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ASSESSMENTS OF DENTAL CARIES SPATIAL PATTERN IN CIAMIS DISTRICT USING LISA SPATIAL AUTOCORRELATION ANALYSIS

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ABSTRACT

One method to study health patterns, including dental and oral health, is to use a spatial approach assisted by a Geographic Information System. Dental caries itself is one of the emerging dental and oral health problems. So this study aims to determine the pattern of grouping and the number of dental caries cases spatially. The grouping pattern or called spatial autocorrelation was analyzed using several spatial autocorrelation methods. The methods include Moran I, Getis-Ord Gi, and LISA analysis. While LISA stands for Local Indicator of Spatial Association. The research sample is 27 subdistricts within Ciamis District. The number of dental caries in 27 subdistricts ranges from 0 to 163 cases. From the results of the study, it is known that the Moran I index ranges from -0.625 to 0.763. It is known that 12 subdistricts have a Moran I value > 0. While the Getis-Ord Gi* index range is from -1,438 to 5,175 with 12 subdistricts having a Getis-Ord Gi* value > 0. Based on LISA analysis, it is known that there is a spatial autocorrelation and grouping with LISA classification goes into the HH class covers 2 subdistricts. This means that in the 2 subdistricts, the number of dental caries cases is known to be the highest, clustered, and has spatial autocorrelation compared to other sub-districts.*
Keywords: *dental caries, Getis-Ord Gi*, LISA, Moran I, teeth*

INTRODUCTION

Dental and oral health is still a problem in the community that needs attention. The prevalence of the population with dental and oral problems in Indonesia according to Riskesdas 2018 is 57.6% (Soni et al., 2020). One indicator of oral health is the number of dental caries. There were significantly related dental caries cases that require permanent dental fillings (599 cases) and 402 cases of permanent tooth extraction, with a ratio for fillings/retractions compared to tooth extractions of 1.49 (Ciamis District Health Office, 2019). Regarding the services of the School Dental Health Unit in elementary schools, dental health checks have been carried out for 18,624 students (48.04%), out of a total of 38,768 elementary children. Of this number, 8,717 students needed treatment, and 5,364 students (61.53%) had received treatment related to dental caries. Dental caries can be an indicator of dental and oral health conditions within the community (Wigati et al., 2016 and Satiti, 2017).

Considering that dental caries is a disease that occupies space, the solution to determine the cause and pattern of caries is by using the Geographic Information System (GIS) approach. GIS offers reliable tools to support the various processes and stages of planning, analysis, problem-solving, decision making, and process management necessary to pursue common goal (Astari, A.J., et al, 2021; Setiawan, 2016). One of the GIS approaches is knowing the spatial pattern of dental caries.

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An important geographical phenomenon is the grouping and autocorrelation of objects. This means that objects on Earth can group together, correlate with each other, and have connectivity. The spatial objects are close to each other and have the same value which is correlated with each other. Currently, the most widely used spatial autocorrelation and grouping analyses are Getis-Ord Gi* and Moran I (Inarossy, 2019; Yenusi et al., 2020). Currently, Moran I is often used to identify local autocorrelation coefficients or spatial correlations in each region. The higher the local Moran I value, it provides information that adjacent areas have almost the same value and forms a clustered distribution.

Currently, the spatial autocorrelation analysis of Getis-Ord Gi* and Moran I has been widely applied in various fields. Used Kernell Density and Getis-Ord Gi* analysis to identify groupings and autocorrelations of students applying to a college (Santoso and Papilaya, 2019). With the Getis-Ord Gi* analysis, it is possible to identify which locations have high-interest students and which students have a moderate interest. This grouping is needed to determine which locations need more promotion so that students are interested in applying to the college in question.

The poor were grouped together and the number of groups of poor people in one location was also followed by an increase in the number of groups of poor people in other locations that were close to each other. This is indicated by the very high Getis-Ord Gi* value approaching 1, reaching 0.723 (Lestari et al., 2020). Getis-Ord Gi* also found that the dropout rate tends to cluster and is related between locations with Getis-Ord Gi* values in the range of 0.008 to 0.01 (Maisaroh, 2020). Using the same method, used the Getis-Ord Gi* method in determining industrial grouping in Java, comparing the spatial pattern of industrial groups according to industry classification, and also analyzing the spatial shift of industrial groups in Java over the last 20 years. In their research using Moran I (Kurniawan and Sadali, 2021). Moran I value obtained was 0.342 indicating that there was a positive spatial autocorrelation between districts/cities (Pratiwi and Kuncoro, 2016).

The positive spatial autocorrelation shows that regencies/cities on the island of Kalimantan have a close relationship with one another based on the variable Gross Regional Domestic Product (GRDP) per capita with 9 districts/cities on the island of Kalimantan having spatial autocorrelation and 46 other regencies/cities there is no spatial autocorrelation. In addition, there are 12 districts/cities which have high GRDP per capita with an average GRDP per capita above the average GRDP per capita for all districts/cities in Kalimantan and surrounded by 34 other districts/cities. This means that by using Moran I, it can be seen that areas with high per capita GRDP will be surrounded by areas with high per capita GRDP, and areas with low per capita GRDP will be surrounded by areas with low per capita GRDP.

Recently, spatial autocorrelation analysis has also been widely used to see disease patterns. Spatial autocorrelation to group locations with the highest stroke rates (Freyssenge et al., 2020). Have grouped several locations that have the same number of COVID-19 (Rotinsulu and Sulistyo, 2021). With the Getis-Ord Gi* analysis it is known that the increase in the number of COVID-19 among these locations is related. From the results of the study, it can be seen that COVID-19 is concentrated in one location and the increase in numbers in that location is also followed by other locations to form groups. Compared to other GIS methods, the Getis-Ord Gi* method is much more effective in determining the pattern of disease spread because this method is able to classify a phenomenon in several locations, in this case, disease, based on the similarity of the case values of the disease.

Currently, as previously explained, the number of dental caries cases is still very high at the district level and information about the spatial pattern of the number of dental caries cases is still very limited. So, related to this condition, this study intends to determine the pattern of dental caries cases by applying the spatial autocorrelation analysis of dental caries cases. The information and results obtained can be used to determine which locations have the highest number of dental caries cases and need to be prioritized to improve oral and dental health in Ciamis District.

RESEARCH METHOD

Research Type

This research type is quantitative research with a descriptive spatial approach. This study uses and combines primary and secondary data. The research variable used was the number of dental caries cases in 2020 which were recorded from 27 subdistricts in Ciamis District.

Research Location and Time

This research was conducted in the period from January 2020 to January 2021. The research location is Ciamis District, West Java Province, Indonesia Figure 1.

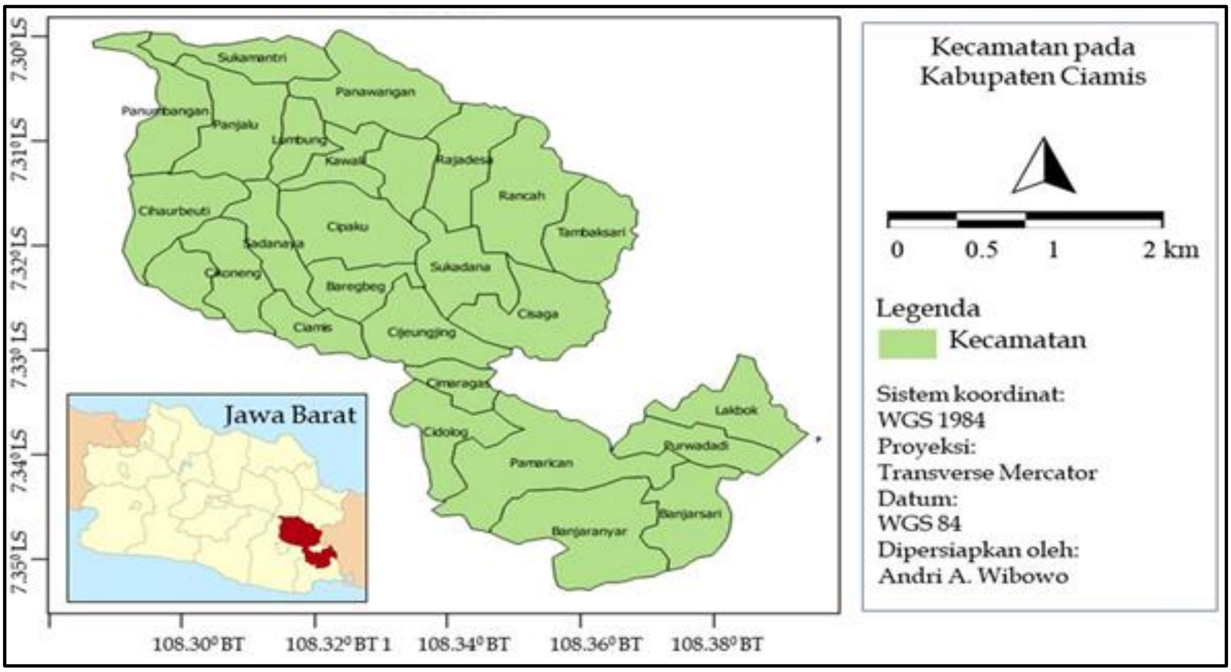

Figure 1. Map of research locations for 27 sub-districts in Ciamis District, West Java

Data Collection Technique

Data on the number of dental caries needed in 2020 (Ciamis District Health Office, 2020) was recorded from 27 subdistricts in the district. The research sample was 27 subdistricts from the sample population in the form of all subdistricts at the district level. All data obtained were then prepared including a base map of the sub-district boundaries and tabulated into the Geographic Information System (GIS) attribute table. The table includes data for south latitude and east longitude, subdistrict, number and number of dental caries, and Getis-Ord Gi*, and Moran I indices. The spatial data will later be needed for analysis of Getis-Ord Gi*, Moran I, and LISA. GIS analysis using QGIS and for Getis-Ord Gi*, Moran I, and LISA using R.

Data Analysis Technique

Moran Index I is the test statistic value used to test the spatial autocorrelation value. The value of the Moran I index is between -1 and 1 with -1 indicating a perfect negative autocorrelation and 1 indicating a perfect positive autocorrelation. The value of the Moran Index I can be calculated using the following equation following Al-Ahmadi and Al-Zahrani (2013):

$$logit\ [\pi(x)] = ln\ ln\ \frac{\pi(x)}{1-\pi(x)} = ß0 + ß1x1 + \cdots . + ßixi \ldots (1)$$

$$Moran\ I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} wij} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} wij\ (xi - x)(xj - x)}{\sum_{i=1}^{n}(xi - x)^2} \ldots (2)$$

With:

n : the number of observations

x : the average value of from n locations

x_i : observation value at location i

x_j : observation value at location j

w_{ij} : spatial weighting matrix element i-th column j

The hypothesis used is as follows:

H0 : I = 0 (no autocorrelation between locations)

H1 : I 0 (there is autocorrelation between locations)

According to Al-Ahmadi and Al-Zahrani (2013), the Moran I index values are grouped as follows Table 1

Table 1. Moran I index value classification

Moran I index value	*Remarks*
Moran I > 0	There is a cluster of objects, meaning that there are several objects that have the same value
Moran I = 0	No cluster or random
Moran I < 0	Random dispersion

Getis-Ord Gi* (Cristea, 2014) uses a statistical approach to measure spatial correlation with a matrix based on the distance of objects in an area. The Getis-Ord Gi* method is used to measure how high or low the value of data centralization is in a certain place of the object. The Getis-Ord Gi* statistic is a local clustering indicator that measures the concentration of the x-attribute variable of an object in a certain place that is spatially distributed. The Getis-Ord Gi* statistic measures the degree of clustering that is the result of the concentration of weights (or the area represented as weights) and all other weighted points that fall within a distance radius d from the original point. In general, the Getis-Ord Gi* statistic of the overall spatial association is expressed and generally calculated using the following equation (Nuarsa, 2015):

$$Gi = \frac{\Sigma\Sigma wij(d)xixj}{\Sigma\Sigma xixj} \ldots (3)$$

Getis-Ord Gi* (Zen et al., 2019) conceptually represents the occurrence of clustering centers with high and low object connectivity and correlation taking into account the distance between spatial objects (d). In this study, a high value of Getis-Ord Gi* represents connectivity and spatial correlation between the number of dental caries cases and indicates the potential for clustering, whereas if the value is less than the expected value, it indicates that there is no potential for clustering in the number of dental caries cases.

The next analysis is data analysis using the LISA (Local Indicator of Spatial Association) method following Saputro et al. (2018) and Luthfi et al. (2019). When compared with the Moran I and Getis-Ord Gi* methods, the two methods do not identify or include the value of the object being analyzed for autocorrelation. Meanwhile, the advantage of LISA is that it includes the value of the object being analyzed. This means that LISA is a combination of object values combined with z values obtained from Moran I analysis. The LISA classification is as follows (Kim & Choi, 2017) Table 2.

Table 2. LISA value classification

LISA value	*Remarks*
If the object value is high, in this case, the number of dental caries (H) and the z value of Moran I > 0 (H)	The LISA classification is HH called hotspot
If the object value is low (L) and the z value of Moran I > 0 (H)	The LISA classification is LH
If the object value is high (H) and the z value of Moran I < 0 (L)	The LISA classification is HL
If the object value is low (L) and the z value of Moran I < 0 (L)	The LISA classification is LL called coldspot

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RESULTS AND DISCUSSION

Spatial Distribution of Dental Caries Cases

The spatial distribution of the number of dental caries in 27 subdistricts in the Ciamis District is provided in Figure 2. The number of dental caries ranges from 0 to over 100 cases. Of the 27 subdistricts, it can be seen that 22 subdistricts have relatively low cases, which is in the range of 0-33 cases. Meanwhile, there are 5 subdistricts with significant numbers of cases, starting from 33 to more than 100 dental caries cases. Regarding the spatial distribution, in general, it appears that the subdistricts with the number of dental caries are more likely to be distributed on the West side of the district. On the other hand, the low number of dental caries is distributed and clustered on the East, Central, and Northwest sides of the district. On the West side, it appears that there are 2 groupings of dental caries cases, namely 1 group on the North side with 2 subdistricts with dental caries at 65-98 and 130-163 cases. The next grouping of dental caries cases appears on the Southeast side with 2 subdistricts with dental caries cases at 33-65 and 98-130 dental caries cases. This means that based on the spatial distribution, there are 2 groups of dental caries cases separated one on the North side and the other on the Southeast side and that group is limited by the subdistrict group with relatively few dental caries cases in the middle.

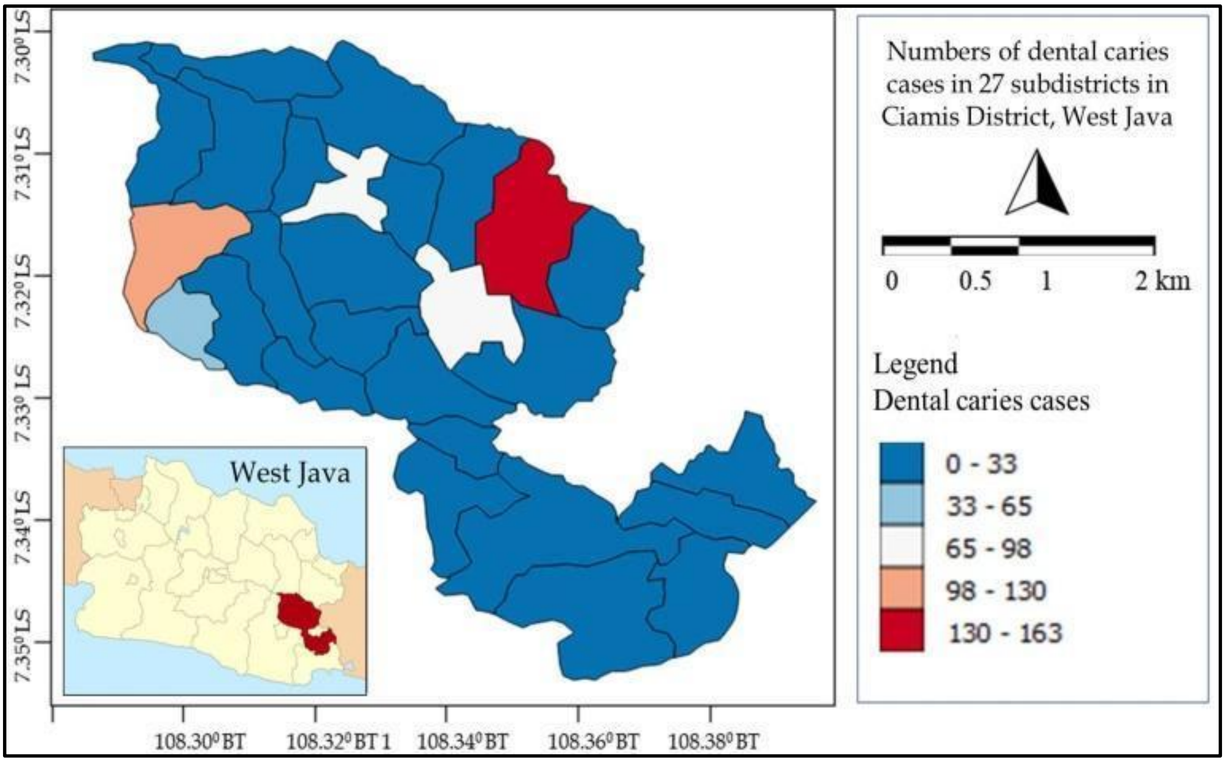

Figure 2. Numbers of dental caries cases in 27 subdistricts in Ciamis District, West Java (data source: Ciamis District Health Office, 2020)

Moran I Autocorrelation Spatial Distribution of Dental Caries Cases

Figure 3 and Table 3 show the spatial distribution of the Moran I autocorrelation numbers of dental caries in 27 subdistricts in the Ciamis District.

Based on the Moran I score, the number of dental caries has 3 distribution patterns, namely clustered, random, and scattered patterns. The clustering pattern is indicated by the Moran I value > 0. In Ciamis District, 12 subdistricts show the number of dental caries tends to cluster.

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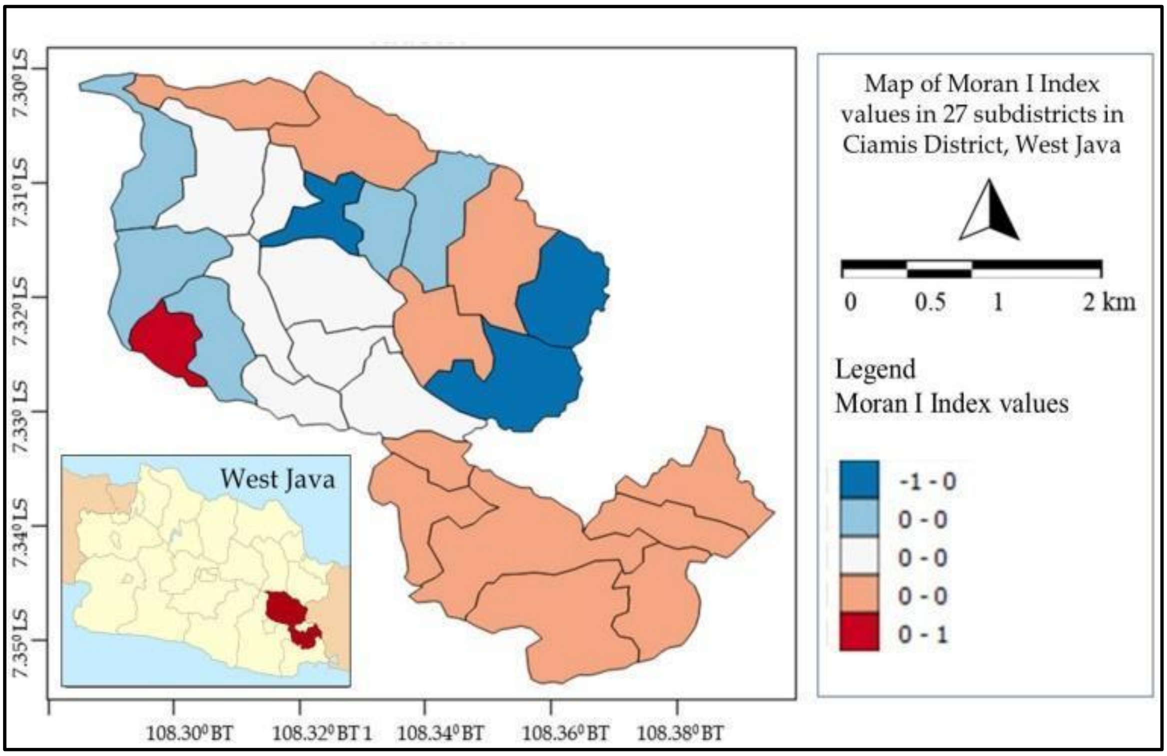

Figure 3. Map of Moran I Index values in 27 subdistricts in Ciamis District, West Java

The grouping includes groups of high and low dental caries cases. The grouping of high dental caries cases was seen in 2 subdistricts on the North side with dental caries cases at 65-98 and 130-163 cases. This means that the number of dental caries is also interrelated between subdistricts with a Moran I value > 0. The second group with a Moran I value > 0 includes the grouping of subdistricts with dental caries cases which tend to be lower in 9 subdistricts with a range of 0-33 dental caries. The rest are subdistricts with dental caries cases that tend to be random and spread out in groups with Moran values I = 0 and < 0. The non-clustered subdistricts are dominated by the numbers of dental caries in the range of 0-33 cases.

Table 3. Distribution of Moran I, Getis-Ord Gi*, and LISA values in 27 subdistricts in Ciamis District, West Java

Classification	*Ranges*	*District numbers*
	-1 - 0	3
Moran I	0 - 0	23
	0 - 1	1
	-1.4 - -1.1	9
	-1.1 - -0.5	6
*Getis-Ord Gi**	-0.5 – 0.4	8
	0.4 – 2.0	3
	2.0 – 5.2	1
	HH	2
LISA	HL	2
	LH	14
	LL	9

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Getis-Ord Gi* Autocorrelation Spatial Distribution of Dental Caries Cases

Spatial autocorrelation analysis using Getis-Ord Gi* as shown in Figure 4 and Table 3 also shows that the results of sub-district grouping are more or less the same.

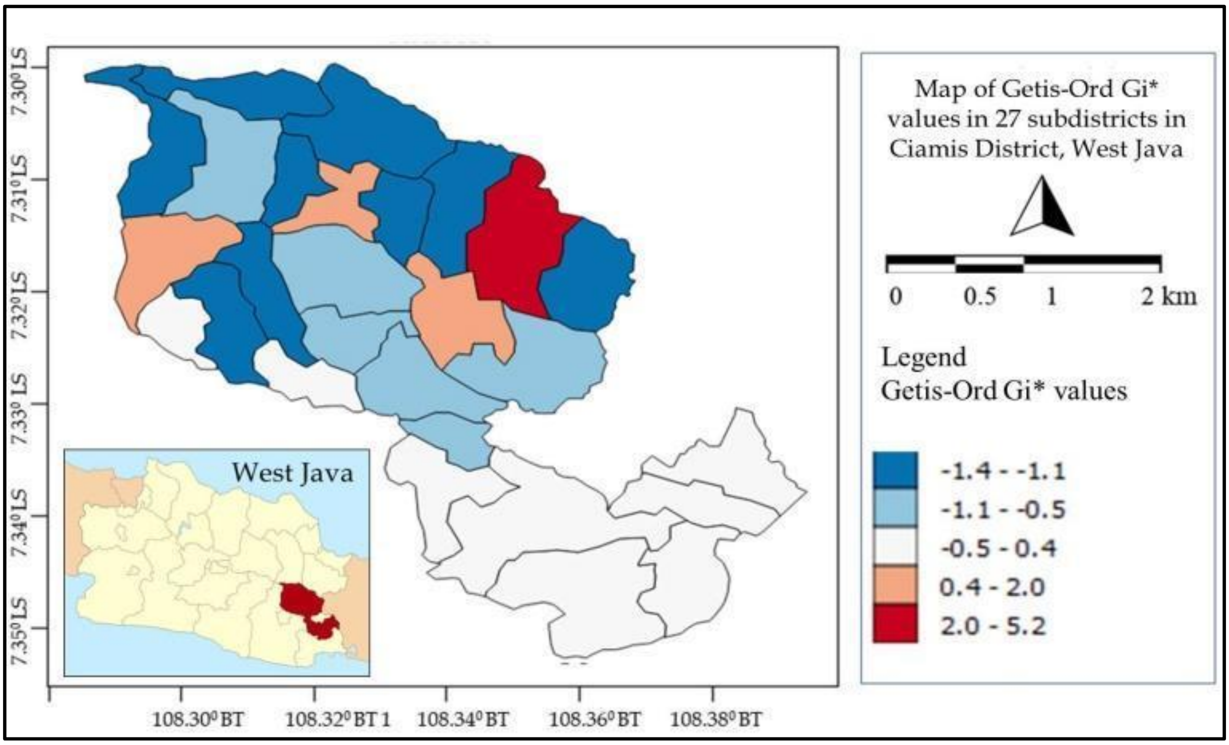

Figure 4. Map of Getis-Ord Gi* values in 27 subdistricts in Ciamis District, West Java

In the Getis-Ord Gi* analysis, it is clear that the subdistricts are grouped based on the number of dental caries with a Getis-Ord Gi* value > 0. There are also 2 groups formed. Slightly different from the analysis using the previous Moran I value, the Getis-Ord Gi* analysis is only specifically grouping the number of teeth that have a high number of only or above 33 dental caries cases. It can be seen that the subdistricts that have fairly high numbers of dental caries are grouped together and correlated.

On the North side, a subdistrict with a dental caries rate of > 130 dental caries cases correlates with a subdistrict with a fairly high number of dental caries in the range of 65-98 cases. This analysis provides a more specific grouping of subdistricts based on the number of teeth with a high incidence of dental caries and can assist in identifying areas for targeted interventions.

LISA Autocorrelation Spatial Distribution of Dental Caries Cases

Spatial autocorrelation analysis using LISA is shown in Figure 5 and Table 3 which also shows the results of subdistrict grouping which are more or less the same. In this LISA analysis, subdistricts are classified into 4 classes, namely HH, HL, LH, and LL. HH is a hotspot, meaning that there is a sub-district grouping and autocorrelation with a high number of dental caries.

On the other hand, LL is a cold spot, meaning that there is no subdistrict grouping and autocorrelation with a low number of dental caries. The HH class covers 2 subdistricts that are next to each other, followed by the HL class which also includes 2 subdistricts. The rest are subdistricts with low dental caries cases that are uncorrelated and not clustered.

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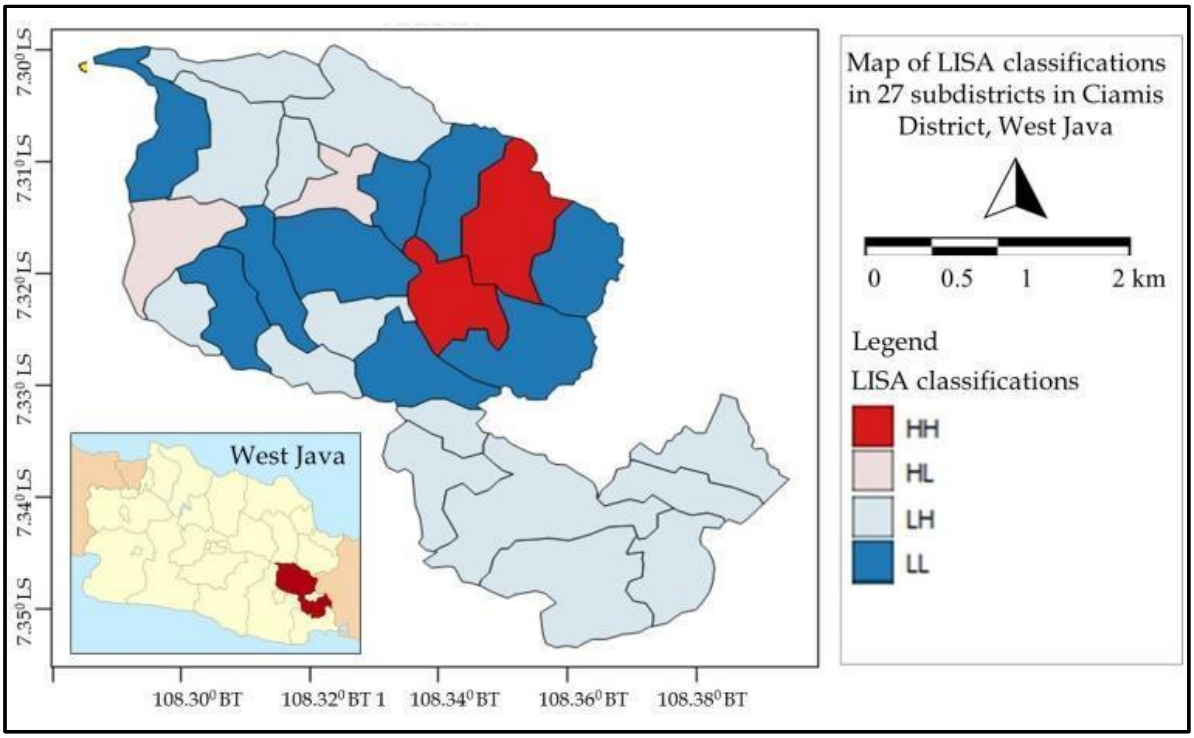

Figure 5. Map of LISA classifications in 27 subdistricts in Ciamis District, West Java

GIS and Spatial Analysis for Effective Dental Caries Management

A disease is a spatial object because its existence is related to space and time. So for time and place-oriented disease management, a spatial approach should also be used. This means that how to prevent the spread of disease from one location to another, of course, must prioritize an approach with spatial aspects assisted by GIS.

A disease that seems to cluster in an area is followed by a need to treat the disease that clusters as well. It starts with the emergence of the disease in a location then followed by the emergence of the disease around it. The disease continues to increase in number and form groups characterized by a high number of diseases. Those groups are called hotspots. In addition, locations with low disease characteristics can also group together to form groups characterized by low disease numbers, and the group is called cold spot.

In disease management, the determination of hotspots or cold spots greatly contributes to the success of dealing with the disease. This is because by knowing hotspots and cold spots, it can be seen which locations are the source of the disease. By knowing which locations are the source of the disease, it can be determined which locations must be prioritized and their needs met in the context of mitigating the disease.

In this study, it is known that groups or clusters that require dental caries exist in any subdistrict in Ciamis District. For subdistricts that are identified as clustered and have higher dental caries cases than others, it means that oral health treatments must be prioritized in that group. In this case, the spatial autocorrelation analysis approach is very useful for classifying needs from various locations and determining which locations need to be focused on and prioritized to be addressed immediately (Jana & Sar, 2016).

The advantage of this study is that it has used LISA analysis as a GIS development from previous research (Yunita et al., 2020). In addition, when compared to previous research, this research must be developed to cover a wider area such as at the provincial or national level (Laohasiriwong et al., 2018; Miheretu, 2020; Dutta et al., 2021; Jesri et al., 2021).

CONCLUSIONS

From this study, it is known that the number of dental caries in 27 subdistricts

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ranges from 0 to 163. Meanwhile, the Moran I index ranges from -0.625 to 0.763. It is known that 12 subdistricts have a Moran I value > 0. The range of the Getis-Ord Gi* index is from -1.438 to 5.175 with 12 sub-districts having a Getis-Ord Gi* value > 0. Based on LISA analysis, it is known that there is a spatial autocorrelation and grouping by classification. LISA is included in the HH class covering 2 subdistricts. This means that in the 2 subdistricts, the number of dental caries is known to be the highest, clustered, and has spatial autocorrelation compared to other subdistricts.

RECOMMENDATIONS

As a suggestion and also a contribution from this research, it is recommended that the fulfillment of dental caries treatment needs to be prioritized in several sub-districts that are clustered that have been identified based on LISA analysis

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