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Geospatial Analysis of Emergency Incidents and Disaster Response Management in Oton, Iloilo

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Abstract

Efficient emergency response, which is one of the main pillars of the Philippine Disaster Risk Reduction and Management (DRRM) framework, is critical in saving lives and properties especially when it comes to dispatch times and coverage areas. Thus, this study examines the spatial and temporal dynamics of emergency response operations in Oton, Iloilo, with the aim of identifying critical gaps in service coverage and response efficiency. Spatial distribution of emergency incident count and average emergency response times were analyzed at a barangay level. Getis Ord hotspot analysis revealed that urbanized barangays experience higher frequency of incidents and quicker response times, while remote and rural barangays experience lower incident counts and longer response times. Global and Local Moran's I were implemented for spatial autocorrelation analysis, with Global Moran's I of 0.34 for incident count and 0.53 for response time suggesting statistically significant clustering. Temporal analysis revealed peak periods of long response times, particularly during evening hours and weekends, which can be attributed due to traffic conditions, limited personnel, or operational constraints. The combined spatial and temporal insights point to areas where response strategies could be optimized through better resource allocation, adaptive staffing, and strategic deployment of response teams. The findings emphasize the need for a more equitable and responsive emergency management system in Oton.

1. Introduction

1.1 Disaster Risk Reduction and Management

Disaster risk reduction and management (DRRM) plays a critical role in the Philippines' national and local socio-political landscape, given its situation as a disaster-prone country. The need for an institutional, comprehensive, and systematic approach to DRRM led to the establishment of the Republic Act No. 10121 or the Disaster Risk Reduction and Management Act of 2010, which mandates a proactive DRRM framework that emphasizes the need for community involvement and multi-sectoral and inter-agency collaboration.

The DRRM framework of the Philippines is structured around four key thematic pillars: disaster prevention and mitigation, preparedness, response, and recovery and rehabilitation (Austria, 2023). Local government units (LGUs) are particularly central to disaster management efforts, as they are both deeply familiar with the hazards facing their communities and directly impacted by the socio-economic consequences of disasters (Domingo, 2017).

1.2 Emergency Response

Emergency response is a crucial component of the Philippine DRRM Framework. The National Disaster Risk Reduction and Management Council (NDRRMC) formulated the National Disaster Response Plan (NDRP) in 2024, which outlines the general directions to take for agencies and networks for operationalizing different emergency response plans. The NDRP places the LGUs as the central entity for tactical response, which focuses on the on-ground implementation of response operations and its overall command and control.

While the National DRRM Framework and the NDRP primarily focus on large-scale emergency response to disasters such as hydrometeorological hazards and geohazards, it is worth noting that local DRRM units have broadened their mandate. Beyond the traditional scope of natural disaster response, some local DRRM units have taken on a role in managing a wider range of life-threatening incidents. These include medical emergencies (such as heart attacks, strokes, and childbirth complications), vehicular and industrial accidents, fire-related incidents, and other critical situations that demand urgent intervention (Municipality of Oton, 2024).

Emergencies may vary in severity, but their danger lies in their unpredictability. They pose a grave threat to people's lives, safety, and stability because they are difficult to predict and can easily trigger a chain reaction of dire events among various industries and groups in society (Wang et al., 2022). Thousands of lives are lost worldwide every year due to inefficiencies in emergency management such as delays in response which leads to preventable loss of lives, injuries, physical harm, and infrastructure damage (Westbrook and Costa, 2025).

Furthermore, the increase of urbanization and population density especially in cities and urban areas complicates planning and response operations due to increased obstacles (Asadzadeh et al., 2022). This therefore underscores the need for a robust and comprehensive emergency management system to minimize the harm and disruption of life-threatening incidents on communities and their citizens.

1.3 Spatial and Temporal Components of Emergency Response

Disaster and emergency response management is inherently driven by spatial (Yılankıran & Guney, 2021) and temporal

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(Westbrook & Costa, 2025) dimensions. Applications of Geographic Information System (GIS) in studies have therefore been on the rise as a necessary component of disaster and emergency management around the world (Abdalla, 2016). Geospatial techniques such as spatial autocorrelation tests (i.e. Moran's I), density mapping, and buffer analysis are utilized to identify delays and service gaps in emergency response, using grid-based mapping and seasonal analysis for more in-depth analysis (Park et al., 2024; Oh et al., 2012). GIS-based methodologies are often extended to incorporate other technologies, such as GPS data and geovisual analytics for analyzing emergency vehicle movement patterns (Maqsood et al., 2020) and SMS and web-based applications for geolocation and crowdsourcing (Šterk & Praprotnik, 2017).

Response time is also a critical factor in studies analyzing emergency response patterns, given its time-sensitive nature. Delays in emergency dispatch significantly decrease the possibility of survival for victims requiring rescue and life-saving intervention, making efficient management of response time highly critical (Park et al., 2024). The temporal dynamics of emergencies have been studied and assessed at different scenarios (Kang et al., 2024). GIS-based spatiotemporal analysis of emergency vehicle arrival times and response durations are especially prominent in existing literature (Oh et al., 2012; Park et al., 2024; Hoff, 2023).

At the local level, spatial analysis techniques have also been applied to DRRM. Studies and initiatives have been focused on GIS-based identification of locations with poor preparedness and recovery from past disasters (Abante, 2022) and development of location-based DRRM reporting applications in the Philippines through the use of SMS and ICT technologies (de los Santos et al., 2020; Ballicud, 2014). However, the adoption of such applications remains limited and lacks nationwide standardization, especially in terms of geolocating and crowdsourcing emergency incident data.

1.4 Rationale

While there are existing DRRM frameworks and digital platforms supporting DRRM planning and operations in the Philippines, a significant gap remains in the use of historical incident records for analyzing recurring spatiotemporal patterns of emergencies. Without such analyses, LGUs are limited in their ability to anticipate, plan for, and effectively respond to future emergencies based on past trends.

This issue is particularly evident in Oton, Iloilo, a coastal municipality in Western Visayas that faces multiple hazards (i.e. flood and landslides), medical cases, and considerable crime incidence as stated in their Comprehensive Development Plan. The local government has made strides in launching DRRM initiatives. The establishment of a functional 24/7 Municipal DRRM Operations Center and the Oton Search and Rescue Team (OSART) by the local government is to enhance emergency response capabilities; they are responsible for responding to Medical Emergencies, Trauma Emergencies, Vehicular Accidents, Rescue Operations and the like (Municipality of Oton, 2024). However, manual processes and use of paper forms for incident record-keeping limits its capacity for data-driven decision-making.

To address this gap, this study demonstrates the application of GIS-based spatiotemporal analysis to historical emergency incident records in Oton, Iloilo. This approach enables the identification of hotpots, temporal patterns, and risk-prone areas, offering insights that can aid emergency response strategies. Through spatial analysis, this research contributes to a more nuanced and practical framework for local emergency management planning.

1.5 Research Objectives

This research aims to analyze the spatial distribution and temporal patterns of emergency response operations in Oton, Iloilo, with a focus on identifying long response times and areas with poor service coverage. Specifically, this study aims:

1. To identify hotspots of emergency incident count and areas with prolonged emergency response times in Oton, Iloilo;
2. To determine the presence and extent of spatial autocorrelation in emergency incident locations and average response times;
3. To identify and analyze spatial and temporal patterns in emergency response operations, including variations across time periods and geographic areas; and
4. To provide insights and recommendations for optimizing emergency response strategies in Oton, Iloilo using the findings of the study.

2. Materials and Methods

2.1 Study Area

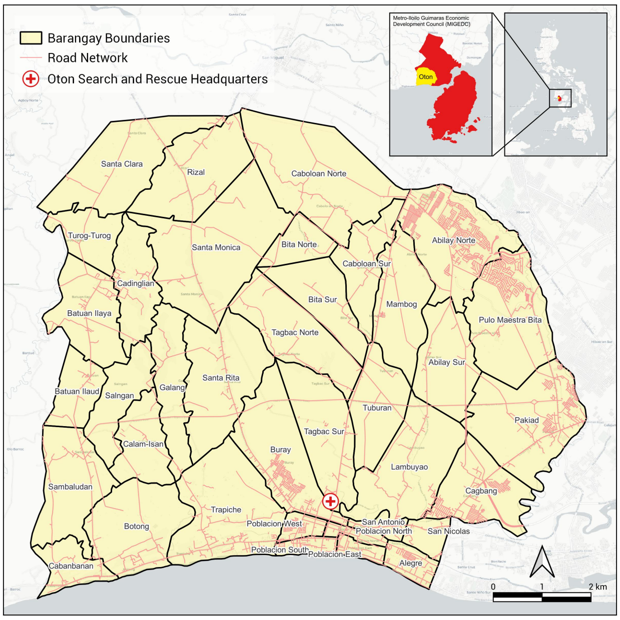

Figure 1. Location map of Oton, Iloilo.

The Municipality of Oton (Figure 1) is a first class municipality in the Province of Iloilo, Philippines, located in the southern portion of the province. The 2020 census places Oton as the most populated town in Iloilo, with a total population of 98,509. Furthermore, Oton is part of the Metro Iloilo—Guimaras Economic Development Council (MIGEDC), an inter-local government unit alliance focused on promoting economic growth and industry development. Out of its 37 barangays, nine (9) are classified as urban and twenty-eight (28) are rural. The topography of the area is predominantly coastal and vegetated, with the western portion consisting of croplands, plains, and rolling hills and a huge portion of the municipality bordered by a coastline (Municipality of Oton, 2023).

The Oton Comprehensive Development Plan (CDP) 2023 - 2028 states that in 2021, the morbidity and mortality cases reached up to 7000 and 500 respectively, most of it attributable to illnesses, injuries, and other medical conditions. Crime incidence is also an issue; there were 159 recorded crimes committed in 2021 with most of it concentrated around urban and populated barangays such as Poblacion South, Poblacion East, and Abilay Norte.

Critical situations such as those stated above are addressed through the Oton 24/7 Emergency Response Service with a specialized team called the Oton Search and Rescue Team (OSART) to handle medical emergencies, trauma emergencies, vehicular accidents, rescue operations, among others (Municipality of Oton, 2024). The OSART was established in 2003, but their headquarters, the Oton Search and Rescue Headquarters, was just established in 2015 beside the Municipal Hall (Delos Santos, 2016) and is currently being handled by the Municipal Disaster Risk Reduction and Management Office (MDRRMO). The emergency response services of Oton have become an integral part of its DRRM framework.

2.2 Data Collection and Digitization

Patient Care Report (PCR) Forms covering July to December 2024, with a total of six months' worth of emergency incident records, were obtained from the Oton MDRRM Office. PCR Forms are the primary instrument of the OSART and the MDRRMO to capturing essential information during emergency responses, including the nature and type of incident, the number of individuals affected or injured, the severity and type of injuries sustained, the exact location of the emergency, and the contact details of those involved. The OSART then hands over the PCR Forms for turnover to the hospital upon arrival, then stored at the MDRRMO for archiving purposes.

The forms were digitized into a spreadsheet format to enable integration into a Geographic Information System (GIS) for further spatial and statistical analyses. A total of 1,428 Patient Care Report (PCR) entries covering July to December 2024 were obtained from the MDRRMO. Upon preprocessing, records with incomplete or missing values in key fields, including barangay name, incident type, date, and response timestamps, were excluded. This amounts to 211 cases or approximately 14.8% of the original dataset. The final cleaned dataset contained 1,217 valid records distributed across all 37 barangays, each with complete information on incident type, barangay, and response details. This ensured the reliability and consistency of the subsequent geospatial and temporal analyses.

2.3 Geospatial Analysis

2.3.1 Hotspot Analysis: The intensity and spatial location of emergency incidents and emergency response times were studied using the Getis-Ord Gi* statistic (Ord and Getis, 1995). The Gi* statistic compares the expected value for a unit with its neighboring features to determine the statistically significant difference in emergency incident count and average response time. Standardization of the Gi* statistic is done using its sample mean $\bar{X}$ and variance S^2:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{n\left[\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)\right]^2}{n-1}}} \tag{1}$$

where x_j = incident count or average response time of a feature j
$w_{i,j}$ = spatial weight between feature i and j
n = total number of features

and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{2}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2} \tag{3}$$

The closeness of the Gi* value to zero is the indicator of the randomness of the spatial events. If the value is closer to zero, the probability of a random distribution is higher. Furthermore, the sign of the Gi* value indicates the type of clustering. Positive and negative values signify high- and low-clustered events respectively. The location of the cluster is considered a hotspot if the calculated index exceeds a statistical threshold (Songchitruksa and Zeng, 2015).

2.3.2 Spatial Autocorrelation Analysis: Spatial autocorrelation was tested using the Anselin Local Moran's I statistic (Anselin, 1995). Moran's I tests the degree of autocorrelation and outputs a value ranging from −1 to +1, where values closer to +1 indicate similarity (spatial clustering of high or low values) and values closer to 0 indicate randomness (Fahad et al., 2022). Moran's Index is calculated as follows:

$$I_i = \frac{x_i - \bar{x}}{\sum_{j=1}^{n}(x_j - \bar{x})^2} \sum_{j=1}^{n} W_{i,j}(x_j - \bar{x}) \tag{4}$$

where n = number of spatial units
x_i and x_j = values of the inspected variable in spatial units i and j
$\bar{x}$ = mean value of variable x
$W_{i,j}$ = weight between two spatial units i and j

For this study, spatial autocorrelation and hotspot analyses were implemented based on the aggregated incident count and average response time at the barangay level. ArcGIS Pro was used to calculate and map the hotspots and clusters in the study area. Because the barangays in Oton share a common boundary (also known as spatial contiguity), the conceptualization of spatial relationships chosen for the analyses was contiguous edges and corners, also known as queen contiguity. Under the assumption that spatial relationships are a function of polygon proximity, polygon contiguity conceptualizations are effective (ESRI, n.d.). Furthermore, queen contiguity is proven to be effective on contiguous polygons that are irregular in shape and size, such as administrative boundaries (Tsai et al., 2009).

2.4 Descriptive Statistics

This study employed additional exploratory data analysis (EDA) techniques to further uncover incident patterns and emergency response operations within the study area. Temporal analysis was also conducted to identify patterns in incident occurrence and response time across various time scales. The goal was to characterize the fluctuations in emergency activity across time and space and assess how these dynamics inform the performance and burden of local emergency services.

Given the six-month span of the dataset, temporal analysis was limited to exploratory visualization (calendar heatmaps, rolling averages, weekday breakdowns) rather than formal time-series decomposition or regression modeling, which would require longer observation periods for robust results.

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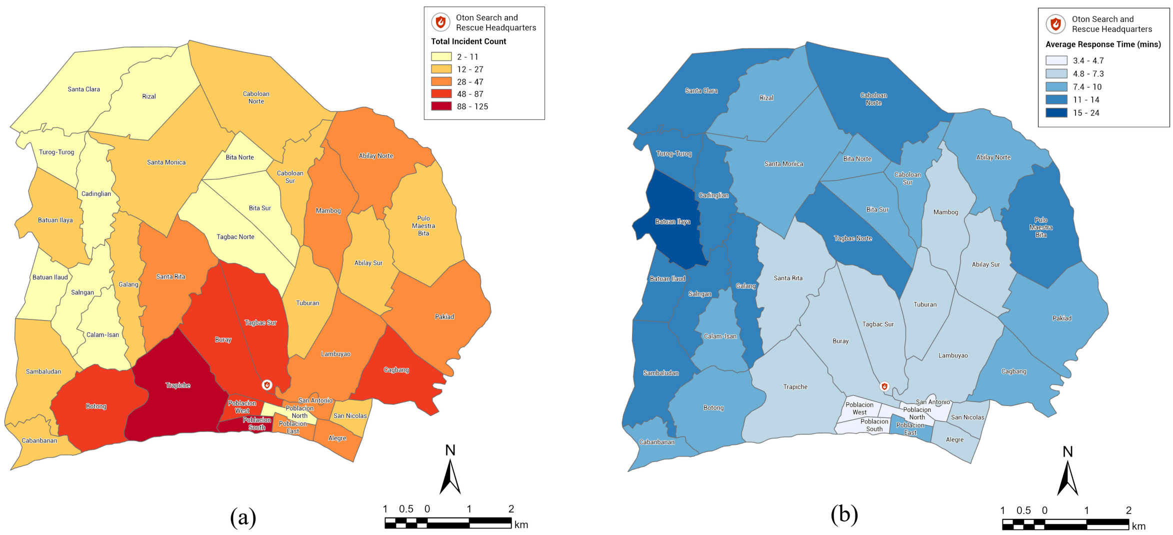

Figure 2. Spatial distribution maps of (a) total emergency incident count and (b) average emergency response times in Oton, Iloilo.

3. Results and Discussion

3.1 Spatial Distribution of Emergency Incidents and Response Times

Choropleth maps were generated based on the data extracted from the digitized PCR Forms (Figure 2). Records were aggregated into barangay level and visualized to determine the spatial distribution of emergency incidents across the municipality. Between July and December 2024, a total of 1,428 emergency incidents were documented. Among the barangays, Poblacion South reported the highest number of incidents with 125 cases (10.8% of total incidents), followed closely by Trapiche with 110 incidents (9.5%), and Botong with 87 (7.5%). In contrast, the barangays with the fewest recorded incidents during this six-month period were Salngan and Tagbac Norte, with only 2 and 3 cases, respectively.

The spatial distribution of emergency incidents (Figure 2a) appears to be concentrated in and around the *poblacion* area or the town proper, indicating that urbanization and high population density are possible contributing factors. Barangays situated in the eastern and southern portions of the municipality recorded moderate levels of emergency incidents, while peripheral or remote barangays generally showed lower incident counts. Notably, urban barangays such as Trapiche, Poblacion South, Poblacion West, Buray, Botong, and Cagbang reported significantly high numbers of emergency cases. However, the rural barangay of Tagbac Sur showed an unexpectedly high number of incidents. Conversely, barangays located on the outskirts of the study area had fewer recorded emergencies, suggesting either a lower population density or underreporting.
Average emergency response times (in minutes) were aggregated at the barangay level by calculating the mean duration between the “Responding” and “Arrived Scene” timestamps. Among all barangays, Batuan Ilaya recorded the longest average response time at 24.154 minutes, indicating delays in reaching the scene. In contrast, the Poblacion barangays demonstrated much faster emergency response times: San Antonio averaged 3.395 minutes, followed closely by Poblacion West (3.418 minutes), Poblacion North (4.091 minutes), and Poblacion South (4.735 minutes). The choropleth map of average response times per barangay is illustrated in Figure 2b.

The spatial distribution of emergency response times in Oton suggests a radial pattern spreading outward from the Oton Search and Rescue Headquarters. Barangays located closer to the headquarters, particularly those within the town center, benefit from shorter response times due to proximity and likely better road access. Meanwhile, barangays situated farther away from the headquarters, like Batuan Ilaya and other barangay in the outskirts, experience increased delays.

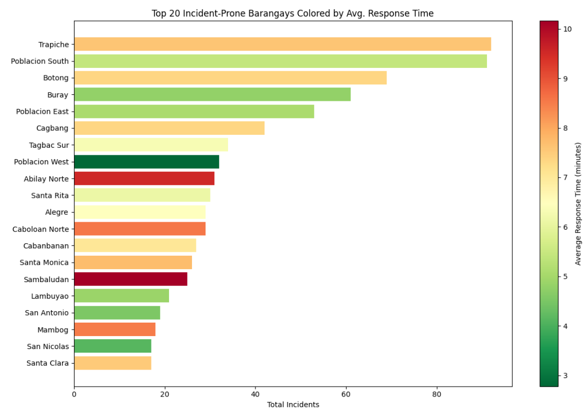

Figure 3. Top 20 incident-prone barangays colored by average response time.

To integrate analysis of incident count and response time, Figure 3 presents the top 20 incident-prone barangays with their respective average response time. Trapiche and Poblacion South registered the highest number of incidents but also displayed moderately long response times, suggesting persistent strain on responders despite proximity. More concerning are barangays like Abilay Norte and Sambaludan, which not only reported substantial incident counts but also exhibited some of the longest average response times, as indicated by deep red shading. Conversely, Poblacion West stands out as a high-demand area with notably fast response times.

3.2 Spatial Autocorrelation Analysis

Global Moran’s I index was calculated to determine whether the emergency incident count and average response times aggregated at the barangay level were spatially dispersed, random, or clustered. Figures 3a and 3b show the results of Global Moran’s

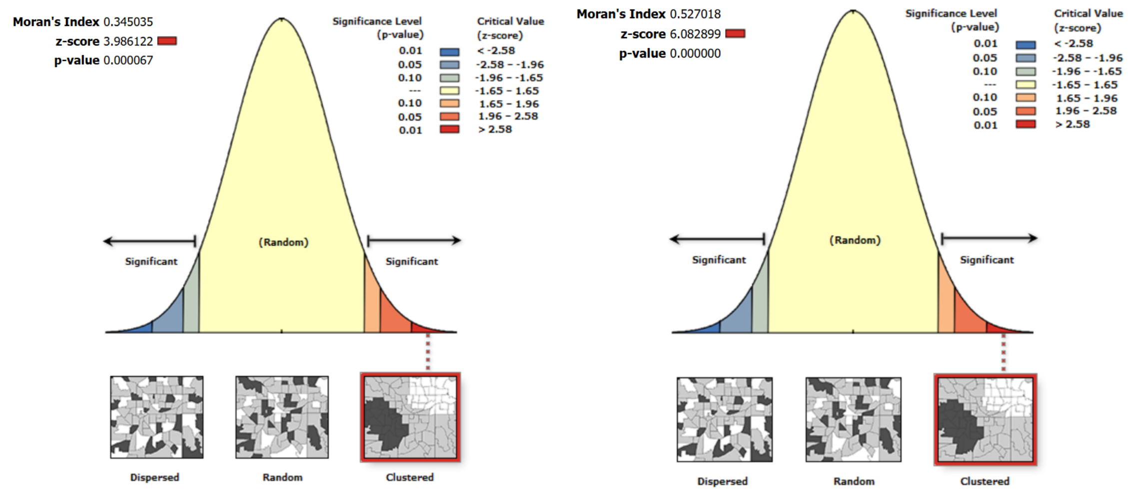

Figure 4. Global Moran's I index analysis results for (a) emergency incident count and (b) average emergency response times.

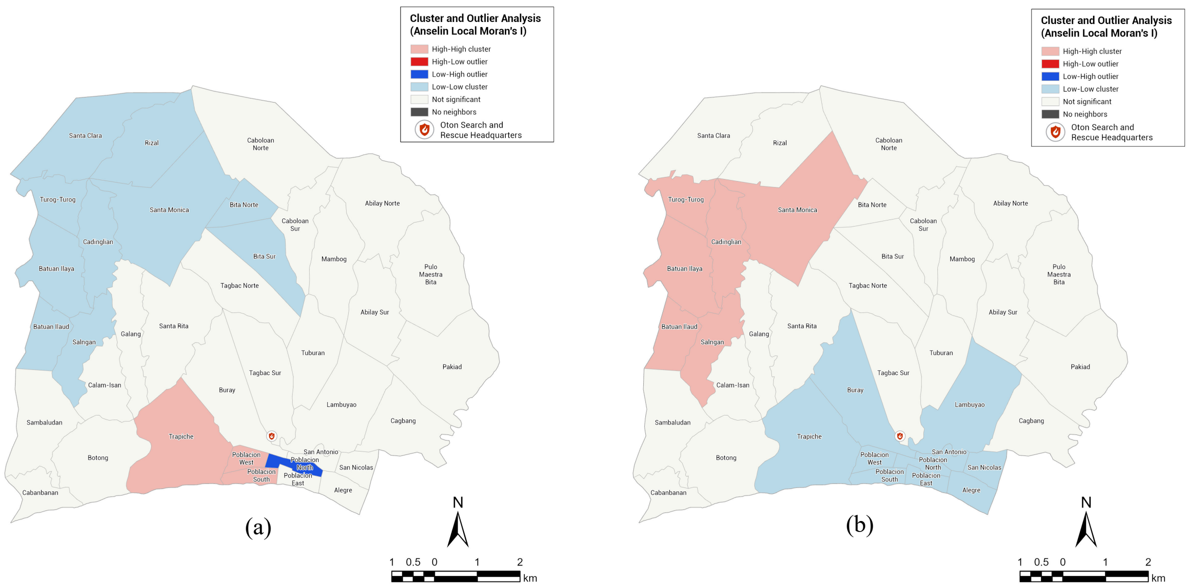

Figure 5. Local Moran's I cluster and outlier maps of (a) emergency incident count and (b) average emergency response times in Oton, Iloilo. High-High clusters (dark red) show barangays with high values surrounded by high-value areas, while Low-Low clusters (dark blue) indicate low values near low-value neighbors. Outliers are areas that differ from their surroundings.

I for incident count and emergency response time respectively. The presence of clusters was identified for both components, with Moran's I of 0.34 for incident count and 0.53 for response time. The associated z-score of 3.99 and 6.08 respectively and p-values both at < 0.01 means that there is a less than 1% likelihood that these clustered patterns could be the result of random chance. The results were therefore deemed to be statistically significant; high and low values of emergency incidents and response times exhibited spatial clustering.

Further insights into the spatial autocorrelation analysis were provided using Anselin Local Moran's I (Figure 5a). Low-Low clusters were concentrated in the northwestern portion of the study area, as shown in Figure 5a, coinciding with the previous hotspot analysis, as these barangays exhibited low frequency of cases. Barangays in the town proper, especially Trapiche, Poblacion West, and Poblacion South, were observed to be High-High clusters, meaning that these areas have high values for incident count, and its neighboring barangays also have high values. Interestingly, one Low-High outlier barangay was observed — Poblacion North, which exhibits low incident count relative to its surrounding neighbors.

For the average response times (Figure 5b), a clear High-High cluster is observed in the western barangays—Turog-Turog, Batuan Ilaya, Batuan Ilaud, Salngan, and Santa Monica—indicating that these adjacent areas collectively experience high response times and are surrounded by similar barangays. Conversely, a distinct Low-Low cluster emerged in the southern corridor, encompassing Trapiche, Poblacion zones, and neighboring barangays like Lambuyao and San Nicolas.

3.3 Hotspot Analysis

Getis Ord hotspot analysis revealed spatial patterns in emergency incident count and response times across the study Area. Figure 6a and 6b show the hotspot maps for emergency incident count and average response times respectively. According to Figure 6a,

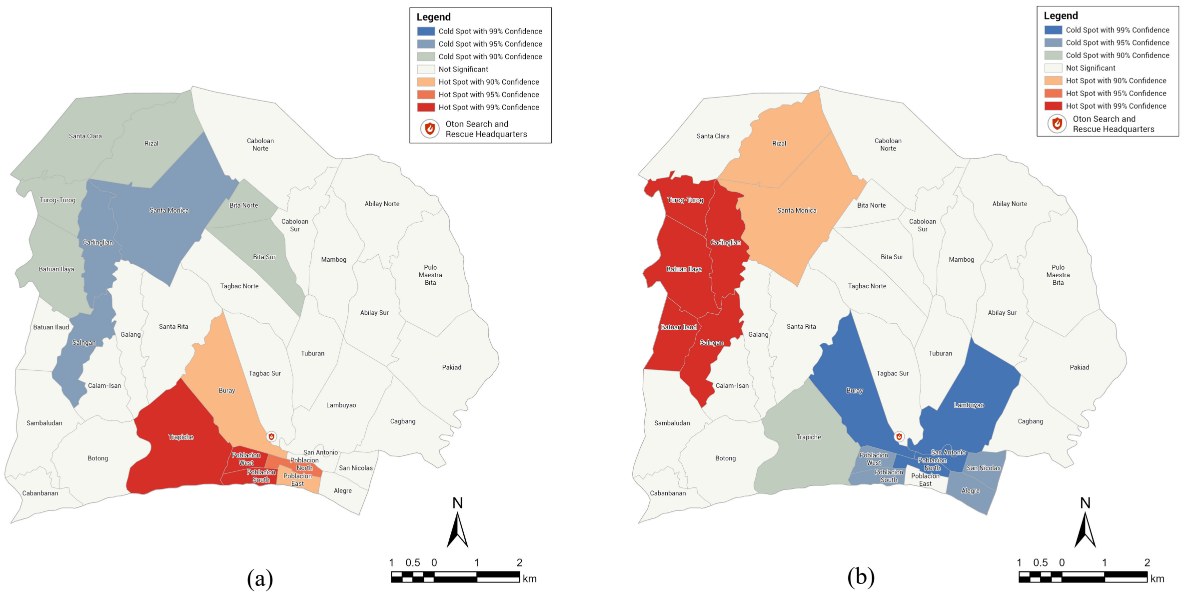

Figure 6. Getis-Ord Gi* hotspot analysis maps of (a) emergency incident count and (b) average emergency response times in Oton, Iloilo. Red denotes barangay hotspots, meaning they have significantly higher numbers of incidents (a) or longer response times (b) compared to other areas. Blue denotes barangay coldspots, with lower incident counts or faster response times. The darker the color, the higher the level of statistical confidence.

prominent clusters of emergency incident hotspots at the 90-99% confidence level were observed in the southern barangays, specifically Trapiche and all four Poblacion barangays (East, West, North, and South). This reflects the urbanized nature and higher population density of the town proper where potentially more incidents occur. In contrast, barangays located in the northwestern and central interior zones, such as Santa Monica, Salngan, and Cadinglian, emerged as cold spots with 90-95% confidence level, indicating a lower frequency of recorded incidents and can possibly be attributed to rural and less densely populated environments. The rest of the municipality shows no significant clustering, indicating a more dispersed or random pattern of incident distribution.

On the other hand, hotspot analysis of emergency response times (Figure 6b) revealed an inverse spatial dynamic. The longest response times (hotspots at 99% confidence level) are heavily concentrated in the western corridor — from Turog-Turog, Cadinglian, Batuan Ilaya, Batuan Ilaud, and Salngan. Nearby barangays such as Rizal and Santa Monica also emerged as hotspots with 90% confidence. These barangays, while less incident-prone, appear to face logistical or accessibility challenges that delay emergency response. Southern-central barangays formed cold spot clusters for response times, meaning emergency responses here are significantly quicker.

Buray, Lambuyao, San Antonio, and Poblacion North appeared as cold spots with 99% confidence; Poblacion South, Poblacion West, Alegre, and San Nicolas as cold spots with 95% confidence, and Trapiche with 90% confidence. These areas are likely closer to central dispatch units, more accessible by road, and better integrated into the local response network.

3.4 Temporal Patterns in Emergency Incidents and Response

To establish a general understanding of the emergency activity distribution over time, a calendar heat map was generated to visualize daily incident counts across the months of the study period (Figure 7). Figure 7 reveals that emergency incidents were not evenly distributed but instead exhibited distinct clusters of heightened activity during the -ber months, particularly November and December.

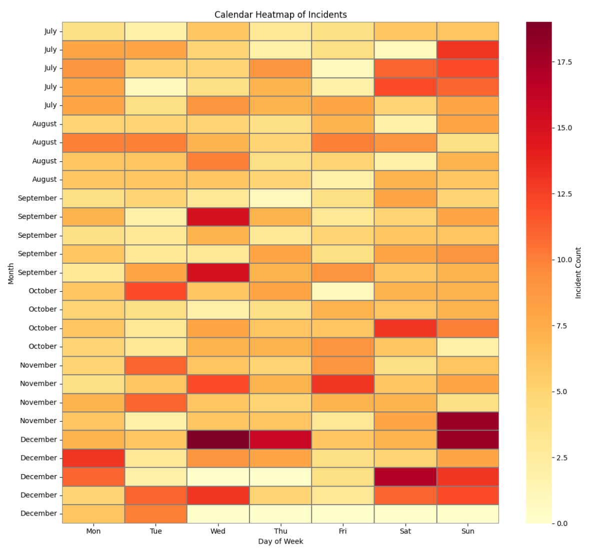

Figure 7. Calendar heatmap of daily emergency incidents across months.

It was also noted that some days, particularly Tuesdays, Wednesdays, and weekends, showed consistently higher incident volumes. This suggests potential event-driven patterns influencing emergency demands on these days. The presence of dark red cells in December weekends, for example, may reflect risks related to holidays like increased mobility and gatherings. In contrast, months like July and August appeared less incident prone.

A seven-day rolling average was applied to better capture the underlying temporal trends in emergency incident volume

(Figure 8). From July to early November, the trend remained moderately stable, fluctuating between four and eight average daily incidents. However, a marked upward shift is visible beginning in mid-November, culminating in a sharp peak in early December, which suggest a sustained build-up of emergency cases leading into the holiday season.

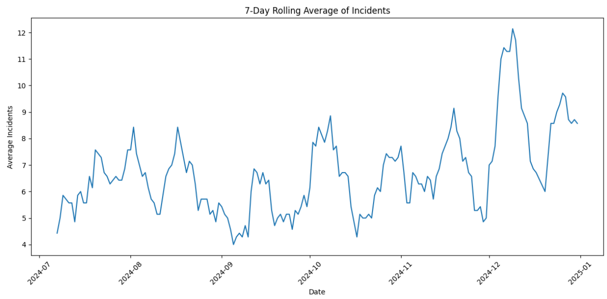

Figure 8. Seven-day rolling average of emergency incident counts.

Incidents were also analyzed by day of the week (Figure 9); a detailed breakdown of incident counts across the week revealed that Sunday consistently had the highest number of incidents, followed by Wednesday and Saturday, while Friday saw the lowest. These findings point to both end-of-week surges and midweek peaks.

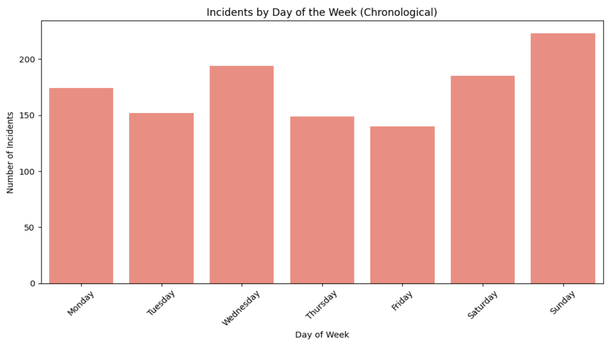

Figure 9. Total emergency incidents by day of the week.

Figure 10 examines how response times varied across different hours of the day during the study period. The data reveal moderate hourly fluctuations, with average response times ranging from just under 4.0 minutes to nearly 7.8 minutes. The most efficient responses were recorded during early morning and late evening hours, particularly around 3:00 AM and 11:00 PM, while the slowest responses occurred during the late morning to early afternoon, peaking at 11:00 AM and 1:00 PM with the highest average response times observed.

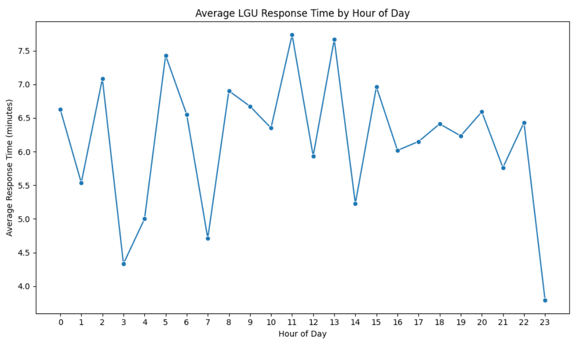

Figure 10. Average LGU emergency response time by hour of day.

4. Conclusions

This study analyzed the spatial distribution and temporal patterns of emergency response operations in Oton, Iloilo. Through geospatial and statistical analyses, critical hotspots of emergency incidents and areas with consistently prolonged response times were identified, indicating unequal service coverage.

Using Getis-Ord Gi*, the study revealed that hotspots of emergency incidents and delayed response times were heavily concentrated in urbanized and highly populated barangays. Moreover, Global Moran's I and Anselin Local Moran's I confirmed strong spatial autocorrelation, indicating non-random clustering of high incident counts and slow response times. However, some peripheral and inland barangays showed significantly longer response times despite having fewer incidents — suggesting logistical challenges, limited access routes, or inadequate station proximity. This can be indicative of a need for decentralization or redistribution of response units to areas with coverage gaps.

Furthermore, temporal analysis revealed notable fluctuations in emergency response performance across different time periods, with certain hours and days associated with longer response times, likely due to traffic congestion, limited personnel availability, or operational inefficiencies. Temporal disaggregation of the data revealed that response times tend to spike during evening hours and weekends, aligning with known periods of high demand and low personnel availability. Emergency incidents also showed cyclical patterns, with certain months, days of the week, and hours of the day experiencing surges.

For future studies, it is recommended to use emergency incident data covering a longer time span. A more extended study period would provide a clearer picture of trends, seasonality, and operational patterns over time. It could incorporate formal time-series decomposition and regression approaches (e.g., Poisson models) to better capture seasonality and day-of-week effects in emergency response patterns. Incorporating additional factors such as road or transport networks, hazard exposure, weather conditions, and population density can further contextualize delays and service coverage gaps.

Additionally, utilizing precise point data for incident locations instead of aggregated barangay-level data will allow for more granular spatial analysis and better identification of micro-level service gaps. Record-keeping practices through the PCR forms can further be improved through digitization, geolocation, and performing redundancy checks to reduce errors and/or missing information. In this way, DRRM units can derive more comprehensive and accurate spatial-temporal patterns from historical emergency incident data.

Finally, it is highly recommended to explore GIS-based optimization models for improving the allocation and dispatching of emergency resources. Tools such as location-allocation analysis, network analysis and modeling, and real-time GIS dashboards can support more efficient and equitable emergency response planning in rapidly growing municipalities like Oton.

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References

Abante, A. M. R., 2022. Assessing Preparedness-Insufficiency Spatial Patterns and Geostatistics to Build-Back-Better: An Application in Malinao Albay, Philippines, 295–301. doi.org/10.1007/978-3-030-72543-3_67.

Abdalla, R., 2016. Evaluation of spatial analysis application for urban emergency management. *SpringerPlus*, 5(1), 1–10. doi.org/10.1186/S40064-016-3723-Y.

Anselin, L., 1995. Local Indicators of Spatial Association—LISA. *Geographical Analysis*, 27(2), 93–115. doi.org/10.1111/J.1538-4632.1995.TB00338.X.

Asadzadeh, A., Kötter, T., Fekete, A., Moghadas, M., Alizadeh, M., Zebardast, E., Weiss, D., Basirat, M., & Hutter, G., 2022. Urbanization, migration, and the challenges of resilience thinking in urban planning: Insights from two contrasting planning systems in Germany and Iran. *Cities*, 125. doi.org/10.1016/J.CITIES.2022.103642.

Austria, K. S., 2023. *4 Thematic Areas of Disaster Risk Reduction and Management*. Philippine Information Agency. mirror.pia.gov.ph/infographics/2023/07/07/4-thematic-areas-of-disaster-risk-reduction-and-management (1 April 2025).

Ballicud, N. P. U., 2014. *Mobi-MAPP: A Mobile Application for Quick Alert and Monitoring of Disasters*. dspace.cas.upm.edu.ph (17 October 2024).

de Los Santos, J. R. N., de Los Santos, M. G., Copino, R. C., & Loyaga, L., 2020. Bandilyo App: A Disaster Risk Reduction Monitoring and Incident Reporting System with Geolocation and SMS Technology. *2020 IEEE 12th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management, HNICEM 2020*. doi.org/10.1109/HNICEM51456.2020.9400138.

Domingo, S. N., 2017. *Institutional issues on disaster risk reduction and management* (Issues 2017–50). Philippine Institute for Development Studies (PIDS). pids.gov.ph (17 October 2024).

ESRI., n.d. Modeling spatial relationships—ArcGIS Pro. pro.arcgis.com (11 June 2025).

Fahad, Md. G. R., Zech, W. C., Nazari, R., & Karimi, M., 2022. Developing a Geospatial Framework for Severe Occupational Injuries Using Moran's I and Getis-Ord Gi* Statistics for Southeastern United States. *Natural Hazards Review*, *23*(3), 04022020. doi.org/10.1061/(ASCE)NH.1527-6996.0000566.

Hoff, A., 2023. Understanding Delays and Improving Emergency Response with GIS - Evergreen Fire Department in Evergreen, Colorado. *Geography and the Environment: Graduate Student Capstones*.

Kang, J., Wang, Z., Wang, Q., Dai, H., Zhang, J., & Wang, L., 2024. Temporal assessment of emergency response and rescue capability for hybrid hydrogen-gasoline fueling stations based on dynamic scenario construction. *International Journal of Hydrogen Energy*, *56*, 358–368. doi.org/10.1016/J.IJHYDENE.2023.12.189.

Maqsood, U., Tahir, A., Fatima, K., & Rahman, A., 2020. Interpreting rescue vehicle patterns using geovisual analytics for spatiotemporal resource allocation. *Arabian Journal of Geosciences*, 13(14). doi.org/10.1007/S12517-020-05643-W.

Municipality of Oton, 2023. Comprehensive Development Plan (CDP) 2023 - 2028. oton.gov.ph (22 May 2025).

Municipality of Oton, 2024. Citizen's Charter. oton.gov.ph (22 May 2025).

National Disaster Risk Reduction and Management Council (NDRRMC), 2024. National Disaster Response Plan (NDRP). ndrrmc.gov.ph (15 May 2025).

Oh, C.-S., Lee, S., & Kho, S.-Y., 2012. A Spatial Analysis about Arrival Delay and Dispatch Distribution of the 119 Rescue-Aid Service utilizing GIS - Gyeongsangbuk-Do Case Study. *KSCE Journal of Civil and Environmental Engineering Research*, 32(1D), 13–22. doi.org/10.12652/Ksce.2012.32.1D.013.

Ord, J. K., & Getis, A., 1995. Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis*, 27(4), 286–306. doi.org/10.1111/J.1538-4632.1995.TB00912.X.

Park, H. S., Kwon, S. A., & Azam, M., 2024. A study on GIS-based spatial analysis of emergency response for disaster management: Focusing on Seoul. *Heliyon*, 10(7). doi.org/10.1016/j.heliyon.2024.e28669.

Songchitruksa, P., & Zeng, X., 2010. Getis-ord spatial statistics to identify hot spots by using incident management data. *Transportation Research Record*, 2165, 42–51. doi.org/10.3141/2165-05.

Šterk, M., & Praprotnik, M., 2017. Improving emergency response logistics through advanced GIS. *Open Geospatial Data, Software and Standards*, *2*(1). doi.org/10.1186/s40965-017-0014-7.

Tsai, P. J., Lin, M. L., Chu, C. M., & Perng, C. H., 2009. Spatial autocorrelation analysis of health care hotspots in Taiwan in 2006. *BMC Public Health*, 9(1), 1–13. doi.org/10.1186/1471-2458-9-464/TABLES/2.

Wang, H., Ye, H., Liu, L., & Li, J., 2022. Evaluation and Obstacle Analysis of Emergency Response Capability in China. *International Journal of Environmental Research and Public Health 2022,* 19(16), 10200. doi.org/10.3390/IJERPH191610200.

Westbrook, T., & Costa, D. G., 2025. Emergency response in smart 15-minute cities: the space-time compression. *Urban, Planning and Transport Research*, 13(1). doi.org/10.1080/21650020.2025.2482831.

Yılankıran, F. Ç., & Guney, C., 2021. Emergency response with mobile geosocial sensing in the post-app era. *Transactions in GIS*, 25(2), 897–922. doi.org/10.1111/TGIS.12706.