Judul Artikel: **Classification of pertussis vulnerable area with location analytics using multiple attribute decision making**

1) Paper Submission by OJS http://www.ijicic.net/ijicic-v2/ (20 Juni 2020)
    - Resubmission (IJICIC-2006-032)
2) Review Result: IJICIC-2006-032 (21 Juli 2020) and Revised Paper (3 September 2020)
3) Acceptance Letter: IJICIC-2006-032 (15 September 2020)
    - Copyright Form (IJICIC)
4) IJICIC-2006-032 Proof (26 Oktober 2020)
    - Final paper revised

1) Paper Submission by OJS http://www.ijicic.net/ijicic-v2/ (20 Juni 2020)
   - Resubmission (IJICIC-2006-032)

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New Submiss | Hi, Irya Wisnubhadra (author)

Manuscript ID	atus	Detail	Actions
IJICIC-2006-03		Detail	
IJICIC-2102-00		Detail	
Under Confirm		Detail	

Type	Short Paper
Title	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

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ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>

Fw: Resubmission (IJICIC-2006-032)

1 pesan

Irya Wisnubhadra, S.T., M.T. <irya.wisnubhadra@uajy.ac.id> 5 Juli 2023 pukul 15.20
Kepada: "ANIK VEGA V, S.Kom.,MT unitomo" <vega@unitomo.ac.id>

From: Irya Wisnubhadra, S.T.,M.T. <irya.wisnubhadra@uajy.ac.id>
Sent: Friday, September 4, 2020 11:49 AM
To: office@ijicic.net <office@ijicic.net>
Subject: Re: Resubmission (IJICIC-2006-032)

Dear IJICIC Editor

Thank you for the update.

regards
Irya Wisnubhadra

From: office@ijicic.net <office@ijicic.net>
Sent: Friday, September 4, 2020 11:23 AM
To: Irya Wisnubhadra, S.T.,M.T. <irya.wisnubhadra@uajy.ac.id>
Subject: Re: Resubmission (IJICIC-2006-032)

Dear Mr. Irya Wisnubhadra,

Your resubmission to IJICIC has been received. We hope to process it within six weeks' time.

Thank you.

Best Regards,

Dr. Yan SHI

Executive Editor, IJICIC

Professor, Center for Liberal Arts, Tokai University

9-1-1, Toroku, Kumamoto 862-8652, Japan

Tel.: 81-96-386-2666, Fax: 81-96-386-2666

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2) Review Result: IJICIC-2006-032 (21 Juli 2020) and Revised Paper (3 September 2020)

ANIK VEGA V, S.Kom.,MT unitomo <vega@unitomo.ac.id>

Fwd: Re:Re: Review Result: IJICIC-2006-032 (1)

1 pesan

Irya Wisnubhadra, S.T., M.T. <irya.wisnubhadra@uajy.ac.id> 5 Juli 2023 pukul 06.33
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From: IJICIC-M <lili_ma@ijicic.net>
Sent: Friday, September 4, 2020 9:24:13 AM
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Cc: office@ijicic.net <office@ijicic.net>
Subject: Re:Re: Review Result: IJICIC-2006-032 (1)

Dear Dr. Irya Wisnubhadra,

Thanks for your contributions to IJICIC.

Please upload "Response Letter" and "Revised Paper" on IJICIC submission System.

The following guide may be helpful.

Please log in IJICIC submission system with your User ID and Password.

Then click "Upload" to upload the required document.

Please feel free to contact us if you have any further question concerning this.

Best Regards,

Lili Ma

On Behalf of Dr. Yan SHI

Executive Editor, IJICIC

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在2020年09月03 17时52分，"Irya Wisnubhadra, S.T.,M.T."<irya.wisnubhadra@uajy.ac.id>写道：

Dear IJICIC Editor

In this email, I attach revised paper and response letter (IJICIC-2006-032)

I am looking forward to your advice

regards
Irya Wisnubhadra

From: office@ijicic.net <office@ijicic.net>
Sent: Tuesday, July 21, 2020 8:11 AM
To: Irya Wisnubhadra, S.T.,M.T. <irya.wisnubhadra@uajy.ac.id>
Subject: Review Result: IJICIC-2006-032 (1)

Dear Mr. Irya Wisnubhadra,

Reference No.: IJICIC-2006-032

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

Author(s): Anik Vega Vitianingsih, Irya Wisnubhadra, Safiza Suhana Kamal Baharin, Achmad Choiron, Dwi Cahyono

The paper above you submitted for possible publication in International Journal of Innovative Computing, Information and Control (IJICIC), has been reviewed by an Associate Editor and/or reviewers. Based on the Associate Editor’s recommendation with which I concur (see the bottom of this email), I am sorry to inform you that your paper is not publishable in its current form. However, it may be publishable after extensive revision and rewriting. If you decide to do this, I would suggest that you carefully consider the comments of the Associate Editor/reviewers, and submit the revised version and response letter to IJICIC Office within three months from the date of this letter.

Thank you for your submission to IJICIC, and we are looking forward to receiving the revision, soon.

Best Regards,

Dr. Yan SHI

Executive Editor, IJICIC

Professor, Center for Liberal Arts, Tokai University

9-1-1, Toroku, Kumamoto 862-8652, Japan

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Comments:
(1) It is of good contribution to present a classification of Pertussis vulnerable area based on location analytics.
(2) What is the meaning of the statement “Variables presented as p. 0.2 in the bivariate analysis selected” on Page 2?
(3) More justifications on the application of MADM into the classification of Pertussis vulnerable area are suggested to be added.
(4) What is the support for the setting “PD3I rate (0.8), epidemic rate (0.6), population density (0.4), and nutrition status (0.2)” on Page 3? Please make clear the point.
(5) More explanations on Table 1 are suggested to be added, to make clear the role of the contents in the table.
(6) The settings “The priority parameter for infant immunization status is 1 with a weight value of w = 1” and “the value of priority parameter PD3I is 2 with a weight value of w = 0.8, and the value level of importance is 1” should be well explained.
(7) Please add more analysis and discussions on the results. It is not proper to just list the results.
(8) Some comparison with existing studies is suggested to be conducted, in order to highlight the advantage of the work.
(9) More up-to-date studies are suggested to be cited, such as “Hendry and Rung-Ching Chen, Predicting Business Category with Multi-Label Classification from User-Item Review and Business Data Based on K-means, ICIC Express Letters, vol.13, no.3, pp.255-262, 2019”.
(10) Some syntax errors or improper expressions exist, such as the “…can effectively preventing Pertussis” on Page 1, the “Multiple Attribute Decision Making (MADM) used as an alternative tool…” and the “The dataset is consists of…” on Page 2.

Dear Editor of the International Journal of Innovative Computing, Information and Control (IJICIC),

We would like to thank you for the opportunity to revise the manuscript:

- Manuscript number: **IJICIC-2006-032**
- Title: Classification of Pertussis Vulnerable Area with Location Analytics Using Multiple Attribute Decision Making

In detail, we include point-by-point changes that are done to revise this paper.

Thank for your attention.

Best regards,
Irya Wisnubhadra

(1) It is of good contribution to present a classification of Pertussis vulnerable area based on location analytics.

Answer: Thank you for your support.

(2) What is the meaning of the statement "Variables presented as p. 0.2 in the bivariate analysis selected" on Page 2?

Answer:

Sorry for this typo, the correction is:

In previous studies, 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][19][20]. The mean of gestation age at vaccination for mothers of controls, presented as $p \leq 0.2$ variables in the bivariate analysis selected, this variable 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]. But this step could help the statistical analysis for reducing this infectious disease as well.

(3) More justifications on the application of MADM into the classification of Pertussis vulnerable areas are suggested to be added.

Answer: Thank you for the suggestion to improve. This the improvement

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 Health Profile Book of East Java Province, Indonesia in 2011-2016 [22][23][24][25][26][27]. The multi-class classification was 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. 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 [28], 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 appropriate 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 popular decision problems [31][32].

(4) What is the support for the setting "PD3I rate (0.8), epidemic rate (0.6), population density (0.4), and nutrition status (0.2)" on Page 3? Please make clear the point.

Answer: Thank you for supporting us, and this is the clearance of the setting.

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] [35] [36].This process effectively helps to obtain preference values for decision-makers [37].

(5) More explanations on Table 1 are suggested to be added, to make clear the role of the contents in the table.

Answer: We added the explanations of the table 1.

The spatial datasets in Table 1 are used as data modeling in the spatial analysis process for the classification of 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] [23] [24] [25] [26] [27].

(6) The settings "The priority parameter for infant immunization status is 1 with a weight value of w = 1" and "the value of priority parameter PD3I is 2 with a weight value of w = 0.8, and the value level of importance is 1" should be well explained.

Answer: We added more detail explanation.

The categories in MADM are defined to show a structural relationship between several criteria given in order to show 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 [38][34].

(7) Please add more analysis and discussions on the results. It is not proper to just list the results.

(8) Some comparison with existing studies is suggested to be conducted, in order to highlight the advantage of the work.

Answer: Thank you for the suggestion, here we add some comparison of the previous works.

Location analytics was important for policy and decision making. Location analytics or spatial analysis has been applied in many case studies in the health and disease sector [21]–[23]. Eccles et al. study 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 spatio-temporal variation of immunization rates for measle, mump, and rubella [24]. Laohasiriwong et al. (2017) proposed a way to 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]. Further, Varathanajan et al. (2018) implement an integrated spatial data analysis that comprises implicit and explicit information. They study a method to identify an effective way to prevents and control of malaria using Inverse Distance Weighting (IDW), a deterministic method, for assigning weight values based on the locality [26]. Rivadeneira et al. (2018) proposed an approach to quantify socioeconomics inequalities associated with measles immunization coverage at the population level using multiple spatial regression and calculated. They calculated slope and relative index of inequalities and found clusters of vulnerable populations for outbreaks [27]. Hendry et al. proposed 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. But, 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, 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 [29]. This review paper becomes our system development reference.

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

(9) More up-to-date studies are suggested to be cited, such as "Hendry and Rung-Ching Chen, Predicting Business Category with Multi-Label Classification from User-Item Review and Business Data Based on K-means, ICIC Express Letters, vol.13, no.3, pp.255-262, 2019".

Answer: Thank you for the suggestion. We add one paragraph to cite this study.

Hendry et al. proposed 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[21].

(10) Some syntax errors or improper expressions exist, such as the "…can effectively preventing Pertussis" on Page 1, the "Multiple Attribute Decision Making (MADM) used as an alternative tool…" and the "The dataset is consists of…" on Page 2.

Answer: Thank you for your suggestion, we have rechecked the manuscript with tools (Grammarly) to find the syntax errors.. and we found more syntax errors. Syntax errors have been removed and edited.

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 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 membahas efektivitas Imunisasi pada Ibu selama kehamilan untuk mencegah Pertussis pada bayi usia <8 minggu, [avv1]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]. The mean of gestation age at vaccination for mothers of controls, presented as $p \leq 0.2$ variables in the bivariate analysis selected, this variable used for inclusion in the multivariable model [18]. [avv2]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 Health Profile Book of East Java Province, Indonesia 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. Epidemic dynamical model dengan vaksinasi pada bayi baru lahir yang rentan pada penyakit untuk menunjukkan a more complicated dynamic behavior system menggunakan the multistage Adomian decomposition method (MADM) [28], pada method ini memiliki karakteristik yang sama dengan Multiple Attribute Decision Making (MADM) yaitu menggunakan pengaruh dari beberapa nilai parameter penting untuk memodelkan sistem. Pemodelan data spasial pada penelitian ini menggunakan alternatif pada skala besar, sehingga MADM dipilih untuk menyelesaikannya. Proses MADM akan mengidentifikasi beberapa alternatif set untuk memudahkan alternatif terbaik yang dipilih, membagi alternatif pada skala besar menjadi beberapa kelompok, dan menentukan bobot atribut parameter, selanjutnya melakukan percobaan numerik dengan metode MADM yang dipilih [29]. MADM dapat digunakan untuk sistem pengambilan keputusan untuk individu atau kelompok, nilai bobot prioritas pada atribut dan sub-atribut nya yang didasarkan pada pengalaman atau pengetahuan seorang pakar yang digunakan untuk memberikan peringkat alternatif keputusan [30]. Metode WSM dan WPM dipilih pada penelitian ini karena memiliki karanteristik kriteria untuk memecahkan masalah keputusan yang populer dengan hasil yang terbaik [31][32].[avv3]

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 [33].

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. Spatial datasets pada Tabel 1 digunakan sebagai pemodelan data dalam proses analisa spasial untuk classification of pertussis vulnerable area. Sumber Kepakaran untuk menentukan attribute dataset, priority value, indicator (annually), range, and level of importance diperoleh dari Bidang Pencegahan dan Pengendalian Penyakit Dinas Kesehatan provinsi Jawa Timur, Indonesia. Cakupan data bersumber dari the Health Profile Book of East Java Province, Indonesia in 2011-2016 [22][23][24][25][26][27][avv4].

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. Pembobotan pada setiap parameter menggunakan proses fuzzification, mendefinisikan indikator set fuzzy untuk memberikan bobot yang menjelaskan level pada tingkat kepentingan parameter untuk digunakan pada proses hasil klasifikasi [34][35][36], proses ini akan secara efektif mendapatkan nilai preferensi bagi para pengambil keputusan [37].[avv5] Kategori dalam MADM dijelaskan untuk menunjukkan hubungan struktural antar beberapa kriteria yang diberikan untuk menunjukkan hubungan yang sangat dekat dengan skala prioritas kriteria parameter [38]. Nilai bobot pada setiap parameter pada spatial datasets diberikan untuk menentukan tingkat pengaruh atau kepentingan attribute datasets terhadap alternatif yang dihasilkan [38] [34][avv6].

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

Attribute Datasets	Priority Value	Weight	Categories (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

Attribute Datasets	Priority Value	Weight	Categories (annually)	Range	Level of importance
			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 $people/km^2$, 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 ≥ 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 [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 [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.

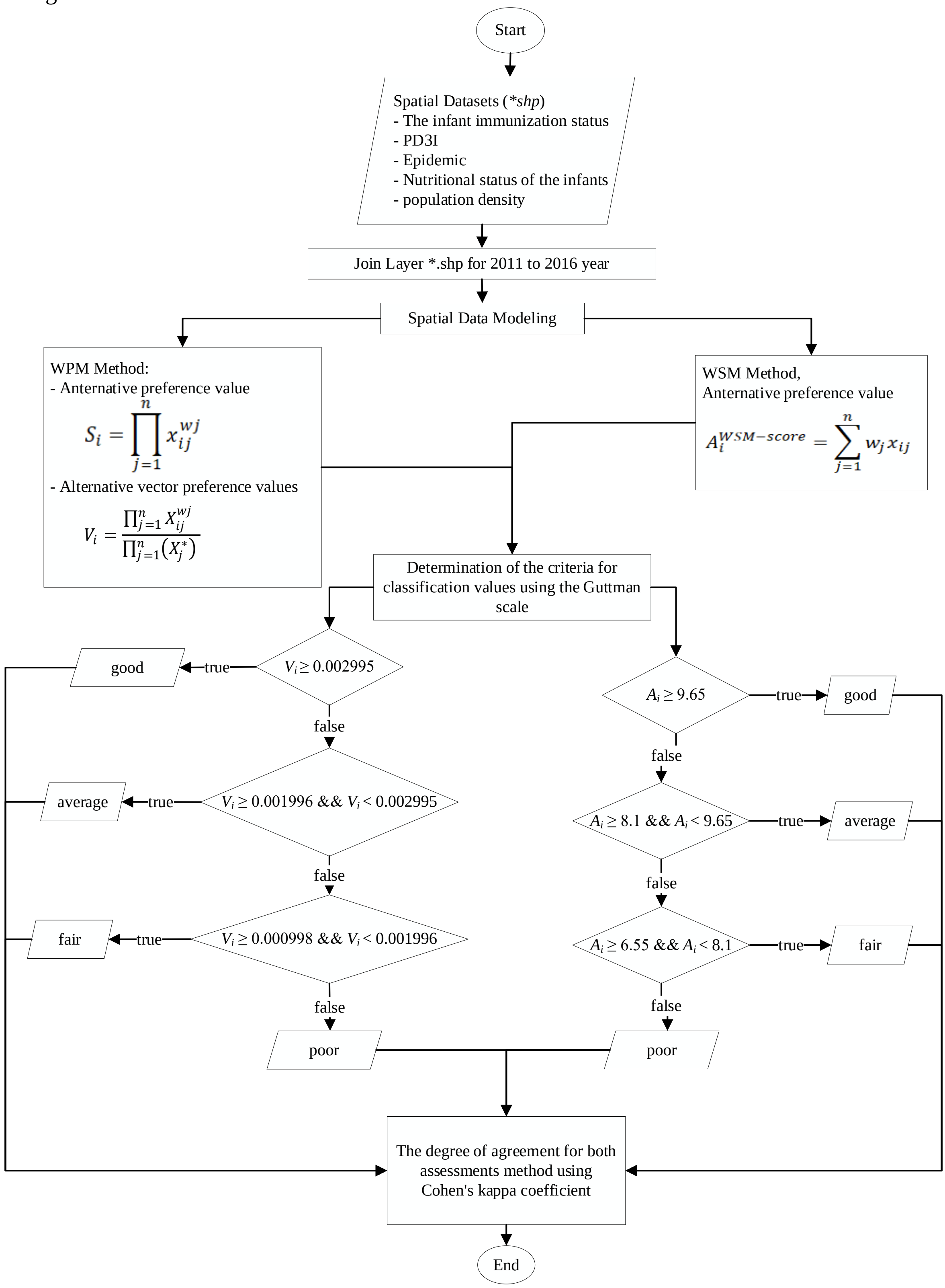

Figure 1. Flowchart of Location Analytics with WPM and WSM Method

In the initial step on 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, 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. urther, 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.

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 generally implemented for discrete domain decision making, where limited alternative decision support systems were determined [44][45], while MODM 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 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) [48].

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

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 [48]. The Max function is used to rank alternative decisions that the most significant score alternatives placed at the top [49]. 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 [48]. 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) [48][47].

$$S_i = \prod_{j=1}^{n} x_{ij}^{wj} \qquad (2)$$

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.

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

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 $Tbpre = Bpre_a + Bpre_b + \ldots n$. 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 $V_s = S_a x S_b x \ldots n$. Calculating the total vector on variable *V* or Tv_s by adding up all the values of V_s, with $Tv_s = V_1 + V_2 + V_3 + \ldots + V_n$, 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 [50]. 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 [51][52][53]. 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 [52] in Eq. (4).

$$I = \frac{R}{K} \quad (4)$$

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) [54].

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

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 [54]: 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 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

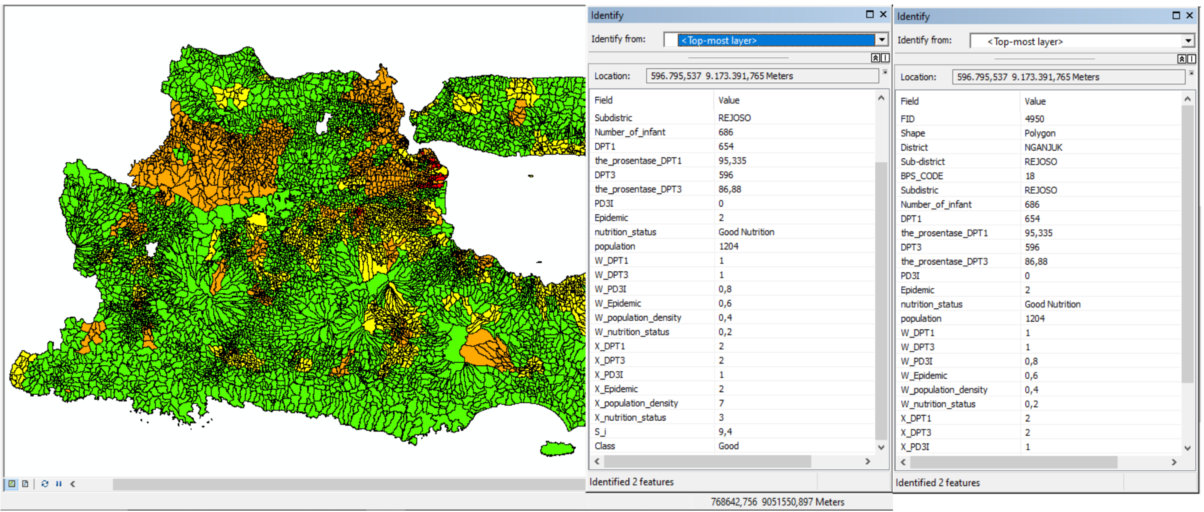

Figure *3* explains the results using the WSM method.

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

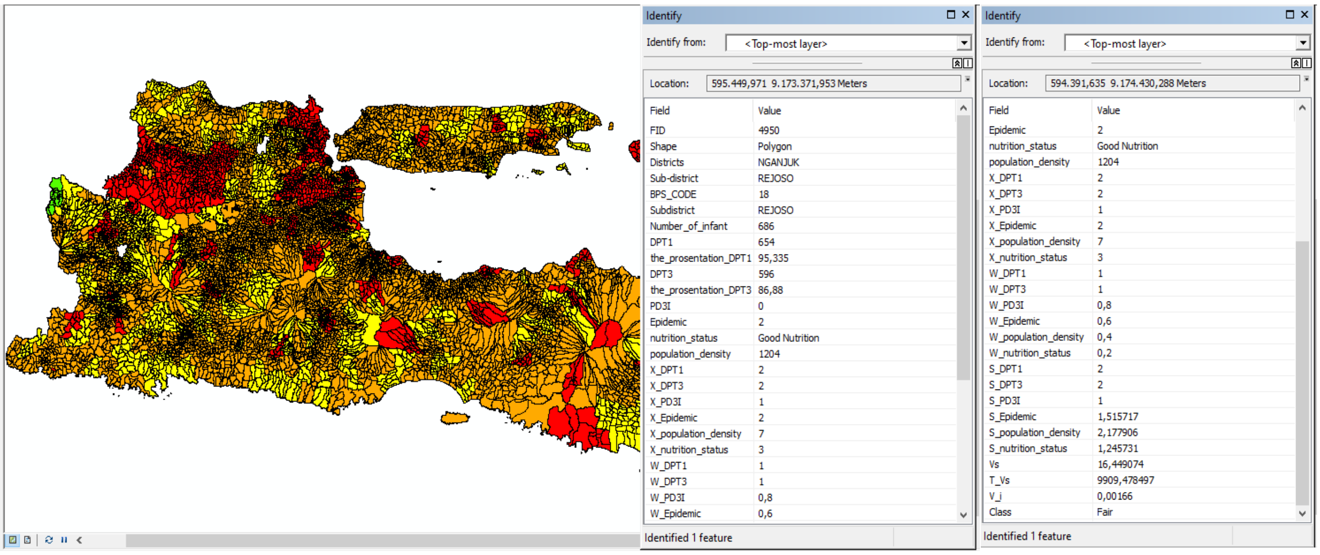

Figure 2. The WPM classification results in East Java map

The sample test Figure 2 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 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 shows the alternative values (V_i) result of the 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. Figure 4 and Figure 5 show the classification results percentage of the WPM and WSM methods, respectively.

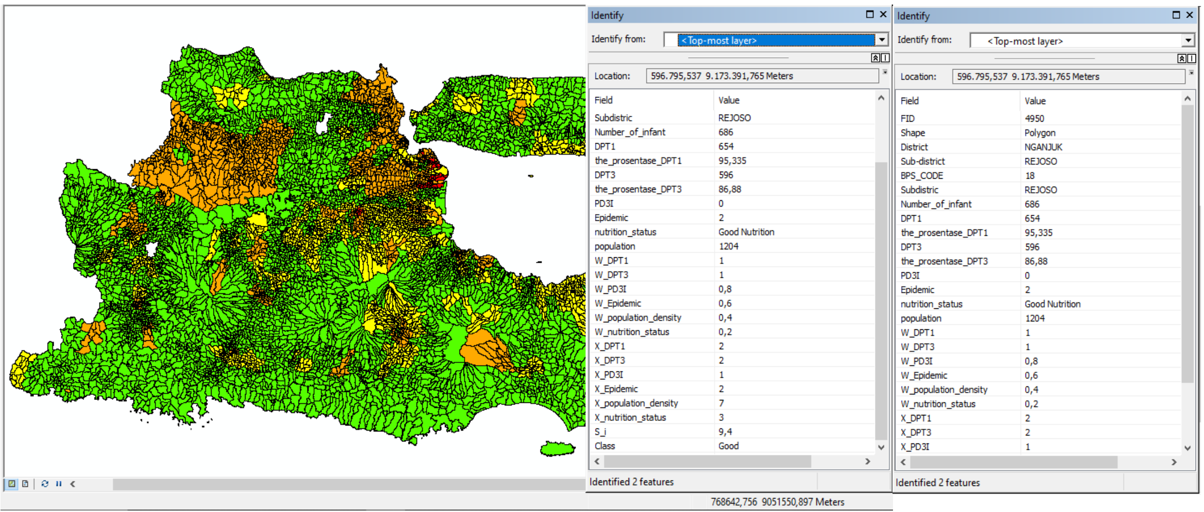

Figure 3. The WSM classification results in East Java map

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

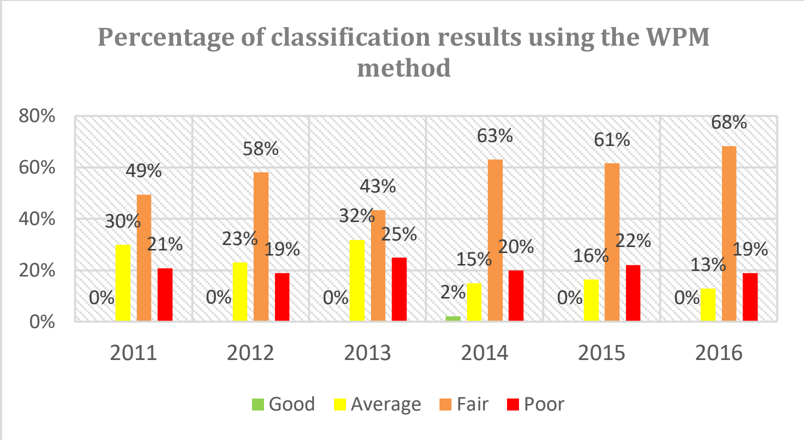

Figure 4. Percentage of classification results using the WPM method

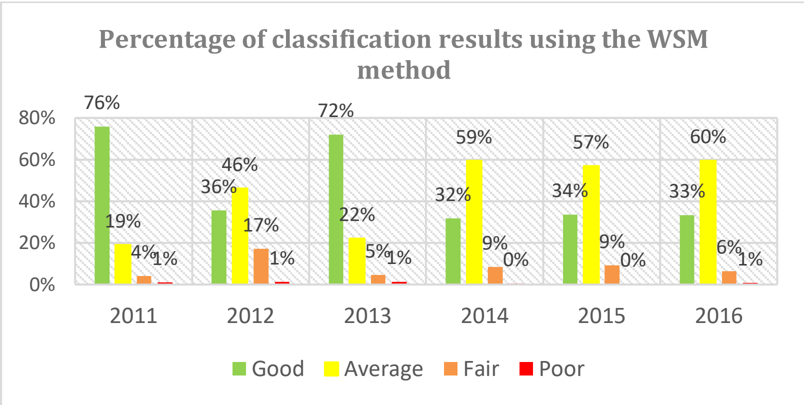

Figure 5.Percentage of classification results using the WSM method

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 the 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 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.

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
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 [55]. 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 [55]. 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 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 [48]. 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 [56].

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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 for the determination of 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 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 was 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 treatment at six weeks of age using whole-cell Pertussis (wP) or Pertussis (aP) acellular vaccine can effectively prevent 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 are 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 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][19][20]. The mean of gestation age at vaccination for mothers of controls presented as $p \leq 0.2$ variables in the bivariate analysis selected, this variable 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]. But this step could help the statistical analysis for reducing this infectious disease as well.

Location analytics was important for policy and decision making. Location analytics or spatial analysis has been applied in many case studies in the health and disease sector [21]–[23]. Eccles et al. study 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 spatio-temporal variation of immunization rates for measles, mump, and rubella [24]. Laohasiriwong et al. (2017) proposed a way of 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].

Further, Varathanajan et al. (2018) implement an integrated spatial data analysis that comprises implicit and explicit information. They study a method to identify an effective way to prevents and control of malaria using Inverse Distance Weighting (IDW), a deterministic method, for assigning weight values based on the locality [26]. Rivadeneira et al. (2018) proposed an approach to quantify 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 et al. 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. But, 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, 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 [29]. This review paper becomes our system development reference.

However, the previous research did not use the approach and parameters proposed in this paper, that is, with a multiple attribute approach to explore the need for supporting factors in the analysis process and interview experts in the field of 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][31][32][33][34][35]. The multi-class classification was 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. 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 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 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 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 [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 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 data modeling in the spatial analysis process for the classification of 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] [23] [24] [25] [26] [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] [35] [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 [38][34].

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

Attribute Datasets	**Priority Value**	**Weight**	**Categories (annually)**	**Range**	**Level of importance**
The infant immunization status (DPT immunization)	1	1	Target reached	DPT $\geq$ 84.5%	2
			Not reaching the target	DPT < 84.5%	1
PD3I Rate	2	0.8	Yes, if a region occurs PD3I $\geq$12 in a year, then the area is determined as a PD3I area	PD3I $\geq$ 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 $\geq$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	Categories (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 [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][31][32][33][34][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 on 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, 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.

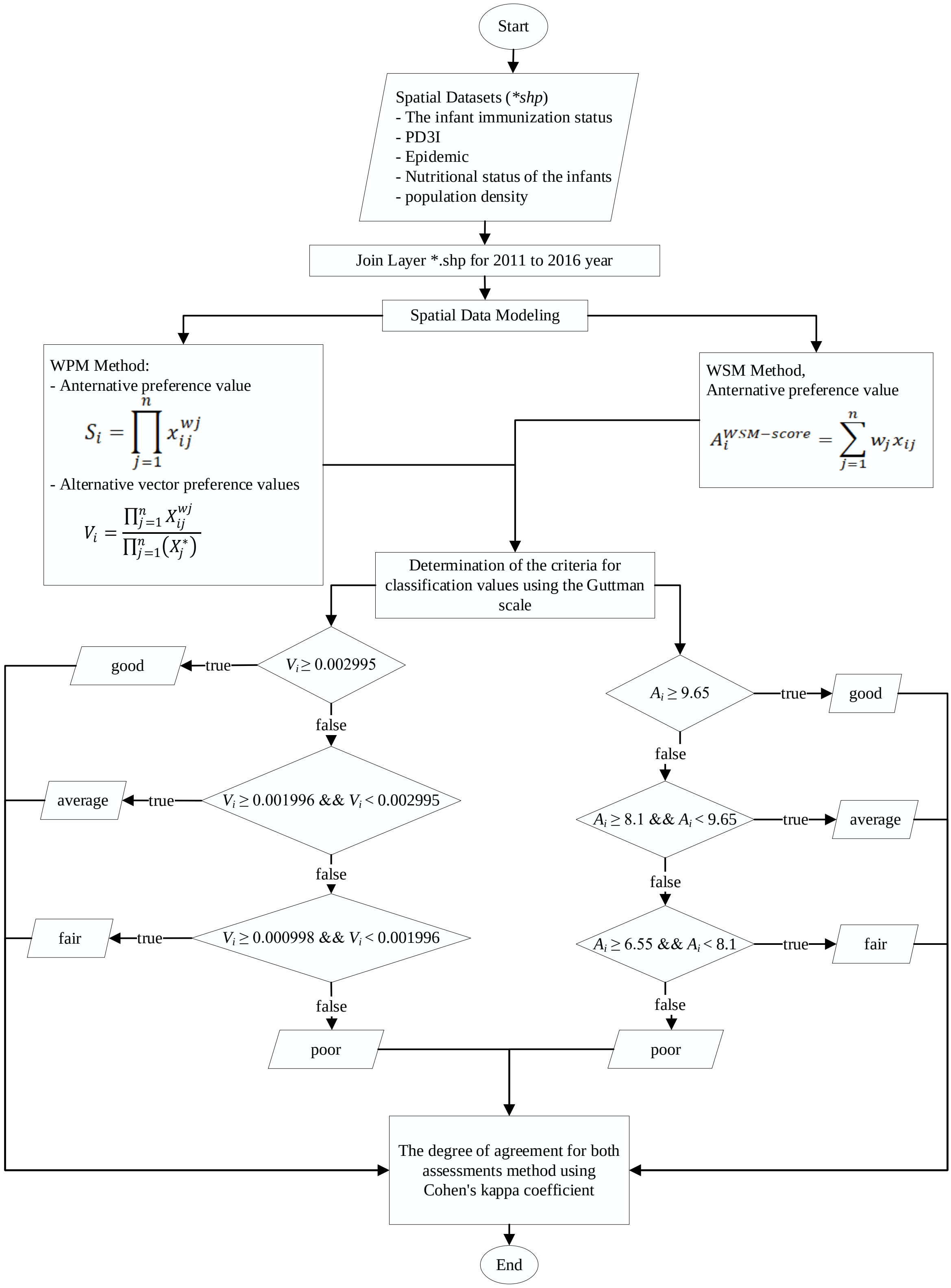

Figure 1. Flowchart of Location Analytics with WPM and WSM Method

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) [39][42][43]. MADM method generally implemented for discrete domain decision making, where limited alternative decision support systems were determined [44][45], while MODM 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) [48].

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

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 [48]. The Max function is used to rank alternative decisions that the most significant score alternatives are placed at the top [49]. 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 [48]. 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) [48][47].

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

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.

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

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 $Tbpre=Bpre_a+Bpre_b+\dots n$. 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 $V_s=S_a x S_b\ x\dots n$. The calculate 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 [50]. In this paper, The Guttman scale is 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 [51][52][53]. 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 [52] 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 is used for qualitative data based on Eq. (5) [54].

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

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 [54]: if the value 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 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 [30][31][32][33][34][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

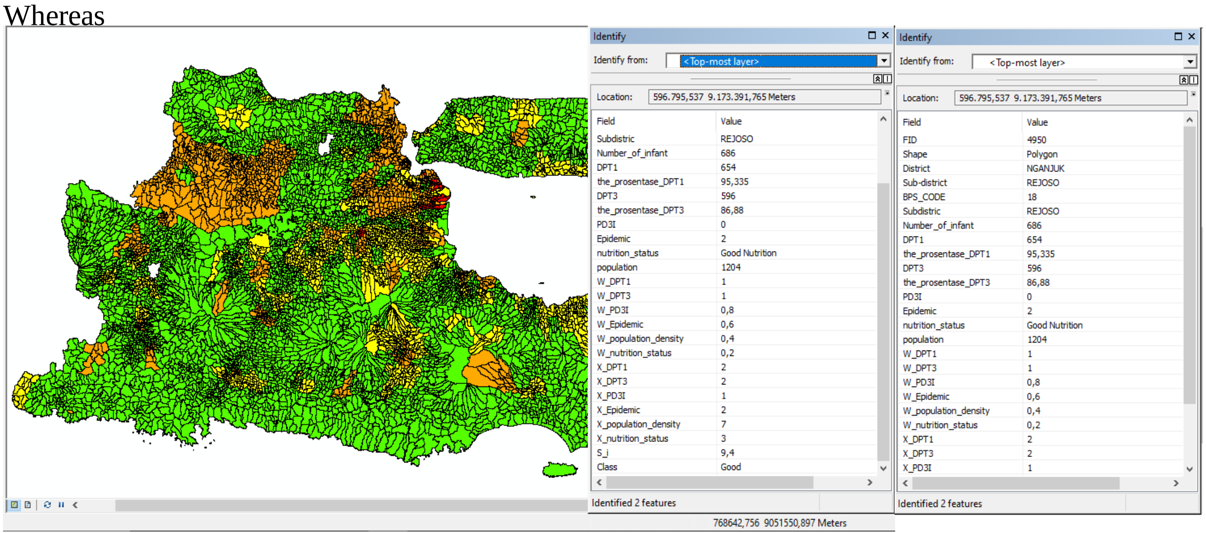

Figure 3 explains the results using the WSM method.

The results of the classification by the WPM and WSM methods are calculated using the Guttman Scale in eq 4, proses the results of guttman scale assessment pada Tabel 2 digunakan untuk mengetahui range nilai akurasi pertussis vulnerable area dengan hasil pada (6) and (7) . 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). Nilai range hasil klasifikasi pada eq (6) and (7) dapat digunakan sebagai policy makers untuk penelitian lanjutan pada bidang analisa spasial classification of pertussis vulnerable area. Data time series pada tahun berikutnya dapat dilakukan pengujian dengan menggunakan range nilai tersebut.

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

$$\begin{cases} good, if\ A_i \geq 9.65 \\ average, if\ A_i \geq 8.1\ and\ V_i < 9.65 \\ fair, if\ A_i \geq 6.55\ and\ V_i < 8.1 \\ poor, if\ A_i < 6.55 \end{cases} \quad (7)$$

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 Figure 2 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.

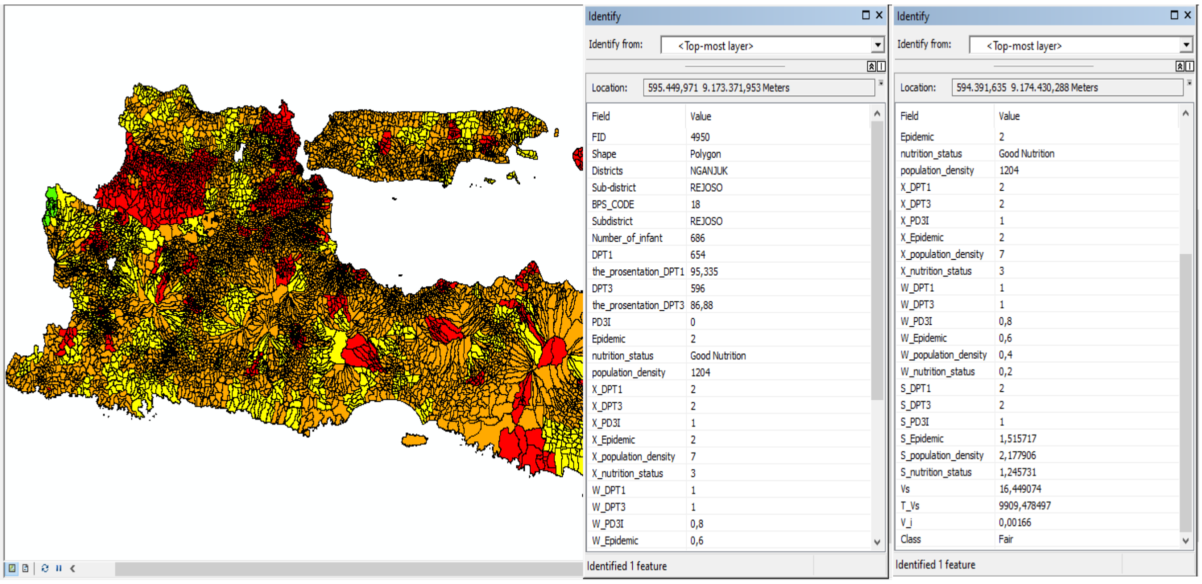

Figure 2. The WPM classification results in East Java map

Figure 3 depicts the alternative preference value (S_i) result from the WPM method based on eq. (2) by multiplying all results from the value of x power of w, resulting S_{DPT1}, S_{DPT3}, S_{PD3I}, $S_{epidemic}$, $S_{population\text{-}density}$, and $S_{nutrition\text{-}status}$ 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 shows the alternative values (V_i) result of the 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. Figure 4 and Figure 5 show the classification results percentage of the WPM and WSM methods, respectively.

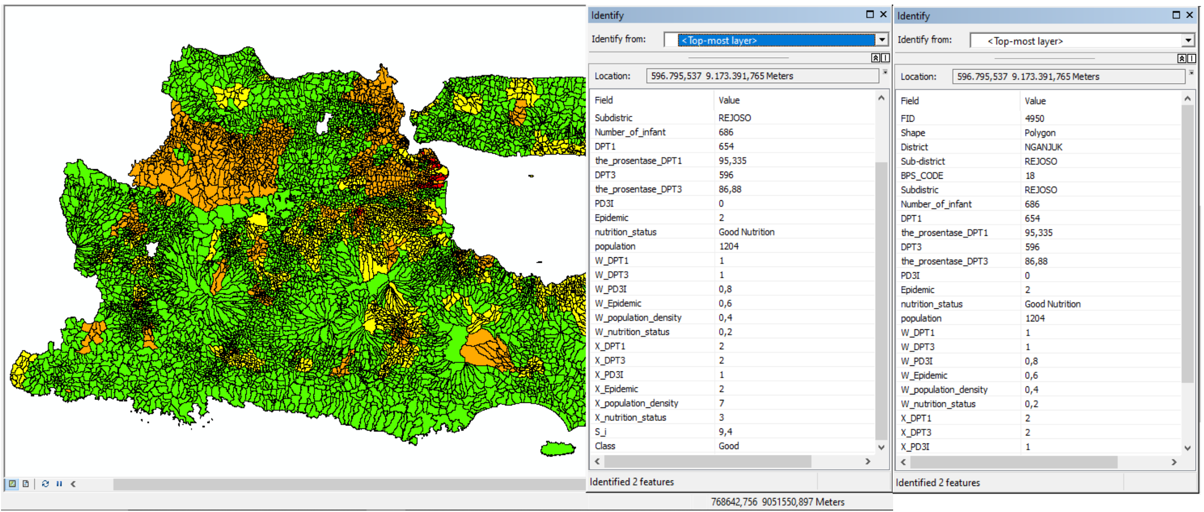

Figure 3. The WSM classification results in East Java map

Hasil keseluruhan proses Analisa spasial menggunakan data time series tahun 2011-2016 from the Health Profile Book of East Java Province, Indonesia [22] [23] [24] [25] [26] [27], pengolahan data spasial dengan metode WPM dengan cakupan hasil pada Tabel 3, dan Tabel 4 merupakan cakupan hasil Analisa spasial dengan metode WSM. Nilai kriteria parameter didapatkan dari variabel cost dan benefit, nilai ini akan sangat mempengaruhi proses keputusan alternatif hasil klasifikasi pada Gambar 2, dan Gambar 3 .

The WSM method on the Table 4, and Figure 5 had classification results based on the Good immunization status category percentage better than the WPM on the 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

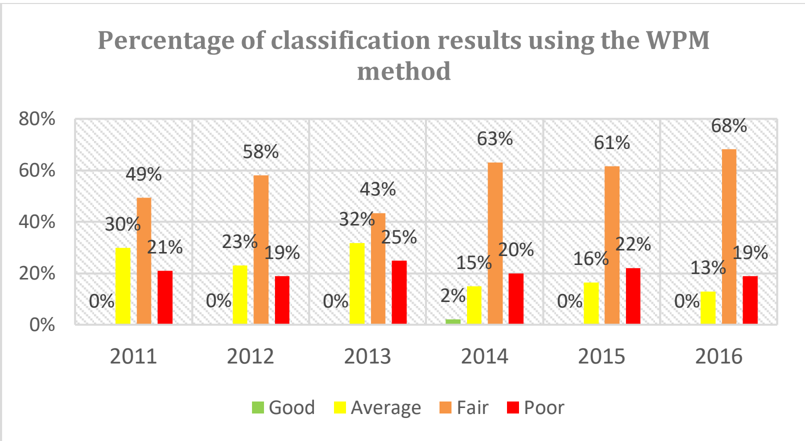

Figure 4. Percentage of classification results using the WPM method

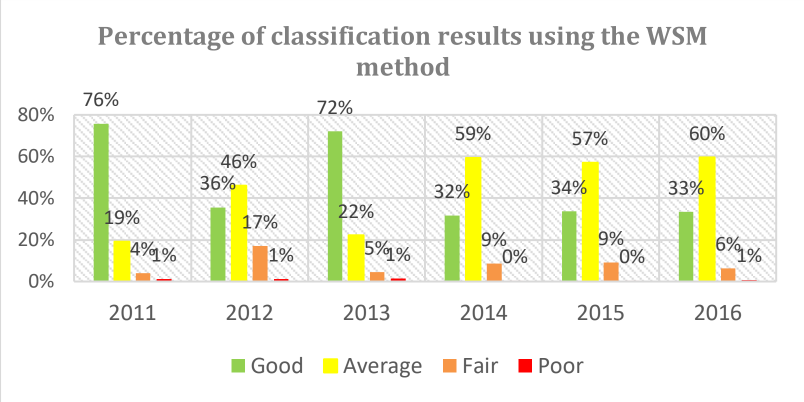

Figure 5.Percentage of classification results using the WSM method

Method Consistency Test (MCT) is performed on the WPM and WSM methods by calculating Cohen's kappa coefficient (κ) from eq. (4) to measure the strength of agreement dengan hasil pada Table 5. Nilai Tabel 5 digunakan untuk mengetahui hasil kedekatan kedua metode yang digunakan dan antar atribut parameter dengan menilai kesesuaian pada hasil pemodelan data spasial. 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 the 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 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.

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
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 [55]. 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 [55]. 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 technique with maximum accuracy [48]. 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 [56].

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发件人： "Irya Wisnubhadra, S.T.,M.T."<irya.wisnubhadra@uajy.ac.id>

发送时间： 2020年10月23 星期五 17:03

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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

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 Pertussis (aP) acellular vaccine can effectively prevent 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 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][19][20]. The mean of gestation age at vaccination for mothers of controls presented as $p \leq 0.2$ variables in the selected bivariate analysis, this variable 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]. But 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 et al. study 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, Varathanajan et al. implement an integrated spatial data analysis that comprises implicit and explicit information. They study a method to identify an effective way to prevents 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 et al. 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. But, 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][31][32][33][34][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 or equal to 0.002995, the average categories for amounts larger or equal to 0.001996 and smaller than 0.002995, the fair categories for amounts larger 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 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 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] [23] [24] [25] [26] [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] [35] [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 [38][34].

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 ≥ 84.5%	2
			Not reaching the target	DPT < 84.5%	1
PD3I Rate	2	0.8	Yes, if the cases occur PD3I ≥12 in a year, then the area is determined as a PD3I area	PD3I ≥ 12 cases per year	2
			No, if the cases occur 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 ≥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

Attribute Datasets	Priority Value	Weight	Categories (annually)	Range	Level of importance
			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 ≥ 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 [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][31][32][33][34][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 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.

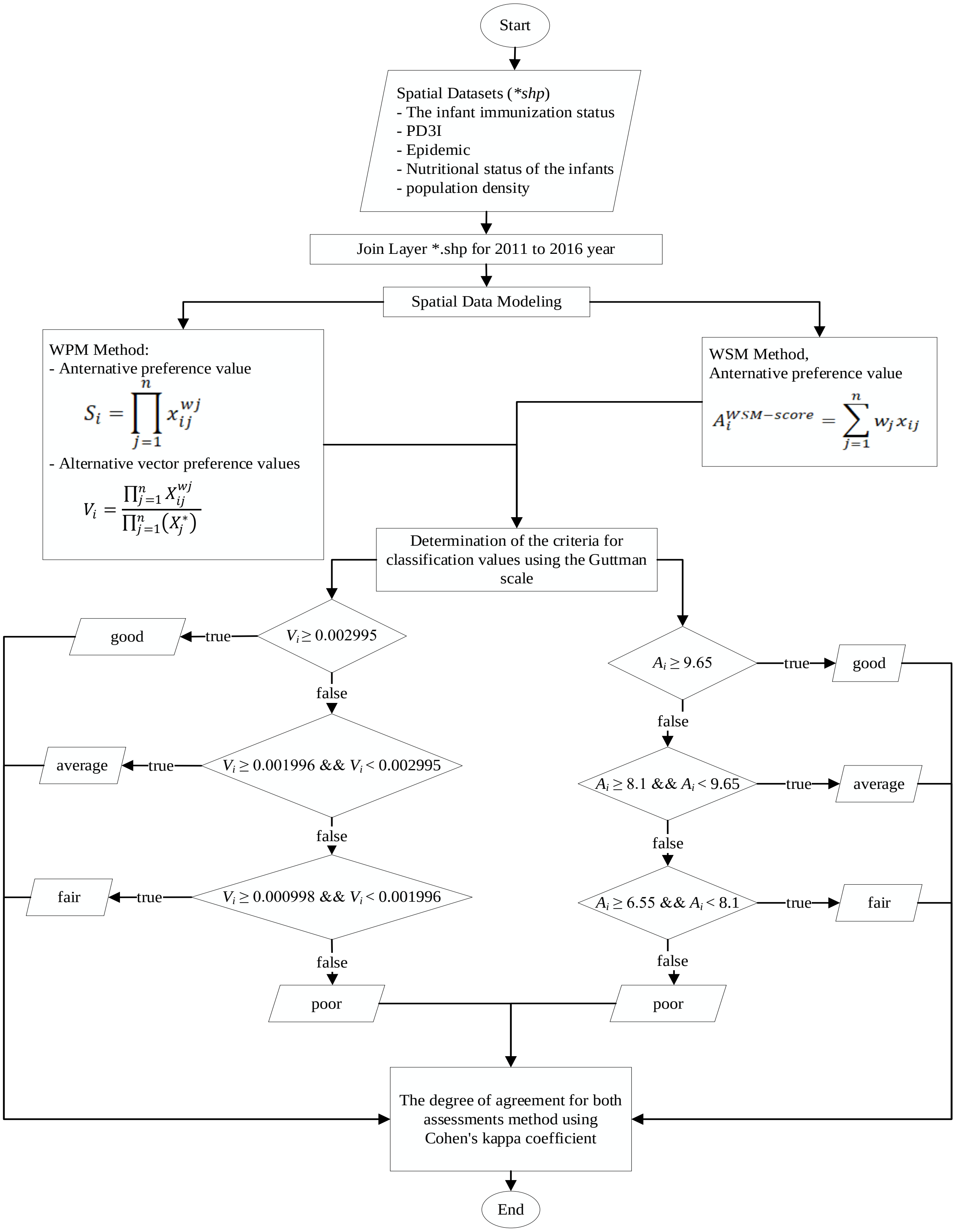

FIGURE 1. Flowchart of Location Analytics with WPM and WSM Method

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) [39][42][43]. MADM method generally implemented for discrete domain decision making, where limited alternative decision support systems were determined [44][45], while MODM 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) [48].

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

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.

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 [48]. The Max function is used to rank alternative decisions that the most significant score alternatives are placed at the top [49]. 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 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 [48]. 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) [48][47].

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

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.

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

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 $Tbpre=Bpre_a+Bpre_b+...n$. 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 $V_s=S_a x S_b x...n$. The calculate the total vector on variable V or Tv_s by adding up all the values of V_s, with $Tv_s=V_1+V_2+V_3+...+V_n$, 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 [50]. 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 [51][52][53]. 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 [52] 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 is used for qualitative data based on Eq. (5) [54].

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

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 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 [54]: 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][31][32][33][34][35]. **Error! Reference source not found.** 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 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 eq. (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 eq. (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 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).

Policymakers can use the range of classification results in eq. (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.

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

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

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 results of the classification of MADM using the WSM, and WPM method in Figures 2, 3, respectively, using a sample test in Rejoso District, Nganjuk Regency, East Java Province, Indonesia. Nilai 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 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 eq. (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 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 2, which is the value of Vs_i divided by the value of Tv_s variable. The classification results state that the area belongs to the fair category of pertussis disease (Table 2, eq. (7)).

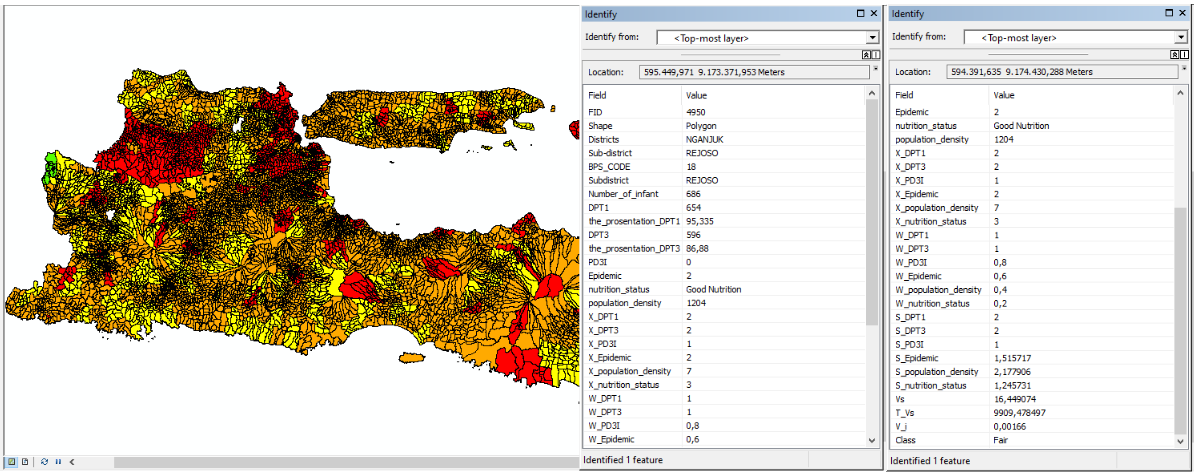

FIGURE 2. The WPM classification results in the East Java map

Figure 3 shows the alternative values (A_i) result of the WSM method based on eq. (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 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 classification of pertussis vulnerable areas by the WPM method and the WSM method, respectively. **Error! Reference source not found.** and **Error! Reference source not found.** show the classification results percentage of the WPM and WSM methods, respectively.

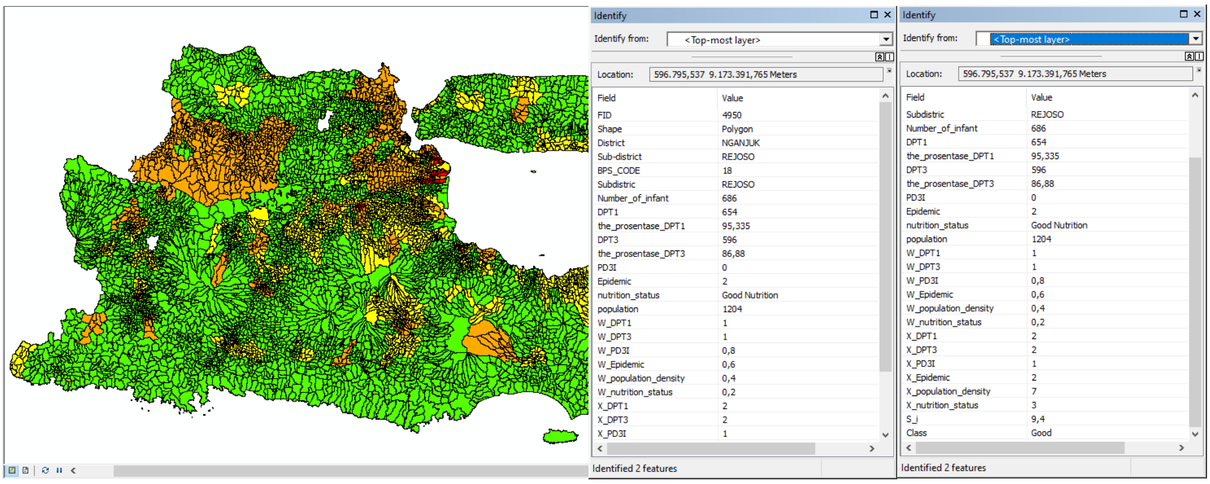

FIGURE 3. The WSM classification results in East Java map

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

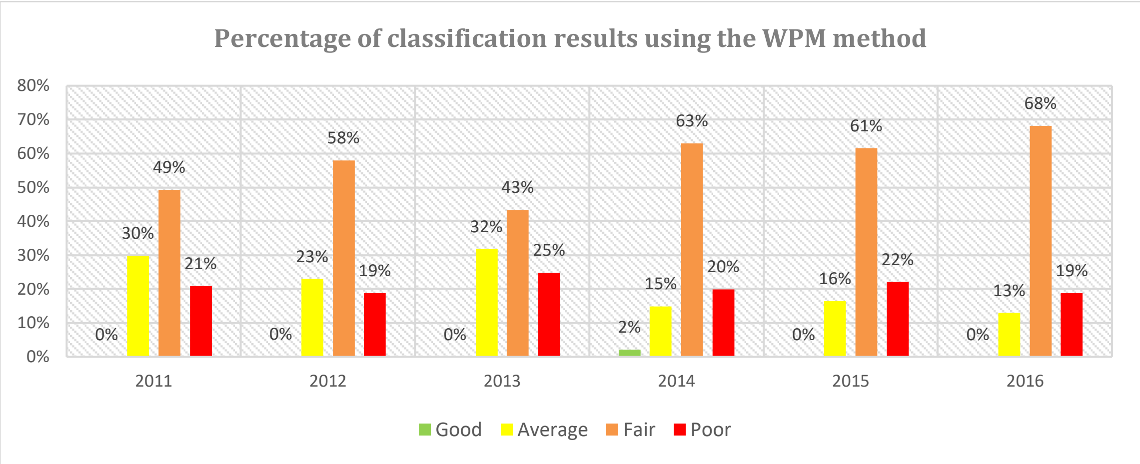

FIGURE 4. Percentage of classification results using the WPM method

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

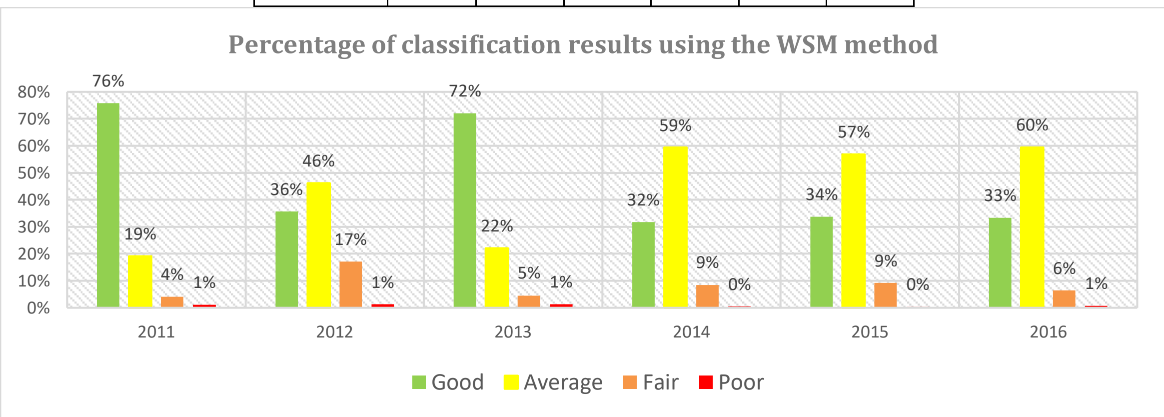

FIGURE 5.Percentage of classification results using the WSM method

Method Consistency Test (MCT) is performed on the WPM and WSM methods by calculating Cohen's kappa coefficient (κ) from eq. (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.

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

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 [55]. 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 [55]. 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 [48]. 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 [56].

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