Identifying areas of opportunity in Bangkok for food delivery service platforms with Local Moran's I

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Abstract

Local Moran's I ($I = 0.241$, $p = 0.0048$) of 83 Bangkok districts' venue value per capita identified one hot spot (4 districts), one cold spot (2 districts) and one geospatial outlier for targeted prospecting and market research. Sensitivity analysis produces an area of interest of districts which self-cluster into the entire southwest region (17 districts). Recommendations to a hypothetical business were made, starting with immediate prospecting in 'doughnut' outliers, which have potential to provide high value like their neighbors. Then, assuming saturation has not been met, hot spot regions would benefit from a specialized campaign and continuous prospecting as they are providing high value and new stores there are likely to also be high-value. Longer-term efforts include cold spot user research to understand why the cold spot is providing less value and adjust marketing strategies in this area. It might take effort to convert these regions.

Keywords Univariate Local Moran's I, geospatial clusters and outliers, local indicators of spatial association (LISA), multiple hypothesis testing, PySal

1 Introduction

Of the industries impacted by the COVID-19 pandemic, online delivery services, specifically food delivery, is experiencing a boom [9]. With millions of consumers sequestered at home, the convenience and security of touchless transactions, no-contact deliveries, special online deals, and a middle-man for troubleshooting orders and payment, numerous local and national food delivery platforms including Lineman, Food Panda, and Grab Food [4] allow residents of Bangkok to receive restaurant-style meals, fast food, and groceries at their doorstep within a matter of hours. The more noodle houses, cafes, food trucks, and grocers signed on, the broader the selection and availability to the consumer. In turn, food service providers gain access to an online consumer base and a third-party delivery motorcycle fleet, which can multiply revenue or even enable delivery in a time where sit-down restaurants are floundering.

When a critical mass of stores are signed onto a food delivery platform, the question of where to focus prospecting efforts becomes paramount. Fortunately, by this point, the marketplace should be saturated with store location data off of which to base this decision. Enter hot spot analysis. Based on the understanding that geographical locations next to each other tend to be similar, Local Moran's I statistic can be used to identify (1) clusters of districts whose neighbors provide similar high or low value and (2) geographical outliers whose neighbors are providing statistically more or less value. With a population of over eight million people, Bangkok, the capital of Thailand, lends itself to geospatial clustering/outlier analysis as its districts are saturated with Foursquare food venues and its geography includes no islands.

This study harnesses the Foursquare Places API to collect a real-world database of food venues to represent storefronts signed onto a hypothetical delivery platform. Given enough location data and that a geospatial trend exists, this same analysis can produce clusters and outliers for any marketplace business. Perhaps the most obvious application is for Foursquare itself. If the company found that food venues were lacking on their site but provide high value to their customers, it could use this exact analysis to pinpoint regions for prospect new venues to add to their platform.

2 Data

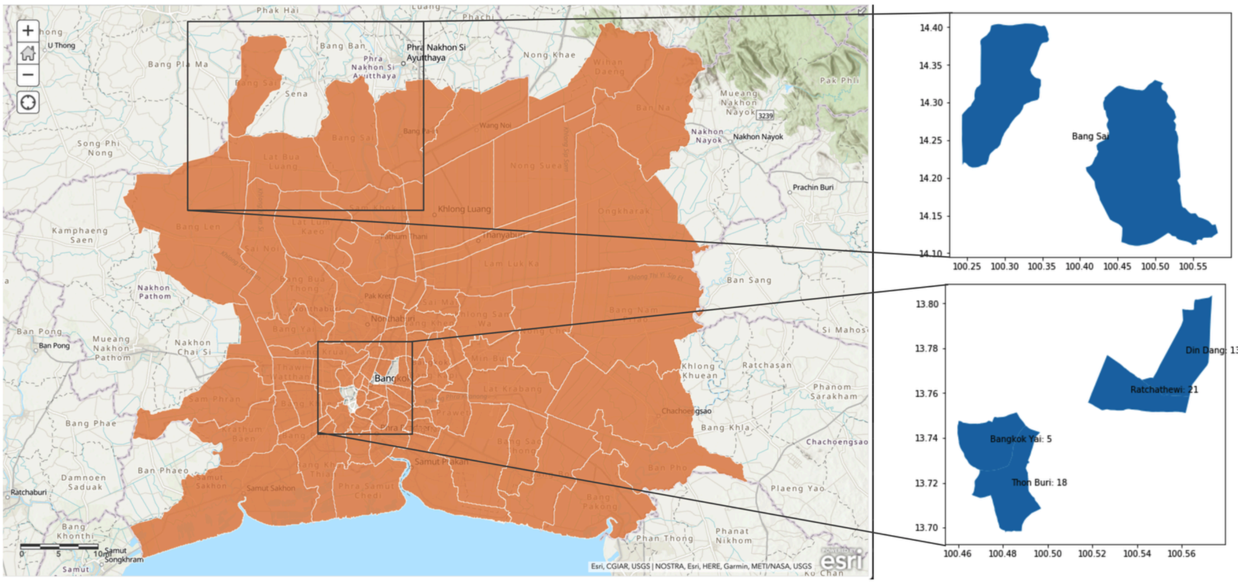
2.1 Bangkok district boundaries

With the goal of identifying areas of interest, the shape and size of focal area must first be defined. While any grid can be used to segment the study area, each region requires enough data to reach statistical significance (30 data points per feature is a rule of thumb) but should still be specific enough to be actionable for marketing and sales reps. Neighborhoods prove to be too compact given the density our dataset, so districts (*khet*), the next largest geographical segmentation, were used instead.

85 districts were investigated. When visualized in ArcGIS software (which imposes a strict lower bound of 30 data points per feature), a few required adjustments are apparent (see Fig 1).

Dissolving bounds of under-saturated adjacent districts While one could choose to drop regions with 30 or fewer venues (seen missing in Fig 1) these districts with lesser count are centrally-located with many neighbors. Since they are conveniently collocated, four districts' shared bounds were dissolved, resulting in two meta-districts, 'Bangkok Yai — Thon Buri' and 'Ratchathewi — Din Dang' with 23 and 34 venues, respectively. While the former still does not satisfy the suggested lower bound for statistical processing, both appear as neighbors of the results set - showing that it is indeed better to keep data when possible than discard it.

Figure 1: Pre-processing District Bounds



4 centrally-located districts' bounds were dissolved into two to account for low data. A MultiPolygon district was broken into two, one of which was dropped for low connectivity to neighbors.

Separating non-adjacent MultiPolygon districts Another modification which will aid hot spot analysis is separating a MultiPolygon region in the northwestern region. For historical reasons, Bang Sai consists of two non-congruent districts. One of them serves as a peninsula of the study area with only one adjacent neighbor, so it is dropped, and its sister district with four first-order neighbors is renamed to 'Bang Sai (1403)'. If this region becomes interesting, it would be worth expanding the area of study to give peninsula-like district 'Bang Sai (1413)' more neighbors.

2.2 Foursquare Places API for district venues and venue value

Food venues A list of Bangkok food venues and their venue type was fetched from Foursquare venue search (`/venues/search`). Foursquare maintains a hierarchy of venue types. For the purposes of this exploration, all venues with highest level 'Food' categorization were used. This is a greedy selection, as it is not guaranteed that all venues provide delivery, but suffices as a placeholder for businesses already signed onto one's platform.

While the API accepts SW and NE bounding box coordinates to enable a grid-wise search, it sometimes returns venues outside of those bounds. Also, the API returns a limit of 50 venues but does not flag if more are available. So the strategy for querying Foursquare Places API was (1) generate a square grid from Bangkok study area bounds, (2) filter results to be within queried region, and (3) when 50 venues are returned, recursively fetch smaller and smaller grids until all venues are collected.

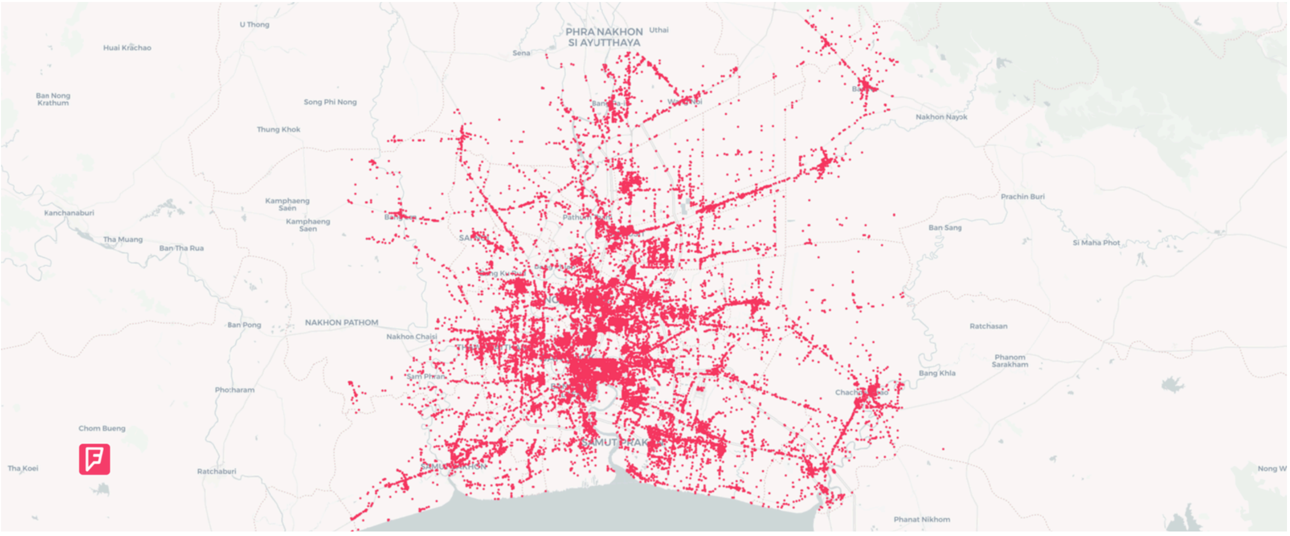
A large number of venues had missing categories. Attempts to fill missing categories by matching patterns on venue name were neither fruitful nor accurate, so only labeled venues were included in the dataset. Over 56,000 Bangkok food venues were fetched and included in this analysis (see Fig 2a).

Venue Likes While count data is enough to run an analysis, a hypothetical food service platform would want a hot spot to represent stores that are performing well and provide more value to the service. To represent store value, *number of likes per venue* was also fetched from Places API (`/venue/VENUE_ID/likes`). Admittedly, this is a crude representation, but store value is more likely to be represented by quantity/quality/variety of orders, business data which is challenging to mock. Four venues returned 404s or '-1' likes and were dropped. Number of likes (0-1216 with the majority of stores having no likes) was transformed to a more normalized distribution via Box Cox transform, then bucketed into four categories of 'low', 'medium', 'high', and 'superior' value (mapping to 0 likes, 1 like, 2-3 likes, and 4+ likes). These categories were used to weight the count data with 0.25, 0.5, 0.75, and 1 multipliers, respectively. Venue values are plotted in Fig 2b. While store value is now numerically represented, a store will only be profitable if it has hungry consumers in the delivery area. To account for demand, district population is included in the metric, too.

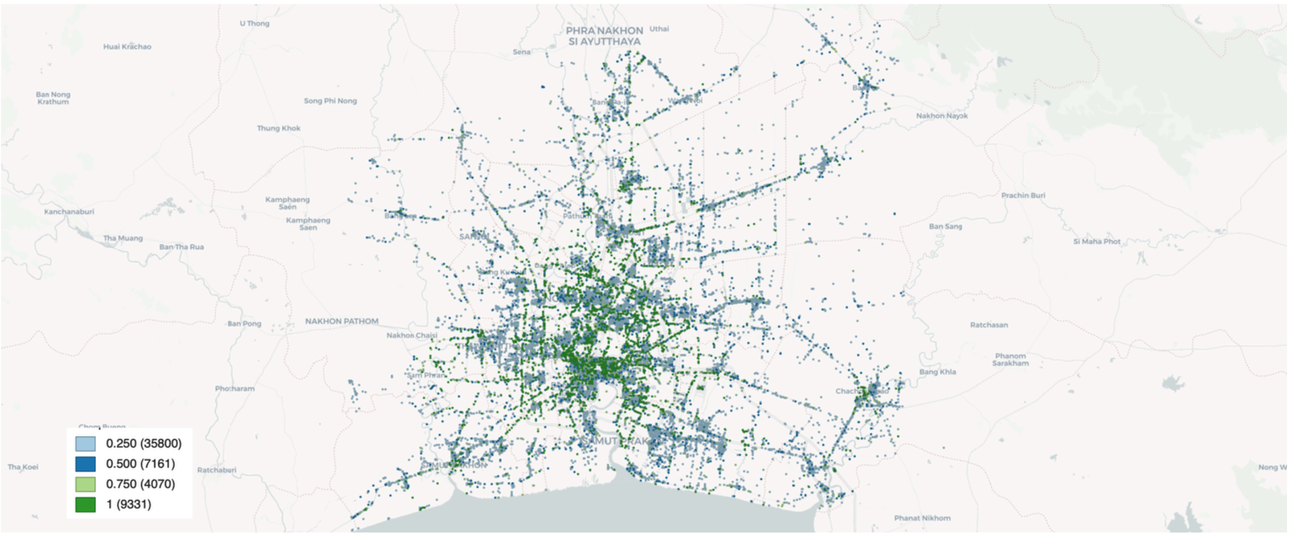
2.3 District Population data

Focal region metrics in hot spot analysis are often normalized by region area or population. To account for demand in this mock data, the district store value metric was normalized by population as sourced by 2010 census data [1]. By making the simplification that delivery area aligns with district bounds, district population is an accurate representation of the scale of hungry consumers. In reality, spatial joins of more granular census blocks and unique delivery Polygons per venue would be more accurate. Visualizing normalized store weights, or *venue value per capita*, starts to reveal patterns (see Fig 2c). While a high concentration of high value per capita venues exists in the city center, perpherial district centers also include high value stores. Additionally, the districts bordering the Gulf of Thailand appear to have higher concentrations of low value per capita venues.

(a) Foursquare Food Venues in Bangkok



(b) Foursquare Food Venue Value from Likes



(c) Foursquare Food Venue Value per Capita

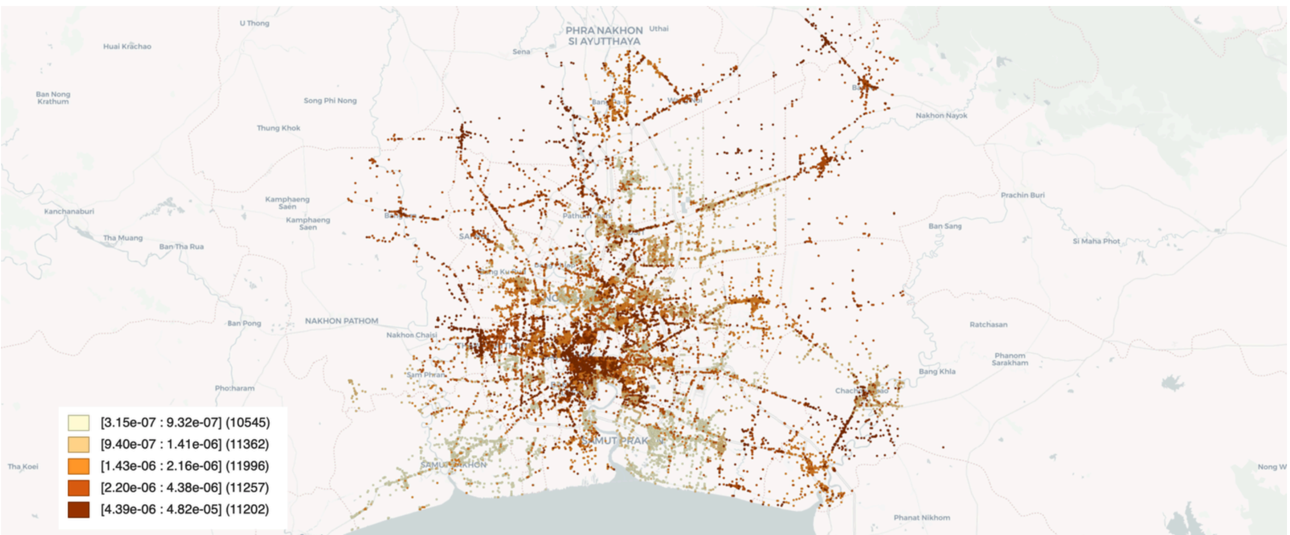
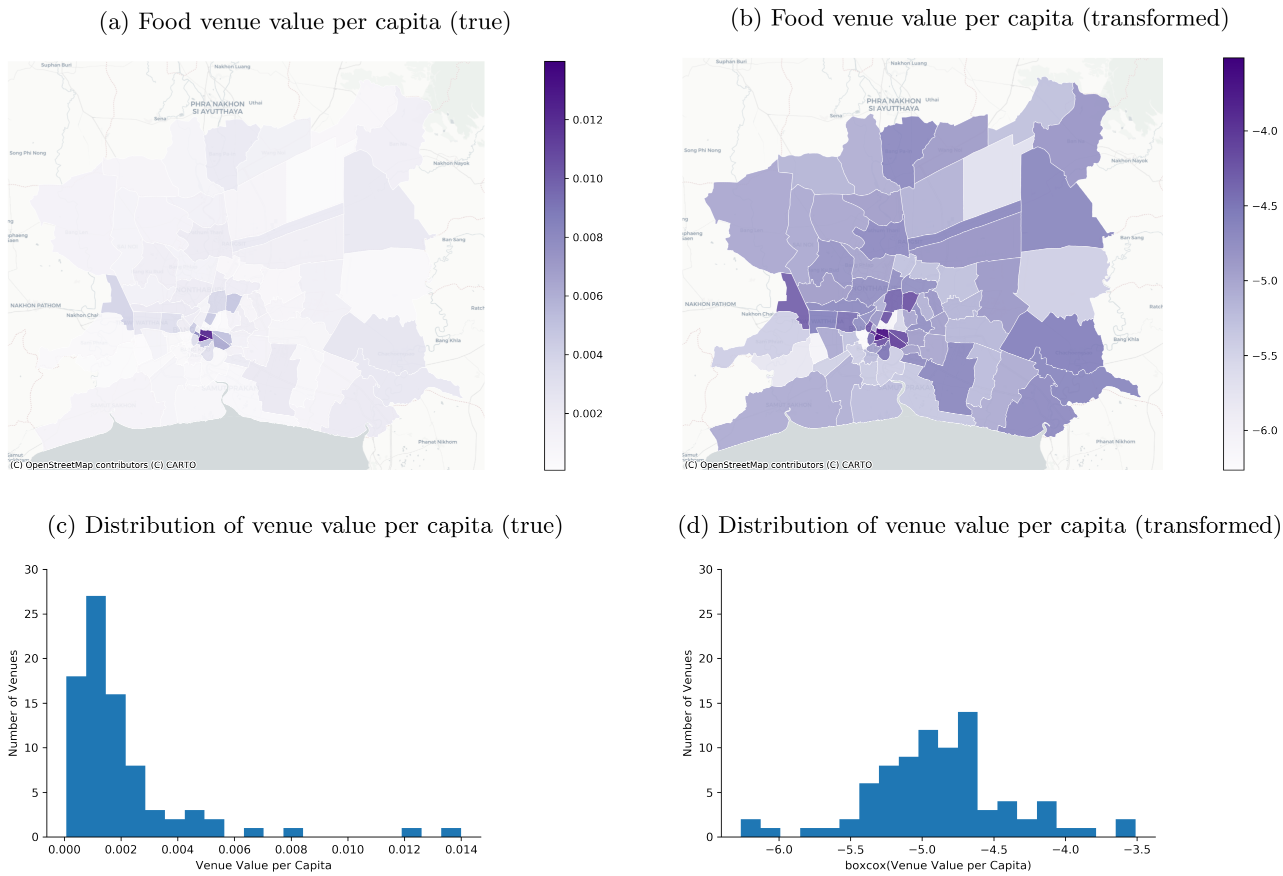


Figure 2: Venue Value per Capita metric is weighted by Venue Likes and normalized by District Population



(a) Food venue value per capita (true)

(b) Food venue value per capita (transformed)

(c) Distribution of venue value per capita (true)

(d) Distribution of venue value per capita (transformed)

Figure 3: Venue value per capita distribution was normalized with Box Cox transformation ($\lambda = 0.095$)

2.4 Computing and Transforming the Venue Value per Capita metric

Accounting for both store value and demand, the metric which was used for this analysis is a weighted sum of stores per district, normalized by population. As seen in Fig 3c, **venue value per capita per district** has a right-skewed distribution. Because Moran's I expects a normally distributed input, the metric was transformed prior to analysis. A log transform was not powerful enough for this data, so a Box Cox transform was used to estimate a λ of 0.095 and transform venue value per capita as:

$$y(\lambda) = \frac{y^{\lambda} - 1}{\lambda}$$

Distributions of true and transformed attribute can be seen in Fig 3.

3 Methodology

3.1 Global Autocorrelation

Prior to testing for local indicators of spatial association, it is good practice to test for global spatial autocorrelation, a measure of overall clustering. Unlike correlation, which compares two independent variables, autocorrelation compares a single variable to a lagged version of itself. Spatially, lag is interpreted as a weighted average of neighboring districts' venue value per capita. Since it is possible to find local indicators given acceptance of the global null hypothesis [10], the global statistic is not a requirement but it is a worthwhile point of discussion as an analogy for the proceeding local analysis.

Moran's I is a popular choice for a measure of spatial autocorrelation and is a fitting statistic for this dataset as it finds not only spatial clusters (hot spots and cold spots) but also spatial outliers (districts surrounded by opposing value districts). Moran's I is a cross-product statistic which uses deviation from the global mean to compare a local value to the weighted average of its neighbors [10]:

$$I = \frac{N}{S_0} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_i z_i^2}$$

where N = 83, w_{ij} is a matrix of spatial weights (as described in 3.2), z_i and z_j are deviations from the mean, and S_0 is the sum of the weights $\sum_i \sum_j w_{ij}$. The statistic ranges from -1 to 1, where 0 represents no autocorrelation and negative values represent negative spatial autocorrelation.

As a basis for rejecting the null hypothesis, which states that any observed global clustering is due to chance, a randomization approach is used to permute districts' values over all locations. A 'pseudo p-value' is generated by comparing the average I over 10,000 permutations (to account for an N of 83) to the true value (see Fig 4).

The code required to calculate Global Moran's I is shown in code listing 1, assuming `districts_gdf` is a `GeoDataFrame` with 'district', 'geometry', and 'boxcox_venue_val_per_capita' as columns. Statistically significant weak global autocorrelation was found and the null hypothesis was rejected. Locally, this same simulation and statistical evaluation process is applied to all 83 districts, only some of which will yield significant I_i statistics. Multiple hypothesis testing will require careful significance considerations.

Listing 1: Compute and visualize Global Moran's I (python)

```
# Make python packages available
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from esda import moran

# Seed random number generator for reproducibility
np.random.seed(123)

# Define weights matrix from geodataframe, and row-standardize
wq = lp.weights.Queen.from_dataframe(districts_gdf, idVariable='district')
wq.transform = 'r'

# Define y as transformed venue value per capita
y = districts_gdf['boxcox_venue_val_per_capita']

# Execute Global Moran's test with input y, weight matrix wq, and 9999 permutations
mi = moran.Moran(y, wq, permutations=9999, two_tailed=False)

# Plot density of permutation I statistics
sns.kdeplot(mi.sim, shade=True)
plt.vlines(mi.I, 0, 1, color='r')
plt.vlines(mi.EI, 0, 1)
```

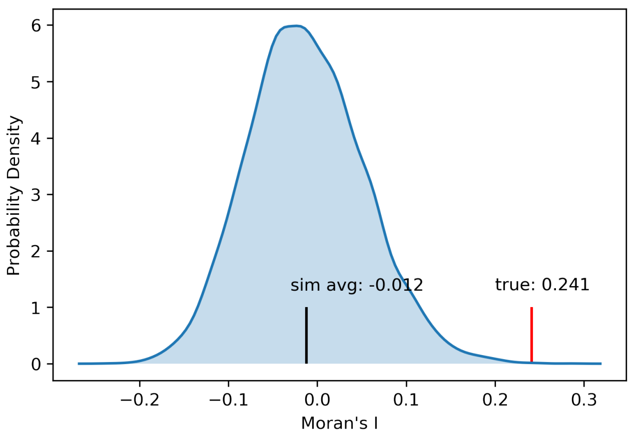


Figure 4: Global Moran's I (permutations=9999, $p = 0.0004$)

3.2 Spatial Lag and Weights Matrix Selection

Hot spot analysis is rooted in a concept called 'spatial lag'. Like time-based analyses where one cycle's data is expected to be similar to the previous cycle's, in a geospatial sense we expect neighboring districts to have similar value.

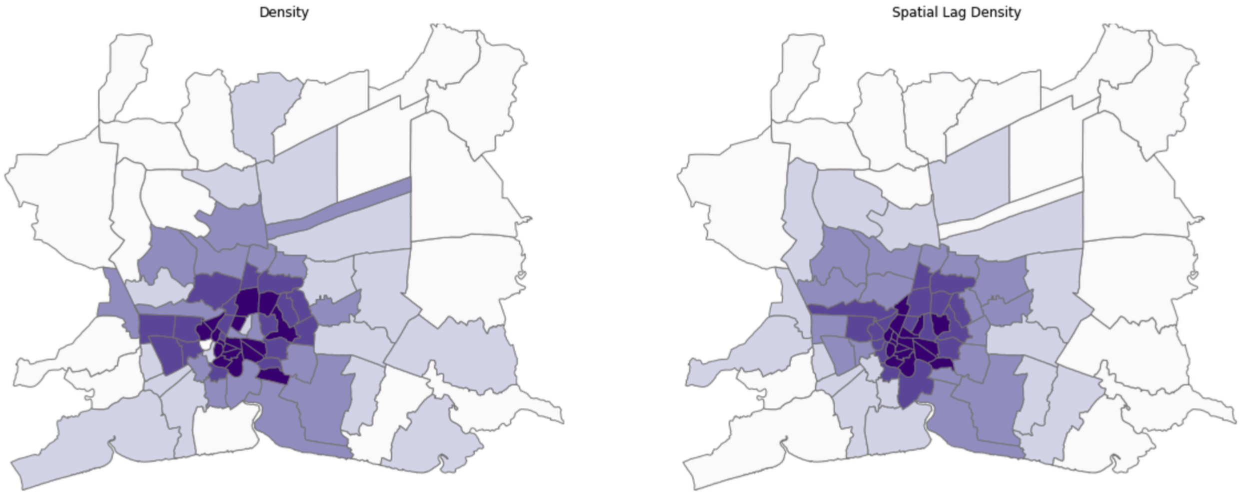
To best illustrate spatial lag within the context of Foursquare food venues, consider *venue density* as a metric (see Fig 6). The first heatmap shows quantiles for venue density, a 'real world' picture of the data. Applying spatial lag takes the average venue density of that district's neighbors, resulting in a smoothed or 'expected' picture of density, which in this case is highly intuitive. As one travels further from city center, one expects the density of food venues to decrease.

Since neighboring regions are critical to this computation, they should be carefully defined based on the details of the study area and its geometry. A queens continuity weight matrix is a satisfactory fit for this data ('queens' meaning both edge and corner districts are neighbors as compared to 'rooks' continuity which only includes edge neighbors). Since downtown areas are more tightly-packed and no districts are islands, district continuity is preferable to a hardcoded distance threshold. This first-order contiguity weights matrix (1s at first-order edge and corner neighbors and 0s elsewhere) results in a median neighbor count of 6:

```
Queens weight median neighbors:  6.0
Queens weight average neighbors:  5.54
Queens weight max neighbors:  10
Queens weight min neighbors:  2
```

Figure 5: Queen's weight output

Figure 6: Spatial Lag as a smoothing function (venue density)



3.3 Local Autocorrelation

Local spatial clusters and outliers are identified as districts or congruent sets of districts for which the Local Moran's I is significant. By definition, local indicators of spatial association decompose the global statistic into contribution of each individual district. Since weights are row-standardized, the sum of all the weights equals the number of observations N. Thus, each local statistic can be calculated [10] by:

$$I_i = z_i \sum_j w_{ij} z_j$$

Once again, 10,000 permutations per district were used as a basis for significance and null hypothesis rejection. A randomization approach was used to hold each district fixed and permute its neighboring districts' values. The PySal `esda` package abstracts the computations into a single method, as shown in code listing 2. Instead of one global statistic, 83 I_i statistics were produced. When $|I_i|$ is large, venue value per capita and its spatial lag for a district have large relative deviations from the global mean. When I_i is positive, a district's venue value per capita and its spatial lag are aligned (both above or below the global mean). Therefore, a strong hot spot and a strong cold spot can have indistinguishable (positive) I_i. The same can be said for opposing spatial outlier types, which have negative I_i.

3.4 Correcting p-value for multiple hypothesis testing and Sensitivity Analysis

Pseudo p-values should be adjusted to account for the N parallel tests. Generally, a Bonferroni correction ($\alpha/N = 0.05/83 = 0.0006$) is considered the proper threshold for significance. However, it tends to be overly conservative since 83 tests have overlapping neighbors and reuse data. Therefore, a False Discovery Rate (FDR) correction was applied, which selects the max p_i value for which the Bonferroni correction scaled by i exceeds p_i:

$$p_{i_{max}} \leq i \times \alpha/N$$

The resultant FDR-corrected threshold ($p = 0.0048$) was instead used to assess significance of results. Since, by definition, a significant cluster or outlier says something about its neighbors, too, neighboring regions might be included as part of the results set. These neighboring regions sometimes include districts with significance greater than corrected p-value but less than 0.05, which would normally get excluded as insignificant. Sometimes these districts are considered 'districts of interest' which will adapt nicely to the business recommendations which conclude this study.

Listing 2: Execute Local Moran's I (python)

```python
# Make required packages available
from statsmodels.stats.multitest import multipletests

# Calculate Local Moran statistics
# with input y, weight matrix wq, and 9999 permutations
li = moran.Moran_Local(y, wq, permutations=9999)

# Apply Benjamini/Hochberg False Discovery Rate to psuedo p-values
corrected_pval_list = multipletests(li.p_sim, method='fdr_bh')
```

4 Results

4.1 Plotting Clusters and Outliers

Upon plotting venue value per capita against its spatial lag, the best-fit line has a slope of Global Moran's I and intersects at means (0,0) since inputs were row-standardized. Quadrants created when space by subdivided by these means are labeled HH (high-high) which contain 'hot spots', LL (low-low) which contain 'cold spots', LH (low-high) for 'doughnut' regions, and HL (high-low) for 'diamond' regions. Seven districts whose local statistic were identified as significant are highlighted in the plot.

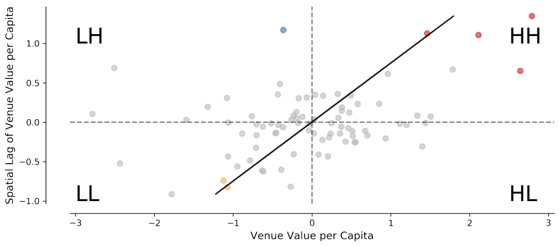


Figure 7: Moran's Local Scatterplot ($I = 0.241$, $p = 0.0048$)

Upon mapping these significant regions, it can be observed that they self-cluster in the central-to-southwestern study area. Two neighboring districts are identified as a cold spot, having low value per capita and neighbors of low value per capita. In close proximity, four neighboring districts are identified as a hot spot, having high value and neighbors of high value per capita. As for outliers, no 'diamond' regions of high value surrounded by low value were identified. Instead, a significant 'doughnut' region is identified adjacent to the hot spot cluster. This low-value district is particularly interesting as it should be high value, according to its neighbors. It will play a big role in proceeding business recommendations.

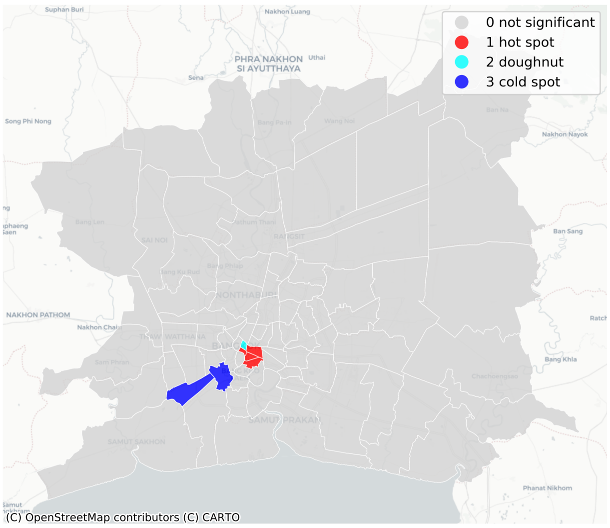


Figure 8: Spatial Anomalies ($p = 0.0048$)

4.2 Sensitivity Analysis to recommend a more interesting region

The purpose of sensitivity analysis is to identify the stage *where the results become interesting* [11]. If we layer less significant regions that do not make the FDR-corrected p-value threshold for significance, we find that the cold spot could be much larger, as could the hot spot and doughnut region. This makes sense because we expect cold spot districts to have low value neighbors, etc.

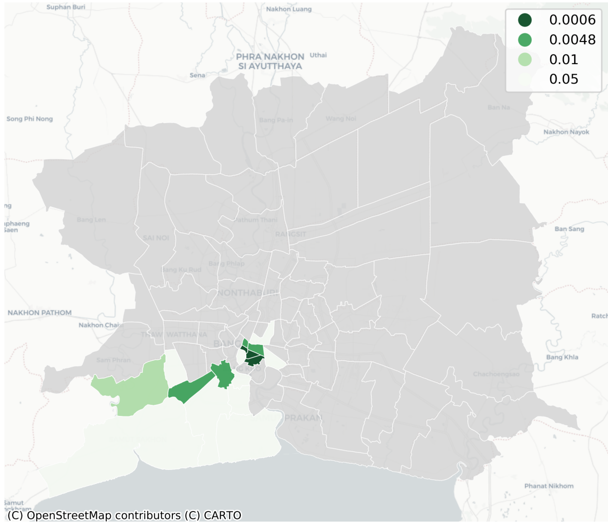


Figure 9: District anomaly significance ($p < 0.05$) binned by levels of significance

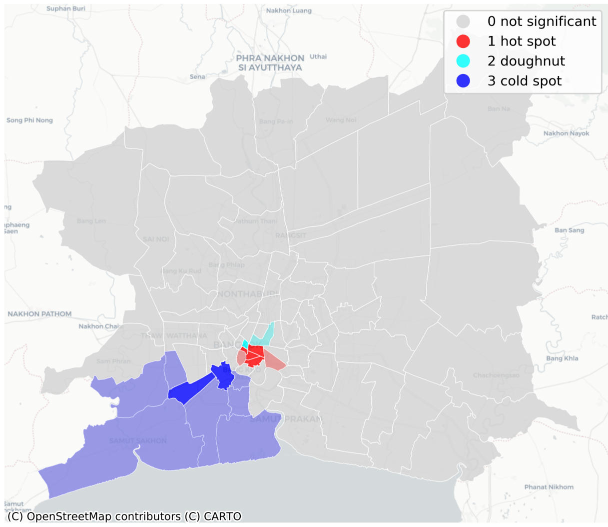


Figure 10: Sensitivity Analysis shows breadth of clusters with inclusion of less-significant neighbors.

When an outline of core districts' neighbors is layered atop cluster/outlier types weighted by significance (see Fig 11), a self-clustered region of recommendation appears, spanning almost the entire southwest corner of the study area. This 'area of interest' spins a more interesting story than its cores alone.

4.3 Reporting Measures of Local Spatial Association for Area of Interest

Figure 11: Statistically-significant spatial anomalies

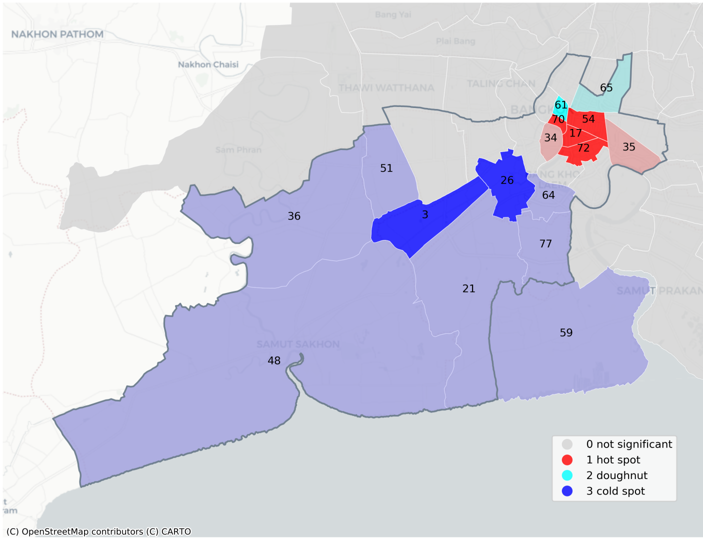


Table 1: Significant Districts of Local Spatial Association

Id	District	Postal Code	Attribute	Spatial Lag	I_i	z_{score}	p	Cluster/Outlier Type
17	Bang Rak	10500	-3.511	-4.003	4.946	3.892	**0.0001**	**1 hot spot**
72	Sathorn	10120	-4.168	-4.148	2.166	3.833	**0.0002**	**1 hot spot**
70	Samphantawong	10100	-3.846	-4.161	3.076	3.525	**0.0004**	**1 hot spot**
61	Pom Pram Sattru	10100	-5.069	-4.12	-0.56	-3.117	**0.0012**	**2 doughnut**
26	Chom Thong	10150	-5.418	-5.436	1.171	2.815	**0.0024**	**3 cold spot**
54	Pathum Wan	10330	-3.584	-4.462	2.26	2.756	**0.0031**	**1 hot spot**
3	Bang Bon	10150	-5.443	-5.38	1.101	2.767	**0.0036**	**3 cold spot**
36	Krathum Baen	74130	-5.769	-5.493	2.15	2.584	0.0055	3 cold spot
35	Khlong Toey	10110	-4.007	-4.45	1.569	2.31	0.0122	1 hot spot
65	Ratchathewi — Din Dang	10400	-6.128	-4.438	-2.263	-2.32	0.0123	2 doughnut
64	Rat Burana	10140	-5.194	-5.304	0.512	2.112	0.0185	3 cold spot
34	Khlong San	10600	-4.414	-4.487	0.775	2.102	0.0206	1 hot spot
48	Muang Samut Sakhon	74000	-5.023	-5.431	0.293	1.925	0.0285	3 cold spot
21	Bangkhuntien	10150	-5.081	-5.289	0.31	1.855	0.0325	3 cold spot
77	Thungkru	10140	-5.357	-5.262	0.706	1.778	0.0356	3 cold spot
51	Nongkheam	10160	-6.092	-5.237	1.694	1.747	0.0391	3 cold spot
59	Phra Samut Jadee	10290	-5.202	-5.295	0.514	1.705	0.047	3 cold spot

For each district, the transformed venue value per capita attribute and its spatial lag are reported, alongside its computed local statistic I_i, the standardized z-value of I_i (computed by subtracting expected value and dividing by standard deviation), and pseudo p-value from permutations. For convenience, postal code is also listed for marketing and prospecting efforts. A full list of these statistics, significance values, and cluster/outlier type are reported in Appendix Table 12.

5 Discussion

While the methodology presented in this report is not particularly novel, the crux of this study lies in the business recommendations adapted to the resulting cluster and outlier districts.

5.1 Clusters

Hot spots *Bang Rak, Sathorn, Samphantawong,* and *Pathum Wan*, along with two secondary neighboring districts *Khlong Tocy* and *Khlong San*, make up an inner-city hot spot which should not be surprising as marketplace applications tend to be most effective in regions of high population density. These regions were identified by Deloitte as key Thai real estate markets in 2018 [5]. Note that the attribute used for analysis is already normalized by population, so districts have higher venue value *given* high population density in these areas. **Marketing should consider a special campaign for the hot spot. Sales should be prospecting in this high-value concentration.** While there is potential for saturation in this region, new restaurants appear annually and are likely to be high value given their neighboring venues.

Cold spots By definition, cold spots are statistically producing less value per customer, so it might be tempting to prioritize prospecting in the region of *Chom Thong* and *Bang Bon*. After all, population has been accounted for, so it is not that these districts don't have demand, but instead have a cumulative value per person that is lesser than the remaining study area.

However, the low-value cluster of interest (when secondary districts *Krathum Baen, Rat Burana, Muang Samut Sakhon, Bangkhuntien, Thungkru, Nongkheam* and *Phra Samut Jadee* are included) composes nine contiguous districts spanning an area of $1000km^2$. This suggests there may be an underlying factor that is causing this region to be low-value by nature. According to Trip Advisor, activities in Chom Thong center around nature, wildlife, and sightseeing [8] so perhaps there is a relationship between tourist region and cheaper on-the-go food. According to the website of Bang Bon, while it was once known for it's agriculture, it is an up-and-coming residential area which could capitalize off its unique native fruits [2]. Since venue value per capita is additive, low value regions can have few stores, low-performing stores, or both. *Longer-term efforts should be made by User Research* to understand why this large cold spot region is providing less value, followed by adjusted Marketing strategies in this area. **It might take effort to convert these regions.**

5.2 Outliers

While no 'diamond' regions (high-value districts with low-value neighbors) were found, Local Moran's I identified one 'doughnut' region, *Pom Pram Sattru*. With a busy mix of residential buildings, markets, and other venues (food and otherwise), this district has no obvious characteristic that would make it organically low-value. The official website states that "the duties of the district are focus on public service" [3]. **Due to it's high-value neighbors, this low-value city-central district has great potential for short-term correction, even conversion to another hot spot.** If this were to happen, neighboring secondary doughnut region *Ratchathewi — Din Dang*, which was artificially combined to account for low data, might then become a more significant doughnut region. Ratchathewi is characterized by Airbnb as "busy, quiet, and residential" [7] and Din Dang as "thriving, hip" and known for its pizza [6], suggesting that they, too, could be converted and absorbed into the inner-city hot spot. Therefore, *all doughnut regions are recommended for immediate prospecting.*

5.3 Translating Spatial Anomalies into Business Intelligence

The following course of action is recommended to a hypothetical business organization supporting the food delivery platform:

1. A small number of Sales reps should start focused prospecting efforts in the doughnut regions for hopefully quick conversion, followed by consistent attention to hot spot districts. Their effectiveness should be tracked and compared to other reps prospecting as usual. Specialized marketing campaigns can be spun up in hot spot and doughnut regions.
2. User Research should start investigating the large cold spot by speaking with current and prospective users. Marketing should adjust strategies in these regions as necessary.
3. These actions should be revisited after some time to determine if this sort of statistic has had a return on investment. Next steps can look like any of the following:
    - Expand study area boundaries to better understand cold spots.
    - Validate Bangkok as a proof of concept by analyzing other cities. A trend may not necessarily exist in all areas of study.
    - Investigate data quality/pipeline if field results were less than desired.
    - Iterate on the definition of venue value and demand. Adjust weights matrix if necessary.
    - Turn area of interest into dashboard for monitoring as hot spots may evolve over time.

6 Conclusion

Traditionally, geospatial hot spot analysis has been used in environmental studies to pinpoint the source of a contamination or epidemic. It can also be used to make geographical conclusions about a market with geospatial trends. The outliers turn out to be the most interesting, making Local Moran's I a better statistic than G_i^*, which only identifies clusters.

Since analytical and visualization software like ArcGIS sometimes impose hard limits (and come with a price tag), there is flexibility in writing a custom analysis, which is easily accomplished with the few lines of code included in this report (see code listings 1 and 2). Python packages like the PySal suite (`libpysal`, `esda`, `splot`), `shapely`, `geopandas`, `scipy`, `statsmodel`, and `matplotlib` made it possible to accomplish all the data mining, data cleaning, transformation, multiple hypothesis testing, analysis, and visualization easily within a Jupyter notebook. GeoDa is an open-source tool for testing, analysis, and visualization, and was used to validate results and generate reported maps in Fig 2.

Finally, the sensitivity analysis that accompanies geospatial multiple hypothesis testing draws a more compelling picture of prospective districts and makes recommendations to company stakeholders actionable. The 'area of interest' identified by this mock data is understandable and consumable by non-technical stakeholders who will use the data to adjust their strategies. Optimistically, analytical strategies like this can help keep food vendors financially afloat and Bangkok residents safely fed.

7 Appendix

Figure 12: Bangkok districts by Id

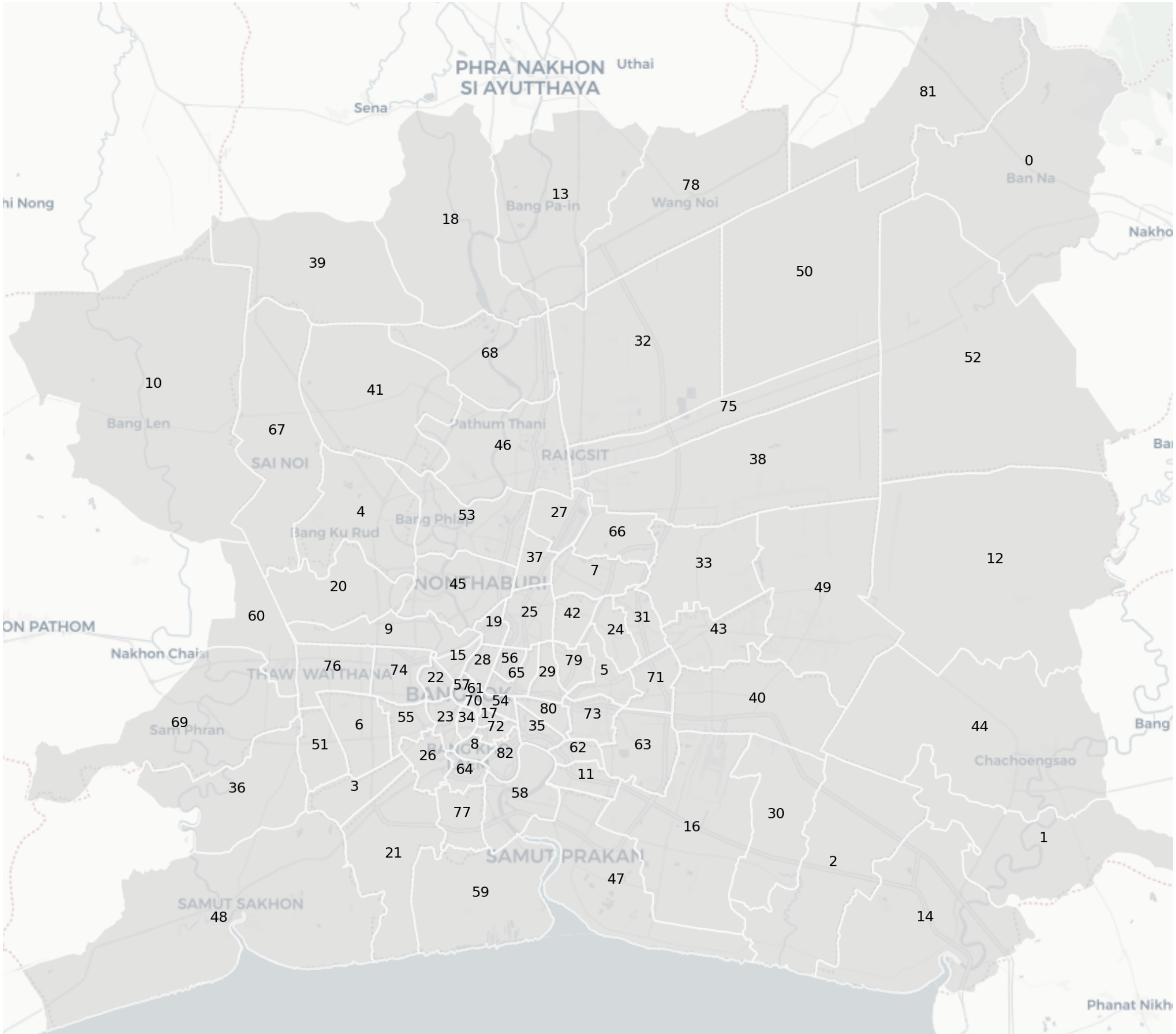


Table 2: Measures of Local Spatial Association

Id	District	Attribute	Spatial Lag	I_i	z_{score}	p	Cluster/Outlier Type
0	Ban Na	-4.79	-5.178	-0.116	-1.025	0.1446	0 not significant
1	Ban Pho	-4.603	-4.739	0.175	0.555	0.2806	0 not significant
2	Bang Bo	-5.018	-4.87	-0.01	-0.111	0.4481	0 not significant
3	Bang Bon	-5.443	-5.38	1.101	2.767	**0.0036**	**3 cold spot**
4	Bang Bua Thong	-4.766	-4.9	-0.005	-0.033	0.4881	0 not significant
5	Bang Kapi	-4.705	-4.93	-0.03	-0.199	0.4194	0 not significant
6	Bang Khae	-5.004	-5.159	0.125	1.253	0.1028	0 not significant
7	Bang Khen	-4.723	-4.855	0.023	0.205	0.4174	0 not significant
8	Bang Kho Laem	-4.902	-4.902	0.001	0.063	0.4739	0 not significant
9	Bang Kruai	-4.645	-4.667	0.22	1.248	0.1049	0 not significant
10	Bang Len	-4.987	-4.807	-0.033	-0.286	0.3737	0 not significant
11	Bang Na	-4.679	-5.053	-0.14	-0.763	0.2182	0 not significant
12	Bang Nam Prieo	-5.422	-4.689	-0.433	-0.788	0.2066	0 not significant
13	Bang Pa-In	-4.634	-5.006	-0.121	-0.396	0.3337	0 not significant
14	Bang Pakong	-4.656	-4.81	0.075	0.223	0.3896	0 not significant
15	Bang Plad	-4.728	-4.654	0.154	1.182	0.1162	0 not significant
16	Bang Plee	-4.621	-5.058	-0.183	-0.857	0.1955	0 not significant
17	Bang Rak	-3.511	-4.003	4.946	3.892	**0.0001**	**1 hot spot**
18	Bang Sai (1404)	-5.07	-4.932	0.032	0.17	0.4267	0 not significant
19	Bang Su	-5.09	-4.572	-0.259	-1.607	0.0539	0 not significant

Id	District	Attribute	Spatial Lag	I_i	z_{score}	p	Cluster/Outlier Type
20	Bang Yai	-4.87	-4.662	0.018	1.157	0.1245	0 not significant
21	Bangkhuntien	-5.081	-5.289	0.31	1.855	**0.0325**	**3 cold spot**
22	Bangkok Noi	-4.713	-4.985	-0.068	-0.439	0.327	0 not significant
23	Bangkok Yai — Thon Buri	-6.265	-4.822	-0.376	-0.327	0.364	0 not significant
24	Bung Kum	-5.103	-4.659	-0.199	-1.07	0.1414	0 not significant
25	Chatuchak	-4.338	-4.905	-0.036	-0.048	0.4818	0 not significant
26	Chom Thong	-5.418	-5.436	1.171	2.815	**0.0024**	**3 cold spot**
27	Don Muang	-5.266	-4.841	-0.074	-0.232	0.4081	0 not significant
28	Dusit	-4.82	-4.67	0.062	1.313	0.0922	0 not significant
29	Huai Kwang	-5.542	-4.763	-0.334	-0.652	0.2557	0 not significant
30	K. Bang Sao Thon	-5.196	-4.928	0.049	0.155	0.4336	0 not significant
31	Khan Na Yao	-4.782	-5.017	-0.056	-0.595	0.2749	0 not significant
32	Khlong Luang	-5.1	-4.915	0.022	0.156	0.4369	0 not significant
33	Khlong Sam Wa	-5.237	-4.908	0.027	0.109	0.4581	0 not significant
34	Khlong San	-4.414	-4.487	0.775	2.102	**0.0206**	**1 hot spot**
35	Khlong Toey	-4.007	-4.45	1.569	2.31	**0.0122**	**1 hot spot**
36	Krathum Baen	-5.769	-5.493	2.15	2.584	**0.0055**	**3 cold spot**
37	Lak Si	-4.702	-4.796	0.071	0.422	0.3301	0 not significant
38	Lam Luk Ka	-4.772	-4.987	-0.046	-0.578	0.2786	0 not significant
39	Lat Bua Luang	-5.118	-4.983	0.087	0.451	0.3251	0 not significant
40	Lat Krabang	-5.146	-4.901	0.012	0.097	0.4626	0 not significant
41	Lat Lum Kaeo	-4.976	-4.896	0.002	0.042	0.4857	0 not significant
42	Lat Phrao	-4.177	-4.897	-0.023	-0.001	0.5	0 not significant
43	Min Buri	-5.113	-4.979	0.082	0.422	0.334	0 not significant
44	Muang Chachoengsao	-4.542	-5.002	-0.159	-0.503	0.3024	0 not significant
45	Muang Nonthaburi	-4.701	-4.766	0.094	0.693	0.2484	0 not significant
46	Muang Pathum Thani	-4.661	-4.94	-0.046	-0.262	0.3991	0 not significant
47	Muang Samut Prakan	-5.327	-4.987	0.173	0.477	0.3119	0 not significant
48	Muang Samut Sakhon	-5.023	-5.431	0.293	1.925	**0.0285**	**3 cold spot**
49	Nong Chok	-4.823	-5.039	-0.04	-0.748	0.2269	0 not significant
50	Nong Sua	-5.676	-4.872	-0.056	-0.038	0.486	0 not significant
51	Nongkheam	-6.092	-5.237	1.694	1.747	**0.0391**	**3 cold spot**
52	Ongkharak	-4.617	-5.059	-0.187	-0.77	0.2195	0 not significant
53	Pak Kret	-4.949	-4.846	-0.011	-0.212	0.4087	0 not significant
54	Pathum Wan	-3.584	-4.462	2.26	2.756	**0.0031**	**1 hot spot**
55	Phasi Charoen	-5.277	-5.212	0.506	1.67	0.0507	0 not significant
56	Phaya Thai	-4.199	-5.094	-0.572	-0.815	0.2016	0 not significant
57	Phra Nakhon	-4.229	-4.836	0.142	0.339	0.354	0 not significant
58	Phra Pra Daeng	-5.413	-4.895	0.011	0.072	0.4699	0 not significant
59	Phra Samut Jadee	-5.202	-5.295	0.514	1.705	**0.047**	**3 cold spot**
60	Phuttha Mon Thon	-4.296	-4.913	-0.056	-0.1	0.4543	0 not significant
61	Pom Pram Sattru	-5.069	-4.12	-0.56	-3.117	**0.0012**	**2 doughnut**
62	Prakanong	-4.922	-4.684	-0.027	-1.032	0.1484	0 not significant
63	Prawet	-4.984	-4.859	-0.012	-0.157	0.4306	0 not significant
64	Rat Burana	-5.194	-5.304	0.512	2.112	**0.0185**	**3 cold spot**
65	Ratchathewi — Din Dang	-6.128	-4.438	-2.263	-2.32	**0.0123**	**2 doughnut**
66	Sai Mai	-5.236	-5.0	0.155	0.485	0.3086	0 not significant
67	Sai Noi	-5.005	-4.836	-0.025	-0.268	0.3926	0 not significant
68	Sam Khok	-4.877	-4.985	-0.005	-0.431	0.3329	0 not significant
69	Sam Phran	-5.415	-5.178	0.614	1.231	0.1041	0 not significant
70	Samphantawong	-3.846	-4.161	3.076	3.525	**0.0004**	**1 hot spot**
71	Saphan Sung	-4.909	-4.958	0.005	0.384	0.3469	0 not significant
72	Sathorn	-4.168	-4.148	2.166	3.833	**0.0002**	**1 hot spot**
73	Suan Luang	-4.875	-4.868	0.001	0.119	0.4571	0 not significant
74	Taling Chan	-4.428	-5.027	-0.257	-0.741	0.233	0 not significant
75	Thanyaburi	-4.635	-4.965	-0.078	-0.325	0.3706	0 not significant
76	Thawi Wattana	-4.555	-4.964	-0.101	-0.404	0.3436	0 not significant
77	Thungkru	-5.357	-5.262	0.706	1.778	**0.0356**	**3 cold spot**
78	Wang Noi	-4.848	-5.162	-0.046	-1.133	0.1249	0 not significant
79	Wang Thonglang	-4.972	-4.691	-0.067	-0.828	0.1968	0 not significant
80	Wattana	-4.145	-4.843	0.14	0.279	0.3858	0 not significant
81	Wihan Daeng	-5.24	-5.105	0.306	0.781	0.2045	0 not significant
82	Yannawa	-4.468	-4.737	0.26	0.723	0.2285	0 not significant

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