# Spatial Autocorrelation of Schools in Brunei Darussalam

Alvin Bong[1], Aniq Najwa[1], Danish Ikhwan[1], and Rayme Hijazi[1]

[1]Mathematical Sciences, Faculty of Science, Universiti Brunei Darussalam, Bandar Seri Begawan, Brunei

Compiled November 23, 2024

**Abstract**

This study analyzes the spatial distribution of all 252 schools across Brunei Darussalam to assess how well current educational facilities serve both urban and rural populations. Using spatial autocorrelation techniques like Moran's I and the Getis-Ord $G_i^*$ statistic, this research identifies clusters of schools and evaluates their alignment with population density. Findings indicate significant school clustering in urban areas, particularly near Bandar Seri Begawan, with comparatively fewer facilities in rural regions. This imbalance suggests potential challenges in accessing education for students in less populated areas. The study offers valuable insights for policymakers to improve resource distribution, aiming to support equitable access to education and inform future spatial planning in educational infrastructure.

**Keywords:** Spatial Autocorrelation; Clusters; Schools; Brunei Darussalam

# Contents

# 1 Introduction

Education is the cornerstone of social and economic development, recognized globally for its transformative impact. The importance of education is underscored by Sustainable Development Goal 4, which advocates for inclusive and equitable quality education for all [1]. Similarly, Brunei Darussalam's national vision, Wawasan Brunei 2035, prioritizes education as a fundamental driver of its development goals [5]. One critical factor in effective education is accessibility, which has spurred interest in understanding the spatial distribution of educational facilities.

This study employs spatial statistical methods, including Global Moran's I and Local Getis-Ord $G_i^*$, to analyze the spatial autocorrelation of schools across the country. It also evaluates whether schools are strategically located to serve the population effectively. Specifically, the study addresses three key research questions:

1. Are schools in Brunei Darussalam spatially clustered or dispersed?
2. If clustered, where are the clusters concentrated?
3. Do school clusters align with areas of high population?

The motivation behind this study is inspired by Tobler's First Law of Geography, which states that "everything is related to everything else, but near things are more related than distant things" [16]. The first two research questions examine the spatial correlation of school locations, while the third provides a practical example of how these results can inform analyses in social sciences and other fields.

Importantly, this study does not assess the quality of education, nor does it aim to address broader social science questions. Instead, the primary goal is to offer essential baseline data on the spatial distribution of schools, serving as a foundation for future research into educational equity and outcomes in Brunei, as well as the relationship between geography and education.

The paper is structured as follows: Section 2 reviews relevant literature, establishing the context and methodological framework. Section 3 introduces the study area and dataset. Section 4 outlines the methodologies, while Section 5 presents the results, identifying key patterns and trends. Finally, Section 6 concludes the paper, summarizing the findings, discussing implications, and proposing directions for future research.

# 2 Literature Review

Extensive studies have explored the development and general aspects of education in Brunei [7] [2] [15] [12]. However, research utilizing quantitative or spatial methodologies to assess educational effectiveness remains limited. Notably, no existing work has provided a comprehensive spatial analysis of educational accessibility and its alignment with population needs. This paper seeks to address this research gap.

Spatial autocorrelation, the measurement of similarity between spatially distributed variables, has evolved significantly since its theoretical origins in the 19th century. Early ideas, such as Ravenstein's exploration of distance effects on spatial phenomena, laid the groundwork for modern spatial analysis [8]. Its formalization began in the mid-20th century through the efforts of many researchers, including Michael F. Dacey and others who advanced the theoretical and practical tools for spatial analysis [8]. These collective advancements have established spatial autocorrelation as a widely used technique in geography, econometrics, and beyond, with applications ranging from cluster detection to modeling spatial relationships.

Several methods exist for measuring spatial autocorrelation, including Geary's C, Moran's I, and Getis-Ord statistics. Among these, Moran's I is the most widely used [10]. A fundamental concept underpinning all spatial autocorrelation methods is the notion of *spatial weight* which quantifies neighbour relationships between regions on a map. If location i is a neighbor of location j, then $w_{ij} \neq 0$, otherwise $w_{ij} = 0$. Usually, a location i is not cosidered to be a neighbour of itself and hence $w_{ij} = 0$. There are various versions of weights including:

1. Contiguity-Based Weights
   - **Rook Contiguity**: Spatial units share a common edge.
   - **Queen Contiguity**: Spatial units share a common edge or vertex (corner).
2. Distance-Based Weights
   - **Inverse Distance Weighting (IDW)**: Closer units have higher weights.
   - **Fixed Distance Weighting**: Units within a specified distance have a weight of 1, others have a weight of 0.
   - **K Nearest Neighbors (KNN)**: Each unit is assigned weights based on the K closest units.

For the purposes of this spatial study, contiguity-based (rook) weights is used. Mukims are treated as non-overlapping polygons, and the neighbour (rook) contiguity structure of the mukims is defined by the common boundary between two mukims.

# 3 Description of Study Area and Data

In this section, we provide an overview of the study area, Brunei Darussalam, and the data used in this study. A preliminary data analysis of the study variable is also presented.

## 3.1 Description of Study Area

Brunei Darussalam, commonly known as Brunei, is located on the northern coast of the island of Borneo in Southeast Asia. With an area of approximately 5,765 square kilometers, Brunei is bordered by the South China Sea to the north and surrounded by the Malaysian state of Sarawak. The nation's territory is divided into two non-contiguous areas: The larger western section comprising Brunei-Muara, Tutong, and Belait districts; and the smaller eastern Temburong district. In the Northeast of the larger section lies Brunei's capital, Bandar Seri Begawan.

The districts of Brunei are subdivided into 39 smaller administrative zones known as *mukims*, each embraces a number of *kampongs* (villages). Brunei's geography is characterized by a mix of urban centers, dense forests, and coastal lowlands. More than 70% of the nation is covered with forests, with majority locating inland, southern parts of Belait and Tutong, as well as most of Temburong [4].

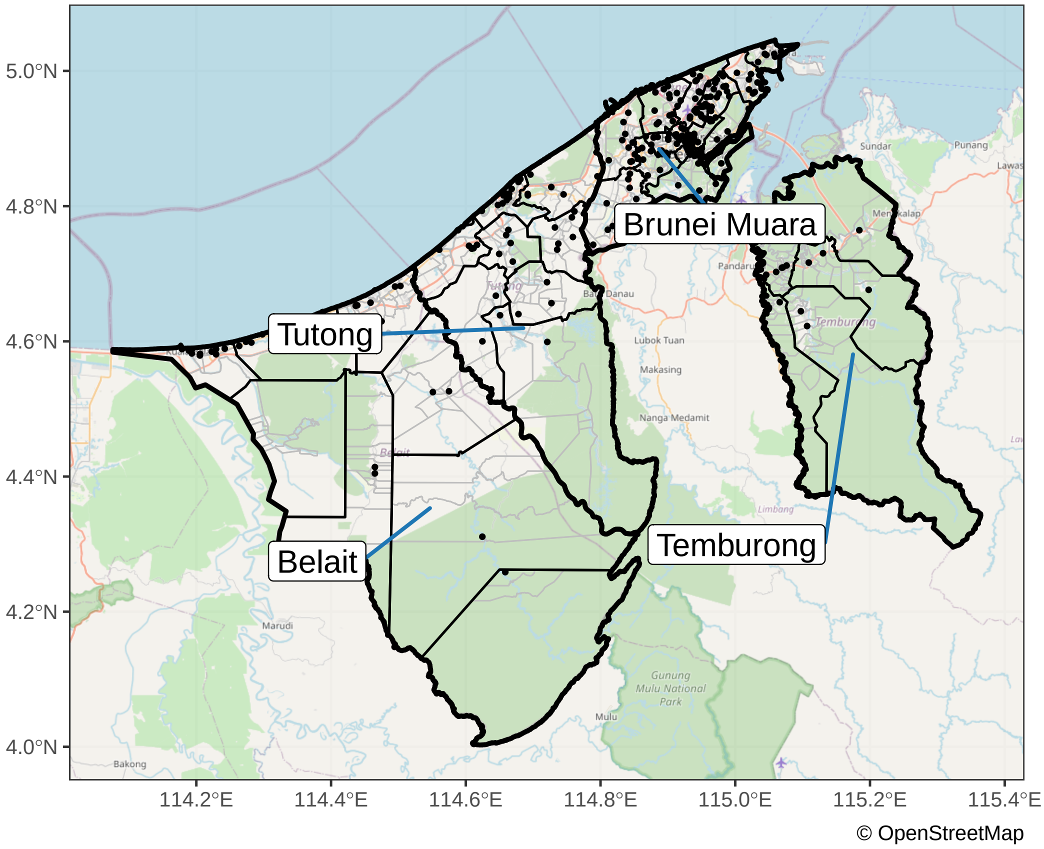


Figure 1: Administrative zones of Brunei, showing the four main districts: Brunei-Muara, Tutong, Belait, and Temburong. Each point represents a school location. Grey lines indicate kampong boundaries, with thicker lines marking mukim boundaries. Forested areas are shaded in green.

According to the 2021 census, Brunei has a population of approximately 445,000 [6]. The majority of the population is concentrated along the coastline, particularly in Bandar Seri Begawan, which serves as the administrative, cultural, and economic center of the nation. Brunei is a high-income country, boasting the second-highest per capita income and Human Development Index (HDI) in Southeast Asia, as well as the highest per capita Gross National Income (GNI) among OECD countries from 2005 to 2020 [3].

Education in Brunei is both free (for citizens) and compulsory for children aged 5 to 16, leading to a high literacy rate across the population. Given the nation's wealth and commitment to education, it would be interesting to leverage spatial analysis in finding patterns and understanding how schools are clustered and distributed across the country.

## 3.2 Data Collection & Processing

The dataset comprises $N = 252$ schools in Brunei Darussalam, sourced from Ministry of Education's *Brunei Darussalam Education Statistics 2018* [11]. The decision to use the 2018 dataset stems from the lack of detailed data in more recent publications, which only provide summary versions. Specifically, the 2018 dataset includes:

1. A complete listing of all schools in Brunei by sector
2. Categorization of pre-primary to sixth forms institutions from Ministry of Education (MOE Sector) into administrative clusters (Cluster 1–6)
3. Student-teacher ratios and enrolment by sector and cluster,

details which are not available in the summarised editions of the statistical book from recent years.

Since [11] is only available in PDF format, we converted it to a spreadsheet format using online converter. The data was then extracted, cleaned and reorganized in Microsoft Excel before being imported into R using the `read_csv()` function.

In order to retrieve the latitudes and longitude of the schools, the `osmdata_sf()` function from the *osmdata* package was initially used. This approach however proved insufficient, as some schools were missing, and others had abbreviated names. Consequently, only partial location data was obtained. To address this, `left_join()` was used to merge the available locations with the school listing, and remaining coordinates was manually collected.

Corresponding Codes

```
# 1. Query locations from OSM
bb <- getbb("brunei darussalam",
            format_out = "polygon",
            featuretype = "country")

q <- opq(bb[2]) %>%
    add_osm_feature(key = "amenity", value = "school") %>%
    osmdata_sf() %>%
    trim_osmdata(bb[2])

sch_sf <- q$osm_polygons %>%
        as_tibble() %>%
        st_as_sf() %>%
        select(osm_id, name) %>%
        drop_na() %>%
        st_centroid()

# 2. Join locations to matching schools
sch_df <-
  left_join(sch_df, sch_sf_match, by = c("School" = "name")) %>%
  select(School, Sector, Cluster, `Education Level`, geometry)

# 3a. Export joined dataset
sch_sf <- st_as_sf(sch_df)
sch_sf$longitude <- st_coordinates(sch_sf)[,1]
sch_sf$latitude <- st_coordinates(sch_sf)[,2]
sch_sf <- st_drop_geometry(sch_sf) %>% data.frame()
write.csv(sch_sf, "school listing v2.csv", row.names = FALSE)

# 3b. Manually add in remaining address using MS Excel
      New version saved as "school listing.xlsx"

# 4. Import and convert to sf
sch_df <- read_excel("data/school listing.xlsx", 1)
sch_sf <- st_as_sf(sch_df,
                   coords = c("longitude", "latitude"),
                   "EPSG:4326")
sch_sf <- st_join(sch_sf, kpg_sf, join = st_within)
```

## 3.3 Preliminary Data Analysis

Generally, from Figure 2, it seems that schools in Brunei are located near the shoreline, particularly towards the South China Sea. With the exception of *Pusat Pembangunan Belia* and *Pusat Latihan Kesenian dan Pertukangan Tangan* which serves as youth and community training centers, academic schools in Brunei are categorized into three main sectors: Ministry of Education (MOE), Ministry of Religious Affairs (MORA) and private institutions. The distribution of schools across these sectors includes 164 under MOE, 9 under MORA, and 77 private, comprising approximately 70% public (MOE, MORA) and 30% private.

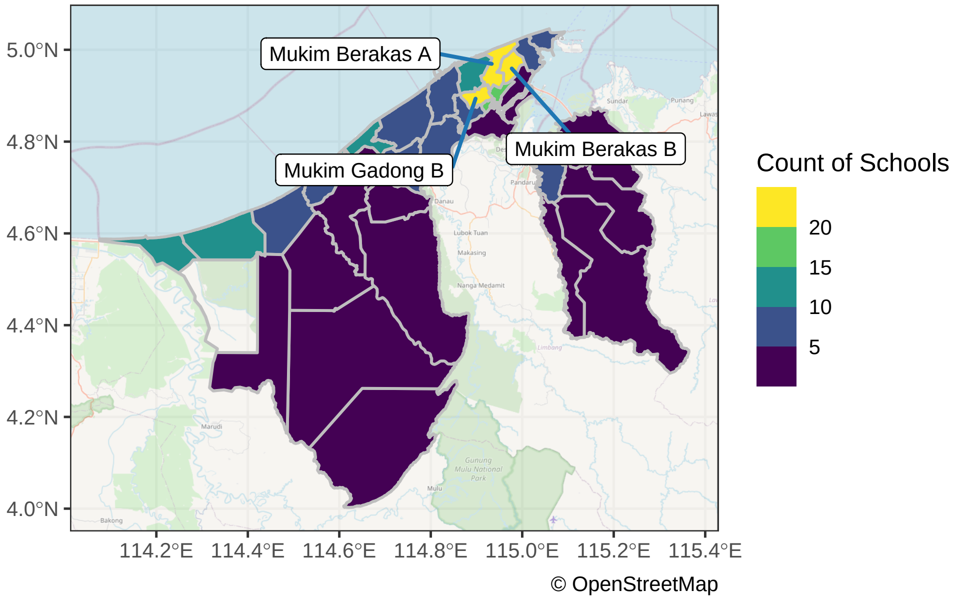


Figure 2: Choropleth map showing count of schools by mukim.

In the MOE sector, schools from pre-primary to sixth form are organized into Clusters 1 to 6. While the number of schools in each cluster is relatively balanced, Clusters 3 and 4 have notably higher class counts and students, followed by Clusters 1 and 2, with Clusters 5 and 6 having the lowest.

Table 1: Count of schools, classes and students by cluster

| Cluster | School | Class | Student |
|---|---|---|---|
| Cluster 1 | 25 | 453 | 9,505 |
| Cluster 2 | 26 | 486 | 9,606 |
| Cluster 3 | 25 | 566 | 11,064 |
| Cluster 4 | 27 | 505 | 10,648 |
| Cluster 5 | 29 | 379 | 6,183 |
| Cluster 6 | 21 | 359 | 6,884 |

In regards to student-teacher ratio, we concentrate on pre-primary through sixth-form schools, excluding vocational and higher education institutions due to their inconsistent structures and varying class arrangements. Across districts, Belait and Brunei-Muara have relatively higher student-teacher ratio (about 10) compared to Temburong and Tutong (approximately 7.6). By sector, MOE and MORA school shares similar values, whereas private schools have nearly double the student-teacher ratio, except in the Temburong district.

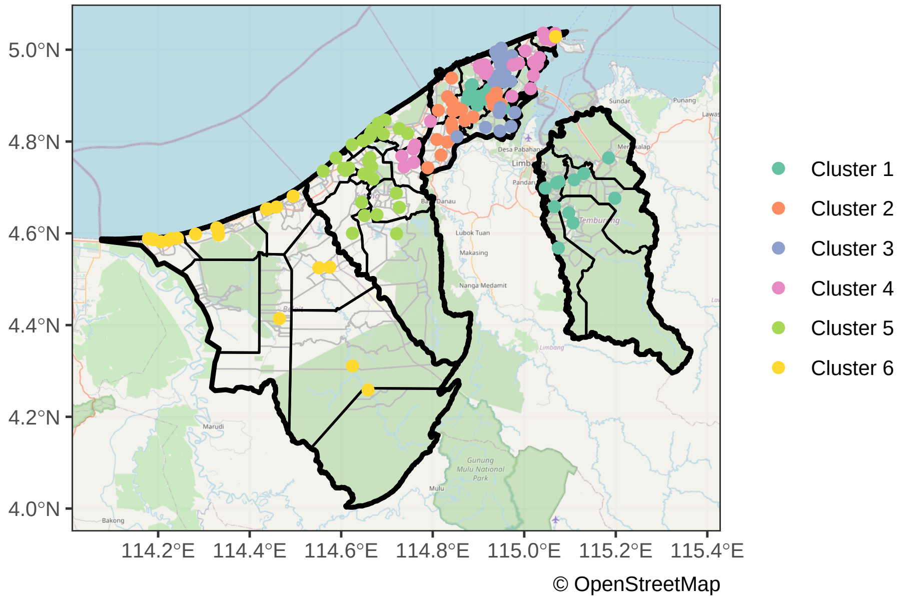


Figure 3: Pre-primary to sixth form MOE schools by cluster.

Table 2: Summary of student-teacher ratio by district

| District | Student | Teacher | Student-Teacher Ratio |
|---|---|---|---|
| Belait | 12,955 | 1,239 | 10.50 |
| Brunei Muara | 68,188 | 6,892 | 9.89 |
| Temburong | 1,893 | 248 | 7.63 |
| Tutong | 9,029 | 1,180 | 7.65 |

Table 3: Summary of student-teacher ratio by sector

| Sector | Student | Teacher | Student-Teacher Ratio |
|---|---|---|---|
| MOE | 53,890 | 6,574 | 8.20 |
| MORA | 5,483 | 670 | 8.18 |
| Private | 32,692 | 2,315 | 14.1 |

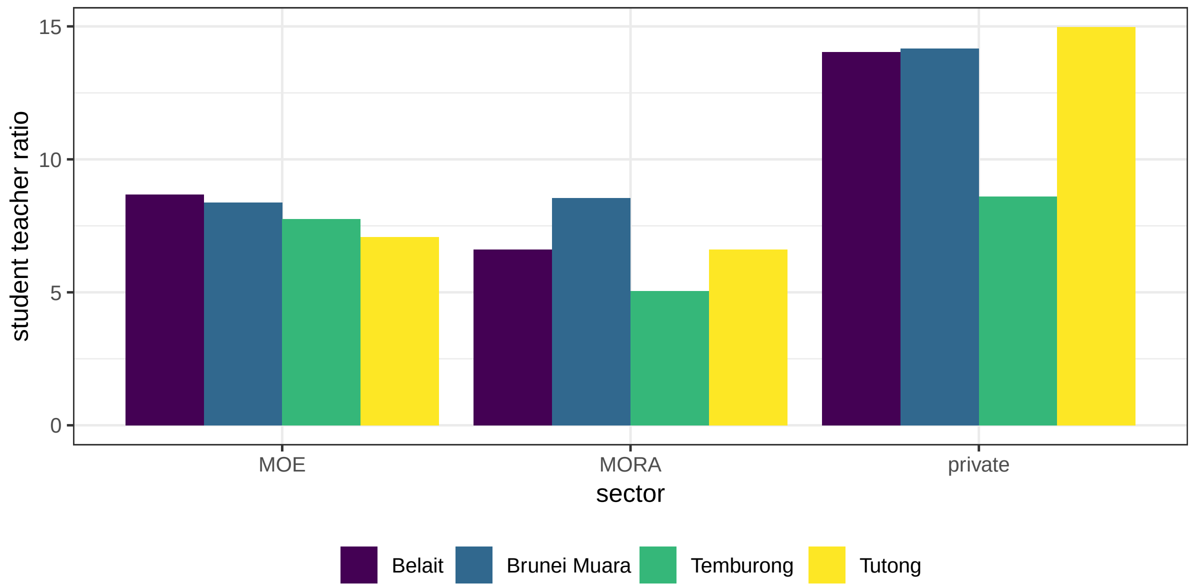


Figure 4: Student-teacher ratio by sector and district.

# 4 Methods

This section provides detailed descriptions of the spatial autocorrelation methods used to analyse the hostpots and clusters of schools. Due to the relatively low amount of schools in Brunei ($N = 252$), the spatial autocorrelation analysis will consider all schools as whole, instead of by sector or cluster.

## 4.1 Global spatial autocorrelation: Global Moran's I

To examine whether schools in Brunei exhibit a clustered, dispersed, or random spatial pattern, we apply the Global Moran's I test [14] using the `global_moran_test()` function from `sfdep` package. This test is computed for each mukim in the study area, indexed by $i, j = 1, 2, \dots, N$. The Moran's I test statistic is defined as follows:

$$I = \frac{N}{\sum_{i=1}^{N} \sum_{i=1}^{N} w_{ij}} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \in [-1, 1], \tag{1}$$

where:

- $x_i$ is the value of the study variable (count of schools) in mukim $i$,
- $\bar{x}$ is the mean number of schools per mukim,
- $w_{ij}$ is the spatial weight between mukims $i$ and $j$

For simplicity, rook contiguity neighbours is used for the spatial weights, as discussed in Section 2. This approach assigns $w_{ij} = 1$ if mukims $i$ and $j$ share one or more boundaries, and $w_{ij} = 0$ otherwise.

Moran's I values are standardized, with values close to $+1$ indicating positive spatial autocorrelation (i.e., clustering), where high or low values are near each other. Values close to $-1$ indicate negative spatial autocorrelation (i.e., dispersion), where neighboring values differ significantly. Values near 0 suggest randomness, indicating an absence of spatial pattern. Figure 5 shows the three configurations of areas.

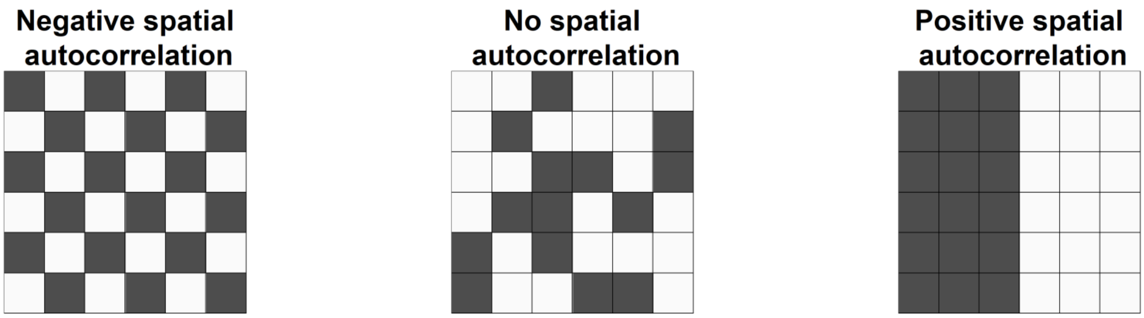


Figure 5: Examples of configurations of areas showing different types of spatial autocorrelation [13].

To determine the significance of the Moran's I statistic, we employ the Central Limit Theorem to calculate p-values based on a Z-score, allowing us to test the following hypotheses:

- $H_0 : I = 0$ (no spatial autocorrelation),
- $H_1 : I \neq 0$ (presence of spatial autocorrelation).

Corresponding Codes

```
mkm_sch <- mkm_sf %>%
            left_join(sch_mkm) %>%
            select(mukim, count_of_schools)

mkm_sch$count_of_schools[is.na(mkm_sch$count_of_schools)] <- 0

nb <- st_contiguity(mkm_sch)
wt <- st_weights(nb)
global_moran_test(mkm_sch$count_of_schools, nb, wt)
```

## 4.2 Local spatial autocorrelation (LISA): Local Getis-Ord

While a visual inspection suggests that certain kampongs may have a higher concentration of schools, we aim to quantify this pattern. Whereas global spatial autocorrelation tests confirm whether clustering exists, we use the Getis-Ord $G_i^*$ statistic [9] to identify the specific areas where schools are concentrated. This statistic is computed using the `hotspot_gistar` function from `sfhotspot` package.

In our analysis, the study area is subdivided into $n$ square grids, indexed by $i = 1, 2, \ldots, n$. By default, `hotspot_gistar` function automatically sets the grid size to be 3,400 square meters. For each grid cell $i$, the $G_i^*$ statistic is calculated as:

$$G_i^* = \frac{\sum_j w_{ij} x_j}{\sum_j x_j} \tag{2}$$

where:

- $x_j$ is the value of the study variable (the count of schools) for grid cell $j$,
- $w_{ij}$ is the spatial weight between grid cells $i$ and $j$

Similar to global spatial autocorrelation in Section 4.1, the spatial weights used are based on rook contiguity neighbours. However, there is one slight modification: the spatial weight $w_{ii}$ are set to 1 rather than 0. This adjustment gives $G_i^*$ a more localized perspective, which is valuable for identifying clusters centered directly on a point of interest rather than merely in its surrounding areas.

A statistically significant high $G_i^*$ value indicates a "hotspot," or a cluster of high values, whereas a low $G_i^*$ value suggests a "coldspot," or a cluster of low values.

To highlight only significant hotspot clusters, the output was filtered to include only values with $\mathbf{G_i^* > 0}$ and **p-value $< \mathbf{0.05}$**. The output dataset is then cropped to Brunei's boundary using `st_intersection` to refine the analysis. This method identifies school hotspots, areas where there are more schools than would be expected if they were distributed randomly.

Corresponding Codes

```
sch_gi <- sch_sf %>%
    st_transform("EPSG:27700") %>%  # sfhotspot rejects EPSG 4326
    hotspot_gistar() %>%
    filter(gistar > 0, pvalue < 0.05) %>%
    st_intersection(st_union(dis_sf) %>%
                    st_transform("EPSG:27700"))
```

# 5 Results

The results section is organized into three parts, each corresponding to one of the topic questions introduced in Section 1.

## 5.1 Are the schools clustered?

The Global Moran's I analysis yielded I value of **0.457**. The positive Moran's I statistic suggests a positive autocorrelation in count of schools across mukims. Given the statistically significant results (low p-value of $\mathbf{4.542 \times 10^{-6}} < 0.001$), there is sufficient evidence to reject the null hypothesis $H_0$, which assumes no spatial autocorrelation in the distribution of schools.

This finding supports the presence of moderate to strong clustering tendency, implying that mukims with a similar number of schools, whether high or low, are geographically close to each other. This results of the Global Moran's I test aligns with our preliminary observation in Section 3.3, that there exists schools clusters. In the following subsection, we will further verify that these clusters are more concentrated near the coastal regions through local spatial autocorrelation.

## 5.2 Locations of School Clusters

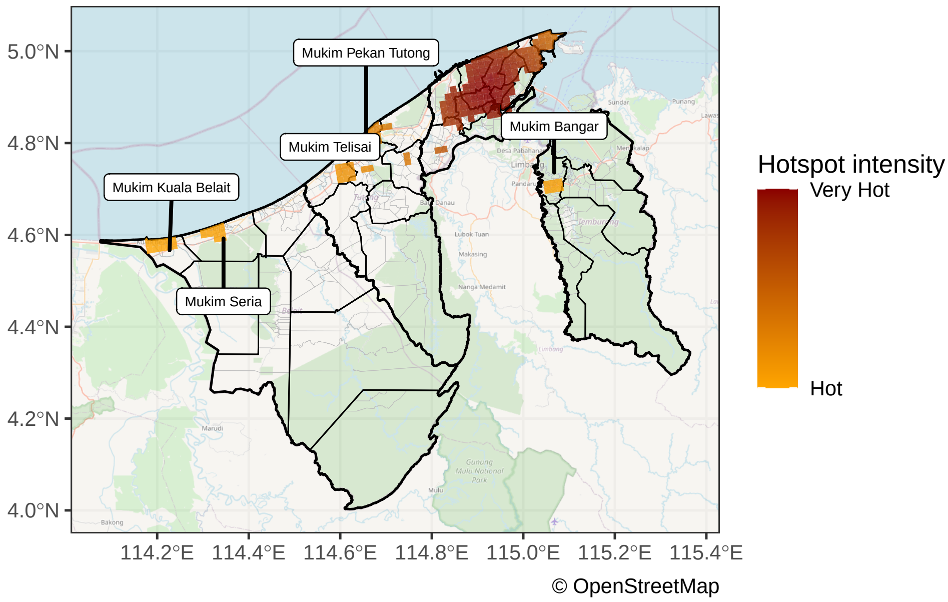


Figure 6: Significant school clusters identified using Getis-Ord Statistics.

As highlighted in Figure 6 (*no pun intended*), the primary concentration of schools is located in central **Mukim Brunei-Muara**, the capital district of Brunei. This is unsurprising given its status as the nation's capital, urban and administrative center. Other notable clusters outside the capital are located in:

- Temburong District: **Mukim Bangar**
- Tutong District: **Mukim Pekan Tutong**, **Mukim Telisai**
- Kuala Belait District: **Mukim Kuala Belait**, **Mukim Seria**

This result confirms that school clusters does indeed concentrate near the coastal regions. Furthermore, schools appear to be less abundant or accessible in the outskirts and areas outside the capital district, Brunei-Muara.

Another insight of the Getis-Ord analysis is its ability to pinpoint specific areas of clustering within each mukim, offering an advantage over the choropleth map in Figure 2. For example, schools cluster in the northeastern areas of Mukim Telisai but are more concentrated toward the south in Mukim Bangar (refer Figure 6). This level of detail enables a more precise understanding of spatial clustering patterns.

## 5.3 Comparison to Distribution of Population

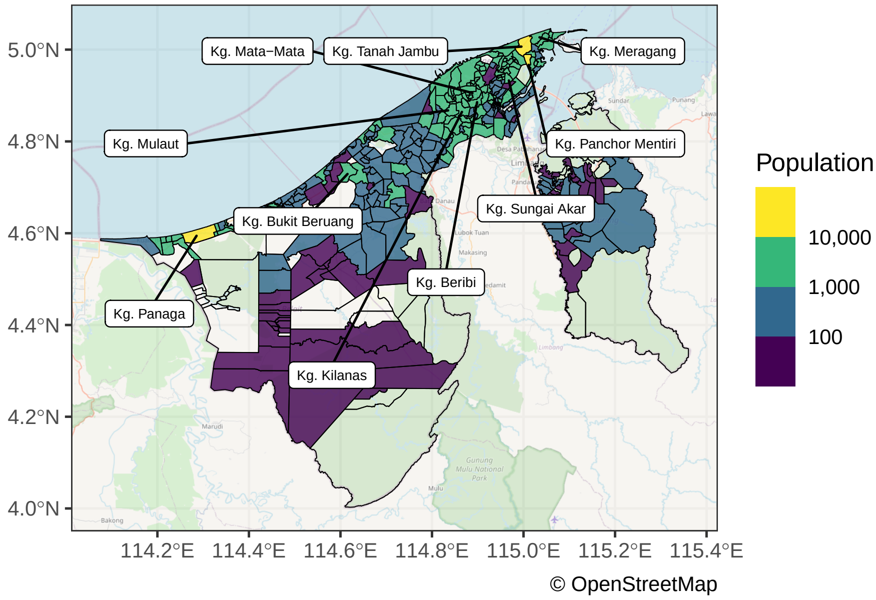


Figure 7: Distribution of Brunei Population by kampong

While visual inspection of Figure 7 and 8 suggests a general alignment between schools and population hotspots, a more detailed comparison reveals some notable patterns. For example, when we examine the top 10 kampongs by school count and by population in Table 4, only three kampongs, namely **Kg. Mata-Mata**, **Kg. Panaga**, and **Kg. Sungai Akar**, are shared across both lists.

At the mukim level, the overlap is more prominent, with six mukims appearing in both top 10 lists for school count and population. This indicates that, while schools are generally located in highly populated mukims, they may not always centered within the kampongs with the highest populations. Instead, the schools may be distributed across several kampongs within a populous mukim, possibly for reasons such as accessibility, land availability, or local demand variations.

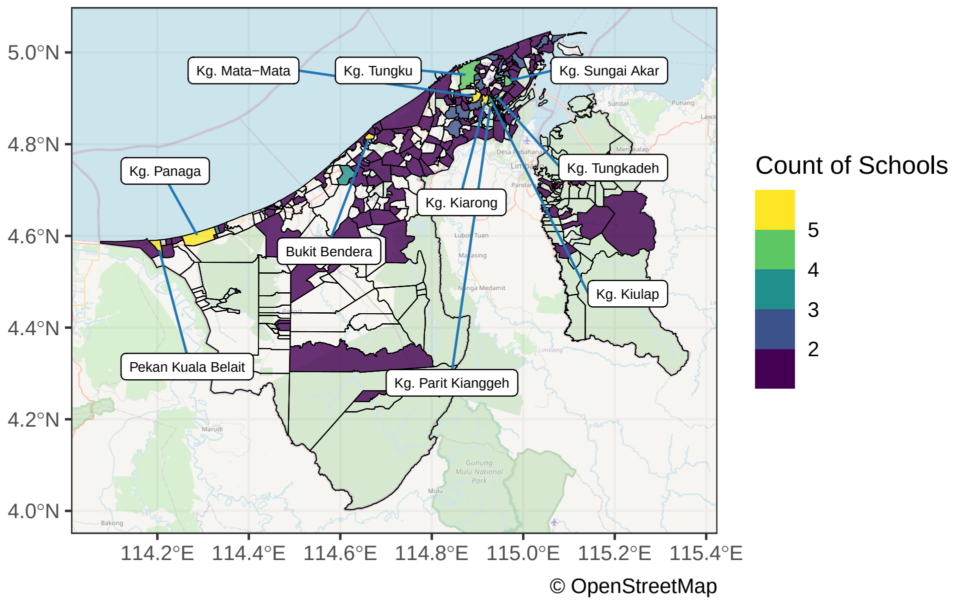


Figure 8: Choropleth map showing count of schools by kampong.

Table 4: Top 10 kampongs by school count and population.

| | Kampong | Schools count | Kampong | Population |
|---|---|---|---|---|
| 1 | Kg. Kiarong | 6 | Kg. Panchor Mentiri | 13,358 |
| 2 | Kg. Mata-Mata | 6 | Kg. Tanah Jambu | 11,695 |
| 3 | Kg. Parit Kianggeh | 6 | Kg. Panaga | 10,301 |
| 4 | Pekan Kuala Belait | 6 | Kg. Bukit Beruang | 9,835 |
| 5 | Bukit Bendera | 6 | Kg. Meragang | 9,190 |
| 6 | Kg. Panaga | 6 | Kg. Mata-Mata | 7,159 |
| 7 | Kg. Sungai Akar | 5 | Kg. Beribi | 6,490 |
| 8 | Kg. Tungkadeh | 5 | Kg. Kilanas | 6,357 |
| 9 | Kg. Tungku | 5 | Kg. Sungai Akar | 6,129 |
| 10 | Kg. Kiulap | 4 | Kg. Mulaut | 5,981 |

Table 5: Top 10 mukims by school count and population.

| | Mukim | Schools count | Mukim | Population |
|---|---|---|---|---|
| 1 | Mukim Gadong B | 24 | Mukim Sengkurong | 40,972 |
| 2 | Mukim Berakas B | 21 | Mukim Mentiri | 39,324 |
| 3 | Mukim Berakas A | 21 | Mukim Berakas B | 39,284 |
| 4 | Mukim Kianggeh | 20 | Mukim Gadong B | 38,067 |
| 5 | Mukim Gadong A | 14 | Mukim Gadong A | 35,424 |
| 6 | Mukim Seria | 12 | Mukim Kuala Belait | 28,793 |
| 7 | Mukim Perkan Tutong | 12 | Mukim Berakas A | 28,311 |
| 8 | Mukim Kuala Belait | 11 | Mukim Kilanas | 24,981 |
| 9 | Mukim Sengkurong | 10 | Mukim Serasa | 18,569 |
| 10 | Mukim Pangkalan Batu | 9 | Mukim Seria | 18,313 |

# 6 Conclusions

This study undertook a comprehensive spatial analysis of the distribution of schools across Brunei Darussalam. By statistically analyzing the locations of 252 schools using Global Moran's I and Local Getis-Ord $G_i^*$, we show that schools are not randomly distributed. Instead, schools are concentrated in central Mukim Brunei-Muara and coastal regions of Mukim Bangar, Mukim Pekan Tutong, Mukim Telisai, Mukim Kuala Belait and Mukim Seria.

When examining the alignment of school locations with population distribution, we found that, while educational facilities are generally situated in mukims with high population, this pattern does not necessarily hold true at the kampong level. This may imply that their specific placement within kampongs may be influenced by other factors such as accessibility, land availability, and specific local demands rather than solely population size.

The implications of these findings are multifaceted. For policymakers and educational planners, understanding the spatial distribution of schools is crucial for optimizing resource allocation, ensuring equitable access to education, and planning for future educational infrastructure development. The concentration of schools in urban and coastal areas suggests a need to investigate and potentially address educational accessibility in more remote or less densely populated regions.

Despite its contributions, this study acknowledges certain limitations. The first is the reliance on the 2018 dataset was necessitated by the lack of more recent detailed data, which may not fully capture recent developments or shifts in school distribution. Additionally, the manual collection of some geographic coordinates introduced potential inconsistencies, although efforts were made to ensure data accuracy. Secondly, our analysis was based on only two spatial autocorrelation methods and contiguity-based weights, leaving other methodological approaches unexplored. Future research could benefit from comparing alternative spatial autocorrelation methods and other forms of weights.

To provide a more holistic understanding of educational accessibility in Brunei, future research could benefit from more current and comprehensive datasets, as well as the incorporation of additional variables such as school capacity, quality of education, and transportation infrastructure given that effective education does not only rely on school locations but also on these qualitative factors.

# 7 Acknowledgements

The authors expresses gratitude OpenStreetMap contributors for the spatial data used in this analysis, and Dr Haziq Jamil, instructor of the module SM2302, for his invaluable insights which enriched this study.

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# A Appendix

There were other attempts to include the usage of the OSRM package in this project. However, due to the elongated chunk of codes committed and the time constraint, we have discontinued branching out and only managed to gather one of the datas. The other agendas are as such:

1. Which of each of these premises are closest to each schools in Brunei;
2. Which roads are the shortest route to each schools in Brunei?

- Hospitals (gathered)
- Police Stations
- Fire stations
- Mosques

Corresponding Codes

```
sch_sff <- st_as_sf(schools_sf,
                    coords = c("longitude", "latitude"),
                    crs = 4326)

hospitals_sf_all <- st_as_sf(rh,
                       coords = c("Longitude", "Latitude"),
                       crs = 4326)


dist_matrix <- st_distance(sch_sff, hospitals_sf_all)

closest_hospital <- apply(dist_matrix, 1, function(x)
hospitals_sf_all$Hospitals [which.min (x)])
sch_sff$closest_hospital <- closest_hospital


sch_hos <- data.frame(School = sch_sff$name,
  Closest_Hospital = closest_hospital)


sch_hos_min_dis_df <- data.frame(
  School = sch_sff$name,
  Closest_Hospital = closest_hospital,
  stringsAsFactors = FALSE
)

sch_hos_min_dis<- sch_hos_min_dis_df %>%
  arrange(School) %>%
  mutate(School = as.character(School),
         Closest_Hospital = as.character(Closest_Hospital))

view(sch_hos_min_dis)
```