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CLASSIFICATION OF PERTUSSIS VULNERABLE AREA WITH LOCATION ANALYTICS USING MULTIPLE ATTRIBUTE DECISION MAKING

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Abstract. *Pertussis is an illness caused by a throat infection from Bordetella pertussis bacteria. Every year, areas vulnerable to pertussis have increased, which can lead to extraordinary incidences or epidemic. This paper discusses location analytics to determine the pertussis-prone regions using the Geographical Information System (GIS). The authors have conducted the study using multiple attribute decision making with Weighted Product Model (WPM) and Weighted Sum Model (WSM) methods based on the spatial dataset containing the infant Diphtheria-Pertussis-Tetanus (DPT) immunization status, some infectious diseases that belong to immunized Preventable Diseases (PD3I) rate, nutrition status, population density, and epidemic rate. The location of the research is in a climate tropical East Java Province, Indonesia. The result of the classification using these two methods is an area in Good, Average, Fair, and Poor category. The result of the measurement of the inter-rater reliability using the Cohen Cappa method conducted in 657 subdistricts shows that, in 2011, the coefficient value of 0.11 (11%) was categorized as Poor. The result of 2012 was higher than the previous year, which was 0.37 (37%) Fair category. Both 2013 and 2015 showed the value of the same results of 0.16 (16%) in the class of Average. The results of 2014 showed of coefficient values 0.60 (60%) Moderate category, and there would be a change in 2015-2016; the coefficient value was 0.31 (31%) with the Fair category. Since the WSM method has a better strength of agreement coefficient value than WPM, it is strongly recommended.*
Keywords: GIS, Location analytics, MADM, WSM, WPM, Pertussis

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1. **Introduction.** Pertussis is a disease that could cause severe illness to humans, especially for young children and toddlers. This disease, also known as whooping cough, often makes a global problem in the health sector. To avoid pertussis, people require a healthy metabolism [1,2]. The emergence of pertussis is because of microbes called Bordetella bacteria [1,3]. The best way to protect against pertussis is by getting children or young people to be vaccinated [4]. The solution to reducing whooping cough in infants and young children is giving them pertussis vaccination [5,6]. The World Health Organization (WHO) [2] reveals that treatment at six weeks of age using whole-cell Pertussis (wP) or acellular Pertussis (aP) vaccine can effectively prevent Pertussis [7-10]. Three kinds of treatment doses are for young children and toddlers, including diphtheria-tetanus cells + Haemophilus influenza b + hepatitis B (DTwP-Hib-HBV) pentavalent vaccine, given at ages 2, 4, and 6 months [11], followed by two driving doses of DTwP at 15 months and four years [3,5,7,12]. The country of Brazil has quite a significant incidence of pertussis, with a breakdown rate of 95% for the national-level data from 2011 to 2014 [12-14].

Many researchers are attracted to study spatial analysis for disease classification. Ntirampeba et al. proposed spatial data analysis to determine whether immunization can affect pertussis disease based on the type of vaccine given to the sufferer [15]. Some researchers apply geostatistical methods based on Bayesian models [15,16]. These methods provide an excellent result of vaccination exposure map with a high definition spatial object and suggest some areas targeted for future developments [17]. The information obtained will be useful for the Ministry of Health and many communities to tackle and reduce the incidence of pertussis.

In previous research, there were studies to determine vaccination intervention to pertussis disease. The studies discussed the effectiveness of maternal immunization during pregnancy to prevent pertussis in infants aged < 8 weeks, including general characteristics and vaccine control where the unadjusted Vaccine Effectiveness (VE) variable value was determined as $VE = 1 -$ Odds Ratio (OR) variable for vaccination in pregnancy [18]. The logistic regression analysis was used to calculate the OR variable. The multiple logistic regression model is carried out based on variables that are statistically related to the results, using a stepwise progressive strategy [18-20]. The mean of gestation age at vaccination for mothers of controls is presented as $p \leq 0.2$ variables in the selected bivariate analysis, and this variable is used for inclusion in the multivariable model [18]. Those who had statistical significance $p < 0.05$ were retained in the final multivariate model [18,20]. However, this step could help the statistical analysis for reducing this infectious disease as well.

Location analytics was important for policy and decision making and has been applied in many case studies in the health and disease sector [21-23]. Eccles and Briggs studied spatial analysis using several methods, including Moran's I, local indicators of spatial association for clustering immunization rates in Alberta. They applied these methods to a time series data with a spatiotemporal variation of immunization rates for measles, mump, and rubella [24]. Laohasiriwong et al. proposed evaluating the spatial heterogeneity of Chronic Respiratory Disease (CRD). They compared spatial heterogeneity derived from local cluster detection with the night-time lights and industrial density correlation by CRD. They found NTLs and ID could work as factors for determining disease hotspots [25].

Furthermore, Varatharajan et al. implemented an integrated spatial data analysis that comprises implicit and explicit information. They study a method to identify an effective way to prevent and control malaria using Inverse Distance Weighting (IDW), a deterministic method, for assigning weight values based on the locality [26]. Rivadeneira et al. proposed quantifying socioeconomics inequalities associated with measles immunization coverage at the population level using multiple spatial regression and calculated. They calculated the slope and relative index of inequalities and found clusters of vulnerable populations for outbreaks [27]. Hendry and Chen proposed a multi-label classification based on k-means clustering using business and user-item reviews dataset. This paper found the k value for the best classification result is three where the k initial value is automatically selected by grid search. However, the initialization of k value did not consider the location-based dataset [28]. The Web GIS technology for public health surveillance has been successfully explored and utilized, known as Web GIS-based Public Health Surveillance System (WGPHSS). The system effectively monitors, maps, and observes disease spread, including pertussis. For some reason, many WGPHSS systems still have yet explored Web 2.0 ability [29]. This review paper becomes our system development reference.

However, the previous research did not use the approach and parameters proposed in this paper, with a multiple attribute approach to explore the need for supporting factors in the analysis process and interview experts in disease prevention and control. The value of priority weights on attributes and sub-attributes was determined based on an expert's experience or knowledge used to rank alternatives to decisions.

In this paper, the authors proposed a location analytics approach to determine pertussis-prone areas, which uses the infant immunization status (DPT), some infectious diseases that belong to immunized preventable diseases (PD3I) rate, nutrition status, population density, and epidemic rate. Multiple Attribute Decision Making (MADM) was used as an alternative tool in multi-parameter coverage for imposing on the dataset from the Health Profile Book of East Java Province, Indonesia in 2011-2016 [30-35]. The multi-class classification was obtained from calculating two methods, Weighted Product Model (WPM) and Weighted Sum Model (WSM), with a Good, Average, Fair, and Poor indicator coverage. Epidemic complex models have been proposed to display a more complicated dynamic behavior network by vaccinating newborns and susceptible ones. This approach uses the Adomian multi-stage decomposition method. This method has the same characteristics as Multiple Attribute Decision Making (MADM), which uses several important system modeling parameter values. In this analysis, spatial data modeling uses large-scale alternatives, but MADM is the best method to solve. The MADM process will identify several alternative sets to facilitate the selection of the best alternative, divide the alternatives into groups on a large scale, and determine the parameter attribute weights, then conduct numerical experiments with the selected MADM method [29]. MADM may be used as a decision-making system for individuals or groups, the value of priority weights on attributes and sub-attributes based on an expert's experience or knowledge used to rank alternatives to decisions [30]. In this study, the WSM and WPM methods were chosen because they have criteria with the best results for solving decision problems [36,37].

The WPM method finds V_i values for the good categories amounts larger than or equal to 0.002995, the average categories for amounts larger than or equal to 0.001996 and smaller than 0.002995, the fair categories for amounts larger than or equal to 0.000998 and smaller than 0.001996, and the poor categories for V_i values smaller than 0.000998. The WSM method obtains A_i values by Good categories for A_i values bigger than or equal to 9.65, average categories for A_i values bigger than or equal to 8.1 and smaller than 9.65, Fair categories for A_i values bigger or equal to 6.55 and smaller than 8.1, and Poor categories for A_i values smaller than 6.55. The location analytics findings have been tested in 38 districts in the East Java Province of Indonesia and display it in the spatial data layer.

The results of this study become a part of the steps to determine the area prone to pertussis disease. Both methods, the WSM and WPM methods, are used to obtain comparable results with reference values issued by the East Java Health Office, to get information on which method has more accurate results. The resulting category will be used to map the classification of pertussis-prone areas so that health authorities can use it for observation, monitoring, and make decisions for Pertussis Management.

The foundation of this research is a framework developed for the identification of tropical disease vulnerable areas in Indonesia. This framework applied Artificial Intelligence (AI) technology for making spatial analysis and patterns using GIS to visualize the endemic and non-endemic area and future epidemiological investigation activities [38].

2. **Spatial Datasets.** This paper is using a spatial dataset to make classification from parameters that contributed to the spread of pertussis disease. The dataset consists of data and its attribute, which become the classification parameters in addition to the predetermined settings of pertussis-prone areas, as shown in Table 1, including the infant immunization status (DPT immunization), PD3I rate, nutrition status, population density, and epidemic rate. The spatial datasets in Table 1 are used as a data model in the spatial analysis process to classify pertussis vulnerable areas. Sources of expertise to determine attribute datasets such as priority value, indicator (annually), range, and level of importance are obtained from the Division of Disease Prevention and Control of the East Java Provincial Health Office, Indonesia. Data coverage is sourced from the Health Profile Book of East Java Province, Indonesia, in 2011-2016 [22-27]. Some settings to determine the level of importance of the parameter are given as a weight value. The weight value could be derived from the method taken and from the competent official agency. The weight values consist of the infant immunization status (DPT immunization) rate (1), PD3I rate (0.8), epidemic rate (0.6), population density (0.4), and nutrition status (0.2). In other words, the priority value of each data set is 1, 2, 3, 4, 5. The weighting of each parameter is carried out using the fuzzification process, which defines a fuzzy set of indicators to provide weights that describe the level of importance of the parameters for use in the classification results process [34-36]. This process effectively helps to obtain preference values for decision-makers [37].

The categories in MADM are defined to show a structural relationship between several criteria given to deliver a very close relationship to the parameter criteria's priority scale [38]. In the spatial datasets, the weight value for each parameter is given to determine the level of influence or significance of the attribute data sets on the resulting alternatives [34,38].

3. **Methods.** Decision-making systems involving spatial GIS data could be equipped with the MADM method, which is used to deal with discrete problems [39]. The technique could combine spatial data and its attribute to conduct spatial data analysis [40,41]. The primary data of the spatial data analysis is a dataset described in Table 1 [30-35]. From this data, the authors investigate and do location analytics to produce a classification of pertussis-prone areas based on immunization status coverage. Figure 1 shows the flowchart of the classification of the pertussis-prone area process based on immunization status coverage. This chart shows an idea of how the classification works, starting from inserting raw data, entering and synchronized spatial data and its attribute data, and choosing the data mining methods that suit the character of the data obtained from various sources. In the initial step of Figure 1, the authors specify the spatial data layer and its attribute in shape (**.shp*) file dataset. The dataset contains an East Java Province, Indonesia map with a level of detail from districts to sub-district. The dataset also fulfills with data about PD3I rate, population density, nutritional status, infant immunization status, and epidemic rate that has qualitative data characteristic. Then, this data is

TABLE 1. Spatial datasets multi-criteria parameter for pertussis diseases

Attribute datasets	Priority value	Weight	Categories (annually)	Range	Level of importance
The infant immunization (DPT) status	1	1	Target reached	DPT $\geq$ 84.5%	2
			Not reaching the target	DPT $<$ 84.5%	1
PD3I rate	2	0.8	Yes, if the cases show PD3I $\geq$ 12 in a year, then the area is determined as a PD3I area	PD3I $\geq$ 12 cases per year	2
			No, if the cases show PD3I $<$ 12 per year, then the area is not included in the PD3I area	PD3I $<$ 12 cases per year	1
Epidemic rate (per year)	3	0.6	very good	ER = 0 cases	3
			good	ER $<$ 12 cases	2
			less	ER $\geq$ 12 cases	1
Population density	4	0.4	If an area with a population density $<$ 500 people/km^2, then the area is classified as a score of 1	$<$ 500 people/km^2	8
			If an area with a population density between 500-1249 people/km^2, then the area is classified as score 2	500-1249 people/km^2	7
			If an area with a population density between 1250-2499 people/km^2, then the area is classified as a score of 3	1250-2499 people/km^2	6
			If an area with a population density between 2500-3999 people/km^2, then the area is classified as a score of 4	2500-3999 people/km^2	5
			If an area with a population density between 4000-5999 people/km^2, then the area is classified as a score of 5	4000-5999 people/km^2	4
			If an area with a population density between 6000-7499 people/km^2, then the area is classified as a score of 6	6000-7499 people/km^2	3
			If an area with a population density between 7500-8499 people/km^2, then the area is classified as a score of 7	7500-8499 people/km^2	2
			If an area with a population density of $>$ 8500 people/km^2, then the area is classified as a score of 8	$>$ 8500 people/km^2	1
Nutritionals status of the infants (SD)	5	0.2	Very good nutrition	SD $\geq$ 2	4
			Good nutrition	$2 > \text{SD} \geq -2$	3
			Less of nutrition	$-2 > \text{SD} \geq -3$	2
			Poor nutrition	$-3 > \text{SD}$	1

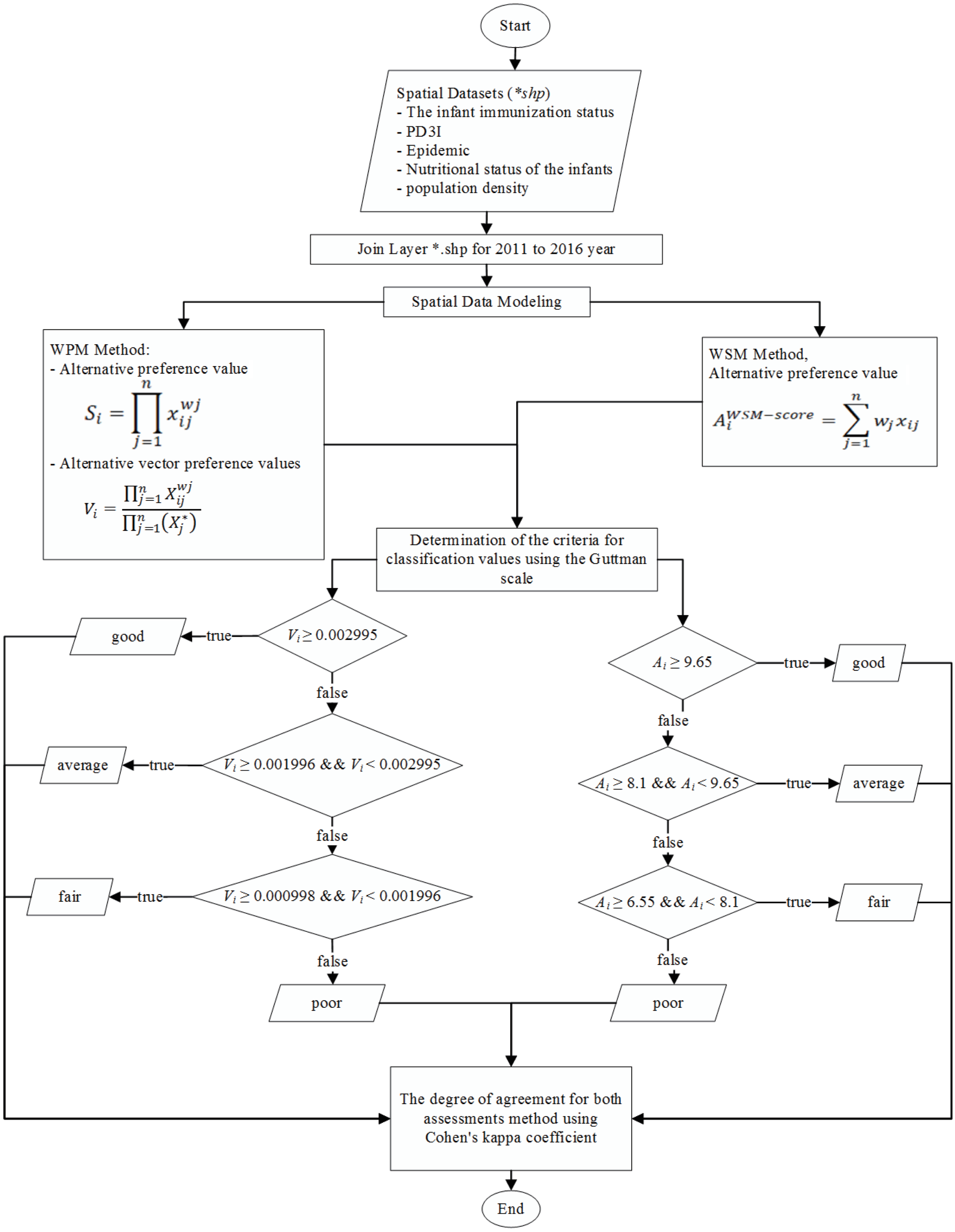

FIGURE 1. Flowchart of location analytics with WPM and WSM method

combining with the overlay layer to produce the pertussis layer (*pertussis*.shp*) for each year.

Further, location analytics was imposed using WPM and WSM methods. The result from these two methods is executed to the Guttman classification. The Guttman method will determine a category where the area is said to be Good or Poor. A good condition will be indicated with the green-colored area. An Average categorized area will be drawn in blue color. An area with the V values less than average or categorized as Fair was indicated with the yellow color, where the area with the V value less than the fair is categorized as Poor, which was shown in red regions.

3.1. **Multiple Attribute Decision Making (MADM).** MADM is a category in the Multi-Criteria Decision-Making system (MCDM), together with Multi-Objective Decision Making (MODM) [39,42,43]. MADM method is generally implemented for discrete domain decision making, where limited alternative decision support systems were determined [44,45], while MODM is applied for continuous domain decision making with many alternatives [45,46]. MADM defines the parameters/criteria used to decide the best alternative based on several appropriate measures [42]. The MADM system will identify the attribute requirements in the spatial analysis process, making decision weights from the related data (Table 1) for producing the decision matrix [45]. MADM deploys Weighted Product Model (WPM) and Weighted Sum Model (WSM).

WSM method is an approach that applies several parameters as input for making the best decision. WSM is a general model used for different applications such as robotics, processors, and others. The method is often used in single-dimensional problems. The basis of the mathematical calculation of the WSM method is to get a weighted sum from all ratings on each alternative attribute data [47]; there are m alternative and n criteria. The best option can be formulated (1) [45].

$$A_i^{\mathit{WSM\text{-}score}} = \sum_{j=1}^{n} w_j x_{ij}, \text{ for } i = 1, 2, 3, \ldots, m \tag{1}$$

where n = number of criteria, w_j = the weight of each criterion, x_{ij} = matrix value x, and $i = 1, 2, 3, \ldots, m$ is an alternative decision.

The value of n is the number of criteria, $w_j x_{ij}$ is the alternative value i on criterion j variable, and w_j is the weight value of the criterion j variable [45]. The Max function is used to rank alternative decisions that the most significant score alternatives are placed at the top [48]. Difficulties in this method arise when the available criteria have more than one dimension or multi-dimension. In order to solve this problem, the multi-dimensional criteria must be merged into one dimension.

WPM method uses product or multiplication to link the rate of each attribute; each score of the attribute must be raised to the power equivalent to the relative weight of the corresponding criterion [45]. WPM method creates a weighted normalized decision matrix to find out the alternative preferences of A_i in S_i vectors, according to Equation (2) [45,47].

$$S_i = \prod_{j=1}^{n} x_{ij}^{w_j} \tag{2}$$

where n = number of criteria, w_j = the weight of each criterion, and x_{ij} = matrix value x.

The S_i vector is an alternative preference. The x_{ij} variable is the matrix value for the alternative per attribute. The w_j variable is the weight values criteria. The n variable is representing the number of criteria declared. The i variable is the chosen alternative value, and j variable is the criteria index. The $\sum w_j$ amount is 1 for the profit attribute, and negative for the cost attribute. Equation (3) shows the formula of relative preference of each alternative.

$$V_i = \frac{\prod_{j=1}^{n} X_{ij}^{w_j}}{\prod_{j=1}^{n} \left(X_j^{*}\right)} \tag{3}$$

where vector V_i is an alternative preference, the weight value is determined for each parameter used to set the priority value on the existing settings accommodated in the *Bpre* variable and do the sum for all priority values $Tbpre = Bpre_a + Bpre_b + \cdots + Bpre_n$. Calculating the value of variable W, with the weight value in variable B divided by the number of values of the overall priority weight $W = B_a/T_b$. Calculating the value of the variable S on each weight value in variable B is raised by the result of the variable W, with $S = B_a{}^\wedge W_a$. It is calculating the value of V_s by multiplying all values in variable S, with $V_s = S_a \times S_b \times \cdots \times S_n$. The calculate the total vector on variable V or T_{V_s} by adding up all the values of V_s, with $T_{V_s} = V_1 + V_2 + V_3 + \cdots + V_n$, then the variable value of $V = V_{sa}/T_{V_{sa}}$.

3.2. **The Guttman scale.** The Guttman scale is an analysis assessment standard to make a qualitative data conclusion [49]. In this paper, the Guttman scale is used to measure the classification values. It estimates the result score of the classification with an intervention value that is still ambiguous due to uncertainty [50-52]. In the type of dataset that uses a score/weight in the analysis process, giving values based on the uncertainty factor of the class of variables described can be measured using the Guttman scale [51] in Equation (4).

$$I = \frac{R}{K} \tag{4}$$

where the variable I is the interval value acquired from the R, that is the range of data values divided by the K, the number of alternative classifications to be produced.

3.3. **Method Consistency Test (MCT).** The two methods applied in this research are tested to measure its consistency using the Cohen Kappa Method; this measurement is used for qualitative data based on Equation (5) [53].

$$\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \tag{5}$$

where the κ variable is the measurement coefficient between the two methods WSM and WPM. The $\Pr(a)$ variable is a percentage of the number of measurements consistent in making comparisons between methods, and the variable $\Pr(e)$ is the percentage change. The range of coefficient values of the κ variable is [53]: if the amount of the variable $\kappa < 0.21$ the strength of agreement is said to be "poor", if the κ value between 0.21 and 0.40 is called "fair", if the κ value between 0.41 and 0.60 is called "moderate", the κ value of 0.61 to 0.80 is called "good" strength of agreement, and if the κ between 0.81 and 1.00 is said to be "very good" strength of agreement.

4. **Results and Discussions.** The results of the study were applied to official data of 657 sub-districts in 38 districts from the year 2011 to 2016. These data were published by the East Java Provincial Health Office, Indonesia [30-35]. Figure 2 shows the results of location analytics for the classification of pertussis-prone areas based on immunization coverage status using MADM with the WPM method. Whereas Figure 3 explains the results using the WSM method. The value of the parameter criteria is obtained from the cost and benefit variables, which greatly influence the alternative decision process of the classification results in Figure 2 and Figure 3.

The results of the classification by the WPM and WSM methods are calculated using the Guttman Scale in Equation (4). The process of the Guttman scale computation in Table 2 is used to determine the range of accuracy values for pertussis' vulnerable area with the results described in Equations (6) and (7). The value of R is taken from the range of values between the maximum and the minimum amount of V. The K variable

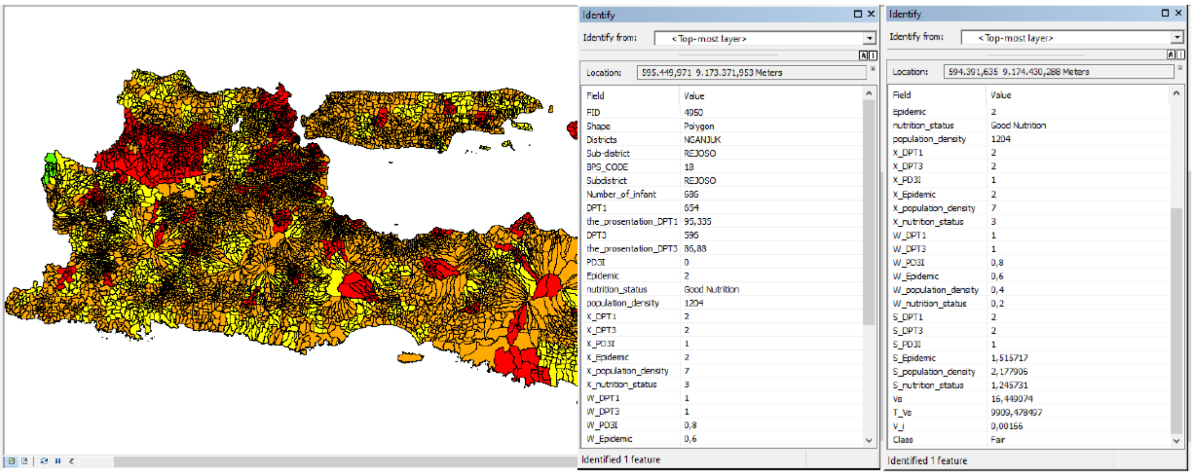

FIGURE 2. (color online) The WPM classification results in the East Java map

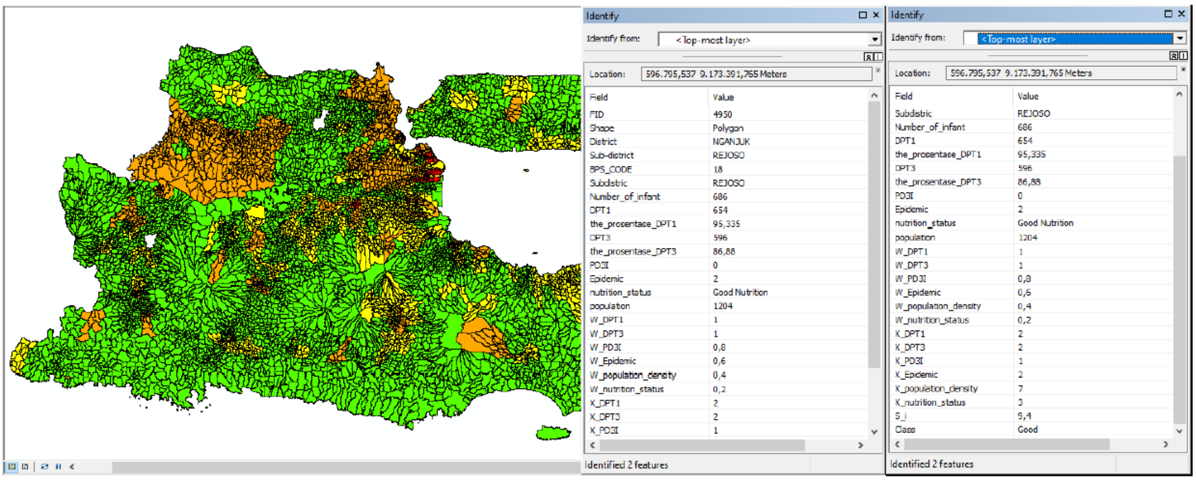

FIGURE 3. (color online) The WSM classification results in East Java map

is the number of alternative classifications, namely Good, Average, Fair, and Poor with the WPM and WSM methods that refer to Equations (6) and (7). Policymakers can use the range of classification results in Equations (6) and (7) for further research on the spatial analysis of the classification of pertussis vulnerable areas. Time series data for the following year can be tested using this range of values.

$$\begin{cases} \text{good}, & \text{if } V_i \geq 0.002995 \\ \text{average}, & \text{if } V_i \geq 0.001996 \text{ and } V_i < 0.002995 \\ \text{fair}, & \text{if } V_i \geq 0.000998 \text{ and } V_i < 0.001996 \\ \text{poor}, & \text{if } V_i < 0.000998 \end{cases} \tag{6}$$

$$\begin{cases} \text{good}, & \text{if } A_i \geq 9.65 \\ \text{average}, & \text{if } A_i \geq 8.1 \text{ and } A_i < 9.65 \\ \text{fair}, & \text{if } A_i \geq 6.55 \text{ and } A_i < 8.1 \\ \text{poor}, & \text{if } A_i < 6.55 \end{cases} \tag{7}$$

The results of the classification of MADM using the WSM, and WPM method in Figures 2 and 3, respectively, using a sample test in Rejoso District, Nganjuk Regency, East Java Province, Indonesia. According to reference Table 1, the infant immunization status for the first Diphtheria, Pertussis, and Tetanus (DPT) immunization is 654 babies out of a

Table 2. The results of Guttman scale assessment

Metode WPM	**Metode WSM**
$R = V_{i_{\max}} - V_{i_{\min}} = 0.003993 - 0 = 0.003993$ $K = 4$ $I = \frac{0.003993}{4} = 0.000998$	$R = V_{i_{\max}} - V_{i_{\min}} = 11.2 - 5 = 6.2$ $K = 4$ $I = \frac{6.2}{4} = 1.55$
Assessment good criteria $=$ highest score $- I$ $= 0.003993 - 0.000998 = 0.002995$ Assessment average criteria $=$ assessment good criteria $- I$ $= 0.00299475 - 0.00099825 = 0.001996$ Assessment fair criteria $=$ assessment average criteria $- I$ $= 0.0019965 - 0.00099825 = 0.000998$ Assessment poor criteria $=$ assessment fair criteria $- I$ $= 0.000998 - 0.000998 = 0$	Assessment good criteria $=$ highest score $- I$ $= 11.2 - 1.55 = 9.65$ Assessment average criteria $=$ assessment good criteria $- I$ $= 9.65 - 1.55 = 8.1$ Assessment fair criteria $=$ assessment average criteria $- I$ $= 8.1 - 1.55 = 6.55$ Assessment poor criteria $=$ assessment fair criteria $- I$ $= 6.55 - 1.55 = 5$

total of 686 babies indicate that the target indicator is 95.335% (Good Immunization). The third DPT immunization is 596 babies out of 686 babies; the target is 86.88% (Good Immunization). The priority parameter for infant immunization status is 1 with a weight value of $w = 1$, the level of importance for the first, and the third DPT immunization is 2. The PD3I rate for the sub-district sample has zero cases per year, the value of priority parameter PD3I is 2 with a weight value of $w = 0.8$, and the value level of importance is 1. The epidemic rate has two cases annually that indicate the good rate with the value of the priority parameter of 3, weight $w = 0.6$, and the value of importance is 2 ($x = 2$). The sample population density of the sub district has 1204 people/m^2 and categorized as score 2, with the priority parameter of 4, weight value $w = 0.4$, and the level of importance value is 7. The nutritional status of the infants is in good condition, the priority parameter is 5, with weight $w = 0.2$, and the value level of importance is 3.

Figure 2 depicts the alternative preference value (S_i) result from the WPM method based on Equation (2) by multiplying all results from the value of x power of w, resulting S_{DPT1}, S_{DPT3}, S_{PD3I}, $S_{epidemic}$, $S_{population\text{-}density}$, and $S_{nutrition\text{-}status}$ variable is 2; 2; 1; 1.515717; 2.177906; 1.245731, respectively. Alternative vector preference values (V_i) is calculated based on Equation (3), where the value of Vs_i is 16.449074 obtained from the product of all S_i variables. Calculating the total vector on variable V or T_{V_s} by adding up all the values of V_s, yields T_{V_s} is 9909.478497. Next, the value of V_i is 0.00166, according to the area sample test in Figure 2, which is the value of Vs_i divided by the value of T_{V_s} variable. The classification results state that the area belongs to the fair category of pertussis disease (Table 2, Equation (7)).

Figure 3 shows the alternative values (A_i) result of the WSM method based on Equation (1). The A_i values computed by $A_i = (1{*}2)+(1{*}2)+(0.8{*}1)+(0.6{*}2)+(0.4{*}7)+(0.2{*}3) = 9.4$. Based on Table 2 and Equation (6), the V_i value is categorized as not prone to pertussis disease area, based on a good category of immunization status. Tables 3 and 4 show the distribution of the classification of pertussis vulnerable areas by the WPM method and the WSM method, respectively. Figure 4 and Figure 5 show the classification results percentage of the WPM and WSM methods, respectively.

The WSM classification results in Table 4 and Figure 5 had the Good immunization status category percentage better than the WPM in Table 3 and Figure 4 with a difference of 76%, 35%, 72%, 30%, 34%, 33%, every year. For the Average category, in 2011 and 2013, the WPM is better than the WSM method with a difference of 11% and 10%. Whereas in 2012, 2014-2016, the WSM method is better than the WPM with a gap of 23%, 44%, 40%, 47%, respectively. The category of regions with a Fair status for the WPM method is higher than the WSM method with a difference of 45%, 41%, 39%, 54%, 52%, 62%, respectively. Areas with Poor classification results based on immunization status in 2011-2016 for the WPM method are higher than the WSM method with a difference of 20%, 18%, 23%, 19%, 22%, 18%, respectively.

Table 3. Classification results using the WPM method

WPM	**Sub-District**					
	2011	**2012**	**2013**	**2014**	**2015**	**2016**
Good	0	1	0	14	0	0
Average	196	151	209	98	108	85
Fair	324	381	285	414	404	448
Poor	137	124	163	131	145	124
Sum	657	657	657	657	657	657

Table 4. Classification results using the WSM method

WSM	**Sub-District**					
	2011	**2012**	**2013**	**2014**	**2015**	**2016**
Good	498	234	473	208	221	219
Average	125	303	145	390	374	391
Fair	27	112	30	56	60	42
Poor	7	8	9	3	2	5
Sum	657	657	657	657	657	657

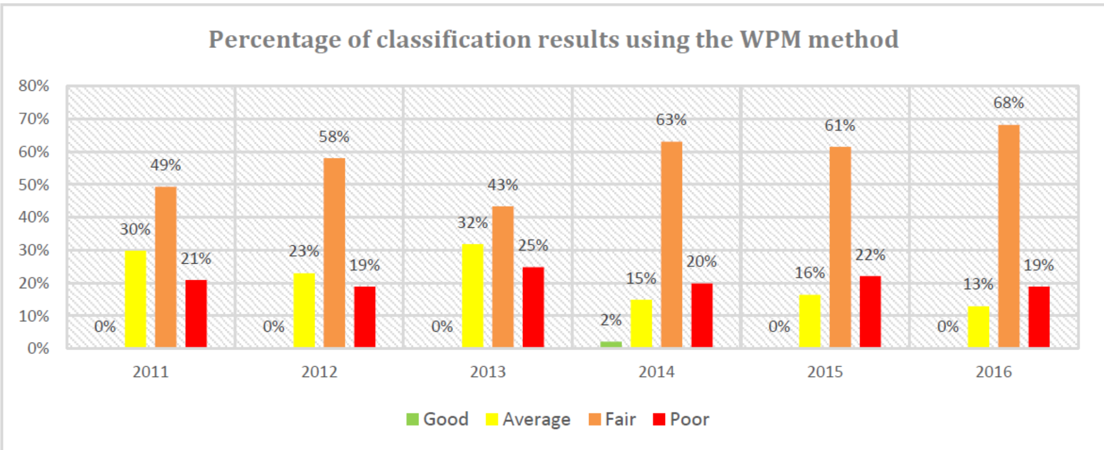

Figure 4. Percentage of classification results using the WPM method

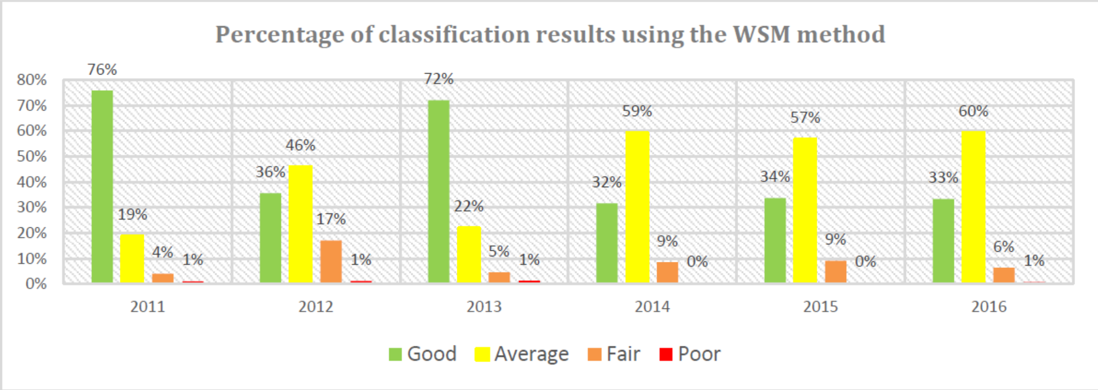

Figure 5. Percentage of classification results using the WSM method

Table 5. The coefficient values of WPM and WSM methods strength of agreement

Years	κ	Strength of agreement
2011	0.11	Poor
2012	0.37	Fair
2013	0.16	Poor
2014	0.60	Moderate
2015	0.16	Poor
2016	0.31	Fair

Method Consistency Test (MCT) is performed on the WPM and WSM methods by calculating Cohen's kappa coefficient (κ) from Equation (4) to measure the strength of agreement. Table 5 shows the MCT test results, which is used to determine the closeness of the two methods used and between parameter attributes by assessing the suitability of the results of spatial data modeling. The 2011 data has a value of $\kappa = 0.11$ and categorized as Poor strength of agreement. The 2012 data has a value of $\kappa = 0.37$ classified as the Fair category. The 2013 data has an amount of $\kappa = 0.16$ categorized as Poor. The 2014 data has an amount of $\kappa = 0.6$ with the Moderate category, 2015 data with κ value is 0.16 with Poor category, and 2016 data with κ value is 0.31 with Fair strength of agreement category.

5. **Conclusion.** This paper discusses qualitative and quantitative techniques for classifying pertussis vulnerable areas. The MADM method is applied using multi-criteria parameters of location analytics [54]. The MADM method needs the pre-processing of several criteria, such as priority value, weight, and importance value. This research used two methods, namely the WSM and WPM, as a comparison tool to make better results of the spatial analysis [54]. The preference value results from WSM and WPM methods, as quantitative data will be imposed on the Guttman scale classification. These findings can provide new insights into combining the two MADM techniques at the same time so that the researchers could make further exploration of the new data that may affect location analytics. The results of the dataset test using the WPM method with the parameter criteria: level of importance, weight, and priority for Good category values indicate that the results of the regional distribution are contrary to the actual conditions. In contrast, the WSM method shows results that are more in line with real situations. Further, these methods could give better result decision for disease management and control planning.

This decision-making system is the starting mitigation planning step to provide information about Pertussis' vulnerable area. The regions which are spatially classified to be Fair and Poor must be regularly observed and monitored by the East Java Provincial Health Office, to take the further step to prevent or mitigate the disease spread. The action could be taken like providing counselling and direction to the community and giving immunization vaccines according to a schedule determined by the East Java Provincial Health Office. For further research, this study could extend to developed MADM and MCDM techniques with Fuzzy and Naive Bayesian methods, so that the function could produce a classification of each method with maximum accuracy [45]. For the development of the system, as a part of the Web GIS-based Public Health Surveillance System, this system could explore the open and interoperable data in Web 2.0. The combination of the GIS with the Web 2.0 technology (like social media, geo mashup, semantic web) could improve the spatiotemporal aspect for supporting spatial analysis [55].

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