*Journal of Quality Measurement and Analysis* *JQMA* 22(SI) 2026, 1-12
*e-ISSN:* 2600-8602 *http://www.ukm.my/jqma*
*https://doi.org/10.17576/jqma.22si.2026.01*

# SPATIAL CLUSTERING FOR NARCOTICS-RELATED ARRESTS IN MALAYSIA

(*Pengelompokan Ruang bagi Tangkapan Berkaitan Narkotik di Malaysia*)

‘ULYA ABDUL RAHIM, RAZIK RIDZUAN MOHD TAJUDDIN, LIM CHOONG WEI, AHMAD AZWAN AMIN NORDIN, MOHAMMAD KASSIM & MOHD FIRDAUS-RAIH

*ABSTRACT*

Malaysia’s proximity to the Golden Triangle has made it highly susceptible to narcotics crimes. Thus, the purpose of this research is to identify the spatial clustering and the hot spots of narcotics-related offences – distribution, possession, and positive urine. Using over 100,000 arrest records obtained from the Royal Malaysia Police for the year 2022, spatial autocorrelation was analyzed using Moran’s $I$ and Getis-Ord $G_i^*$. The results indicated significant positive spatial autocorrelation for all three offences, and among them, the distribution offences tended to cluster more than the other two offences. Furthermore, the hot spots for the distribution and possession offences were concentrated in the northern as well as central regions of Peninsular Malaysia, while the hotspots for positive urine offences were primarily located in the east coast region of Peninsular Malaysia. Sabah and Sarawak exhibited weak or insignificant clustering, suggesting limited spatial concentration of arrests for all three offences. These findings highlight the need for geographically targeted enforcement strategies and provide spatial intelligence that supports data-driven decision-making in narcotics prevention and rehabilitation policy planning.

*Keywords*: crime distribution pattern; Getis-Ord $G_i^*$; hot spots analysis; Moran’s $I$ index; narcotics arrests; spatial autocorrelation

*ABSTRAK*

Kedudukan Malaysia yang berhampiran dengan Segi Tiga Emas menjadikannya sangat terdedah kepada jenayah narkotik. Justeru, kajian ini bertujuan mengenal pasti pengelompokan ruang serta titik-titik panas bagi kesalahan berkaitan narkotik iaitu pengedaran, pemilikan, dan ujian air kencing positif. Dengan menggunakan lebih daripada 100,000 rekod tangkapan daripada Polis Diraja Malaysia bagi tahun 2022, autokorelasi ruang dianalisis menggunakan indeks Moran $I$ dan Getis-Ord $G_i^*$. Hasil kajian menunjukkan autokorelasi ruang positif yang signifikan bagi ketiga-tiga jenis kesalahan, dengan kesalahan pengedaran menunjukkan tahap pengelompokan yang lebih tinggi berbanding yang lain. Titik-titik panas kesalahan pengedaran dan pemilikan didapati tertumpu di bahagian utara dan tengah Semenanjung Malaysia, manakala kes ujian air kencing positif lebih tertumpu di pantai timur Semenanjung Malaysia. Sabah dan Sarawak pula menunjukkan pengelompokan yang lemah atau tidak signifikan, menandakan kepekatan ruang tangkapan yang terhad bagi ketiga-tiga kesalahan. Dapatan ini menekankan keperluan strategi penguatkuasaan yang disasarkan secara geografi serta menyediakan maklumat ruang untuk menyokong pembuatan keputusan berasaskan data dalam perancangan dasar pencegahan dan pemulihan narkotik.

*Kata kunci*: corak taburan jenayah, Getis-Ord $G_i^*$; analisis titik-titik panas, indeks Moran’s $I$; tangkapan narkotik, autokorelasi ruang

## 1. Introduction

Malaysia occupies a strategic position in Southeast Asia that is close to the hub of narcotics production known as the Golden Triangle, encompassing Myanmar, Thailand and Laos and has thus become the target and transit point for various narcotics crime related activities (Organization for Economic Cooperation and Development (OECD) 2023). Direct or indirect involvement of Malaysia in narcotics activities can result in higher crime rates that would pose a challenge to law enforcement and public health. Narcotics-related offences in Malaysia generally include, but are not limited to distribution, possession and urine samples that are positive for narcotics (positive urine). The types and amount of the illegal substances differentiate a possession offence versus a distribution offence.

It is important to note that there is some distinction between arrests and crimes. Crimes are genereally defined as acts that violates formal norms and laws, as well as break social norms (Little 2016). On the other hand, arrests have no standard definition as it depends on the police practices (Harmon 2016). However, it can be explained as a reflection of both the underlying incidence of crime and law enforcement because not all crimes lead to arrests and consequently, the arrest probabilities vary by place, crime type and policing intensity (Black 1970).

A recent bibliometric review revealed that there is a clear imbalance in spatiotemporal analysis of narcotics-related activities (Tajuddin *et al*. 2025). Identifying areas that are prone to narcotics-related offences provides significant informative advantages to the authorities and government in combating narcotics misuse as well as effective policymaking. Therefore, geographical patterns of these offences can be examined and leveraged via the use of spatial association indicators. Conventionally, spatial autocorrelation statistics such as Moran's $I$ (Moran 1950) and Getis-Ord $G_i^*$ (Getis & Ord 1992) statistics are used in explaining spatial association. These two statistics are often used in quantitative criminology, as seen in numerous studies (Abdulhafedh 2017; Ahmad *et al*. 2024; Anselin 1995; Getis & Ord 1992; Moran 1950; Newton 2015; Ord & Getis 1995), including overdose mortality (Jones *et al*. 2018; Marotta *et al*. 2019; Stopka *et al*. 2023).

Moran's $I$ may be defined as the measure concerning spatial autocorrelation, which describes the extent of grouping of similar values in some set and their dispersion among the geographical space. Moran's $I$ helps in identifying spatial patterns, indicating whether low or high values with regard to a variable are spatially clustered, dispersed, or randomly distributed (Moran 1950). This measure also helps to determine whether these offences are dispersed randomly, exhibit a clustered pattern, or are evenly distributed across the region (Chainey & Ratcliffe 2013; Moran 1950).

Getis and Ord (1992) established a set of statistics called $G$ that can be used to assess spatial association in any situation. This measure enables the assessment regarding the spatial association with respect to a variable at a given distance from a single point. Furthermore, Getis and Ord (1992) highlighted the need to employ both $G$ statistics and Moran's $I$ index to reveal aspects of spatial patterns that Moran's $I$ alone may not be able to detect. The $G$ statistics were further explored in regards to the analysis of local patterns in spatial data, enabling the non-binary weights and establishing a connection between these statistics and Moran's $I$ index (Ord & Getis 1995).

Similarly, Abdulhafedh (2017) introduces a novel hybrid approach for identifying crash clustering patterns by combining 30% of Moran's $I$ with 70% of Getis-Ord $G_i^*$ statistic. The discovery was a new set of statistically significant spatial clusters that reveal low as well as high values of spatial autocorrelation and found significant differences in distinct weights (Abdulhafedh 2017). Similarly, Mohammed and Baiee (2020) utilized the Getis-Ord $G_i^*$ statistic for spatial analysis to determine statistically substantial crime areas, including hot spots and cold spots in Baltimore City, from 2012 to 2018 for several crimes such as shootings, homicides, and assaults.

The use of Getis-Ord $G_i^*$ statistics application in crime incidents mapping and hot spot analysis using Geographic Information Systems (GIS) are well recognized (Ahmad *et al*. 2024; Mokhtar *et al*. 2023). Mokhtar *et al*. (2023) have applied the Getis-Ord $G_i^*$ statistics in developing hot spots and cold spots while incorporating GIS. On the other hand, Ahmad *et al*. (2024) examined the relationship that exists between temporal patterns, violent criminal activities, as well as land use across the states of Selangor, Putrajaya Federal Territory, and Kuala Lumpur Federal Territory in Malaysia from the year of 2015 to 2020. The study underscores the influence of land use on criminal behaviour, showing a significant correlation between violent crime hot spots and residential areas or transportation infrastructures (Ahmad *et al*. 2024). Furthermore, Nix *et al*. (2024) and Santos and Santos (2021) emphasized the significance of preventing crime at the neighbourhood level. Hence, it is important to investigate the effects of gun ownership on its relation to other crimes, such as property crimes, to establish policy solutions (Jubit *et al*. 2020; Tavares & Costa 2021).

Both indices are also commonly used in studying on overdose mortality, especially opiod-related deaths (Jones *et al*. 2018; Marotta *et al*. 2019; Stopka *et al*. 2023). Jones *et al*. (2018) have investigated the relationship between buprenorphine provider availability and opiod deaths in US counties and significant clustering in the distribution of both providers and deaths were identified using Moran's *I* index. Using Moran's *I* index as well, a study conducted by Marotta *et al*. (2019) revealed that the opiod overdose deaths are clustered in New York, which may be along the opioid trafficking routes in New York. Getis-Ord $G_i^*$ statistics helped in producing dynamic heatmaps of opiod-related mortality in Massachussets for all types of opiods, genders and races, which collectively showed intense heat in the heatmaps from 2016 to 2021.

This study employs Moran's *I* to investigate the spatial distribution of narcotics-related offences across various regions in Malaysia. By examining whether these offences are randomly distributed or exhibit significant spatial clustering, the objective of this analysis is to outline the underlying spatial behaviour. Hence, identifying hot spots as well as cold spots for narcotics-related offences is critical for effective resource allocation and targeted intervention strategies. To achieve this, the Getis-Ord $G_i^*$ statistics was employed to highlight statistically substantial hot spots where narcotics activities are most concentrated.

This research aligns with the United Nations Sustainable Development Goals (SDG), specifically Goal 3 (Good Health and Well-being) as well as Goal 16 (Peace, Justice, and Strong Institutions). By studying the spatial distribution of narcotics-related offences, this research supports efforts to combat substance abuse, enhance public safety in urban areas, and strengthen institutions to reduce narcotics activities, crime and violence. This approach promotes data-driven policymaking to create healthier, safer and more sustainable communities in Malaysia.

## 2. Moran's *I*

Moran's *I* measures the spatial autocorrelation that measures how similar values in a dataset are in a geographic space or how grouped they are. Consequently, the null as well as alternative hypotheses are given as:

$$H_0 : I = 0$$
$$H_1 : I \neq 0$$

Alternatively, we can write:

$H_0$ : There is no spatial autocorrrelation
$H_1$ : There is spatial autocorrrelation

Moran's $I$ statistic is among the best-known measures of spatial autocorrelation and may be utilized for the analysis of both the local as well as global spatial autocorrelation for continuous variables. Concerning any continuous variable $x_i$, the mean $\bar{x}$ may be determined, and thus, for any of the observations, the deviation can be obtained by summing the products of deviations and cross-products of deviations. As such, the statistic in question simply equates the value with regard to the variable at a particular place with the values of the variable at every other place (Anselin 1992; Goodchild 1986; Griffith 1987). For $n$ observations of a variable $x$ at locations $i$ and $j$, Global Moran's $I$ may be determined as given below (Anselin 1995) :

$$I = \frac{n\sum_{i}^{n}\sum_{j}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{S_0 \sum_{i}^{n}\left(x_i - \bar{x}\right)^2}, \tag{1}$$

in which
$n =$ the number of observations,
$x_i =$ the value of the variable $x$ at location $i$,
$x_j =$ the value of the variable $x$ at location $j$,
$\bar{x} =$ the sample mean of the variable $x$,
$w_{ij} =$ the elements with regard to the weight matrix,
$S_o =$ the sum of the elements with regard to the weight matrix, $S_o = \sum_i^n \sum_j^n w_{ij}$.
Note that the mean and the variance of the Moran's $I$ are correspondingly given as:

$$\begin{aligned} E(I) &= -\frac{1}{n-1}, \\ Var(I) &= \frac{nS_4 - S_3 S_5}{(n-1)(n-2)(n-3)S_0^2} - \left(\frac{1}{n-1}\right)^2, \end{aligned} \tag{2}$$

in which

$$S_1 = \sum_i \sum_j \left(w_{ij} + w_{ji}\right)^2,$$

$$S_2 = \sum_i \left(\sum_j w_{ij} + \sum_j w_{ji}\right)^2,$$

$$S_3 = \frac{\frac{1}{n}\sum_i \left(x_i - \bar{x}\right)^4}{\left[\frac{1}{n}\sum_i \left(x_i - \bar{x}\right)^2\right]^2},$$

$$S_4 = \left(n^2 - 3n + 3\right)S_1 - nS_2 + 3S_0^2,$$

$$S_5 = n\left(n-1\right)S_1 - 2nS_2 + 6S_0^2.$$

Moran's $I$ can be converted into z-scores to arrive at the p-value. Moran's $I$ interpretation is sometimes based on previous research. In general, a favourable Moran's $I$ value suggests that the various values are clustered, meaning that they are located close to each other in space. If Moran's $I$ is negative, then this further indicates spatial dispersion in which the values that are dissimilar are actually clustered together. The Moran's $I$ value, which is very close to zero, resembles the spatial pattern described in the study and is completely random, with no tendency for clustering or dispersion (Moran 1950).

## 3. Getis Ord $G_i^*$ Statistic

The Getis-Ord $G_i^*$ statistic refers to a spatial analysis tool utilized in the identification of hot and cold spots from spatial data. It identifies hot spots as well as cold spots by computing the density of values within a given radius of each data point relative to an overall average. This method is especially applied in such disciplines as geography, epidemiology, criminology, and environmental science (Getis & Ord 1992). The $G_i^*$ statistic returned with regard to each feature in the dataset refers to a z-score. If the z-scores are positive and statistically significant, the higher the z-score, the higher the level of clustering, denoting hot spots. For statistically substantial negative z-scores, the smaller the z-score is, the stronger the cluster of low values or cold spots (Getis & Ord 1992).

### 3.1. *Local $G_i^*$ statistic*

The Getis-Ord $G_i^*$ statistic is determined based on a user-defined threshold distance, unlike Moran's $I$, which relies on inverse distance (Getis & Ord 1992). The Global $G$ statistic provides a singular value representing spatial autocorrelation across the entire study area, whereas the $G_i^*$ statistic gives the local spatial autocorrelation for individual data points. The local $G_i^*$ statistic is computed as given below (Getis & Ord 1992):

$$G_i{*} = \frac{\sum_{j}^{n} w_{ij} x_j}{\sum_{j}^{n} x_j}, \qquad (3)$$

where

$$w_{ij} = \begin{cases} 1 \;;\; \text{if } i \text{ and } j \text{ are neighbours} \\ 0 \;;\; \qquad\qquad \text{otherwise} \end{cases},$$

with its Z-score given as:

$$Z\left(G_i^*\right) = \frac{\sum_{j}^{n} w_{ij} x_j - \bar{x} \sum_{j}^{n} w_{ij}}{S \sqrt{\frac{n \sum_{j}^{n} w_{ij}^{2} - \left( \sum_{j}^{n} w_{ij} \right)^{2}}{n-1}}},$$

in which

$n =$ the number with regard to observations,

$x_j =$ the attribute value at location $j$,

$w_{ij}$ = the spatial weight that exists between location $i$ and $j$,
$\bar{X}$ = the mean with regard to the attribute values,
$S$ = the standard deviation with regard to the attribute values.

The neighbours are identified using k-NN approach where $k = 4$ and row standardized spatial weight is used to allow for even isolated locations to have connection with neighbouring locations. General conclusions from $G_i^*$ statistics and $Z(G_i^*)$ values are presented in Table 1.

Table 1: $G_i^*$ statistics and $Z(G_i^*)$ interpretation and conclusions.

| $G_i^*$ statistics | $Z(G_i^*)$ values | Observation | Interpretation | Conclusion |
|---|---|---|---|---|
| High | $Z \geq 1.96$ | Significant hot spot | Cluster of high values. | Area has significantly higher narcotics arrests than expected by chance |
| Near zero | $-1.96 < Z < 1.96$ | No significant clustering | Random distribution of values. | No spatial pattern detected |
| Low | $Z \leq -1.96$ | Significant cold spot | Cluster of low values. | Area has significantly lower narcotics arrests than expected by chance |

## 4. Data, Results and Discussions

### 4.1. *Data*

The data used in this study is 141,352 individual arrests data for the year of 2022. The data was obtained directly from the Royal Malaysia Police (RMP). The type of offences associated with each arrest, as well as the name of the police department that made the arrests are provided as well in the dataset. The names of the police department are converted into latitude and longitude in order to obtain the spatial weight between location $i$ and $j$, $w_{ij}$.

### 4.2. *Moran's I statistics*

Applying Moran's $I$ global statistic is handy in terms of analyzing the spatial clustering of narcotics-related offences within the area of interest. This section displays the findings of Moran's $I$ analysis, in which we assess the degree of spatial autocorrelation. The outcomes from Moran's $I$ analysis are vital in understanding the spatial behaviour of narcotics-related offences. By revealing whether these activities are clustered, randomly distributed, or dispersed, Moran's $I$ statistic helps to identify underlying spatial patterns that might not be evident through simple observation. This information is invaluable for law enforcement and policymakers, as it can guide the implementation of targeted interventions and resource allocation, as well as the development of strategies aimed at disrupting these clusters.

Table 2 presents Moran's $I$ value for three types of narcotics-related offences. Since all three offences returned a p-value of less than 0.0001, it is clear that the spatial pattens observed are not a result of random chance, meaning that the narcotics-related arrests across Malaysia follow a consistent and statistically significant clustering pattern.

That said, the degree of clustering differs across the offences. Among them, distribution arrests showed the strongest spatial clustering, with a Moran's $I$ value of 0.6767. This demonstrates that areas with high or low distribution activity tend to be geographically close to one another, pointing to well-defined zones where drug distribution is concentrated. Possession arrests followed with a Moran's $I$ value of 0.5999, reflecting a similarly strong but slightly less notable clustering pattern. Positive urine arrests recorded the lowest Moran's $I$ value of 0.3134, which, while comparatively weaker, still indicates meaningful spatial clustering that goes beyond random variation.

Table 2: Type of narcotics-related offences identified by Moran's $I$ value

| Type of narcotics-related offences | Moran's $I$ | p-value | Interpretation |
|---|---|---|---|
| Distribution | 0.6767 | < 0.0001 | Statistically significant positive spatial autocorrelation |
| Possession | 0.5999 | < 0.0001 | Statistically significant positive spatial autocorrelation |
| Positive urine | 0.3134 | < 0.0001 | Statistically significant positive spatial autocorrelation |

Taken together, these results make it evident that narcotics-related arrests in Malaysia do not occur at random, in which there are clearly identifiable areas where such activities are more concentrated than others. Distribution offences appear to be the most spatially defined, followed by possession and positive urine offences. To better understand where exactly these concentrations occur, the analysis proceeds with Getis-Ord $G_i^*$ statistics to pinpoint specific hot spot and cold spot locations.

### 4.3. *Getis-Ord $G_i^*$ statistic*

Interpreting Getis-Ord $G_i^*$ results involved the understanding of how spatial patterns of the variables are distributed across a geographic area. The graph usually employs a colour gradient to represent the significance of hot spots and cold spots areas. The hot spot areas are denoted by warm colours, such as red or orange, whereas the cold spots areas use cool colours, such as blue or light blue. Areas with no significant clustering might be shown in neutral colours, such as white or grey (Chainey & Ratcliffe 2013; Getis & Ord 1992). In this study, the hot spots are denoted by the clour of red whereas the cold spots are denoted by the colour of blue. The neutral zone are denoted by dark grey. For standardization purposes, the $G_i^*$ statistics is converted into $Z(G_i^*)$ values and used for mapping.

#### 4.3.1 *Distribution arrests*

Figure 1 illustrates the hot spot and not significant areas for distribution arrests identified using the Getis-Ord $G_i^*$ method. The analysis identified ten statistically significant hot spot areas in the central region of Peninsular Malaysia, namely Brickfields, Ampang Jaya, Sentul, Dang Wangi, Wangsa Maju, Cheras, Gombak, Petaling Jaya, Sungai Buloh, and Kajang, where high values of narcotics distribution activities are significantly clustered. Meanwhile, in the northern region of Peninsular Malaysia, six statistically significant hot spot areas were identified, specifically Seberang Perai Utara, Yan, Kuala Muda, Timur Laut, Seberang Perai Tengah, and Barat Daya, all demonstrating significant spatial clustering of narcotics distribution arrests. These concentrations are likely attributable to urban density and transportation accessibility, which make drug trafficking operations more feasible in these areas (Desrosiers *et al*. 2016; Jamaluddin *et al*. 2018; Rahimin & Ken 2025).

In contrast, the East Malaysia states of Sabah and Sarawak, as well as the remaining areas of Peninsular Malaysia, showed no statistically significant clustering, as indicated by the Not Significant classification. This suggests that distribution arrests in these areas are spatially random and do not form identifiable clusters, which may be partly explained by lower population density compared to Peninsular Malaysia (Pierce 2024). Notably, no cold spots were detected for distribution arrests, indicating the absence of any significant clustering of low narcotics activity across Malaysia.

These findings highlight specific areas that may require more targeted intervention strategies by the Royal Malaysia Police (RMP), including increasing the frequency of targeted raids and enhancing police presence in identified hot spot locations. By focusing resources on these hot spots, enforcement efforts can be allocated more efficiently, potentially reducing the incidence of narcotics distribution activities in these regions.

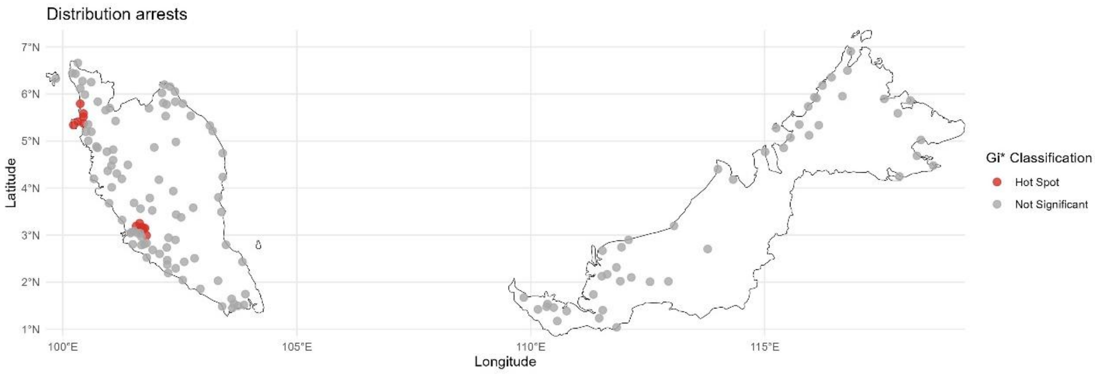


Figure 1: Getis-Ord $G_i^*$ analysis for distribution arrests

### 4.3.2 *Possession arrests*

Figure 2 illustrates the hot spot, not significant, and cold spot areas for possession arrests identified using the Getis-Ord $G_i^*$ method. The analysis identified 14 statistically significant hot spot areas in the central region of Peninsular Malaysia, namely Brickfields, Ampang Jaya, Sentul, Dang Wangi, Wangsa Maju, Cheras, Gombak, Sungai Buloh, Petaling Jaya, Shah Alam, Kuala Selangor, Klang, Klang Utara and Putrajaya, where high values of narcotics possession activities are significantly clustered. In the northern region of Peninsular Malaysia, 12 statistically significant hot spot areas were identified, namely Seberang Perai Utara, Kulim, Bandar Bharu, Kuala Muda, Timur Laut, Seberang Perai Tengah, Seberang Perai Selatan, Yan, Tumpat, Bachok, Pasir Mas and Barat Daya, all demonstrating significant spatial clustering of narcotics possession arrests. These concentrations may be attributed to intense policing (Zhang *et al*. 2022) or the presence of active localised drug markets in these areas (Donnelly *et al*. 2021).

In contrast, several areas in southwestern Sarawak which are Saratok, Lubuk Antu, Betong, Sibu, Sri Aman and Kapit exhibited statistically significant cold spots, indicating clusters of significantly low narcotics possession activity in those locations. This pattern suggests lower rates of narcotics offences in these areas, which may reflect either genuinely safer environments or limited policing presence in rural and less populated neighbourhoods. Meanwhile, Sabah and the remaining areas of Peninsular Malaysia showed no statistically significant clustering, as indicated by the Not Significant classification, suggesting that possession arrests in these areas are spatially random.

These findings highlight specific areas that may require more focused intervention strategies by the Royal Malaysia Police (RMP), such as increasing the frequency of targeted raids and enhancing police presence in identified hot spot locations (Braga 2001). By directing resources towards these hot spots, enforcement efforts can be allocated more efficiently, potentially reducing the incidence of narcotics possession activities across Malaysia.

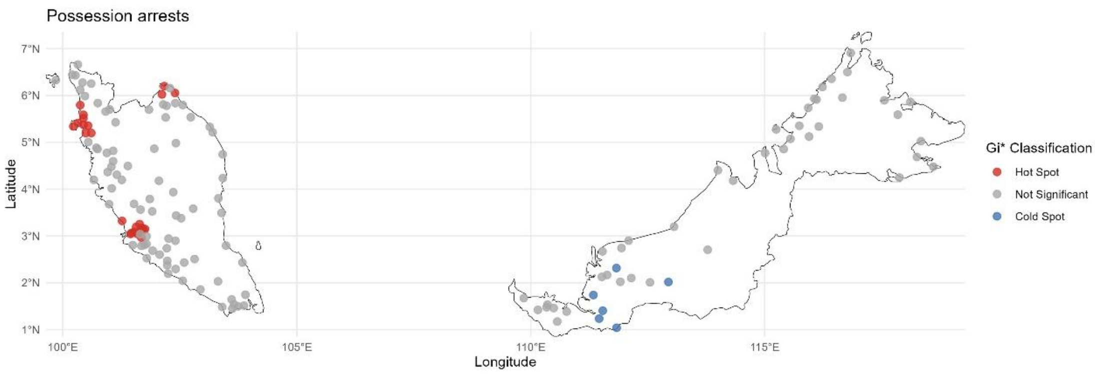


Figure 2: Getis-Ord $G_i^*$ analysis for possession arrests

### 4.3.3 *Positive urine arrests*

Figure 3 illustrates the hot spot, not significant, and cold spot areas for positive urine arrests identified using the Getis-Ord $G_i^*$ method. The analysis identified eleven statistically significant hot spot areas on the east coast of Peninsular Malaysia, namely Dungun, Pekan, Kemaman, Maran, Hulu Terengganu, Marang, Setiu, Kuantan, Bachok, Tumpat, and Kuala Terengganu, where positive urine arrest activities are significantly clustered. These findings suggest that positive urine arrests are densely concentrated in specific geographic areas, pointing to locations with potentially higher drug consumption activity, which could be linked to higher nightlife activity or more frequent urine screening operations conducted by enforcement agencies in these areas.

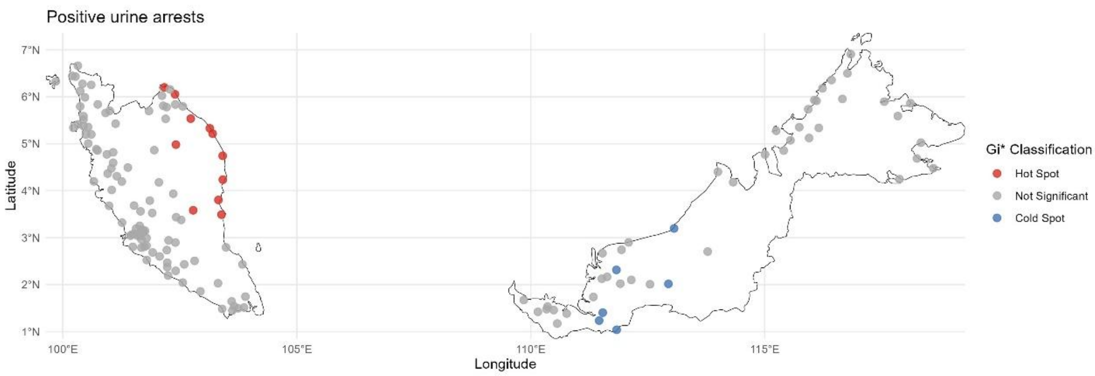


Figure 3: Getis-Ord $G_i^*$ analysis for positive urine arrests

Interestingly, areas in central Peninsular Malaysia that previously showed hot spots for distribution and possession arrests appear as Not Significant for positive urine arrests. This contrast may suggest that these areas function as narcotics distribution hubs, where drugs are trafficked and sold but consumed elsewhere. Alternatively, it could reflect a deterrence effect resulting from intense law enforcement operations in these areas, causing users to relocate their consumption activities to other regions (Braga 2001).

In East Malaysia, several areas in Sarawak which are Lubuk Antu, Sibu, Bentong, Bintulu, Sri Aman and Kapit exhibited statistically significant cold spots, indicating significantly low positive urine arrest activity, while Sabah and the remaining areas showed no statistically significant clustering. These patterns are consistent with the findings observed in the distribution and possession arrest analyses.

These findings suggest that hot spot areas identified for positive urine arrests may require more targeted intervention strategies by the Royal Malaysia Police (RMP), particularly in rehabilitation and urine screening programmes. By focusing resources on these hot spots, enforcement and rehabilitation efforts can be allocated more efficiently, potentially reducing narcotics consumption activities across Malaysia.

## 5. Conclusion

The findings of this study reveal that there is significant spatial clustering for all three types of offences – distribution, possession and positive urine tests, indicating that narcotics activities are generally clustered into specific regions rather than randomly distributed. Consequently, these results underscore the need for location-based strategies for effective intervention.

It is important to note that the analysis presented here is based on the arrest records and thus, may not reflect the true narcotics crimes. Therefore, our findings should be interpreted as spatial patterns of arrest distribution, which is useful for operational planning but caution must be exercised when explaining true underlying narcotics crime prevalence.

The spatial intelligence such as the recognition of clustering patterns through hot spots, demonstrated in this study can support efficient enforcement by the Royal Malaysia Police (RMP), especially in high-risk zones, thereby optimizing manpower and funding allocation. Local communities and agencies should also cooperate with the RMP by introducing and implementing successful rehabilitation programs whilst identifying any emerging hot spots in neighbouring areas.

This study demonstrates the practical value of spatial analytics in drug enforcement and policymaking, contributing to SDG 3 (Good Health and Well-being) and SDG 16 (Peace, Justice, and Strong Institutions). Future research should consider integrating socioeconomic and demographic factors such as unemployment, income inequality, urbanization, enforcement intensity, family and education background to better understand the underlying causal effect driving the spatial clustering patterns of narcotics activities. Incorporating these factors at a microlevel can provide more comprehensive insights for evidence-based policymaking and targeted interventions.

## Acknowledgement

The funding for this study was provided by the Universiti Kebangsaan Malaysia Geran Galakan Penyelidik Muda grant scheme (Grant code: GGPM-2023-052) and the NCID-UKM technical collaboration program (Grant code: ST-2023-041). Narcotics crimes data were provided by the Narcotics Criminal Investigation Department, Royal Malaysia Police.

### References

Abdulhafedh A. 2017. A novel hybrid method for measuring the spatial autocorrelation of vehicular crashes: Combining Moran's index and Getis-Ord $G_i^*$ statistics. *Open Journal of Civil Engineering* **7**(2): 208–221.

Ahmad A., Masron T., Kimura Y., Barawi M.H., Jubit N., Junaini S.N., Redzuan M.S., Mohd Ali A.S. & Bismelah L.H. 2024. Unveiling urban violence crime in the State of the Selangor, Kuala Lumpur and Putrajaya: A spatial–temporal investigation of violence crime in Malaysia's key cities. *Cogent Social Sciences* **10**(1): 2347411.

Anselin L. 1992. *SpaceStat: A Program for the Statistical Analysis of Spatial Data*. National Center for Geographic Information and Analysis, University of California.

Anselin L. 1995. Local indicators of spatial association—LISA. *Geographical Analysis* **27**(2): 93–115.

Black D.J. 1970. The social organization of arrest. *Stanford Law Review* **23**: 1087–1111.

Braga A.A. 2001. The effects of hot spots policing on crime. *The ANNALS of the American Academy of Political and Social Science* **578**(1): 104–125.

Chainey S. & Ratcliffe J. 2013. *GIS and Crime Mapping*. Chichester, UK: John Wiley & Sons.

Desrosiers A., Chooi W.-T., Zaharim N.M., Ahmad I., Mohd Yasin M.A., Syed Jaapar S.Z., Schottenfeld R.S., Vicknasingam B. & Chawarski M.C. 2016. Emerging drug use trends in Kelantan, Malaysia. *Journal of Psychoactive Drugs* **48**(3): 218–226.

Donnelly E.A., Wagner J., Stenger M., Cortina H.G., O'Connell D.J. & Anderson T.L. 2021. Opioids, race, and drug enforcement: Exploring local relationships between neighborhood context and Black–White opioid-related possession arrests. *Criminal Justice Policy Review* **32**(3): 219–244.

Getis A. & Ord J.K. 1992. The analysis of spatial association by use of distance statistics. *Geographical Analysis* **24**(3): 189–206.

Goodchild M.F. 1986. *Spatial Autocorrelation*. Norwich, UK: Geo Books.

Griffith D. 1987. *Spatial Autocorrelation: A Primer Resource Publications in Geography*. Washington, DC: Association of American Geographers.

Harmon R.A. 2016. Why arrest? *Michigan Law Review* **115**(3): 307–369.

Jamaluddin A.S., Rasam A.R.A., Khalid N. & Halim M.A. 2018. Exploring open source GIS for drug mapping and analysis in Malaysia. *Proceedings of the 2018 IEEE 8th International Conference on System Engineering and Technology*, pp. 91–96.

Jones C.W., Christman Z., Smith C.M., Safferman M.R., Salzman M., Baston K. & Haroz R. 2018. Comparison between buprenorphine provider availability and opioid deaths among US counties. *Journal of Substance Abuse Treatment* **93**: 19–25.

Jubit N., Masron T. & Marzuki A. 2020. Analyzing the spatial temporal of property crime hot spots. A case study of Kuching, Sarawak. *Planning Malaysia* **18**(4): 1–11.

Little W. 2016. *Introduction to Sociology.* (2nd Canadian Ed.). Victoria, British Columbia, Canada: BCcampus.

Marotta P.L., Hunt T., Gilbert L., Wu E., Goddard-Eckrich D. & El-Bassel N. 2019. Assessing spatial relationships between prescription drugs, race, and overdose in New York State from 2013 to 2015. *Journal of Psychoactive Drugs* **51**(4): 360–370.

Mohammed A.F. & Baiee W.R. 2020. Analysis of criminal spatial events in GIS for predicting hotspots. *IOP Conference Series: Materials Science and Engineering* **928**(3): 032071.

Mokhtar E.S., Ghazali N., Md Sadek E.S.S., Mohd Sidek N.Z., Shaharudin M.R., Effendi L. & Ramli A.R.A. 2023. Pemetaan hotspot kes jenayah kawasan Lembah Klang menggunakan kaedah Geographical Information System (GIS). *Journal of Public Security and Safety* **15**(1): 1–15.

Moran P.A.P. 1950. Notes on continuous stochastic phenomena. *Biometrika* **37**(1/2): 17–23.

Newton A. 2015. Crime and the NTE: Multi-classification crime (MCC) hot spots in time and space. *Crime Science* **4**(1): 30.

Nix J., Huff J., Wolfe S.E., Pyrooz D.C. & Mourtgos S.M. 2024. When police pull back: Neighborhood-level effects of de-policing on violent and property crime, a research note. *Criminology* **62**(1): 156–171.

Ord J.K. & Getis A. 1995. Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis* **27**(4): 286–306.

Organization for Economic Cooperation and Development. 2023. *Malaysia Country Profile: Organized Crime Index 2023.* https://ocindex.net/assets/downloads/2023/english/ocindex_profile_malaysia_2023.pdf (2 May 2025).

Pierce J. 2024. Variation in the drug-crime relationship across rural-urban contexts. University of Maryland.

Rahimin D.N.A. & Ken D.W.T. 2025. Thailand-Malaysia border: A strategic route for illicit drug trade from the Golden Triangle (Sempadan Thailand-Malaysia: Laluan Perhubungan strategik bagi perdagangan haram dadah dari kawasan Segi Tiga Emas). *Asian Journal Of Environment, History and Heritage* **9**(1): 59–76.

Santos R.B. & Santos R.G. 2021. Proactive police response in property crime micro-time hot spots: Results from a partially-blocked blind random controlled trial. *Journal of Quantitative Criminology* **37**(1): 247–265.

Stopka T.J., Larochelle M.R., Li X., Bernson D., Li W., Ackerson L.K., Bayly R., Dammann O. & Bauer C. 2023. Opioid-related mortality: Dynamic temporal and spatial trends by drug type and demographic subpopulations, Massachusetts, 2005–2021. *Drug and Alcohol Dependence* **246**: 109836.

Tajuddin R.R.M., Ismail N., Kamaluddin M.R., Nordin A.A.A. & Firdaus-Raih M. 2025. Imbalance in spatiotemporal analysis of narcotics-related activities: A bibliometric review. *Humanities and Social Sciences Communications* **12**(1): 215.

Tavares J.P. & Costa A.C. 2021. Spatial modeling and analysis of the determinants of property crime in Portugal. *ISPRS International Journal of Geo-Information* **10**(11): 731.

Zhang A., Balles J.A., Nyland J.E., Nguyen T.H., White V.M. & Zgierska A.E. 2022. The relationship between police contacts for drug use-related crime and future arrests, incarceration, and overdoses: a retrospective observational study highlighting the need to break the vicious cycle. *Harm Reduction Journal* **19**(1): 67.

*Deanery Office*
*Faculty of Medicine*
*Universiti Kebangsaan Malaysia*
*56000 Cheras*
*Kuala Lumpur, MALAYSIA*
*E-mail: ulyaabdulrahim@ukm.edu.my*

*Department of Mathematical Sciences*
*Faculty of Science and Technology*
*Universiti Kebangsaan Malaysia*
*43600 UKM Bangi*
*Selangor, MALAYSIA*
*E-mail: rrmt@ukm.edu.my*[*]

*Narcotics Crime Investigation Department*
*Royal Malaysia Police Headquarters*
*50560 Bukit Aman*
*Kuala Lumpur, MALAYSIA*
*E-mail: limchoongwei@rmp.gov.my, aazwan@rmp.gov.my*

*Department of Chemical Sciences*
*Faculty of Science and Technology*
*Universiti Kebangsaan Malaysia*
*43600 UKM Bangi*
*Selangor, MALAYSIA*
*E-mail: mb_kassim@ukm.edu.my*

*Department of Applied Physics*
*Faculty of Science and Technology*
*Universiti Kebangsaan Malaysia*
*43600 UKM Bangi*
*Selangor, MALAYSIA*
*E-mail: firdaus@mfrlab.org*

Received: 8 August 2025
Accepted: 9 April 2026

[*]Corresponding author