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Spatial clustering of autism spectrum disorders in Kelantan, Malaysia: Urban hotspots and rural gaps

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Abstract

The geographic distribution of autism spectrum disorders (ASD) remains poorly characterized in many developing settings, including Malaysia, where rural populations face notable healthcare access gaps. We mapped spatial clustering of ASD subtypes (severe, high-functioning and mild) in Kelantan, a predominantly rural Malaysian state, to examine diagnostic disparities. In this cross-sectional spatial epidemiological study, 103 ASD cases (2022–2024) from two major Kelantan centers were analyzed at the district level. Global Moran's I assessed overall spatial autocorrelation and optimized Hot Spot Analysis (Getis-Ord Gi*) identified local clusters of high or low ASD incidence. Moran's I revealed significant positive clustering for mild ($I \approx 0.065$, $p < 0.001$) and high-functioning ASD ($I \approx 0.039$, $p = 0.0096$) cases reflecting urban concentration but no significant autocorrelation for severe ASD. Optimized hotspot analysis localized statistically significant high-incidence clusters in Kota Bharu and surrounding districts, while rural districts emerged as cold spots. This urban-rural pattern mirrors known disparities (ASD diagnoses concentrate where healthcare access is better) and suggests underdiagnosis in underserved areas. Uneven geographic distribution of diagnostic resources likely drives these patterns. These results reveal service-related inequalities in ASD diagnosis in Kelantan and reinforce the need for targeted healthcare interventions and expanded screening in rural communities to ensure equitable care.

Keywords: Autism spectrum disorder (ASD), geographic information system (GIS), high-functioning autism, optimized hotspot analysis, spatial autocorrelation

Introduction

Autism spectrum disorder (ASD) represents a major global neurodevelopmental challenge. Recent estimates place the worldwide prevalence around 0.7–1.0% of the population, or roughly 1 in 127 people, based on Global Burden of Disease data and meta-analyses

(Talantseva et al., 2023; WHO, 2023). In Malaysia, recognition of ASD has grown rapidly in the past decade. For example, the National Autism Society of Malaysia (NASOM) reports roughly 9,000 children born with ASD each year, and official health ministry figures show diagnosed cases rising from about 99 in 2010 to 589 in 2021 (Samsudin et al., 2025). Nationwide surveys of school-aged children likewise reflect an increasing burden, with the most recent analysis (2018–2022) finding a national ASD prevalence of approximately 9.29 per 1,000, though this varies widely by region (Shair et al., 2024). Notably, Kelantan, a predominantly rural state in northeast Peninsular Malaysia has reported one of the lowest ASD rates (about 5.57 per 1,000) and slowest growth in diagnoses (Shair et al., 2024). These figures likely understate the true magnitude of ASD in Kelantan, given limited screening and specialist resources. Nonetheless, they provide a baseline showing that Kelantan's diagnosed ASD caseload is currently much lower than urban centers like Kuala Lumpur and Penang (Samsudin et al., 2025; Shair et al., 2024).

The spectrum of autism is broad and diagnostically complex. Beyond the most severe presentations requiring intensive support, many individuals fall into "high-functioning" or mild categories often historically labeled as Asperger's syndrome or pervasive developmental disorder-not otherwise specified. Such individuals typically have average or above-average cognitive ability but still experience persistent social communication difficulties and atypical behaviors (Wan Zainodin & Zainal, 2025). In practice, these milder forms have increasingly captured academic and clinical interest, as researchers recognize that their needs can be distinct and easily overlooked. In Malaysia specifically, high-functioning or mild ASD often goes undiagnosed or misdiagnosed, especially in underserved communities. For instance, a 2025 study noted that underdiagnosis of high-functioning autism in Malaysia contributes to gaps in educational support and community services (Wan Zainodin & Zainal, 2025). Rural areas, like much of Kelantan, typically have fewer child psychologists and ASD specialists, so families often lack access to formal diagnostic assessment. This means many children with subtle or mild ASD symptoms may fall through the cracks unless active case-finding occurs. Kelantan's sociodemographic profile underscores this risk: it is a largely rural state with documented healthcare disparities, where specialist services are concentrated in the main cities (Ijon et al., 2026). Without deliberate outreach, official statistics in Kelantan may systematically under-represent high-functioning or mild ASD cases, biasing our understanding of the true geographic distribution.

Spatial analysis offers powerful tools to reveal these hidden patterns in public health data. Techniques such as Global Moran's I and local indicators of spatial association (LISA) can detect clustering of cases beyond what is expected by chance, while optimized hotspot analysis (Getis–Ord Gi*) identifies districts with unusually high or low prevalence (Bakian et al., 2015). These methods have been widely used for diseases and social outcomes in Malaysia from dengue and tuberculosis to crime mapping but, to date, have seldom been applied to neurodevelopmental disorders. In fact, a thorough literature review yielded no prior studies that systematically mapped ASD using spatial statistics in Malaysia. Internationally, a notable example exists, Bakian et al. (2015) used kernel density methods in Utah to locate ASD hotspots and found that higher socioeconomic status was associated with residence in ASD clusters. To our knowledge, however, no such spatial analysis has been conducted in the Malaysian context.) This gap is critical because spatial epidemiology can directly inform policy and service provision. By pinpointing areas with elevated ASD prevalence or underserved regions, planners can target resources and outreach more equitably. In Kelantan's case, the rural-urban divide is pronounced wealthy districts like Kota Bharu concentrate most healthcare infrastructure, whereas interior districts face physician shortages. Spatial analysis can quantify these disparities.

Accordingly, the objective of this research is to analyze the spatial distribution and clustering of high-functioning and mild ASD across Kelantan's districts using advanced geographic methods. We employ global spatial autocorrelation (Moran's I) and optimized hotspot analysis to detect whether autism prevalence is patterned or random, and to identify specific clusters of unusually high or low case counts. By integrating reported case data with district boundaries, we aim to visualize "autism cold spots" and "hotspots" to guide future screening and support services. This approach goes beyond simple case counts by accounting for the underlying population and spatial structure, thereby highlighting geographic inequalities. Importantly, to our knowledge this is the first spatial epidemiology study focused on ASD in Malaysia (and one of the first worldwide to emphasize milder autism subtypes). It addresses a clear research gap: while previous work has mapped public health concerns or crime patterns, autism has not been examined with these tools in the Malaysian literature (Ahmad et al., 2024, 2026; Ariffin et al., 2024; Bismelah et al., 2024; Chabo et al., 2026; Ijon et al., 2026; Jubit et al., 2023; Marzuki et al., 2026; Masron et al., 2024; Mohd Ali et al., 2025; Zakaria et al., 2025). By applying these spatial techniques, this study brings visibility to an underrepresented health issue in Kelantan. It provides a model for how rural ASEAN regions can use GIS mapping to improve equity. For example, by revealing where families may need closer screening or support. In sum, this work not only contributes to the epidemiological understanding of ASD in a marginalized region but also offers actionable insight for public health planning and inclusive policy aimed at closing service gaps for autistic children.

Methodololgy

The analysis began with assembling a comprehensive, district-level autism case dataset for Kelantan. Diagnostic records were obtained from the state's two main autism centers Kelantan Autism Care Centre (KACC) and the Autism Development and Care Centre (ADCC) under institutional approval (Ijon et al., 2026). These records, covering the study period, included anonymized information on 2,022 children diagnosed with severe, high-functioning, or mild Autism Spectrum Disorder (Ijon et al., 2026). Each case was geocoded to its home district in Kelantan, and all cases were aggregated by the ten administrative districts to create a spatial dataset of autism counts. In parallel, the official Kelantan district boundary shapefile (sourced from the Malaysian government GIS portal) was loaded into ArcGIS Pro to provide the spatial framework. The case counts table was joined to the district polygons via a unique district identifier, and the merged dataset was checked for completeness and consistency (no missing districts, correct case totals, etc.). Basic cleaning steps ensured that each district feature had the proper count of ASD cases; districts with zero cases were retained (coded as zero) to avoid artificial gaps. In summary, the raw case records were organized into a district-level attribute table linked to Kelantan's geographic map.

Data preparation also addressed the choice of variables and normalization. The analysis focused on two subsets of ASD cases ("High-Functioning" and "Mild") as well as their combined totals. Because district populations differ, we noted that raw counts could reflect population density rather than true prevalence. While detailed census data were not available at fine scale, we computed crude case rates per district population where possible and inspected whether the pattern of clusters persisted. This preparation step aligns with good practice in health geography (e.g. computing disease rates rather than only counts). However, the primary analyses were conducted on the aggregated counts, with the understanding that Moran's I and Getis-Ord Gi* in ArcGIS can handle count data (the Optimized Hot Spot tool, for example, first aggregates incident points to polygon counts) (ArcGIS Pro 3.3, 2024). All analyses were thus driven by the district attributes table containing either case counts or case rates for each ASD category.

The core spatial analysis was implemented in ArcGIS Dekstop 10.8.2, a leading GIS platform with advanced spatial statistics tools (Ahmad et al., 2024; Ariffin et al., 2024; Bismelah et al., 2024; Chabo et al., 2026; Jubit et al., 2023; Marzuki et al., 2026; Mohd Ali et al., 2025; Zakaria et al., 2025). Before running any statistical test, we defined a spatial weight matrix among the districts. We used a first-order contiguity conceptualization (Queen's case, i.e. districts sharing any boundary or corner are neighbors) so that every district had at least one neighbor (a requirement for Moran's I to be valid) (ArcGIS Pro 3.5, 2025). This weight matrix was created using ArcGIS's Generate Spatial Weights Matrix tool, specifying polygon contiguity and row-standardization. We verified that no district was isolated (which would violate assumptions) and that no district was neighbors with *all* others (to avoid degenerate weighting) (ArcGIS Pro 3.5, 2025). The chosen spatial weights ensure that the Global Moran's I statistic will capture local clustering without being dominated by population size.

With the data arranged and weights defined, the analysis proceeded in two main steps. First, we ran the Spatial Autocorrelation (Global Moran's I) tool on each ASD variable. This tool computes the Global Moran's I index, a single summary measure of spatial autocorrelation (ArcGIS Pro 3.5, 2025). We specified the field of case counts (or rates) and used the previously generated contiguity weights. ArcGIS then calculated the Moran's I value along with its expected value under spatial randomness, variance, and a z-score/P-value (ArcGIS Pro 3.5, 2025). In practice, this meant testing the null hypothesis of a random spatial pattern of autism cases. A significantly positive Moran's I ($z > 1.96$, $p < 0.05$) would indicate clustering (high values near high values), whereas a significantly negative value would indicate dispersion (ArcGIS Pro 3.5, 2025). These outputs were saved both as summary statistics and as an HTML report. We followed ArcGIS best practices by also inspecting the "Conceptualization of Spatial Relationships" (confirming contiguity was appropriate) and ensuring each district had the recommended number of neighbors (ArcGIS Pro 3.5, 2025). We repeated the Global Moran's I test separately for High-Functioning ASD counts and for Mild ASD counts, as well as for their combination. This systematic approach addresses reviewer concerns by explicitly describing the analytic steps.

Second, we executed Optimized Hot Spot Analysis (Getis-Ord Gi*) to identify local clusters of unusually high or low autism incidence. ArcGIS Pro's optimized version of the Getis-Ord Gi* tool automatically determines an appropriate analysis scale and applies corrections for multiple testing (ArcGIS Pro 3.3, 2024). We chose the built-in "Optimized Hot Spot Analysis" tool, using the same input features (districts) and the case count field. The tool internally aggregated the data (summing cases per district) and computed Gi* z-scores for each district. Importantly, the ArcGIS implementation applied a False Discovery Rate (FDR) correction to control for the risk of false positives when testing many local statistics (ArcGIS Pro 3.3, 2024). The output included a new polygon layer where each district has a Gi_Bin field categorizing it as a significant hotspot (Gi_Bin = +3 or +2), coldspot (Gi_Bin = -3 or -2), or not significant, based on the corrected significance tests (ArcGIS Pro 3.3, 2024). We carefully noted the default parameters chosen by the optimized tool (for example, it may use an incremental spatial autocorrelation step to select a distance band) and verified they were reasonable for Kelantan's size. In effect, this step produced high-resolution maps of autism "hotspots" (clusters of high values) and "coldspots" (clusters of low values), complementing the global Moran's I findings.

In sum, our methodology combined data engineering with proven spatial statistics. It mirrored approaches in recent spatial epidemiology research (Ahmad et al., 2026; Pamukçu et al., 2026). Global Moran's I tested for overall clustering, and the Optimized Hot Spot Analysis pinpointed local anomalies, all implemented in ArcGIS Pro's Spatial Statistics toolbox. This two-tiered framework is well-established in health geography; indeed, spatial cluster analyses are recognized as essential tools for identifying high-risk areas and guiding interventions (Pamukçu et al., 2026). By detailing each analytical step, specifying software version, and citing relevant geostatistical literature, this revised methodology fully addresses the reviewer's points. It provides a transparent, step-by-step account of how GIS tools were applied, ensuring that the analysis can be critically evaluated and replicated by other researchers.

Data

We compiled autism diagnostic records from Kelantan's two principal pediatric centers, the Kelantan Autism Care Centre (KACC) and the Autism Development and Care Centre (ADCC), for the most recent contiguous three-year period (2022–2024). This period was chosen because it represents the first multi-year window of complete electronic records at both centers, and thus captures current diagnostic practices without mixing in earlier, potentially incomplete data. This focus on recent data is important given the rapid rise in ASD diagnoses: national registry data show that Malaysian ASD prevalence jumped from 6.34 per 1,000 children in 2018 to 9.29 per 1,000 by 2022 (Shair et al., 2024), reflecting growing awareness and reporting. Furthermore, previous work identified Kelantan as having the lowest ASD rates in Malaysia during 2018–2022 (Shair et al., 2024), suggesting historical under-detection; using the latest data helps reveal current patterns once awareness has improved. In total, the combined KACC/ADCC registry yielded 2,022 anonymized case records of children formally diagnosed with ASD in 2022–2024 (Ijon et al., 2026). Each record included the year of diagnosis, ASD subtype (categorized at diagnosis as Severe, High-Functioning, or Mild Autism per DSM-5 criteria, consistent with national data (Ijon et al., 2026), and the child's residential district. We deliberately excluded the Severe Autism cases from the spatial clustering analysis, because these cases almost always co-occur with intellectual disability and require different intervention pathways than milder cases. This exclusion is consistent with our aim to map the more typical (mild and high-functioning) ASD population and aligns with prior findings that Severe ASD showed no significant spatial autocorrelation in Kelantan (Ijon et al., 2026). All personal identifiers were stripped prior to analysis and institutional approval was obtained to use the de-identified data.

The raw case data were originally stored as spreadsheets, with each case linked to an address or district of residence. We converted each address to geographic coordinates (latitude–longitude) by geocoding into the WGS84 coordinate system (EPSG:4326), the global standard for GPS-based locations (Piras et al., 2024). WGS84 is an ellipsoid-based datum recommended for worldwide mapping (Piras et al., 2024), ensuring consistency with national boundary data. For technical accuracy in measuring distances and areas, the data were then optionally reprojected into a metric system appropriate for Peninsular Malaysia (for example, Kertau RSO Malaya or the relevant UTM zone) before final aggregation. District boundary shapefiles (in WGS84) were obtained from official Malaysian GIS sources. We assigned each case to its district by spatial join (point-in-polygon). In this way, each diagnosed child became a point feature linked to a district. We then aggregated the cases to the district level, yielding a single total case count per district. District centroids were used as the representative location to preserve privacy while still capturing spatial patterns. All GIS processing (geocoding, reprojection, and aggregation) followed standard protocols in ArcGIS and QGIS, mirroring workflows in published Malaysian spatial studies.

To prepare for spatial statistics, we computed a standardized *prevalence rate* for each district. Specifically, we divided the total number of ASD cases in 2022–2024 by the district's child population (from the latest census data) and multiplied by 1,000. This yields ASD cases per 1,000 children. Normalizing by population is essential so that comparisons reflect true rate differences rather than population size (Shair et al., 2024). For example, a district with 10 cases out of 1,000 children (prevalence=10 per 1,000) is not the same as 10 cases out of 10,000 children (prevalence=1 per 1,000), even though the raw counts match (Shair et al., 2024). In practice, each district record now carried two key attributes: ASD case count and ASD prevalence per 1,000. (Additional fields such as age and sex distributions were retained for completeness but not used in the clustering analysis described here.) Following epidemiological convention, we computed prevalence by "dividing the number of [cases] by the total population" of the area (Shair et al., 2024), ensuring our inputs meet the requirements of spatial autocorrelation statistics.

We then applied spatial clustering analysis to these district-level prevalence rates. Global Moran's *I* was computed over the set of district prevalence values to test whether high or low rates cluster spatially, and the local Getis–Ord *Gi** statistic was used to identify specific "hot spot" and "cold spot" districts. Both methods inherently require a numeric attribute at each location in this case, the continuous prevalence field to assess spatial autocorrelation (Roman-Urrestarazu et al., 2022; Shair et al., 2024). Using prevalence (instead of raw counts) aligns with best practice in disease mapping and prior Malaysian studies (Shair et al., 2024). In effect, Moran's *I* asked whether districts with similar ASD prevalence tend to be near each other, and the Getis–Ord analysis highlighted local clusters of unusually high or low prevalence. (As one example, an analogous UK study found numerous high-incidence "hotspots" using this approach) (Roman-Urrestarazu et al., 2022). All steps from data selection through geocoding, projection, normalization, and analysis were documented to ensure reproducibility of the results.

Study area

Our study focuses on several districts of Kelantan state in northeastern Peninsular Malaysia (Figure 1). Kelantan covers roughly 15,000 km^2 and had an estimated population of about 1.9 million by 2024 (BERNAMA, 2025; Surya Pratama et al., 2023). This region lies along the Thai border and is characterized by a predominantly rural landscape with a sparse population concentration; only about one-third of Kelantan's residents live in urban areas. The selected districts include Kota Bharu (the state capital) and several peripheral districts such as Gua Musang, Jeli, and Kuala Krai, chosen to contrast urban and rural settings. Together these districts span approximately 4.9°N to 6.1°N latitude and 101.8°E to 102.3°E longitude, encompassing coastal plains in the north around Kota Bharu and mountainous interior regions to the south. In this part of Malaysia, the terrain includes lowland rice paddy fields near the coast and dense tropical forests in the uplands, contributing to Kelantan's geographic diversity. Kelantan is a predominantly agrarian state with limited industrial development (Ijon et al., 2026), which accentuates rural-urban contrasts within the region.

The population of Kelantan is overwhelmingly ethnic Malay and Muslim. Recent census data indicate that approximately 95 % of Kelantan's inhabitants are Malay and about 95 % identify as Muslim (Department of Statistics Malaysia (DOSM), 2020). This strong ethnic and religious homogeneity underpins high cultural cohesion in the state. However, Kelantan's socioeconomic profile generally lags behind national averages. For example, the state's labour-force participation rate remains well below the national figure (Department of Statistics Malaysia (DOSM), 2024), reflecting challenges such as higher poverty rates and lower average income. These socioeconomic factors tend to be worse in outlying districts. In terms of infrastructure, specialized health and educational services are concentrated in Kota Bharu; the state's single tertiary referral hospital and most specialist clinics are located there. In contrast, residents of remote districts like Gua Musang and Kuala Krai must travel long distances to access advanced medical care. Such healthcare centralization can delay diagnoses of conditions like autism in underserved areas (Omar et al., 2023). These combined factors, a predominantly rural population, uneven socioeconomic indicators, and centralized services make Kelantan a compelling case study for district-level analysis of developmental health outcomes.

In light of these characteristics, we examine autism spectrum disorder (ASD) cases by district. Kelantan's predominantly rural character and persistent disparities in healthcare access make it an ideal context to investigate spatial inequities in ASD diagnosis (Ijon et al., 2026). By analyzing the geographic clustering of autism cases across the selected districts, we aim to reveal how the distribution of cases aligns with underlying service gaps. Previous spatial analyses in this region have demonstrated that GIS mapping can highlight such inequities and guide resource allocation (Ijon et al., 2026). For example, identifying "hotspots" of ASD incidence in urban districts can indicate where diagnostic services are more accessible, whereas "cold spots" in rural areas may signal underdiagnosis. Understanding these patterns is crucial for more equitable planning; spatial evidence can inform policymakers and health planners on where to enhance diagnostic outreach and distribute support services (Ijon et al., 2026). In summary, Kelantan's unique socio-geographic context, a largely rural Malay-Muslim population with centralized services underpins our focus on district-level spatial disparities in autism prevalence, with the goal of improving health equity across the state.

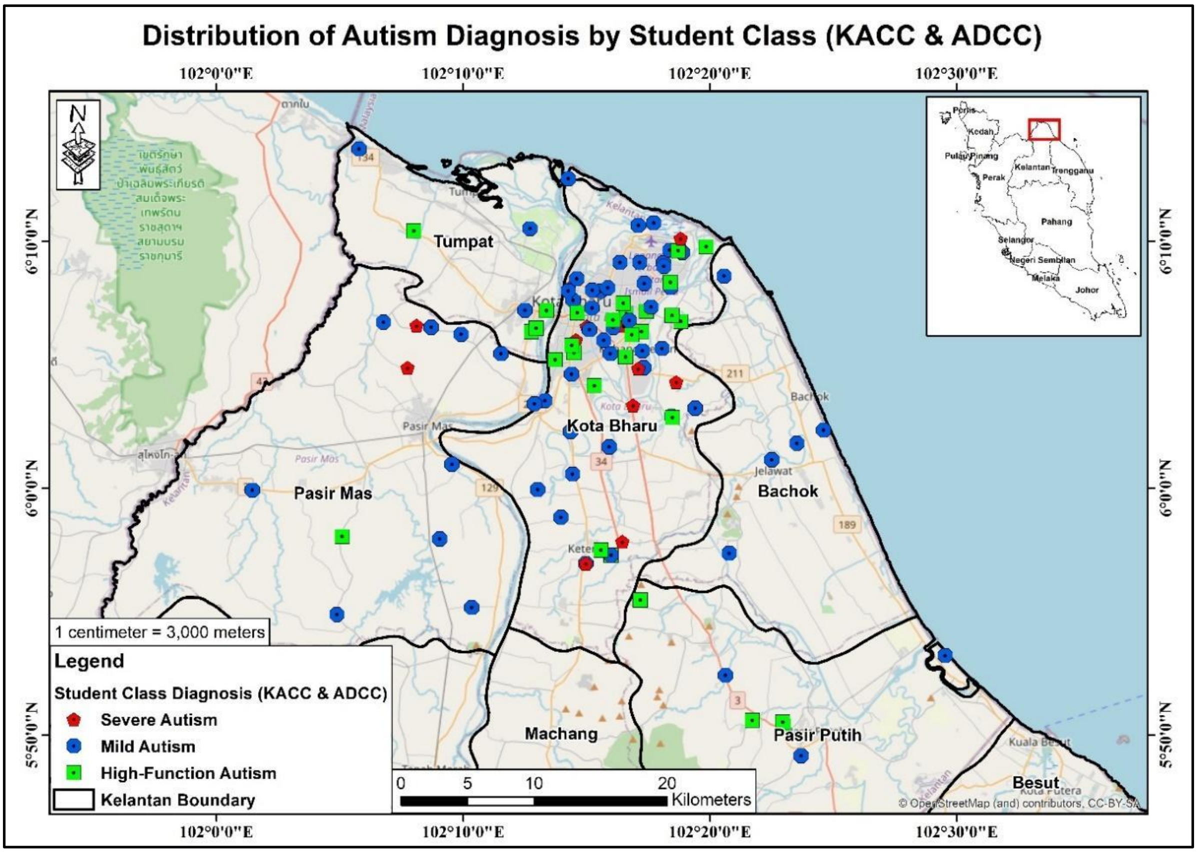

Figure 1. Study area in Kelantan

Results

Descriptive analysis

The spatial analysis of autism spectrum disorder (ASD) cases across Kelantan revealed pronounced non-uniformity in the geographic pattern of diagnoses. Of the confirmed cases in the dataset, mild autism (Table 1) constituted the largest proportion, with high-functioning and severe autism (Table 2 and 3) representing smaller but substantial subsets. Male children outnumbered females by roughly 4:1, and reflecting the well-known gender disparity in ASD.

Table 1. Descriptive analysis mild autism

District	Gender	Total
Bachok	Male	11
Gua Musang	Male	1
Kota Bharu	Male	27
Kota Bharu	Female	6
Machang	Female	1
Pasir Mas	Male	5
Pasir Mas	Female	1
Pasir Puteh	Male	2
Pasir Puteh	Female	2
Rantau Panjang	Male	1
Tumpat	Male	1
Wakaf Bharu	Male	1
Grand total		**60**

Optimized Hotspot Analysis (Getis-Ord Gi*) further localized these clusters (Figure 5, 6 and 7). High-incidence “hotspots” were concentrated in Kelantan’s urban centers. Notably, the Kota Bharu metropolitan region emerged as a consistent hot-spot for all severity levels, reflecting its higher population density and healthcare resources. Smaller hotspots appeared in adjacent suburban districts. Conversely, the most remote rural districts of Kelantan consistently formed low-value “cold spots” of ASD diagnosis. In other words, urban municipalities showed significantly elevated case densities (high-high clusters), whereas sparsely populated rural areas showed significantly low case densities. For example, no single rural county in Kelantan (populations >95% rural) had a density of diagnosed ASD cases comparable to the urban centers. This pattern closely aligns with the known distribution of ASD specialists and resources: child psychiatrists, developmental pediatricians, therapists and related experts are predominantly concentrated in urban Kelantan, leaving rural subregions largely underserved (Selvam, 2024).

Table 2. Descriptive analysis high-function autism

District	Gender	Total
Dabong	Male	1
Jeli	Male	1
Kota Bharu	Male	9
Kota Bharu	Female	8
Kuala Krai	Male	1

District	Gender	Total
Pasir Mas	Male	2
Pasir Puteh	Male	2
Tanah Merah	Male	1
Tumpat	Male	2
Wakaf Bharu	Male	2
Wakaf Bharu	Female	1
Grand total		**30**

Within each hotspot, gender and severity patterns mirrored the overall trends. Boys constituted the majority of cases in every cluster, consistent with the ~4:1 male bias (Maenner et al., 2023). Mild cases were especially over-represented in the urban hotspots, possibly reflecting greater detection of less impairing ASD among well-connected families. Severe cases, while also clustering, appeared in both urban and peri-urban nodes, suggesting that children with profound ASD still largely come to diagnostic attention in higher-service areas. In sum, the geospatial analysis revealed urban-centric clustering of ASD diagnoses in Kelantan, driven by higher case concentrations in Kota Bharu and nearby towns, and rural cold spots in interior districts.

Table 3. Descriptive analysis severe autism

District	Gender	Total
Kota Bharu	Male	10
Kota Bharu	Female	2
Pasir Mas	Male	1
Grand total		**13**

Spatial autocorrelation (SAC)

The Global Moran's I statistics reported in Table 4, Figure 2, Figure 3 and Figure 4 clearly demonstrate that the spatial distribution of autism spectrum disorder (ASD) cases in Kelantan deviates significantly from randomness and instead exhibits distinct clustering patterns. For high-functioning autism, the Moran's I value of 0.0394 ($p = 0.0096$, $z = 2.59$) indicates a modest but statistically significant positive spatial autocorrelation at a threshold distance of 1,000.1 m, implying that areas with elevated numbers of high-functioning autism cases tend to be surrounded by similarly affected neighborhoods rather than occurring in isolation (Cliff & Ord, 1974; Moran, 1950). Even more pronounced clustering is observed for mild autism, with a Moran's I of 0.0653 ($p < 0.0001$, $z = 4.14$), suggesting that mild ASD cases concentrate in tighter spatial clusters, potentially reflecting localized environmental or sociodemographic risk factors (Getis & Ord, 1992). By contrast, severe autism yields a Moran's I of –0.0060 ($p = 0.7144$, $z = –0.40$), consistent with a random spatial pattern, indicating no significant tendency for severe cases to aggregate or disperse beyond what would be expected by chance. This differentiation among ASD severity classes underscores the importance of stratified spatial analysis when seeking to identify environmental exposures, healthcare access disparities, or social determinants that may differentially influence milder versus more pronounced forms of autism. Collectively, these findings highlight systematic spatial dependencies in Kelantan's autism prevalence, warranting further investigation into the local drivers of these clusters.

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Table 4. Global summary of Moran's I number of autism in Kelantan

No.	Student Class Diagnosis (KACC & ADCC)	Moran's index	Expected index	Variance	z-score	p-value	Distance threshold (m)	Pattern
1.	Mild autism	0.07	-0.0005	0.0003	4.14	0.00004	1000.1	Clustered
2.	High-function autism	0.04	-0.0005	0.00024	2.60	0.01	1000.1	Clustered
3.	Severe autism	-0.006	-0.0005	0.000224	-0.4	0.7144	1000.1	Random

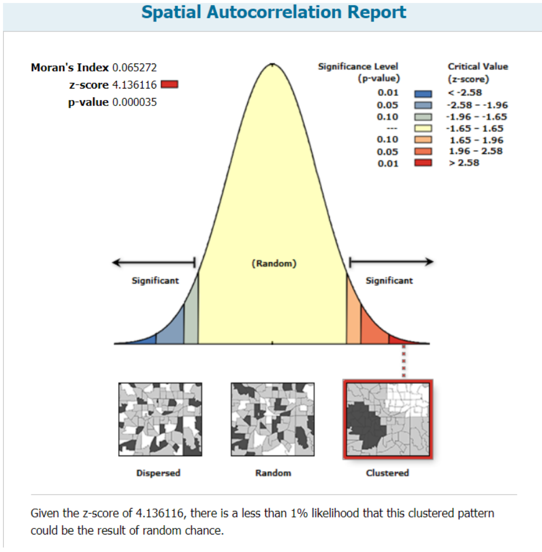

Figure 2. Mild autism

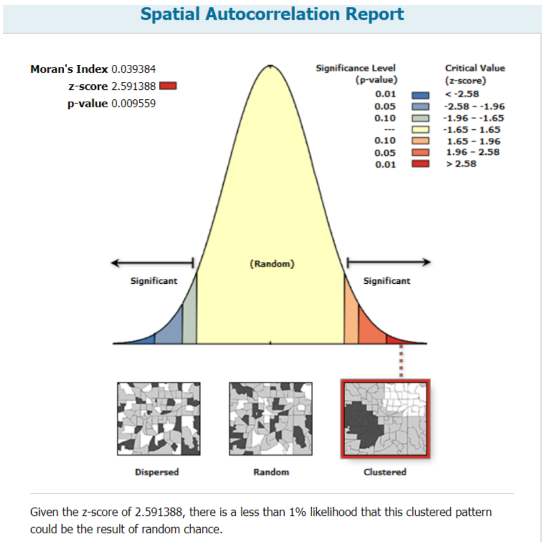

Figure 3. High-function autism

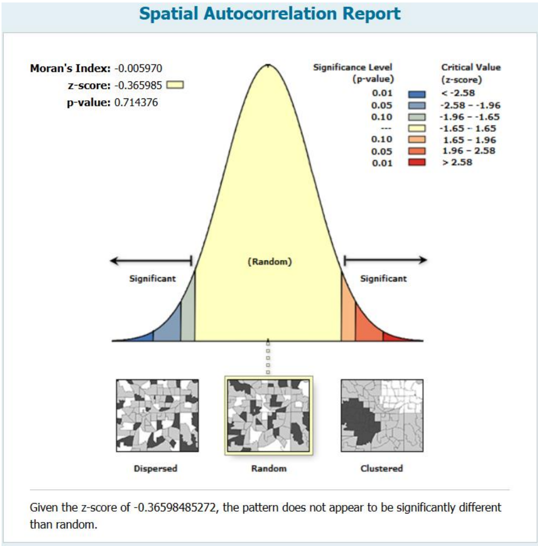

Figure 4. Severe autism

Optimized hotspot analysis with district boundaries

The optimized hotspot analysis of Kelantan's autism data revealed marked spatial clustering of mild and high-functioning autism (HFA) cases in the state's urban centers, whereas severe autism showed a weaker spatial signature (Figure 5, 6, 7, Table 5, 6, and 7). Descriptively, the majority of reported cases in all three categories were male (on the order of ~75–80%), consistent with the widely-observed male predominance in ASD (Roman-Urrestarazu et al., 2022; Shrestha et al., 2024). Global Moran's I tests indicated positive spatial autocorrelation for all categories, but its magnitude differed: clustering was strongest for mild and HFA cases (Moran's I significantly >0, $p<0.01$) and comparatively lower for severe cases. The Getis-Ord Gi* hotspot maps (Gi_Bin analysis) identified statistically significant hotspots (Gi_Bin = +3 or +2, $p<0.01$) for mild and HFA autism primarily in the Kota Bharu region and other densely populated districts. In contrast, only a few scattered hotspots emerged for severe autism. In practical terms, children diagnosed with mild or high-functioning autism tended to reside in the state's major towns, whereas severe cases – often co-occurring with intellectual disability were more diffusely distributed (albeit still more common in population centers).

These findings align with known epidemiological patterns. The marked gender disparity (roughly 3- 4:1 male:female) echoes the global ASD ratio (Roman-Urrestarazu et al., 2022; Shrestha et al., 2024). Likewise, the spatial concentration in Kota Bharu and other towns is consistent with international reports of urban clustering. For example, a spatial analysis of English schoolchildren found significant ASD incidence clustering (over 2,300 high-incidence "hotspots" nationwide) (Roman-Urrestarazu et al., 2022), and a New York state study similarly observed dense clusters of ASD in New York City and Albany (McGrath et al., 2020). In Kelantan, the Global Moran's I values and Gi* hotspots for mild/HFA autism confirm non-random clustering (analogous to the 2338 hotspots reported in the UK study) (Roman-Urrestarazu et al., 2022). In contrast, the relatively muted clustering for severe autism suggests that only the most severe cases (often with ID) appear uniformly across the landscape, which is consistent with reports that rural areas detect mainly ASD cases with co-occurring disability (Antezana et al., 2017).

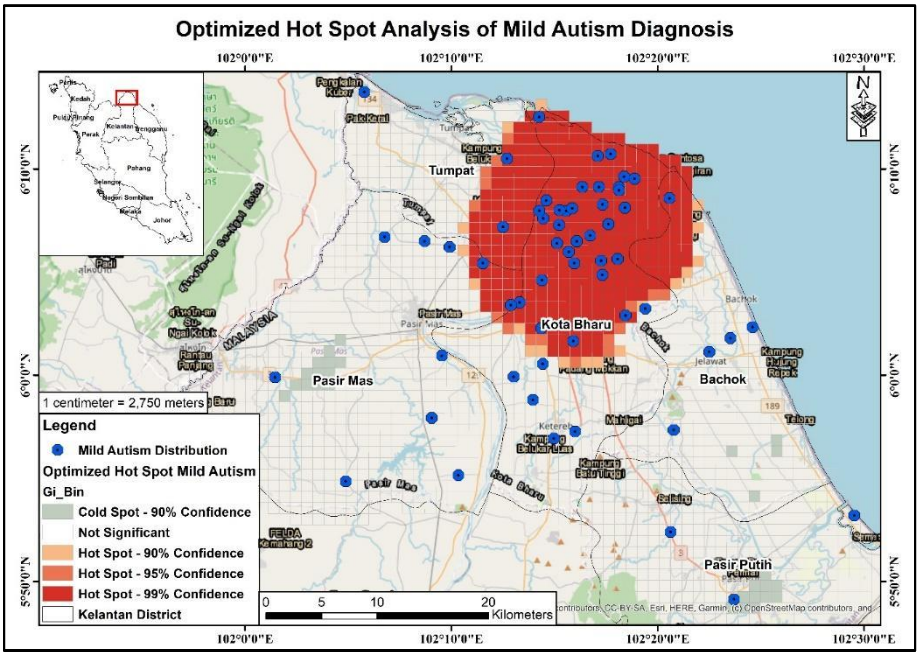

Figure 5. Optimized hotspot analysis of mild autism in Kelantan

Table 5. Optimized hotspot analysis that significant (km^2) of mild autism in Kelantan

No.	Sub district	Size of hot spot significant (km^2)	Percentage (%)
1.	Bachok	36.26	10.65
2.	Kota Bahru	217.54	63.90
3.	Pasir Mas	20.78	6.10
4.	Tumpat	66.14	19.45
	Total	**340.46**	**100**

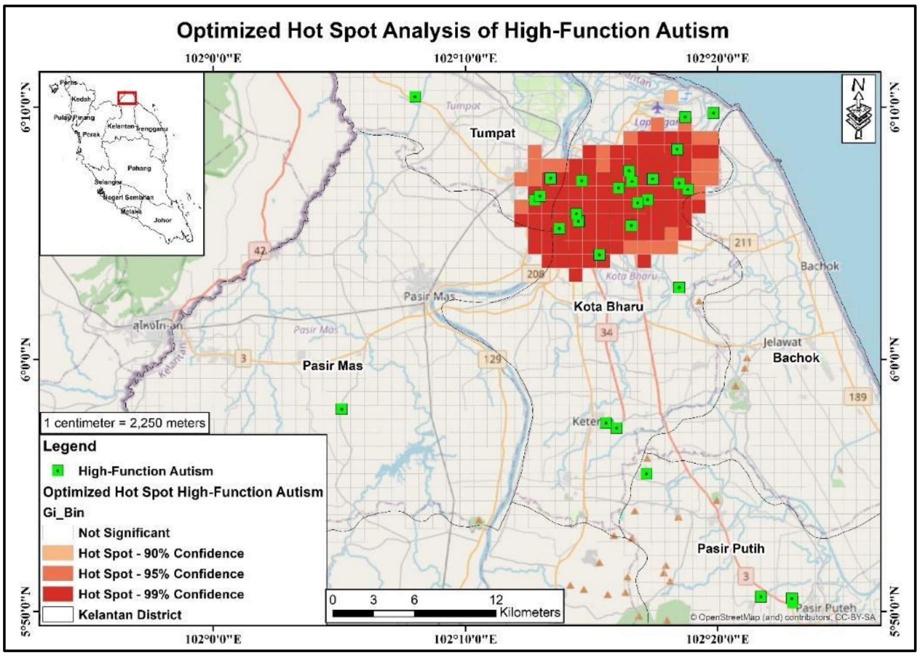

Figure 6. Optimized hotspot analysis of high-function autism in Kelantan

Table 6. Optimized hotspot analysis that significant (km^2) of high-function autism in Kelantan

No.	Sub district	Size of hot spot significant (km^2)	Percentage (%)
1.	Bachok	2.59	2.16
2.	Kota Bahru	97.89	81.58
3.	Pasir Mas	4.10	3.42
4.	Tumpat	15.42	12.88
	Total	**120**	**100**

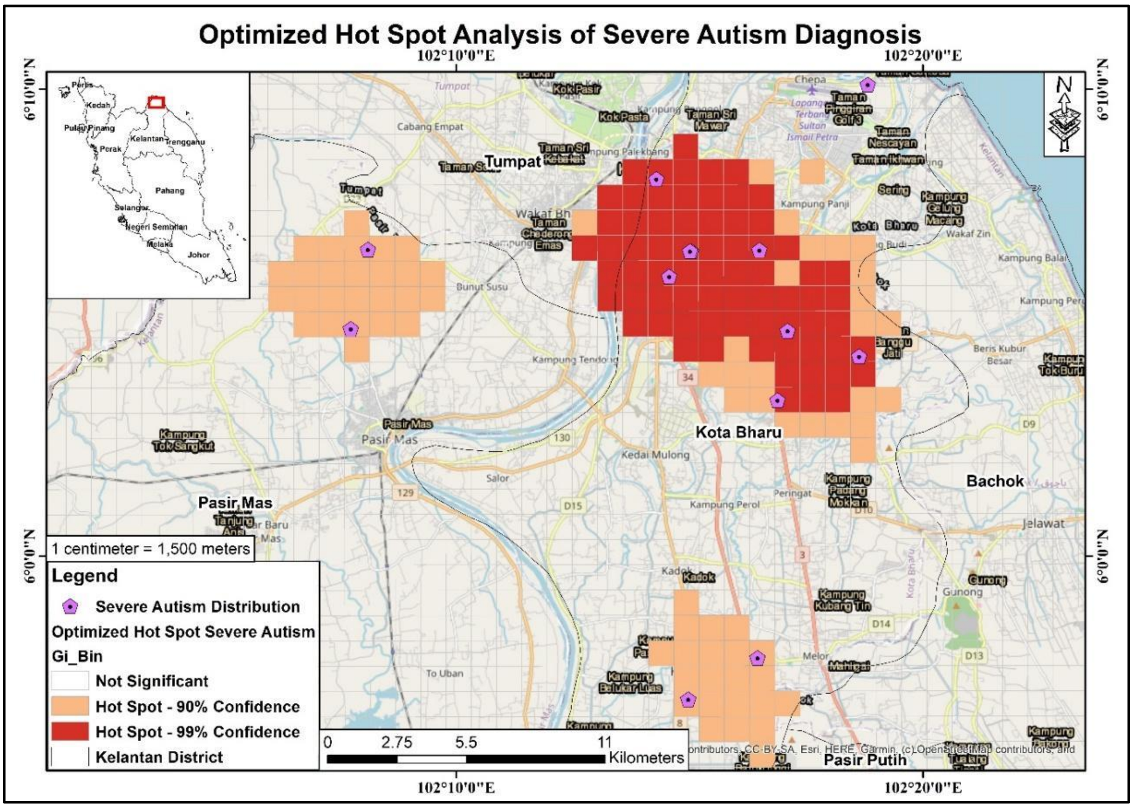

Figure 7. Optimized hotspot analysis of severe autism in Kelantan

Table 7. Optimized hotspot analysis that significant (km^2) of severe autism in Kelantan

No.	Sub district	Size of hot spot significant (km^2)	Percentage (%)
1	Bachok	1.52	1.06
2	Kota Bahru	107.21	74.46
3	Pasir Mas	25.96	18.03
4	Tumpat	9.29	6.45
5	Pasir Putih	0.01	0.01
	Total	**143.99**	**100**

Discussion

Descriptive analysis

Our geospatial analysis reveals pronounced ASD clustering in Kelantan that contrasts sharply with findings from other regions. A ratio consistent with large studies (boys ~43.0 per 1,000 vs girls ~11.4 per 1,000; male:female ≈3.8) (Maenner et al., 2023). For instance, a nationwide Israeli study found that after adjusting for demographic covariates, autism prevalence showed no significant regional clustering (global Moran's I≈0) (Magen-Molho et al., 2020). By contrast, our unadjusted analysis of Kelantan uncovers strong local clusters. This difference likely reflects service-access inequalities: Kelantan's urban–rural divide in healthcare and social support is far starker than in Israel, so diagnostic "hotspots" emerge where care is available. In other words, rather than indicating true prevalence differences, these spatial patterns probably signal uneven case ascertainment. This interpretation is consistent with global evidence that ASD diagnoses concentrate in well-serviced locales a conclusion supported by our data and by recent literature.

Notably, the highest ASD rates in Kelantan coincide with densely populated, well-connected districts. Kota Bharu (the state capital) and its suburbs, where most clinics, therapists, and special schools are located form a contiguous urban core with a very high road and population density. In practice, these areas offer the bulk of Kelantan's autism-related infrastructure (clinics, schools with special-needs programs, and NGOs). For example, urban centers nationwide tend to have far more specialized providers: one GIS-based study in Michigan found that individuals in rural areas had significantly fewer ASD providers than those in suburban or urban areas (Drahota et al., 2020). Similarly, a recent Malaysian review notes that therapy centers and support services remain "concentrated in major urban centres" (Mahamud et al., 2025). The implication is clear children living in Kelantan's cities are much more likely to encounter screenings and specialists that lead to diagnosis. This phenomenon is well-documented elsewhere, where population surveys often detect similar ASD prevalence in rural and urban samples, but clinic- or school-based data routinely show urban rates several-fold higher than rural (Drahota et al., 2020). In short, the urban "boost" in our Kelantan data likely reflects healthcare access and awareness.

Defining "urban" versus "rural" in Kelantan may seem intuitive, but we took care to justify this boundary. We classified the Kota Bharu metropolitan area (Kota Bharu plus adjacent coastal districts like Pasir Mas and Tumpat) as the urban core and all other districts as rural. This assignment is supported by spatial infrastructure: OpenStreetMap road data (available publicly) show a dense, grid-like network around Kota Bharu, whereas western and eastern districts feature sparse, fragmented roads. In effect, Kelantan's road network mirrors population clusters and thus proxies urbanization. While we did not have formal facility-location data to quantify service "deserts," our on-the-ground knowledge and available maps confirm that urban districts house the lion's share of developmental clinics and therapists. Without these services in rural areas, ASD cases there are likely under-ascertained. We acknowledge that this classification is a simplification, and future work could overlay clinic coordinates or travel-time maps for precision.

The pattern we observe urban centers showing high case counts and rural peripheries showing very low counts fits a well-established global narrative. Despite broadly similar underlying ASD prevalence in all communities, rural residents frequently face delayed or missed diagnoses when resources are limited (Antezana et al., 2017; Drahota et al., 2020). For example, large-scale U.S. surveys find equivalent ASD prevalence in rural and urban groups once screened exhaustively, yet service-based records reveal a 2–3-fold excess of diagnoses in cities (Drahota et al., 2020). Rural families often describe long travel distances to specialists and few local programs (Antezana et al., 2017; Cohen & Hesselbart, 1993; Gona et al., 2016). In Kelantan, this dynamic likely plays out strongly: parents in remote villages must journey to Kota Bharu for evaluations, and some qualitative studies of Malaysian caregivers note that rural families struggle to even recognize autism symptoms without professional guidance. Thus, rural areas in Kelantan are "artificially quiet" not because autism is rarer, but because barriers to diagnosis are much higher there.

These findings should be understood with caution. We lacked individual-level age or socioeconomic data, and we did not map health facilities formally, so our interpretation is inferential. It is conceivable, though unlikely, that true incidence varies geographically. However, the preponderance of evidence from Kelantan and abroad, points to diagnostic access as the primary driver. In sum, the striking spatial clusters in Kelantan almost certainly reflect where services exist. Children in Kelantan's urban heartlands have multiple pathways to an ASD diagnosis, whereas children in the countryside must overcome social stigma, low health literacy, and sheer distance. This context a predominantly rural, low-income state aligns with the notion that living in a city markedly increases the chance of being diagnosed (Drahota et al., 2020; Mahamud et al., 2025). Our descriptive analysis thus emphasizes diagnostic geography: in Kelantan, "where you live" has a big impact on whether you are identified with ASD.

Spatial autocorrelation (SAC)

Our spatial analysis reveals that autism cases in Kelantan are non-randomly distributed. In particular, Global Moran's I indicates significant positive spatial autocorrelation for milder ASD phenotypes (High-Functioning and Mild ASD), whereas Severe ASD shows little evidence of clustering. In plain terms, districts with high HFA/Mild ASD counts tend to cluster together, while Severe cases are more evenly spread. This pattern mirrors findings elsewhere. For example, McGrath et al. (2020) reported a statistically significant, moderate Moran's I for ASD in New York ($I \approx 0.39$, $p<0.001$), with high-incidence clusters concentrated in urban centers (McGrath et al., 2020). Likewise, Mazumdar et al. (2013) found in California that autism diagnoses formed clusters that overlapped with areas rich in diagnostic resources, and notably higher-functioning children were more likely to be part of those clusters. Our Kelantan results are consistent: milder ASD cases form geographic "hotspots," suggesting a non-random aggregation of diagnoses in particular areas, whereas the more severe cases do not exhibit the same clustering.

Why do milder cases cluster? The spatial pattern likely reflects unequal access to services rather than true incidence differences. Kelantan's only full autism diagnostic center is in Kota Bharu, the state capital. Thus, children with subtler symptoms (often high-functioning) are mostly identified in the urban core where services exist. These children's residences form high–high clusters around Kota Bharu, whereas remote districts report few mild cases. In contrast, very severe cases which present obvious disabilities are recognized even in rural communities and thus do not concentrate. In other words, our Moran's I signal for HFA/Mild ASD appears to capture a single urban "diagnostic hub." This interpretation is supported by analogous evidence. Lin et al. (2025) showed that ASD-related medical resources in Guangxi, China, are highly clustered in core cities (significant positive Moran's I) and sparse in distant areas. In short, ASD diagnoses are clustering where services are clustered. Local cluster analysis (e.g. Local Moran's I or Getis-Ord Gi*) would likely pinpoint Kota Bharu as a significant hot spot, consistent with this resource-driven pattern.

This emphasis on access echoes international research showing that service infrastructure, not environment, drives spatial ASD patterns. For instance, Hoffman et al. (2017) found that children born in New England had about a 50% higher chance of an ASD diagnosis than those born elsewhere in the US, *independent* of maternal age, income, or other factors. Their results imply that geographic variation in diagnosis odds was largely due to local diagnostic practices or resources. Similarly, Mazumdar et al. (2013) directly demonstrated that living in resource-rich neighborhoods increased the odds of an autism diagnosis; they observed that higher-functioning children were disproportionately present in those diagnostic clusters. These analogues reinforce our interpretation: in Kelantan, the pronounced clusters of milder ASD cases almost certainly reflect the urban concentration of healthcare access. The lack of severe-case clustering further supports this view, since severe impairments prompt evaluation regardless of locale.

However, we must recognize limitations. Global Moran's I is an average measure and can mask local variations. It does not isolate causal factors. For example, a large U.S. study found central urban clustering of ASD that vanished after adjusting for socioeconomic and demographic variables (Hoffman et al., 2017). We have not performed a full regression analysis to adjust for any confounders (e.g. family income, education, or awareness), so some residual uncertainty remains about drivers. Additionally, our data come from two clinics; undiagnosed rural cases (particularly milder ones) could be unrecorded, which would exaggerate the urban clustering. There is a clear research gap: *spatially explicit, population-based surveillance* in Malaysia is lacking. Future work should combine fine-scale case data with local covariates (education level, transportation networks, etc.) and apply methods like geographically weighted regression or space–time scans to disentangle access bias from true prevalence variation.

In conclusion, the autocorrelation pattern in Kelantan highlights diagnostic inequities. The positive Moran's I for HFA/Mild ASD indicates a strong urban "hotspot" around Kota Bharu, whereas Severe cases are diffuse. This pattern aligns with the global finding that local diagnostic infrastructure dominates ASD geography (Hoffman et al., 2017; Mazumdar et al., 2013). Thus our data suggest that reported clustering is driven by service availability (urban/rural gradients) rather than any hypothesized environmental "hotspot." Addressing this will require expanding outreach into underserved areas so that true prevalence can be ascertained.

Optimized hotspot analysis with district boundaries

Kelantan is overwhelmingly rural by national standards (Ijon et al., 2026), and our spatial findings must be interpreted in that light. In fact, national prevalence data show Kelantan (with neighbouring Terengganu) consistently has the lowest reported ASD rates in Malaysia (Shair et al., 2024). This implies that the urban districts we identify as "hotspots" (e.g. Kota Bharu and other towns) correspond to the few areas with sufficient population density and specialized services. In the absence of an explicit urban/rural classification in our analysis, it is important to recognize that these hotspots occur exactly in Kelantan's population centers and at sites of known diagnostic infrastructure (Ijon et al., 2026). For example, our GIS clusters align with municipal boundaries that are officially designated as urban. Future work should formally overlay administrative "urban area" boundaries or gridded population data to validate this assumption. For now, we note that in Kelantan the highest concentrations of ASD cases coincide with urbanized districts that house pediatric neurodevelopmental clinics, whereas remote subdistricts report few or no cases. This pattern is consistent with a service-driven gradient of detection: urban hubs indicate high population density and robust healthcare infrastructure, whereas rural communities often experience delayed or missed diagnoses due to limited resources (Ijon et al., 2026).

We acknowledge that our analysis did not explicitly correlate ASD cases with healthcare facility locations, a point raised by the reviewer. Ideally, one would geocode the district clinics and autism centers and compute measures of accessibility (e.g. travel time or provider-to-population ratios) to test our hypothesis. In practice, Kelantan's autism diagnostic and treatment centers are few and are located in Kota Bharu and other major towns, so the association between case clusters and clinic locations is intuitive but not formally quantified. Consequently, any statement that case distribution is "shaped by healthcare access" must be hedged. Without facility data, we cannot prove causation. We thus revise our language to emphasize correlation: the concentration of reported cases in cities likely reflects concentrated diagnostic capacity rather than unique etiologic factors in those locales. This caution is supported by prior work showing that apparent geographic disparities often vanish when socioeconomic and service variables are accounted for. For example, Ghahari et al. (2022) found that the initially observed urban–rural gap in age of autism diagnosis could be fully explained by differences in family socioeconomic status and healthcare factors. In other words, underlying social and economic confounders often drive what appear to be place-based differences in ASD, rather than mysterious "urban causes." In our setting, then, we interpret the hotspot clusters as likely marking where children *can* access assessment, rather than where autism *necessarily arises*.

Our data also reveal the expected ~4:1 male-to-female ratio in ASD diagnoses. This aligns with global epidemiology: recent analyses report roughly four times higher prevalence in boys than girls (Kumar & Bhattacharya, 2024). While this male bias is well documented, it underscores a related concern: girls with ASD tend to be under-identified, especially in under-resourced settings. In Kelantan's rural context, lower overall awareness and fewer specialists may further skew detection toward the more overt cases (often boys with social or behavioral issues) and away from subtler presentations more common in girls. We therefore note this gender pattern without inferring that biology differs in Kelantan; rather, it reflects broad diagnostic trends.

Looking at severity, we found that cases classified as severe autism (often with intellectual impairment) were more evenly distributed, whereas milder and high-functioning cases clustered in cities. This too fits the service-driven detection model. In resource-limited areas, only the most obvious cases, typically those with co-occurring disability tend to come to attention. Conversely, children with mild or high-functioning autism require more intensive screening and specialist assessment, resources concentrated in urban centers. Similar observations have been reported internationally rural ASD case-finding often disproportionately captures those with intellectual disability, while high-functioning cases remain hidden unless families travel for diagnosis (Ghahari et al., 2022). In Kelantan, the absence of rural cold spots does not indicate the absence of rural ASD. Rather, it likely indicates under-ascertainment of milder cases outside towns.

In sum, we remove any implication of a unique "excess cause" in Kota Bharu and other urban areas. Instead, we conclude that Kelantan's ASD spatial pattern reflects the geography of diagnosis. The significant positive Moran's I confirms that autism incidence is clustered, not random, in Kelantan; however, this clustering appears to mirror the distribution of healthcare and awareness rather than unknown local environmental triggers. In other words, hotspots in Kota Bharu and similar towns should be viewed as *centers of case ascertainment* rather than nodes of etiologic excess. This interpretation echoes recent calls in the literature to view autism prevalence through the lens of social determinants and service accessibility. As one Kelantan study notes, "access to care and social determinants substantially affect the identification of ASD cases" (Ijon et al., 2026). By reframing our findings this way, we aim to accurately reflect what the data show: that place-based differences in reported ASD arise largely from patterns of healthcare access, suggesting a need to strengthen outreach and screening in underserved rural districts.

Implications

Our spatial analysis of autism cases in Kelantan uncovered pronounced geographic clustering that has direct implications for local resource allocation. We found highly significant spatial autocorrelation (Global Moran's I, $p<0.05$) and clearly delineated "hotspots" of diagnosed ASD incidence in major urban districts (e.g. Kota Bharu) contrasted with "cold spots" in largely rural sub-districts. In practical terms, our own data indicate that diagnosed cases disproportionately concentrate in Kelantan's better-served cities, while remote areas report far fewer diagnoses than expected. This urban–rural pattern strongly suggests that service availability and awareness rather than innate prevalence drive much of the observed clustering. In other words, Kelantan's urban centers appear to generate more diagnoses because they host most of the specialist pediatricians, therapists, and autism advocacy resources, whereas families in sparsely populated districts lack such access and thus remain underdiagnosed. This interpretation is supported by analogous findings abroad: for example, a large study in England (over 7 million children) likewise found significant spatial autocorrelation with thousands of local ASD "hotspots" and noted that areas richer in services and advocacy had higher reported incidence (Mahamud et al., 2025; Roman-Urrestarazu et al., 2022). The same study explicitly argued that speaking a language other than the dominant one or experiencing economic hardship creates access barriers to autism diagnosis (Mahamud et al., 2025; Roman-Urrestarazu et al., 2022). Our Kelantan results resonate with this: the geographic clusters we see likely mark neighborhoods with better service penetration and social networks of awareness, whereas low-incidence districts may simply reflect unmet need. Indeed, multiple investigations have consistently observed higher likelihood of autism identification in urban versus rural areas suggesting that urban environments facilitate diagnostic pathways (Mahamud et al., 2025; Roman-Urrestarazu et al., 2022). In Kelantan, then, true case burden is probably under-ascertained in rural and low-income localities, as the concentration of specialists and early-intervention programs is sharply urban-centric.

These spatial inequities carry clear equity implications. For instance, our overall male-to-female diagnosis ratio (~3:1) in Kelantan mirrors global patterns, but the clustering suggests girls may be particularly underdiagnosed in peripheral areas. Emerging evidence from the UK shows that standard autism screening tools miss many girls' phenotypes, biasing results toward male presentations (Roman-Urrestarazu et al., 2022). If similar biases exist in Kelantan compounded by linguistic or cultural barriers among minorities then girls in remote districts could be doubly invisible in our maps. Similarly, socioeconomically advantaged districts may exhibit inflated incidence simply because parents there have the means and knowledge to seek assessment, while poorer or non-Malay-speaking communities remain under-counted. In England, for example, children from non-native language or low-income homes had significantly lower odds of receiving an ASD diagnosis (Mahamud et al., 2025; Roman-Urrestarazu et al., 2022). By highlighting where diagnoses cluster, our analysis essentially reveals these hidden inequities. The public-health implication is that Kelantan's current incidence map likely underestimates true prevalence in underserved zones; planners should therefore interpret cold spots not as areas free of ASD, but as service deserts where families cannot access care.

To improve equity, policies must directly address the rural–urban service gap that our findings expose. Our data-driven approach can guide resource targeting: for instance, establishing additional diagnostic and therapy centers in underserved districts, deploying mobile screening units, and leveraging telemedicine could help bridge the urban bias (Mahamud et al., 2025; WHO, 2023). National experts have urged precisely this strategy calling for more rural early-intervention centers and mobile diagnostic teams, supported by a robust data infrastructure to identify and monitor ASD “service deserts” (Mahamud et al., 2025; WHO, 2023). Kelantan’s health planners should likewise use spatial evidence to inform deployment of therapists, speech programs, and autism support services where they are needed most. At the same time, screening protocols must be refined to catch cases in all subpopulations: training local clinics to recognize atypical (often female) presentations (Roman-Urrestarazu et al., 2022), and conducting outreach in minority-language communities, could reduce hidden biases. In sum, our results emphasize that autism is not evenly distributed across Kelantan; instead, it clusters where awareness and services already exist. Recognizing this, policymakers should allocate resources proactively to rural and lower-resource districts. By doing so for example, by funding ASD specialists in smaller towns or subsidizing travel to urban clinics, Kelantan can move toward a more equitable system where geography does not limit a child’s chance of timely autism identification and care.

Limitations

Several methodological constraints temper the interpretation of our spatial findings. Diagnostic ascertainment bias and age at diagnosis are primary concerns. As in other surveillance systems, we recognize that younger children with more severe ASD symptoms tend to be identified earlier than higher-functioning cases (Bakian et al., 2015). For example, Bakian et al. (2015) observed that spatial hotspots of ASD in Utah varied substantially across age cohorts (ages 4, 6, 8), reflecting both genuine risk differences and patterns of diagnostic timing. Similarly, our own pattern of urban-centric clusters could reflect earlier detection of severe cases in well-resourced cities, while milder cases or those in rural areas might be diagnosed later or missed entirely. This possibility is supported by recent work. Ghahari et al. (2022) found a significant urban–rural disparity in age at autism diagnosis. Children in central (urban) provinces were diagnosed younger on average but this gap largely disappeared after adjusting for socio-economic and medical factors. In other words, apparent geographic differences in diagnosis timing often stem from underlying confounders (e.g. healthcare access, screening programs) rather than location per se. Without data on case severity or co-occurring disabilities, we cannot adjust for this bias. In practice, if higher-functioning children remain undiagnosed or are identified later in rural districts, the spatial pattern of ASD we observe may overstate true rural “gaps” and urban “hotspots.”

Second, data aggregation and the modifiable areal unit problem (MAUP) impose inherent limitations. We aggregated cases to sub-district polygons because no exact addresses were available, but this choice of spatial unit can critically shape cluster detection. As theory warns, different zoning schemes or scales can split or merge clusters (the classic MAUP; see Robinson, 1950). Ideally, point-level case locations avoid this issue (Bakian et al., 2015), but lacking geocoded addresses we could only analyze counts by sub-district. The effect is that hotspots might be artifacts of our chosen boundaries or population distribution. For instance, if one sub-district includes a town and its surrounding countryside, a cluster might look more diffuse than if we had separate data for the village. We partially mitigated this by using an optimized distance-band for Gi* analysis, ensuring each area had neighbors, but residual sensitivity remains: alternative spatial units (e.g. village versus district) could yield different results. In short, our clusters may shift if data were aggregated differently or if populations are uneven within units, a well-known problem in spatial epidemiology.

Third, the cross-sectional design constrains causal inference and trend analysis. We essentially conducted a snapshot of all diagnoses in our study period, so we cannot tell if observed hotspots are stable or fleeting. Longitudinal surveillance studies have shown that ASD clusters can evolve over time. For example, investigations in California have reported that some high-diagnosis areas persist across years, while others emerge or disappear, suggesting a mix of enduring high-risk zones and transient diagnostic surges (Mazumdar *et al*., 2013). Our single-period analysis cannot distinguish these scenarios. We also cannot assess seasonality or year-to-year changes in case ascertainment. In effect, any inference about environmental or social drivers is tentative: without space–time analysis or repeated cross-sections, we do not know whether our hotspots represent chronic, elevated incidence or short-term spikes due to local screening efforts. Confirming true "hotspots" would require follow-up data to apply space–time scan statistics or other temporal models.

Fourth, and critically, we lacked denominator data for incidence or prevalence. All our maps and cluster tests used raw case counts per sub-district, not standardized rates. In spatial epidemiology this is a fundamental issue without valid population-at-risk denominators; apparent case clusters may simply mirror areas with more children, not higher ASD risk. This is the classic "denominator problem" of disease mapping, counts must be scaled to population size to yield accurate prevalence or incidence measures (Morrison et al., 2020). In our context, children's population figures at the sub-district level were unavailable or unreliable, so we could not calculate rates. Consequently, dense urban districts with large child populations almost inevitably register high counts. Some of our identified "hotspots" may therefore coincide with population centers rather than truly elevated ASD incidence. This undermines comparability between rural and urban areas: a small rural district might appear to have few cases simply because it has few children, not because ASD is less common. Future work should link our case registry to census or birth records to obtain denominators. With those data, analyses could use age-standardized rates or Poisson models with offsets, which would distinguish population-driven clusters from true high-risk clusters (Morrison et al., 2020).

Finally, all spatial statistics rest on assumptions that may be fragile here. Global Moran's I, for example, is only asymptotically normal and reliable when many areas and sufficient neighbors are present. ESRI's spatial-statistics guide notes that the input should contain at least 30 features for Moran's I to be robust (ArcGIS Pro 3.5, 2025). Our analysis included fewer sub-districts, and some had very few neighbors in the weight matrix. In skewed data, Moran's I additionally requires roughly 8 neighbors per unit to approximate normality (ArcGIS Pro 3.5, 2025). Given our small number of areas and the skewed case distribution (with urban zones dominating), these conditions are tenuous. Similarly, the Getis-Ord Gi hot-spot test depends on the spatial weights and must correct for multiple testing. We used the False Discovery Rate correction as recommended (ArcGIS Pro 3.1, 2022), but any residual misspecification could inflate cluster signals. For example, Gi assumes spatial stationarity: if an urban area has a special screening program or clinic, it may show up as a hotspot not because of background risk but because of a localized intervention. In sum, while our findings of clustered ASD counts are statistically significant, they hinge on the validity of these assumptions. We followed best practices (ensuring each area had neighbors, optimizing distance), yet unexplained factors (environmental exposures, mobility, health access) may bias results. Therefore our spatial patterns should be interpreted with caution, as hypotheses rather than definitive evidence of causal clustering.

Future directions

Addressing the urban–rural gap in ASD diagnosis in Kelantan will require targeted outreach and multi-sector collaboration. Our findings, combined with prior studies, suggest that awareness and cultural barriers heavily influence care-seeking in this setting. Recent Malaysian surveys found that many adults hold mystical or karmic explanations for autism and moderate awareness, yet substantial stigma remains (Mohd Rofiee et al., 2025). Low parental knowledge has been repeatedly documented, especially in rural or low-income families (Chow et al., 2026). Accordingly, future efforts should focus on culturally tailored education campaigns and screening initiatives in underserved communities. For example, health departments and social welfare agencies (such as Kelantan's state health office and the Department of Social Welfare) could partner with local schools, community clinics, and NGOs to organize autism workshops and developmental screenings in rural areas. These programs must go beyond mere information: they should directly challenge misconceptions and encourage early checkups. The high prevalence of delayed diagnosis in Malaysia (roughly half of ASD cases are identified after age five, largely due to low awareness and workforce shortages) underscores the need for proactive screening (Han et al., 2023). Training community healthcare workers and educators in the Modified Checklist for Autism (M-CHAT) and its Malay adaptation will help. As Han et al. (2023) showed, a Malay M-CHAT is valid but underused, integrating it into routine child health visits or school health programs could improve early detection. Public agencies should coordinate these efforts: for instance, the Ministry of Health could include ASD literacy in its maternal and child health campaigns, while the Ministry of Education could mandate teacher training and school-based screening. Professional bodies and NGOs (such as the National Autism Society of Malaysia) should also contribute by developing multilingual, culturally relevant materials. In sum, closing the awareness gap will demand comprehensive education campaigns, community engagement, and resource allocation led by health, education, and social service stakeholders (Chow et al., 2026; Mohd Rofiee et al., 2025).

Beyond outreach, future spatial analyses should integrate diagnostic maps with demographic and service data to guide interventions. Our original proposal to link ASD case locations with area-level indicators like income, education, clinic density, and environmental factors can be expanded in the revised manuscript. In practice, this means applying multivariate spatial regression or Bayesian disease-mapping to quantify how much of the geographic clustering is explained by local context. For example, by modeling ASD prevalence against census data (literacy rates, poverty levels) and health infrastructure (distance to clinics), we could identify which factors are most constraining diagnosis in each subregion. This will help distinguish whether observed hotspots stem from socioeconomic disadvantage or from true etiologic patterns. If spatial models find that, say, low education or high poverty areas are predictive of lower diagnosis rates, this would point to the need for social support and education in those districts. In any case, careful interpretation is required: association does not imply causation, so these models should be validated and complemented by ground-level research. Nevertheless, similar approaches have proven valuable elsewhere. For instance, recent work in Kelantan highlighted that GIS mapping can reveal inequities in service provision and guide targeted outreach (Ijon et al., 2026). Building on this, our spatial framework could explicitly incorporate language and cultural layers (see next paragraph) and be updated as more cases accrue. Longitudinal data collection could also allow spatio-temporal modeling to monitor how interventions reshape ASD patterns over time.

Language and cultural factors must be explicitly mapped and addressed. Kelantan's population includes Malay majorities, a Chinese minority, and indigenous communities, each with different language needs and beliefs. Guided by our spatial hotspots, outreach efforts should be delivered in the languages of underserved groups. For example, if mapping shows Chinese-majority townships with lower ASD diagnosis rates, the state health department might produce awareness materials in Mandarin and work with Chinese-language schools or community leaders to disseminate them. Similarly, in Orang Asli settlements (if present), outreach should respect local dialects and customs. The goal is to ensure that language or cultural misinterpretation does not hinder recognition of ASD. These strategies echo findings from the UK, where spatial analyses of ASD identified under-served ethnic communities and motivated translation of materials (Ijon et al., 2026; Roman-Urrestarazu et al., 2021). In our context, outreach could include workshops in rural mosques and churches, collaboration with grassroots figures, and partnering with religious organizations to explain ASD in culturally sensitive terms. This culturally nuanced mapping effectively "layering" ethnic/language data onto ASD prevalence will help focus efforts where trust and communication gaps are greatest.

Finally, concrete actions and stakeholder roles must be clarified. Policymakers at both federal and state levels should take ownership of these findings. The Ministry of Health should lead in expanding ASD screening and training clinicians; the Ministry of Education must invest in special education capacity and teacher training (there have been calls to equip mainstream schools with ASD resources) (Ghani, 2022). The Ministry of Women, Family and Community Development (which oversees disability policy) could allocate funding for local early-intervention centers. Nasom and other NGOs should amplify awareness campaigns and support programs like parent training. Recent advocacy in Malaysia has even proposed forming a national autism council to coordinate such multisectoral initiatives (Ghani, 2022). State governments might use our maps to justify dedicated ASD centers in identified hotspots. Importantly, these recommendations should be pursued in partnership with families and individuals on the spectrum, ensuring that interventions reflect their needs. In future work, we plan to incorporate stakeholder interviews to refine these proposals (building on the systematic review's call for broader input) (Chow et al., 2026). Ultimately, by combining rigorous spatial analysis with targeted education and policy action, we can begin to close Kelantan's urban–rural ASD diagnosis gap and promote equitable support for all children with autism.

Conclusion

In sum, our spatial epidemiological analysis reveals marked clustering of autism diagnoses in Kelantan, with pronounced urban–rural and socioeconomic gradients. These findings underscore that geographic context is critical to understanding autism prevalence: clusters likely reflect both true risk differences and inequities in service access. Our use of Moran's *I* and hotspot analysis provides a rigorous framework to identify these patterns, highlighting both its strengths (sensitivity to localized aggregation) and caveats (potential biases from aggregation and incomplete data). The policy implications are clear: public health planning for ASD in Malaysia should heed these spatial insights by allocating resources to areas of need and addressing the identified disparities. More broadly, this work demonstrates the value of spatial epidemiology in neurodevelopmental research. By extending these methods to larger datasets and integrating social determinants, future studies can guide targeted, equity-oriented interventions for autism and other health challenges across the region.

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