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Building Density Level of Urban Slum Area in Jakarta

Tenty Melvianti Legarias[1 *], Renny Nurhasana[1], Edy Irwansyah[2]
[1] Urban Studies Program, School of Strategic and Global Studies, Universitas Indonesia, Jakarta, 10430, Indonesia
[2] School of Computer Sciences, Bina Nusantara University, Jakarta, 11480, Indonesia
*Corresponding Author: melvi.legarias@gmail.com

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Abstract

Currently, the number of urban residents is increasing and some of the urban population live in slum areas. Therefore, identifying the characteristics of slum areas has become crucial. This study aimed to identify more specific slum locations in Jakarta through the pattern of building densities analysis between case studies of neighborhoods association (RT) in 15 hamlets (RW) that classified as heavy slums category. This study also attempted to determine the relation between building density levels in the slum area and Jakarta spatial detail planning. This study engaged the Cluster and Outlier Analysis (Anselin Local Moran's I) method. This study also observed socio-economic factors of citizen census data based the Dasawisma Census of Family Welfare Empowerment in 2019. The result shows that slum locations that had direct neighbors towards areas which was designated at spatial detail planning as industrial zones and ware housing areas as well as office, trade and service zones, obtained a higher level of building density compared to slum locations that secured neighbors to areas that were designated as housing zones. High economic opportunities provided attraction and affected the growth of slum locations. The results also reveal that slum areas were not a concentrated population with low income and/or low education. Applying cluster and outlier modeling of building density levels of urban slums in Jakarta based on RT cluster level could reveal more specific slum locations and could identify factors that influence the differences of building density levels.

Keywords**:** Slums; Spatial Detail Planning; Cluster and Outlier Analysis; Geographic Information System

1. Introduction

By 2030, the cities population are projected to be increased up to 60 percent with 1 of 4 city residents living in slums (United Nations, 2019). The phenomenon of rapid urbanization affects escalation of slums, increasing the number of infrastructure and inadequate services (such as sewage treatment facilities, availability of clean water and sanitation, roads, and transportation), as well as escalation of air pollution and also influences cities expansion that are unplanned. Some people settled and struggled in slums, sometimes those were only a few meters away from the upper community and commercial areas.

There are several definitions and conditions to define slums. The most convenient of 'slum' term is a dense urban area that does not meet the standard housing conditions and indicates poverty area (UN Habitat, 2004). This explanation contributes to the main characteristics of slums which are performing high density and low housing standards (structure and services), and poverty. In Indonesia, slum is defined as inappropriate settlement to live, due to erratically building, the presence of high density, low-quality buildings, facilities and amenities shortages, and low affordability of infrastructure(Ministry of Public Works and Indonesian Public Housing-PUPR, 2016). There are several methods could be utilized to identify slums in a city or region and to determine whether the certain area could affect slums escalation. Each slum performs different conditions, slums may develop or new slums may emerge, both could be enhanced through high rural-urban migration rates or location circum stance that usually being indicated as inappropriate for housing (river banks, steep slopes, landfills, uninhabitated land, railroad lines, adjacency towards industrial areas or markets and all over river banks) (Roy *et al.*, 2014).

In Lagos, Nigeria, a study of slums characteristics was performed through a census using respondents from 120 slums as samples, and the results showed that 7.7% of respondents received incomes above US $ 352.94, 13.8% were graduated of formal education and 67% were non-native, also, 5.6% of buildings were built with wood, while 91.5% of buildings were more 10 years (Adedayo & Malik, 2015). Research relating slum was also performed engaging questionnaires towards respondents, revealed that the major factors affecting slums were affordability, cultural, kinship and markets adjacency, and then followed by other factors (Badmos *et al.*, 2020). Friesen *et al.* (2018) also utilized population data of slum area to indicate that slum development was strongly related to demographic development of a country.

Some studies utilizing building maps and spatial methods to identify urban areas based on building density levels. Buildings data could be used to describe community residence or to describe a business district within down town compared to population data (De Bellefon *et al.*, 2020). High density is also one of the physical characteristics that is frequently used to describe slums. Furthermore, in term of physical characteristics, there are also the small roof size and irregular patterns (Kuffer *et a*l., 2016). Spatial statistical method also measures spatial concentration including high-density buildings. Arribas-Bel *et al.* (2019) also engaged building density measurements based on machine learning algorithms, proposed to obtain the distribution of building groups with significant values that could reach the minimum building density limit. De Bellefon *et al.* (2020) compared building density with engaging building data in France. Hence, the definition of urban area is characterized by high building density.

Few researchers combined some methods to draw slum characteristics. The Object-Based Slum Detections research in Jakarta by Pratomo *et al.* (2017) conducted Object-Based Image

Analysis (OBIA) with distance variable upon the river or railroad, building size, building density, roofing materials, and illegal land expansion. All of these variables were taken from expert agreements. Similar research employed remote sensing to identify slum areas was conducted in Bandung (Leonita *et al.*, 2018) performed a method which combining remote sensing imagery with machine learning by gathering all the input from the experts based on slum indicators.

Wijaya *et al*. (2019) conducted a field study of a slum located in Kelurahan Manggarai, South Jakarta, to calculate the usage intensity of communal space occupied by slum residents. The results showed the communal space usage not only in public locations that already remained in spatial planning, but also communal space utilization also occupied a huge of space for roads. In the same location, Wati (2018) revealed that due to improper housing space conditions, the private space engagement spread out and utilized public space.

Slum issues and spatial detail planning are closely interrelated. This is comformable to the New Urban Agenda which is committed to promote the planning and replenishment of city expansion, includes a commitment to recover slums. Slums in Jakarta were classified using RW (Rukun Warga/hamlet) administrative boundaries and there was still limited information regarding slums in the smaller areas or certain slum locations and limited information to determine the effect of spatial detail planning factors on these locations.

The previous studies concerned in identifying the characteristics of slums based on the population census, field study and remote sensing methods. There have been limited studies focused on slum areas interrelated to spatial detail planning in Jakarta using building density. Therefore, this study aimed to identify more specific slum locations in Jakarta through the pattern of building density analysis between case studies neighborhoods association (RT) in 15 hamlets (RW) that classified as heavy slums category. This study committed to investigate the affiliation between building density level in slum area and Jakarta spatial detail planning. The current research also observed socio-economic factors based on population census data reported by the *Dasawisma* Census of Family Welfare Empowerment in 2019.

2. Methods

2.1 Study Area

The study area employed in this study was Jakarta Municipality. Jakarta Municipality was the capital city which was divided into five regions (*Kota Administrasi*) composed of 42 sub-district *(Kecamatan)* that consisted of 262 urban villages *(Kelurahan)* and divided into 2,718 citizen associations *(RW).* Each RW was divided into 10-20 neighborhoods *(RT).* Jakarta is the capital and largest city of Indonesia that covers 662,33 square kilometers.

Jakarta Provincial Government had classified 445 RW as slums according to DKI Jakarta Provincial Governor Regulation Number 90/2018 related to Improvement of Quality of Settlements in the Context of Integrated Housing Area Regulations, which are categorized as heavy, medium, light and very light priority. However, 15 RW of 445 RW were categorized as heavy slum were selected for this study namely: West Jakarta with seven locations consisted of *Jati Pulo* urban village RW 006, RW 008, RW 009, *Kapuk* urban village RW 012, RW 016, *Jembatan Besi* urban village RW 003, *Keagungan* urban village RW 003, North Jakarta with four locations consisted of *Kalibaru* urban village RW 004, RW 007, *Penjaringan* urban village RW 008, RW 017, East Jakarta with two locations consisted of *Kampung Melayu* urban village RW 007, RW 008, South Jakarta with one location namely *Manggarai* urban village RW 004 and Central Jakarta with one location namely *Tanah Tinggi* urban village RW 012.

These 15 locations were considered as heavy slums category were taken as samples, since those were assumed to be locations with the highest slum level compared to others. It was necessary to analyze these fifteen (15) locations as priority locations to improve slums and the analysis results could be utilized as references for other categories. The distribution of fifteen RW locations is presented in Figure 1 with heavy slum legend.

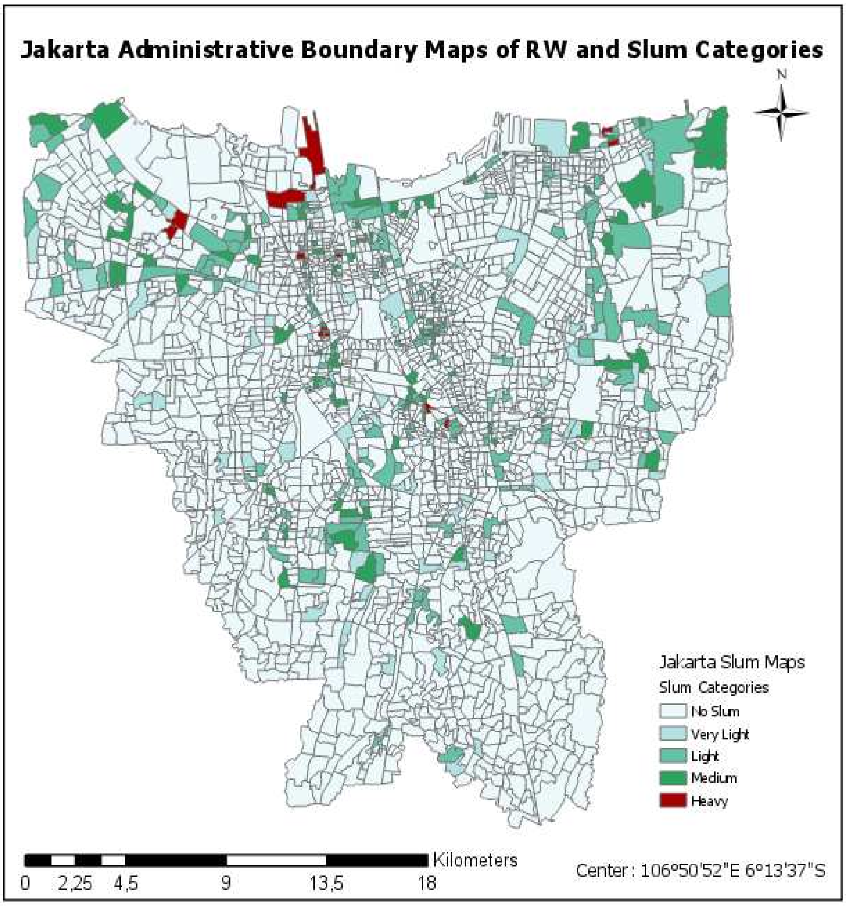

Figure 1. Jakarta Slum Maps

2.2 Data Resources

Spatial data sources were building map, administrative boundary map, and the spatial detail planning map provided by Human Settlement, Spatial Planning and Land Authority Department of Jakarta Provincial Government, and citizen census data reported by the *Dasawisma* Census of Family Welfare Empowerment in 2019. Jakarta buildings map dataset in GIS format which mapped in National Geospatial Standard precision for the year 2019 was taken from aerial photography in 2014. The building map was engaged to generate building density levels by overlaying it along with administrative boundary map of RW. All maps were officially published online at https://jakartasatu.jakarta.go.id.

Jakarta administrative boundary maps composed of areas boundaries *(Kota Administrasi),* sub-district *(Kecamatan),* urban villages *(Kelurahan),* hamlets *(RW)*, and neighborhoods association *(RT)*. This research employed RW and RT administrative boundary maps. A smaller scale of analysis unit of RW was required to determine the focus of slum locations within RW area, thus this research utilized RT map scale. The current study also utilized Jakarta Spatial Detail Planning Map, a map with detailed plans on district-level spatial planning which was equipped with zoning regulations that were translations for 2011-2030 Regional Spatial Plan with a map scale of 1: 5,000 (Jakarta Regional Regulation, 2014). Zoning is the regions division into zones based on original functions and characteristics or directed to the development of other functions.

Other data resources were data sets reported by the *Dasawisma* Census of Family Welfare Empowerment in 2019. This data was generated from census results by Jakarta Provincial Family Welfare Empowerment conducted from January to May 2019. Collection data method used by *Dasawisma* was over direct interviews by *Dasawisma* Officers towards each family member then conducted input data online through both mobile applications and web applications.

Data analysis employed dependent and independent variables. The dependent variable was building density level which was one of the physical indicators of slums (Ministry of Public Works and Indonesian Public Housing-PUPR, 2016). A high level of building density that located within metropolitan cities and large cities is > 250 units/Ha, this parameter is engaged for Jakarta. The parameter value was 5 if the building density was in the range of 76% - 100% of the indicator, the value 3 was if the building density was in the range of 51% - 75% of the indicator, and the value was 1 if the building density was in the range of 25% - 50 of the indicator, a value of 5 was categorized a high score, a value of 3 was categorized a medium score and a value of 1 is categorized a low score.

The independent variables employed for this study were taken from two sources. The first source was acquired based geographical factors, namely the spatial detail planning map and the second source was socio-economic factor,which was according to *Dasawisma* data composed of education, level of family activity in the settlement, and income which was represented by the head of the family.

2.3 Analysis Method

The research methods used were descriptive analysis and spatial analysis to accomplish the research objectives that related to spatial/regional aspects. Overlay analysis is an operation of GIS to superimpose several layers of a dataset which representing different themes together to analyze or identify the relationships of each layer. Overlay analysis represents a composite map with a combination of various attributes and the geometry of a data set or entity. An overlay is an operation of comparing variables among several scopes. During analysis process with applying overlay method, a new map could be generated which wasa combination two or more layers of input maps results. This current study, overlay analysis was performed between building maps, administrative boundary maps, and the spatial detail planning map.

In addition, Local Moran's I index (LMI) was applied to detect the clusters and outliers based on dependent variables building density level in neighborhoods (RT) administrative boundary maps. This spatial analysis namely Cluster and Outlier Analysis. The analysis was needed to be completed in order to identify the geographical distribution of slum phenomenon and to determine the factors statistically whether result in dependence phenomenon on other regions or it was an independent phenomenon. In order to formulate statistical calculations into clusters and outliers, LMI calculated the Moran I value, z-score, p-value, co-type. Z-score is the standard deviation, and the p-value is the opportunity value of mistrust that spatial patterns are random.

The Local Moran's *I* statistic of spatial association (Anselin, 1995) is presented below:

$$Ii = \frac{xi-\bar{X}}{S_i^2}\sum_{j=1,j\neq i}^{n} W_{i,j}(x_i-\bar{X}) \quad (1)$$

Where x_i is attribute for feature *i*, $\underline{X}$ is the mean of the corresponding attribute, $w_{i,j}$ is the spatial weight between feature *i* and *j*, and:

$$S_i^2 = \frac{\sum_{j=1,j\neq i}^{n}(xi-\bar{X})^2}{n-1} \quad (2)$$

With *n* equating to the total numbers of features.

The ZI_i score for the statistics are computed as:

$$ZI_i = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \quad (3)$$

where:

$$E[I_i] = -\frac{\sum_{j=1, j\neq i}^{n} w_{ij}}{n-1} \quad (4)$$

$$V[I_i] = E[I_i^2] - E[I_i]^2 \quad (5)$$

The result I value reveals the positive or negative value of the feature. If the value of I was positive, it meant that the feature was part of a cluster with neighboring features that were equally high or low value, whereas if the value of I was negative then the feature was an outlier where the feature had a different value than its neighbors. In both conditions, the p-value must be of very small value, thus it could be considered a significant value. In the sense of this statistic, a maximum p-value of 0.05, could be categorized as significant was set at a 95% confidence level. Co-type on statistical results was an attribute that distinguished whether a high-value significant cluster (HH), or a low-value significant cluster (LL), and for the outlier category would distinguish whether a feature was surrounded by high-value features (LH) or whether a feature was surrounded by low value features (HL). The Co-type statistical results of RT area conducted in this study is presented on Figure 2.

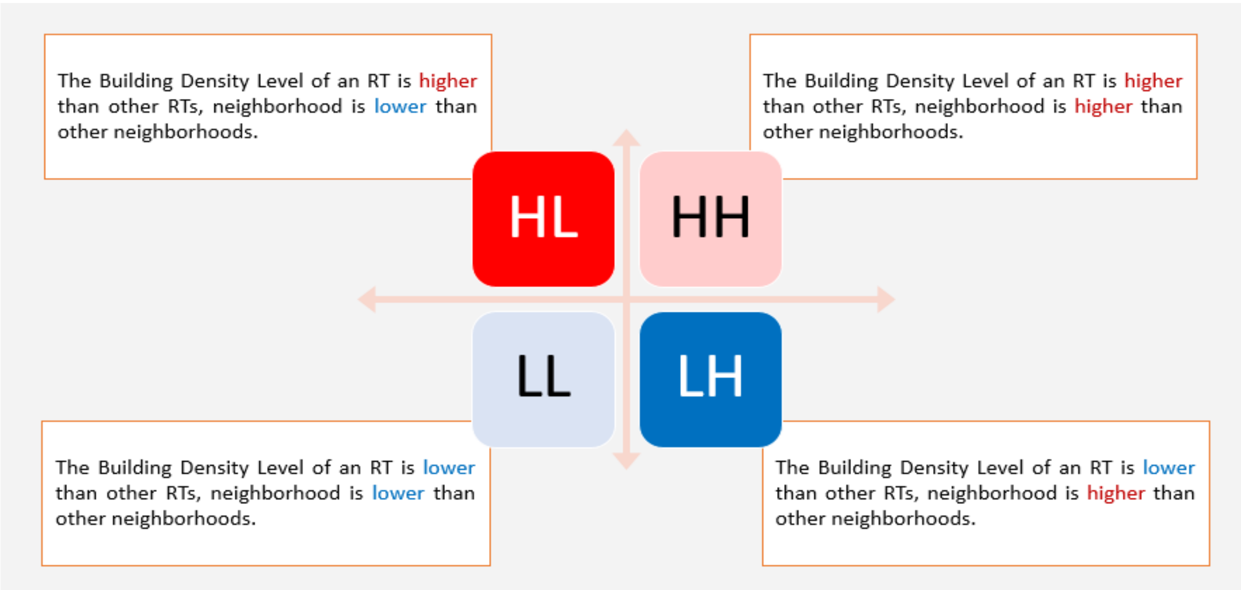

Figure 2. Cluster type for each significant feature statistically
Source: Author's Illustration.

3. Results and Discussion

3.1 Distribution of 15 RW's Building Density Level of Heavy Slums

The initial stage was observing the distribution of the building density level of 15 RW's in heavy slum which limited the scope of this study to identify the characteristics of each RW. Spatial overlay analysis was performed between the administrative boundary map of 15 RW and the building map to calculate the level of building density. The results can be seen on Table 1.

Table 1. Distribution of 15 RW's Building Density Level of Heavy Slums

Location	Number of Buildings	RW Area (Hectare)	Building Density Level (Units/ha)	Score of Building Density
Jati Pulo RW 009	849	5.79	146.62	Medium
Jati Pulo RW 008	606	4.28	141.60	Medium
Jati Pulo RW 006	600	4.40	136.44	Medium
Kapuk RW 016	4645	42.17	110.13	Low
Kalibaru RW 004	1273	11.63	109.42	Low
Tanah Tinggi RW 012	204	2.09	97.79	Low
Kampung Melayu RW 008	415	4.28	97.00	Low
Kampung Melayu RW 007	321	3.32	96.76	Low
Kalibaru RW 007	1523	17.38	87.64	Low
Kapuk RW 012	3475	41.13	84.48	Low
Jembatan Besi RW 003	677	10.14	66.76	Low
Keagungan RW 003	185	4.11	45.10	Low
Manggarai RW 004	305	11.21	27.20	Low
Penjaringan RW 017	4607	181.97	25.32	Low
Penjaringan RW 008	1904	103.25	18.44	Low

The building density score of RW could not yet indicate that the RW location was a heavy slum area, the scores were in between low and medium, referring to the indicator of the building density level with the highest level was 146.62 units/ha. Considering these results, it was necessary to perform deeper observations upon smaller units of analysis to focus on certain areas within the RW boundaries which were considered slum based on building density and whether the neighborhood factors within the RW boundaries affect the location or not, which in the current study were applied using RT boundary maps which were fractions of RW boundary maps. The analysis was completed using Cluster and Outlier Analysis.

3.2 Cluster and Outlier Analysis

During this analysis phase, six samples were taken of 15 RW's in heavy slum which gained a total of more than 1,000 buildings. The six locations were *Kapuk* RW 016 with 4,645 buildings, *Penjaringan* RW 017 with 4,607 buildings, *Kapuk* RW 012 with 3,475 buildings, *Penjaringan* RW 008 with 1,904 buildings, *Kalibaru* RW 007 with 1,523 buildings and *Kalibaru* RW 004 with total 1,273 buildings. These six locations were also the largest RW area out of 15 RW's within heavy slum areas. In addition, based on RT boundary maps analysis, the exact RW location was also presented with a spatial detail planning map that would be applied for further observation.

3.2.1 *Kapuk* RW 016

In *Kapuk* RW 16 area, 69.78% of the area was planned as a residential zone, 28.24% as a green open space or blue open space zone, and 1.98% as a social and government zone. The results of the analysis identified HH clusters from four RT areas with an average level of building density was 173.83 units/Ha, which was identified into medium category, and this cluster occupied a residential zone and then grew in the green open space zone. LL cluster was also identified as a residential zone, but it had more old buildings. LH cluster was an area that covered the social and government zone and also green open space/blue open space zone near *Kali Apuran Bawah* river. Cluster and outlier analysis formulated map and spatial detail planning map for *Kapuk* RW 16 that could be observed on Figure 3. The Cluster and outlier analysis result is presented on Table 2.

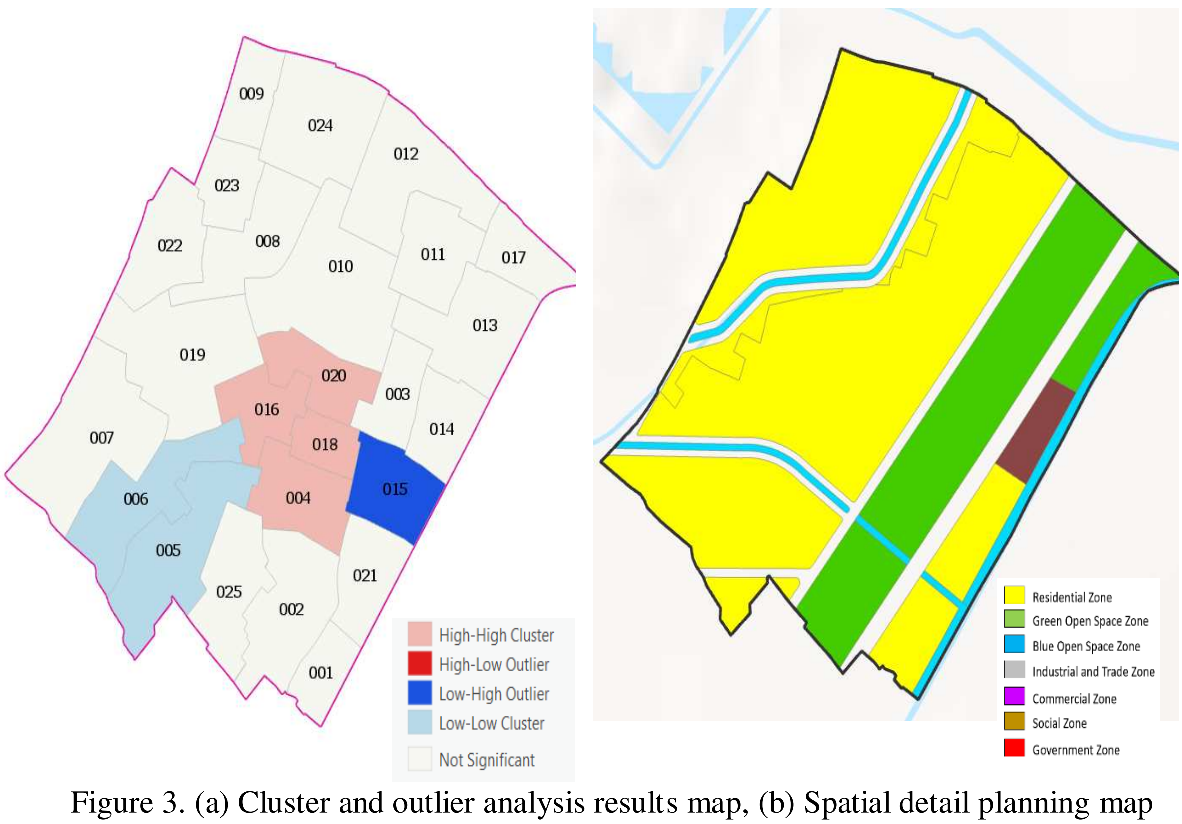

Figure 3. (a) Cluster and outlier analysis results map, (b) Spatial detail planning map

Table 2. Cluster and Outlier Analysis Results of *Kapuk* RW 016

RT Number	Area (Ha)	Building Density Level	Lmi Index	Z-Score	P-Value	Co-Type	Neigh-bors	Spatial Lag
001	0.78890752	131.827873	0.001508562	0.387145471	0.364	-	2	-0.004701344
002	2.14651369	140.6932558	5.4235E-05	1.214925052	0.108	-	3	-0.018824558
003	1.00498735	172.14147	0.033296671	1.825571949	0.052	-	4	0.029592984
004	1.46244218	148.3819347	0.0123515	2.991055859	0.006	HH	2	0.045258697
005	2.46784838	103.7340875	0.02905614	1.566515726	0.038	LL	2	-0.021869871
006	2.14748691	114.5525026	0.030704491	2.340752554	0.004	LL	2	-0.032645604
007	3.00384643	90.88347439	0.015047986	1.104568131	0.178	-	1	-0.008408863
008	1.80339314	149.7177701	0.000924891	0.147887924	0.422	-	3	0.002882855
009	0.9364856	134.5455812	-0.0014358	-0.455550344	0.322	-	2	0.006427158
010	3.26639455	111.7440022	-0.007981297	-0.557024516	0.29	-	2	0.007664893
011	1.46873319	169.5338549	0.007327559	0.688213256	0.228	-	2	0.007102963
012	2.37001674	157.8047922	0.006688868	1.075411377	0.212	-	1	0.010949147
013	2.08209823	142.6445668	0.000792132	0.831162656	0.208	-	3	0.011803195
014	1.13174822	153.7444433	0.005909034	0.857355567	0.204	-	3	0.012700498
015	1.3356222	136.266079	-0.004879763	-1.900817882	0.036	LH	4	0.0301812
016	1.09323106	178.370343	0.043264785	2.293780083	0.016	HH	3	0.032081698
017	1.00928455	135.7397179	-0.000103513	-0.020345199	0.428	-	1	0.000573283
018	0.67348341	212.3289118	0.078562803	2.109136513	0.018	HH	5	0.030608937
019	3.03095282	116.7949555	0.004076958	0.672323026	0.28	-	1	-0.004740077
020	1.2031728	156.2535327	0.0244037	2.514767948	0.012	HH	4	0.043950037
021	1.2412121	123.2666035	0.00242926	0.42138908	0.36	-	3	-0.003868443
022	1.52970121	122.8998175	-0.003649544	-0.394841901	0.322	-	3	0.005692408
023	0.93869414	173.6454862	-0.003607513	-0.100977414	0.492	-	3	-0.003059541
024	2.377284	127.8770227	0.000913782	0.204525798	0.454	-	1	-0.001975342
025	1.64110897	113.947339	0.013429807	1.086381045	0.134	-	2	-0.013956718

3.2.2 *Penjaringan* RW 017

In *Penjaringan* RW 17 area, 43.74% of the area was designed as an industrial and trade zone, 32.28% as a commercial zone, 18.89% as green open space or blue open space zone, only 4.38% as a residential zone, and 0.71% as a social and government zone. HH cluster was an RT area with 100% in green open space or blue open space zone. This area had the densest population in Jakarta. HL cluster was also location extension occupied by residents who arrived into risky zone location (green open space or blue open space zone). The LH and LL locations were industrial zones which the edges were occupied as residences by dwellers. Cluster and outlier analysis results map and spatial detail planning map for *Penjaringan* RW 17 are presented on Figure 4. The map shows the impact of industrial zones and commercial zones towards slum areas. The Cluster and outlier analysis results are shown on Table 3.

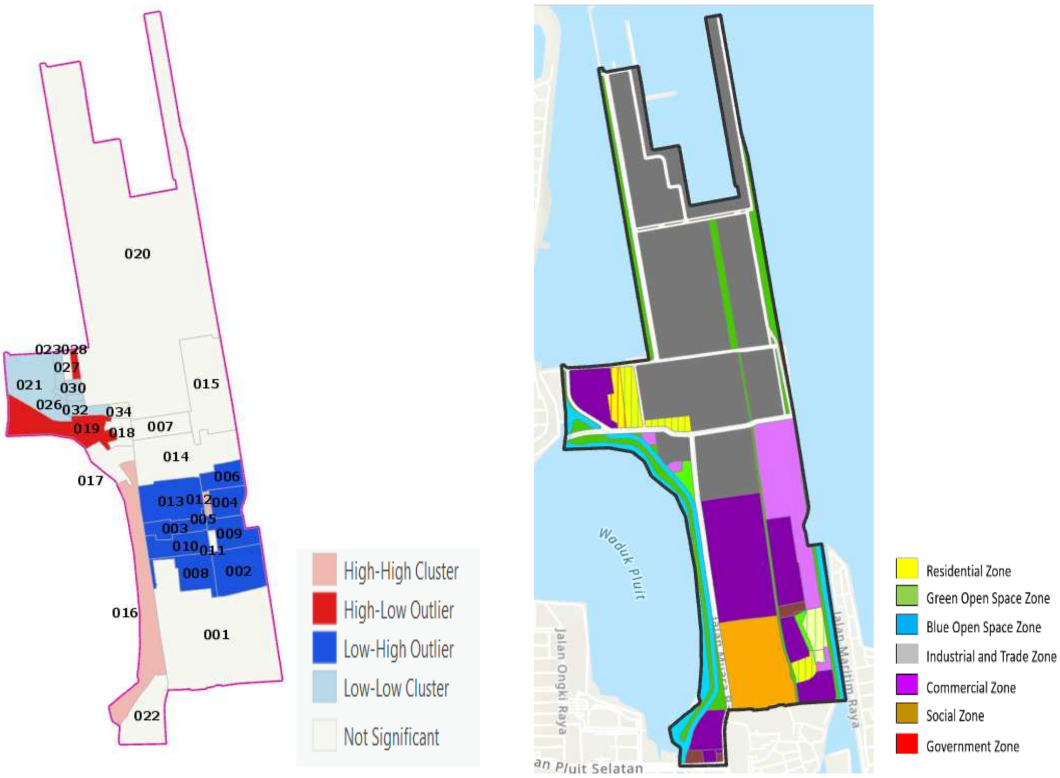

Figure 4. (a) Cluster and outlier analysis results map, (b) Spatial detail planning map

Table 3. Cluster and Outlier Analysis Results of *Penjaringan* RW 017

RT Number	Area (Ha)	Building Density Level	Lmi Index	Z-Score	P-Value	Co-Type	Neigh-bors	Spatial Lag
001	24.6804102	39.78864177	-0.002616779	-1.670152585	0.064	-	9	0.010441781
002	4.824186568	33.99536848	-0.007855146	-2.531712022	0.01	LH	12	0.024575347
003	2.085333118	32.60869902	-0.011999175	-2.346268865	0.028	LH	16	0.035695071
004	2.049918123	9.756487235	-0.038284232	-3.577396182	0.004	LH	14	0.062921035
005	0.139748327	329.1631544	0.15481202	3.271550776	0.004	HH	17	0.048418412
006	2.118680853	34.45540177	-0.010985832	-2.55834858	0.012	LH	16	0.034969605
007	2.618886236	45.82100525	0.000703032	0.492226613	0.308	-	23	-0.003933508
008	3.253114738	49.18363258	-0.003363218	-1.995818093	0.04	LH	13	0.024254728
009	2.755275956	29.03520419	-0.019206518	-3.225429746	0.002	LH	13	0.050712012
010	2.875708737	30.25341157	-0.011723986	-2.070478514	0.034	LH	15	0.032189144
011	0.32690227	281.429676	0.053681346	1.780152457	0.052	-	13	0.020421872
012	0.220512094	276.628818	0.137826164	3.296947998	0.01	HH	17	0.053599316
013	5.350504813	27.47404313	-0.013279142	-2.509172762	0.01	LH	18	0.033420202
014	9.009023645	31.85694824	-0.005614526	-1.576171251	0.068	-	18	0.016268559
015	8.638203131	11.11342238	-0.003542517	-0.845140368	0.204	-	11	0.005981147
016	9.159645356	112.558943	0.007461217	1.86864637	0.044	HH	11	0.012103057
017	2.433667166	111.3545861	-0.004304425	-0.634164665	0.278	-	24	-0.007148742
018	1.288795694	119.4913986	-0.011370445	-1.033328876	0.128	-	22	-0.016264959
019	5.772279279	93.5505671	-0.011904918	-1.805523987	0.02	HL	15	-0.030526746
020	77.01502484	4.310847146	-2.69606E-05	-0.028552754	0.228	-	1	4.00404E-05
021	5.827540297	39.46776655	0.007115157	1.770287707	0.02	LL	14	-0.027965099
022	4.836226834	83.74297027	0.00018264	0.205037776	0.26	-	2	0.00066871
023	0.415659292	14.43489923	0.020400431	1.416291322	0.036	LL	15	-0.036910218
024	0.321622248	18.65542585	0.025864	1.876704738	0.012	LL	15	-0.051479327
025	0.201663089	4.958765662	0.035010541	1.442291566	0.024	LL	15	-0.052598772
026	0.233895101	38.47878805	0.015023239	1.734740977	0.014	LL	15	-0.056432968
027	0.524453793	22.88094807	0.019272681	1.230817008	0.068	-	15	-0.042632365
028	0.478334564	62.71760871	-0.00111759	-1.541090036	0.008	HL	16	-0.04945287
030	0.561350404	1.781418509	0.037086594	1.825113834	0.01	LL	15	-0.052719193
031	0.252174583	3.965506699	0.037865571	1.756201831	0.008	LL	16	-0.055894254
032	0.580194553	8.617798926	0.027070382	1.549926773	0.028	LL	16	-0.043520348
033	0.522154356	1.915142503	0.020374635	1.757167935	0.024	LL	18	-0.029028623
034	0.608065523	1.644559611	0.009971823	1.031768244	0.124	-	20	-0.014142324

3.2.3 *Kapuk* RW 012

In *Kapuk* RW 012 area, 58.81% of the area was planned as green open space or blue open space zone, 29.43% as a residential zone, and 11.77% as a commercial zone. The average level of building density in the HH cluster was 179.39 units/ha, which categorized into medium category, and this cluster occupied a residential zone and then grew into the green open space zone. For LL clusters, based on the results during observing aerial photo maps and building information maps, these locations were worked for commercial zones and burial grounds. Cluster and outlier analysis results map and spatial detail planning map for *Kapuk* RW 12 can be seen on Figure 5. The Cluster and outlier analysis results could be seen on Table 4.

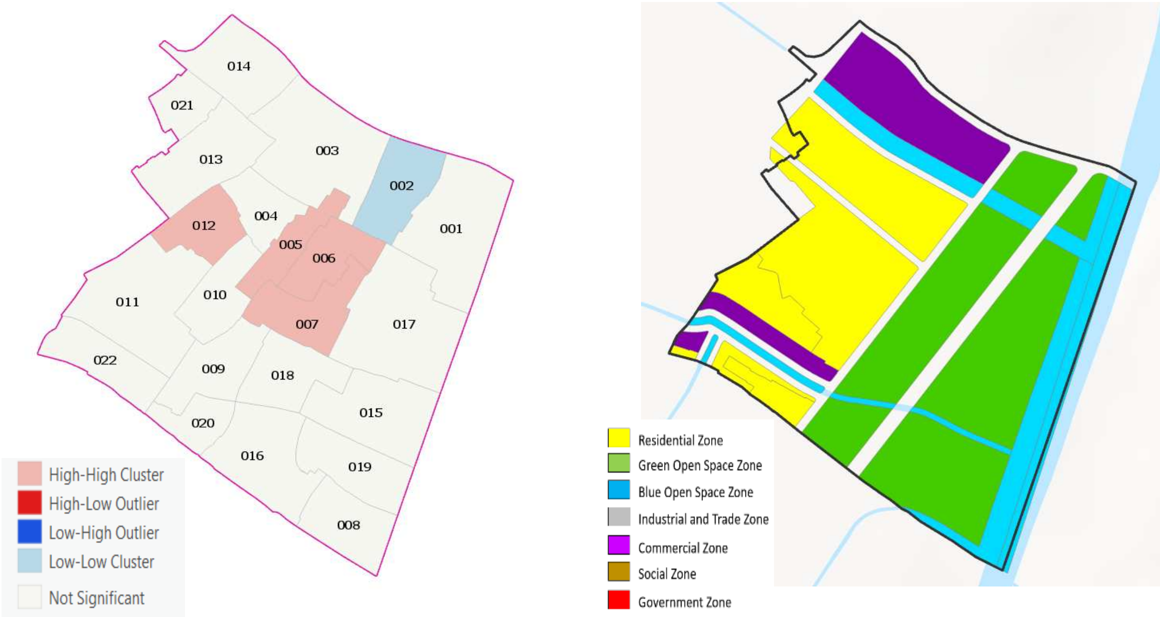

Figure 5. (a) Cluster and outlier analysis results map, (b) Spatial detail planning map

Table 4. Cluster and Outlier Analysis Results of *Kapuk* RW 012

RT Number	Area (Ha)	Building Density Level	Lmi Index	Z-Score	P-Value	Co-Type	Neigh-bors	Spatial Lag
001	3.050279876	63.27288244	0.013005688	1.383595715	0.066	-	1	-0.01011694
002	1.602879138	68.62650926	0.020564999	1.855241209	0.036	LL	2	-0.017500441
003	3.423131314	79.4594116	0.001705587	0.20036579	0.428	-	2	-0.001792192
004	1.071603848	165.1729791	0.022594483	1.599814094	0.07	-	5	0.027681558
005	1.01385894	215.02005	0.091155771	2.95665696	0.002	HH	5	0.049424034
006	1.28523603	184.4019265	0.054167684	2.500547328	0.002	HH	3	0.044661859
007	1.605481942	176.8939236	0.047054637	2.996412639	0.002	HH	4	0.044475847
008	1.537244856	113.8400297	0.002126715	0.903418694	0.282	-	1	-0.00876811
009	1.589758677	164.8048875	0.017564833	1.522328007	0.078	-	3	0.021721542
010	1.328513767	188.932931	0.022516053	1.470343221	0.084	-	5	0.017236573
011	3.339938804	49.10269607	-0.009542732	-0.506884261	0.318	-	2	0.006048102
012	1.23188494	141.2469577	0.010045428	2.041435921	0.016	HH	4	0.031125746
013	2.237282831	120.2351336	-0.001570291	-0.799388461	0.21	-	3	0.01419185
014	1.932980531	68.80565937	-0.004851992	-0.415373767	0.394	-	1	0.004141982
015	2.334479253	87.81401667	0.010465548	1.213058723	0.132	-	2	-0.013428443
016	2.381764559	141.9115919	0.000943805	0.31907043	0.376	-	3	0.002805225
017	3.58094228	91.87525916	0.003578863	0.797924913	0.35	-	1	-0.00514507
018	1.573707442	156.9542047	0.012007035	1.57992754	0.082	-	3	0.018566322
019	1.682986199	84.96801702	0.007066262	0.670539879	0.282	-	3	-0.008431714
020	0.873744495	151.0739132	0.005892325	0.880595533	0.23	-	2	0.011214395
021	0.841537554	147.3493362	-0.005376213	-0.792084643	0.242	-	2	-0.011984346
022	1.528143157	101.4302877	0.006741018	1.591998624	0.052	-	1	-0.013522301

3.2.4 *Penjaringan* RW 008

In *Penjaringan* RW 08 area, 46.96% of the area was planned as a commercial zone, 28.99% as industrial and trade zone, only 11.16% as a residential zone, 8.06% as a social and government zone and 4.83% as green open space or blue open space zone. The average level of building density in the HH cluster was 241.88 units/ha, which categorized into high category. The area of HH cluster was an average of 81% in the residential zone, all RT's outside this cluster were located within commercial zones and industrial zones. The LH cluster and LL cluster were put in locations that designated as industrial and trade zones, despite people settled in the area. Cluster and outlier analysis results map and spatial detail planning map for *Penjaringan* RW 008 is presented on Figure 6. The map reveals the impact of industrial zones and commercial zones towards slum areas. The Cluster and outlier analysis results can be seen on Table 5.

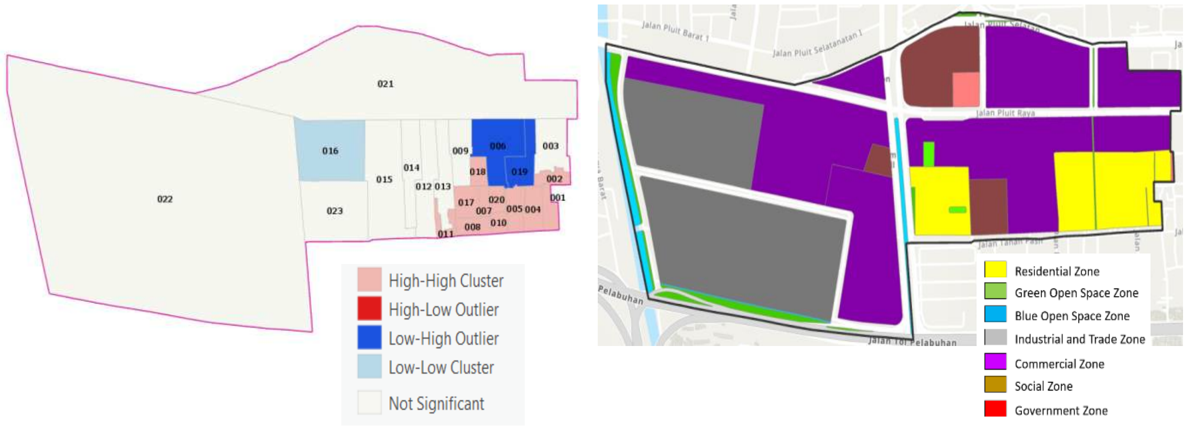

Figure 6. (a) Cluster and outlier analysis results map, (b) Spatial detail planning map

Table 5. Cluster and Outlier Analysis Results *Penjaringan* RW 008

RT Number	Area (Ha)	Building Density Level	Lmi Index	Z-Score	P-Value	Co-Type	Neigh-bors	Spatial Lag
001	0.495802821	244.0486317	0.035181464	1.977457897	0.026	HH	18	0.035410012
002	0.452813873	147.9636645	0.00340027	1.85192352	0.03	HH	18	0.030411088
003	1.487034681	70.61032358	-0.012887621	-1.426214046	0.082	-	19	0.021550046
004	0.739700924	178.4505004	0.024978276	2.593193752	0.008	HH	18	0.063789024
005	0.709476909	207.1949038	0.04808212	3.239845847	0.002	HH	19	0.073368285
006	2.299074609	80.90211568	-0.012279053	-1.774914495	0.028	LH	20	0.024383117
007	0.271360063	361.1437843	0.140781393	3.33463788	0.002	HH	21	0.068073355
008	0.539745467	155.6289123	0.012273384	3.848469814	0.002	HH	21	0.067380165
009	1.217307666	76.39810595	-0.007389487	-0.797000292	0.198	-	21	0.013560685
010	0.309755994	229.2126752	0.060621196	3.725490858	0.002	HH	20	0.070703378
011	0.354582012	304.5839785	0.024249285	1.997014978	0.024	HH	21	0.015654237
012	1.854919545	79.78782714	0.003178869	0.481377685	0.356	-	21	-0.006186812
013	1.367295966	62.1664966	-0.008427159	-0.380773793	0.382	-	21	0.012475107
014	1.498585816	31.36290194	0.010542954	0.963948072	0.18	-	21	-0.011002978
015	4.008211452	10.22900126	0.010665893	1.157341626	0.15	-	21	-0.009257553
016	3.667775876	30.26357219	0.01191103	1.775755486	0.04	LL	14	-0.012301236
017	0.713209099	210.3170026	0.043696009	3.241898475	0.002	HH	21	0.063882751
018	0.437556513	196.5460404	0.0181026	2.454770154	0.008	HH	21	0.032463326
019	1.109129785	102.7832825	-0.009126339	-1.847478581	0.032	LH	19	0.030140513
020	0.374971588	306.689903	0.127608409	3.619860606	0.002	HH	21	0.081363146
021	20.2275822	5.635868828	0.005646748	1.414963492	0.078	-	18	-0.004728168
022	55.5765592	7.233265352	0.002338318	1.161014202	0.132	-	1	-0.001982265
023	3.533284563	23.77391306	0.009257242	1.434316635	0.072	-	15	-0.009006569

3.2.5 *Kalibaru* RW 007

In *Kalibaru* RW 007 area, 89.25% of the area was plotted as an industrial and trade zone and 10.75% as green open space or blue open space zone. The average level of building density in the HH cluster was153.05 units/ha, which categorized into medium category. Within this RW, there was no area had spatial detail planning for residential zones. The HH cluster was100% in the industrial zone.Cluster and outlier analysis results map and spatial detail planning map for *Kalibaru* RW 007is presented on Figure 7. This map reveals the impact of industrial upon slum areas. The Cluster and outlier analysis results is shown on Table 6.

Figure 7. (a) Cluster and outlier analysis results map, (b) Spatial detail planning map

Table 6. Cluster and Outlier Analysis Results *Kalibaru* RW 007

RT Number	Area (Ha)	Building Density Level	Lmi Index	Z-Score	P-Value	Co-Type	Neigh-bors	Spatial Lag
001	1.737144174	99.58874027	0.00458499	0.509644235	0.284	-	1	-0.005055485
002	1.055307687	124.1344127	-0.002695798	-0.291010523	0.404	-	3	0.005994252
003	0.84579522	169.0716579	-0.005497731	-0.688305876	0.246	-	4	-0.014195057
004	0.576624363	201.1708272	0.01444728	0.940784057	0.18	-	5	0.014664336
005	1.211330157	152.7246712	0.002984804	1.931780157	0.022	HH	3	0.036044119
006	0.549578745	151.0247634	0.003037311	2.086063318	0.006	HH	4	0.059384902
007	0.585524499	239.1018655	0.014094885	0.76339319	0.254	-	5	0.00833166
008	0.672974678	130.7627208	-0.00464367	-0.651168343	0.27	-	3	0.014232711
009	0.46403552	185.3306404	0.01278412	1.010676774	0.152	-	4	0.018523708
010	1.875343705	75.71945323	0.009775126	1.00673682	0.196	-	1	-0.007232595
011	2.86229691	106.2084087	-0.01056085	-0.666811523	0.292	-	3	0.013476807
012	0.559880211	155.3903823	0.005647758	1.991396856	0.03	HH	6	0.042636513
013	0.934507631	168.0029084	-0.001303836	-0.067590477	0.474	-	2	-0.003548897
014	0.761461633	215.3752638	0.017805913	0.983593321	0.18	-	3	0.014247248
015	2.708752569	50.57678637	-0.00776916	-0.32882532	0.296	-	1	0.004269095

3.2.6 *Kalibaru* RW 004

In *Kalibaru* RW 04 area, 72.25% of the area was expected to be green open space or blue open space zone and 27.75% as industrial and trade zone. The average level of building density in the HH cluster was 299.13 units/ha, that turned to be high category. Furthermore, the highest indicator was 250 units/ha. Within this RW, there was noarea had spatial detail planningfor residential zones. The HH cluster was 100% of the industrial zone. LL cluster was performed for fish auction, thusthe building was better organized and less dense compared to residential area, although this area was expected as a blue open space zone. Cluster and outlier analysis results map and spatial detail planning map for *Kalibaru* RW 004 is presented on Figure 8. This map illustrates the impact of industrial towards slum areas. The Cluster and outlier analysis resultscould be observed on Table 7.

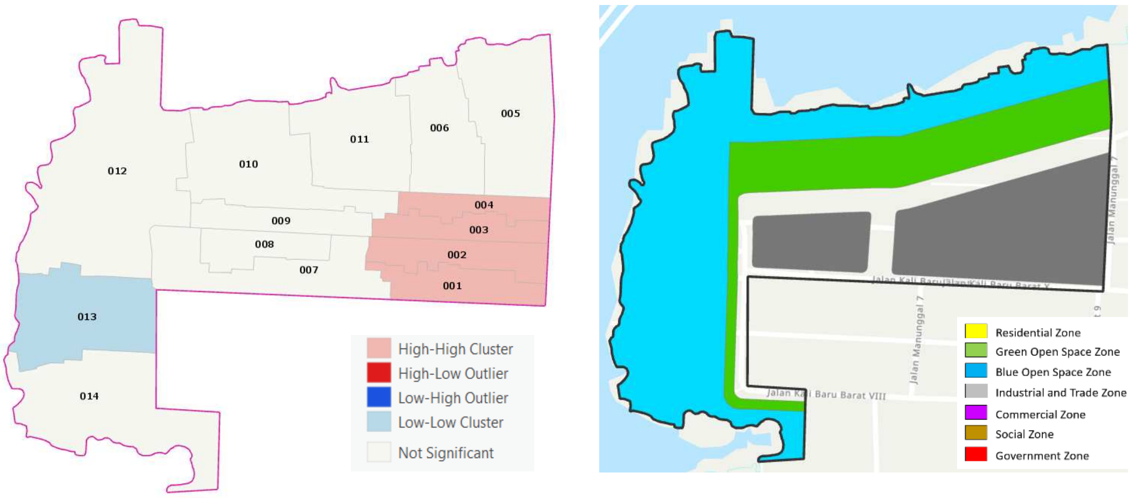

Figure 8. (a) Cluster and outlier analysis results map, (b) Spatial detail planning map

Table 7. Cluster and Outlier Analysis Results of *Kalibaru* RW 004

RT Number	Area (Ha)	Building Density Level	Lmi Index	Z-Score	P-Value	Co-Type	Neigh-bors	Spatial Lag
001	0.436869348	235.7684293	0.024902118	2.239643163	0.01	HH	3	0.094305378
002	0.456607682	310.9890737	0.116878753	2.089503004	0.022	HH	4	0.101034507
003	0.350335746	353.946183	0.137817159	2.206303646	0.018	HH	6	0.082690636
004	0.283954308	295.8222424	0.085300183	2.104603301	0.026	HH	6	0.087325124
005	1.054127606	126.170683	-0.023863091	-1.126039608	0.166	-	3	0.02301808
006	0.723276474	193.5636027	-0.005356458	-0.867204751	0.194	-	5	0.022615129
007	0.839642029	152.445918	-0.02602809	-0.640549153	0.284	-	3	0.03590769
008	0.351977421	230.1283976	-0.000381847	-0.014604488	0.486	-	4	-0.001937138
009	0.388837959	329.1859679	-0.031896561	-0.417994391	0.388	-	4	-0.023234821
010	1.170541928	175.9868613	-0.007655461	-0.677320645	0.26	-	4	0.017185376
011	0.896925791	177.2721909	-0.01288667	-1.556943245	0.068	-	6	0.029954463
012	2.353795432	124.9046523	0.003343953	0.548240084	0.464	-	1	-0.003179458
013	0.986840146	179.3603561	0.009617887	1.843403771	0.01	LL	2	-0.023722966
014	1.339964566	103.7340864	0.006273934	0.562931197	0.466	-	1	-0.004814987

3.3 Socio-economic Condition Observation

A brief observation of the socio-economic factors was conducted and decided that 6 RW locations were selected based on the *Dasawisma* Census of Family Welfare Empowerment 2019 results. The observation was comparing the categories of analysis clusters and outliers which are presented on Table 8. Considering the socio-economic conditions observation of six RW's based on analysis results of clustering and outlier, education and income factors did not significantly affect the building density in the area. However, for family factors that were active in community environmental activities, two regions have HH were categorized with percentages much lower than other categories (LL, LH, and HL) namely *Kapuk* RW 016 and *Kalibaru* RW 004.

Table 8. Socio-economic Conditions for 6 (Six) Slum Areas

Location/ Cluster - Outlier	% of Average Education is elementary school	% of Average families active in the community	% of Average Revenue Category 0-5 million/month
Kapuk RW 016			
HH	0.243635	*0.532892*	0.967116
LH	0.229358	0.908257	0.844037
LL	0.182019	0.730123	0.938806
Not Significant	0.225758	0.659241	0.940755
Penjaringan RW 017			
HH	0.547804	0.976744	0.281654
HL	0.134615	0.990385	0.298077
LH	0.476021	0.919210	0.249729
LL	0.121622	1.000000	0.216216
Not Significant	0.222666	0.412545	0.959620
Kapuk RW 012			
HH	0.166345	0.305419	0.982918
LL	-	-	-
Not Significant	0.163368	0.391151	0.926129
Penjaringan RW 008			
HH	0.181128	0.416882	0.938323
LH	0.150148	0.476811	0.987539
LL	-	-	-
Not Significant	0.135797	0.215532	1.000000
Kalibaru RW 007			
HH	0.300550	0.331892	0.912108
Not Significant	0.385699	0.234935	0.986591
Kalibaru RW 004			
HH	0.314215	*0.277953*	0.966667
LL	0.426230	0.721311	0.967213
Not Significant	0.302216	0.428198	0.964598

Source: *Dasawisma* Census 2019 Dataset, Jakarta Family Welfare Empowerment Team

The current study discussed the analysis results of the 6 RW's heavy slum category with two RWs located exactly alongside the coastal. The analysis was performed to reveal the fact that slums did not cover the entire RW area by analyzing patterns of distribution of building densities to smaller areas, that were areas based on RT administrative boundaries.

The results show that slum locations had direct neighbors to areas were designated as industrial zones and warehousing areas as well as office, trade and service zones, obtained a higher level of building density compared to slum locations that had neighbors to areas that were designated as housing zones according to Jakarta spatial detail planning. These results are in accordance with (Roy & Lees, 2020) which revealed attractive economic opportunities would likely attract residents of slums. In addition, (Takyi *et al.*, 2020) stated where all slum areas in their analysis were located around the Central Business District. The result is also in line with (Badmos *et al.*, 2020) that discovered a factor influenced the choice of residence for slum was markets adjacency. Zain *et al.*, (2018) in his research indicated that engaging space for the development of the trade and services area had an impact on the growth of slums.

The expansion of an area or space interm of developing trade and services is proportional to the growth of slums which could also escalate regional microeconomic growth, where slum dwellers operate small-scale businesses (Zain *et al.*, 2018). Slums are growing near strategic areas including business centers, trade, markets, or industries (Badmos *et al.*, 2020; Prianto & Amalia, 2019; Zain *et al.*, 2018). Slums also contribute to the development of a nearby business district, since this sector could provide man power to support the operations of the business district (Ray, 2017), and most of the dwellers make living close the slum (Saika & Matsuyuki, 2017). This condition could be observed clearly, where within slums there is a great human potential to support a region's sustainable development policy by involving local communities and civil society (Elrayies, 2016).

The results also show that slum areas are not a concentrated population with low income and/or low education. These results are supported by (Roy *et al.*, 2018) and (Uddin, 2018) where income levels vary among residents in slums. There are land owners and land tenants upon socio-economic system that have been established for a long time in slums, and the arrival of poor individuals who stepped in into this circle has no impact towards overall environment (Duah & Bugri, 2016; Nakamura, 2016). The impression of poverty attached to slums is a result of building density, while slums located in the downtown perform good economic opportunities (Bird *et al.*, 2017).

This study is considered essential to investigate the priority location of slum improvement management, hence it was right on target. Studies based on spatial analysis of physical indicators of building density would complement previous studies conducted based on population censuses, as those studies were able to reduce bias data, where population data were not equivalent to location of residence.

4. Conclusion

Applying cluster and outlier modeling of building density levels of urban slums in Jakarta based on RT boundary level revealed more specific slum locations and identified factors that influencing differences of building density levels. Slum locations that had direct neighbors to areas designated at Jakarta spatial detail planning as industrial zones and warehousing areas as well as office, trade and service zones, possed a higher level of building density compared to slum locations that had neighbors to areas that were designated as housing zones. This current study showed the level of income and education in each RT area did not significantly providing influence upon slum area. Further studies could be applied by analyzing the level of building density in all areas of Jakarta combined with other variables to obtain more specific slum distribution clusters. This study suggests that DKI Jakarta Provincial Government could determine the more appropriate solution based on the characteristics of each slum area in dealing with slum improvement in Jakarta.

Conflict of Interests

The authors declare that there is no conflict of interest with any financial, personal, or other relationships with other people or organizations related to the material discussed in the article.

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