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Spatial Autocorrelation Analysis of Nutrition Personnel as a Basis for Environmental Health Management in East Java

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ABSTRACT

Nutrition professionals are essential for delivering effective nutrition interventions, yet their distribution is often uneven across regions. In East Java Province, Indonesia, evidence on the spatial structure of the nutrition workforce remains limited. This study aims to examine the spatial distribution of nutrition personnel across districts and municipalities in East Java, to (1) assess the presence of global spatial autocorrelation and (2) identify local clusters of relative surplus and deficit. A cross-sectional ecological design was applied using data on the number of nutrition workers in 38 districts/municipalities. Each unit was georeferenced using centroid coordinates. A K-Nearest Neighbors (KNN) spatial weights matrix was constructed based on geographic proximity and row-standardized. Global spatial autocorrelation was evaluated using Moran's I with permutation tests, while Local Indicators of Spatial Autocorrelation (LISA) were used to detect significant local clusters and spatial outliers. Results were visualized through Moran scatterplots and LISA significance and cluster maps generated in R. Moran's I indicated weak and statistically non-dominant global spatial autocorrelation, suggesting an absence of strong province-wide clustering. However, LISA revealed distinct local patterns. High–high clusters of nutrition personnel were concentrated in the metropolitan core, particularly around Surabaya, Sidoarjo, and Gresik, whereas several southern, western, and peripheral districts formed low–low clusters, indicating contiguous areas of relative deficit. Isolated high–low and low–high outliers were also identified. The distribution of nutrition personnel in East Java is characterized by modest global dependence but marked local inequalities. Integrating spatial analysis into human-resources-for-health planning can support more targeted and equitable allocation of nutrition workers, especially towards identified low–low clusters and spatial outlier districts.

I. Introduction

The availability and distribution of health personnel are critical determinants of the performance of health systems. Among them, nutrition professionals play a strategic role in preventing and managing nutritional problems such as stunting, wasting, and chronic malnutrition [1]. In decentralized health systems, the adequacy of the nutrition workforce at the local level directly affects the reach and quality of nutrition interventions delivered through primary care facilities and community-based programs [2]. For a large and demographically diverse province such as East Java, Indonesia, ensuring that every district and municipality has sufficient nutrition personnel is therefore a substantial policy challenge [3].

Previous discussions on human resources for health in Indonesia have largely emphasized absolute shortages and aggregate numbers, while paying less attention to how those personnel are distributed in space [4]. In practice, two districts with a similar total number of workers may face very different realities depending on how they are positioned relative to one another and to surrounding areas [5]. Spatially concentrated surpluses in urban centers may coexist with persistent deficits in peripheral or rural regions, creating inequities in access to nutrition services [6]. Understanding these spatial patterns is essential for designing targeted and efficient redistribution policies rather than relying on uniform, province-wide interventions [7], [8].

Spatial analysis provides an appropriate framework for investigating such patterns. Measures of spatial autocorrelation, such as Moran's I and Local Indicators of Spatial Autocorrelation (LISA) [1], [2], [9], [10], [11], enable researchers to test whether units with similar values tend to cluster together or are dispersed randomly. Moran's I summarizes the overall, or global, degree of spatial dependence in the data, while LISA decomposes this global statistic to identify local clusters and spatial outliers [12], [13], [14]. Through LISA, areas can be classified into high–high, low–low, high–low, and low–high types, each of which has distinct policy implications.

A key requirement for these techniques is the specification of a spatial weights matrix that captures the pattern of spatial interactions between units. In the context of East Java, the administrative boundaries of districts and municipalities are irregular and do not form a simple lattice. For that reason, a K-Nearest Neighbors (KNN) approach was used to define spatial neighbors based on geographic proximity rather than solely on contiguity. This method assumes that each area is most strongly influenced by a fixed number of closest neighbors, reflecting the potential for cross-border service utilization and regional labor markets for health professionals [15].

Against this background, the present study aims to assess the spatial structure of the distribution of nutrition personnel across 38 districts and municipalities in East Java Province [16]. Specifically, it seeks (1) to examine whether the number of nutrition workers exhibits significant global spatial autocorrelation, and (2) to identify local clusters of relative surplus and deficit using LISA. The findings are expected to provide empirical evidence to support more spatially informed planning and redistribution of the nutrition workforce at the provincial level.

II. Method

This study employed a cross-sectional ecological design with the district/municipality (kabupaten/kota) as the unit of analysis. The study area comprised all 38 administrative units in East Java Province, Indonesia. For each unit, two types of information were assembled: (1) the total number of nutrition personnel working in public health facilities and related services, and (2) the geographic coordinates of the administrative centroid. The primary outcome variable was the absolute number of nutrition workers per district/municipality. Although population data were not available to construct ratios, the analysis focused on identifying spatial patterns in the distribution of the existing workforce.

All observations were georeferenced using longitude and latitude coordinates expressed in decimal degrees. These coordinates were used to construct the spatial weights matrix and to produce thematic maps. Prior to spatial analysis, the nutrition workforce variable was standardized using a z-score transformation to facilitate interpretation and comparability. Standardization ensured that deviations from the provincial mean could be evaluated in terms of standard deviations, which is particularly useful for Moran scatterplots and LISA statistics.

To model spatial dependencies, a K-Nearest Neighbors (KNN) approach was applied. For each district/municipality, a fixed number of geographically closest neighbors was identified based on Euclidean distance between centroids. The number of neighbors was chosen to guarantee that the resulting spatial weights matrix was fully connected, thereby avoiding isolated units that could distort the computation of spatial statistics. The weights were row-standardized so that the influence of neighboring units on each observation summed to one. This specification reflects the assumption that each district is primarily influenced by the relative, rather than absolute, configuration of its nearest neighbors.

Global spatial autocorrelation was assessed using Moran's I statistic. Moran's I measures the degree to which similar or dissimilar values cluster in space, with positive values indicating spatial clustering of similar values (high with high, low with low), negative values indicating a checkerboard pattern of dissimilar values (high with low), and values near zero suggesting spatial randomness. Statistical significance was evaluated through a permutation procedure with a large number of random permutations of the observed data across locations. The pseudo p-value was derived from the reference distribution of simulated Moran's I statistics, and a significance level of 0.05 was applied.

Local spatial patterns were investigated using Local Indicators of Spatial Autocorrelation (LISA). For each district/municipality, a local Moran's I value was computed, capturing the extent to which the value of the unit was similar to the weighted average of its neighbors. Statistically significant local Moran statistics (based on permutation tests) were then classified into four categories: high–high, low–low, high–low, and low–high. High–high and low–low categories designate local clusters of similar high or low values, respectively, whereas high–low and low–high categories identify spatial outliers. These classifications were used to interpret the pattern of relative surplus and deficit across the province.

All spatial analyses and mapping procedures were conducted using the R statistical environment. Packages for spatial data handling, spatial dependence analysis, and visualization were employed to compute Moran's I, generate Moran scatterplots, and produce LISA significance and cluster maps. Cartographic outputs were inspected to ensure consistency between numerical results and their graphical representation. As the study used aggregated, non-identifiable administrative data, no individual-level information was analyzed and ethical approval was not required.

III. Results and Discussion

The Moran scatterplot of standardized nutrition personnel against their spatially lagged values provides an initial overview of the spatial structure. Most districts and municipalities are concentrated around the origin, indicating that many areas have values close to the provincial mean and that their neighbors similarly exhibit average levels. Only a limited number of points appear in the outer quadrants of the scatterplot, corresponding to units with substantially higher or lower values relative to both the mean and their neighbors. This visual impression is consistent with the computed Moran's I statistic, which is low in magnitude and not strongly significant, suggesting that, at the global level, the distribution of nutrition personnel does not follow a pronounced clustered or uniformly dispersed pattern.

The absence of strong global autocorrelation implies that, on average, neighboring districts do not systematically resemble one another in terms of the number of nutrition workers. This finding indicates that the allocation of nutrition personnel has not been strongly shaped by broad regional dynamics, such as a simple urban–rural gradient or a systematic east–west divide. Instead, local conditions and individual district characteristics appear to exert a greater influence. Factors such as the presence of referral hospitals, administrative status, fiscal capacity, or attractiveness as a place of residence and work may contribute more to staffing patterns than geographic position alone.

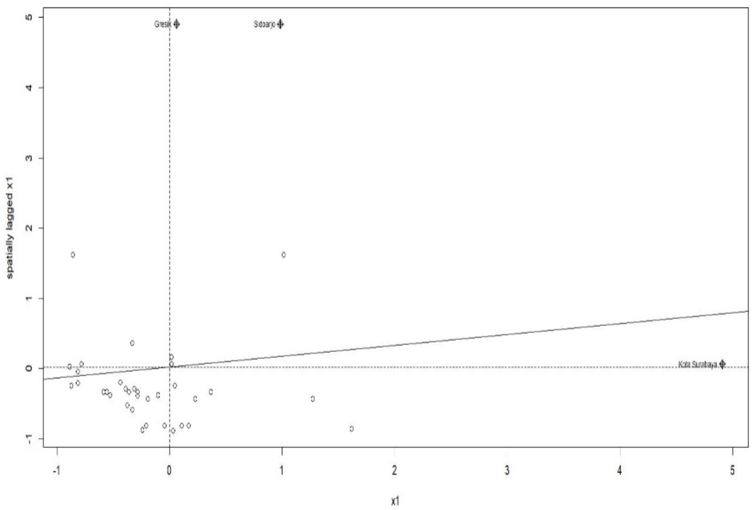

Fig. 1. Spatially Lagged

However, the global statistic masks important local heterogeneity. The LISA significance map reveals that only a subset of districts forms statistically significant local clusters. These significant areas are concentrated primarily along the central urban corridor of East Java, encompassing municipalities such as Surabaya, Sidoarjo, and neighboring districts including Gresik and Lamongan. In these locations, high numbers of nutrition personnel are surrounded by similarly high values in adjacent units, constituting high–high clusters. This pattern is consistent with the role of the

Gerbangkertosusila metropolitan region as the economic and administrative core of the province, which tends to attract and retain health professionals.

The LISA cluster map further clarifies the configuration of these local patterns. High–high clusters indicate zones of relative surplus or concentration of nutrition personnel. These areas likely host major hospitals, universities, and administrative centers that generate demand for specialized staff and create more favorable working and living conditions. From a policy perspective, high–high clusters may function as regional hubs for training, supervision, and technical support, but they also highlight potential imbalances if surrounding areas suffer from shortages.

In contrast, several districts in the southern and western parts of the province, as well as parts of Madura, fall into the low–low category. These units exhibit low numbers of nutrition personnel and are surrounded by neighbors with similarly low values, signaling geographically contiguous areas of relative deficit. Such low–low clusters are of particular concern, because the lack of human resources is not easily compensated through neighboring districts that face similar constraints. Populations residing in these areas may experience reduced access to qualified nutrition services, limited outreach activities, and weaker implementation of nutrition programs. Prioritizing these low–low clusters for additional recruitment, incentives, or reallocation of staff may therefore contribute more to equity than allocating new personnel to already well-served regions.

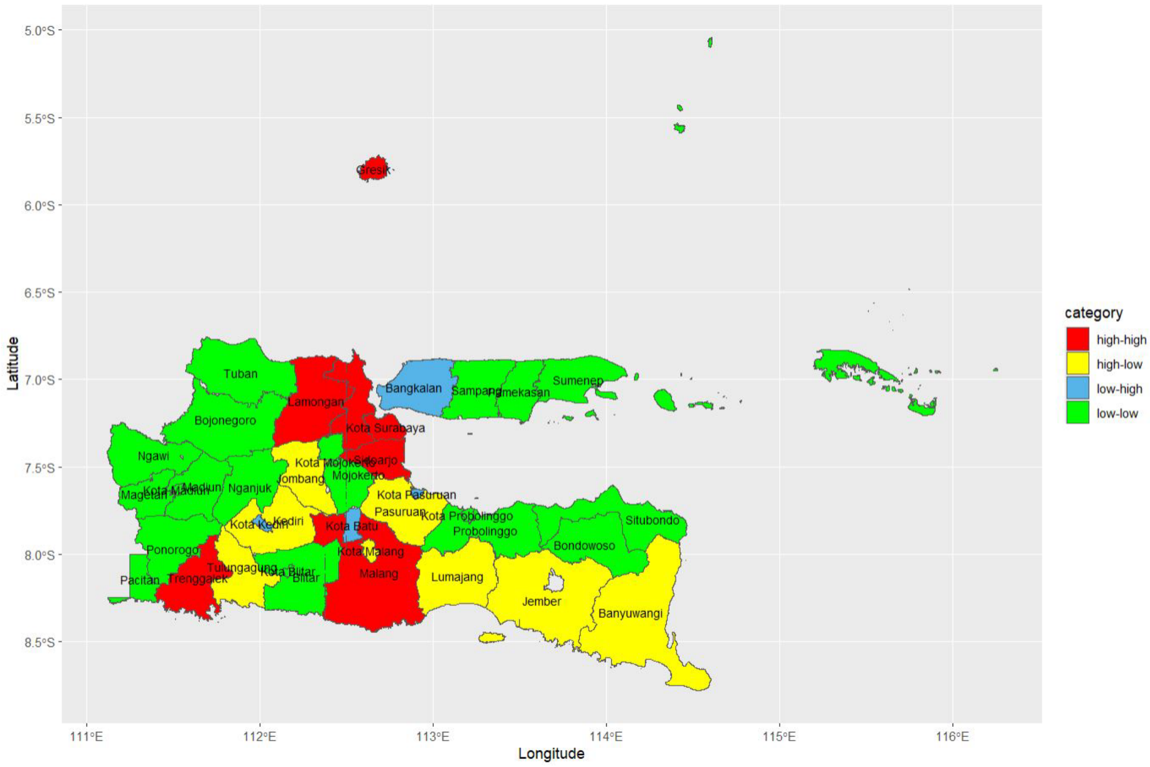

Fig. 2. Spatial Analysis with KNN

The high–low and low–high categories, although less prevalent, are also informative. A high–low area is characterized by a relatively high number of nutrition personnel surrounded by neighbors with predominantly low values. Such a configuration may reflect the presence of a single district that has successfully attracted staff through local policies or facilities, while adjacent districts have not. Conversely, a low–high unit is a district with comparatively low staffing in the midst of well-resourced neighbors. In both cases, there may be opportunities to strengthen inter-district collaboration, for example by establishing shared outreach teams, referral mechanisms, or rotational schemes that allow personnel from high-resource areas to support less-resourced neighbors.

Overall, the findings demonstrate that the spatial distribution of nutrition personnel in East Java is characterized by modest global spatial dependence but marked local inequalities. The dominance of high–high clusters in the metropolitan core and low–low clusters in peripheral regions reflects broader patterns of regional development and infrastructure. Urbanized areas offer more attractive employment conditions, while remote districts may struggle with limited facilities, housing, transportation, and professional development opportunities. These contextual factors, though not directly analyzed in the present study, likely contribute to the observed spatial configuration.

The use of a KNN-based spatial weights matrix is appropriate given the irregular shapes and varying sizes of the administrative units. By linking each district to its nearest neighbors, the analysis captures the functional proximity that may underlie service use and labor mobility. Nonetheless, the results should be interpreted with caution, particularly in the absence of population data and other indicators of health need. High numbers of personnel do not necessarily imply oversupply if the population or burden of malnutrition is also high. Future research could extend this work by examining ratios of nutrition personnel to population, incorporating socio-economic variables, and exploring temporal changes.

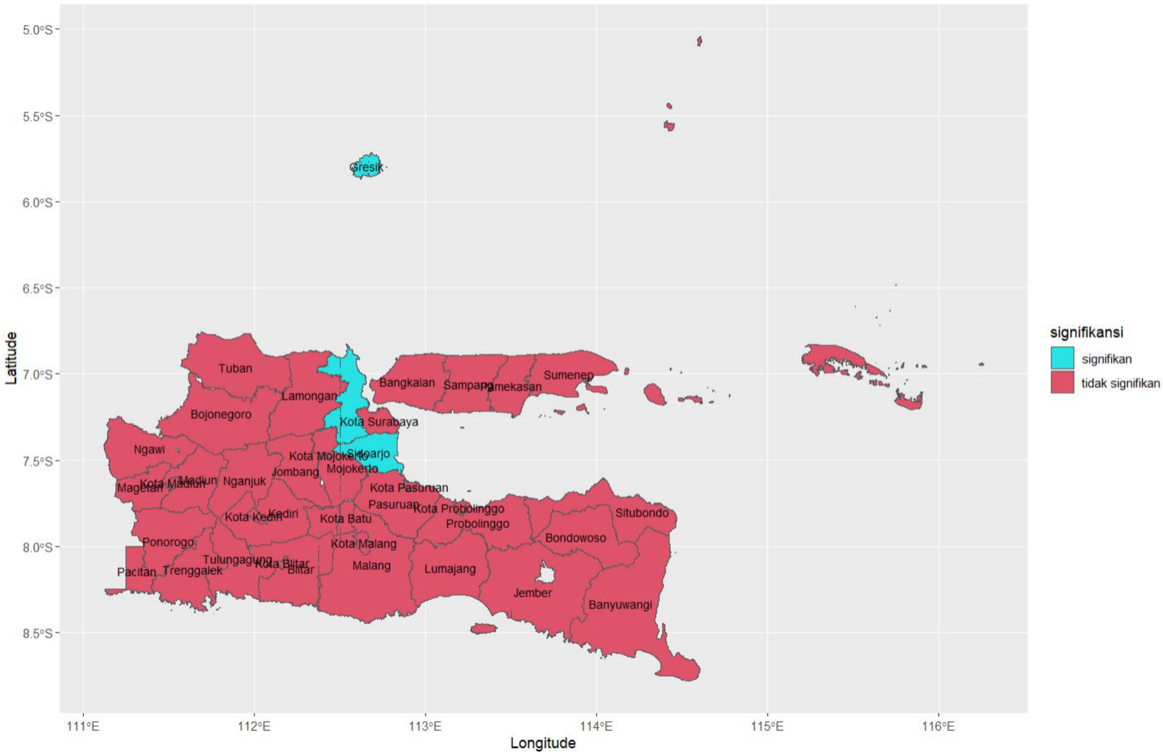

Fig. 3. Significance

Despite these limitations, the present analysis offers a clear spatial picture that can inform planning. It identifies where clusters of relative surplus and deficit are located, highlights outlying districts whose staffing levels diverge from their neighbors, and underscores the importance of targeting interventions at specific local clusters rather than assuming uniform conditions across the province.

IV. Conclusion

This study examined the spatial distribution of nutrition personnel across 38 districts and municipalities in East Java Province using a K-Nearest Neighbors spatial weights matrix, Moran's I, and Local Indicators of Spatial Autocorrelation. The results indicate that global spatial autocorrelation is weak, suggesting that, overall, neighboring districts do not systematically share similar levels of staffing. Nevertheless, significant local clusters are evident. High–high clusters are concentrated in the metropolitan core, while low–low clusters appear in several southern, western, and peripheral districts, indicating geographically contiguous areas of relative deficit. These findings demonstrate that inequities in the distribution of nutrition personnel are localized rather than uniform and that targeted interventions focusing on identified low–low and spatial outlier areas are warranted. Incorporating spatial analysis into human resources for health planning can therefore enhance the effectiveness and equity of policies aimed at strengthening nutrition services in East Java.

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