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Spatial Analysis for Dengue Cases in Northern Mindanao, Philippines Using DSS-DBSCAN Algorithm

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Abstract

This study applied an enhanced DBSCAN algorithm to analyze dengue cases in Northern Mindanao, Philippines. The variables considered in the spatial analysis using the enhanced DBSCAN algorithm are limited to the proximity and density of dengue incidence. By considering both case density and geographic proximity, the analysis revealed distinct clustering patterns in specific areas. The findings suggest that dengue cases tend to concentrate in urban centers and gradually spread to neighboring municipalities. This pattern may be influenced by factors such as high population density, frequent human movement, and mosquito breeding environment. Additionally, a temporal analysis shows that dengue cases peak during the rainy season, underscoring the impact of climate and environmental factors on disease transmission. These insights emphasize the importance of geographically and seasonally targeted public health strategies to enhance dengue prevention and control efforts.

1 Introduction

The dengue virus that causes dengue fever (DF) in humans is spread mostly via the bites of the *Aedes albopictus* and *Aedes aegypti* mosquitoes [14]. Since DF is so common in many tropical and subtropical regions, including Southeast Asia, the Western Pacific, and southern Africa, it poses a threat to almost a third of the world's population [4]. Dengue has become a significant global public health concern due to its expanding geographic range, increasing frequency of cases, and increasing severity of the illness [13, 34]. Contributing factors include increased international travel, climate change, a growing number of susceptible human hosts, and an expanded range for the dengue vector [25, 12].

Previous researches have shown that climatic factors significantly influence the seasonal fluctuations and global spread of dengue [44, 38]. Statistical methods have been employed to explore associations between new dengue cases and climatic variables such as humidity, temperature,

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and rainfall, enabling predictions of potential outbreaks in specific areas [21, 22, 33]. While climate plays a pivotal role in dengue outbreaks, land use and sociocultural practices are also critical determinants [17, 36]. Furthermore, recent studies have highlighted concerns about how green spaces, vegetation, and land-cover features affect mosquito populations, thereby influencing dengue transmission risks [27]. The mosquito spatial distribution of surrounding greenness are connected because vegetation may serve as a mosquito's resting or feeding site or as a proxy for the availability of breeding grounds [43, 24]. Studies also show that major transportation hubs can facilitate the movement of dengue vectors and infected individuals, thereby increasing the risk of local transmission [11]. Additionally, research has identified transportation hubs as significant factors in the spatial distribution of dengue cases, indicating that areas near these hubs are more prone to higher dengue incidence [15].

According to the Department of Health of the Philippines in 2016, dengue epidemic is one of the top eight most prevalent infectious diseases in the Philippines. The Department of Health documented 585,324 dengue cases between 2008 and 2012 [7], ranking the country fourth among the ten Association of Southeast Asian Nations (ASEAN) members [8]. Dengue fever has become endemic in several regions of the Philippines due to its rising prevalence over the years. Prior research in the Philippines has primarily focused on dengue fever, including statistical analyses of dengue incidence, literature evaluations, and surveillance studies [19]. This study adds a new dimension by employing spatial clustering analysis to understand the epidemiological patterns of dengue cases in the study region.

In epidemiological studies, studying disease patterns often involves spatial, temporal, and spatio-temporal analysis. Spatial analysis focuses on the geographical distribution of disease cases, it identifies clusters based on location [18]. In contrast, temporal analysis looks at how disease changes over time, exposing seasonal trends, epidemic peaks, or long-term variations [1]. Spatio-temporal analysis, on the other hand, combines spatial and temporal elements to examine how disease patterns change across time and space simultaneously [32]. In this study, enhanced DBSCAN algorithm is used for spatial analysis, considering only geographic proximity and density of dengue cases to identify clusters in Northern Mindanao, Philippines. Identifying high-density clusters and patterns provides valuable insights into the drivers of dengue outbreaks. In addition, a temporal analysis was conducted to examine dengue incidence trends from 2009 to 2022.

This study employs enhanced DBSCAN algorithm termed DSS-DBSCAN (Dual Stratified Sampling - DBSCAN) to identify clusters of dengue cases in Northern Mindanao, Philippines. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is widely used in spatial clustering, discovering clusters of arbitrary shapes and handling noise. However, DBSCAN performance is highly sensitive to the selection of its two parameters: epsilon (ε) and minimum points ($minPts$). Integrating Dual Stratified Sampling in the DBSCAN framework improved the selection of key parameters. This method introduced two levels of stratification, first by average distance and then by local density. By incorporating dual stratification into DBSCAN, the robustness to density variation is improved and the bias towards the high-density region is reduced, producing a more reliable clustering outcome.

This study focuses specifically on the application of DSS-DBSCAN (Dual Stratified Sampling - DBSCAN) algorithm to identify spatial patterns of dengue cases in Northern Mindanao, Philippines. Although other clustering techniques, could offer comparative insights, the scope of this study is limited to the application of DSS-DBSCAN for spatial epidemiological analysis.

2 Research Methodology

2.1 Study Area

The study area for this research is Northern Mindanao, a region situated in the north-central part of the Mindanao Island in the Philippines. The geographic coordinates of the region are approximately 8°45′N latitude and 124°55′E longitude. Northern Mindanao is made up of five provinces, namely, Bukidnon, Camiguin, Misamis Occidental, Misamis Oriental, and Lanao del Norte, along with two highly urbanized cities, Cagayan de Oro and Iligan. It is divided into seven component cities and 84 municipalities (see Figure 1), each with its unique cultural and environmental characteristics. The region's population, as of the 2020 census, is 5,022,768, with a population density of approximately 250 people per square kilometer (630 people per square mile). Covering a land area of 2,049,602 hectares (5,064,680 acres), with over 60% of the land classified as forested. The region is rich in natural resources, including abundant vegetation, natural springs, and marine life.

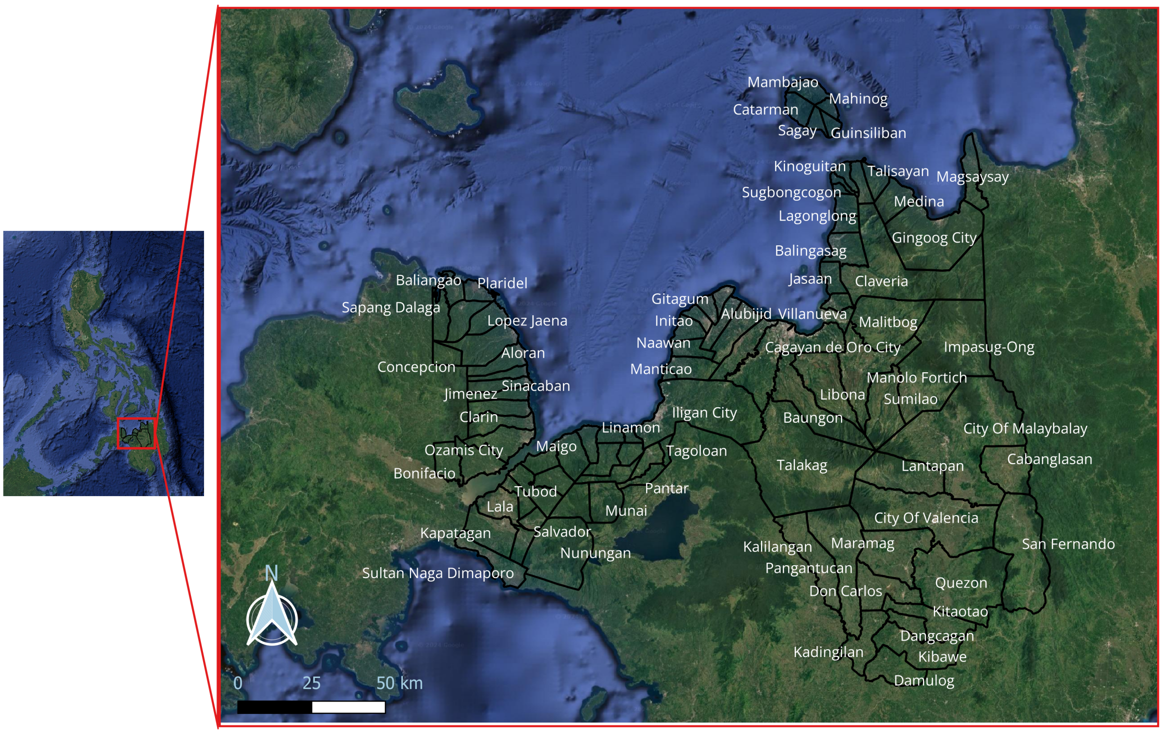

Figure 1: *Map of Northern Mindanao with Municipality/City Boundaries*

2.2 Dataset

The dengue data set comprises 144,119 dengue case samples collected from Northern Mindanao, Philippines, covering the period 2009 to 2022. The dataset is provided by the Department of Health (DOH), and includes detailed records of reported dengue cases. Geographic locations are represented using a shapefile, which maps municipalities and cities across the region. The clustering process specifically considers only proximity and case density, focusing on spatial distribution patterns without incorporating additional factors. This dataset serves as a resource for identifying clustering patterns and understanding dengue transmission dynamics across urban and rural areas over the 14-year period.

2.3 Dual Stratified Sampling - DBSCAN (DSS-DBSCAN)

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is a clustering algorithm used to discover clusters with varying densities in spatial datasets. Its performance heavily depends on two key parameters: epsilon (ε) and minimum points ($minPts$). The accuracy of the clustering results are significantly influenced by how these parameters are selected. Choosing the optimal values is therefore essential to ensure reliable outcomes. This study applies an enhanced version of DBSCAN called DSS-DBSCAN (Dual Stratified Sampling-DBSCAN) to analyze dengue cases in Northern Mindanao, Philippines. The DSS-DBSCAN method provides a way to determine the optimal epsilon (ε) value using dual stratified sampling and the minimum points ($minPts$) value through grid search. The method improves parameter selection for DBSCAN algorithm by introducing dual stratification for ε estimation. It extends the single stratification approach used in SS-DBSCAN of Monko and Kimura [9] by incorporating two levels of stratification.

DSS-DBSCAN follows a sequence of procedures. It begins with tuning the initial parameters: r, k, p, and m. This is done using a grid search approach, where a predefined range of values is explored to determine the most suitable combination. The number of nearest neighbors taken into account while determining the average distance for each data point is denoted by the parameter k. The parameter p specifies how many partitions, or strata, the sorted list of average distances is divided. The number of sample points chosen from the strata is denoted by parameter m. Lastly, r defines the local neighborhood around each point by counting how many other points fall within that radius.

Once these parameter are tuned, the pairwise Euclidean distance between all points in the dataset is computed. The Euclidean distance formula is used to calculate the distance between two points x_i and x_j in d-dimensional space:

$$d(x_i, x_j) = \sqrt{\sum_{l=1}^{d} (x_{il} - x_{jl})^2}. \tag{1}$$

For each point, the average distance to its k-nearest neighbors is computed. The average distance can be presented as:

$$D(x_i) = \frac{1}{k} \sum_{j=1}^{k} d(x_i, x_j). \tag{2}$$

The sorted average distances are then divided into p strata to create distance-based strata:

$$S_j = \{x_i \mid D(x_{p_{j-1}}) \leq D(x_i) < D(x_{I_j})\}, \quad j = 1, 2, \ldots, p, \tag{3}$$

where

- p is the total number of strata into which the dataset is divided.
- D(x_i) the average distance of the point x_i to all other points in the dataset.
- $D(x_{pj-1})$ and $D(x_{I_j})$ define the lower and upper bounds of each stratum.

- S_j is the set of points whose average distances fall within the interval.

Within a distance-based stratum, the local density is calculated based on the number of points within a predefined radius r. The local density for a point x is calculated as:

$$\rho(x_i) = \sum_{j=1, j \neq i}^{n} I(d(x_i, x_j) < r), \tag{4}$$

where

- x_i is the point on the dataset where the local density is calculated.
- $d(x_i, x_j)$ is the Euclidean distance between point x_i and point x_j.
- $I(\cdot)$ is an indicator function that equals 1 if $d(x_i, x_j) < r$ (i.e., if the point x_j is within the radius r of point x_i), and 0 otherwise.

Once the density for each point is computed, the density values are combined with the average distances to create tuples $(D(x_i), \rho(x_i))$. These tuples are sorted based on density and then divided into p strata that account both distance and density.

A sample is drawn from the strata after the points are stratified. To make sure that the points are not sampled twice, random sampling without replacement is used. Following this, we randomly sample m_j points without replacement:

$$S_{j2} = \{x_{i_j} \mid x_{i_j} \in S_j, \quad i_j \sim \text{Uniform}(S_j, m_j), \} \tag{5}$$

where

- S_{j2} is the set of sampled points.
- m_j is the number of samples selected from each stratum.
- $\sim$ Uniform(S_j, m_j) , m_j samples are drawn uniformly at random from s_j.

The distances of the sampled points are then sorted and used to construct a k-distance graph. The knee point of the k-distance curve is used to determine the optimal ε. The k-distance graph is used because it handles noise well, adjusts to areas with different point densities, and helps automatically choose a good ε value. This makes it a good fit for DSS-DBSCAN, which aims to fairly capture both dense and sparse regions in the data.

The grid search method is used to determine the optimal $minPts$. Unlike ε, there is no universally accepted heuristic for $minPts$. Through grid search, different candidate values of $minPts$ are systematically evaluated over a specified range to identify the one that yields the most meaningful clustering results. For each value within the grid search range, DBSCAN is run with a fixed ε (determined in the prior steps) while varying $minPts$. The algorithm selects the best combination of ε and $minPts$ values that produces the highest Silhouette Score. The optimal ε and $minPts$ are then applied to cluster dengue dataset using the DBSCAN algorithm.

2.4 Analysis Workflow

The dataset used is dengue cases in Northern Mindanao. However, it lacks barangay or purok-level information specifying the exact locations where cases were recorded. This limitation poses a challenge for spatial analysis, as clustering methods rely on precise geographic coordinates to identify high-density areas. To address the absence of barangay or purok-level data, a random point assignment method [40] was implemented. For municipalities with multiple cases, random points were generated within the municipal boundaries for each recorded case. This ensured that the cases were not artificially clustered at a single coordinate. The random assignment process was performed in Python to generate spatially distributed points while maintaining municipal boundaries.

While this method provides a workaround for missing barangay-level data, a more precise approach would involve requesting detailed records from the Philippine Department of Health (DOH). Access to barangay-level records could improve spatial resolution. However, even with barangay-level data, random assignment may still be necessary if multiple cases share the same recorded coordinate. This is particularly relevant unless specific geographic coordinates for each case are available.

The spatial processing of dengue data follows a structured workflow, as shown in Figure 2. The process begins with loading the shapefile, which contains the municipal boundaries of Northern Mindanao. This serves as a spatial reference, ensuring that dengue cases are correctly assigned within their respective municipalities. Simultaneously, the dengue case data is loaded from an Excel file.

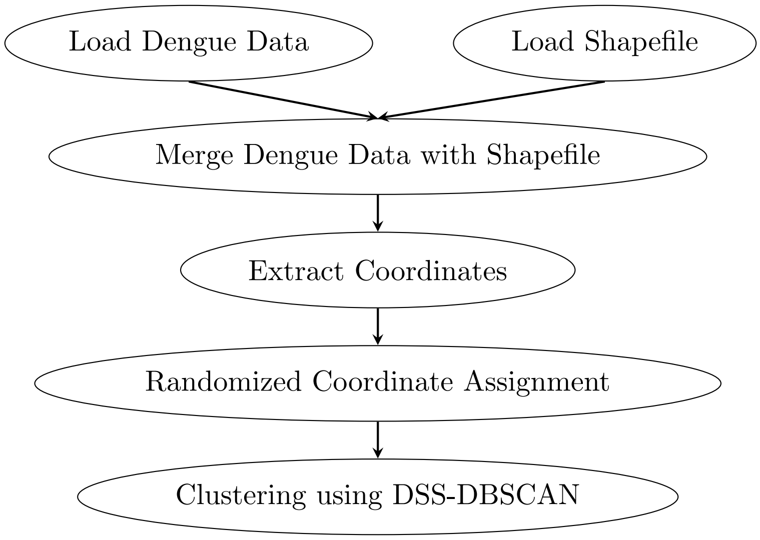

Figure 2: Workflow of Spatial Clustering of Dengue Cases using DSS-DBSCAN Algorithm

To integrate spatial information, the dengue dataset is merged with the shapefile using municipal names as the common key (join key). This step associates each dengue case count with a specific geographic boundary, making it possible to conduct spatial operations. Once merged, the dataset now contains municipal boundaries and case counts, allowing for the extraction of coordinates from the municipalities' centroids.

Since the dataset does not provide exact case coordinates, a random point assignment method is applied. For municipalities with multiple cases, random points are generated within the municipal boundaries to prevent clustering at a single coordinate. Finally, the spatially processed data is visualized and analyzed using DSS-DBSCAN.

3 Results and Discussion

This section provides an analysis of dengue cases in Northern Mindanao, Philippines, from 2009 to 2022. The spatial clustering was conducted using the enhanced DBSCAN algorithm, which considered only the proximity and density of dengue cases. The resulting cluster is based on the concentration of cases but do not directly incorporate other factors. However, to aid interpretation, factors such as population size, reported number of cases, urbanization, human movement, and mosquito breeding environment are considered. This section also presents figures and tables that provide insights into the spread of dengue.

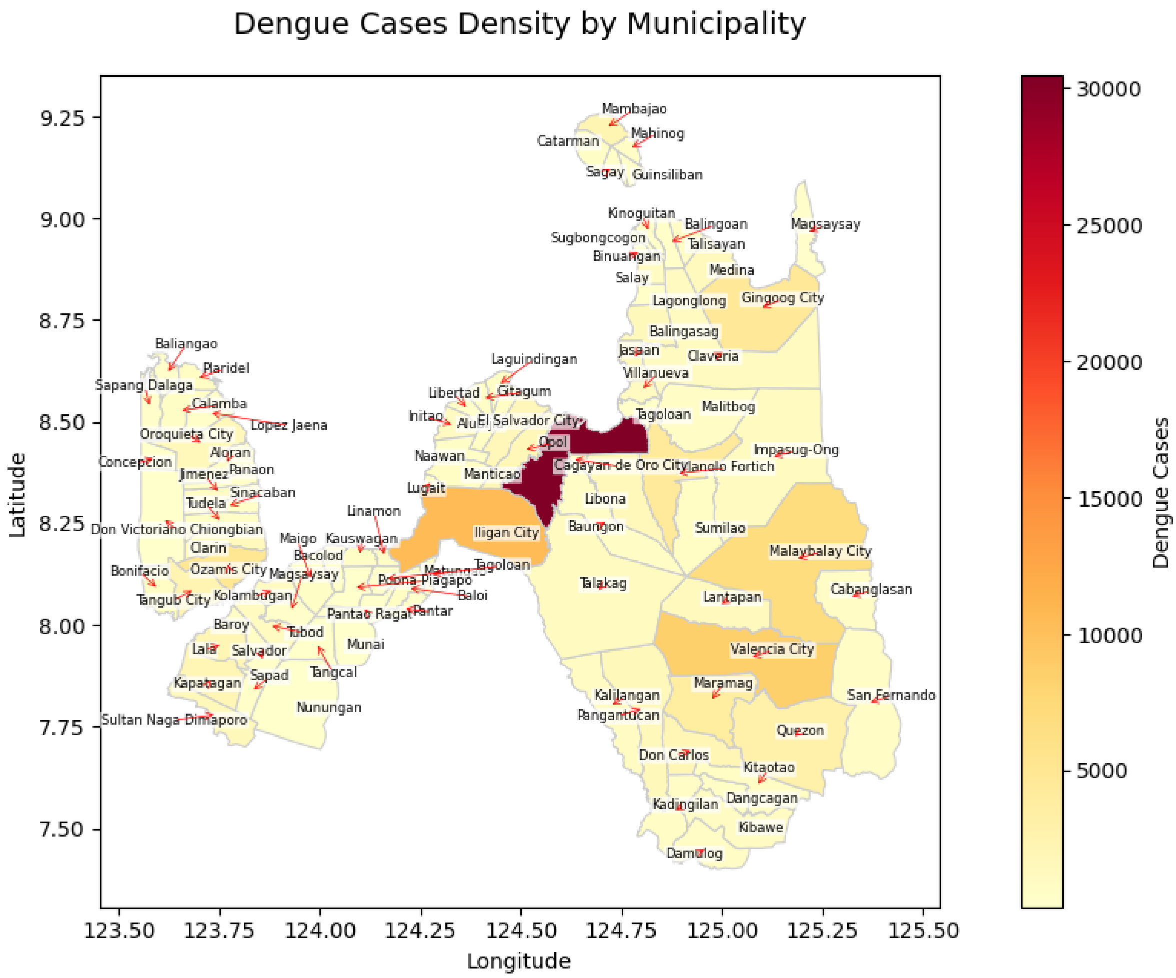

Figure 3: *Density of Dengue Cases in Northern Mindanao, Philippines*

Figure 3 shows the density of dengue cases in Northern Mindanao, with Cagayan de Oro City having the highest number of reported cases, as indicated by its deep red color. As a highly urbanized and densely populated city, it provides ideal conditions for dengue transmission, including numerous breeding sites such as stagnant water in containers and construction areas [20, 37]. Its role as a regional hub with high human mobility, along with the presence of surrounding rivers (e.g., Cagayan River, Agusan River, Alae River) and coastal area (see Figure 4), create favorable conditions for mosquito breeding [26, 2, 29]. Additionally, Aedes aegypti thrives in urban environments, breeding in man-made containers and biting both indoors and outdoors [16]. The city's access to major transportation hubs, such as the Laguindingan Airport and seaports (see Figure 4), may facilitate the movement of infected individuals and mosquitoes from other areas, increasing the risk of local transmission and contributing to the high dengue case density.

Iligan and Ozamis City report high dengue cases due to their geographic conditions. Iligan's proximity to Iligan Bay, waterfalls, and cold springs, creates ideal mosquito breeding grounds. Its industrialization, urbanization, and tourism further increase human-mosquito interactions, increasing the risk of dengue. Similarly, Ozamis City's location near Ozamiz Bay, seaports, and

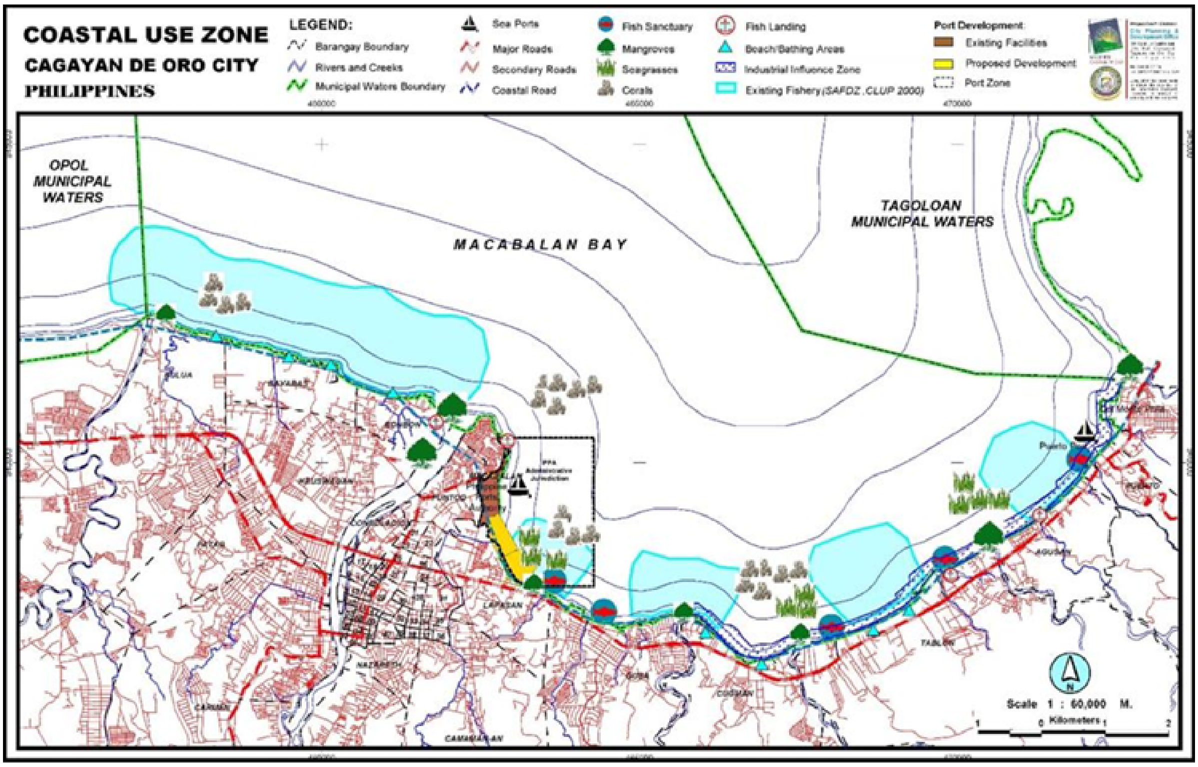

Figure 4: Coastal use zones in Cagayan de Oro City showing transportation hubs and port development areas. *Source: City Government of Cagayan de Oro, Comprehensive Land Use Plan.*

agricultural areas attracts a dense population, facilitating disease transmission. Its strategic role in commerce and transportation also contributes to human movement and mosquito exposure.

Malaybalay and Valencia report high dengue cases due to their forested and agricultural landscapes, which provide ideal mosquito habitats. Forested areas support Aedes albopictus, which breeds in natural containers like banana trees, tree holes, and cut bamboo [35], while agricultural activities create breeding sites through water storage and irrigation. Additionally, natural attractions such as watersheds and mountains draw tourists, potentially introducing dengue from other regions. Outdoor recreational activities also increase human exposure to mosquito bites, heightening dengue transmission risk.

The high dengue cases in these cities stem from diverse geographical features, including bays, rivers, waterfalls, and plateaus, which provide ideal mosquito breeding sites. Tourism and economic activities further contribute by increasing human movement, potentially introducing or spreading the virus. In urban areas like Cagayan de Oro, Iligan, and Ozamis City, large domestic water tanks used for water storage create stable larval habitats [28]. Additionally, high relative humidity, averaging 85% annually recorded in Cagayan de Oro weather station [41], enhances mosquito survival and infection rates [42], while vegetation cover provides resting and breeding sites, influencing dengue transmission risk [6].

Table 1 provides a summary of dengue cases, population, and incidence rates per 10,000 people across various municipalities and cities. The data highlight areas with the highest and lowest dengue cases. Urban centers such as Cagayan de Oro City, Iligan City, and Valencia City report the highest number of dengue cases, with Cagayan de Oro City leading at 30,455 cases and an incidence rate of 418.11 per 10,000 people. These cities are characterized by dense populations, rapid urbanization, and inadequate drainage systems, which create ideal

Table 1: *Summary of Dengue Cases, Population, and Incidence Rate per 10,000 by Municipality/City*

Municipality/City	**Cases**	**Population**	**Incidence Rate**
Cagayan de Oro City	30,455	728,402	418.11
Iligan City	10,524	363,115	289.83
Valencia City	8,496	216,546	392.34
Malaybalay City	6,976	190,712	365.79
Ozamis City	5,053	140,334	360.07
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Gingoog City	4,536	136,698	331.83
Manolo Fortich	4,390	113,200	387.81
Maramag	3,922	108,293	362.17
Tangub City	2,367	68,389	346.11
Mambajao	2,164	41,094	526.60
...	...	...	...
Nunungan	67	18,827	35.59
Tangcal	58	16,075	36.08
Don Victoriano Chiongbian	57	9,664	58.98
Poona Piagapo	53	29,183	18.16
Concepcion	13	9,324	13.94

conditions for mosquito breeding and disease transmission. Similarly, Iligan City (10,524 cases, 289.83 incidence rate) and Valencia City (8,496 cases, 392.34 incidence rate) exhibit high case counts.

In contrast, several municipalities and cities exhibit high dengue incidence rates, such as Mambajao (526.60), Mahinog (423.67), Cagayan de Oro City (418.11), Valencia City (392.34), and Manolo Fortich (387.81). A high incidence rate indicates that a significant proportion of the population has been affected, suggesting potential risk factors such as poor sanitation, environmental conditions conducive to mosquito breeding, and inadequate vector control measures. On the other hand, municipalities such as Tangcal, Nunungan, Munai, Poona Piagapo, and Concepcion report the lowest number of cases and incidence rates. However, these figures may also indicate underreporting due to limited healthcare access and inadequate disease surveillance. Strengthening monitoring and laboratory confirmation of cases in these areas is essential to ensure accurate reporting. The complete data are presented in appendix.

There is considerable variation in dengue cases across different months for the studied period (2009-2022) which can be observed in Figures 5. Certain months consistently have higher case counts, such as January, June, July, August, and September, which coincide with the peak of the rainy season in many regions. According to climatological data from Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) over a 30-year period [30], the Malaybalay weather station in Bukidnon recorded an average annual rainfall of 2,569.9 mm, with peak rainfall occurring from May to October (ranging from 224.8 to 315.7 mm). These months provide favorable conditions for mosquito breeding, leading to increased dengue transmission [10, 23]. Furthermore, the number of cases tends to decrease during the dry season particularly for the months of February (106.1mm avg. rainfall), March (112.5mm avg. rainfall), and April (115.6mm avg. rainfall), since there is less stagnant water for mosquitoes to breed, and mosquitoes have a shorter lifespan and lower survival rates in drier conditions [46]. While dengue cases tend to decrease during the dry season, dengue can still occur throughout the

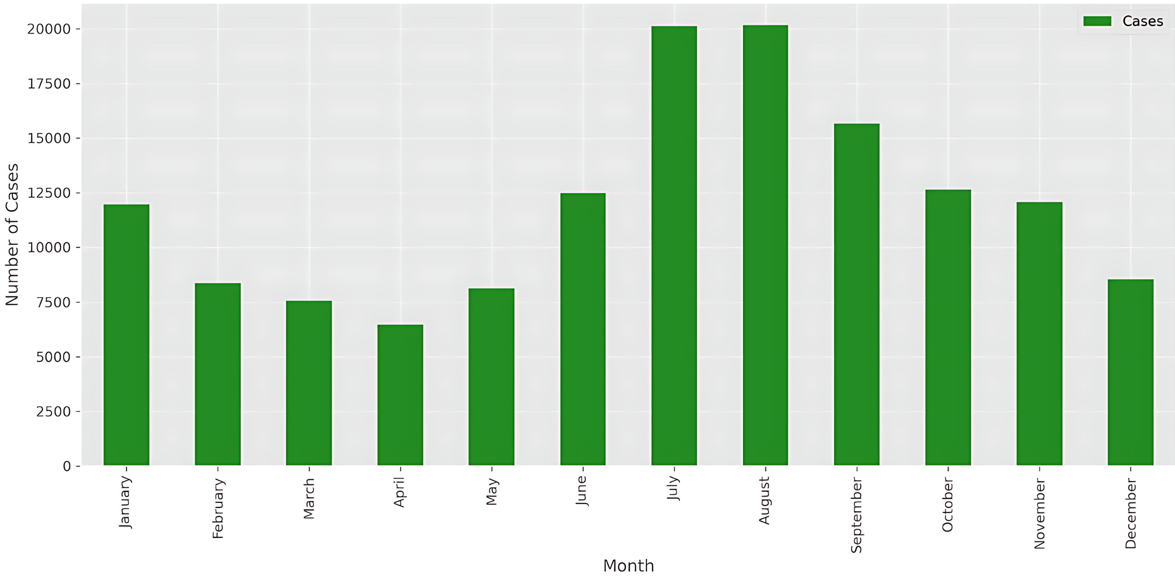

Figure 5: *Histogram of Total Number of Cases by Month (Year 2009-2022)*

year in areas with favorable conditions for mosquito breeding, such as urban environments with inadequate sanitation and water storage practices [28].

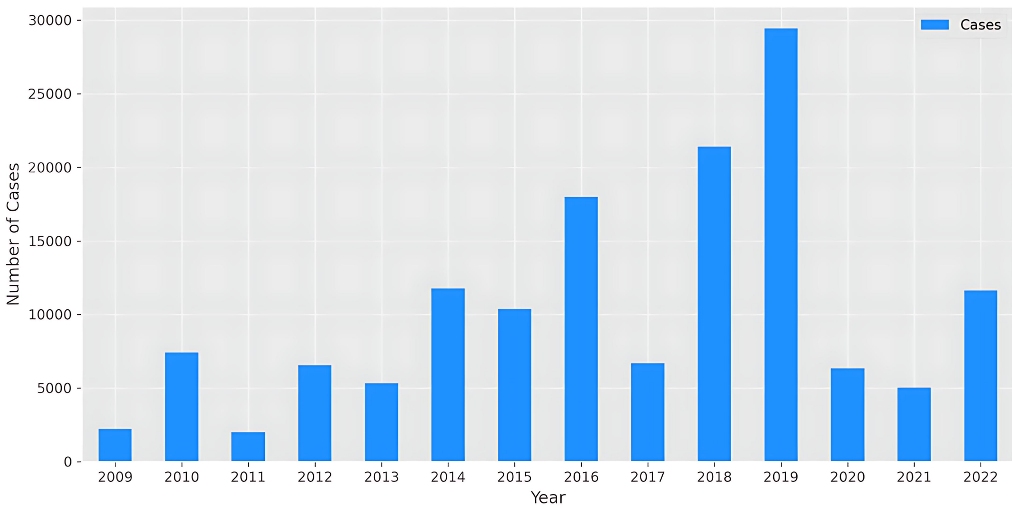

Figure 6: *Total Number of Cases by Year*

Figure 6 highlights that the highest recorded dengue cases occurred in the year 2019, followed by 2018, 2016 and 2014. This indicates that these specific years experienced particularly severe dengue outbreaks or higher transmission rates compared to other years in the study period. The number of dengue cases varies significantly from year to year. Some years' experience higher numbers of cases, while others have lower numbers. The highest number of dengue cases occurred in 2019, while the lowest number was recorded in 2009.

The clustering results as shown in Figure 7 revealed significant groupings, with areas such

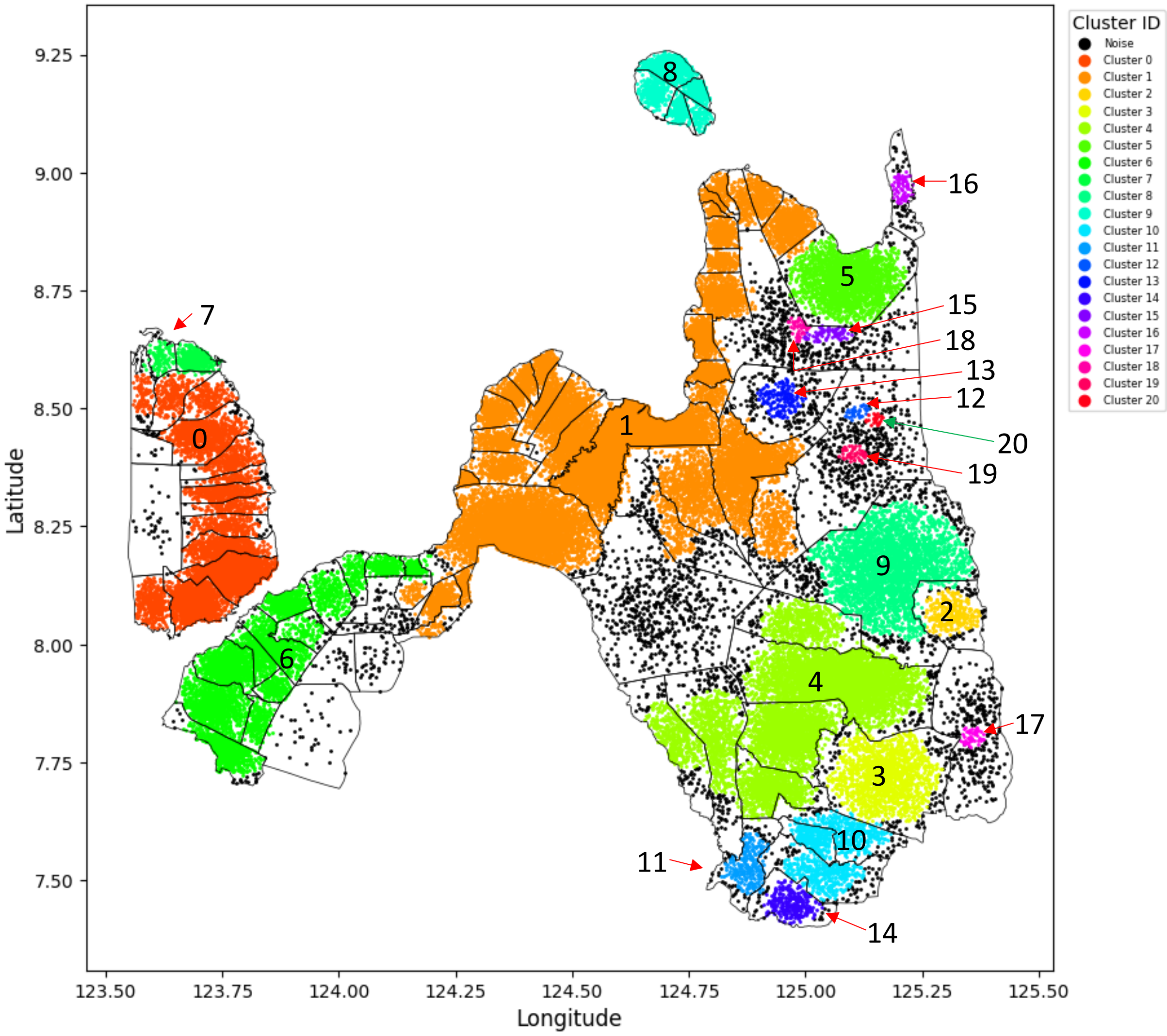

Figure 7: *Clustering Result of Dengue Cases using DSS-DBSCAN Algorithm*

as Cagayan de Oro City, Iligan City, and Manolo Fortich forming a single cluster (Cluster 1). These findings were corroborated by Figure 3 that showed these cities as hotspots for dengue transmission. This cluster represents a densely populated and economically active region with significant urban development. Both Iligan City and Cagayan de Oro City are major urban centers, characterized by high human activity, increased mobility, and dense residential areas. Manolo Fortich and other nearby municipalities likely share socio-environmental connectivity with these cities, such as frequent inter-city travel and trade.

Cluster 0 comprises of Ozamis City, Tangub City, Oroquieta City and nearby areas in Misamis Occidental. This cluster shared coastal environment that may contribute to similar mosquito breeding conditions, such as water stagnation in fishing equipment and inadequate sanitation. Ozamis City, Tangub City and Oroquieta City are relatively urbanized compared to other municipalities in the province. This cluster's formation can be attributed to the high density of cases in urban centers spilling over into surrounding rural areas.

Cluster 4 consist of Lantapan, Valencia City, Maramag, Don Carlos, and nearby areas.

This cluster consists of semi-urban and rural municipalities with moderate to high dengue case densities. Valencia City, being a key economic hub in Bukidnon, likely acts as a central point for this cluster due to its relatively higher population density and connectivity to smaller municipalities like Maramag and Don Carlos. These areas share moderate levels of urbanization and agricultural activity, which may provide suitable breeding grounds for mosquitoes.

Cluster 6 comprises of Bacolod, Magsaysay, Kulambogan, Baroy, Lala, and nearby areas. This cluster comprises coastal and rural municipalities in Lanao del Norte. Proximity and interdependence for trade and daily activities likely increase the interconnectivity of dengue case transmissions.

4 Conclusion

This study utilized an optimized DBSCAN algorithm to analyze dengue cases in Northern Mindanao, Philippines. Specifically, it employs dual stratification and grid search to optimize DBSCAN parameters. By incorporating dual stratification, the method strengthens the reliability and effectiveness of DBSCAN in practical application. Traditional DBSCAN often faces challenges in handling datasets with varying densities, particularly when differentiating between high-density and low-density areas. The method used in this study ensures a balanced representation of cases across regions with varying dengue cases, ensuring a more accurate clustering result. This is particularly important in Northern Mindanao, which includes municipalities/cities with high and low dengue cases. Compared to traditional methods, this approach offers a more refined way to determine epsilon and an automated process in selecting minimum points which improved the DBSCAN algorithm to adapt to varying data densities.

The clustering results reveal the presence of localized dengue case clusters in Northern Mindanao, showing that infections tend to concentrate in specific areas rather than occurring randomly. Each cluster includes municipalities and nearby regions with shared risk factors, suggesting that dengue transmission is influenced by spatial characteristics. Key contributors to this spread include urbanization, frequent human movement, and environmental conditions that support mosquito breeding. Densely populated urban centers with high mobility may act as hubs for disease transmission, while natural factors such as standing water create ideal mosquito habitats.

A temporal assessment revealed a seasonal trend, with dengue cases reaching their highest levels in July, August, and September. This pattern corresponds with the rainy season, when increased water accumulation fosters mosquito reproduction. Yearly trends also showed fluctuations in case numbers, with 2019 recording the highest incidence.

These insights underscore the importance of focusing interventions on high-risk locations. The risk of dengue transmission can be decreased by strengthening vector control efforts, such as fogging to kill mosquitoes, treating or eliminating breeding sites to manage larval source, and community awareness campaigns to promote practices like covering water containers and proper waste disposal [39, 45]. Improving sanitation practices, and implementing well-planned public health strategies can help combat dengue outbreaks more effectively.

A Appendix

Table 2: *Summary of Dengue Cases, Population, and Incidence Rate by Municipality/City*

Municipality/City	Cases	Population	Incidence Rate
Cagayan de Oro City	30,455	728,402	418.11
Iligan City	10,524	363,115	289.83
Valencia City	8,496	216,546	392.34
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Ozamis City	5,053	140,334	360.07
Gingoog City	4,536	136,698	331.83
Manolo Fortich	4,390	113,200	387.81
Maramag	3,922	108,293	362.17
Quezon	3,060	109,624	279.14
Tangub City	2,367	68,389	346.11
Mambajao	2,164	41,094	526.60
Lala	2,104	73,425	286.55
Kapatagan	2,094	62,571	334.66
Don Carlos	2,037	69,273	294.05
Opol	1,906	66,327	287.36
El Salvador City	1,689	58,771	287.39
Oroquieta City	1,670	72,301	230.98
Libona	1,626	48,965	332.07
Pangantucan	1,550	56,580	273.95
Balingsag	1,530	74,4385	205.69
Sultan Naga Dimaporo	1,506	60,904	247.27
Jassan	1,497	57,055	262.38
Lantapan	1,376	65,974	208.57
Medina	1,278	35,612	358.87
Clarin	1,250	39,356	317.61
Tubod	1,157	50,073	231.06
Impasug-ong	1,145	53,863	212.58
Claveria	1,144	52,478	218.00
Talakag	1,123	77,027	145.79
Kolambugan	1,061	28,265	375.38
Villanueva	1,019	40,149	252.11

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Table 3: Table 2 continuation...

Municipality/City	Cases	Population	Incidence Rate
Initao	973	33,902	287.00
Kalilangan	933	43,711	213.45
Jimenez	911	28,909	315.13
Kibawe	906	41,897	216.24
Salay	906	29,998	302.02
Sumilao	817	29,531	276.66
Plaridel	799	39,840	200.55
Manticao	796	29,469	270.11
Kitaotao	772	53,796	143.51
Bonifacio	749	34,558	216.74
Alubijid	740	32,163	230.08
Baloi	733	68,465	107.06
Talisayan	714	25,761	277.16
Cabanglasan	705	36,286	194.29
Baungon	700	37,111	188.62
San Fernando	700	63,045	111.03
Damulog	689	39,322	175.22
Baroy	669	24,683	271.04
Malitbog	657	26,741	245.69
Kadingilan	634	33,735	187.94
Mahinog	620	14,634	423.67
Languindingan	603	26,363	228.73
Dangcagan	599	26,075	229.71
Naawan	598	22,444	266.44
Catarman	584	17,569	332.40
Linamon	575	21,269	270.35
Aloran	568	27,934	203.34
Kauswagan	565	24,193	233.54
Tudela	562	28,599	196.51
Maigo	544	23,337	233.11
Lugait	528	20,559	256.82
Gitagum	510	17,290	284.60
Calamba	502	23,327	216.13
Salvador	449	32,115	139.81
Lagonglong	449	22,194	158.61
Sapad	424	22,974	184.56
Sinacaban	420	19,671	213.51

Table 4: Table 2 continuation...

Municipality/City	**Cases**	**Population**	**Incidence Rate**
Libertad	417	12,948	322.06
Sagay	416	12,826	324.34
Lopez Jaena	409	25,507	160.35
Kinoguitan	377	14,091	267.55
Baliangao	337	11,020	305.81
Bacolod	310	24,367	127.22
Tagoloan	307	15,091	203.43
Panaon	261	10,797	241.73
Magsaysay	245	36,802	66.57
Sapang Dalaga	229	20,490	111.76
Sugbongcogon	228	9,764	233.51
Baliangao	224	18,433	121.52
Guinsiliban	218	6,685	326.10
Matungao	140	14,756	94.88
Binunangan	131	7,441	176.06
Pantao Ragat	119	30,247	39.34
Pantar	110	26,599	41.35
Munai	84	35,020	23.99
Nunungan	67	18,827	35.59
Tangcal	58	16,075	36.08
Don Victoriano Chiongbian	57	9,664	58.98
Poona Piagapo	53	29,183	18.16
Conception	13	9,324	13.94

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