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CHARACTERISTICS OF DENSITY DISTRIBUTION AND DENSIFICATION ON MEDIUM AND SMALL INDONESIAN MUNICIPALITIES

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ABSTRACT

While many studies on urban compactness measured built-up area (intensity), this study explored population density in the forms of gradients. Also, medium and small cities (in this case, municipalities due to having autonomous economies), through inquiring about their characteristics in common, could provide early insights for anticipating further growths. A density database was made, combined with cadastral data. Two urban growth patterns (i.e., concentric and linear) were comprehended to extract gradient patterns from the cities using three indices. By assigning a period (2010–2018), the densification rates were also derived. The results indicate that there was a transformation from linear to concentric patterns while populations increased, yet not rare to total sprawling. Besides, there were influences on the compactness states from how the cities are positioned among the others within their local clusters where, on one hand, being too close to large cities would promote sprawling in the long term while, on the other hand, being surrounded evenly by other cities is likely advantageous. Nevertheless, the degree of these advantages was not prevailing fairly across the Indonesian regions. Given the complexity and multidisciplinary nature of urban form, these findings are considerable for further planning and studies.

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1. Introduction

Urbanization has become a topical issue given the shockwave of population explosion since two centuries ago. It is associated with the degradation of life quality, made complicated by multiple factors including sprawling urban expansion. Concepts such as the *compact city* have been being explored to promote compactness.

While compactness is associated with many aspects or attributes, many would agree that population density is an essential one, being equivocal in definition but indispensable in most indications. Population density is supposed to correlate positively with the efficiency and effectiveness of services. Nevertheless, many contrasting empirical evidences suggest observing it conjointly with other attributes (e.g., economic figure and spatial structure), resulting in further discoveries such as capacity thresholds (e.g., Libertun de Duren & Guerrero Compeán, 2016; Su et al., 2017). This condition is found more prevailing in developing and Asian countries wherein cities have already gained high densities and, to some extent, compact urban forms (Jenks & Burgess, 2004). While increasing density in developed countries would, for instance, enhance the viability of public transports, implementing the same in developing countries might barely be as expected (e.g., Schoonraad; in ibid.).

Meanwhile, densification – the change of density in time – is effective in disclosing more actual occurrences. An occupied area may expand more or less proportional to population increase, consolidating a more compact footprint or capturing an exorbitant amount of land regardless of the prior density. Therefore, cities with the same densities may have different urban form qualities.

Cities vary in size and, thus, in characteristics. Since compact city was later introduced to developing countries and that these countries are substantially different in compactness from the developed ones (Roychansyah, 2008), regional or national cross-sectional (macro) studies would provide the big picture of the general characteristics. Compared to large cities, cities of medium and small size (i.e., population up to 500,000; OECD, 2020) would retain more characteristics in common that will be advantageous for anticipating and directing developments. Furthermore, it has been recognized that, in developing countries with low and middle income, cities of this size have the ability to spread the developmental momentum they and, particularly, the large cities generate toward the surrounding regional area, which is hardly implemented through either those large cities or functional districts (Rondinelli, 1986, as cited in Gunaratna, 2018, p. 84).

Globally, macro-scale studies on compactness and density, often related to urban expansion/growth, took objects from global (e.g., Angel et al., 2018; Clark, 1951; Marshall, 2007; Xu et al., 2020), continental (e.g., Marshall, 2007; Murakami et al., 2005; Xu et al., 2019a; Xu et al., 2019b), or national or smaller scope (e.g., Habibi & Zebardast, 2016; Mustafa et al., 2018; Xu & Gao, 2019). However, the data type that was spatially analyzed is mostly built-up area rather than population density. Built-up area could provide more precise mapping and double indicators for activity intensity as well as population density. Nevertheless, population density, though lacking information (Clark, 1951), is indispensable in relation to compactness since a compact urban district should accommodate the needs of its residents locally. Inspirationally, Clark (1951), Newling (1969, as cited in Murakami et al., 2005, p. 254), and Marshall (2007) combined density with incremental distances between points or areas on a lower hierarchical unit of area (Habibi & Zebardast, 2016) to produce gradients. Such method is versatile for presenting simple concept (in this case, monocentric city; Kraus, 2006) with much more details.

Indonesia has had above half of its population residing in urban areas. Given all of these issues as well as that there is no investigation of this type taking the national scope yet, this study will provide another viewpoint. To be noted, municipalities were chosen since they have exclusive records of figures (in this case, economic) that enable the attempts of measuring performances.

2. Literature Review

Population density is a significant indicator of other compactness qualities though not pertaining to the whole. There are several evidences connecting them such as physical barriers (e.g., steep slope, waterbody, wetland, and elevation; Angel et al., 2018; de Bellefon, Combes, & Duranton et al., 2019; Mustafa et al., 2018), transportation corridors (e.g., interregional streets and rail lines; Angel et al., 2018; Li & Yeh, 2004; Mustafa et al., 2018), zoning policy (e.g., green belt designation; Angel et al., 2018; Mustafa et al., 2018), and the structural unification of spatially separated urban areas (e.g., Angel et al., 2018; Li & Yeh, 2004). To be noted, a negative influence from transportation corridors subtly indicates the dominant use of private modes as well as a low control on land market. The dominant use of public modes is instead a valuable instrument for controlling expansion. This is highly beneficial for actuating linear growth pattern (e.g., Curitiba, Brazil; Acioly Jr.; in Jenks & Burgess, 2004).

In developing countries, there are several distinct conditions regarding compactness such as the already high level of density, exceeded environmental capacity, and the great role of informal sectors (Jenks & Burgess, 2004; Roychansyah, 2008).

Population density demonstrates diverse correlations since it is substantially linked with the particular objects of urban dynamics – human beings. Angel et al. (2018) report the considerable significance of it toward area density, street network density, and the degree of sprawling. Roychansyah et al. (2016) disclose that it correlated with the number of healthy houses in Yogyakarta, Indonesia. Also, Xu et al. (2019a) suggest its correlation with the mitigation of greenhouse gas emissions in Europe. Nevertheless, it is not satisfactorily sufficient. For instance, Angel et al. (2018) note that it had no correlation with the shape roundness of urban extents. Haaland and van den Bosch (2015) also discovered that it did not correlate with the amount of urban green space area, implying the necessity of further concepts such as the *smart-compact-green city* (Artmann et al., 2019).

To depict population density spatially, several basic principles are adoptable. The first one is the delineation of the urban extent. This could be determined based on commuting patterns (e.g., Dijkstra & Poelman, 2012) or using rasterization methods on built-up area (e.g., Angel et al., 2018; de Bellefon, Combes, & Duranton et al., 2019; Mustafa et al., 2018; Xu et al., 2019b; Xu et al., 2020). The second one is designating the center point of a city or an agglomeration (e.g., CBD, historical urban center, and the center of mass or centroid of the area; Angel et al., 2018; Xu et al., 2019b; Xu et al., 2020), followed by drawing a series of concentric rings with a constant interval (e.g., Clark, 1951; Xu et al., 2019b) from the center to the outermost part of the delineation. Lastly, the idea of directional observation (e.g., Xu & Gao, 2019) offers an alternative pivotal observation by circling an urban extent rather than traversing it.

Converting to figures, equation-based density gradients (Clark, 1951; Newling, 1969, as presented in Murakami et al., 2005, p. 254) are generated. This is by splitting and grouping the units of area or census tracts based on the rings, summing up their densities, and finally depicting the change in an exponential model across the rings.

3. Research Method

Since no satisfying method in the literature fit the data characteristics in this study, only the basic concepts were adopted (i.e., density gradient, urban growth patterns, center point, physical barriers, concentric rings, and pivotal direction).

Regarding the gradients, an index type, compared to the equation, enables the density dynamics to be compared cross-sectionally. Also, the resulting figures are simpler to be tested statistically. Regarding the delineation, the circle shape unlikely fits the prescription in this study. An urban extent confined by a circle is seemingly treated as historically having equal interests toward all directions to expand where any obstruction to the circle (excluding exogenous restrictions) is deemed as a deviation from the good practice. Meanwhile, interests also put reasons on exogenous attractions such as adjacent settlements or land with cheaper utilizations. Moreover, it would need kinds of correction factors (e.g., Angel et al., 2018) on the many "inevitable" broader factors. To eliminate this, irregular shape was selected.

Overall, this exploratory study only presents relative evaluation and interpretation between the observed objects, presenting initial insights and any clue for the further inclusions of other interrelated aspects.

3.1 Scope

The observed objects are 67 Indonesian municipalities with population up to 500,000 in 2018 (see Appendix 1), mostly added with surrounding regions. The observed urban growth concepts are the concentric (monocentric) and the linear types. To be noted, these cities are treated as a population rather than samples of objects since they already account for all of the prescribed objects.

3.2 Data and Attributes

The attributes in Table 1 were derived from four sets of data: demographic population on the scale of *kelurahan* (urban-village) and *desa* (village); municipal GDRP; the administrative boundary of *kelurahan/desa;* and topography. The population and GDRP figures were derived from the websites of regional statistical bureaus while the administrative boundary and topography data were provided by the national geospatial agency. The detailed workflow is shown in Figure 1.

3.3 Spatial Data Processing

For this process, four steps were defined: (1) designating center point; (2) delineating study area; (3) drawing concentric segments to divide and group the neighborhoods (*kelurahan/desa*); and (4) trimming physical barriers such as lakes/reservoirs, large rivers and slope over 15% (Badan Standardisasi Nasional, 2004).

Concerning Step (1), the selected option is the centroid of the densest neighborhood. This is since density gradient is not exclusively related to expansion (pertaining to a city's actual start point) more than densification.

Concerning Step (2), gradient flattening was argued to represent the limit of spatial interests. The process was started by dividing a base map into 20 pie segments with lines radiating from the center point. Then, they were, by the distance of the neighborhood's centroid to the center point, inputted orderly into spreadsheet platform to derive decline rates and smoothened decline rates by averaging (arithmetic mean) three to seven decline-rate figures depending on the neighborhood counts. Looking at the smoothened trend and the density, one neighborhood in each segment having flattening density or the smoothened trendline approaching 1 (one; assumedly indicating flattening) was marked. Then, all of the outmost marked neighborhoods from any segments were bounded, forming a final delineation.

Then, two rules on Step (3) were defined. Since the delineations from Step (2) are barely circular, the shapes of the rings must be scalably uniform with them. This is the first rule. However, some objects have some of their peripheral neighborhoods located next to vast physical barriers (e.g., sea or mountain). This implies that these areas are unlikely influenced equivalently as the others since they have no buffering spaces to accommodate demographic dynamics. To maintain juxtaposition in each ring, therefore, the second rule describes that any circumferential portion of a concentric ring that is within the perimeter of an area confined by the center point and part of the delineation adjoining a vast physical barrier must be drawn as an arc, overriding the first rule.

Having set the rules, two maps were produced for each city: concentric map, comprising 20 ring segments; and radial map, comprising 20 pie segments. To be noted, the pie segments were already generated on Step (2).

3.4 Indexing Operation

Two growth patterns are comprehended. The first one is the concentric pattern, describing a city as being initiated to expand and to densify from a point toward all directions. To observe it, two indices were formulated: *Linear Density Index* (LDI) and *Radial Density Index* (RDI). LDI measures gradients starting from center points to the circumferential edges of urban extents. However, it was realized remaining possible for such areas to actually have rather poor distributions of density but show good LDI. To capture this, RDI measures gradients from the other maps in circular sweeps pivoted at center points.

Meanwhile, the second type – linear pattern – has a dissimilar structure yet is also favorable. It is probable for an urban area to have a narrow range of high-density pie segments (low RDI) yet indicate a dense urban corridor. Therefore, *Linear Growth Index* (LGI) extracts the scores of such possibilities from RDI.

To be noted, the terms *standardized* and *adjusted*

Table 1. List of Attributes

No	Attribute	Indicator	Reference
1	Municipal Population	Number of the official municipal population	Ahmadian et al. (2019), Boyko and Cooper (2011)
2	Observed Population	Number of population on the delineated area	
3	Municipal Area	Land area of the municipality	
4	Observed Area	Land area of the delineated area	
5	Municipal Density	Figure of *Municipality Population* per *Municipality Area*	
6	Observed Density	Figure of *Observed Population* per *Observed Area*	
7	Linear Density Index (LDI)	Arithmetic mean of the progressive-weighted-**standardized** traversal concentric densities on *kelurahan/desa* scale	Ahmadian et al. (2019), Angel et al. (2018), Arifwidodo (2012), Clark (1951), Habibi and Zebardast (2016), Jenks and Burgess (2004), Xu et al. (2019b), Xu and Gao (2019)
8	Radial Density Index (RDI)	Arithmetic mean of the **adjusted** pivotal/circular concentric densities on *kelurahan/desa* scale	
9	Linear Growth Index (LGI)	Arithmetic mean of the **standardized** peaking-density range extracted from *RDI*	
10	LDI Rate	Ratio of 2018 to 2010 *LDI*	Angel et al. (2018), Marshall (2007), Roychansyah et al. (2005)
11	RDI Rate	Ratio of 2018 to 2010 *RDI*	
12	LGI Rate	Ratio of 2018 to 2010 *LGI*	
13	GDRP	Constant-price-based GDRP of the municipality	Libertun de Duren and Guerrero Compeán (2016), Su et al. (2017)
14	GDRP Growth Rate	Ratio of 2018 to 2010 *GDRP*	
15	Non-Primary Specialization	Ratio of *GDRP* excluding primary sector to the total	
16	N-P Spec. Change Rate	Ratio of 2018 to 2010 *Non-Primary Specialization*	
17	Tertiary Specialization	Ratio of *GDRP* on tertiary sector to the total	
18	T Spec. Change Rate	Ratio of 2018 to 2010 *Tertiary Specialization*	

Source: Author's Analysis (2020)

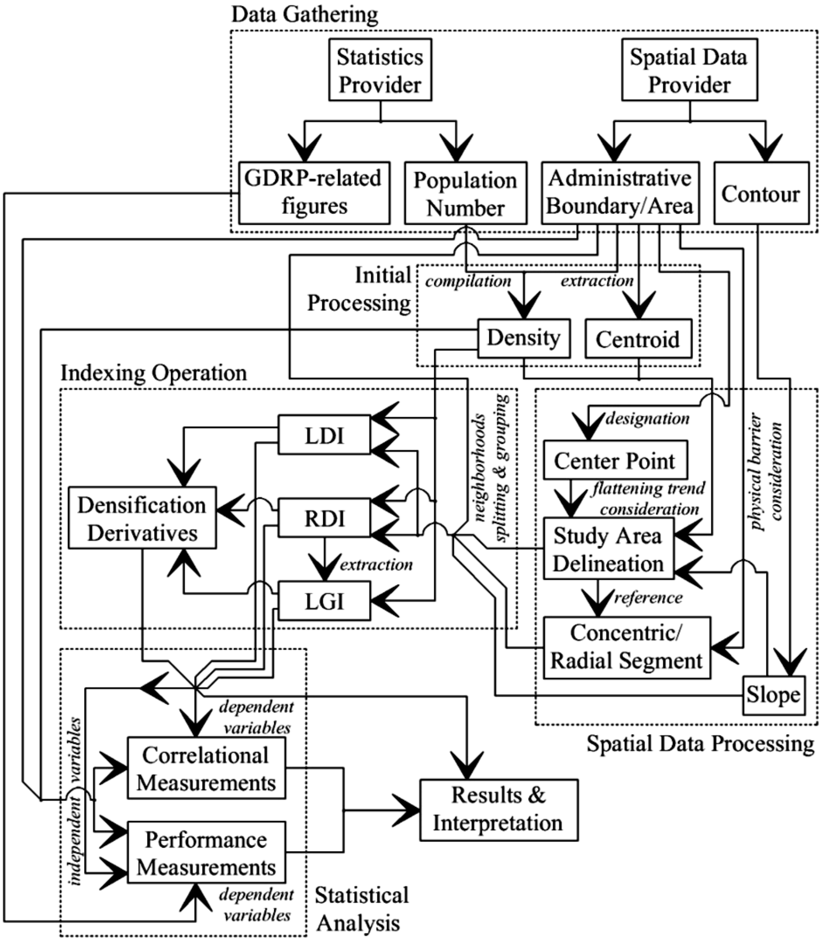

Figure 1. Methodological Workflow
Source: Author's Analysis (2020)

mentioned in Table 1 differ in the way the bottom edge of a dataset is treated. *Standardized* means the top and the bottom edges are set to one and zero, respectively. Meanwhile, *adjusted* means only the top edge is set to one. It is because, in traversal direction, ring segments are conceptually infinite (open-ended), making the peripheral potentials to be nonexclusive. Meanwhile, the extent in circular direction is otherwise limited to 360° (closed) except that extracted for LGI (open-ended).

Regarding LDI, a straight trendline is posited to have been an outstanding example and, thus, valued as 1 (one). The steeper the decline rate, the poorer the quality. To accommodate the idea that a less steep trend is better, a series of arithmetical-progressive weights ranging from two (for the central segment) to one (for the outmost segment) were used. The formulas are simply expressed below where Y_a is the arithmetic mean of densities in ring a, D_i is the density of split neighborhood i, A_i is the area of split neighborhood i, and n is the count of all split neighborhoods in ring a, Z_a is the weighted arithmetic mean of density in ring a, W_a is the weight for ring a, Z_{max} and Z_{min} are, respectively, the highest and the lowest value among the weighted arithmetic means of density in an urban extent, and n is 20 (the count of the segments).

$$Y_a = \sum_{i=1}^{n}(D_i \times A_i) \Big/ \sum_{i=1}^{n} A_i \tag{1}$$

$$Z_a = Y_a \times W_a \tag{2}$$

$$LDI = \left(\sum_{a=1}^{n}\left(\frac{Z_a - Z_{min}}{Z_{max} - Z_{min}}\right)\right) \Big/ (n/2) \tag{3}$$

For RDI, it is assumed that the excellent condition will resemble a straight horizontal line whereas a sprawling urban structure will dwarf the other pie segments of lower density. Two equations compose the operation: Equation (1) that differs on the term radial/pie replacing concentric/ring; and Equation (4) where Y_a is the arithmetic mean of densities in segment a, Y_{max} is the highest value among the arithmetic means of density in an urban extent, and n is 20.

$$RDI = \left(\sum_{a=1}^{n}\left(\frac{Y_a}{Y_{max}}\right)\right) / n \tag{4}$$

Since this construct is still possible to generate distorted figures when an urban extent adjoins a vast physical barrier, a quasi area – area confined by the edge facing the physical barrier and the modifying arc pertaining to the prior spatial process – is added to the urban extent. Its density, as well as for the trimmed areas, is the arithmetic mean of the actual densities.

Lastly, LGI measures 3–5 peaking pie segments against the central neighborhood's density. The formula is expressed below where Y_a is the arithmetic mean of densities in segment a, Y_{min} is the lowest value among the arithmetic means of the extracted segments, Y_{max} is the density of the neighborhood at the center point, and n is the count of the segments.

$$LGI = \left(\sum_{a=1}^{n}\left(\frac{Y_a - Y_{min}}{Y_{max} - Y_{min}}\right)\right)\Big/(n/2) \qquad (5)$$

3.5 Additional Tools

Initially, Pearson's Correlation tests were taken against these figures. However, the results were unexceptionally insignificant. Therefore, they were observed in groups. Each set of the gradient figures is equally divided into three-level (high-medium-low; for the indices) or two-level (increasing-decreasing; for the densification rates) groups based on their *standardized* range. So, the "high" groups comprise cities having the highest 1/3 of the range and so do the other groups respectively.

Then, a *position* scheme depicts a group's averaged attribute value also in its *standardized* range. At a strong correlation, the Position of each group is assumed to be close to its median (16.7%, 50%, or 83.3% for three-level or 25% and 75% for two-level groups). A narrow distribution yet close to 100% or 0% could indicate a fair correlation while another one around 50% could indicate randomness. For the three-level groups, nonetheless, there are more probable patterns than just the gradual one (either positive or negative) such as V shape. However, only gradual trends were considered.

For inquiring uniformity, there is a kind of *variance* as expressed below where x_i is the attributive value of grouped city i, μ is the mean of the attributive dataset in the group, and n is the count of the cities in the group.

$$Var = \left(\sum_{i=1}^{n}\left|\frac{x_i - \mu}{\mu}\right|\right)\Big/(n-2) \qquad (6)$$

In the discussion part, two space-related phenomena were disclosed and conceptualized: *gravity*-based and *surrounding-state*-based measures. The first one is based on the Newtonian law of gravity (Equation (7); see also Wagner, 1974). Equation (8) is to calculate the gravity center. Actually, it was supposed to be more ideal to use transportation networks rather than centroids. However, the clue was discovered lately.

$$\frac{Pop_{mun.i}}{\left(\sqrt[2]{\left(x_{grav} - x_{mun.i}\right)^2 + \left(y_{grav} - y_{mun.i}\right)^2}\right)^2} \qquad (7)$$

$$x, y_{grav} = \frac{\sum_{i=1}^{n}(Pop_{mun.i} \times x, y_{mun.i})}{\sum_{i=1}^{n} Pop_{mun.i}} \qquad (8)$$

The second one measures the exposure of other cities to a city relatively by location in a cluster. Theoretically, three measures have to be combined: the count of the surrounding cities, their populations relative in distance from the observed city (effectual masses), and how they are circularly distributed. Eventually, the triangle shape is deemed suitable for depicting the progressive dispersion of an effectual mass where the peak of each triangle represents population and the leaning sides resemble the dispersion effect (Figure 2). If cities are located close to each other, their triangles will get more overlapping, reducing the effect. The method comprises matrix-based operation. The angular range of a triangle is 180° (90° for each side) since it separates two cities at their farthest radial extent where the exposures are assumedly the least.

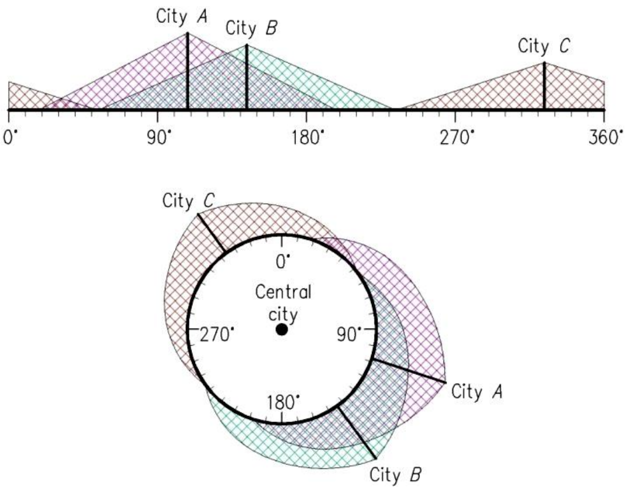

Figure 2. Triangle-based dispersion idea (top) and the complete *surrounding* concept (bottom)
Source: Author's Illustration (2021)

4. Results and Discussions

4.1 Initial Results

The groups of the municipalities are shown in Appendixes 1 to 3. On LDI, most morphological attributes (population, area, and density) show positive correlation trends (Table 2) where, for instance, Group 1, as of the high LDI, also holds the highest range at the other attributes, including population. However, the Position figures indicate uneven distributions. The high variances (see Appendix 4) also imply this. Yet, one interesting part is that most attributes of delineation (observed population, area, and density) show rather even distribution among the groups though with fair variance (0.125–1.000) and weak Pearson's coefficient at 0.259 and 0.298 for population and density, respectively.

Most of the economic attributes also show positive trends. The low (good) variance (<0.125) implies narrower ranges among the figures in groups. Regarding regions (Figure 3), municipalities in Jawa are dominant in Groups 1 and 2, which is significant on Kruskal-Wallis Test (α = 0.01). Looking at the transposed version (Figure 4), however, Maluku and Kalimantan actually share greater proportions of their cities to Group 1 than Jawa. Meanwhile, Sumatera contributes the most to Group 3.

On RDI, the trends are mixed. Observed population, proportion of slope, municipal and observed densities, and GDRP growth rate are positive while municipal area and T spec. change rate are negative. Municipal and observed densities are significant (α = 0.05) despite having weak correlations (0.251 and 0.366, respectively). Regarding regions, Jawa is generally of good RDI except that Sumatera takes the dominance in Group 2, leaving a large share in Group 3 mostly to Kalimantan. Yet, the region-based shares of Nusa Tenggara and Maluku are greater than Jawa. Following behind, Papua, Sumatera, and Sulawesi still show remarkable shares in Group 2. Meanwhile, Kalimantan is the only one being dominant in

Group 3. This is overall significant (α = 0.01).

On LGI, the figures were initially divided arithmetically. However, the variances were quite poor because of a very imbalanced configuration. Alternatively, a geometrical division was applied. In contrast with LDI, the trends are generally negative. This means that the cities of good LGI are averagely of lower populations or areas. Turning to the economic attributes, the apparent trends on GDRP Growth Rate and N-P Spec. affirm the aforementioned trends where the municipalities of higher populations have higher economic figures too. Similarly, the trend is inverted for the regions where Sumatera dominates Groups 1 and 2 while Jawa is mostly in Group 3, yet Maluku is consistently of the highest by the region-based share to Group 1.

There is no significant correlation between the index and the densification rate figures. Yet, there are two significant (α = 0.01) correlations found among the densification rates: LDI Rate–LGI Rate and RDI Rate–LGI Rate with coefficients of 0.676 (strong) and -0.471 (weak), respectively. To be noted, there is no municipality undergoing decreasing population within the period although there were decreases in the indices.

On LDI Rate, the common trends (i.e., on observed population, area, and density, and GDRP and its rate, and the sector specializations) are of negative correlations. There is a 0.01 significant yet weak correlation between the rate and observed density at -0.345. The trends on RDI Rate are mixed where, while there are positive correlations on the proportion of slope, observed area, and GDRP, there are also considerable negative ones on observed population and area, GDRP Growth Rate, and the sector specializations. Meanwhile, the common trends on LGI Rate are contrary to that of LDI Rate (positive). Among the three sets of index-densification rate figures, the radial-concentric type is the most varying. Nevertheless, these trends are likely weak due to the narrow range of Positions between the groups and the averagely fair variances on the morphological attributes, yet they are not rejectable.

Regarding the regions, those having numerous municipalities (i.e., Sumatera, Jawa, and Sulawesi) tend to have more equal share across the densification rate attributes compared to the rest. Yet, it is apparent that the proportion of cities with increasing indices is overall higher (increasing: 62.8%; decreasing: 37.2%).

4.2 Space-Related Results

There are recognizable patterns found through observing the cities within their local clusters. Regarding this, two types of clusters were considered: satellite and

Table 2. Trends of *Positions* in LDI, RDI, and LGI-Based Groups

	Municipal Population	Obs. Population	Municipal Area	Obs. Area	% of Slope	Municipal Density	Obs. Density	GDRP	GDRP Growth	N-P Spec.	N-P Spec. Change Rate	T Spec.	T Spec. Change Rate
LDI	+	+		+	+	+	+	+	+	+		+	–
RDI		+	–		+	+	+		+				–
LGI	–	–		–		–			–	–			
LDI Rate	+	–	–	–	+	–	–	–	–	–	+	–	+
RDI Rate	–	–	+	–	+	–	+	+	–	–		–	+
LGI Rate	+	+	–	–	–	+	+	+	+	+	–	+	–

Note : "+" : positive; "–" : negative; blank : either V-shaped, inverted V-shaped, or inconsiderable.
Source: Author's Analysis (2021)

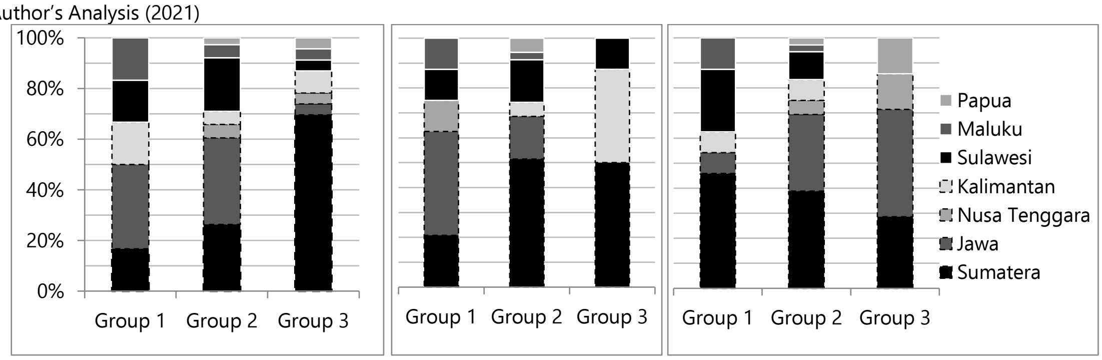

Figure 3. Region-based distribution in LDI (left), RDI (middle), and LGI-based (right) groups
Source: Author's Analysis (2021)

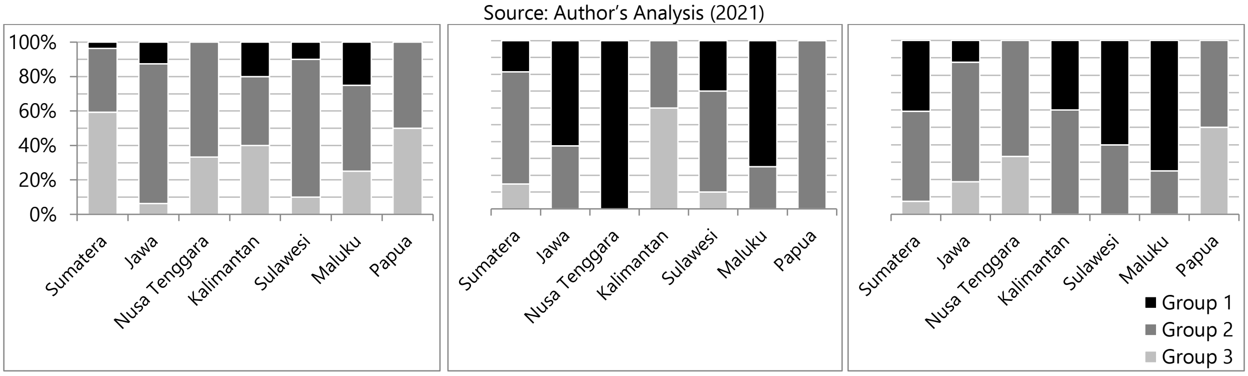

Figure 4. Region-based share in LDI (left), RDI (middle), and LGI-based (right) groups
Source: Author's Analysis (2021)

corridor clusters. Each city was given local ranks based on population and indices. In addition, the municipalities unlisted by the terminology of this research (those with population over 500,000) are also presented.

In some clusters, it is found that the low populated city close to the centroid of the cluster has the highest LDI. The first one is Tebing Tinggi (see Appendix 5) which has the lowest population and the highest scores of all indexes within its cluster. Meanwhile, Binjai, having the lowest scores, is far from the centroid yet the closest one to the provincial capital (Medan). In another cluster, Padang Panjang also has the highest scores on all indices while, interestingly, the remaining cities likely demonstrate a gradual decrease in LDI by the shortening distance to Padang – the most populated city and also the capital. The last one is Batu that was the highest on two indices. While it was indicated that the low-populated cities tend to have low LDI, these cities are contrary.

Nevertheless, these clusters are the only confirmatory cases. Banjar, being juxtaposed with Tegal, is not really close to the cluster centroid though it also has the highest LDI. Yogyakarta, having the highest LDI, is contrarily at the edge of the cluster. Also, the cluster of Manado is not really of satellite configuration due to Kotamobagu being located rather far. If it is excluded, anyway, Manado is seemingly the closest one to the centroid.

Next, the corridor clusters (see Appendix 6) also confirm the evidence. For instance, Banjar Baru, in the vicinity of the capital (Banjarmasin) and with a higher population than that of Palangka Raya, has lower scores.

Initially, there were significant (α = 0.01) contrary trends between LGI Rate and RDI Rate with N-P Spec. at 0.324 and -0.438, respectively. However, another trend was discovered by taking into account observed populations and distances between these cities within their clusters (see Appendix 7). The cluster members were determined based on proximity and matchable circumstances. Also, by summing up the adjusted figures from LDI and RDI [$(LDI_a / LDI_{max}) + (RDI_a / RDI_{max})$], their combined index was made to look whether the evidence of the concentric compactness would be better described.

In relation to the gravity-based evidence, the indices are found insignificant (α = 0.10). Fortunately, the tests on LDI and LGI Rates against population-per-squared-distance are valid (α = 0.01) with rather strong coefficients at -0.654 and -0.535, respectively. This means higher LDI and LGI Rates are associated with the lower population (as being demonstrated by the centrally-located cities within the satellite clusters) and the longer distance from the gravity center.

So, while this trend of LGI Rate against population contradicts the prior one, they are all correct by contexts. Breaking down the numbers, the average of the figures on increasing LGI (LGI Rate > 1) against those of decreasing (LGI Rate < 1) generates a ratio of 1.43 : 1 (positive) formerly and a ratio of 1 : 9.82 (negative) from this latter inquiry. This huge difference is caused by the squared distance attribute as the divisor. Since the latter ratio is much wider (indicating stronger correlation) and significant, it is considered improving the former one.

Proceeding to the *surrounding-state*-based evidence, several syntaxes were alternatively arranged to look for better coefficients. Eventually, there are four (Table 3) found to be the most significant. The results (see Appendix 7) were then combined with the *gravity*-based figures using mathematical operators experimentally. Also, exponential functions were added for improving precisions since the trends are unlikely linear. Using Pearson's Test, slightly higher coefficients on the densification rates were gained and the indices became significant (Table 4). Regarding the notations, $Pop/dist_{gv}^2$ or $Pop/dist_{gv}$ refers to the gravity-based figure, $Surr_1$ to $Surr_4$ refer to those in Table 3, and the $[...]_{ad}$ function refers to the *adjustment* operation in order to match the sizes of the variables in summations.

Table 3. Most Significant Surrounding Syntaxes in Correlation with Density-Gradient Figures

No	Name	Syntax
1	$Surr_1$	$\sum A_{[\alpha,\beta]} \langle \sqrt[2]{\Sigma_{[\alpha]} \langle \frac{Pop_A}{d_A^{\,2}} \rangle / Pop_{Cn}} \rangle$
2	$Surr_2$	$\sum A_{[\alpha,\beta]} \langle \sqrt[2]{\Sigma_{[\alpha]} \langle \frac{Pop_A}{d_A} \rangle / Pop_{Cn}} \rangle$
3	$Surr_3$	$\sum A_{[\alpha,\beta]} \langle \sqrt[2]{\Sigma_{[\alpha]} \langle \frac{Pop_A}{d_A^{\,2}} \rangle} \rangle$
4	$Surr_4$	$\sum A_{[\alpha,\beta]} \langle \sqrt[2]{\Sigma_{[\alpha]} \langle Pop_A \rangle} \rangle$

Source: Author's Analysis (2021)

Being favored by the summation connectors, greater coefficients were generated using regressional analysis (only for gaining greater scores). Looking at the results, LDI is not listed because its significance level eventually decreases, implying that LDI is the most multifaceted

Table 4. Results of Pearson's Correlation and Regressional Tests on Gravity- and Surrounding-Based Evidence

No	Pearson's Test				Regressional Test		
	Variables		Coef.	α	Variable	R Coef.	α
	***Gravity*-based only**						
1	LDI Rate	$\frac{Pop}{dist_{gv}^{\,2}}$	-0.654	0.01	*N/A*		
2	LGI Rate		-0.535	0.01	*N/A*		
	***Gravity* + *Surrounding* states**						
3	LDI Rate	$\left(\frac{Pop}{dist_{gv}^{\,2}}\right)/Surr_1$	-0.665	0.01	*N/A*		
4	LGI Rate	$\left(\frac{Pop}{dist_{gv}^{\,2}}\right) \times \sqrt[2]{Surr_2}$	-0.574	0.01	*N/A*		
5	LDI	$\left[\frac{Pop}{dist_{gv}}\right]_{ad} + [Surr_3^{\,3}]_{ad}$	0.345	0.05	*Insignificant*		
6	LDI-RDI		0.456	0.01	$a + b_1.\left(\frac{Pop}{dist_{gv}}\right) + b_2.(Surr_3^{\,3})$	0.479	0.01
7	RDI	$\left[\frac{Pop}{dist_{gv}^{\,2}}\right]_{ad} + [Surr_4^{\,2}]_{ad}$	0.412	0.01	$a + b_1.\left(\frac{Pop}{dist_{gv}^{\,2}}\right) + b_2.(Surr_4^{\,2})$	0.414	0.05
8	LGI	$\left[\frac{Pop}{dist_{gv}^{\,2}}\right]_{ad} + [Surr_1^{\,3}]_{ad}$	0.490	0.01	$a + b_1.\left(\frac{Pop}{dist_{gv}^{\,2}}\right) + b_2.(Surr_1^{\,3})$	0.515	0.01

Note: The numbers of the regressional coefficients (a, b_1, and b_2) are unnecessary to be shown since the measurements are not for prediction purposes.

Source: Author's Analysis (2021)

phenomenon among the three. The coefficient on RDI only gains a small increase (0.412 to 0.414) yet at the expense of a poorer significance level. The hybrid LDI-RDI index seems more deterministic for depicting the compactness states. However, the Surrounding syntax attached to it is incomplete in the sense that it uses "raw" figures rather than the proportionate ones. Lastly, LGI got into the strong range of correlation (above 0.5) though was adjusted with the third-power function.

4.3 Discussions

Since there is no logic for any substantial link between the attribute levels with the gradient shape, the correlations between them have taken place at least communally. The averagely higher variances (high disparities) of Group 1 on LDI might at a glance indicate that the more populated cities (being closer to the large-city category) are less generalizable, opposing the initial idea regarding the commonality of medium-sized cities. However, when the clustering is switched based on observed population (which is more proper) geometrically (to comply with the geometrical nature of population growth), the variances were 0.117, 0.176, and 0.148 which fortunately confirmed the suitability of the classification.

Concerning the economic attributes, the cities of low LDI were likely at high industrialization rates, holding low populations and about growing rapidly. The averagely greater RDI figures than those of LDI also affirm that it is more affordable for a city to utilize sporadically empty or low-intensity tracts rather than to deliberately improve the density "skyline" on the already dense areas. In addition, there was a saturated transformation into the tertiary sector though still in balance with the secondary sector. The figures on RDI, furthermore, confirm that the cities of Group 2 were of greater growth momentum though particularly to the secondary sector.

The averagely very low LGI (Appendix 3) possibly indicate a low capacity in any Indonesian municipality to have a dominant linear growth pattern. This is reasonable since it should be compelled by high public transportation ridership. Relying mainly on private modes, urban systems would likely be shaped by distance-based gravity (see also Kraus, 2006), leading to concentric forms. If it is simulated that the LDI of a city increases in a condition where the densification rates on all neighborhoods in each ring are equivalent, its LGI value should have been increasing. In fact, they are in opposition, suggesting that it is unnatural for these cities to accommodate and balance both patterns.

Combined with the population trends, larger cities seem to be more on concentric patterns whereas the smaller ones are more on the linear patterns. This gives a clue where a city, at its early urbanizing stage, had its concentrations only around a single street while it would later expand toward all directions (cf. Anas & Moses, 1979). The problem is that this historical downtown may get intensified and densified much faster than the surrounding, triggering dramatic land price hikes and leapfrogging developments. This double-ended issue gives resistance to the efforts on compactness.

However, the trends on LDI and LGI Rates are contrary to the indices. If all of these arguments are combined, there is a deducible idea regarding an urbanization scenario (Figure 5). Briefly, an urbanized area in Indonesia perhaps started to become a city with a linear pattern (averagely represented by the smaller cities in this study). While growing, it likely transformed into a more concentric pattern even until reaching equilibrium. This continued until the densification rates became inverted yet the density structure had far changed (represented by the larger cities). Eventually, the city still maintained similar densification rates yet the density structure had not changed very much.

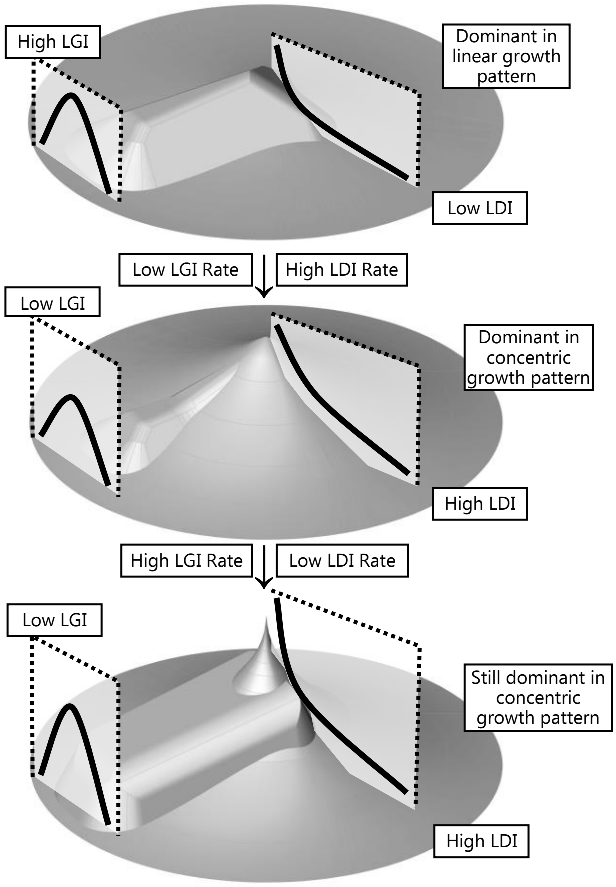

Figure 5. Scenario of Urban Density Structure Transformation
Source: Author's Illustration (2021)

This transformation is probably because expanding toward all radial directions will provide the shortest distances from the centers to as many citizens as possible and, thus, more preferred. Also, activity generators would naturally accumulate or emerge hierarchically (Hotelling, 1929; Mulligan, 1984) rather than sporadically (excluding the case of merging; e.g., Angel et al., 2018). This results in extreme densification in the central areas until they reach economical equilibriums.

Concerning the space-related evidence, it seems that there is an influence from being surrounded by other cities. Although the centrally located cities in the satellite clusters are of low population or, assumedly, having later momentum of rapid urbanization compared to the others, this condition enhances their densification paces. In addition, the fair correlations between LDI and LGI Rates against population-per-squared-distance mean that higher LDI and LGI Rates are associated with lower population and longer distance from the gravity center.

Although the latter sounds unfavorable, there is an argumentation on it.

When a medium or small city (not considering economic capability) is located fairly, not extremely, distant from a core city (the city potentially drawing in the cluster's gravity center the strongest), its building blocks (in this sense, settlements, activity generations, employments, etc.) are concentrated inwardly within its own boundary, promoting more compactness. Reversely, a city very close to a core city would have its integrity shifted toward the core one, scattering its developmental momentum and, thus, promoting more sprawling developments (see also Dawkins, 2003). This reminds the argument in the introduction regarding the potentials of secondary cities (Rondinelli, 1986, as cited in Gunaratna, 2018, p. 84). This could also mean that there should be an effective distance between these cities. Being too close, this potential will get too much drawn to the larger ones.

The last thing is the matter that only the densification rates had significant correlations. Simply comprehended, the indices measure qualities being accumulated since various historical events of urbanization while the densification rates measure the same values within a specified fixed duration (in this case, 2010–2018). Therefore, if two cities were initially established under different "urbanization eras," the comparison of their current populations may not represent their compactness states due to the different "coefficient" of urbanization in each era. However, it is much more correlational with the densification rates due to the exact time period assigned.

The formulas in Table 4 even bring extended assumptions (Table 5). The most obvious thing is, again, the inverse trends of the densification rates with the indices, especially against the gravity measures. Given new insights here, the indices are associated with the current, static, or very short-term (i.e., daily) levels of compactness while the densification rates represent long-term growths. Daily, all activities generated in an agglomeration would favor all cities regardless of the hierarchical levels or roles. The gravity center theoretically marks most activities and circulations inside, providing more advantages to cities in proximity. On the contrary, the long-term shifts would favor those of the highest hierarchy due to their greater range of services, accelerating their growth. Consequently, a secondary city, if not fairly distant from the core one, may often be bypassed by the smaller cities preferring to access the core city's market and services (see Dawkins, 2003).

Back to the initial results, the fair variances (see Appendix 4) imply that the cities are rather scattered, for instance, from the linear-concentric (high LDI) to the radial quality (high RDI). Even, some concentric-dominant (union of linear- and radial-concentric qualities) cities are concentrically less compact than the linear-dominant (high LGI) ones (Figure 6). This initially suggests that there was either this phenomenon occurring in each city: transformation from linear to concentric compactness (Figure 5) or sprawling. The first one is mostly contributed by Jawa (14 cities), Sulawesi, Sumatera (7 each), and Maluku (3) and of coastal type (20) while the second one is mostly by Sumatera (19), Kalimantan (5), and Sulawesi (3), and of inland type (17). By comparing other data, there are evidences of all-positive and all-negative densification found. Regarding the densifications, five cities have undergone decreases in LGI and LDI-RDI by over 5% (total sprawling) since 2010, namely Binjai (9.4%), Madiun (9.6%), Palu (10.1%), Tual (17.1%), and Ternate (32.2%). The factors look varying. For instance, Binjai is alone located too close to its core city, dissipating its integrity. On the contrary, Madiun seems rather isolated within its cluster and also far from cities in any cluster. There is no direct factor related to Palu, Tual, and Ternate except that two of them are islands, and they are far from Jawa. These opinions converge to the idea that, while

Table 5. Assumptions Inferred from Gravity- and Surrounding-Based Evidence

No	Attribute	Linked Attribute	State	Assumption
1	LDI	Gravity value	Basic (*Pop/d*)	Influence is still maintained on a greater extent of distance
		Surrounding state	Unproportionate ($Surr_3$)	Being dictated more by the external situations (e.g., other city's mass)
		Connector	Summation	Gravity or Surrounding state may be either dominant
		Coefficient	Positive	Both Gravity and Surrounding state indicate the good performance of LDI
2	LDI-RDI	Gravity value	Basic (*Pop/d*)	Influence is still maintained on a greater extent of distance
		Surrounding state	Unproportionate ($Surr_3$)	Being dictated more by the external situations (e.g., other city's mass)
		Connector	Summation	Gravity or Surrounding state may be either dominant
		Coefficient	Positive	Both Gravity and Surrounding state indicate the good performance of LDI-RDI
3	RDI	Gravity value	Squared (Pop/d^2)	Sensitive to change in distance
		Surrounding state	Unprocessed ($Surr_4$)	Primarily affected by a medium (i.e., intercity road) between the cities
		Connector	Summation	Gravity or Surrounding state may be either dominant
		Coefficient	Positive	Both Gravity and Surrounding state indicate the good performance of RDI
4	LGI	Gravity value	Squared (Pop/d^2)	Sensitive to change in distance
		Surrounding state	Full set ($Surr_1$)	More independent in dictating the central city's quality
		Connector	Summation	Gravity or Surrounding state may be either dominant
		Coefficient	Positive	Both Gravity and Surrounding state indicate the good performance of LGI
5	LDI Rate	Gravity value	Squared (Pop/d^2)	Sensitive to change in distance
		Surrounding state	Full set ($Surr_1$)	More independent in dictating the central city's quality
		Connector	Division	Greater Gravity is unfavorable while Surrounding state enhances LDI Rate
		Coefficient	Negative	
6	LGI Rate	Gravity value	Squared (Pop/d^2)	Sensitive to change in distance
		Surrounding state	Less sensitive ($Surr_2$)	While independent, influence is still maintained on a greater extent
		Connector	Multiplication	A low level of either Gravity or Surrounding state would still maintain a good LGI Rate
		Coefficient	Negative	

Source: Author's Analysis (2021)

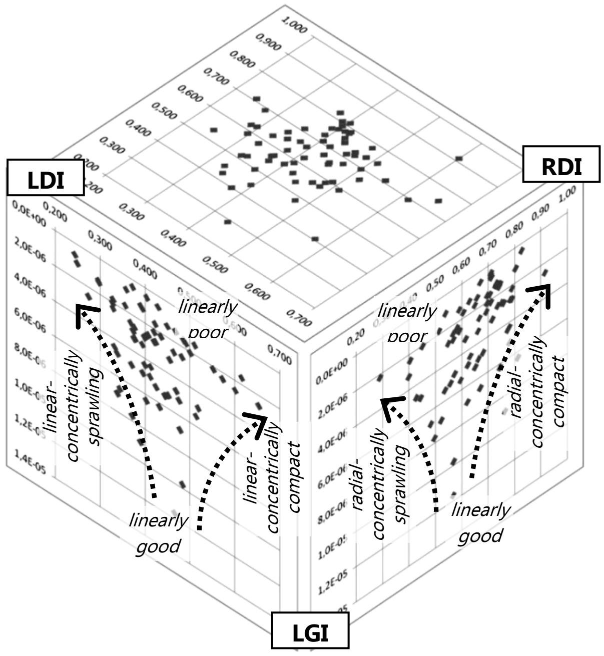

Figure 6. LDI-RDI-LGI Distributions of the Observed Cities
Source: Author's Analysis (2021)

Indonesia is geographically archipelagic, its developments are too much toward land-based economy, concentrated heavily in Jawa (Tirtosudarmo, 2014).

Meanwhile, there are also cities getting more compact such as Ambon (6.5%), Bitung (7.2%), Manado (7.6%), Prabumulih (7.9%), Lubuk Linggau (8.1%), and Cilegon (11%). An apparent factor would be, again, related to clusters. Bitung and Manado, together with Tomohon, become a small agglomeration wherein it would be easier to maintain fair competitions though, probably, the coastal situations delivered more advantages to the two compared to Tomohon (inland). Another one, Prabumulih and Lubuk Linggau, though spatially far from the core cities, are equivalent to one another and, together with Pagar Alam, the only secondary cities in the cluster (Bengkulu is a provincial capital and, thus, of higher level). For Cilegon, nothing was suspected but the communal similarities in Jawa that not only the populations but also the agglomeration ratios (ratio of observed to municipal population) are averagely great (Figure 7).

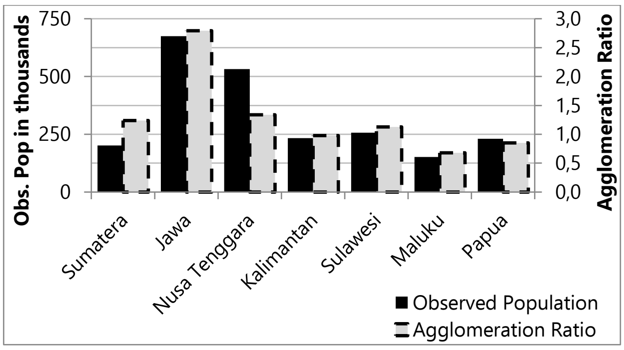

Figure 7. Obs. Population vs. Agglomeration Ratio by Regions
Source: Author's Analysis (2021)

This condition perhaps positively affected LDI and RDI. However, a conjecture has to be put into awareness that an expanding agglomeration may adversely generate longer commutes, expanding land market, and sprawling expansion (e.g., Jones; in Jenks and Burgess, 2004). It was evident in Figure 8 where seven out of 16 cities were sprawling (to be noted, *concentric-compactness change* is the average of LDI and RDI Rates by their indices minus 1; negative figure indicates sprawling).

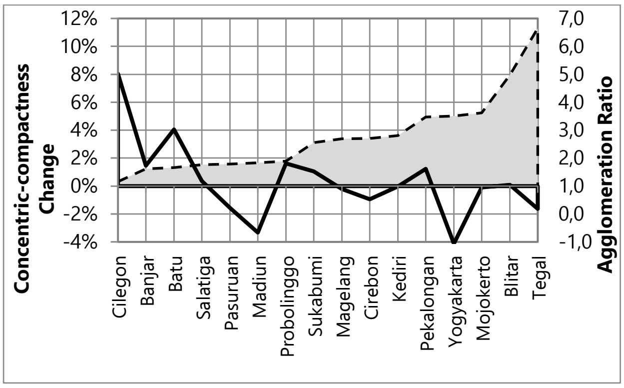

Figure 8. Agglomeration Ratio vs. Concentric-Compactness Change in Jawa
Source: Author's Analysis (2021)

Concerning the regions, several cities were selected, comprising those with high and low compactness scores and high GDRP (Table 6). Regarding the notations, *Pop* refers to the *adjusted* observed population, *AR* refers to agglomeration ratio, *S* refers to proportion of slope, *C* refers to the *adjusted* LDI-RDI, *ΔC* is the concentric-compactness change as in Figure 8, *L/R* is the *adjusted* LDI divided by the *adjusted* RDI minus 1, *L* refers to the *adjusted* LGI, *ΔL* refers to LGI Rate minus 1, *G* refers to the *adjusted* GDRP, and *T* refers to T Spec. To be noticed, while *C* and *L* are associated with the concentric and linear types of compactness, *L/R* describes the concentric degree between linear and radial qualities.

Although the cities with good compactness are averagely higher on T Spec., some outside Jawa-Nusa Tenggara or Sumatera are still slightly lower (excluding Ambon). Besides, Batu and Ambon are the only special cases where the proportion of slope strongly affected concentric compactness. This possibly implies that the slope areas in them have been significantly utilized due to the great pressures of demands upon supplies (the high population of Jawa and the limited land of Ambon island; Pemerintah Kota Ambon, n.d.). However, this means that such phenomena were not endogenous and intentional.

Another presumption is that high compactness level (high *C)* should be accompanied by high linear-concentric pattern (positive-high *L/R)*. Unlikely, Palangka Raya, as well as Banjar Baru, has a very high *L/R* compared to the *C* value. Looking at the maps, the reason on Palangka Raya could be of the less-intensely utilized area around the river eastward (exogenous resistance; Figure 9) but the attractive force from Banjarmasin, a provincial capital, (exogenous interest) for Banjar Baru (see Appendix 6).

Looking at the comparison, Bengkulu considerably shows an outstanding profile. This city maintained dominant concentric compactness, considerable linear compactness, and positive change rates on both types. Moreover, coastal situations unlikely limit expansion on continental islands such as Sumatera. In this case, it seems that deliberate interventions did play the main role.

Turning to the category of low compactness score, the

Table 6. Profile of Cities Across Regions

City	Region	Geographical Situation	Pop	AR	S	C	ΔC	L/R	L	ΔL	G	T
High Compactness Score												
Bengkulu	Sumatera	Coastal	24%	105%	0%	89%	3.8%	0.23	14%	36%	17%	84%
Batu	Jawa	Inland	21%	166%	164%	100%	4.0%	-0.08	22%	-7%	13%	70%
Kupang	Nusa Tenggara	Coastal	29%	113%	11%	81%	0%	-0.08	14%	6%	18%	80%
Palangka Raya	Kalimantan	Inland	12%	71%	0%	69%	0%	0.98	21%	0%	12%	75%
Palu	Sulawesi	Coastal	23%	99%	14%	79%	-9.3%	0.09	42%	-10%	18%	66%
Ambon	Maluku	Coastal	20%	73%	193%	95%	5.9%	0.22	22%	14%	12%	85%
Sorong	Papua	Coastal	13%	85%	34%	74%	1.8%	-0.16	15%	2%	12%	58%
Low Compactness Score												
Binjai	Sumatera	Inland	27%	163%	0%	52%	-7.6%	0.01	18%	-17%	9%	71%
Madiun	Jawa	Inland	20%	183%	0%	69%	-3.3%	-0.17	28%	-31%	12%	75%
Mataram	Nusa Tenggara	Coastal	59%	204%	20%	69%	2.2%	-0.30	7%	19%	15%	75%
Banjar Baru	Kalimantan	Inland	28%	179%	1%	51%	2.0%	1.09	19%	-23%	7%	70%
Kendari	Sulawesi	Coastal	22%	97%	7%	56%	0.1%	-0.10	16%	0%	18%	59%
Tual	Maluku	Coastal	4%	93%	4%	62%	2.4%	-0.10	42%	-43%	2%	53%
Jayapura	Papua	Coastal	15%	84%	148%	51%	-0.5%	-0.35	9%	0%	26%	72%
High GDRP												
Dumai	Sumatera	Coastal	12%	68%	0%	64%	0%	-0.02	25%	2%	28%	27%
Kediri	Jawa	Inland	48%	280%	13%	72%	0%	-0.10	5%	7%	100%	18%
Bontang	Kalimantan	Coastal	10%	100%	2%	62%	2.1%	-0.27	38%	-3%	48%	10%
Manado	Sulawesi	Coastal	25%	97%	5%	75%	4.3%	0.21	47%	19%	28%	83%

Source: Author's Analysis (2021)

matter of distance as explained before would have told much about Binjai and Madiun. Nevertheless, whether being too far from the gravity center is better or it was the situations in Jawa that stimulate compacting, Madiun was more compact than Binjai on both types. Being in this state and with a lower population, Madiun would get more opportunities to anticipate further growth.

Geographical situations could explain some differences between Kendari and Tual in responding to narrow waterbodies. Although both of them already have bridges, Kendari had more area accessible through land which then led to developments mainly surrounding the bay while Tual has to utilize the land on both sides (Figure 9). This eventually turned Tual to be more compact.

Regarding the last category, there are several common themes such as that Kediri, compared to the non-Jawa cities, had a larger GDRP and larger population mainly gathered from the agglomerating regions. Also, these cities tended to rely heavily on manufacturing (excluding Manado), resulting in more radial-concentric urban forms (including Kupang and Jayapura which also had the highest GDRPs in Nusa Tenggara and Papua, respectively, yet were not from manufacturing). Positively, these financial gains likely stimulated them to restrain from being more sprawling. Regarding Manado, this city seemingly enjoyed the exclusive agglomeration with Bitung and Tomohon, enabling it to develop more on tertiary sector and linear-concentric pattern.

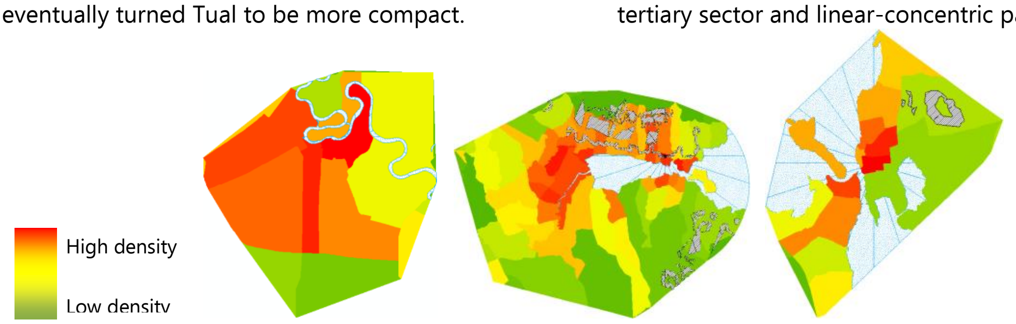

Figure 9. Geographical Situations of Palangka Raya (left), Kendari (middle), and Tual (right)

Source: Author's Analysis (2021)

5. Conclusion

Since the previous studies mainly focused on built-up area or equation-based gradient, this exploratory study will provide an extended perspective about population density to studies on compactness. Also, the argument regarding the potentials of secondary cities is indirectly confirmed through the suspected industrialization rates and the space-related influences. To be reminded, getting more compact is not as easy as getting more concentric.

The levels within the local clusters and geographical features highly influenced the interactions and the opportunities. Deliberate actions and interventions (e.g., through planning and management stages as well as community involvement) are crucial. Competitions do exist between the cities. Some of them would be potentially overtaken by the larger ones. Rather than relying only on the local authorities, it could be more implementable to assign interregional or national-scale measures (see also Barca et al., 2012). To respond to the inevitable market competitions, it could be working to adopt the idea of the economic cluster (Porter, 1998) where companies or institutions can be bound flexibly by cities, and the design of the interconnections and the transfers of externality within a cluster could consider the opportunities and the lacking from each city.

Still, local actions are possible. Any interested parties (e.g., municipal authorities) may compose relative comparisons between their and other similarly populous cities using the figures. Then, successful programs in any city can be adjustably adopted with the supports of complementary studies. If one believes that all of the combined good examples of compactness qualities from these cities have shared the complete puzzle of being compact with good quality of life in Indonesia, this could be a simple step to add.

Also, informal sectors play the main role in housing provisioning (e.g., Zillmann; in Jenks and Burgess, 2004; Roychansyah and Diwangkari, 2009). An informal housing may eventually become more mixed-use and self-contained but barely develop a thorough comprehension of sustainability. Of course, participation-based approaches could incorporate knowledge sharing.

While these would be directly applicable to cities in Jawa and Sumatera, those of the eastern part of Indonesia would substantially demand more maritime-based infrastructures (see also Tirtosudarmo, 2014). Although this would benefit coastal cities the most, this will buy some time for figuring out, on one side, the best way in utilizing the rainforests and other ecological assets in Kalimantan and Papua and, on the other side, the prospective sustainable schemes for developing the inland urban systems rather than getting overwhelmed by the accelerating urban form transformations that are faster than our ability to anticipate.

For further research, one apparent clue is that transportation networks possibly have a better linkage with compactness than the centroid-based distances. Also, built-up area could be incorporated to improve the delineation process. Overall, these are for obtaining stronger correlations. Another challenging yet substantial aspect to incorporate would be from the social domain. Once the correlation levels get remarkably high, actions or programs with high precision targets and inputs are very much prospective.

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7. Appendixes

Appendix 1. LDI-Based Grouping

No.	Name	LDI	No.	Name	LDI	No.	Name	LDI	No.	Name	LDI
	Group 1		17	Tomohon	0.468	35	Metro	0.403	52	Payakumbuh	0.367
1	Ambon	0.653	18	Gunung Sitoli	0.466	36	Tidore Kep.	0.403	53	Mataram	0.357
2	Bengkulu	0.614	19	Salatiga	0.463	37	Sabang	0.399	54	Tanjung Pinang	0.355
3	Batu	0.600	20	Banda Aceh	0.455	38	Magelang	0.399	55	Sawah Lunto	0.343
4	Palangka Raya	0.573	21	Pangkal Pinang	0.452	39	Dumai	0.398	56	Lubuk Linggau	0.339
5	Yogyakarta	0.552	22	Tegal	0.449	40	Lhokseumawe	0.395	57	Tanjung Balai	0.338
6	Palu	0.518	23	Kotamobagu	0.444	41	Gorontalo	0.394	58	Bontang	0.332
	Group 2		24	Banjar Baru	0.435	42	Madiun	0.393	59	Kendari	0.329
7	Manado	0.513	25	Ternate	0.432	43	Cirebon	0.390	60	Subulussalam	0.328
8	Banjar	0.510	26	Kediri	0.429	44	Padang Panjang	0.390	61	Binjai	0.328
9	Pekalongan	0.500	27	Mojokerto	0.424		**Group 3**		62	Prabumulih	0.297
10	Bitung	0.490	28	Bima	0.423	45	Langsa	0.377	63	Pariaman	0.296
11	Kupang	0.485	29	Sorong	0.422	46	Padang Sidimpuan	0.376	64	Sungai Penuh	0.285
12	Tebing Tinggi	0.483	30	Sukabumi	0.420	47	Bukit Tinggi	0.376	65	Solok	0.274
13	Pasuruan	0.482	31	Probolinggo	0.420	48	Pematang Siantar	0.373	66	Jayapura	0.249
14	Pare-Pare	0.477	32	Palopo	0.412	49	Blitar	0.372	67	Pagar Alam	0.243
15	Cilegon	0.475	33	Sibolga	0.411	50	Tarakan	0.371			
16	Bau-Bau	0.469	34	Singkawang	0.407	51	Tual	0.370			

Appendix 2. RDI-Based Grouping

No.	Name	RDI	No.	Name	RDI	No.	Name	RDI	No.	Name	RDI
	Group 1		18	Gorontalo	0.732	35	Tegal	0.658	53	Gunung Sitoli	0.567
1	Batu	0.914	19	Tomohon	0.727	36	Pangkal Pinang	0.651	54	Mojokerto	0.558
2	Blitar	0.826	20	Banda Aceh	0.715	37	Tanjung Pinang	0.649	55	Pematang Siantar	0.548
3	Tidore Kep.	0.813	21	Mataram	0.713	38	Bontang	0.632	56	Jayapura	0.538
4	Cirebon	0.804	22	Metro	0.711	39	Pariaman	0.628	57	Kotamobagu	0.537
5	Magelang	0.789	23	Yogyakarta	0.710	40	Sibolga	0.624	58	Tanjung Balai	0.523
6	Probolinggo	0.789	24	Pagar Alam	0.710	41	Sungai Penuh	0.622	59	Kendari	0.514
7	Sukabumi	0.782		**Group 2**		42	Bukit Tinggi	0.615		**Group 3**	
8	Cilegon	0.782	25	Sorong	0.706	43	Bitung	0.606	60	Tarakan	0.497
9	Palopo	0.780	26	Pekalongan	0.697	44	Manado	0.595	61	Pare-Pare	0.482
10	Sabang	0.774	27	Bengkulu	0.696	45	Singkawang	0.591	62	Binjai	0.452
11	Padang Panjang	0.764	28	Solok	0.692	46	Pasuruan	0.590	63	Lhokseumawe	0.445
12	Bima	0.759	29	Bau-Bau	0.680	47	Prabumulih	0.589	64	Lubuk Linggau	0.426
13	Ambon	0.749	30	Sawah Lunto	0.671	48	Subulussalam	0.581	65	Palangka Raya	0.405
14	Ternate	0.745	31	Kediri	0.670	49	Tual	0.574	66	Langsa	0.399
15	Banjar	0.745	32	Padang Sidimpuan	0.666	50	Tebing Tinggi	0.570	67	Banjar Baru	0.291
16	Kupang	0.741	33	Palu	0.663	51	Payakumbuh	0.569			
17	Salatiga	0.736	34	Madiun	0.661	52	Dumai	0.569			

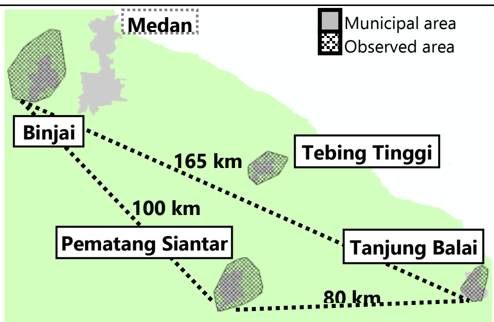
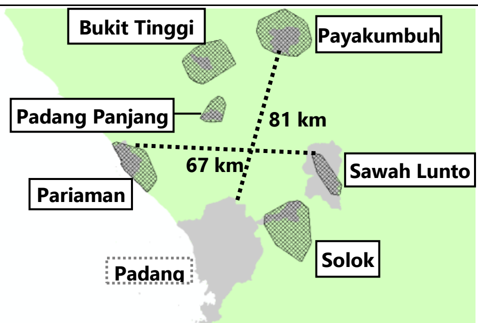
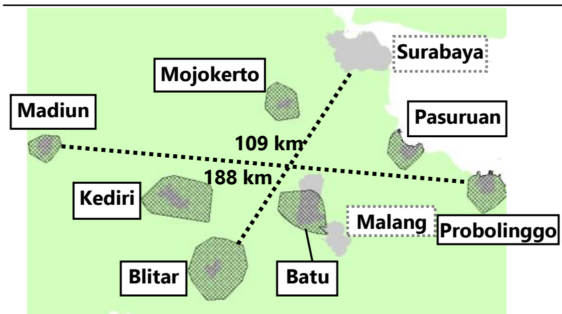
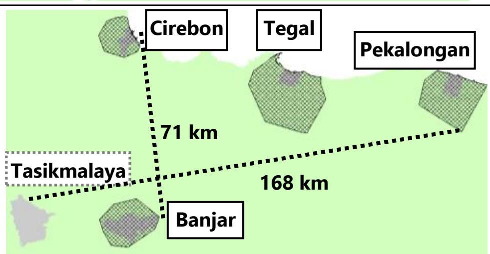
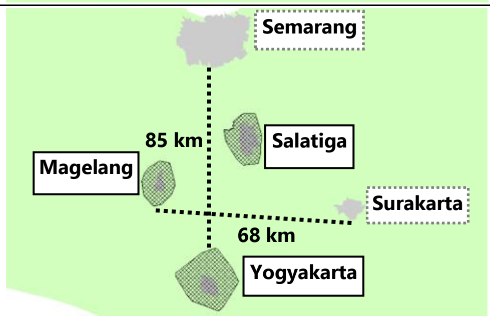
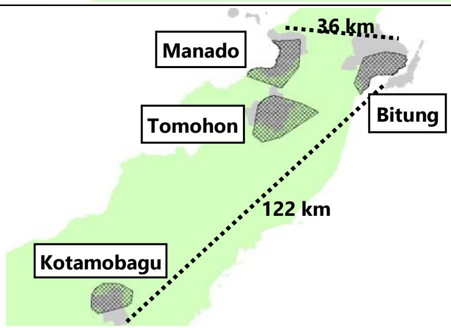
Appendix 3. LGI-Based Grouping (values in E-07)

No.	Name	LGI	No.	Name	LGI	No.	Name	LGI	No.	Name	LGI
	Group 1		18	Sibolga	48.70	35	Padang Sidimpuan	26.30	53	Bengkulu	16.26
1	Gunung Sitoli	116.88	19	Tual	48.69	36	Ambon	26.05	54	Kupang	16.15
2	Tebing Tinggi	97.98	20	Lubuk Linggau	47.38	37	Pasuruan	26.04	55	Banjar	14.90
3	Padang Panjang	89.06	21	Bau-Bau	47.28	38	Singkawang	25.73	56	Tomohon	13.95
4	Tarakan	77.16	22	Bontang	44.40	39	Batu	25.68	57	Prabumulih	13.76
5	Tanjung Balai	69.89	23	Sabang	43.96	40	Solok	25.42	58	Tegal	13.73
6	Sungai Penuh	69.33	24	Palopo	42.80	41	Payakumbuh	25.26	59	Pariaman	12.90
7	Pare-Pare	68.00		**Group 2**		42	Palangka Raya	23.99	60	Gorontalo	12.79
8	Sawah Lunto	66.33	25	Madiun	33.10	43	Subulussalam	23.23		**Group 3**	
9	Tidore Kep.	63.60	26	Bukit Tinggi	33.03	44	Probolinggo	22.01	61	Cirebon	12.01
10	Ternate	62.36	27	Langsa	32.74	45	Banjar Baru	22.00	62	Jayapura	10.85
11	Manado	54.41	28	Banda Aceh	32.07	46	Yogyakarta	21.71	63	Mataram	7.79
12	Kotamobagu	54.19	29	Pematang Siantar	28.99	47	Pekalongan	20.87	64	Pagar Alam	6.67
13	Pangkal Pinang	52.59	30	Dumai	28.66	48	Binjai	20.56	65	Kediri	6.33
14	Mojokerto	52.29	31	Magelang	28.00	49	Kendari	18.22	66	Metro	5.14
15	Cilegon	51.72	32	Sukabumi	27.54	50	Tanjung Pinang	17.24	67	Blitar	4.22
16	Palu	49.29	33	Bima	27.08	51	Sorong	16.99			
17	Lhokseumawe	49.23	34	Salatiga	26.45	52	Bitung	16.89			

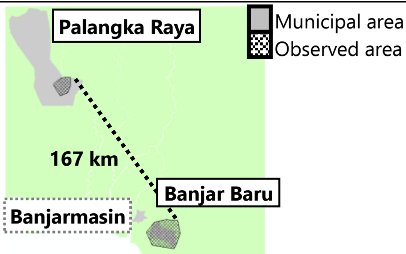
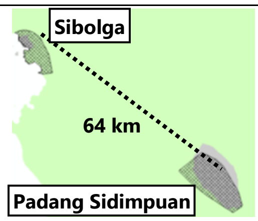
Appendix 4. Variances in LDI, RDI, and LGI-Based Groups (bolded number = low variance)

LDI	Municipal Population	Obs. Population	Municipal Area	Obs. Area	% of Slope	Municipal Density	Obs. Density	GDRP	GDRP Growth	N-P Spec.	N-P Spec. Change Rate	T Spec.	T Spec. Change Rate
Group 1	0.314	0.924	1.730	0.591	1.883	1.475	0.696	0.430	**0.061**	**0.063**	**0.023**	**0.116**	**0.015**
Group 2	0.362	0.648	1.000	0.638	0.981	0.731	0.415	0.844	**0.075**	**0.063**	**0.015**	0.192	**0.062**
Group 3	0.464	0.616	0.815	0.508	1.205	0.864	0.434	0.831	**0.083**	**0.098**	**0.024**	0.206	**0.083**
All	0.401	0.630	0.949	0.554	1.097	0.795	0.456	0.759	**0.074**	**0.072**	**0.017**	0.186	**0.062**
RDI													
Group 1	0.493	0.654	0.960	0.638	0.950	0.772	0.512	0.815	**0.054**	**0.073**	**0.018**	0.159	**0.025**
Group 2	0.414	0.655	0.918	0.505	1.177	0.837	0.362	0.815	**0.078**	**0.083**	**0.020**	0.217	**0.071**
Group 3	0.239	0.516	1.411	0.826	1.501	0.698	0.535	0.624	0.196	**0.039**	**0.020**	0.138	0.186
All	0.401	0.630	0.949	0.554	1.097	0.795	0.456	0.759	**0.074**	**0.072**	**0.017**	0.186	**0.062**
LGI													
Group 1	0.488	0.536	0.752	0.625	1.059	0.838	0.436	1.040	**0.110**	**0.087**	**0.020**	0.197	**0.122**
Group 2	0.343	0.574	1.094	0.453	1.154	0.781	0.482	0.504	**0.062**	**0.063**	**0.018**	0.171	**0.027**
Group 3	0.517	0.708	1.553	0.699	1.654	0.906	0.718	1.243	**0.078**	**0.087**	**0.009**	0.350	**0.063**
All	0.401	0.630	0.949	0.554	1.097	0.795	0.456	0.759	**0.074**	**0.072**	**0.017**	0.186	**0.062**

Appendix 5. Satellite Clusters

Map	City	Rank: Population	LDI	RDI	LGI
	Tebing Tinggi	4	1	1	1
	Pematang Siantar	2	2	2	3
	Tanjung Balai	3	3	3	2
	Binjai	1	4	4	4
	Padang Panjang	5	1	1	1
	Bukit Tinggi	1	2	5	3
	Payakumbuh	2	3	6	5
	Sawah Lunto	6	4	3	2
	Pariaman	4	5	4	6
	Solok	3	6	2	4
	Batu	6	1	1	4
	Pasuruan	5	2	6	3
	Kediri	1	3	4	6
	Mojokerto	3	4	7	1
	Probolinggo	4	5	3	5
	Madiun	7	6	5	2
	Blitar	2	7	2	7
	Banjar	4	1	2	2
	Pekalongan	2	2	3	1
	Tegal	1	3	4	3
	Cirebon	3	4	1	4
	Yogyakarta	1	1	3	3
	Salatiga	2	2	2	2
	Magelang	3	3	1	1
	Manado	1	1	3	1
	Bitung	2	2	2	3
	Tomohon	3	3	1	4
	Kotamobagu	4	4	4	2

Appendix 6. Corridor Clusters

Map	City	Rank			
		Population	LDI	RDI	LGI
	Palangka Raya	2	1	1	1
	Banjar Baru	1	2	2	2
	Sibolga	2	1	2	1
	Padang Sidimpuan	1	2	1	2

Appendix 7. Local Clusters with Space-Related Figures

No.	Cluster (additional city)	Municipality	Distance from cluster's gravity center (km)	$Surr_1$	$Surr_2$	$Surr_3$	$Surr_4$
1	A (Medan)	Tanjung Balai	128.64	3.26	35.42	1399.41	171016.3
2		Pematang Siantar	68.88	4.07	35.35	2486.46	193006.1
3		Tebing Tinggi	48.32	9.2	70.72	3896.48	234244
4		Binjai	36.23	9.6	47.21	6405.9	170909.9
5	B	Sibolga	36.44	1.63	13.02	662.68	42254.63
6		Padang Sidimpuan	27.32	1.22	9.76	573.75	36584.21
7	C (Padang)	Solok	27.19	11.44	64.09	4702.52	157391.1
8		Sawah Lunto	34.75	19.25	125.39	3659.95	161361.8
9		Padang Panjang	26.00	21.33	117.33	5787.91	186533.5
10		Bukit Tinggi	43.09	6.58	40.14	3601.73	148469.8
11		Payakumbuh	56.09	5.76	39	2691	134314.7
12		Pariaman	33.13	8.85	59.92	3313.55	154005.8
13	D (Palembang)	Prabumulih	28.51	5.31	50.73	2017.76	192924.2
14		Pagar Alam	133.45	4.11	47.91	1341.23	189221.6
15		Lubuk Linggau	135.42	2.94	33.65	1339.95	184198.6
16		Bengkulu	211.29	1.23	15.44	777.06	138228.1
17	E (Bandar Lampung)	Metro	24.17	4.76	27.08	2823.93	91508.49
18	F (Batam)	Tanjung Pinang	41.69	4.01	28.35	2072.18	103784.1
19	G (Jakarta, Bekasi, Depok, Tangerang, Tangerang Selatan, Bogor, Serang)	Sukabumi	72.50	6.74	56.3	6150.15	443116.1
20		Cilegon	87.95	9.42	69.85	6672.44	442034.2
21	H (Tasikmalaya)	Cirebon	56.40	3.09	27.13	2856.72	225898.1
22		Banjar	61.97	7.54	58.77	4096.02	262874.6
23		Pekalongan	79.02	2.02	17.96	2077.05	176442.3
24		Tegal	17.07	2.5	21.12	3222.83	232096.1
25	I (Semarang, Surakarta)	Magelang	25.44	10.02	66.69	5734.51	259321.6
26		Salatiga	9.13	12.13	77.54	7044.29	290219.7
27		Yogyakarta	43.37	2.55	19.28	3117.31	186172.2
28	J (Surabaya, Malang)	Kediri	61.26	5.77	44.09	5161.16	321155.5
29		Blitar	66.80	5.82	43.13	4878.89	295081.2
30		Probolinggo	77.47	5.2	44.74	3468.52	273482.9
31		Pasuruan	39.85	11.67	81.75	6960.39	352851.2
32		Mojokerto	20.36	10.12	73.62	6884.56	356653.4
33		Madiun	112.69	4.31	44.51	2450.99	260608.3
34		Batu	30.01	15.66	93.05	9162.97	373727.1
35	K (Denpasar)	Mataram	49.79	0.86	8.71	851.99	86820.85
36	L (Banjarmasin)	Palangka Raya	129.13	1.45	17.74	650.62	97730.53
37		Banjar Baru	38.73	4.02	22.01	2719.14	89303.08
38	M (Balikpapan, Samarinda)	Bontang	101.26	2.76	26.41	1149.72	110427.2
39	N	Manado	16.31	4.25	22.25	2746.08	85006.9
40		Bitung	39.70	4.83	30.11	2034.51	83731.85
41		Tomohon	4.17	10.72	55.32	4141.21	120035
42		Kotamobagu	85.78	2.15	21.44	795.21	79918.73
43	O	Ternate	2.07	2.37	9.21	994.7	15052.68
44		Tidore Kep.	13.06	14.94	58.13	2499.43	37823.71