number of health posts located there. Finally, a chi-square test [23] [24] was used to statistically confirm the existence of at least one preferred direction in the distribution of health posts. The chi-square equation is:

$$\chi^2 = \frac{\left(f_i - \overline{f}_i\right)}{\overline{f}_i} \tag{4}$$

with $\overline{f}_i = \frac{E}{C}$ (theoretical workforce), with E = total sample size, f_i = observed workforce in the direction i and C = number of categories.

2.3.3. Ripley Statistics to Verify the Existence of a Heterogeneous Spatial Distribution Structure

While these centrographic measurements allow for a description of the overall spatial distribution, they do not reveal the existence of a heterogeneous spatial distribution structure. The use of Ripley's statistics was therefore necessary.

There are several methods for describing the spatial structure of a point pattern [25]-[29]. These methods have been used particularly in the field of forestry [29] [30]. These methods include those based on quadrats and those based on distances. For quadrat methods, the data are the number of points/positions in quadrats [31], while for distance-based methods, the data are the distances between points/positions.

Distance-based methods include those that require only knowledge of the nearest neighbors of each point such as the method of [32], used for small domains) and more expensive ones requiring a map of the entire study area. Ripley's method is one of the latest methods and is used for large domains.

The advantage of Ripley's method over other distance-based methods is that it allows to describe the spatial distribution structure simultaneously at multiple distances [29], revealing the variation of spatial aggregation or dispersion of features when the neighborhood size changes. However, the Ripley function is always difficult to interpret, as the curve obtained for the null hypothesis is in the form of a parabola. In addition, the graphs are very difficult to present. Therefore, we chose to use a modified function $L(d)$ proposed by Besag [33], which is easy to use. This function is normalized and thus allows us to compare the structure of seedlings with different sizes. The equation of the function $L(d)$ is:

$$L(d)=\sqrt{\frac{A\sum_{i=1}^{N}\sum_{i=1.\,j\neq i}^{N}k(i,j)}{\pi N(N-1)}} \tag{5}$$

where A represents the area, N is the number of points, d is the distance, and $k(i,j)$ is the weight. If no boundary correction is applied, the weight is 1 when the distance between i and j is less than or equal to d; it is 0 when the distance between i and j is greater than d. If boundary correction is applied, the weight of $k(i,j)$ is slightly modified.

2.4. Kernel Density Method for Mapping Spatial Trends in the Distribution of Health Facilities

The kernel density method is a spatial smoothing technique that highlights spatial trends and areas of high or low concentration of the phenomenon [34]. It consists of creating a continuous density layer of the phenomenon, based on its locations. This layer (grid) is made up of small cells. The density value associated with each cell is the estimate of the phenomenon to be analyzed. This estimate is made for the center point of each grid cell. It can be made using several types of kernel functions. Determining the shape of the data's influence, the kernel density function counts the number of events within a region called the kernel density kernel, around the location where the estimate is made. The (spatial) weights closest to the events are the most significant. According to Berlinet A. and Devroye L. (1989) [35], the kernel density estimator $F_n(X)$ is calculated as follows:

$$F_n(X)=\frac{1}{nh}\sum_{i=1}^{n}k\left(\frac{(x-X_i)}{h}\right) \tag{6}$$

with n: the sample used to make the h: neighbor search radius; k: kernel function; X_i = known point, x = point to interpolate.

2.5. Local Spatial Association Indicators to Determine Local Spatial Association Clusters of Health Posts

Centrographic measures and directional statistics are used to describe the overall spatial distribution of health posts. The kernel density method offers the possibility of revealing spatial trends. However, these measures have some limits, as they do not allow statistically significant clusters of local spatial association to be highlighted. To detect these clusters, we used the local indicators of spatial association developed by Anselin [36]. Indeed, with these measures we can determine and visualize the types of local spatial association and their levels of statistical significance.

Their formula is:

$$I = \frac{\sum_j w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_i \left(x_i - \bar{x}\right)^2} \tag{7}$$

with, x_i: value taken by the observation x_i, x_j: value taken by the neighboring observation x_j, $\bar{x}$: mean of the variable *x*, w_{ij} spatial weight.

The overall methodological approach is illustrated in Figure 2.

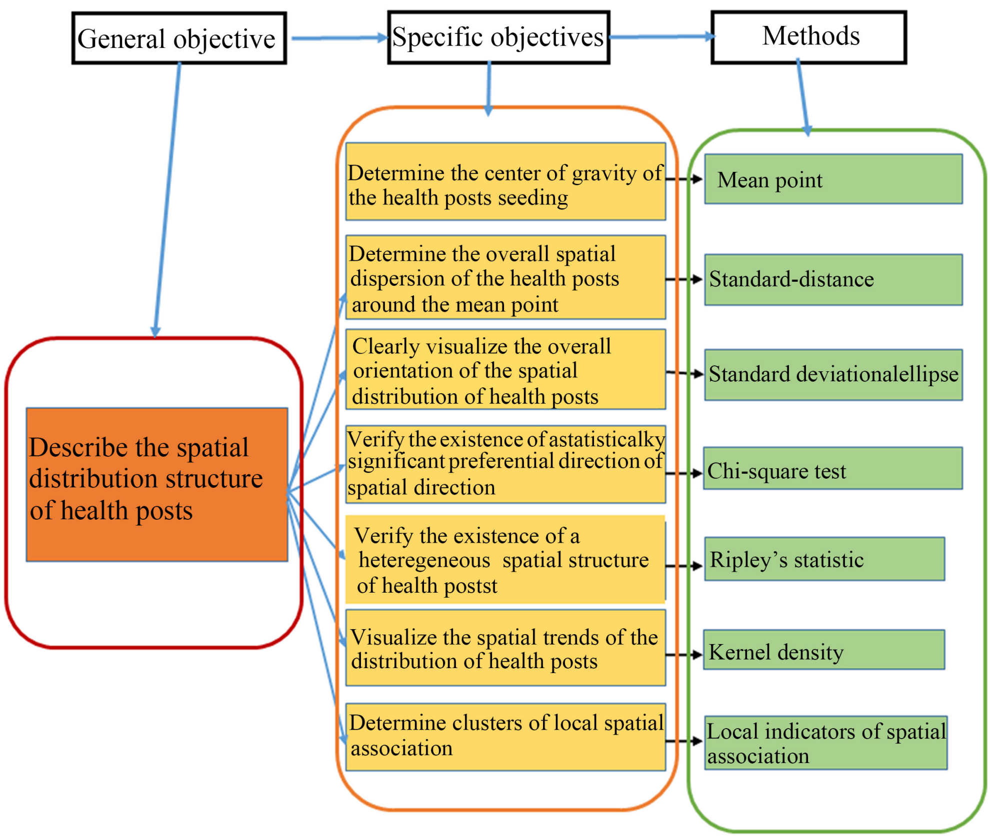

Figure 2. Overall methodological approach.

3. Presentation of the Results

3.1. Overall Spatial Distribution of Concentrated Health Posts

The number of geolocated health posts is 2127 (Figure 3), which is more than sufficient for the analysis. To determine whether the overall distribution of health posts is concentrated, dispersed, or random, we calculated centrographic indicators, including the dispersion index and the associated significance test. The dispersion index is interpreted as follows: If it is greater than 1, we say there is a tendency toward dispersion; if it is equal to or very close to 1, we say the distribution is random; and if it is less than 1, we say there is a tendency toward spatial concentration of the phenomenon.

The results of this test show a low dispersion index (0.69) and a z-value of −27.12, much higher than that of the centered-reduced normal distribution (1.96), with a risk of error of 5%; moreover, the observed average distance is much lower than the theoretical average distance (**Table 1**). The overall spatial distribution of health posts is therefore concentrated at the national level.

Table 1. Centrographic indicators of health posts at the national level.

Indicators	Values
Average observed distance (m)	4215.64
Theoretical distance (m)	6089.01
Dispersion index	0.69
Z-score	−27.12
Standard distance	188905.87
Number of health posts	2127

We also sought to determine whether distribution patterns are the same across all administrative regions of Senegal. To do this, we measured the centrographic indicators for each region (**Table 2**). Analysis of the results of these measurements allows us to make the following observations.

Table 2. Overall indicators of health posts by region.

Region	Observed average distance	Theoretical average distance	Disper sion index	Z-score	Standard distance	Long axis/short axis ratio of the standard deviation ellipse	Number of health centers
Dakar	777.9	1188.80	0.654	−9.3*	10957.18	2.24	195
Thiès	2544.2	3540.6	0.71	−8.86*	37285.25	1.82	271
Diourbel	3147.90	3297.08	0.95	−1.05	32028.09	2.76	149
Fatick	3582.63	4902.07	0.73	−6.55*	42005.85	1.44	162
Kaolack	3193.19	3490.68	0.91	−2.13*	33096.59	1.76	171
Louga	6075.93	6840.34	0.88	−2.74*	56228.81	1.75	165
St Louis	4599.38	706.40	0.68	−8.33*	98459.41	3.97	192
Matam	5869.11	8347.39	0.70	−6.64*	57401.10	1.32	137
Kaffrine	5810.25	5368.25	1.082	1.69	41987.91	1.53	116
Tambacounda	7854.95	9664.4	0.81	−4.67*	102517.3	2.20	170

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Continued

Kédougou	9895.97	10418.7	0.95	−0.65	59008.65	1.95	47
Kolda	5759.78	5988.95	0.96	−0.80	57401.10	2.07	121
Sedhiou	5056.57	5257.6	0.96	−0.63	35367.72	1.27	76
Ziguinchor	3457.05	3586.74	0.96	−0.86	33327.10	1.08	155
Niveau national	**4215.64**	**6089.01**	**0.69**	**−27.1***	**188905.8**	1.31	**2127**

NB: *Significant at 5%.

The overall spatial distribution varies from one region to another. Three groups of regions emerge. The first consists of regions that record the highest and statistically significant levels of spatial concentration of health posts. These regions are mainly found in the west of the country (Dakar, Thiès, Fatick, Saint-Louis). The second group includes regions where levels of spatial concentration are noted, although significant, but lower. These are Louga, located in the center-west and Kaolack, located in the center of the country. Finally, the last group is made up of regions where health posts are distributed randomly in space. These regions are mainly found in the south of the country.

These results reflect the heterogeneity of the national area in terms of health center coverage. However, they do not allow us to visualize the spatial distribution of health centers. This is what we will do by analyzing the map of mean points and the standard deviation ellipse.

3.2. Spatial Distribution Generally Oriented Northwest/Southeast

Figure 3 shows the distribution of health posts, mean points, and standard deviation ellipses at the national and regional levels. At the national level, the overall spatial distribution of health posts is oriented northwest/southeast, as indicated by the pink directional ellipse in Figure 3. This figure also shows that the center of gravity of health posts is located in the center-west of the country. Furthermore, the extent of the standard deviation ellipse covers this part of the country, revealing that the majority of health posts are located in this part of the national territory. The existence of this preferential direction in the overall spatial distribution of health posts is statistically confirmed by the results of the chi-square test, as the calculated chi-square (880.5) is significantly higher than the theoretical chi-square (7.81) (Table 3).

Table 3. Chi-square at the national level.

	Cardinal Directions					Chi-Square
Health posts	**North-East**	**South-East**	**North-West**	**South-West**	**Total**	
	221	218	1040	648	2127	880.5*

*Significant at 5%, for a ddl = 3 and a theoretical chi-square = 7, because the chi-square calculated is 880.5.

Analysis of the standard deviation and mean point ellipses at the national level conceals significant spatial disparities. To reveal these disparities, we will examine the standard deviation and mean point ellipses at the regional level.

3.3. Spatial Distribution Patterns, Varying by Region

The variation in the distribution shapes of health posts by region is summarized in Figure 3. This figure indicates that the standard deviation (or dispersion) ellipses do not have the same size, shape, or orientation. Thus, the regions of Tambacounda and Saint-Louis have the largest ellipses, while those of Diourbel, Kaolack, Sédhiou and Ziguinchor have small ellipses. Ellipses with more elongated shapes are found in the regions of Tambacounda, Saint-Louis, and Dakar, as illustrated in Figure 3. In addition, Table 4 shows the regions with more elongated shapes. Indeed, the long axis/short axis ratios of the standard deviation ellipse are the highest (3.97 for Saint-Louis, 2.72 for Diourbel, 2.24 for Dakar).

While the ellipses of the Tambacounda and Kédougou regions are oriented northeast/southwest, those of the Diourbel and Saint-Louis regions are oriented east/west. The ellipses of the Ziguinchor and Sédhiou regions indicate that the spatial distribution of health posts is almost unoriented, which is confirmed by values of the long axis/short axis ratios of the standard deviation ellipse very close to 1 (Table 4).

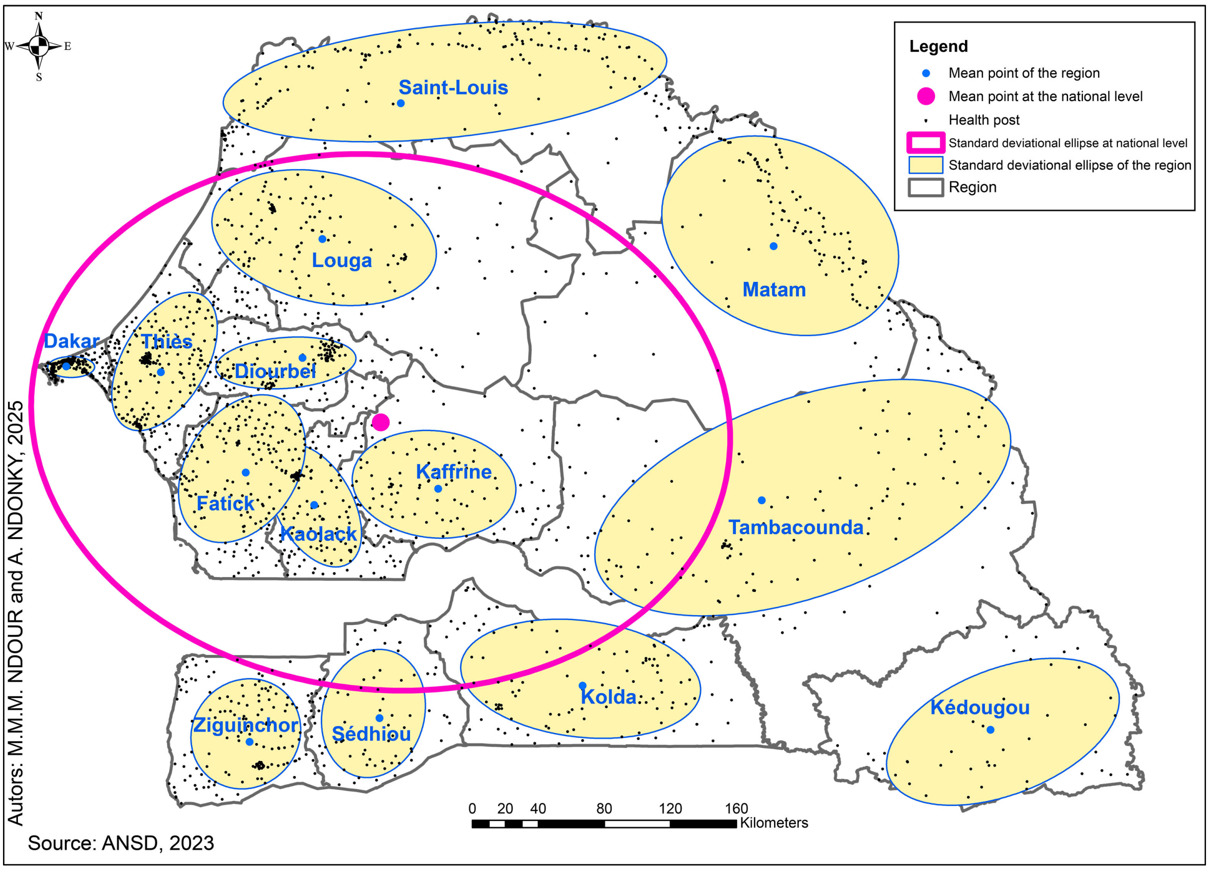


Figure 3. Characteristics of standard deviation ellipses.

Table 4. Characteristics of the standard deviation ellipses.

Region	Rotation of the standard deviation ellipse (in degrees)	Long axis/short axis ratio of the standard deviation ellipse
Dakar	89.87	2.24
Thies	30.26	1.82
Diourbel	85.79	2.76
Fatick	32.22	1.44
Kaolack	150.51	1.76
Louga	102.07	1.75
St louis	84.27	3.97
Matam	115.80	1.32
Kaffrine	96.11	1.53
Tambacounda	70.51	2.20
Kédougou	68.61	1.95
Kolda	96.79	2.07
Sédhiou	14.62	1.27
Ziguinchor	43.45	1.08
National level	96.45	1.31

Table 5. Chi-square by region.

Region	North-East	South-East	North-West	South-West	Total	Chi-square
Dakar	13	23	85	74	195	79.85*
Thiès	58	28	48	137	271	101*
Diourbel	52	22	26	49	149	19*
Fatick	57	34	32	39	162	9.6*
Kaolack	11	45	79	36	171	56*
Louga	14	23	75	53	165	57*
St louis	73	18	60	41	192	36*
Matam	91	26	14	6	137	131*
Kaffrine	12	30	21	53	116	32*
Tambacounda	71	16	19	64	170	60*
Kédougou	13	13	1	20	47	16*
Kolda	29	26	33	33	121	1.1
Sédhiou	11	19	20	26	76	6
Ziguinchor	43	50	30	32	155	6.9

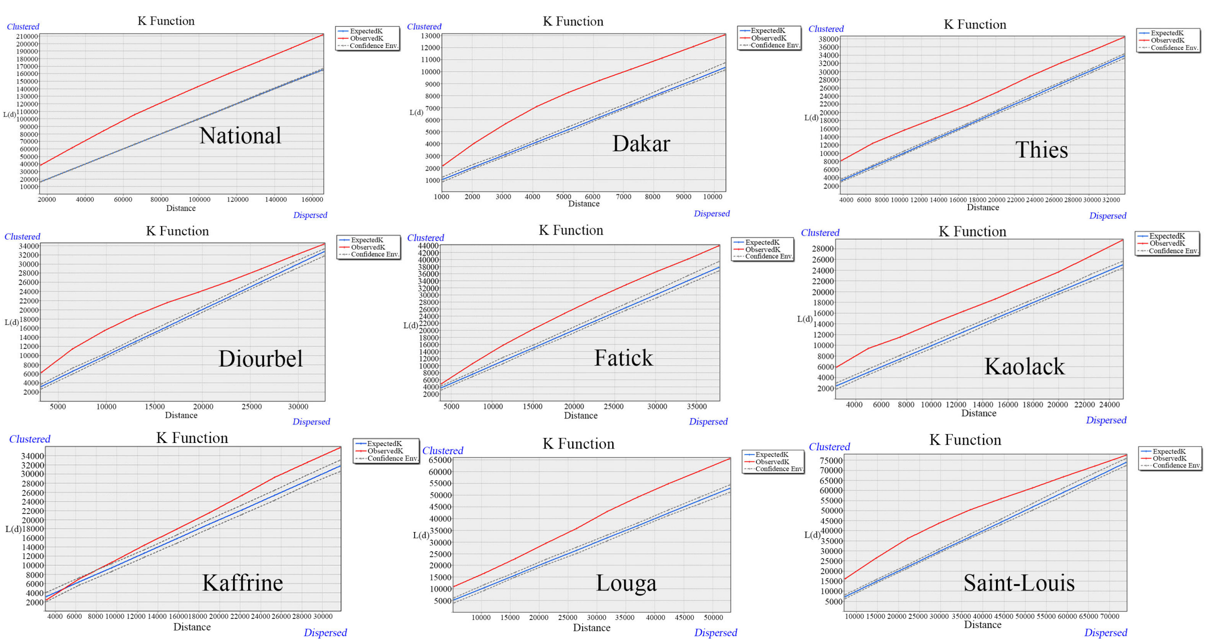
*Significant at the 5% level, for a dof = 3 and a theoretical chi-square = 7.81.

Certainly, the ellipses of the standard deviation can highlight the preferential direction of the distribution of health posts. However, they do not provide the possibility of knowing whether this is statistically significant (Table 5). It is the results of the chi-square tests contained in **Table 5** that make it possible to know this. They show that there is no preferential direction of distribution of health posts in all regions of Senegal. Indeed, the three southern regions (Ziguinchor, Sédhiou and Kolda) do not record any preferential direction of distribution of health posts. In other words, health posts are distributed randomly in these regions.

In regions where there is a statistically significant preferential direction, the significance levels are not the same. For example, they are higher in the Matam, Thiès, Dakar, Tambacounda, and Louga regions, and lower in the Fatick and Diourbel regions. Furthermore, the preferred distribution directions for health centers vary by region. While in Matam, the preferred distribution axis is northeast, in Thiès, it is southeast.

3.4. A Trend toward Spatial Aggregation of Health Posts at Different Scales

Figure 4 shows the multi-distance spatial clusters of health posts. We note, in a way, a trend toward spatial aggregation of health posts across different distance classes (spatial scales). Indeed, the red curve, representing the observed values, is above the gray curve (confidence envelope) and the blue curve (expected/theoretical values) in almost all distance classes in most regions and at the national level. However, this overall trend hides local specificities. For example, in the Kaffrine region, we observe a random distribution over short distances. From 5 km, we note the beginning of spatial aggregation, which increases with distance. In contrast, in the Saint-Louis and Diourbel regions, we observe a concentration phenomenon that diminishes with distance. Still as an example, the regions of Kédougou, Kolda and Sédhiou are territories where no spatial aggregation of health posts is recorded, whatever the spatial scale.



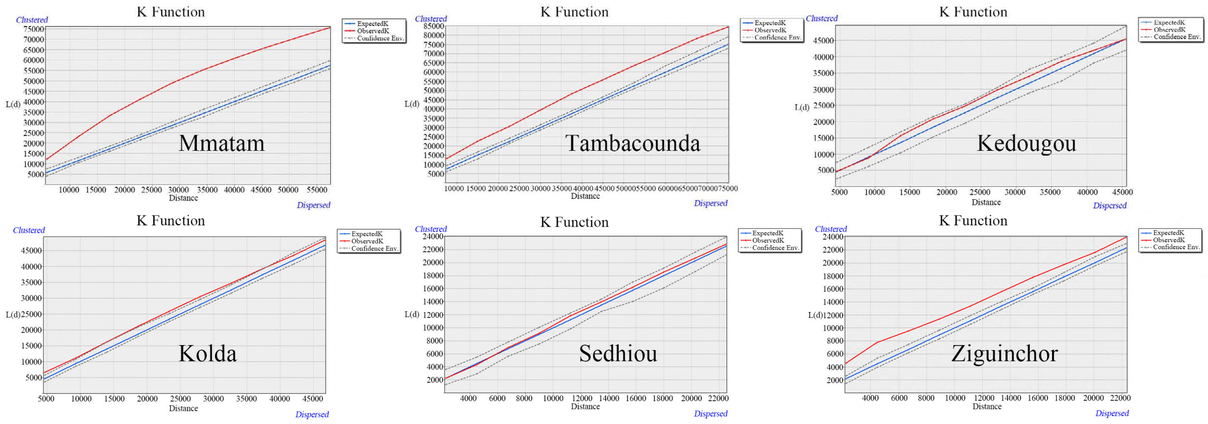


Figure 4. Multi-distance spatial clusters of health posts in Senegal in 2023.

The results presented so far are very interesting, as they have revealed the center of gravity of the health post distribution, the dispersal ellipses, the existence of statistically significant preferential spatial distribution directions, and the spatial aggregation clusters of health posts at several spatial scales (or over several distances).

However, they do not allow us to visualize the density of health posts or the types of local spatial aggregation clusters.

3.5. Health Post Density Higher in the West

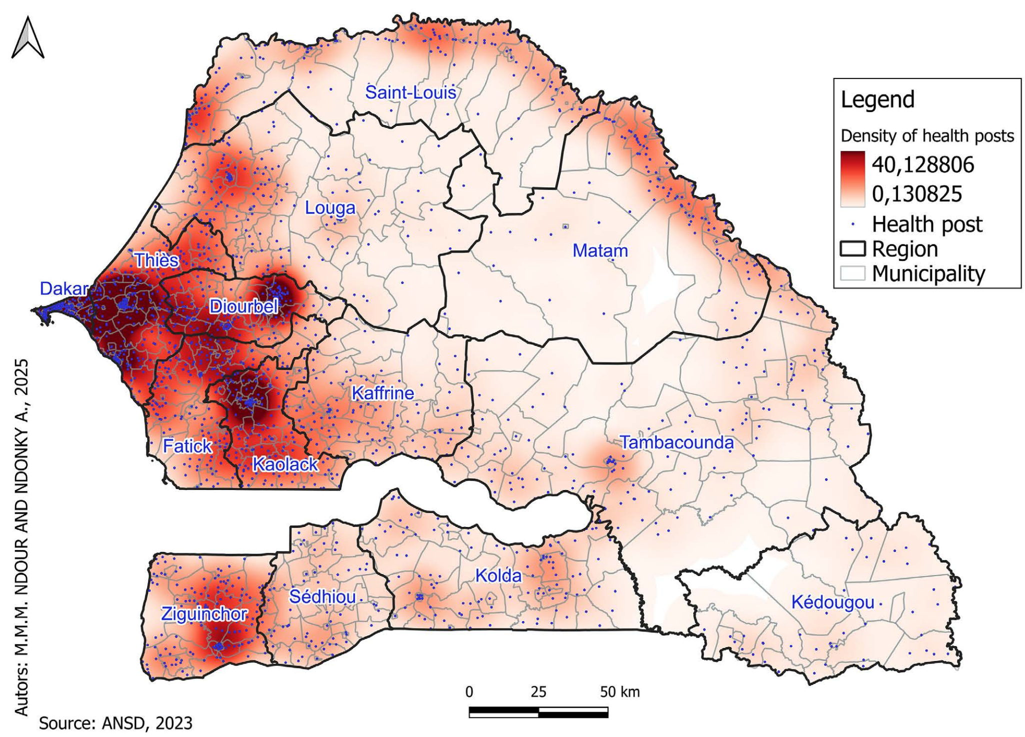


Figure 5. Density of health posts in Senegal.

The results produced so far have highlighted the center of gravity, orientation, and presence of clusters of spatial aggregation at several scales of health posts. However, these methods have limitations, as they do not allow for a clear visualization of spatial trends in the spatial distribution of health posts. For all these reasons, we present the results obtained from smoothing using the kernel density method.

These results are shown in **Figure 5**. To produce this figure, we used a smoothing radius of 30 km and a grid of square cells with sides of 3 km. Observation of **Figure 6** allows the following observations. The highest densities of health posts are found in the west, particularly in the regions of Dakar, Thiès, Fatick, Diourbel, Kaolack, and Ziguinchor. Conversely, the eastern part of the territory has a low density of health posts. There is a sort of west-east gradient, with a decrease in the density of health posts from west to east.

3.6. Clusters of Local Spatial Association, Revealing the Contrast between the Well-Endowed West and the Very Poorly Endowed East in Health Posts

The health post density map produced by the kernel method shows global and local spatial trends in the spatial distribution of health posts. However, it does not indicate the types of local spatial association and their level of statistical significance. This is why we produced the map of local indicators of spatial association (**Figure 6**). To produce this map, we first generated a grid of square cells with sides of 3 km and projected the layer of health posts onto it. Then, using the spatial join method, a count of the number of health posts per square was carried out. Finally, we started calculating the local indicators of spatial association contained in **Figure 7**.

This figure highlights four types of statistically significant spatial association. The first type includes red tiles with positive values (index above the average) in an environment of tiles with positive values corresponding to positive autocorrelation. This association is called strong-strong. This type of tiles is found almost exclusively in the west. The second type consists of blue tiles with negative values (index below the average) in an environment of tiles with negative values corresponding to negative autocorrelation. This association is called weak-weak. This type of tiles is found almost exclusively in the east, on a diagonal that starts from the south of the Saint-Louis region, passing through the east of the Louga region, the west and center of the Matam region, the Tambacounda region, and ends in the Kédougou region (**Figure 6**).

The light blue tiles constitute the third type and record negative values (index below the average) in an environment of points with positive values corresponding to positive autocorrelation. This association is called weak-strong (**Figure 6**). The fourth type consists of light red tiles with positive values (above-average index) in an environment of negative-valued points corresponding to negative autocorrelation. This association is referred to as strong-weak (**Figure 7**). Atypical tiles comprise types three and four, but they are very weakly represented.

Gray tiles are those where the local spatial association is not significant.

Certainly, the description of centrographic indicators and clusters of local spatial association of health posts is of great interest. However, it is also important to know whether the number of health posts is locally associated with the population in the space.

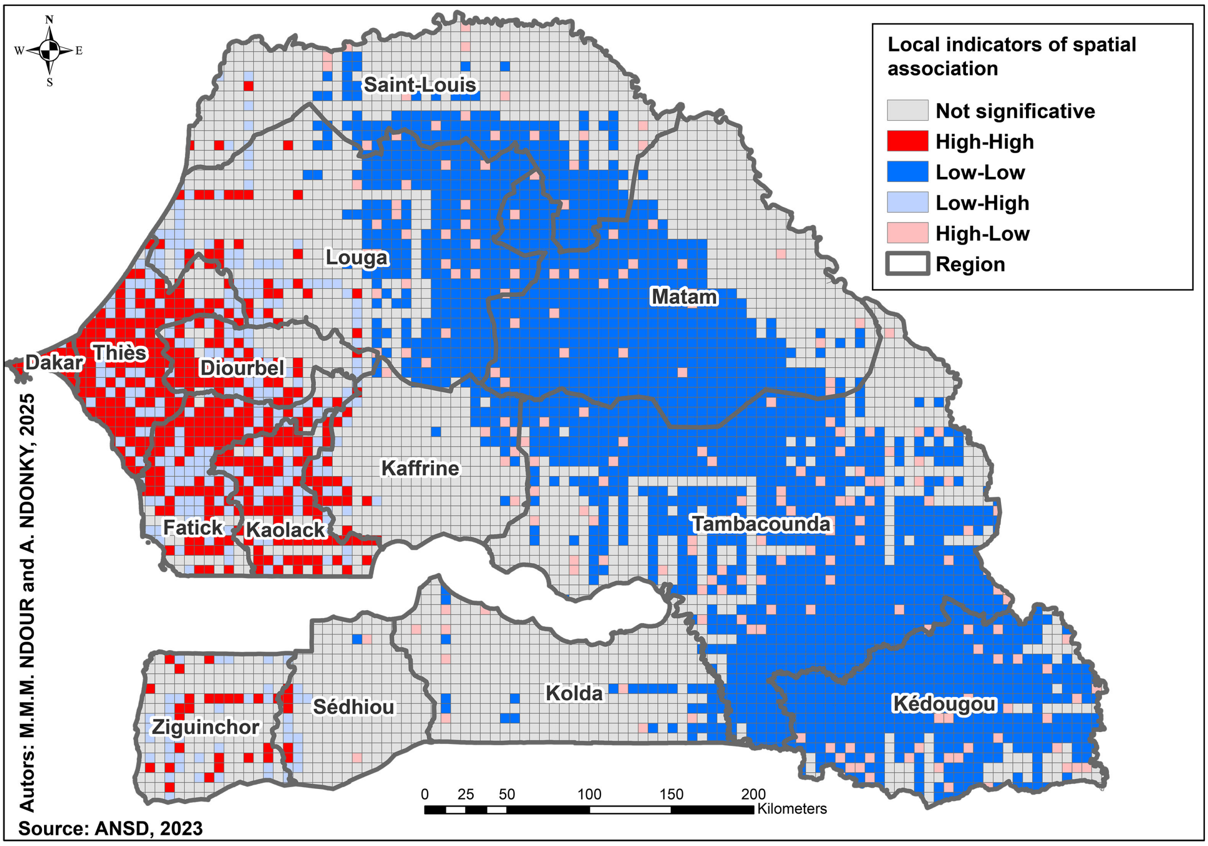


Figure 6. Clusters of local spatial association of health posts in Senegal in 2023.

3.7. A Strong Local Spatial Association between Health Posts and the Overall Population Is Weak

To measure the local spatial association between the number of health posts and population size, we had to aggregate the number of health posts at the commune level, where data on population size are available. The results of this measurement are shown in Figure 7, which highlights four types of local spatial association between health posts and population. The first type (red areas) shows areas with a high number of health posts and a high population size. This type is poorly represented and is located almost exclusively in the far west of the country. The second type (dark blue areas), which is more represented, describes communes where a local spatial association is noted between a low number of health posts and a low population size.

It is mainly found in the southeast and southwest. The third type (light blue areas), which is almost absent, highlights communes where a local spatial association is recorded between a low number of health posts and a large population size. It is found mainly in the southeast and southwest. Almost absent, the third type (light blue areas) highlights the municipalities where a local spatial association is recorded between a low number of health posts and a large population size. Fairly well represented, the fourth type (light red areas) shows the aggregation of municipalities where a local spatial association is observed between a high number of health posts and a small population size. The gray areas represent the municipalities where the local spatial association between the number of health posts and the population size is not statistically significant.

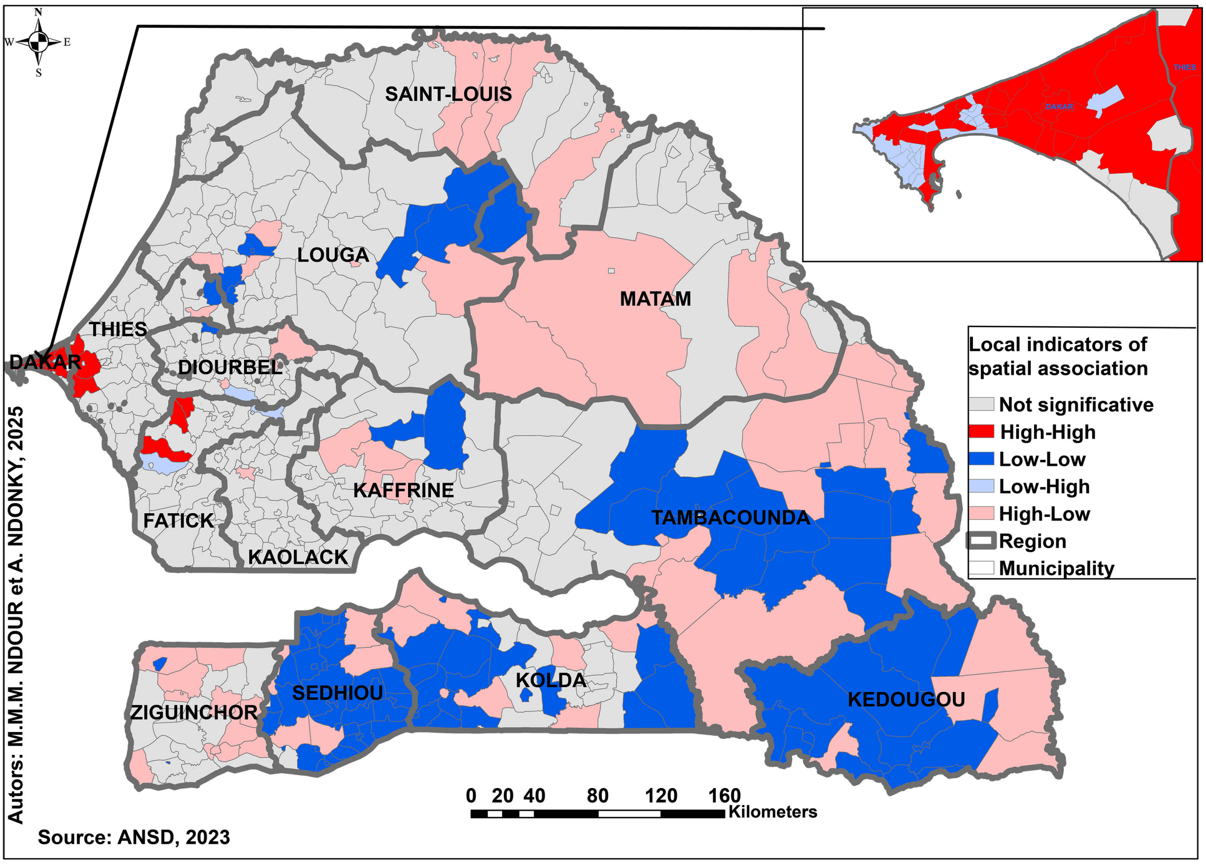


Figure 7. Clusters of local spatial association between health centers and the population of Senegal in 2023.

4. Discussion

Our results revealed a high spatial concentration of health centers at both the national and regional levels, a west-east spatial distribution of these centers, and little consideration of the spatial distribution of population sizes in the spatial allocation of health centers. They also revealed significant spatial disparities, notably the contrast between the west, which is well-equipped with health centers, and the east, which is very poorly equipped.

We do not have demographic and socioeconomic data on the same spatial scale as the spatial distribution data for health posts. The availability of these data would have made it possible to verify the influence of population size and certain socioeconomic factors on the spatial distribution of health posts. This situation therefore limits the possibilities of analysis and the scope of the results. However, in view of the objectives of the study, these limitations did not affect the quality of our results.

We will now interpret our results in light of other studies on the same topic. We are not aware of any studies on the spatial distribution of health centers in our study area; hence, it is difficult to compare our results with other studies in the same area. However, we can compare them with the results of studies conducted elsewhere on the same issue. Thus, our results can be compared with those of Niang, A. and Handschumacher, [37], which revealed spatial disparities in the distribution of health personnel in the Senegal River Valley. The work of Poné Paliouo Irie Lou Fidèle [38] on the spatial dynamics and evolution of health facilities in Bouaflé (Côte d'Ivoire) also highlighted spatial disparities in the distribution of health infrastructure and services. Ymba Maimouna [39], in his study on access to and use of modern healthcare in urban Abidjan (Côte d'Ivoire), also demonstrated spatial disparities in the distribution of healthcare infrastructure and services. Belarem, M. *et al.* [16], in their study on the distribution of dispensaries (health posts) in the city of Jeddah (Saudi Arabia), also highlighted spatial disparities and preferred directions in the spatial distribution of healthcare infrastructure, using centrographic measurements. The advantage of our study over that of these authors is that we verified whether the preferred direction of spatial distribution is statistically significant. Furthermore, our study revealed statistically significant clusters of spatial association.

These results are consistent with ours and tend to confirm the relevance of our approach.

The location of the center of gravity and the spatial aggregation clusters of health centers is an expression of the State's strategies for allocating health resources in space. Indeed, the State has always favored urban centers, places of high concentration of populations and socioeconomic activities and more accessible. However, urban centers are located mainly in the west. This policy has given the possibility to increase the level of endowment of health centers in the west to the detriment of the less urbanized and less populated east of Senegal. Moreover, the location of certain infrastructures and services, such as private health centers, in the context of a liberal economy as is the case in Senegal, is linked to the action of private actors. For these actors, the value of space is greater in urban areas than in rural areas. Therefore, they will tend to locate their health infrastructures in urban areas to attract a larger and more economically solvent clientele.

The trend towards spatial concentration of health posts is confirmed by the analysis of multi-scale (multi-distance) spatial clusters and local indicators of spatial association. This spatial concentration means that spatial disparities in the allocation of health posts are significant, despite the efforts made by the State to equip the territories. With the liberalization of the economy, economic actors are free to settle in places they consider economically advantageous. The more attractive a place is, the more it tends to attract activities and infrastructure and services. This phenomenon, which refers to a profit maximization function [40], leads to the long run to the spatial aggregation of health posts.

In an attempt to understand the spatial distribution of health centers, we believe it is important to consider the effects of the spatial organization of roads and the hierarchy of localities in the study area. Indeed, roads make localities more accessible and attractive. Larger urban centers have greater potentialities to attract than smaller ones. Consequently, they favour the establishment of health centers.

There is a diversity of forms of spatial distribution of health centers, revealing the differences in strategies of socioeconomic actors regarding the location of health facilities in the study area and the levels of spatial value. This suggests the presence of several spatial processes at work: contagion processes, random processes, and hierarchical processes. This reflects the heterogeneity of the distribution space of health centers.

These results globally show that strategies for allocating health care facilities across space do not adequately take into account the spatial distribution of population sizes. Indeed, there is a small number of municipalities where a positive local spatial association between the number of health care facilities and population size is observed. Opposing to them, there is a larger number of municipalities where this association does not exist.

Our study is truly original. It has produced various and complementary results by combining several spatial data analysis methods. This study has better helped us in understanding the spatial distribution of health care facilities in Senegal, since, to our knowledge, no study of this kind has yet been conducted in this area.

5. Conclusions

The objective of this study was to analyze the distribution patterns of health centers. This objective has been achieved, as the following lessons can be learned from our study. A preferred direction for the spatial distribution of health centers is observed: the west, where there is greater spatial agglomeration. The results show a spatial concentration of health centers, particularly in the west and center-west.

From a methodological point of view, the use of several analysis methods made it possible to produce rich and complementary results. Thus, the centrographic indicators revealed the direction, the center of gravity and the level of concentration of the spatial distribution of the health post seeding. The chi-square test offered the possibility of statistically confirming the existence of this preferred direction. The Ripley method revealed the heterogeneity of the spatial structure of the distribution of health posts, in particular their spatial concentration. The kernel density method contributed to the visualization of the clusters of spatial concentration of health posts, while the local indicators of spatial association helped in revealing the types of local spatial association.

Our results can be useful for policies on the spatial allocation of health infrastructure. Indeed, identifying different types of spatial aggregates and highlighting the preferred directions of the spatial distribution of health facilities provides essential information for correcting spatial disparities in access to health services.

The production of these results constitutes an encouraging first step in analyzing the spatial distribution of health facilities. However, improvements remain to be made, particularly in measuring the effects of socioeconomic factors on the spatial distribution of these health facilities and in deepening our understanding of the spatial relationship between health facilities and the population using finer spatial resolution.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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