Spatial Autocorrelation of Incarceration Counts Across National Capital Region (NCR) Jails

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Abstract: This study determines spatial autocorrelation of the number of commit across Bureau of Jail Management and Penology (BJMP) jails in National Capital Region (NCR). Data gathered is secondary data from the Regional Operations Division of BJMPRO-NCR including the quarterly count of commit from year 2021 to 2023 of both male and female jail dormitories of NCR.

Using Moran's Index to measure spatial autocorrelation to indicate the degree to which similar values cluster together in a spatial data set and further analysis using Getis-Ord Local Statistics.

1. Introduction

The Bureau of Jail Management and Penology (BJMP) is an agency under the Department of the Interior and Local Government (DILG) in the Philippines. It is responsible for overseeing the administration and management of all city, district, and municipal jails across the country. The BJMP's primary functions include the safekeeping and development of inmates, ensuring their welfare and security, and implementing rehabilitation programs to facilitate their reintegration into society. The bureau aims to promote humane treatment and provide opportunities for personal growth and development to reduce recidivism among the incarcerated population (BJMP Comprehensive Operations Manual 2015 Edition).
In the analysis of crime rates, the number of incarcerations jails can be considered a significant factor. This factor varies across different regions and cities and can be regarded as spatial data. This study aims to analyze the patterns of incarcerations in jails within the National Capital Region using spatial autocorrelation.
Spatial analysis encompasses a range of techniques and methods designed to explore spatial relationships, patterns, and structures within geographic data. It focuses on how phenomena are distributed across space and the factors influencing these distributions. This type of analysis involves processes such as mapping, spatial statistics, and the use of geographic information systems (GIS) to understand spatial patterns, identify trends, and support informed decision-making. Spatial analysis is extensively applied in fields like urban planning, environmental science, public health, and transportation to tackle complex spatial questions and address other real-world challenges.

In this study the researcher aims to answer questions such as:

1. What are the Moran's Indices of quarterly incarcerations for all jails in NCR for the years 2021 to 2023?
2. What is the Moran's Index of population in NCR for the year 2020?
3. What is the pattern of quarterly incarcerations and population based on their respective Moran's Indices? Dispersed, clustered or random?
4. What are the effects of being dispersed, clustered or random of the data?
5. Does the pattern of population imply the pattern for quarterly incarcerations?

2. Methodology

Data used in this study is a secondary data consolidated from Regional Operations Division of Bureau of Jail Management and Penology (BJMP) for quarterly male and female commit and a secondary data from Philippine Statistics Authority (PSA) for population. Analyzing patterns on Spatial Statistic Tools of ArcMap® were used to calculate Moran's Index, its z-value, p-value and to determine whether the data shows dispersed, clustered of random patterns. The shapefile of the Philippines and the National Capital Region are free and readily available at GitHub further enhancements and input of related attributes such as population (based on PSA data for the year 2020), area (in km^2) and the total number of quarterly commits were done using QGIS Software.

2.1 Spatial Autocorrelation

One of the most popular measures of spatial association for spatial data, comparable to the covariance function and variogram, is Moran's Index also called Moran's I. This index, an adaptation of Pearson's correlation coefficient, summarizes the level of spatial autocorrelation in the data (Sahu, S., 2022). The measure I is calculated by comparing each observed area i to its neighboring areas using weights w_{ij} from the proximity matrix. The formula is given by:

$$I = \frac{n}{\sum_{i\neq j} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}$$

where Y_i is the random sample from n spatial units and $\overline{Y}$ is its sample mean. The index $I \in [-1,1]$ and the interpretation depends on the calculated p-value and z-value as tabulated below:

p-value	z-value	Interpretation
<0.10	Less than 1.65	Dispersed
---	-1.65 to 1.65	Random
<0.10	Greater than 1.65	Clustered

Further analysis can be conducted to check the intensity of the patterns using High/Low Clustering under Analyzing Pattern Spatial Statistical Tools of ArcMap® also known as Getis-Ord Local Statistics given as (Sampson, N., 2013):

$$G^* = \frac{\sum_{j=1}^{n} w_{ij}x_j - \overline{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij}\right)^2}{n-1}}}$$

where x_j is the attribute value for feature j and w_{ij} is the spatial weight between feature i and j. $\overline{X}$ and S are attribute's mean and standard deviation, respectively. The interpretation of G^* is:

p-value	z-value	Interpretation
<0.10	Less than 1.65	Low dispersed/clustered
---	-1.65 to 1.65	Random
<0.10	Greater than 1.65	Highly dispersed/clustered

2.2 Symbology and Quantile Classification in ArcMap®

In this study, quantile symbology was used to spatially visualize both data on population and quarterly incarcerations.

Graduated color symbology displays quantitative differences between mapped features by varying their colors. Data is classified into ranges; each assigned a distinct color from a chosen scheme. For example, with a five-class scheme, five different colors are used. The symbol sizes remain constant. Maps using this color variation technique are typically known as choropleth maps. Generally, a continuous color scheme is selected, where lighter shades represent lower data values and darker shades represent higher data values.

In a quantile classification, each class contains an equal number of features, making it well-suited for linearly distributed data. This method ensures that each class has the same number of data values, preventing empty classes or classes with too few or too many values.

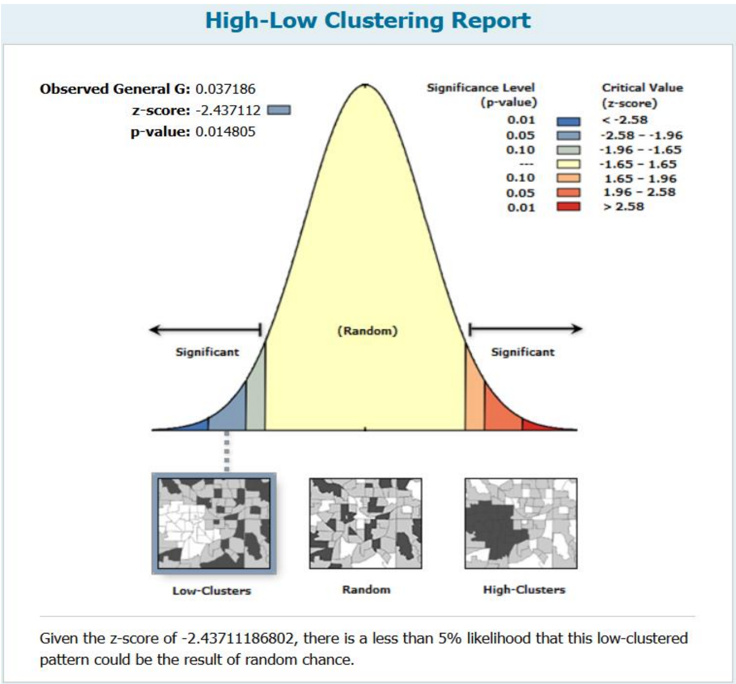
3. Results

Table 1. Results of Moran's Index of spatial autocorrelation for quarterly male commit from years 2021 to 2023.

	Year	Quarterly	Moran's I	z-value	p-value	Result
Male Commit	2021	Q1	-0.01149	0.21736	0.82793	Random
		Q2	0.08927	0.62620	0.53118	Random
		Q3	-0.04526	0.09406	0.92506	Random
		Q4	-0.19481	-0.06167	0.53742	Random
	2022	Q1	-0.16846	-0.43251	0.66537	Random
		Q2	-0.10983	-0.19487	0.84550	Random
		Q3	-0.06661	-0.01715	0.98632	Random
		Q4	0.07072	0.53617	0.59184	Random
	2023	Q1	0.09407	0.64715	0.51754	Random
		Q2	0.40627	2.04930	0.04043	Clustered
		Q3	0.36732	1.73553	0.08265	Random
		Q4	0.24882	1.25039	0.21116	Random

For years 2021 to 2023, almost all quarterly data shows no spatial autocorrelation or a random result of Moran's Index except for 2nd quarter of the year 2023 which tends to have a clustered pattern. With this, the researcher proceeded to further analysis and conducted the Getis-Ord Local Statistics and the result hereby presented.

Illustration 1. High-Low Clustering Report for 2nd Quarter of year 2023 using Getis-Ord Local Statistics.



General G Summary

Observed General G:	0.037186
Expected General G:	0.062500
Variance:	0.000108
z-score:	-2.437112
p-value:	0.014805

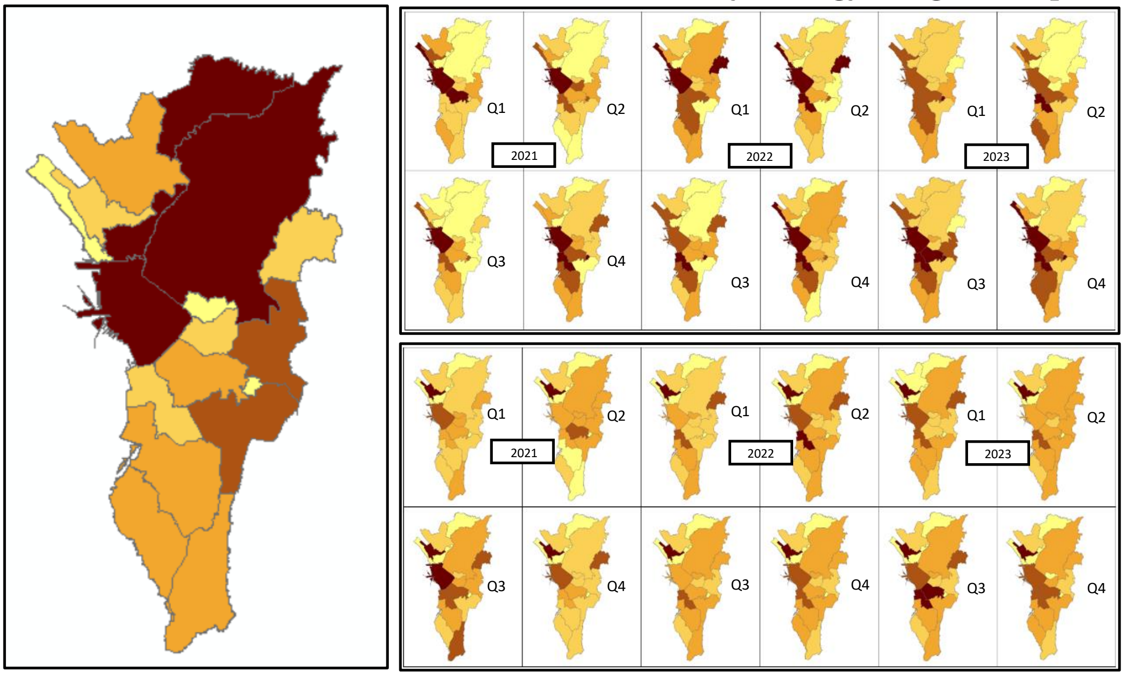
With a z-core of -2.4371 and p-value of 0.0148, $G^* = 0.0372$ results a low-clustering pattern of incarceration data for the 2nd quarter of the year 2023.

Table 2. Results of Moran's Index of spatial autocorrelation for quarterly female commit from years 2021 to 2023.

	Year	Quarter	Moran's I	z-value	p-value	Result
Female Commit	2021	Q1	-0.28667	-1.23274	0.21767	Random
		Q2	-0.28683	-1.54003	0.12355	Random
		Q3	-0.35101	-1.19244	0.23309	Random
		Q4	-0.39728	-1.83410	0.06664	Random
	2022	Q1	-0.34121	-1.33669	0.18132	Random
		Q2	-0.31926	-1.29715	0.19458	Random
		Q3	-0.26826	-0.92551	0.35470	Random
		Q4	-0.34909	-1.45657	0.14524	Random
	2023	Q1	-0.39435	-1.56697	0.11712	Random
		Q2	-0.39337	-1.75415	0.07940	Random
		Q3	-0.28658	-0.97980	0.32718	Random
		Q4	-0.33097	-1.13830	0.25500	Random

All results lead to no spatial autocorrelation or a random result of Moran's Index for the female commit data and there's no need to proceed to further analysis of spatial autocorrelation.

Illustration 2. Quantile Graded Color Symbology using ArcMap®



The above illustrations show quantile graduated color symbology for data of the population (left), male commit (upper right) and female commit (lower right) created by setting population data as normalization value for every quarterly data of incarcerations. Although the symbology of the population seems clustered, with Moran's I of -0.1729 and z-value of -0.5247, population has no spatial autocorrelation.

For the male commit, symbology illustrates the clustered pattern (i.e. yellow, orange and brown colors persistently adjacent to each other) for the 2nd quarter of 2023 while symbology for female commit clearly shows no spatial autocorrelation.

4. Conclusions

1. All quarterly data for female commit and almost all quarterly data for male commit shows no spatial autocorrelation or random result of the Moran's Index.
2. Incarceration data for 2nd quarter of the year 2023 shows spatial autocorrelation with z-value and p-value of 2.0493 and 0.0404, respectively resulting to conclusion of clustered pattern using Moran's I and further, a z-core of -2.4371 and p-value of 0.0148 for Getis-Ord Local Statistics hence, low-clustering pattern.
3. The data on population also shows no spatial autocorrelation with Moran's I of -0.1729 and z-value of -0.5247.
4. Although 2nd quarter of the year 2023 differs from the rest it is obvious that since population is random that is, there is no spatial autocorrelation it implies that incarcerations for both male and female also has random spatial pattern.
5. Random patterns of incarcerations had been statistically revealed using Moran's index. Therefore, law violators as well as crimes are randomly spread across the entire region.

5. Recommendations

1. Data on population used in this study is based on available and latest data published by Philippine Statistics Authority and did not match the latest data of commit from Bureau of Jail Management and Penology. It is recommended to conduct similar study using similar and latest years of data to ensure more accurate results.
2. Government agencies such as the Philippine National Police must be aware of the result of this study that the crimes occur randomly across the region hence it is recommended that they must not focus on single city in patrolling and strict implementation of the law.
3. Conduct of similar study using other measures of spatial autocorrelation is recommended to compare and to attempt improvement of the result presented in this study.

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