Spatial Inequality and Clustering of Environmental Health Personnel Distribution in East Java: Evidence from Moran's I Spatial Autocorrelation Analysis

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ABSTRACT

The distribution of healthcare workers is a key factor in determining access to and quality of public health services. This study aims to analyze the distribution of healthcare workers in regencies/cities in East Java using a quantitative approach and spatial analysis. Data on healthcare workers (Environmental Health Workers) were obtained from each regency/city and analyzed using descriptive statistics, spatial clustering (High-High, High-Low, Low-High, Low-Low), significance testing, and spatially lagged plots to detect outliers. The results of the spatial autocorrelation analysis using Global Moran's I show a value of 0.3877, with an expected value (Expectation) of -0.0270, a variance of 0.03946, a Z-score of 2.0878, and a p-value of 0.0184. These findings strongly indicate spatial dependence in the distribution of environmental health workers in the study area. The results show significant variation among regencies/cities, with the highest concentration in Surabaya City and the lowest in Pasuruan City. Spatial cluster analysis revealed high concentrations in city centers and disparities in remote areas. Statistical significance and spatial outliers strengthen evidence of uneven healthcare worker distribution. These findings provide a scientific basis for planning policies to redistribute healthcare workers, support service equity, and improve service quality across regions. This research emphasizes the importance of data-driven allocation strategies to reduce disparities in healthcare access.

I. Introduction

Health workers are a key component of the healthcare system, influencing the quality and accessibility of medical services for the community [1]. The equitable distribution of health workers is crucial to achieving health development targets, including equal service distribution in urban and remote areas [2], [3]. Unfortunately, in many regions, including East Java, the distribution of health workers is still uneven, leading to disparities in services between city centers and rural areas [4], [5]. This situation directly affects the community's health levels, the availability of medical facilities, and the effectiveness of government health programs.

The distribution of healthcare personnel in Indonesia remains uneven, with a higher concentration in urban areas compared to rural regions. Purwaningsih reported that Indonesia is among the 57 countries facing a shortage of health workers according to the World Health Organization [6]. Aditya and Laksono highlighted that this uneven distribution undermines the quality of healthcare services across several regions, exacerbating urban-rural disparities, particularly in East Java [7]. Febriyanti et al. documented that human resource constraints and unequal allocation across primary healthcare facilities are major barriers to implementing health programs in various Indonesian regions, including East Java [8]. Supporting this view, Leosari et al. found that only 20% of doctors practice in rural areas, despite nearly 70% of the population residing there, resulting in a doctor-to-population ratio of 6 per 100,000 in rural areas compared to 36 per 100,000 in urban areas [9]. Dumitrache et al. emphasized that such disparities between urban and rural areas contribute to inequitable access to health services [10]. The uneven distribution of health infrastructure further influences these urban-rural disparities, poorer working conditions in rural areas, and the concentration of income-generating opportunities in cities, with Indonesia's archipelagic geography compounding resource allocation challenges [11]. Putri et al. also observed that remote, underdeveloped, and rural regions have lower doctor-to-population ratios than urban areas, reflecting persistent inequalities in the distribution of the healthcare workforce [12].

Previous studies have shown that geographic factors, population density, and economic centers influence the distribution of healthcare workers. City centers generally have a higher concentration of healthcare professionals due to access to educational facilities and professional personnel, while remote districts tend to have fewer healthcare workers. This disparity can lead to gaps in service quality and increase health risks in areas with low healthcare worker distribution. Therefore, spatial analysis of healthcare worker distribution is crucial to support evidence-based health policy planning.

A spatial approach to analyzing healthcare worker distribution enables the identification of clusters with high or low concentrations, the detection of outliers, and the evaluation of the statistical significance of the distribution across regions. This analysis provides more comprehensive information than descriptive statistics alone, as it considers interactions between districts/cities and the spatial influence on the distribution of healthcare workers. Additionally, identifying clusters such as High-High, High-Low, Low-High, and Low-Low helps the government prioritize areas that need redistribution interventions.

The spatial autocorrelation approach has also been applied at subnational levels. Yu et al. utilized spatial autocorrelation to analyze the spatial distribution characteristics of healthcare resources in Chinese centers for disease control and prevention, finding that all three types of healthcare resources showed spatial aggregation, with the global Moran index for disease control personnel density increasing from 0.4782 to 0.5067 ($p < 0.01$) [13]. Furthermore, Xu et al. employed Moran's I, calculated via R software, to map mobility patterns of primary healthcare personnel in Nanning, China, revealing an absence of spatial clustering in the mobility of primary healthcare personnel in the city [14].

This study aims to analyze the distribution of environmental health workers across districts/cities in East Java using 2025 data from the East Java Central Statistics Agency. It identifies spatial clusters and outliers and assesses the significance of these distributions. These findings are expected to provide a scientific basis for decision-making in health workforce allocation planning, improve service equity, and support more effective health development strategies. Through this approach, the study emphasizes the importance of evidence-based policies to reduce disparities in access and improve the quality of health services across the region.

II. Method

This study uses a descriptive quantitative approach with spatial analysis to assess the distribution of health workers (Environmental Health Workers) in East Java. The primary data consists of the number of health workers per regency/city, collected from regional health agencies and official public sources. This data includes regional identification, geographic coordinates (longitude and latitude), and the number of health workers available in each regency/city.

Table 1. Amount of Environmental Health Workers

ID	Regency / City	Longitude	Latitude	Environmental Health Workers
1	Pacitan	111.099692	-8.195569	161
2	Ponorogo	111.46661	-7.866688	478
3	Trenggalek	111.713129	-8.08641	226
4	Tulungagung	111.964173	-8.091221	610
5	Blitar	112.220009	-8.130866	389
6	Kediri	112.190712	-7.82324	655

ID	Regency / City	Longitude	Latitude	Environmental Health Workers
7	Malang	112.715213	-8.242209	1044
8	Lumajang	113.23349	-8.134774	393
9	Jember	113.700931	-8.173312	801
10	Banyuwangi	114.369227	-8.219233	601
11	Bondowoso	113.820641	-7.918759	181
12	Situbondo	113.995279	-7.705053	149
13	Probolinggo	113.47761	-7.871756	208
14	Pasuruan	112.858217	-7.785996	567
15	Sidoarjo	112.70155	-7.449772	1637
16	Mojokerto	112.435107	-7.469891	461
17	Jombang	112.28609	-7.574087	489
18	Nganjuk	111.899348	-7.604372	429
19	Madiun	111.618375	-7.609331	301
20	Magetan	111.338159	-7.649341	333
21	Ngawi	111.457399	-7.419073	271
22	Bojonegoro	111.886929	-7.152479	439
23	Tuban	112.05	-6.9	314
24	Lamongan	112.414981	-7.118111	567
25	Gresik	112.652642	-7.163456	728
26	Bangkalan	112.751982	-7.025282	182
27	Sampang	113.246701	-7.193902	140
28	Pamekasan	113.47391	-7.154249	266
29	Sumenep	113.858299	-7.009557	209
30	Kediri City	112.017829	-7.848016	557
31	Blitar City	112.160906	-8.095463	204
32	Malang City	112.632632	-7.96662	1034
33	Probolinggo City	113.203713	-7.776423	156
34	Pasuruan City	112.899923	-7.646919	129
35	Mojokerto City	112.434084	-7.472638	252
36	Madiun City	111.530016	-7.631059	501
37	Surabaya City	112.752088	-7.257472	3842
38	Batu City	112.533449	-7.883065	205

The first stage of analysis involves descriptive statistics to calculate the mean, minimum, maximum, and distribution of Environmental Health Workers. This analysis provides an overview of the variation in the number of health workers across regions. Next, spatial clustering classification is performed using Moran's I analysis to identify spatial relationships between regencies/cities.

Spatial autocorrelation is then analyzed using Global Moran's I, formulated as:

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(x_i - \bar{x} \right) \left(x_j - \bar{x} \right)}{\sum_{i=1}^{n} \left(x_i - \bar{x} \right)^2}$$

Where n is the number of spatial units, x_i is the value of region i, $\bar{x}$ is the mean value, w_{ij} represents the spatial weight between regions i and j, and S_0 is the sum of all spatial weights.

Clusters are categorized into four types: High-High (high concentration near high-value areas), High-Low, Low-High, and Low-Low (low concentration near low-value areas) [15]. This classification helps identify regions experiencing disparities in distribution.

The following stage involves spatial significance analysis to determine whether the distribution of health workers in each regency/city is statistically significant. Regions with significant results indicate a tangible influence of health worker distribution on surrounding areas, while non-significant regions suggest a relatively homogeneous distribution or no clear spatial effect.

Additionally, a spatially lagged analysis is conducted to detect spatial outliers—regencies/cities whose health worker distributions significantly differ from those of neighboring areas. Scatter plots of spatially lagged variables reveal positive and negative outliers, indicating regions with strong or weak spatial influence [16]. This analysis helps identify priority regencies/cities for redistribution interventions.

The results of these analyses are combined to produce visual maps of health worker distribution, spatial clusters, and regional significance. All spatial analyses are conducted in R using the spdep and sf packages. These visualizations use bar charts and thematic maps to facilitate the interpretation and presentation of the data. The combination of descriptive statistics, Moran's I spatial autocorrelation, cluster analysis, significance testing, and spatial lag provides a solid foundation for scientific discussion and evidence-based policy recommendations for the government in planning and allocating health workers in East Java.

III. Results and Discussion

The distribution of healthcare workers (Environmental Health Workers) in regencies/cities in East Java shows significant variation. The average number of healthcare workers per regency/city is 529.18, with the highest concentration in Surabaya City (3,842) and the lowest in Pasuruan City (129) (Table 1). This disparity reflects an uneven distribution that can affect the quality and access to healthcare services in remote and urban areas. Bar chart analysis indicates that most regencies have fewer healthcare workers than the average, while some large cities, such as Surabaya, have high concentrations, thereby widening regional gaps.

Based on the results of Moran's I calculation, it was found that:

Moran's I	Expectation	Variance	Z-Score	P-Value
0.387723169	-0.027027027	0.03946358	2.087797436	0.018408055

The results of the spatial autocorrelation analysis using Global Moran's I show a value of 0.3877, with an expected value (Expectation) of -0.0270, a variance of 0.03946, a Z-score of 2.0878, and a p-value of 0.0184. These findings strongly indicate the presence of spatial dependence patterns in the distribution of environmental health workers in the study area.

Moran's I value of 0.3877 indicates a moderate positive spatial autocorrelation, meaning that areas with a high number of healthcare workers tend to be close to other areas with high numbers of healthcare workers. Similarly, areas with low values tend to be near other low-value areas. This condition indicates that the distribution of healthcare workers is not random but exhibits spatial clustering.

The Expectation value of -0.0270 represents the null hypothesis condition, which assumes that the data distribution is spatially random. Comparing the obtained Moran's I value with the expected value reveals a clear deviation from randomness, thereby strengthening the indication of spatial structure in the data.

Next, the Z-score value of 2.0878 indicates that Moran's I statistic is more than two standard deviations above the expected value under the normality assumption. Statistically, this suggests that the observed pattern does not occur by chance but reflects a significant spatial structure.

This is also supported by a p-value of 0.0184, which is less than the significance level of 0.05. Therefore, the null hypothesis stating there is no spatial autocorrelation is rejected. This means there is statistically significant evidence that the distribution of environmental health workers in the research area exhibits spatial dependence.

Overall, these results indicate that the distribution of environmental health workers in the study area exhibits significant spatial clustering. This condition suggests regional disparities in distribution, with some areas concentrated at high values while others at low values. These findings are important as a basis for formulating spatial policies to equalize the distribution of health workers, particularly to reduce disparities between regions.

The spatially lagged plot illustrates the relationship between the independent variable values for districts/cities (x1) and their spatially lagged values. This analysis evaluates spatial autocorrelation in the distribution of healthcare personnel across districts/cities and identifies spatial outliers that significantly influence neighboring areas. The plot depicts the position of each district/city in a two-dimensional coordinate system, where the horizontal axis represents the original x1 values, and the vertical axis represents the spatially lagged values, which correspond to the weighted average of x1 values from neighboring regions. Therefore, the locations of points on this plot can be used to assess spatial clustering and distributional heterogeneity and to identify positive or negative outliers.

From the plot, most districts/cities are located in the lower-left quadrant, indicating low x1 values alongside low spatially lagged values. This suggests that these regions have relatively low healthcare personnel and are surrounded by districts/cities with similar conditions. This phenomenon aligns with the observed inequality in the distribution of healthcare personnel, typically occurring in peripheral areas or regions with lower population density. The clustering reflects significant spatial dependence, in which districts/cities with low values tend to be adjacent to similar regions, forming a Low-Low pattern that can affect the effectiveness of healthcare delivery in those areas.

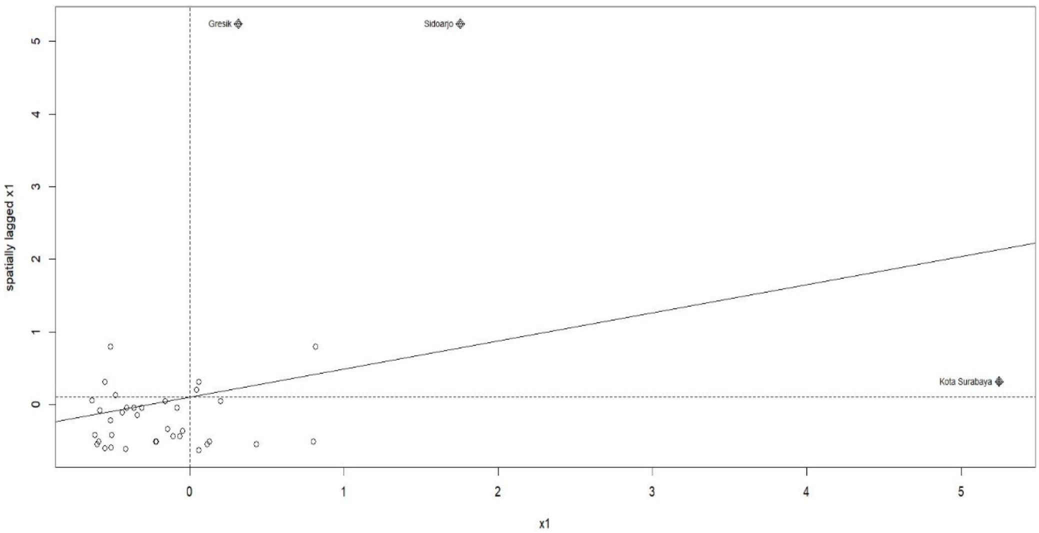

Fig 1. Spatially Lagged

Visually, spatial outliers appear in the upper-right quadrant, particularly Surabaya, which lies at an extreme position on both axes. Surabaya's position, far from the zero line of the spatially lagged variable, indicates a high number of healthcare personnel and proximity to districts/cities with similarly high values, forming a High-High category. This outlier denotes a dominant healthcare distribution center that significantly influences neighboring districts/cities. This demonstrates that major urban centers not only concentrate healthcare personnel but also exert spatial influence on surrounding areas.

Additionally, several points exhibit higher spatially lagged values than their local x1 values, indicating potential High-Low relationships. This represents regions with low healthcare personnel located near areas with high personnel numbers, receiving spatial influence from their surroundings. Such regions are strategic targets for interventions to balance distribution without disrupting major concentration centers in urban hubs.

The plot also conveys information on point density along the axes. Points clustered around zero represent regions with low healthcare personnel and minimal spatial influence. This analysis helps identify areas vulnerable to distributional inequalities, enabling more targeted allocation and placement of healthcare personnel. Identification of outliers and clusters in the spatially lagged plot provides a quantitative framework to prioritize districts/cities for redistribution interventions while avoiding misinterpretations that may arise from basic descriptive analyses.

Furthermore, the spatially lagged plot facilitates empirical evaluation of spatial correlation hypotheses. Positive autocorrelation is indicated by the upward slope of the regression line, confirming that regions with high levels of healthcare personnel tend to be surrounded by similarly high levels, and vice versa. This strengthens understanding of local variation and distributional heterogeneity, which is essential for effective regional healthcare planning. Visual interpretation of the plot allows researchers to assess disparities and heterogeneity that inform spatially targeted healthcare policies.

This spatially lagged plot provides both visual and quantitative evidence of spatial dependence in the distribution of healthcare personnel in East Java. Positive outliers, especially Surabaya, highlight dominant distribution centers, while low-value clusters in the lower-left quadrant reflect regions with minimal resources. This analysis offers robust empirical foundations for planning the redistribution of healthcare personnel, identifying priority regions, and devising spatially informed allocation strategies. Consequently, spatially lagged plots serve not only as visual aids but also as essential analytical instruments for guiding equitable and efficient healthcare policy.

The spatial cluster map illustrates the categorization of districts and cities in East Java based on the distribution of healthcare personnel, employing the High-High, High-Low, Low-High, and Low-Low classification scheme. This form of spatial analysis provides a detailed representation of how healthcare resources are concentrated, dispersed, and potentially clustered across the region. The map uses color coding to distinguish clusters: red for High-High, yellow for High-Low, blue for Low-High, and green for Low-Low. Each category conveys critical information about local resource availability and the spatial relationships among neighboring districts, allowing policymakers and researchers to identify priority areas for intervention and resource allocation.

High-High clusters, shown in red, denote districts with healthcare personnel counts significantly above the regional average and are surrounded by neighboring districts with similarly high values. This pattern is prominently observed in major urban centers such as Surabaya, Sidoarjo, and Lamongan. The presence of High-High clusters indicates not only a concentration of healthcare resources within these urban hubs but also a reinforcing spatial effect whereby the abundance of personnel influences adjacent areas. This spatial autocorrelation reflects a regional dynamic in which central districts act as attractors for healthcare professionals due to factors such as better facilities, infrastructure, professional opportunities, and living conditions.

Conversely, High-Low clusters, denoted in yellow, highlight districts with relatively high numbers of healthcare personnel adjacent to districts with lower numbers. These areas are often transitional zones between urban and peripheral districts. The High-Low pattern underscores potential disparities in access to healthcare, as neighboring low-resource areas may not benefit from the spillover effects of adjacent high-resource districts. Identifying High-Low areas is crucial for targeted policy interventions that aim to redistribute personnel, incentivize resource sharing, and improve service accessibility in neighboring lower-density regions.

Low-High clusters, depicted in blue, represent districts with low levels of healthcare personnel that are surrounded by districts with higher-than-average levels. These areas are particularly significant because they may indicate that they are underserved despite their proximity to resource-rich districts. From a planning perspective, Low-High clusters suggest the need for strategic deployment of additional personnel or mobile healthcare services to mitigate disparities. Such interventions can help ensure that healthcare access is more evenly distributed, preventing populations in Low-High areas from being disadvantaged by local shortages.

Finally, Low-Low clusters, represented in green, consist of districts with below-average healthcare personnel surrounded by similarly low-resource neighboring districts. These clusters are commonly found in rural, remote, or peripheral areas with lower population density and limited infrastructure. The persistence of Low-Low clusters underscores systemic challenges in achieving equitable healthcare distribution. Policymakers must recognize these regions as critical targets for intervention, possibly through comprehensive resource planning, incentives for healthcare professionals to work in underserved areas, and investment in local healthcare infrastructure.

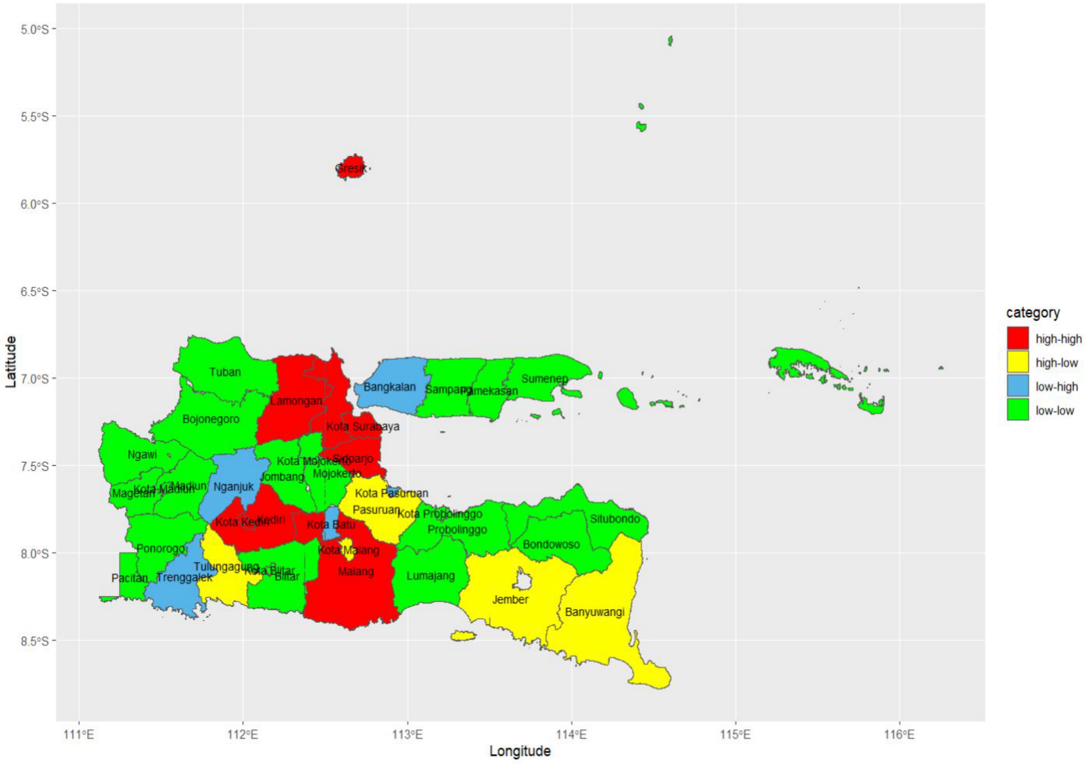

Fig 2. Spatial Cluster

The spatial clustering depicted on this map provides empirical evidence of regional disparities in the distribution of healthcare personnel. By visualizing spatial relationships and district categorization, the map facilitates the identification of priority areas for resource allocation. High-High clusters indicate zones of concentrated resources that may benefit from supportive policies to maintain quality and efficiency, while Low-Low clusters highlight regions requiring urgent interventions. Furthermore, transitional High-Low and Low-High clusters reveal nuanced spatial dynamics in resource availability, underscoring the need for targeted policies that address both local and neighboring influences.

The spatial cluster map serves as a critical analytical tool for understanding healthcare distribution patterns across East Java. It allows researchers and policymakers to identify high-priority districts, evaluate the spatial interdependencies among regions, and design evidence-based interventions to improve healthcare equity. The categorization into High-High, High-Low, Low-High, and Low-Low clusters provides a comprehensive framework for assessing both absolute and relative resource distribution, thereby facilitating more informed and effective decision-making in healthcare planning and policy implementation.

The significance map illustrates the statistical relevance of healthcare personnel distribution across districts and cities in East Java. The map employs a binary color scheme to denote regions with significant and non-significant spatial patterns: red denotes statistically significant areas, whereas cyan denotes non-significant areas. This visualization clearly depicts which districts exhibit patterns unlikely to occur by chance and which are more spatially homogeneous or randomly distributed. Assessing significance is a critical component of spatial analysis as it allows researchers and policymakers to distinguish areas where spatial clustering is meaningful from those where observed patterns may not reflect underlying spatial dependencies.

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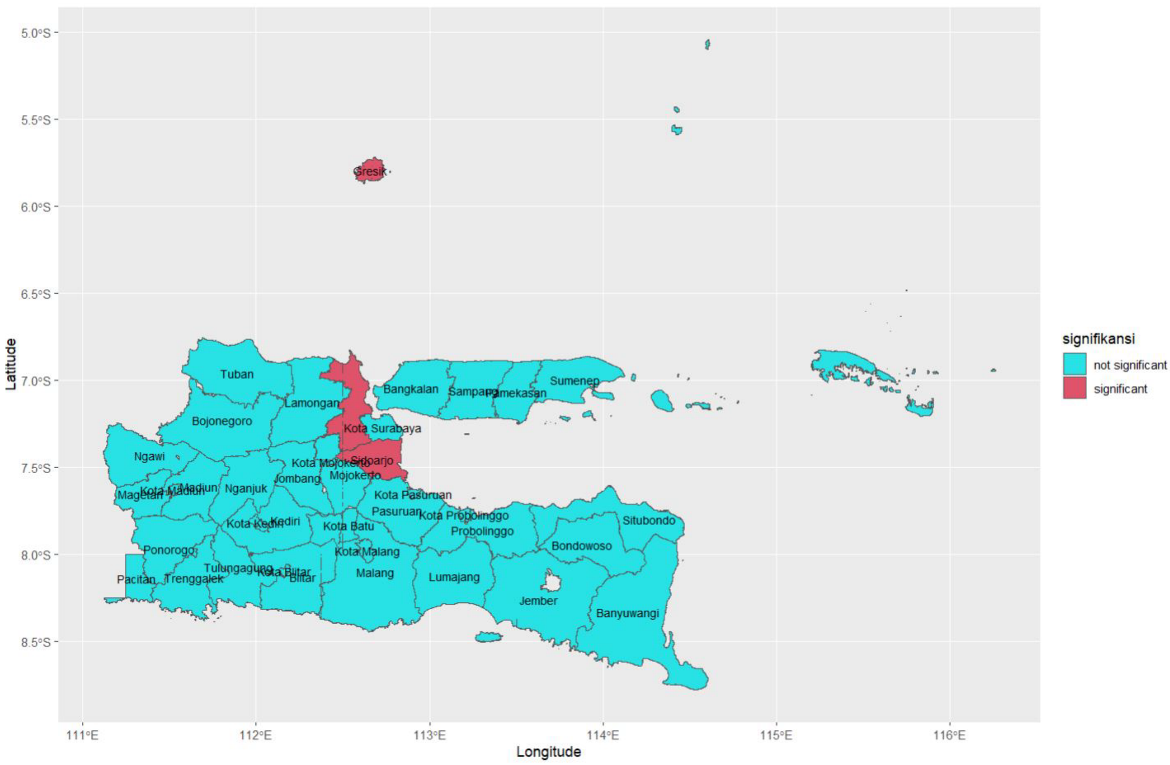

Fig 3. Significance map

The map reveals that only a limited number of districts, primarily concentrated around major urban centers such as Surabaya, Sidoarjo, and Gresik, exhibit statistically significant patterns. These regions demonstrate that the concentration of healthcare personnel is not only high locally but also exerts measurable spatial influence on adjacent districts. This suggests that urban hubs serve as central nodes in the healthcare distribution network, potentially attracting personnel through superior infrastructure, greater service demand, and professional opportunities. The statistical significance of these clusters implies that interventions or policy adjustments in these areas could have cascading effects on surrounding districts, emphasizing the importance of spatially informed planning.

Conversely, most districts are shown in cyan, indicating non-significant spatial patterns. These areas typically correspond to peripheral or rural districts with relatively few healthcare personnel. In these districts, the distribution appears more random or homogeneous, lacking the spatial autocorrelation observed in significant regions. While these non-significant areas do not form strong clusters, their identification is equally important. They represent regions where localized policies or redistribution efforts may be necessary to achieve equity, as their patterns do not naturally benefit from adjacency to high-resource districts.

The significance map also underscores the spatial heterogeneity inherent in the region. By differentiating between significant and non-significant areas, the map enables the identification of priority intervention zones. High-significance districts indicate both a concentration of personnel and spatial influence, warranting focused strategies to maintain or optimize resource allocation. Non-significant districts, although less influential spatially, highlight potential gaps in healthcare access that must be addressed through targeted deployment or support programs.

This map serves as an essential analytical tool in spatial epidemiology and health resource management. It provides empirical evidence for the uneven distribution of healthcare personnel and clarifies where strategic policy interventions could be most impactful. The distinction between significant and non-significant regions enhances understanding of regional disparities and guides resource allocation to maximize efficiency and equity. Furthermore, integrating the significance map with other spatial analyses, such as spatially lagged plots and cluster categorization, strengthens the assessment of healthcare distribution patterns, enabling multidimensional interpretation and informed decision-making.

In conclusion, the significance map identifies key districts exhibiting meaningful spatial patterns in the distribution of healthcare personnel and highlights regions where spatial dependencies are absent. This differentiation facilitates evidence-based planning, enabling policymakers to target interventions more precisely. By integrating insights from significant and non-significant areas, regional health authorities can design more effective redistribution strategies, improve access to healthcare, and ensure a more equitable allocation of resources across both urban and rural districts in East Java.

IV. Conclusion

The results of the spatial autocorrelation analysis using Global Moran's I show a value of 0.3877, with an expected value (Expectation) of -0.0270, a variance of 0.03946, a Z-score of 2.0878, and a p-value of 0.0184. These findings strongly indicate spatial dependence in the distribution of environmental health workers in the study area. The distribution of healthcare workers in East Java is uneven, with the highest concentration in large cities like Surabaya and the lowest in some remote districts. Spatial cluster analysis and statistical significance identify areas with high disparities and spatial outliers, indicating the influence of urban areas on regional distribution. These findings emphasize the need for data-driven, spatially evidence-based redistribution strategies that focus on equitable service delivery in underserved areas. This analysis provides a scientific basis for more effective health resource planning, thereby improving access and quality of healthcare services across all districts and cities.

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