Assignment#10

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Submission date: 23-Jun-2020 08:02AM (UTC+0700)

Submission ID: 1348312938

File name: Pertussis_Classification_Paper_for_IJICIC_2.0.docx (2.54M)

Word count: 5890

Character count: 31661

Classification of Pertussis Vulnerable Area
With Location Analytics Using Multiple Attribute Decision Making

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 for the determination of the pertussis-prone regions using the Geographical Information System (GIS). The authors have conducted the study using Weighted Product Model (WPM) and Weighted Sum Model (WSM) methods based-on the spatial dataset containing the infant Diphtheria, Pertussis, and 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 a category of an area in Good, Average, Fair, and Poor. 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%), which means it categorized as Poor. In 2012, the result was higher than the previous year, which was 0.37 (37%) with the Fair category. The 2013 and 2015 results, having the same value of 0.16 (16%) with the class of Average. The results of 2014 showed of coefficient values 0.60 (60%) with the Moderate category, and there would be a change in 2015-2016, the coefficient value was 0.31 (31%) with the Fair category. The WSM method is recommended to be used because it has a better strength of agreement coefficient value than WPM.

Keywords: GIS, location analytics, MADM, WSM, WPM, Pertussis

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 vaccination at six weeks of age using whole-cell Pertussis (wP) or Pertussis (aP) acellular vaccine can effectively preventing Pertussis [7][8][9][10]. Three kinds of treatment doses 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][12][7][5]. 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 [13][12][14].

Many researchers attracted to study spatial analysis for disease classification. Ntirampeba et al. proposed spatial data analysis used 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 studies, there were studies to determine vaccination intervention to pertussis disease. The studies 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][19][20]. Variables presented as *p*. *0.2* in the bivariate analysis selected. Then this variable used for inclusion in the multivariable model. Those who had statistical significance $p < 0.05$ were retained in the final multivariate model [18][20]. But this step could help the statistical analysis for reducing this infectious disease as well.

The Web GIS technology for public health surveillance has been successfully explored and utilized, as known as Web GIS-based Public Health Surveillance System (WGPHSS). The system effectively monitors, maps, and observes disease spread, including Pertussis. But, for some reason, many WGPHSS systems still have yet explored Web 2.0 ability [21]. This review paper becomes our system development reference.

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) used as an alternative tool in multi-parameter coverage for imposing on the dataset from the administrative profile of East Java Province in 2011-2016 [22][23][24][25][26][27]. Multi-class classification obtained from the calculation of two methods, Weighted Product Model (WPM) and Weighted Sum Model (WSM), with a Good, Average, Fair, and Poor indicator coverage.

The WPM method finds V_i values for Good categories amounts larger or equal to 0.002995, average categories for amounts larger or equal to 0.001996, and smaller than 0.002995, Fair categories for amounts larger or equal to 0.000998 and smaller than 0.001996, and 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 or equal to 9.65, average categories for A_i values bigger 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 6.55. The location analytics findings have 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 in this study 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 [28].

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 is consists of data and its attribute, which become the classification parameters in addition to the predetermined settings of pertussis-prone areas, as in

Table *1*, including the infant immunization status (DPT immunization), PD3I rate, nutrition status, population density, and epidemic rate.

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/or 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.

Table 1. Spatial Datasets Multi-Criteria Parameter for Pertussis Diseases

Attribute Datasets	Priority Value	Weight	Indicator (annually)	Range	Level of importance
the infant immunization status (DPT immunization)	1	1	Target reached	DPT ≥ 84.5%	2
			Not reaching the target	DPT < 84.5%	1
PD3I Rate	2	0.8	Yes, if a region occurs PD3I ≥12 in a year, then the area is determined as a PD3I area	PD3I ≥ 12 cases per year	2
			Not, if the cases occur under 12 PD3I cases per year, then the area is not included in the PD3I area	PD3I < 12 cases per year	1
Epidemic Rate	3	0.6	very good	ER = 0 cases	3
			good	Epidemic <12 cases per year	2
			less	Epidemic ≥12 cases per year	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	7500 – 8499 $people/km^2$	2

Attribute Datasets	Priority Value	Weight	Indicator (annually)	Range	Level of importance
			$people/km^2$, then the area is classified as a score of 7		
			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 ≥ 2	4
			Good nutrition	2 > sd ≥ -2	3
			Less of nutrition	-2 > sd ≥ -3	2
			Poor nutrition	-3 > sd	1

3. Methods

Decision-making systems involving spatial GIS data could be equipped with the MADM method, which is used to deal with discrete problems [29]. The technique could combine spatial data and its attribute to conduct spatial data analysis [30][31]. The primary data of the spatial data analysis is a dataset described in table 1 [22][23][24][25][26][27]. 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, the authors specify the spatial data layer and its attribute in shape (*.*shp*) file dataset. The dataset contains an East Java Province, Indonesia map, that has 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 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 Fair is categorized as Poor, which shows in red regions.

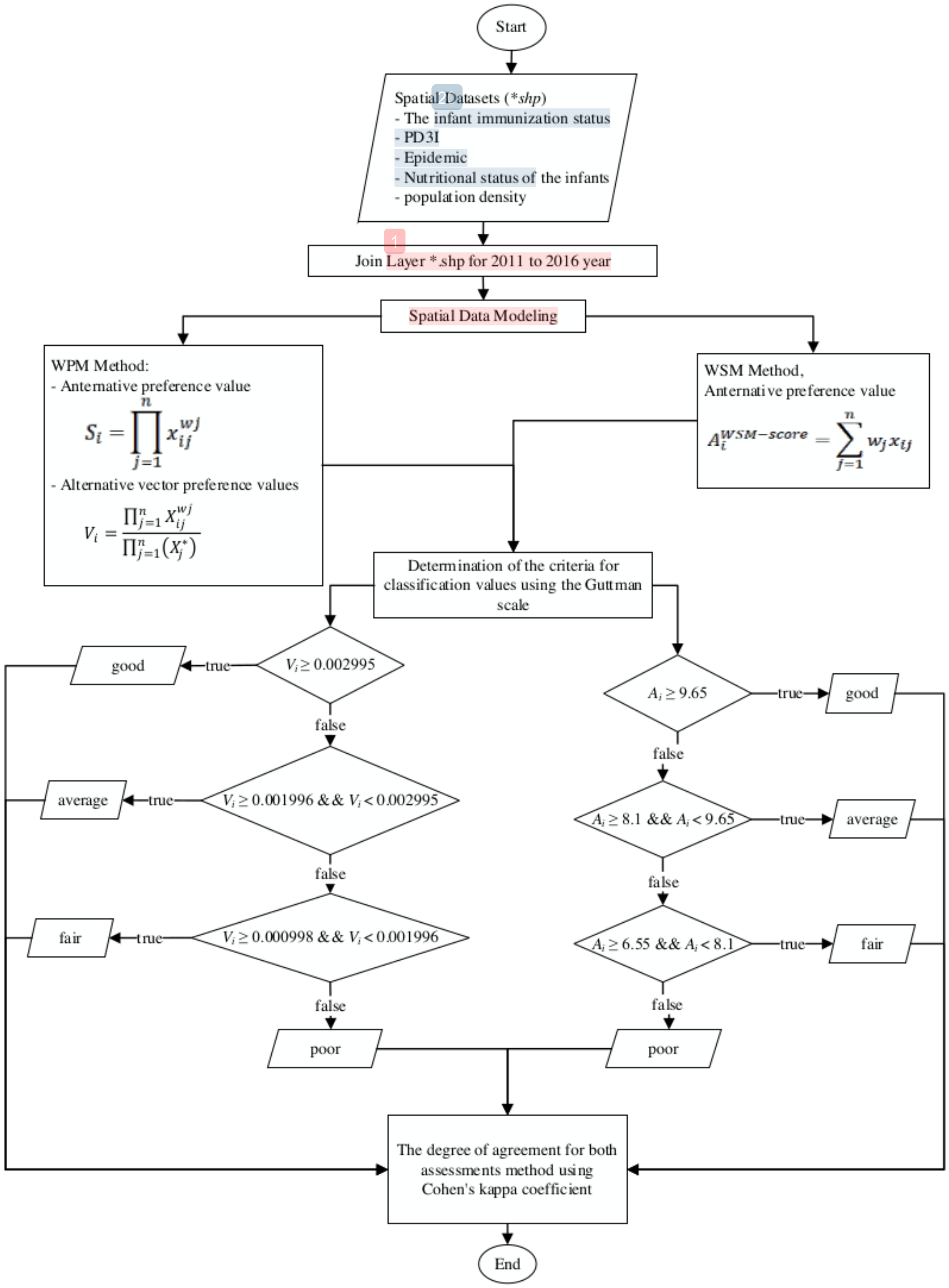

Figure 1. Flowchart of Location Analytics with WPM and WSM Method

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) [29][32][33]. MADM method generally implemented for discrete domain decision making, where limited alternative decision support systems were determined [34][35], while MODM applied for continuous domain decision making with many alternatives [35][36]. MADM defines the parameters/criteria used to decide the best alternative *based on several appropriate measures [32]. 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 [35]. 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 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 [37], ff there are *m* alternative and *n* criteria, then the best option can be formulated (1) [38].

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

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

Value of n is the number of criteria, $w_j x_{ij}$ is the alternative value i on criterion j, and w_j is the weight value of the criterion j [38]. The Max function is used to rank alternative decisions that the most significant score alternatives placed at the top [39]. Difficulties in this method arise when the available criteria have more than one dimension or multi-dimension, to solve this problem, the multi-dimensional criteria must be merged into one dimension.

WPM method use 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 [38]. WPM method creates a weighted normalized decision matrix to find out the alternative preferences of A_i in S_i vectors, according to Eq. (2) [38][37].

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

where:
n = number of criteria
w_j = the weight of each criterion
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. Eq. (3) shows the formula of relative preference of each alternative.

$$V_i = \frac{\prod_{j=1}^{n} x_{ij}^{wj}}{\prod_{j=1}^{n} (x_j^*)} \tag{3}$$

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 $Tbpre = Bpre_a + Bpre_b + \dots n$. 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 $S = B_a^W_a$. It is calculating the value of V_s by multiplying all values in variable S, with $V_s = S_a x S_b\ x \dots n$. Calculating the total vector on variable V or Tv_s by adding up all the values of V_s, with $Tv_s = V_1 + V_2 + V_3 + \dots + V_n$, then the variable value of $V = V_{sa} / Tv_{sa}$.

3.2 The Guttman Scale

The Guttman scale is an analysis assessment standard to make a qualitative data conclusion [40]. In this paper, The Guttman scale used as a way to the measurement of the classification values. It estimates the result score of the classification with an intervention value that is still ambiguous due to uncertainty [41][42][43]. 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 [42] in Eq. (4).

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

Where, the variable *I* 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 used for qualitative data based on Eq. (5) [44].

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

Where the *K* variable is the measurement coefficient between the two methods WSM and WPM. The $Pr(a)$ variable is a percentage of the number of measurements that are 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 [44] : if the value of the variable $\kappa < 0.21$ the strength of agreement is said to be "low", if the κ value between 0.21 and 0.40 is called "not bad", if the κ value between 0.41 and 0.60 is called "moderate", the κ value of 0.61 to 0.80 is called "strong" strength of agreement, and if the κ between 0.81 and 1.00 is said to be "very strong" strength of agreement.

4. Results and Discussion

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 [22][23][24][25][26][27]. Figure 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 **Error! Reference source not found.** explains the results using the WSM method.

The results of the classification by the WPM and WSM methods are calculated using the Guttman Scale in eq 4. The value of *R* taken from the range of values between the maximum and the minimum amount of *V*. The *K* variable is the number of alternative classifications, namely Good, Average, Fair, and Poor with the WPM and WSM methods that refer to eq (6) and (7).

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

$$\begin{cases} good, if\ V_i \geq 0.002995 \\ average, if\ V_i \geq 0.001996\ and\ V_i < 0.002995 \\ fair, if\ V_i \geq 0.000998\ and\ V_i < 0.001996 \\ poor, if\ V_i < 0.000998 \end{cases} \tag{7}$$

Table 2. The Results of Guttman Scale Assessment

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

The sample test for MADM classification with WSM and WPM was carried out in the Rejoso sub-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 total of 686 babies indicate that the target indicator is 95.335% (Good Immunization). The third DPT immunization is 596 babies out of a total 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.

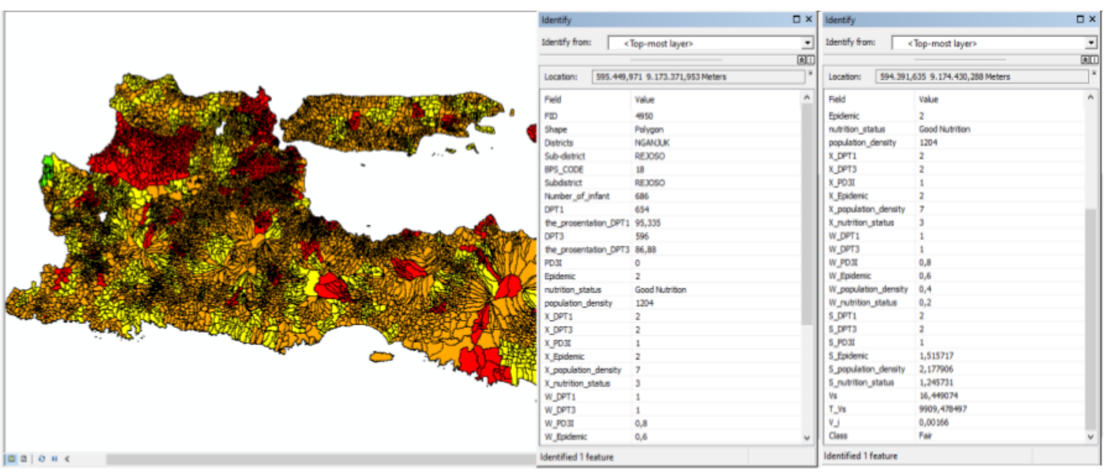

Figure 3. The WPM classification results in East Java map

Figure 3 depicts the alternative preference value (S_i) result from the WPM method based on eq. (2) by multiplying all result from the value of x power of w, resulting S_{DPT1}, S_{DPT3}, S_{PD3I}, $S_{epidemic}$, $S_{population\text{-}density}$, and $S_{nutrition\text{-}status}$ is 2; 2; 1; 1.515717; 2.177906; 1.245731, respectively. Alternative vector preference values (V_i) is calculated based on eq. (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 Tv_s by adding up all the values of V_s, yields Tv_s is 9909.478497. Next, the value of V_i is 0.00166 according to the area sample test in Figure 3, which is the value of Vs_i divided by the value of Tv_s. The classification results state that the area belongs to the **fair category** of pertussis disease (Table 2, eq. 5).

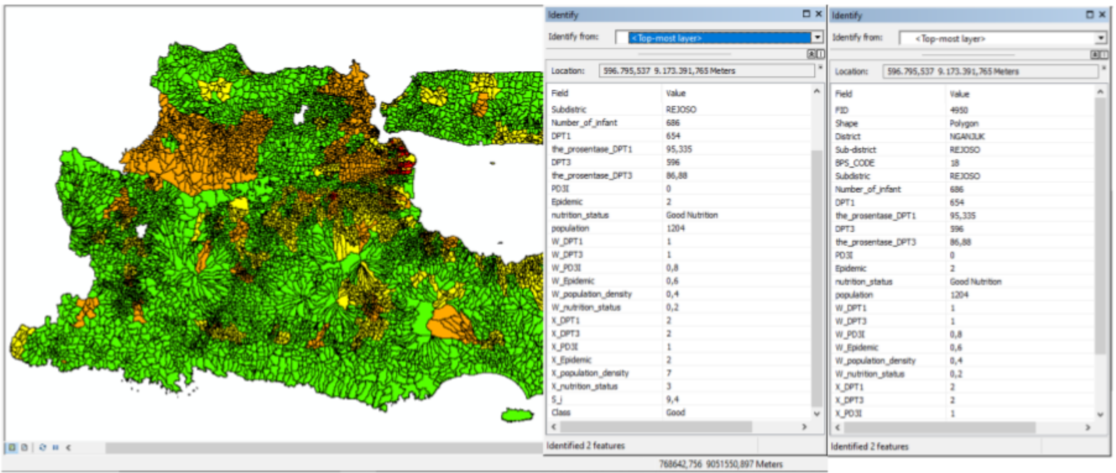

Figure 3. The WSM classification results in East Java map

Figure 3 shows the alternative values (V_i) result of WSM method based on eq. (1). The V_i values computed by $V_i = (1*2) + (1*2) + (0.8*1) + (0.6*2) + (0.4*7) + (0.2*3) = 9.4$. Based on Table 2 and eq. 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 results of the classification of pertussis vulnerable areas by the WPM method and the WSM method, respectively. Figures 4 and 5 shows the classification results percentage of the WPM and WSM methods, respectively.

In 2011-2016, the WSM method had classification results based on the Good immunization status category percentage better than the WPM 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

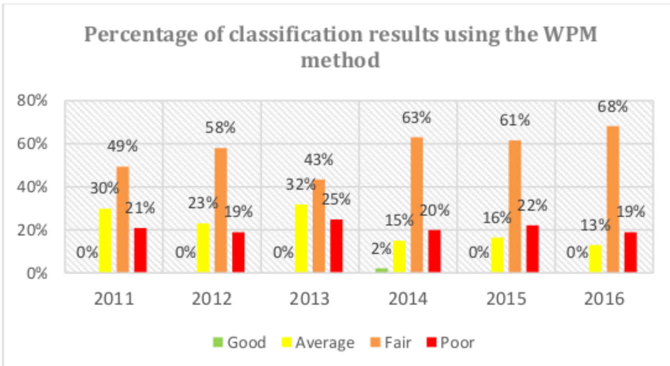

Figure 4. Percentage of classification results using the WPM method

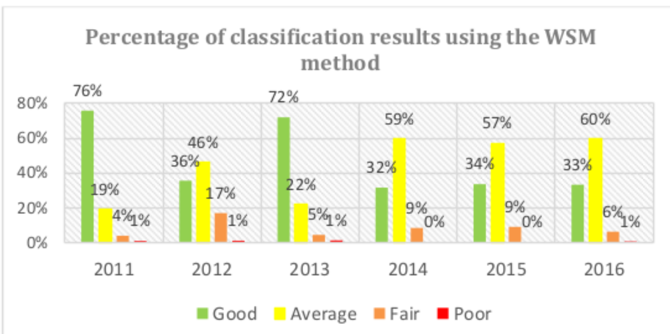

Figure 5. Percentage of classification results using the WSM method

Method Consistency Test (MCT) is performed on the WPM and WSM methods by calculating Cohen's kappa coefficient (κ) from eq. (7) to measure the strength of agreement. The 2011 data has a value of κ is 0.11 and categorized as Poor strength of agreement. The 2012 data has a value of κ = 0.37 classified as Fair category. The 2013 data has an amount of κ = 0.16 categorized as Poor. The 2014 data has an amount of κ = 0.6 with 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.

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

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

Years	κ	Strength of agreement
2016	0.31	Fair

5. Conclusion

This paper discusses qualitative or quantitative techniques for classifying pertussis vulnerable areas. The MADM method applied using multi-criteria parameters of location analytics [45]. The MADM method needs the preprocessing 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 [45]. 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 in 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, this methods could give the 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 counseling 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 technique with maximum accuracy [38]. 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 [46].

Acknowledgments

This paper is one of the results of the 2018 National Strategic and the 2019 National Competitive Research activities. This research funded by the Directorate General of Research Strengthening and Development of the Ministry of Research, Technology, and Higher Education with Contract Number: 120 / SP2H / LT / DRPM / 2018 dated 30 January 2018, and Directorate of Research and Community Service of Region VII Higher Education Service Institutions with Contract Number 113 / SP2H / LT / DRPM / 2019 dated 11 March 2019. The authors give the highest appreciation to the East Java Provincial Health Office of Indonesia for accessing data on "East Java Province Health Profile Book 2011-2016," and providing parameter criteria used for method testing.

References

[1] S. Mattoo and J. D. Cherry, "Molecular Pathogenesis, Epidemiology, and Clinical Manifestations of Respiratory Infections Due to," *Clin. Microbiol. Rev.*, vol. 18, no. 2, pp. 326–382, 2005, doi: 10.1128/CMR.18.2.326.

[2] T. Tan *et al.*, "Pertussis Across the Globe: Recent Epidemiologic Trends From 2000 to 2013," *Pediatr. Infect. Dis. J.*, vol. 34, no. 9, pp. e222–e232, 2015, doi: 10.1097/INF.0000000000000795.

[3] Q. Chen and S. Stibitz, "The BvgASR virulence regulon of Bordetella pertussis," *Curr. Opin. Microbiol.*, vol. 47, pp. 74–81, 2019, doi: 10.1016/j.mib.2019.01.002.

[4] L. H. Falleiros Arlant, A. De Colsa, D. Flores, J. Brea, M. L. Avila Aguero, and D. F. Hozbor, "Pertussis in Latin America: Epidemiology and control strategies," *Expert Rev. Anti. Infect. Ther.*, vol. 12, no. 10, pp. 1265–1275, 2014, doi: 10.1586/14787210.2014.948846.

[5] Y. Zhang *et al*., “Increased susceptibility to pertussis in adults at childbearing age as determined by comparative seroprevalence study, China 2010–2016,” *J. Infect*., vol. 79, no. 1, pp. 1–6, 2019, doi: 10.1016/j.jinf.2019.04.011.

[6] V. Zavatti, H. Budman, R. L. Legge, and M. Tamer, “Investigation of the effects of oxidative stress-inducing factors on culturing and productivity of Bordetella pertussis,” *Biotechnol. Prog*., vol. 36, no. 1, pp. 1–11, 2020, doi: 10.1002/btpr.2899.

[7] T. Nakayama, E. Suzuki, and A. Noda, “Vaccine acquired pertussis immunity was weakened at 4 years of age and asymptomatic pertussis infection was suspected based on,” *J. Infect. Chemother*., no. xxxx, pp. 2012–2014, 2019, doi: 10.1016/j.jiac.2019.03.027.

[8] M. States, W. H. O. Strategic, A. Group, and T. Grade, “Pertussis vaccines: WHO,” *Wkly. Epidemiol. Rec. Relev. épidémiologique Hebd*., vol. 90, no. 35, pp. 433–458, 2015.

[9] P. Kapil and T. J. Merkel, “ScienceDirect Pertussis vaccines and protective immunity,” *Curr. Opin. Immunol*., vol. 59, pp. 72–78, 2019, doi: 10.1016/j.coi.2019.03.006.

[10] J. M. Oviedo *et al*., “Shotgun proteomic analysis of Bordetella parapertussis provides insights into the physiological response to iron starvation and potential new virulence determinants absent in Bordetella pertussis,” *J. Proteomics*, vol. 206, no. June, p. 103448, 2019, doi: 10.1016/j.jprot.2019.103448.

[11] M. Dou, N. Macias, F. Shen, J. Dien Bard, D. C. Domínguez, and X. J. Li, “Rapid and Accurate Diagnosis of the Respiratory Disease Pertussis on a Point-of-Care Biochip,” *EClinicalMedicine*, vol. 8, pp. 72–77, 2019, doi: 10.1016/j.eclinm.2019.02.008.

[12] T. Tantawichien, C. Thisyakorn, and P. Buchy, “International Journal of Infectious Diseases Pertussis in the Association of Southeast Asian Nations : epidemiology and challenges,” *Int. J. Infect. Dis*., vol. 87, pp. 75–83, 2019, doi: 10.1016/j.ijid.2019.07.016.

[13] E. G. Fernandes *et al*., “Challenges of interpreting epidemiologic surveillance pertussis data with changing diagnostic and immunization practices : the case of the state of São Paulo , Brazil,” pp. 1–7, 2018.

[14] L. R. A. Vaz-de-Lima *et al*., “Association between the timing of maternal vaccination and newborns’ anti-pertussis toxin antibody levels,” *Vaccine*, vol. 37, no. 36, pp. 5474–5480, 2019, doi: 10.1016/j.vaccine.2019.04.079.

[15] D. Ntirampeba, I. Neema, and L. Kazembe, “Modelling spatio-temporal patterns of disease for spatially misaligned data : An application on measles incidence data in Namibia from,” no. i, pp. 1–18, 2018.

[16] A. B. Lawson, “Hotspot detection and clustering: Ways and means,” *Environ. Ecol. Stat*., vol. 17, no. 2, pp. 231–245, 2010, doi: 10.1007/s10651-010-0142-z.

[17] C. E. Utazi *et al*., “High resolution age-structured mapping of childhood vaccination coverage in low and middle income countries,” *Vaccine*, vol. 36, no. 12, pp. 1583–1591, 2018, doi: 10.1016/j.vaccine.2018.02.020.

[18] E. Gatti *et al*., “The effectiveness of maternal pertussis vaccination in protecting newborn infants in Brazil : A case-control study,” *Vaccine*, no. xxxx, pp. 3–6, 2019, doi: 10.1016/j.vaccine.2019.03.049.

[19] X. Wang *et al*., “Seroprevalence of Measles Antibodies and Predictors for Seropositivity among Chinese Children,” doi: 10.3390/ijerph14060605.

[20] E. Leuridan, “Pertussis vaccination in pregnancy : State of the art,” *Vaccine*, pp. 10–13, 2017, doi: 10.1016/j.vaccine.2017.03.061.

[21] H. Luan and J. Law, “Web GIS-Based Public Health Surveillance Systems: A Systematic Review,” *ISPRS Int. J. Geo-Information*, vol. 3, no. 2, pp. 481–506, 2014, doi: 10.3390/ijgi3020481.

[22] Dinas Kesehatan Provinsi Jawa Timur, *2011 East Java Province Health Profile*. Dinas Kesehatan Provinsi Jawa Timur, 2012.

[23] Dinas Kesehatan Provinsi Jawa Timur, *2012 East Java Province Health Profile*. Dinas Kesehatan Provinsi Jawa Timur, 2013.

[24] Dinas Kesehatan Provinsi Jawa Timur, *2013 East Java Province Health Profile*. Dinas Kesehatan Provinsi Jawa Timur, 2014.

[25] D. K. P. J. Timur, *2014 East Java Province Health Profile*. Dinas Kesehatan Provinsi Jawa Timur, 2015.

[26] Dinas and K. P. Jawa, *2015 East Java Province Health Profile*. Dinas Kesehatan Provinsi Jawa Timur, 2016.

[27] Dinas Kesehatan Provinsi Jawa Timur, *2016 East Java Province Health Profile*. Dinas Kesehatan Provinsi Jawa Timur, 2017.

[28] A. V. Vitianingsih, D. Cahyono, and A. Choiron, "Analysis and design of web-geographic information system for tropical diseases-prone areas: A case study of East Java Province, Indonesia," in *2017 4th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)*, 2017, pp. 255–260, doi: 10.1109/ICITACEE.2017.8257713.

[29] G. Haseli, R. Sheikh, and S. S. Sana, "Base-criterion on multi-criteria decision-making method and its applications," *Int. J. Manag. Sci. Eng. Manag.*, vol. 00, no. 00, pp. 1–10, 2019, doi: 10.1080/17509653.2019.1633964.

[30] A. V. Vitianingsih, A. Choiron, D. Cahyono, A. Umam, and S. Suyanto, "Spatial data modeling on GIS for classification of measles-prone region using multiple attribute decision making," *Int. J. Intell. Eng. Syst.*, vol. 12, no. 3, pp. 97–107, 2019, doi: 10.22266/IJIES2019.0630.11.

[31] A. M. Alzouby, A. A. Nusair, and L. M. Taha, "GIS based Multi Criteria Decision Analysis for analyzing accessibility of the disabled in the Greater Irbid Municipality Area, Irbid, Jordan," *Alexandria Eng. J.*, vol. 58, no. 2, pp. 689–698, 2019, doi: 10.1016/j.aej.2019.05.015.

[32] A. Boostani, F. Jolai, and A. Bozorgi-amiri, "Optimal Location Selection of Temporary Accommodation Sites in Iran via a Hybrid Fuzzy Multiple-Criteria Decision Making Approach," vol. 144, no. 4, pp. 1–14, 2018, doi: 10.1061/(ASCE)UP.1943-5444.0000479.

[33] L. M. Goulart Coelho, L. C. Lange, and H. M. G. Coelho, "Multi-criteria decision making to support waste management: A critical review of current practices and methods," *Waste Manag. Res.*, vol. 35, no. 1, pp. 1–26, 2016, doi: 10.1177/0734242X16664024.

[34] C. Science, E. M. Mohamed, B. Bouikhalene, F. Ouatik, S. Safi, and A. Info, "AHP and TOPSIS methods applied in the field of scientific," vol. 14, no. 3, pp. 1382–1390, 2019, doi: 10.11591/ijeecs.v14.i3.pp1382-1390.

[35] E. Triantaphyllou, "Multi-criteria Decision Making Methods: A Comparative Study (Applied Optimization)," *Multi-criteria Decis. Mak. methods A Comp. study*, no. August, pp. 3–7, 2000, doi: 10.1007/978-1-4757-3157-6.

[36] M. Bystrzanowska and M. Tobiszewski, "How can analysts use multicriteria decision analysis?," *TrAC - Trends Anal. Chem.*, vol. 105, pp. 98–105, 2018, doi: 10.1016/j.trac.2018.05.003.

[37] Z. Chourabi, F. Khedher, A. Babay, and M. Cheikhrouhou, "Multi-criteria decision making in workforce choice using AHP, WSM and WPM," *J. Text. Inst.*, vol. 110, no. 7, pp. 1092–1101, 2019, doi: 10.1080/00405000.2018.1541434.

[38] E. Triantaphyllou, *Multi-Criteria Decision Making Methods: A Comparative Study*. Springer, Boston, MA, 2000.

[39] K. Mela, T. Tiainen, and M. Heinisuo, "Comparative study of multiple criteria decision making methods for building design," *Adv. Eng. Informatics*, vol. 26, no. 4, pp. 716–726, 2012, doi: 10.1016/j.aei.2012.03.001.

[40] L. Guttman, "A Basis for Scaling Qualitative Data," *Am. Sociol. Rev.*, vol. 9, no. 2, p. 139, 1944, doi: 10.2307/2086306.

[41] L. H. De Souza, "The development of a scale of the Guttman type for the assessment of mobility disability in multiple sclerosis," *Clin. Rehabil.*, vol. 13, no. 6, pp. 476–481, 1999, doi: 10.1191/026921599667699509.

[42] W. P. Krijnen, T. K. Dijkstra, and R. D. Gill, "Conditions for factor (in)determinacy in factor analysis," *Psychometrika*, vol. 63, no. 4, pp. 359–367, 1998, doi: 10.1007/BF02294860.

[43] R. E. Tractenberg, F. Yumoto, P. S. Aisen, J. A. Kaye, and R. J. Mislevy, "Using the Guttman Scale to Define and Estimate Measurement Error in Items over Time : The Case of Cognitive Decline and the Meaning of ' Points Lost ' Using the Guttman Scale to Define and Estimate Measurement Error in Items over Time : The Case of Cognit," no. February, 2012, doi: 10.1371/journal.pone.0030019.

[44] C. M. W. Razia Azen, *Categorical Data Analysis for the Behavioral and Social Sciences*. Taylor & Francis Group, 2011.

[45] N. Manic, I. Hot, and V. Šerifi, “Forming Set and Verification of Relevance Criteria on Evaluation of Alternative Corridors of the Infrastructure Facilities,” in *Procedia Technology*, 2016, vol. 22, pp. 1051–1058, doi: 10.1016/j.protcy.2016.01.149.

[46] I. Wisnubhadra, S. S. K. Baharin, and N. S. Herman, “Modeling and querying spatiotemporal multidimensional data on semantic web: A survey,” *J. Theor. Appl. Inf. Technol.*, vol. 97, no. 23, pp. 3608–3633, 2019.

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